Gambling Behavior of Private Investors in Financial Markets: A Comprehensive Empirical Analysis

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List of Abbreviations

CAPM .... Capital Asset Pricing Model

CRSP .... Center for Research in Security Prices

ed. .... Edition

Ed. .... Editor

Eds. .... Editors

et al. .... et alii (and others)

ESG .... Environmental, Social, and Governance

ESMA .... European Securities and Markets Authority

ETC .... Exchange Traded Commodity

ETF .... Exchange Traded Fund

ETN .... Exchange Traded Note

ETP .... Exchange Traded Product

EU .... European Union

e.g. .... exempli gratia (for example)

HCMC .... Hellenic Capital Markets Commission

ICO .... Initial Coin Offering

IPO .... Initial Public Offering

ISIN .... International Security Identification Number

i.e. .... id est (in other words)

KFDL .... Kenneth French Data Library

MLB .... Major League Baseball

NFL .... National Football League

p. .... page

pp. .... pages

RDSC .... Research Data and Service Centre

SD .... Standard Deviation

SHS .... Securities Holdings Statistics

US .... United States (of America)

w/o .... without

1 Introduction

1.1 Motivation and Research Questions

Standard finance[1] assumes that all individuals are represented by rational agents[2]. These agents all invest in the same diversified portfolio known as the market portfolio.[3] Those predictions are challenged by a comprehensive body of empirical literature showing that investors do not invest as suggested by this normative approach[4], but rather exhibit preferences for certain categories of assets.[5] These assets include lottery-like stocks.[6]

Furthermore, rational agents do not buy lottery tickets or participate in casino gambling as these resemble negative sum games.[7] Yet, the global prevalence of (state-run) lotteries[8] and the casino industry[9], as well as the more recent emergence and growth of online sports betting vendors[10], suggest that (some) investors are more than willing to participate in gambling.

When replacing rational agents with real people[11], gambling matters. This dissertation studies the gambling behavior of private investors in financial markets by applying comprehensive empirical analyses. The distinct contributions of this dissertation are elaborated in the rest of this section.

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[1] Standard finance is a synonym used to describe the theoretical framework (i.e paradigm) of neoclassical finance (see Ackert 2014, Baker and Nofsinger 2010, Campbell 2006, Statman 2014). In this context, the term traditional finance is likewise commonly used (see Ackert 2014, Baker and Nofsinger 2010, Bloomfield 2010, Statman 2014).
[2] Rational agents are discussed in *Section 2.1*.
[3] The concept of the market portfolio originates from theoretical work by Markowitz (1952a) and Tobin (1958) that is used by Sharpe (1964), Lintner (1965), and Mossin (1966) to establish an asset pricing model. For a more detailed review see *Section 2.1*.
[4] In the context of a normative scientific approach in economics / finance, Campbell (2006, p. 1554) notes the following: “Research in finance, as in other parts of economics, can be positive or normative. Positive research describes what economic agents actually do, while normative research prescribes what they should do.”. See also Morgenstern (1972) and Oehler (1992), (1995) for a discussion of the normative approach (regarding decision theory) in economics and finance.
[5] Inter alia, these preferences express themselves in an overinvestment in domestic stocks (see French and Poterba 1991, Oehler et al. 2008), stocks with high levels of volatility (see Dorn and Huberman 2010), low-priced stocks (see Kumar and Lee 2006), and stocks that pay (high) dividends (see Graham and Kumar 2006).
[6] In this dissertation, lottery-like stocks are defined in accrodance with Kumar (2009) and Bali et al. (2011).
[7] See *Section 3.2* for a brief discussion of negative sum games.
[8] See *Section 3.1* for a brief discussion of (state-run) lotteries.
[9] See Eadington (1999), Barberis (2012), and Prentice et al. (2017).
[10] As bookmakers keep some of the funds collected from bettors as compensation for their service (i.e. profit), as with lotteries and casino games, sports betting resembles a negative sum game (see Cain et al. 2003, Elaad et al. 2020).
[11] See, inter alia, Statman (2005), (2014) for the differentiation between rational and normal investors.

Within the area of financial market gambling, this dissertation has three focal points. First, the holding preferences of private investors for stocks with lottery features[12] are assessed in an attempt to replicate and extend previous research.[13] Second, after studying the preferences of private investors for stocks with lottery features, the conducted research focalizes on social trading[14], a financial innovation – made possible by digitalization – that allows private investors to act as asset managers for other private investors. In the context of social trading, the transactions with lottery assets (i.e. stocks and currency pairs with lottery features) of those private investors acting as asset managers are analyzed. Third, building on existing behavioral research describing how private investors evaluate their portfolios[15], a variety of portfolios that include returns from different forms of gambling, that is an investment in stocks with lottery features and sports betting, are analyzed. From those focal points, the following three primary aims are derived:

- To assess the preferences of the German private sector for stocks with lottery features.
- Given the design features of social trading, to study the factors that induce signal providers to trade lottery assets.
- To model and compare realistic multi-layer portfolios with a speculative high aspiration layer that is used for gambling.

As initially shown by Kumar (2009) and Bali et al. (2011), private investors exhibit preferences for stocks with lottery features. The majority of existing research assessing lottery-like stocks focuses on the US and correspondingly the preferences of US private investors – research regarding countries other than the US is rare. Furthermore, existing studies have relied on discount brokerage data to examine private investors' holdings regarding lottery-like stocks.[16] Dorn and Sengmueller (2009) provide evidence that investors who use discount brokers (partly) consider trading as entertainment and thus engage in it excessively. Dorn et al. (2015) provide

[12] Stocks with lottery features (or lottery characteristics) are likewise labeled as lottery or lottery-like stocks (see Kumar 2009).
[13] The foundation for the analyses conducted in this dissertation is provided by Kumar (2009) and Bali et al. (2011); many subsequent studies have since addressed stocks with lottery features. For a detailed literature review see *Section 3.4.1*.
[14] Social trading is sometimes referred to as copy trading; see *Section 3.4.3* for a detailed literature review.
[15] See, inter alia, Oehler (1995) and Shefrin and Statman (2000) for a discussion with regard to a multi-layer portfolio approach.
[16] See, for example, Kumar (2009), Han and Kumar (2013), and Meng and Pantzalis (2018).

further evidence that the clients of discount brokers substitute between participating in lottery games and financial market gambling. Hence, investors who access the stock market via discount brokers may use stocks to gamble.[17] In contrast, investors holding stocks via the deposit account of their house bank (i.e. retail broker) may follow a rather passive buy-and-hold approach that involves stocks for which lottery-like characteristics are less common. Since discount brokerage data, as applied in other studies, only capture a fraction of all investor holdings, the results of previous studies may potentially be biased. This issue, however, can be tackled by applying a database that captures the aggregate holdings of a country's entire private sector – such a database is collected and provided by the German central bank's (*Deutsche Bundesbank*) *Securities Holdings Statistics* (*SHS*).[18] Moreover, regarding lottery-like characteristics, most studies focus on investors' preferences for domestic stocks; however, respective preferences for foreign stocks may be substantially different. Since the analyses conducted in this dissertation consider German private investors' preferences for German (domestic) as well as US (foreign) stocks, a comparison between domestic and foreign preferences regarding holdings is possible. Considering those gaps in the existing literature, the first part of the empirical analyses in this dissertation focuses on the following research questions:

RQ1: Do German private investors, on an aggregate level, display preferences for lottery-like stocks?

RQ2: Are there certain lottery characteristics that drive an aggregate overinvestment of German private investors?

Social trading involves a distinction between signal providers and signal followers. Regarding signal providers, social trading platforms enable visibility and traceability, i.e. trading strategy specifications, conducted transactions, and resulting returns are published. Platform users can freely access this information and subsequently subscribe to one or several signal providers. By delegating their investment decisions to another (mostly non-professional) trader, platform users become signal followers. Social trading involves severe asymmetries regarding the distribution of economic consequences between signal providers and signal followers. When an administered portfolio performs well, the corresponding signal provider is remunerated via

[17] See Statman (2002) and Barberis and Huang (2008).
[18] See *Section 4.2.2*.

performance fees. Furthermore, portfolios with good past performance are placed at the top of the platforms' selection lists and thus generate attention – the increased attention leading to higher inflows and, in consequence, a continued eligibility for remuneration.[19] On the other hand, a failing portfolio barely bears any (monetary) consequences for the signal provider.[20] Considering these asymmetries, signal providers are exposed to a range of incentives which, in different contexts, have been shown to impact trading behavior. As elaborated by Carpenter (2000), portfolio managers face option-like (or convex) incentives, and thus may be led to increase risk after performing poorly.[21] Furthermore, even though signal provider compensation may not be directly linked to a corresponding ranking, social trading compensation schemes indirectly impose tournament incentives as administered accounts have to occupy a position reasonably suited for generating attention from followers.[22] Motivated by the present asymmetries, it is assessed whether signal provider transactions involving stocks which exhibit lottery characteristics are driven by the relative past performance of their corresponding operated portfolios. By trading lottery-like stocks, signal providers would expose their (perhaps unknowing) followers to a lottery-like return structure, i.e. trigger gambling. Based on these considerations, the second part of the conducted empirical analyses addresses the following research question:

RQ3: Are signal provider transactions with lottery-like stocks driven by the prior peer performance?

While there is ample evidence that certain stocks may be perceived and employed by (individual) investors as lotteries, currency pairs seem to have been overlooked as a potential gambling instrument by existing research.[23] The foreign exchange market, however, may be particularly suited for private investor gambling; as this market offers substantially fewer feasible choices in comparison to international equity markets, private investors may be able to assess the full range of available

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[19] See Röder and Walter (2019) for evidence on the flow-performance relationship in social trading.
[20] See *Section 4.2.3* and *Section 4.2.4*.
[21] A detailed discussion with regard to the incentives of portfolio managers in a principal-agent framework is provided in *Section 2.2*. In the context of social trading, evidence that signal providers face convex incentives and thus increase risk when approaching their high watermark is provided by Doering and Jonen (2018).
[22] In the presence of tournament incentives, there is empirical evidence that risk-taking is increased by underperforming traders (see Kirchler et al. 2018). See *Section 3.4.3* for a discussion regarding tournament incentives in social trading.
[23] Financial market gambling instruments are discussed in *Section 3.4*.

investment opportunities. That is, the selection range of foreign exchange products is unlikely to stress the cognitive capacity of private investors[24], therefore gambling opportunities, i.e. investments involving lottery features, may be easily identified. In addition, due to the complex nature of currency price developments, the foreign exchange market exhibits particularly speculative qualities which offer a convenient framework for gambling. Choosing a social trading platform primarily offering foreign exchange trading – previously discussed asymmetries between signal providers and signal followers apply – it is assessed whether the transactions involving currency pairs with lottery characteristics are impacted by the relative past performance of signal providers. In this regard, the third part of the empirical analyses in this dissertation addresses the following research question:

RQ4: Are signal provider transactions with lottery-like currencies driven by the prior peer performance?

Since its introduction by Oehler (1995) and Shefrin and Statman (2000), the multi-layer portfolio framework has been widely discussed.[25] Building on the existing research, realistic two-layer portfolios are constructed. It is assume that investors use the main part of their available funds for long-term oriented capital accumulation in a basic (low aspiration) portfolio layer; in addition, a minor share of existing funds, that is the high aspiration layer, is used for gambling.[26] Previous studies have highlighted preferences of individual investors with regard to stocks with lottery-characteristics.[27] Furthermore, there is a substantial body of research discussing the popularity of sports betting, a form of gambling that has become a wide-spread and commonly accepted leisure activity.[28] Therefore, constructing portfolios where the high aspiration layer is either represented by an investment in lottery-like stocks, or by returns from different sports betting approaches, may present a functional approximation with regard to real-world private investor portfolios. Thus, the last empirical analysis in this dissertation addresses the following research question:

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[24] For a discussion on limits with regard to the cognitive capacities of private investors see Kahneman (1973), Oehler (1992), (1995), (2013a), (2013d), and Shiller (1999).

[25] See *Section 3.3.1*.

[26] In this regard, Oehler and Horn (2021a, p. 1744) note that "households are not ultimately reliant on the wealth in the high aspiration layer and could even bear a total loss (e.g., use this wealth for 'speculative' investments)."

[27] See the literature review in *Section 3.4.1*.

[28] See, inter alia, Bunn et al. (2019), Raymen and Smith (2020), and Seal et al. (2022). See also *Section 3.4.4*.

RQ5: Are there substantial differences between multi-layer portfolios with a lottery-like stock gambling layer and multi-layer portfolios including a sports betting gambling layer?

Theoretical foundations and the applied methodological approaches are described in the next section. At the end of this dissertation, all research questions are revisited – providing appropriate answers to all research questions can be considered the main contribution of this dissertation.

1.2 Research Outline

In *Section 2*, the theoretical foundations that present the framework for the upcoming analyses are elaborated. First, a review of neoclassical finance is conducted. When discussing gambling behavior in regard to financial markets, the neoclassical finance paradigm can serve as an adequate benchmark for ideal (i.e. rational) behavior. As many of the aspects of (financial market) gambling cannot be explained by models assuming strictly rational agents (and perfect capital markets), this dissertation relies on the concepts from other research frameworks. Consequently, *Section 2* further includes reviews on essential aspects of new institutional economics, market microstructure, financial intermediation, and behavioral economics and finance.

Literature on gambling, gambling behavior, and financial market gambling is reviewed in *Section 3*. In this section, the focus is on the factors that drive the human propensity to participate in gambling (including gambling on financial markets). Moreover, several financial instruments which may be perceived and employed as gambling instruments are introduced and discussed based on existing research.

Section 4 introduces factor models as these are applied throughout the empirical analyses of this dissertation. Furthermore, all data sources are described and discussed in this section. The empirical analyses conducted in *Section 6* and *Section 7*, as well as the subsequent interpretation of the obtained results, require an understanding with regard to the operating principles and design features of social trading platforms. Therefore, the social trading platforms depicting the research object for the analyses in this dissertation are reviewed.

Section 5, *Section 6*, *Section 7*, and *Section 8* cover the empirical analyses that are meant to assess the previously introduced research questions. In *Section 5*, private sector stock holding preferences – for stocks with lottery features – are analyzed. *Section 6* and *Section 7* study signal provider gambling transactions on social trading platforms. That is, in those two sections the factors influencing the propensity of signal providers to engage in gambling are assessed. In *Section 8*, a variety of realistic two-layer portfolios, including a high aspiration layer that is reserved for gambling, are constructed, compared, and discussed.

The main findings from the empirical analyses of *Section 5*, *Section 6*, *Section 7*, and *Section 8* are reviewed and discussed with reference to existing theoretical and empirical research in *Section 9.*

As a conclusion of this dissertation, *Section 10* points to certain limitations regarding the conducted analyses and outlines implications relating to the obtained results.

2 Theoretical Foundations

2.1 Neoclassical Finance and Market Efficiency

The neoclassical finance paradigm is applied to describe how investors should make (financial) decision – neoclassical finance follows a normative approach which requires an appropriate framework with regard to rational decision making. In this context, Ackert (2014, p. 26) notes the following: "Classical decision theory, which assumes that rational decision makers evaluate all possible outcomes, serves as the basis for developing the traditional view in finance. The optimal choice is determined by finding the highest possible expected utility. Finance theorists then assume that these rational people are averse to risk, so that investors must receive compensation if they are going to take on risk. With this basis, theorists can provide models of important financial decisions including portfolio composition and asset pricing.".

The axiom-based expected utility theory, developed by von Neumann and Morgenstern (1944), presents a fundamental pillar of normative decision theory. Based on the utility considerations introduced by Bernoulli (1954), von Neumann and Morgenstern (1944) initially establish a plausible axiomatic system. von Neumann and Morgenstern‘s (1944) work formulates requirements for the preferences of a decision maker and, based thereon, derives a utility function representing these preferences; this presents the foundation of the prevailing normative approach for describing human behavior in (economic) decision theory and finance.[29] The axioms of von Neumann and Morgenstern's (1944) expected utility theory are as follows: Completeness, transitivity, independence, and continuity.[30]

The neoclassical finance paradigm involves financial decision making under risk.[31] In the context of neoclassical finance, "*risk* refers to situations where the perceived likelihoods of events of interest can be represented by probabilities"[32] or, in other words, "[w]hen a person is not sure what will occur, but knows the probabilities of

[29] See Oehler (1992, p. 98), (1995, pp. 13–14). See also Schoemaker (1982) for a review on expected utility theory.
[30] For a description of the axioms of von Neumann and Morgenstern's (1944) expected utility theory see also Herstein and Milnor (1953), Schoemaker (1982), and Oehler (1992), (1995, pp. 15–17).
[31] See Ackert (2014, p. 26).
[32] See Epstein (1999, p. 579).

each state precisely"[33].[34] Transferring this concept of risk "to financial aspects leads to the definition of financial risks as the threat or danger which results from uncertainty that a financial variable deviates negatively from the respective financial target."[35].[36]

Neoclassical investors (agents / decision makers) are associated to crucial properties. In neoclassical finance, investors are assumed to be rational, i.e. investors present clones of the hypothetical concept referred to as homo-oeconomicus. Thus, investors are perfectly informed[37] and reach decisions in accordance with the previously described axiomatic system.[38] Furthermore, investors are assumed to be risk averse: Investors dislike risk. That is, given the fundamental trade-off between risk and return, (most) investors require (an increase in) return as a compensation for (an increase in) risk.[39]

Neoclassical capital markets are assumed to be perfect and complete.[40] Schmidt and Terberger (1997, p. 57) describe perfect and complete capital markets as follows: A capital market is said to be perfect when the price of a (traded) cash flow at a given point in time is identical and given for all market participants, irrespective of whether the market participant acts as a buyer or seller. Thus, there is no one with the ability to influence (market) prices. A capital market is said to be complete if any cash flow

[33] See Ghosh and Ray (1997, p. 82).
[34] Decisions under risk are not to be confused with decisions under uncertainty / ambiguity. A differentiation between risk and uncertainty / ambiguity is introduced by Knight (1921). Oehler et al. (2015a, p. 35) sum up uncertainty / ambiguity as follows: "In fully uncertain or ambiguous situations decision-makers are not aware of all (possible) states of the nature and/or all alternatives. Instead, they only know some states or bundles of them and they can merely estimate some states' probabilities of occurrence.". See also Ellsberg (1961), Sherman (1974), Hogarth and Kunreuther (1989), Ghosh and Ray (1997), Oehler and Unser (2002, pp. 10–13), and Smith et al. (2002). For studies on ambiguity tolerance see Furnham and Ribchester (1995), Furnham and Marks (2013), and Guidolin and Rinaldi (2013).
[35] See Oehler et al. (2015a, p. 36).
[36] See also Bitz (1993, p. 642) and Oehler and Unser (2002, p. 21).
[37] Perfectly informed investors have unrestricted access to information and possess the cognitive capabilities to immediately perceive and process all available information. This is incompatible with research on attention (see *Section 3.3.3*) where the general premise implies that individuals have to narrow their focus due to basic human cognitive constraints (see Kahneman 1973). See also Hirshleifer and Teoh (2003), Da et al. (2011), Engelberg and Parsons (2011), Chen (2017), Colaco et al. (2017), Girardi and Nico (2017), Boyacı and Akçay (2018), Engelberg et al. (2018), Gargano and Rossi (2018), and Wang et al. (2018).
[38] See Oehler (2000b), (2002), (2004), (2006a, pp. 298–299), (2013a, p. 235), (2013d, pp. 45–46), Oehler et al. (2015a, pp. 36–37), and Oehler and Wendt (2017, p. 181). See also Thaler (2000), Statman (2005), (2014), and De Bondt et al. (2008).
[39] See Ackert (2014, p. 27). For the concept of risk aversion see Pratt (1964) and Arrow (1965). See also Menezes and Hanson (1970), Morin and Suarez Fernandez (1983), Kimball (1993), Oehler (1998a), Oehler and Unser (2002), and O'Donoghue and Somerville (2018).
[40] See also Miller and Modigliani (1961), Oehler and Unser (2002, p. 3), and Oehler et al. (2015a, p. 37). See Stapleton and Subrahmanyam (1977) for a study with regard to market imperfections.

can be traded, regardless of its amount, temporal structure, and corresponding uncertainty.

In addition to knowledge regarding future states of nature and their corresponding probabilities, the evaluation of a decision problem under risk requires practical measures for return and risk. In this regard, Markowitz (1952a) considers expected return[41] and the variance[42] of the corresponding expected return as suitable evaluation criteria. Based on these two criteria, Markowitz (1952a) introduces a portfolio selection model. Given less than perfect correlation[43] of two – or any given number – present assets, the combination of those assets will yield diversification[44] benefits. That is, the portfolio resulting from combining those assets will yield an expected return equal to the (value-weighted) mean of the assets included in the portfolio, however, the portfolio variance will be less than the (value-weighted) mean of the portfolio components. This leads to investors – depending on the individual level of risk aversion – choosing portfolios from an efficient line (comprising efficient portfolios). That is, given a respective variance, there is no present portfolio offering a higher expected return; or alternatively, given a respective expected return, there is no present portfolio with lower variance. Tobin (1958) refines the Markowitz's (1952a) portfolio choice model by introducing a riskless asset. Through the introduction of a riskless asset, all investors will gravitate towards the same (risky) portfolio – this portfolio is labeled as the tangency portfolio. In dependence of an investor's degree of risk aversion, the tangency portfolio is then mixed with the riskless asset. All portfolios that present combinations of the riskless asset and the tangency portfolio are superior to all other portfolios on the (former) efficient frontier of risky portfolios.[45] An investor may choose to invest all of her funds in the riskless asset, to solely invest in the tangency portfolio, or to borrow funds at the risk-free rate and invest more than 100 percent of her current funds in the risky tangency portfolio. Like all other combinations of the riskless asset and the tangency portfolio, these

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[41] Expected return is the probability-weighted mean of the possible outcomes (see Markowitz 1952a, Schmidt and Terberger 1997, pp. 282–283).

[42] Variance is the dispersion measure corresponding to the expected return (see Markowitz 1952a, Schmidt and Terberger 1997, pp. 283–284).

[43] Less than perfect correlation refers to a correlation coefficient unequal to positive or negative one (see Mondello 2018, pp. 96–118, Schmidt and Terberger 1997, pp. 321–332).

[44] See also Evans and Archer (1968), Klemkosky and Martin (1975), Jorion (1985), and Driessen and Laeven (2007).

[45] In this context, superior means that – in comparison to the portfolios located on the (former) efficient frontier – the portfolios presenting combinations of the tangency portfolio and the riskless asset yield a higher return given a respective variance, or given a respective return, are subject to lower variance.

portfolios would be considered as efficient. In this framework – all investors choose the (same) risky tangency portfolio – the tangency portfolio becomes the market portfolio[46].[47]

Based on the approach for (optimal) portfolio selection established by Markowitz (1952a) and Tobin (1958), Sharpe (1964), Lintner (1965), and Mossin (1966) (simultaneously) introduce an equilibrium model for asset pricing: The capital asset pricing model (CAPM). As all investors can diversify via an investment in the market portfolio[48], risk that can be diversified (i.e. unsystematic or idiosyncratic risk) is not taken into account by neoclassical investors; these investors only consider undiversifiable risk, that is, risk affecting the entire market (i.e. systematic risk). Therefore, "the risk of an asset cannot be evaluated in isolation. Instead, the risk of the asset has to be based on its contribution to the risk of the portfolio. Further, the risk of the asset is defined in relation to the market portfolio."[49]. The result is the introduction of a risk measure referred to as (market) beta which is computed as the quotient of an asset's covariance with the market portfolio and the variance of the market portfolio. Beta expresses the sensitivity of an asset's return to the market portfolio. By definition, the beta of to the market portfolio equals one while the beta corresponding to the riskless assets equals zero. Theoretically, beta has no lower or upper bounds and can take any given value.[50] Asset pricing models are further elaborated in *Section 4.1*.

Asset pricing models – like the CAPM – provide a tool for neoclassical investors to identify mispricing.[51] These rational agents would immediately identify any given

[46] See, for example, Schmidt and Terberger (1997, p. 339): If the capital market (for risk-free investment or debt) is perfect, if all investors have the same (homogeneous) expectations, and if they are all – to varying degrees – risk averse, all investors will hold the same stock portfolio, namely the tangency portfolio. Stocks are then only held as part of this portfolio. Equilibrium on the stock market exists when all stocks with a positive value are held. Under the above assumptions, the tangency portfolio contains all stocks circulating in the market in proportion to their market values. The tangency portfolio is therefore referred to as the market portfolio.

[47] For a description of the portfolio selection framework according to Markowitz (1952a) and Tobin (1958), see also Schmidt and Terberger (1997, pp. 277–340), Ackert (2014, pp. 27–29), and Mondello (2018, pp. 3–164).

[48] While the market portfolio is occasionally presented as a mere stock portfolio, it (theoretically) comprises all risky assets; these, inter alia, include stocks, bonds, real estate, and commodities (see Mondello 2018, p. 149). For studies with regard to the market portfolio see Brown and Brown (1987), Athanasoulis and Shiller (2000), Levy and Roll (2010), and Doeswijk et al. (2014).

[49] See Ackert (2014, p. 29).

[50] For a description of the asset pricing considerations of Sharpe (1964), Lintner (1965), and Mossin (1966), see also See Schmidt and Terberger (1997, pp. 341–379), Ackert (2014, pp. 29–30), and Mondello (2018, pp. 165–204).

[51] See Ackert (2014, p. 30).

mispricing and directly (and aggressively) take positions against the mispricing, driving prices back to equilibrium (see *Section 2.3*). The same rationale applies for the processing and inclusion of new information into market prices. However, not all market participants need to be (fully) rational to establish market equilibrium.[52] Given the presence of an adequate number of rational agents acting as if they were fully rational[53], through the possibility of arbitrage, the effects of irrational transactions will be eliminated immediately causing markets to remain in equilibrium.

The (immediate) incorporation of (new) information into market prices is referred to as market efficiency. Fama (1965) notes that "[a]n 'efficient' market is defined as a market where there are large numbers of rational, profit-maximizers actively competing, with each trying to predict future market values of individual securities, and where important current information is almost freely available to all participants. In an efficient market, competition among the many intelligent participants leads to a situation where, at any point in time, actual prices of individual securities already reflect the effects of information based both on events that have already occurred and on events which, as of now, the market expects to take place in the future. In other words, in an efficient market at any point in time the actual price of a security will be a good estimate of its intrinsic value.". In a subsequent publication, Fama (1970, p. 387) notes that "it is easy to determine *sufficient* conditions for capital market efficiency. For example, consider a market in which (i) there are no transactions costs in trading securities, (ii) all available information is costlessly available to all market participants, and (iii) all agree on the implications of current information for the current price and distributions of future prices of each security. In such a market, the current price of a security obviously 'fully reflects' all available information.". As these conditions are not representative of real-world markets, Fama (1970) introduces tests for different forms of market efficiency; these are categorized into tests for weak, semi-strong, and strong form market efficiency. Weak form market efficiency renders that current prices reflect all information included in historical price data. Regarding semi-strong form market efficiency, in addition to historical price data, prices reflect

[52] In this context, Rubinstein (2001, p. 16) notes the following: "Clearly, markets can be rational even if not all investors are actually rational. So, in a rational (but not maximally rational) market, investors may trade too much or fail to diversify enough for their own good. These matters are not in contention here, and in fact, I do not dispute them. In rational markets, money managers acting in the interests of their clients work to correct their own and their clients' irrational investment choices.".

[53] This is referred to as the as-if approach; see Oehler (1998b, p. 78), (2006b), (2011), (2012c), (2013a), (2013d).

all publicly available information. Strong form market efficiency suggests that, in addition to information in historical price data and all publicly available information, even private (or insider) information is reflected in market prices.[54] Fama (1970, p. 416) concludes that "the evidence in support of the efficient markets model is extensive, and (somewhat uniquely in economics) contradictory evidence is sparse.".[55]

2.2 New Institutional Economics

Eggertsson (1990b, p. 450) describes new institutional economics[56] as "an attempt to generalize neoclassical economics and provide tools needed for understanding the logic of economic organizations and institutions that affect production and exchange, whether in tribal societies or mature industrial states." Furthermore, Eggertsson (1990b, p. 450) notes that new institutional economics "constitutes a modification of the protective belt of the neoclassical paradigm, primarily by introducing transaction costs and the constraints of property rights." In addition to theoretical conceptions regarding transaction costs[57] and property rights[58], information economics[59], and the principal-agent framework[60] are captured under the umbrella of new institutional economics.

As the research questions, empirical analyses, and discussion of results in this dissertation partly relate to the principal-agent framework, the focus of this section is the discussion of the principal-agent relationship. As defined by Jensen and Meckling (1976, p. 308), the principal-agent relationship constitutes "a contract under which one or more persons (the principal(s)) engage another person (the agent) to perform

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[54] Studies regarding insider / private information and market efficiency are provided by Heitmann et al. (2000) and Oehler et al. (2000). For research on insider trading see also Oehler et al. (2015b).

[55] For the efficient market framework see also Malkiel (1989), (2003), (2005), Fama (1991), Shiller (2003), and Ackert (2014, pp. 30–31). For further empirical tests of market efficiency see Lim et al. (2008), Lim and Brooks (2011), and Schmitz (2020). See also Oehler et al. (2017b) for a case study on BREXIT – an information-bearing rather unexpected event (see Best et al. 2017, Jain 2017) – and the subsequent reflection of information in market prices. See Oehler et al. (2013c) for a more gernal discussion with regard to the impact of election results on stock prices.

[56] See Eggertsson (1990a), (1990b), Williamson (1996), (2000), Menard (2001), Rao (2003), Blum et al. (2005), and Höfer and Oehler (2013).

[57] See Coase (1937), Eggertsson (1990a), (1990b), and Williamson (1996), (2000).

[58] See Coase (1937), Nutzinger (1982), Libecap (1986), and Eggertsson (1990a), (1990b).

[59] See Akerlof (1970), Alchian and Demsetz (1972), and Stiglitz (2000).

[60] See Jensen and Meckling (1976), Fama (1980), Fama and Jensen (1983), Sappington (1991), and Höfer and Oehler (2013). The stewardship theory, an extenstion of the principal agent theory / framework, is inter alia discussed by Oehler and Schalkowski (2013).

some service on their behalf which involves delegating some decision making authority to the agent. If both parties to the relationship are utility maximizers there is good reason to believe that the agent will not always act in the best interests of the principal. The principal can limit divergences from her interest by establishing appropriate incentives for the agent and by incurring monitoring costs designed to limit the aberrant activities, of the agent.". In asset management, there are prominent agency conflicts between mutual fund companies / managers and investors. "Consumers would like the fund in which they invest to use its judgment to maximize risk-adjusted expected returns. Mutual fund companies, however, are motivated by their own profits, and the information they possess and how they use it are not directly observable."[61].

There is a vast body of literature describing a highly significant flow-performance relationship with regard to mutual funds.[62] This relationship is generally found to be nonlinear, that is, good performing funds are chased more than funds with poor performance are sold.[63] In this context, Chevalier and Ellison (1997) argue that the flow-performance relationship presents an implicit incentive contract: As mutual fund companies / managers are compensated with a fixed percentage of assets under management, they have an incentive to take measures in order to increase a fund's total assets.[64] Carpenter (2000) argues that the asymmetry with regard to the flow-performance relationship may generate a convex compensation function. These incentives have a substantial impact on risk-taking; Chevalier and Ellison (1997) show that, towards the end of the year, especially younger funds are inclined to gamble (i.e. increase risk) when having previously underperformed the market, but play it safe (i.e. mimic index funds) when being ahead of the market. Furthermore, Chevalier and Ellison (1997) find that funds being well ahead of the market are strongly inclined to

[61] See Chevalier and Ellison (1997, p. 1167).

[62] See Oehler (1998c) for a discussion of herding behavior with regard to German mutual funds. See also Oehler and Wendt (2007) for a discussion with regard to the governance structure and mechanisms of invetsment funds.

[63] See Ippolito (1992), Chevalier and Ellison (1997),Goetzmann and Peles (1997), Sirri and Tufano (1998), and Ferreira et al. (2012). See also Spiegel and Zhang (2013) who argue that pre-existing empirical literature suffers from misspecifications and conclude that the flow-performance relationship is linear.

[64] See also Borenstein and Zimmerman (1988) and Berkowitz and Kotowitz (1993) for studies assessing market demand as an implicit incentive scheme. Research examining explicit incentive schemes is, inter alia, provided by Healy (1985), Asch (1990), Ehrenberg and Bognanno (1990a), (1990b), and Knoeber and Thurman (1994). For a review on financial incentives and performance see Jenkins et al. (1998).

gamble – Chevalier and Ellison (1997) note that this behavior may perhaps be driven by an attempt to attain a position on year-end lists of top-performing funds.

In contrast to mutual fund managers, hedge fund[65] managers face fee structures designated to align managers' incentives with fund performance. Incentive schemes in the hedge fund industry involve considerable performance fees in combination with the high watermark principle[66].[67] Compensation schemes in the hedge fund industry, however, establish another principal-agent conflict, as hedge fund managers are exposed to option-like incentives. That is, hedge fund managers have to recover past losses – surpass previously established thresholds – to become eligible for compensation via performance fees.[68]

Buy-side analysts depict another group of market participants (or employees of financial intermediaries) that may systematically violate the expected behavior and internal or legal requirements; for a discussion see Oehler et al. (2011a).

Social trading involves severe asymmetries regarding the distribution of economic consequences between agents (i.e. signal providers) and principals (i.e. signal followers). In short, when a portfolio performs well, the administering signal provider can (potentially) receive (extensive) remuneration via performance fees (that are tied to high watermarks). On the other hand, a poorly performing portfolio barely brings any (monetary) consequences for the signal provider.[69] Therefore, in line with the previously discussed literature, signal providers in social trading face convex or option-like incentives.[70] The incentive structure established by social trading will remain a focal point throughout the course of this dissertation.

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65 For empirical research with regard to hedge funds see, inter alia, Schmitz (2020) and Oehler and Schmitz (2021).

66 See Liang (1999, p. 72): „The incentive fee is usually paid only after a hurdle rate has been achieved. A majority of hedge funds also have a 'high watermark' provision, under which the manager is required to make up any previous losses before an incentive fee will be paid (i.e., the cumulative returns have to be above the hurdle rate). Furthermore, a manager could 'owe' the investors a rebate of fees charged in previous years. All these features give managers better incentives to act in investors' interests than is the case with mutual funds and other traditional investment vehicles.".

67 Regarding hedge funds, fund manager compensation and fund performance are discussed by Liang (1999).

68 See Ackermann et al. (1999), Carpenter (2000), Brown et al. (2001), Hodder and Jackwerth (2007), Kouwenberg and Ziemba (2007), Agarwal et al. (2009), Burschi et al. (2014), Guasoni and Obłój (2016), and Lim et al. (2016).

69 For a detailed description of the compensation schemes corresponding to the two social trading platforms analyzed in this dissertation, see *Section 4.2.3* and *Section 4.2.4*.

70 See Doering and Jonen (2018).

2.3 Market Microstructure

Easley and O'Hara (1995, p. 357) present market microstructure as "the study of the process and outcomes of exchanging assets under explicit trading rules.". According to Stoll (2003, p. 556), "[m]arket microstructure deals with the purest form of financial intermediation – the trading of a financial asset, such as a stock or a bond. In a trading market, assets are not transformed (as they are, for example, by banks that transform deposits into loans) but are simply transferred from one investor to another.". Madhavan (2000, p. 206) states that market microstructure is "concerned with the process by which investors' latent demands are ultimately translated into transactions.".

As elaborated in *Section 2.1*, neoclassical finance depicts a theoretical framework with rational agents and frictionless markets operating without costs. As frictionless markets are a useful assumption for theoretical models but not an accurate representation of reality, research in market microstructure assesses the cost associated to trading securities and the corresponding impact on asset pricing.[71]

One of the causes of mispricing – especially of mispricing persisting after its publication through academic research[72] – are market microstructure induced limits to arbitrage. Mispricing may be caused by noise traders[73]; rational traders (i.e. arbitrageurs) would bet against and therefore exploit any emerging mispricing, thereby driving prices back to equilibrium.[74] However, there are certain limitations which may hinder arbitrageurs from exploiting mispricing.

Shleifer and Vishny (1997) point out that real world arbitrage is substantially more complex than propagated in textbook descriptions. Thus, Shleifer and Vishny (1997, p. 35) note that "the millions of little traders are typically not the ones who have the knowledge and information to engage in arbitrage. More commonly, arbitrage is conducted by relatively few professional, highly specialized investors who combine their knowledge with resources of outside investors to take large positions.". Shleifer

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[71] See Stoll (2003). Furthermore, discussions with regard to market microstructure are provided by Garman (1976), Easley and O'Hara (1995), O'Hara (1995), (2015), Spulber (1996), Madhavan (2000), Easley and O'Hara (2003), and Stoll (2003). See also Oehler (1998b), (2000f), (2001g), (2002) for discussions with regard to various aspects of market microstructure.
[72] See McLean and Pontiff (2016).
[73] See De Long et al. (1990).
[74] See *Section 2.1*.

and Vishny (1997) acknowledge that real-world arbitrage is generally risky and requires sophisticated arbitrageurs.

Regarding limits to arbitrage, Pontiff (1996, 2006) differentiates between transaction costs and holding cost. Transaction costs include brokerage fees, commissions, and market impact. These costs hinder arbitrage as the profits of any transaction conducted by market participants – or arbitrageurs – will be lowered.[75] "Thus, for securities with larger transaction costs, arbitrage pressure will only take place at larger magnitudes of mispricing. Securities with high transaction costs should be subject to higher mispricing in equilibrium than securities with lower transaction costs."[76]. Garman and Ohlson (1981) provide a theoretical framework for the pricing of an asset with transaction costs. Given a scenario with transaction costs, Garman and Ohlson (1981, p. 272) argue that the price of an asset is that of the asset in a scenario without transaction costs plus / minus a discrepancy "bounded by some function of transaction cost magnitudes.". This concept is illustrated by Pontiff (2006).[77]

De Long et al. (1990) argue that arbitrage is substantially hindered by noise trader risk. De Long et al. (1990, p. 705) summarize noise trader risk as "the risk that noise traders' beliefs will not revert to their mean for a long time and might in the meantime become even more extreme.". That is, "[i]f noise traders today are pessimistic about an asset and have driven down its price, an arbitrageur buying this asset must recognize that in the near future noise traders might become even more pessimistic and drive the price down even further. If the arbitrageur has to liquidate before the price recovers, she suffers a loss. Fear of this loss should limit his original arbitrage position. Conversely, an arbitrageur selling an asset short when bullish noise traders have driven its price up must remember that noise traders might become even more bullish tomorrow, and so must take a position that accounts for the risk of a further price rise when he has to buy back the stock."[78]. Noise trader risk as a substantial limit to arbitrage is further discussed by Lee et al. (1991) and Scruggs (2007). While

[75] See Pontiff (1996), (2006).
[76] See Pontiff (1996, p. 1138).
[77] For a discussion on the importance of transaction costs see Mashruwala et al. (2006).
[78] See De Long et al. (1990, p. 705).

finding that noise traders have an impact on asset prices, Gemmill and Thomas (2002) reject the hypothesis that noise trader risk drives long-run mispricing.

More recent literature focuses on idiosyncratic risk as the main factor hindering arbitrage.[79] Pontiff (2006, p. 49) argues that "[a]rbitrageurs are unable to hedge idiosyncratic risk, and thus they must trade off between the expected profit from a position and the idiosyncratic risk to which the position exposes them.". Doukas et al. (2010) show that mispricing is more pronounced in stocks that are highly idiosyncratic. That is, Doukas et al. (2010) provide empirical evidence that price divergence from fundamental value is related to arbitrage risk – arbitrage risk being measured as idiosyncratic risk. Based on research showing that highly shorted stocks are subject to low subsequent returns[80], Duan et al. (2010, p. 565) note: "[I]t is puzzling that this mispricing is not arbitraged away by rational traders. Specifically, why do short sellers spend resources to find mispriced securities, but then not completely arbitrage the mispricing away? Moreover, why don't other investors, who can observe short interest, use short interest as an investment signal, and arbitrage the short interest anomaly away?". In their study, Duan et al. (2010) find evidence that idiosyncratic risk imposes a substantial cost to short sellers; therefore, the persistence of the short interest anomaly may be explained by idiosyncratic risk and the corresponding cost imposed for short sellers.[81] Idiosyncratic risk as a substantial factor with regard to hindering arbitrage is further discussed by Stambaugh et al. (2015), Stambaugh and Yuan (2017), Gu et al. (2018), and Guidolin and Ricci (2020).

In addition to transaction costs and fundamental (i.e. idiosyncratic) risk, Pontiff (1996) argues that there are two more factors impacting the profitability of arbitrage. These are dividend yields and interest rates. Regarding dividends, Pontiff (1996, p. 1136) states that these "enhance arbitrage profits since they reduce holding costs.". Concerning interest rates, Pontiff (1996, p. 1136) notes that these "are an opportunity cost, since arbitrageurs do not receive full interest on short-sale proceeds.".

[79] Treynor and Black (1973) and Pontiff (2006) establish a model describing how idiosyncratic risk deters arbitrage. A recap of this model is provided by Duan et al. (2010).
[80] See Dechow et al. (2001), Desai et al. (2002), and Asquith et al. (2005). Duan et al. (2010) label the observed effect as the short interest anomaly.
[81] Further studies showing that (the persistence of) anomalies is related to arbitrage costs are provided by Wurgler and Zhuravskaya (2002), Ali et al. (2003), Mashruwala et al. (2006), Scruggs (2007), and McLean (2010).

As has been discussed in this section, market microstructure can have a substantial impact on asset pricing. When taking into account market microstructure peculiarities – especially limits to arbitrage – one does not have to depart from the assumption of a sufficiently large number of rational market participants[82] in order to explain deviations from market equilibrium.

As the asset category of lottery-like stocks has been shown to be subject to mispricing[83], considerations with regard to market microstructure and limits to arbitrage have direct implications for research on financial market gambling. Lottery-like stocks exhibit high levels of idiosyncratic risk. Thus, mispricing may persist as arbitrageurs are unwilling to expose themselves to substantial levels of idiosyncratic risk and therefore do not (aggressively) trade against the mispricing. As a result, market prices are not forced back into equilibrium.

2.4 Financial Intermediation

Agents which mediate between capital supply and capital demand are referred to as financial intermediaries.[84] Depending on the provided services[85], vendors of financial services may be categorized as financial intermediaries conform with a narrow definition, or financial intermediaries in accordance with a broad definition.[86]

Financial intermediaries conform with a narrow definition are institutions entering directly into individual contracts, either borrowing money (i.e. acting as borrower), or lending money (i.e. taking the role of financier). Examples include banks taken deposits and granting loans, venture capital funds financing startups, and insurance companies.[87]

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[82] See *Section 2.1*.
[83] See Kumar (2009) and Bali et al. (2011). See also *Section 3.4.1*.
[84] See Hartmann-Wendels et al. (2019, pp. 2–3).
[85] Financial intermediaries perform intermediation functions which can essentially be described as transformation services. These transformation services are, inter alia, described and discussed by Kürsten (1993), Oehler (2004), (2006b), (2011), and Hartmann-Wendels et al. (2019). As financial markets perform intermediation functions, they can themselves be classified as financial intermediaries (see Hartmann-Wendels et al. 2019, Oehler 2006c).
[86] Financial intermediaries are, inter alia, discussed by Oehler (2004), (2005b), Allen et al. (2013), and Bitz and Stark (2015). Furthermore, see Pyle (1971), Diamond (1984), Merton (1995), Allen and Santomero (1997), and Scholtens and van Wensveen (2000) for various discussions and perspectives with regard to the theory of financial intermediation.
[87] See Hartmann-Wendels et al. (2019, p. 3) and Oehler (2006c).

Financial intermediaries in accordance with a broad definition include institutions that enable or facilitate agents (providing or taking up capital) to find counterparties with fitting objectives for the conclusion of (financial) contracts. This category includes, for example, credit, stock, and insurance brokers, rating agencies, and service agents provide information with regard to financial markets.[88]

Organized financial markets – such as stock exchanges – present financial institutions helping to balance the supply and demand of financial assets; thus, financial markets perform intermediation functions and are consequently recognized as financial intermediaries in accordance with a broad definition.[89]

The financial sector is substantially driven by technology.[90] In the last decades, digitalization has had a major impact on the entire financial sector.[91] Regarding financial intermediation, "[t]he newest developments in information technologies, including digitalization, enable financial market participants on the supply side and on the demand side of money to directly enter into contracts with each other, without involving financial institutions. In this sense, digitalization appears to unwind the need for financial intermediaries. However, retail investors still need financial service providers, which help them enter into contracts by providing coordination via online platform solutions, advice or brokerage, and payment services. This change means that—as a result of digitalization—universal banks enter into fewer transactions in their own name and focus more on brokerage instead. In this sense, FinTech (a contraction of Financial Services & Technology) does not necessarily lead to disintermediation, but to a shift from intermediation, where financial service providers *enter into contracts* with consumers on the demand side and on the supply side, to

[88] See Hartmann-Wendels et al. (2019, p. 3) and Oehler (2006c).
[89] See Oehler (2006c). See also Oehler (1998b, p. 73), (2000f), (2001b), (2002, p. 847), (2012a, pp. 3–4), (2013c, pp. 16–20). See Santos and Scheinkman (2001) for a discussion regarding the competition among exchanges. See Oehler (2000g) for a discussion of the European financial and stock exchange system. See Oehler et al. (2001) for experimental research regarding the comparison of different stock exchange trading mechanisms.
[90] See Arner et al. (2016).
[91] For the impact of digitalization on the financial sector, including retail clients as consumers of financial services, see Oehler (2015b), (2016b), (2016c), (2017a), (2021c), Reisch et al. (2015), Oehler et al. (2016b), (2016c), (2016d), (2017c), (2018c), (2018d), (2020), Oehler and Horn (2018), and Wendt and Horn (2021).

intermediation, where financial service providers *facilitate contractual agreements* between consumers on the demand side and on the supply side."[92].[93]

FinTech is not exclusively provided by start-up companies; instead, established technology companies with existing platforms have started to offer financial services.[94]

Financial service providers which have emerged through the digitalization of financial markets include digital and mobile payments[95], crowdfunding[96], robo-advisory[97], and social trading[98].

The empirical analyses in *Section 6* and *Section 7* of this dissertation assess social trading platforms. These enable agents, i.e. signal provider and signal follower, to enter into contracts with each other. However, in order to carry out (real-world) trades / trading signals, signal providers and signal followers rely on brokers (see *Section 4.2.3* and *Section 4.3.4* for the design of social trading platforms). Research on how social trading can serve as a substitute for long-term asset management has yet to emerge. As of now, it seems that social trading has rather complemented than replaced pre-existing financial intermediation.

2.5 Behavioral Economics and Finance

2.5.1 Deviation from Fully Rational Investors

Empirical research shows that individuals' decision making tends to deviate substantially from decisions in conformity with the axioms established by von Neumann and Morgenstern (1944). A comprehensive overview of these deviations – labeled as anomalies, irrationalities, or biases – is provided by Oehler (1992, 1995).[99]

[92] See Horn et al. (2020, p. 310).
[93] For the disruption of financial intermediation by FinTech see Cai (2018) and Frost et al. (2019). See also Nuyens (2019).
[94] See Oehler et al. (2016c), Frost et al. (2019), and Horn et al. (2020, p. 310).
[95] See Oehler (2015b) and Oehler et al. (2016c).
[96] See Oehler (2016c), (2018), (2020), (2021b) and Oehler et al. (2018c). See also *Section 3.4.5*.
[97] See Oehler et al. (2016e), Wendt et al. (2018), Horn and Oehler (2020), and Oehler et al. (2022a).
[98] See Oehler et al. (2016a), (2017d), (2020). See also *Section 3.4.3, Section 4.2.3*, *Section 4.2.3*, *Section 6*, and *Section 7*.
[99] See Tversky and Kahneman (1974) for the description of heuristic principles that individuals rely on in order to assess probabilities / predict values. Tversky and Kahneman (1974) note that, although these heuristics are generally useful, they may lead to systematic errors (i.e. biases).

These empirical findings give rise to a new paradigm, behavioral finance[100], which Oehler (2000b, p. 978) describes as follows: The behavioral finance paradigm „focuses on the individual and the market-level behavior using empirical data as well as non-equilibrium models. Behavioral Finance refers to decision processes of private and institutional investors which are determined by heuristics and biases. Additionally, semi-rational behavior is modelled through weakening the traditional assumptions of homo-oeconomicus behavior.".

Behavioral finance substitutes rational people (i.e. those acting in conformity with the theoretical concept of the homo-oeconomicus) with normal people.[101] Agents are no longer expected to act strictly rational; in behavioral finance, individuals correspond to a concept labeled bounded rationality[102]. In this context, Simon (1955) states that "[b]ecause of the psychological limits […] actual human rationality-striving can at best be an extremely crude and simplified approximation to the kind of global rationality that is implied, for example, by game-theoretical models.".

Kahneman and Tversky's (1979) prospect theory[103] is a preference framework that describes how individuals systematically violate the axioms of von Neumann and Morgenstern's (1944) expected utility theory.[104] Thaler (2018, p. 1267) describes prospect theory as a "conceptional breakthrough": "It broke new ground in two ways. First, it offered a simple theory that could explain a bunch of empirical anomalies (and some of my stories), and second it illustrated by example that economics needs two completely different types of theories: normative and descriptive. By normative here I mean a theory of what is considered to be rational choice (rather than a statement about morality). In contrast, a descriptive theory just predicts what people will do in various circumstances. The basic flaw in neoclassical economic theory is that it uses one theory for both tasks, namely a theory of optimization.".

[100] See Oehler (1991), (1992), (1994), (1995), (1998b), (1999), (2000b), (2000c), (2000d), (2000e), (2001a), (2001c), (2001d), (2001e), (2001f), (2002), (2004), (2011), (2015c), (2021g), Heilmann et al. (2001), Oehler et al. (2003), (2007), (2018b), (2018g), (2018f), (2021), (2022a), Reisch and Oehler (2009), Oehler and Wedlich (2018), and Oehler and Horn (2021a). For summaries with regard to behavioral economics / finance see also Statman (1999), (2008), (2014), Barberis and Thaler (2003), Shiller (2003), De Bondt et al. (2008), Hirshleifer (2015), and Thaler (2016), (2018).
[101] See Statman (2014).
[102] See Simon (1955), (1956), Oehler (2004), (2011), (2012d), and Reisch and Oehler (2009).
[103] See also Tversky and Kahneman (1992), Benartzi and Thaler (1995), Oehler (1995, pp. 40–43), Barberis and Thaler (2003), De Bondt et al. (2008), and Thaler (2016), (2018) for descriptions / discussions of prospect theory.
[104] See De Bondt et al. (2008).

Kahneman and Tversky's (1979, p. 274) "[p]rospect theory distinguishes two phases in the choice process: an early phase of editing and a subsequent phase of evaluation. The editing phase consists of a preliminary analysis of the offered prospects, which often yields a simpler representation of these prospects. In the second phase, the edited prospects are evaluated and the prospect of highest value is chosen.".

The key features of prospect theory are summarized by Thaler (2016, p.°1592) who states that "most of [… its] predictive power comes from three crucial assumptions about preferences.". These are listed below.

Within the neoclassical paradigm – the framework corresponding to expected utility-based theories – utility is derived from levels of wealth. In contrast, regarding prospect theory, utility is derived from changes in wealth relative to a reference point (i.e. the value function is defined over gains and losses).[105]

The value function transferring changes in wealth (i.e. gains and losses) into utility has three essential properties: A kink at the origin, convexity in the domain of gains, and concavity in the domain for losses.[106] This implies risk aversion regarding gains and risk seeking regarding losses.[107] In the words of Shiller (2003, p. 100), this "suggests that individuals are far more upset by losses than they are pleased by equivalent gains; in fact, individuals are so upset by losses that they will even take great risks with the hope of avoiding any losses at all.". This phenomenon has been labeled as loss aversion.[108]

Decision weights are derived from stated probabilities (i.e. decision weights and stated probabilities are not identical). In this context, Kahneman and Tversky (1979, pp. 282–283) state that "[b]ecause people are limited in their ability to comprehend and evaluate extreme probabilities, highly unlikely events are either ignored or overweighted, and the difference between high probability and certainty is either

[105] See Kahneman and Tversky (1979) and Thaler (2016, p. 1592). See also Oehler (1995, p. 41) and Thaler (2018).
[106] Kahneman and Tversky (1979, p. 280) further note that the value function is "considerably steeper for losses than for gains.".
[107] See Kahneman and Tversky (1979) and Thaler (2016, p. 1582). See also Oehler (1995, p. 41) and Barberis and Thaler (2003, p. 1072).
[108] See Tversky and Kahneman (1991) and Oehler (2001f).

neglected or exaggerated.". Furthermore, "moderate and high probabilities are underweighted"[109].[110]

Subsequent to their initial prospect theory, Tversky and Kahneman (1992) propose a modified version which they label cumulative prospect theory. Opposed to the original model, with regard to cumulative prospect theory, Tversky and Kahneman (1992) introduce explicit models for the value function and the decision weights.

In a paper following prospect theory, Tversky and Kahneman (1981) discuss how the framing of a decision problem can substantially impact decision makers' preferences; this, again, "violates the […] fundamental requirement [of expected utility theory] that preferences should be independent of problem description."[111].[112] "[P]rospect theory [… can] explain why people [… make] different choices in situations with identical final wealth levels. This illustrates an important feature of the theory, namely that it can accommodate the effects of problem description, or of *framing*."[113].[114]

Based on the value function proposed by prospect theory, Thaler (1985) introduces the concept of mental accounting.[115] Individuals tend to separate different (perceived) types of alternatives, assign them to different mental accounts, and subsequently form decisions (almost exclusively) for the range of one mental account (consequently the reference point for a decision problem is determined within the corresponding mental account).[116] Thaler (1999) points to the three following essential features of mental accounting. The first relates to the perception and experience of outcomes and the subsequent decision making and evaluation; by means of mental accounting, individuals perform ex-ante as well as ex-post cost-benefit analyses. The second mental accounting component involves individuals assigning activities (i.e. sources and uses of funds) to specific accounts. The third feature relates to heterogenous evaluation frequencies of mental accounts – different

[109] See Tversky and Kahneman (1981, p. 454).
[110] For this paragraph, see also Oehler (1995, p. 42), Barberis and Thaler (2003, p. 1072), and Thaler (2016, p. 1592).
[111] See Tversky and Kahneman (1981, p. 456).
[112] The principals of invarinace and dominance are violated (see Tversky and Kahneman 1986).
[113] See Barberis and Thaler (2003, p. 1073).
[114] See also Oehler (1992, p. 101), (1995, p. 26), Redelmeier and Tversky (1992), Kühberger (1995), Barberis and Thaler (2003), and Barberis et al. (2006) for a description / discussion of framing.
[115] See also Henderson and Peterson (1992), Thaler (1999), (2018), Langer and Weber (2001), Barberis and Thaler (2003), De Bondt et al. (2008), and Das et al. (2010).
[116] See Oehler (1992, p. 106), (1995, p. 34).

mental accounts correspond to different evaluation frequencies. In the initial publication, Thaler (1985, p. 207) notes that mental accounting "violate[s] the economic principle of fungibility.".[117] Implications with regard to the violations of fungibility are discussed by Thaler (1999).

The emergence and recognition of behavioral economics / behavioral finance does not entail that, theoretical frameworks with (strictly) rational agents, can subsequently be disregarded. In this context, Thaler (2016, p. 1577) states the following: "On the theory side, the basic problem is that we are relying on one theory to accomplish two rather different goals, namely to characterize optimal behavior and to predict actual behavior. We should not abandon the first type of theories [i.e. those with rational agents] as they are essential building blocks for any kind of economic analysis, but we must augment them with additional descriptive theories that are derived from data rather than axioms.".

2.5.2 The Impact of Prior Gains and Losses on Risk Taking

This section describes two behavioral phenomena referred to as the house money and the break-even effect. In line with the framework of behavioral economics / finance, these two effects present deviations from rational behavior. Both effects will be referenced when discussing the empirical results of this dissertation.

As postulated by Kahneman and Tversky's (1979) prospect theory, decisions are made with regard to a reference point. Based on this framework, Thaler and Johnson (1990) provide experimental evidence on how prior gains and losses have a major impact on risk taking behavior.

The house money effect described the tendency of individuals to become more prone to take risks after experiencing a gain: "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. The intuition behind this effect is captured by the expression in gambling parlance of 'playing with the house money.'

[117] Thaler (2018, p. 1269) further notes that "[i]f one puts labels on specific budget categories and adds rules that money from one account cannot be used for something that belongs in another category, the assumption of fungibility is destroyed. This is no minor matter. Theories as basic to economic theory as Modigliani's life-cycle hypothesis start with the premise that people are smoothing consumption from a lifetime stock of wealth, full stop. In this model, wealth has no categories. But people and organizations do create categories.".

Gamblers often use this phrase to express the feeling of gambling while ahead. The essence of the idea is that until the winnings are completely depleted, losses are coded as reductions in a gain, as if losing some of ‘their money’ doesn't hurt as much as losing one's own cash.”[118].

With regard to horse race betting, Suhonen and Saastamoinen (2018) find strong evidence for the house money effect. As one of the main results of their study, Suhonen and Saastamoinen (2018, p. 2807) state that “[b]ettors become risk seeking after gains as they take riskier wagers in the domain of gains. Moreover, they spend the money they have won but try to avoid entering the domain of losses.”.[119]

Regarding prior losses, Thaler and Johnson (1990, p. 656) find that “an initial loss might cause an increase in risk aversion”, especially when a subsequent gamble does not provide the chance to break even.[120] However, “while an initial loss may induce risk aversion for some gambles, other gambles, which offer the opportunity to break even, will be found acceptable.”[121]. This phenomenon, i.e. the propensity of individuals to accept high-risk gambles (risk seeking behavior) when provided with the chance to entirely make up for prior losses, is labeled the break-even effect.[122]

Regarding the effect of prior outcomes, Weber and Zuchel (2005) find that the presentation format (i.e. framing) of the decision problem impacts subsequent risk taking. In their experiment, Weber and Zuchel (2005, p. 31) “confront subjects with two versions of a sequential decision making problem under risk. From an economic perspective they are identical in the sense that the probability distributions over outcomes are identical.”. The two versions of the decision making problem differ only with regard to the respective presentation format. That is, the first version is presented as a dynamic portfolio choice model while the second version is framed as a lottery betting game. Weber and Zuchel (2005, p. 31) find that “[w]ith the portfolio treatment,

[118] See Thaler and Johnson (1990, p. 657).
[119] Suhonen and Saastamoinen (2018) provide an overview of research finding evidence for the house money effect, listing the following studies: Experimental evidence is provided by Keasey and Moon (1996), Ackert et al. (2006), and Corgnet et al. (2015); field evidence from a game show featuring gambling aspects is provided by Gertner (1993). With regard to financial markets, field evidence is provided by Frino et al. (2008), Liu et al. (2010), Hsu and Chow (2013), and Huang and Chan (2014).
[120] Suhonen and Saastamoinen (2018) provide further evidence for this behavioral pattern; the effect is labeled the playing safe effect.
[121] See Thaler and Johnson (1990, p. 658).
[122] Suhonen and Saastamoinen (2018) provide an overview of research finding evidence for the break-even effect, listing the following studies: McGlothlin (1956), Ali (1977), Smith et al. (2009), Zhang and Semmler (2009), and Huang and Chan (2014).

subjects take significantly greater risk following a loss than following a gain". Thus, in the context of their experiment, Weber and Zuchel (2005) do not find evidence of a decrease in risk taking subsequent to suffering losses.[123] However, regarding the lottery treatment, Weber and Zuchel (2005, p. 31) report "greater risk taking after a gain than after a loss" which in turn is in line with the house money effect reported by Thaler and Johnson (1990).

With regard to risk-taking after prior losses, Imas (2016) finds that there is a substantial difference between realized and paper losses. In his study, Imas (2016) provides empirical evidence that individuals exhibit less risk-taking subsequent to a realized loss, and more risk-taking following a paper loss.

The results obtained by Thaler and Johnson (1990) appear to contradict what is postulated by prospect theory, as the utility function suggested by Kahneman and Tversky (1979, p. 269) predicts "risk aversion in the domain of gains and risk seeking in the domain of losses.".[124] Thus, based on their empirical findings, Thaler and Johnson (1990) introduce quasi-hedonic editing by modifying hedonic editing as discussed by Thaler (1985).

Hedonic editing[125] assumes that decision makers code outcomes to minimize pain and maximize pleasure – taking into account the shape of the value function offered by prospect theory.[126] In this context, Thaler (1985, p. 204) formulates the following four principles: Segregation of gains, integration of losses, segregation from small gains from larger losses, integration (or cancellation) of small losses with larger gains. However, with regard to hedonic editing, Thaler and Johnson (1990) fail to provide experimental evidence in their study. In line with their experimental results, Thaler and Johnson (1990, p. 652) introduce the quasi-hedonic editing hypothesis: "[W]hen faced with a two-stage gamble involving a prior loss, subjects will not integrate

[123] In this regard, the results of Weber and Zuchel (2005) are not in line with the findings of Thaler and Johnson (1990) and Suhonen and Saastamoinen (2018). Weber and Zuchel (2005) link the observed pattern to an effect previously labeled escalation of commitment (see Staw 1976).
[124] The house money effect implies decreasing risk aversion after experiencing a gain while the playing safe effect implies increasing risk aversion after suffering a loss (see Suhonen and Saastamoinen, 2018, Thaler and Johnson 1990).
[125] For hedonic editing in a stock market context see Lehenkari (2009).
[126] For a detailed description see Thaler (1999).

subsequent losses with the initial loss. (However, after prior gains, subsequent losses will be integrated with (cancelled against) the prior gain.)”.[127]

Regarding risk preferences and decision making patterns, there is a body of literature – labeled as gambling for resurrection – that discusses how situations of distress trigger (extreme) risk taking. Examples include banks experiencing financial distress[128] and financially distressed firms biding for procurement contracts[129].[130]

2.5.3 Overconfidence

In this section, overconfidence – a behavioral phenomenon that cannot be reconciled with the neoclassical assumption of rational agents – is described and discussed. Overconfidence is used as a potential explanation when discussing the empirical results of this dissertation.

Overconfidence depicts a well-documented behavioral bias with substantial implications in the context of financial decision making.[131] Moore and Healy (2008) outline that there are three distinct forms in which the existing scientific literature defines overconfidence. These three classifications are labeled overestimation, overplacement, and overprecision.

Overestimation presents the general “overestimation of one’s actual ability, performance, level of control, or chance of success.”[132]. Overplacement is the believe of individuals to be superior to others (i.e. the believe of being superior to a sizeable part of the general population).[133] Overplacement is also referred to as the better-

[127] Quasi-hedonic editing is a convenient model for explaining the experimental results obtained by Thaler and Johnson (1990). Notwithstanding, Thaler and Johnson (1990) acknowledge that with regard to two-stage decision problems, prospect theory and quasi-hedonic editing may yield diverging predictions.
[128] See Bruche and Llobet (2014) and Freixas et al. (2008).
[129] See Calveras et al. (2004).
[130] Freixas et al. (2008) argue that insolvent banks may continue to invest, even when facing negative expected net present values, for a (small) chance of (potential) recovery. Bruche and Llobet (2014) argue that insolvent banks continue lending to insolvent borrowers as the realization of losses is avoided while there is a (small) remaining chance for the insolvent borrowers’ recovery. Calveras et al. (2004) provide evidence that because of limited liability, firms facing financial distress have an incentive to bid for procurement contracts more aggressively (i.e. undercut their competitors).
[131] An early study of overconfidence is provided by Oskamp (1965).
[132] See Moore and Healy (2008, p. 502).
[133] See Moore and Healy (2008, p. 502).

than-average effect.[134] Overprecision depicts the “excessive certainty regarding the accuracy of one’s beliefs”[135].[136]

Oehler (1992, 1995) describes overconfidence as long-term excessive self-confidence with regard to one's own judgment which may partially be driven by two further behavioral phenomena referred to as curse of knowledge[137] and hindsight bias[138].

A vast variety of theoretical and empirical research explicitly assesses the relation between overconfidence and financial decision making behavior.[139] Benos (1998) conducts a theoretical study of a market environment including (informed) investors who overestimate the precision of their private information. These overconfident traders compete (regarding quantities) with a group of informed traders exhibiting rational expectations. In his study, Benos (1998, p. 355) provides theoretical evidence that “under a risk neutral market maker, market depth, trading volume, price volatility and price informativeness increase when there are overconfident informed investors participating in the market. Since [these overconfident informed investors …] put more weight on their signal than they should rationally do, they submit larger orders. This increases price volatility and informativeness since it reveals a larger part of the private signals to the public. The market maker, realizing that a part of the total order flow is due to aggressive behaviour, increases market depth.”. Furthermore, Benos

[134] Self-Evaluation in comparison to others is discussed by Alicke (1985), with the result that, in comparison to the average, positive self-ratings are increasing with the desirability of a corresponding trait. Literature reviews with regard to the better-than-average effect are provided by Alicke and Govorun (2005) and Zell et al. (2020). Kim et al. (2017) discuss a relatively novel explanatory approach for the better-than-average effect.

[135] See Moore and Healy (2008, p. 502).

[136] Studies with regard to overprecision are provided by Alpert and Raiffa (1982), Klayman et al. (1999) and Soll and Klayman (2004).

[137] Individuals are in hindsight not surprised with regard to actual results; for the corresponding results, individuals readily bring forth plausible explanations. That is, made possible by an a posteriori consideration, an a priori assessment is changed in the direction of the event that has occurred (see Oehler 1992, 1995). For empirical / experimental studies see Fischhoff (1982) and Camerer et al. (1989).

[138] The hindsight bias depicts a special case of the curse of knowledge bias. This phenomenon describes a behavior of individuals in which a priori estimates of the probabilities of random variables are distorted by a posteriori estimates of these probabilities in the direction of the occurred event (see Oehler 1992, 1995). For empirical / experimental studies see Fischhoff (1975), (1976), Fischhoff and Beyth (1975), Camerer et al. (1989), Hoch and Loewenstein (1989), and Hawkins and Hastie (1990). For meta-analyses see Christensen-Szalanski and Willham (1991) and Guilbault et al. (2004).

[139] Studies discussing overconfidence in the context of financial decisions are provided by Oehler (1992), (1995), (2000b), (2000c), (2002), (2011), (2013a), (2013d). A meta-analysis on overconfidence and financial decision making is conducted by Grežo (2021). Oehler et al. (2015c) discuss overconfidence with regard to corporate finance (mergers and acquisitions).

(1998, p. 356) notes that "individual profits of overconfident traders may be positive and even higher than those of their rational opponents. Since rational traders fear pushing the price too much in one or the other direction, they are forced to scale down their own demands, when confronted to aggressive traders. Overconfidence becomes, therefore, an (unconscious) first-mover advantage".

Further theoretical studies on overconfident traders and their persisting in financial markets – in spite of competition through rational traders – are provided by Hirshleifer and Luo (2001) and Wang (2001).[140] In Hirshleifer and Luo's (2001, p. 74) model "overconfident traders trade more aggressively based on valid information than do rational traders. As a result, overconfident traders are better able to exploit risky profit opportunities created by the trades of liquidity-motivated traders or the mistakes of noise traders.". Therefore, Hirshleifer and Luo (2001, p. 83) conclude "that unless the degree of overconfidence is infinite, the long-run steady-state equilibrium always involves overconfident traders surviving as a positive fraction of the population.". Likewise, Wang (2001) concludes that moderately overconfident traders can in the long-run survive in a market environment with rational traders.

Odean (1998) models financial markets with overconfident market participants, finding that overconfidence increases expected trading volume and market depth and decreases traders' expected utility. Furthermore, Odean (1998, p. 1889) argues that "[o]verconfident traders can cause markets to underreact to the information of rational traders, leading to positive serially correlated returns.".

Odean (1999) and Barber and Odean (2000, 2001) provide empirical evidence that, driven by overconfidence, individual investors trade too frequently.[141] As individual traders exhibit poor market timing capabilities and incur trading costs with each transaction, overconfidence is detrimental for their corresponding returns.

Overconfidence is positively related to financial risk taking; that is, investors with higher levels of overconfidence generally expose themselves to more financial risk by holding riskier portfolios.[142]

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140 See also Kyle and Wang (1997) for a theoretical study on the survival of overconfident traders. For a model describing the development cycle of overconfidence in traders see Gervais and Odean (2001).
141 Investor overconfidence and trading volume is further discussed by Statman et al. (2006).
142 See Odean (1998), Barber and Odean (2001), Nosić and Weber (2010), and Broihanne et al. (2014).

3 Gambling, Gambling Behavior, and Financial Market Gambling

3.1 A Short Summary of the History of Gambling

Gambling is an activity of which there are traces throughout all of human history.[143] The longevity and popularity of varies forms of gambling is not particularly surprising as there seems to be a desire for gambling rooted in the human psyche[144] and, furthermore, gambling vendors make major profits[145] by providing gambling consumers (i.e. gamblers) with the opportunity to participate in games of chance (i.e. gambling).

Mikesell and Zorn (1986) argue that (state-run) lotteries are popular (among providers) as they represent revenue independent of any (additional) taxation. However, Mikesell and Zorn (1986) further elaborate that establishing lotteries does not result in free income which is disentangled from any negative consequences. Mikesell and Zorn (1986) conclude that, inter alia, lotteries have to be marketed aggressively in order to produce revenue, lotteries are subject to high administration costs in comparison to taxes, and when regarded as an excise tax[146], lotteries present a regressive[147] revenue source. The contribution of lotteries to government finances is further discussed by Mikesell (2001).

Mikesell (1994) analyzes the elasticity of lottery sales through the economic cycle. In the context of his study, Mikesell (1994) finds a positive income elasticity of lottery sales, i.e. as personal income increases, lottery ticket sales experience a surge. Arguing that personal income may not be an appropriate fit to capture the economy's (cyclical) condition[148], Mikesell (1994) includes the unemployment rate in his model.

143 For a comprehensive overview of the history of gambling see France (1902) and David (1962).
144 See France (1902) and David (1962). See also *Section 3.3*.
145 For the profitability of the casino industry see Eadington (1999) and Prentice et al. (2017). Regarding online sports betting, Elaad et al. (2020) point out that, through increased competition, commission rates and profit margins have been reduced among online bookmakers. Casadesus-Masanell and Campbell (2019) point to an example where the competition among online betting platforms as well as the competition between a newly established online betting platform with traditional bookmakers has led to overall positive outcomes for all competitors.
146 Mikesell and Zorn (1986) argue that, similar to the voluntary purchase of heavily taxed goods like alcohol and cigarettes, the lottery presents an excise tax on the participation in a state-provided entertainment service.
147 As low-income individuals spend proportionally more on lotteries than their mid- and high-income counterparts, Mikesell and Zorn (1986) point to a corresponding regressivity.
148 Mikesell (1994, p. 166) states the following: "Personal income may not, however, capture the full influence of the cyclical condition of the state economy, especially in brief downturns, because personal income includes transfer payments that work to mitigate cyclical decline. A cyclical measure, like the unemployment rate, can capture the effects that may be masked if only personal income is examined.".

The empirical results suggest a statistically significant positive elasticity of lottery sales to unemployment, i.e. an increase in unemployment leads to an increase in lottery sales. These effects, working in opposite directions, are (partially) offsetting. Given that personal income increases and the "unemployment rate falls, as will often be the case, the unemployment effect will offset some of the personal income effect."[149]. Considering the empirical results, Mikesell (1994, p. 170) concludes that: "Reduced prospects in the regular economy appear to make the tiny but real chances of winning a large lottery prize more attractive to households.".

Similarities between lotteries – or general gambling – and certain forms of financial market participation have been recognized by previous research. Analyzing surveyed clients from a Dutch discount brokerage, Hoffmann and Shefrin (2014, p. 496) report that about 40 percent of the individuals participating in the survey list "entertainment and gambling" as the main objective with regard to using brokerage firm. Dorn et al. (2015) provide empirical evidence that individual investors substitute between buying lottery tickets and financial market participation for gambling. Various forms of financial market participation which (may potentially) resemble gambling are discussed in *Section 3.4*.

3.2 Neoclassical Investors and Gambling

Rational investors, i.e. investors within the paradigm of neoclassical finance (see *Section 2.1*), do not buy lottery tickets as these resemble negative sum games. Only a fraction of the collected funds is returned as prices, thus the expected return of buying lottery tickets is negative.[150] Likewise, casino games offer a negative expected return, thus rational agents do not participate in those games either.[151]

The unwillingness of rational investors to participate in gambling activities, i.e. take wealth bets yielding a negative expected value, is independent of individual risk preferences. Within neoclassical finance, that is applying Markowitz's (1952a) mean-variance portfolio theory and Tobin's (1958) two-fund separation, all investors split their funds between the market portfolio and a risk-free asset. Individual risk aversion

[149] See Mikesell (1994, p. 170).
[150] See Paulson (1992) and Statman (2002).
[151] For an overview with regard to the economics of casino gambling see Eadington (1999). A theoretical explanatory approach why individuals participate in casino gambling – even though casino games offer less skewness (see *Section 3.3.2*) than a lottery ticket – is discussed by Barberis (2012).

is accounted for by how much of total funds are invested into the market portfolio relative to the risk-free asset. Investors with very low levels of risk aversion take up leverage, i.e. borrow money at the risk-free rate, and invest more than 100 percent of their original funds in the market portfolio.[152]

Regarding the willingness of investors to take risk, it is essential to differentiate between (very) low levels of risk aversion and risk seeking behavior. Risk averse investors, behaving in accordance with von Neumann and Morgenstern's (1944) expected utility theory, are depicted by utility maximizers with diminishing marginal wealth utility (i.e. a concave utility function).[153] Friedman and Savage (1948, p. 280) note in this context that, given diminishing marginal utility, "an individual seeking to maximize utility will never participate in a 'fair' game of chance, for example, a game in which he has an equal chance of winning or losing a dollar. The gain in utility from winning a dollar will be less than the loss in utility from losing a dollar, so that the expected utility from participation in the game is negative. Diminishing marginal utility plus maximization of expected utility would thus imply that individuals would always have to be paid to induce them to bear risk.". Naturally, these investors restrain from participating in gambles that offer a negative expected return.

In order to explain why individuals do not generally avoid gambling, and financial market gambling more specifically, requires venturing beyond the realm of neoclassical finance. That is, assumptions about rational investors who form decisions in accordance with rational choice models have to be adjusted. However, this does not imply that neoclassical finance can be regarded as a relic of the past. For this dissertation, as well as for all other areas associated to (research in) finance, neoclassical finance yields an exceptional value as it "is a useful benchmark for – and not an exact image of – reality."[154].

Furthermore, it is worth noting that in a principal-agent framework (see *Section 2.2*), accepting gambles or lotteries may as well be the rational, i.e. utility maxing, decision for the agent. This issue is appropriately assessed and discussed in *Section 6* and *Section 7*.

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[152] See *Section 2.1* for a detailed assessment of the neoclassical portfolio selection approach.
[153] See *Section 2.1* for a detailed assessment of expected utility theory.
[154] See Schneider and Oehler (2021, p. 2).

3.3 Human Decision Making and the Propensity to Gamble

3.3.1 Behavioral Portfolio Theory in the Context of Gambling

Shefrin and Statman's (2000) behavioral portfolio theory, which incorporates mental accounting[155], is a fundamental component of behavioral finance.[156]

Behavioral portfolio theory has crucial implications helping to explain commonly observed phenomena that are not in line with the assumption of strictly rational agents. In this context, Statman (2004) argues that the frequently observed poor diversification of individual investors[157] which cannot be reconcilable with the standard neoclassical mean-variance portfolio theory, can however be explained with regard to a behavioral portfolio theory-based framework. Statman (2004) reasons that investors may willingly forgo the benefits of diversification as their stock portfolios mirror the high / highest aspiration layer which is geared toward enabling a chance to get riches.[158] As diversification has overall portfolio benefits[159], it similarly diminishes the chances of participating in a major positive return event. Speculative (high aspiration) portfolio layers are considered separately from layers that are associated to lower levels of aspirations. These low(er) aspiration portfolio layers may, for example, contain funds designated for emergency situations (i.e. accidents or events of severe illness) or retirement provisions[160].[161]

Considering portfolio layers associated to levels of aspiration likewise helps to understand why individual investors accept gambles that yield negative expected returns. Statman (2004, p. 45) notes that the investors' desire "to attain their upside-potential aspirations leads them to take higher risks in these layers than they take in the downside-protection layers. For example, their aspirations lead investors to buy

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155 Mental accounting – as introduced by Thaler (1985) – is discussed in *Section 2.5.1*.

156 See also Oehler et al. (2018b) and Oehler and Horn (2019), (2021a). Prior to the introduction of Shefrin and Statman's (2000) behavioral portfolio theory, a multi-layer portfolio framework for individual investors is discussed by Oehler (1995).

157 In the normative neoclassical framework, all investors hold the market portfolio and, thus, are perfectly diversified (see *Section 2.1*). For empirical research challenging this assumption see, inter alia, Blume and Friend (1975), Kelly (1995), Odean (1999), Polkovnichenko (2005), and Goetzmann and Kumar (2008).

158 See the two-layer model introduced by Shefrin and Statman (2000).

159 For the benefits of diversification see *Section 2.1*. Furthermore, see Bloomfield et al. (1977), Campbell et al. (2001), Statman and Scheid (2008), and Oehler and Wendt (2016a).

160 Retirement provisions / pension plans are, inter alia, discussed by Oehler (2005a), (2012b), (2012c), (2012f), (2017c), (2019), (2021f), (2021h).

161 See Oehler (1995, pp. 91–92).

aggressive growth funds, individual stocks, and call options, all of which have positive expected returns accompanying their high risks. Moreover, at the extreme, the desire of investors to reach their aspirations leads them to buy lottery tickets and participate in other gambles that have negative expected returns.”.

When discussing why investors engage in gambling, the tools provided by behavioral finance (see *Section 2.5*) and the theoretical framework established by Shefrin and Statman’s (2000) behavioral portfolio theory, are essential building blocks. Those concepts will be (re)applied throughout the course of this dissertation.

3.3.2 Preferences for Skewness

In this section, preferences for skewness are discussed as a driving force for gambling preferences. As discussed in *Section 2.1*, higher distributional moments – e.g. skewness – are not considered in Markowitz’s (1952a) mean-variance portfolio selection framework. Yet, there is theoretical and empirical evidence that accounting for skewness is essential when assessing decision making behavior.

Analyzing factors in addition to variance that impact an investment’s required return, Arditti (1967, p. 21) notes the following: “A risk averter is reluctant to undertake any investment that presents him with the possibility – however small – of a large loss and only a limited gain. Skewness is a measure of this asymmetry factor. Consequently, the investor who is a risk averter dislikes negative skewness and likes positive skewness.”. In Arditti’s (1967) empirical analysis, the required return – mirrored by the actual return over a multi-year period – is regressed on variance and skewness as corresponding risk measures. Arditti (1967) finds a (significantly) positive regression coefficient for variance and a (significantly) negative coefficient for skewness. That is, the required return (dependent variable) increases with variance but decreases with skewness. Arditti (1967) concludes that the market dislikes increases in variance but favors positive skewness.[162]

[162] Arditti (1971) critiques Sharpe’s (1966) finding that mutual fund managers do not accomplish to outperform the *Dow Jones Industrial Average* after management fees, as Sharpe (1966) does not account for skewness. Arditti (1971, p. 912) concludes that “fund managers are willing to give up some expected return or to take on a bit more variability in exchange for a greater chance at a large annual return.”.

Numerous studies extend the conventional CAPM – as described in *Section 2.1* – in order to account for the effect of skewness on asset valuation. Motivated by evidence that points to a poor empirical performance of the CAPM[163], Kraus and Litzenberger (1976) incorporate systematic (i.e. nondiversifiable) skewness[164], thereby transforming the one-factor into a two-factor model. With regard to the conventional CAPM, Sharpe (1977, p. 128) notes that “a security's beta relative to the market portfolio can be expressed as a weighted average of beta values relative to any desired number of portfolios, the collection of which equals the market portfolio. When the beta values are scaled appropriately, the applicable weights represent the relative contributions of the portfolios to the uncertainty of the market portfolio, and will sum to equal one.”. Hence, in Kraus and Litzenberger’s (1976) model, gamma (i.e. the coefficient relating to skewness) presents the relative contribution to the skewness of the market, with the market’s gamma coefficient being equal to one. Friend and Westerfield (1980) conduct a series of comprehensive empirical test of the Kraus and Litzenberger (1976) model. In their study, Friend and Westerfield (1980) find some evidence that, in addition to co-variance, co-skewness[165] is needed in order to explain individual risky asset returns.[166]

The Kraus and Litzenberger (1976) model is, inter alia, discussed and evaluated by Kane (1982), Barone-Adesi (1985), Sears and Wei (1985), and Lim (1989). All of these studies find (some) evidence that systematic skewness is priced – nonetheless, remaining concerns with regard to the overall validity are expressed.

Harvey and Siddique (2000) study the impact of systematic skewness in the presence of the Fama and French (1993) asset pricing factors[167]. In the context of their analysis, Harvey and Siddique (2000, p. 1281) “show that conditional skewness can explain a significant part of the variation in returns even when factors based on size and book/market like SMB and HML are added to the asset pricing model.”. In

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[163] Kraus and Litzenberger (1976) inter alia point to studies by Friend and Blume (1970), Fama and MacBeth (1973), and Blume and Friend (1973).
[164] Systematic skewness, conditional skewness and co-skewness are used synonymously.
[165] In their article, Friend and Westerfield (1980) denote systematic skewness as co-skewness.
[166] However, Friend and Westerfield (1980) take issue with Kraus and Litzenberger’s (1976) conclusion that portfolios with zero beta and zero co-skewness generate the (actual) risk-free rate of return. That is, contrary to Kraus and Litzenberger’s (1976) prediction, Friend and Westerfield (1980) find a regression intercept using the two-factor model – with beta and co-skewness as corresponding factors – significantly different from zero. Therefore, Friend and Westerfield (1980) label Kraus and Litzenberger’s (1976) attempt to develop / substantiate a modified form of the conventional one-factor CAPM as unsuccessful.
[167] Factor models / asset pricing factors are discussed in *Section 4.1*.

addition, Harvey and Siddique (2000) provide evidence that systematic skewness is related to momentum, with high expected return portfolios (i.e. winners) having lower skewness than low expected return momentum portfolios (i.e. losers).[168]

Simkowitz and Beedles (1978), Conine and Tamarkin (1981), and Mitton and Vorkink (2007) argue that the commonly observed poor diversification of investors, which is not reconcilable with the standard neoclassical mean-variance framework, may be driven by investors' preferences for positive skewness. Furthermore, Mitton and Vorkink (2007, pp. 1284–1285) provide evidence that "idiosyncratic skewness, and not just coskewness with the market portfolio, appears to be relevant for investor holdings and asset prices.".[169]

Barberis and Huang (2008) study the pricing of securities when investors make decisions in accordance with Tversky and Kahneman's (1992) cumulative prospect theory.[170] As main novel result of their analysis, Barberis and Huang (2008) show that – within a framework of cumulative prospect theory investors – the (idiosyncratic) skewness of a security can be priced. That is, relative to what is predicted by expected utility theory, a (positively) skewed security can become overpriced. In their study, Barberis and Huang (2008, p. 2067) state that: "In particular, some investors take a large, undiversified position in the skewed security, because by doing so, they make the distribution of their overall wealth more lottery-like, which, as people who overweight tails, they find highly desirable. The skewed security is therefore very useful to these investors; as a result, they are willing to pay a high price for it and to accept a negative average excess return on it.". Mitton and Vorkink (2007) note that, with regard to the pricing of idiosyncratic skewness, the prediction of their model is similar to the prediction of the model established by Barberis and Huang (2008). However, the prediction in Barberis and Huang's (2008) model "arises from the assumption of investors having preferences based on cumulative prospect theory, and not from heterogeneous preference for skewness."[171].

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[168] Momentum is initially discussed by Jegadeesh and Titman (1993). In this dissertation, momentum and its corresponding impact with regard to asset pricing is discussed in *Section 4.1*.
[169] The importance of idiosyncratic skewness with regard to individual investors' preferences is, inter alia, addressed by Kumar (2009).
[170] Prospect theory (see Kahneman and Tversky 1979) and cumulative prospect theory (see Tversky and Kahneman 1992) are described and discussed in *Section 2.5.1* and *Section 2.5.2*.
[171] See Mitton and Vorkink (2007, p. 1256).

Skewness is a major component of gambling[172] with some studies arguing that, in the context of gambling, it is substantially more important than risk expressed in variance.[173] Thus, when discussing (financial market) gambling, taking into account preferences for skewness is of crucial importance. The empirical body of work in this dissertation (see *Section 5* to *Section 8*) will further include / recognize skewness as a factor with regard to individual investors' behavior.

3.3.3 Sensation Seeking, Entertainment, and Attention

In this section, it is discussed how sensation seeking, entertainment, and attention have an impact on financial market gambling. Within the paradigm of neoclassical finance where all market participants are assumed to be fully rational, these factors do not affect asset selection. However, when taking a behavioral perspective, sensation seeking, entertainment, and attention have to be discussed as drivers with regard to (individual) investor decisions.

"Sensation seeking is a trait defined by the seeking of varied, novel, complex, and intense sensations and experiences, and the willingness to take physical, social, legal, and financial risks for the sake of such experience"[174].[175] In the context of gambling, individuals classified as sensation seekers are more involved in gambling, i.e. spend more time gambling and place larger bets.[176] Grinblatt and Keloharju (2009) link sensation seeking to trading frequency; their empirical results suggest that investors who are prone to sensation seeking trade more frequently.[177] Dorn et al. (2015) argue that playing the lottery and trading in the stock market provide similar thrills for sensation seeking individuals. In this regard, Dorn et al. (2015) find evidence

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[172] See Kumar (2009).
[173] See Garrett and Sobel (1999) and Golec and Tamarkin (1998). For analysis of lottery design see Walker and Young (2001).
[174] See Zuckerman (1994, p. 27).
[175] Extensive descriptions with regard to sensation seeking are provided by Zuckerman (1994), (2007). Sensation seeking is commonly measured using Zuckerman's (1979) *Sensation Seeking Scale*, *Form V* (*SSS-V*). For a discussion – including critic – of Zuckerman's (1979) assessment scale see Deditius-Island and Caruso (2002) and McDaniel and Mahan (2008).
[176] See Anderson and Brown (1984) and Dickerson et al. (1987). For the relationship between sensation seeking and gambling see also McDaniel and Zuckerman (2003). The relationship between sensation seeking and pathological gambling is discussed by Blaszczynski et al. (1986) and Raylu and Oei (2002). In the context of sensation seeking, Barrault and Varescon (2013) conduct a comparison with regard to pathological and non-pathological gamblers.
[177] Grinblatt and Keloharju (2009) do not use Zuckerman's (1979) *Sensation Seeking Scale*; instead, Grinblatt and Keloharju (2009) employ investors' speeding convictions, i.e. speeding tickets, over a multiyear period to proxy sensation seeking. The interrelation between sensation seeking and driving behavior has been previously assessed by Zuckerman (1979) and Jonah (1997).

of a negative relationship between lottery jackpot size and individual investor trading. Furthermore, Dorn et al. (2015) find that small trade participation, i.e. trading activity which is most likely conducted by individual investors, in stocks with lottery features[178] is particularly sensitive to lottery jackpot size. In a related study, with regard to stocks mainly traded by individual investors, Gao and Lin (2015) find evidence that lottery jackpot size is adversely related to individual investors' trading volume. As the buy as well as sell volume in these stocks decreases on days with large jackpots, Gao and Lin (2015) conclude that the evidenced substitution is driven by individual investors' desire to participate in fun / exciting gambling activities, rather than being driven by the financial risk exposure provided by the two speculative instruments. If the substitution was driven by financial risk exposure considerations of individual investors, large lottery jackpots would correspond to a decline in individual buy volume that is stronger than the decline in individual sell volume.[179] Regarding professional investors, evidence for an explicit relation between sensation seeking and financial market gambling with lottery-like stocks is provided by Brown et al. (2018). In their study, Brown et al. (2018) find that hedge fund managers who are sensation seekers exhibit stronger preferences for lottery-like stocks as defined by Kumar (2009) and Bali et al. (2011).[180] Lee et al. (2019) argue that alcohol consumption and trading of lotter-like stocks both represent sensation seeking activities. In their study, Lee et al. (2019) provide strong empirical evidence that individual investors' preferences for lottery-like stocks are more pronounced in areas where the corresponding culture is more tolerant of sensation seeking – sensation seeking being in turn reflected in higher levels of alcohol consumption.[181]

Previous research regards speculative trading by individual investors[182] and playing the lottery as substitutes.[183] Entertainment and sensation seeking have both been identified as major motivational factors for these high-risk activities. Yet, previous research does not concisely differentiate between entertainment and sensation

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[178] Lottery featrues in line with Kumar's (2009) definition of lottery-like stocks (see *Section 3.4.1*).
[179] According to Gao and Lin (2015, p. 2132) "the decline in buy volume is indistinguishable from the decline in sell volume because both buying and selling stocks can generate fun and excitement for individual investors.".
[180] Brown et al. (2018) classify hedge fund managers with performance cars, i.e. vehicles with pro-sensation attributes like sports cars, as sensation seekers.
[181] There is existing evidence for a relation between alcohol consumption and sensation seeking (see Hittner and Swickert 2006) as well as alcohol consumption and (pathological) gambling (see Crockford and el-Guebaly 1998, Lorains et al. 2011, Petry et al. 2005, Welte et al. 2001).
[182] Speculative retail trading is assessed by Han and Kumar (2013).
[183] See Dorn et al. (2015) and Gao and Lin (2015).

seeking; the terms are rather utilized synonymously. Constructing a concise differentiation with regard to entertainment and sensation seeking as drivers for speculative trading and gambling is not part of this dissertation.

Regarding asset selection, attention is one of the pertinent factors that stems from the inability of private investors to perfectly perceive and process all available information.[184] Analyzing the trading behavior of individual investors, Odean (1999) argues that investors limit their search for suitable equities to a subset of stocks that recently have caught their attention, thus managing the selection problem when faced with an overstraining variety of available options. Barber and Odean (2008) explicitly analyze the relation between attention and the buying behavior of individual investors. In the context of their study, Barber and Odean (2008) classify attention-grabbing stocks as stocks which are likely to be associated with attention-grabbing events. In this regard, the following three observable measures are applied: News coverage, unusual trading volume, and extreme daily returns. Barber and Odean (2008) provide empirical evidence that individual investors are net buyers of attention-grabbing stocks. Furthermore, Barber and Odean (2008) argue that the described dynamics are different when individual investors are selling – rather than buying – stocks. Within the neoclassical finance paradigm, the search problem investors are faced with remains unchanged when selling stocks. Neoclassical investors are perfectly diversified (i.e. hold the market portfolio which includes every available asset) and are willing to short sell stocks if they identify (temporary) mispricing.[185] As discussed, real world investors, however, may substantially deviate from their neoclassical description. In this regard, Barber and Odean (2008) state two factors which mitigate the search problem when individual investors want to sell assets. First, individual investors mostly have portfolios which include relatively few common stocks; second, individual investors seldomly conduct short sales. In consequence, the sell decision for individual investors is limited to the (manageable) number of stocks they already own. Finally, Barber and Odean (2008) argue that institutional investors are not subject to the same limitations regarding time and resources as individual investors. Thus, institutional investors are unlikely to display attention-driven purchasing behavior. Likewise analyzing the impact of attention on asset selection, Jacobs and

[184] The necessity of (limited) attention in an environment with sheer endless available information and individuals with limited information processing power is elaborated by Kahneman (1973).

[185] As these investors are assumed to have unlimited processing capacities, the so-called search problem does not present an issue within the neoclassical framework.

Hillert (2016) provide empirical evidence that stocks placed at the top of alphabetically ordered lists experience higher trading activity and liquidity.[186]

3.4 Financial Market Gambling / Gambling Instruments

3.4.1 Stocks

Stocks have been compared to lotteries in a wide variety of existing studies. Friedman and Savage (1948) note that there are certain speculative stocks which are similar to lottery-tickets. Statman (2002) points out fundamental similarities between lottery players and stock traders and, furthermore, offers behavioral explanations for the propensity of individuals to participate in either of the two. Dorn and Sengmueller (2009) identify trading as being an activity similar to gambling. Dorn et al. (2015) provide empirical evidence that investors substitute between gambling in financial markets and playing the lottery. Arthur et al. (2016) connect financial speculation to problem gambling. Grall-Bronnec et al. (2017) argue that excessive trading may be categorized as a gambling disorder. Cox et al. (2020) provide further evidence that a subgroup of individual investors displays symptoms of an addiction to trading.

Attaching all financial market activities to gambling is not an appropriate classification – however, similarities between a subset of financial market activities and gambling are hard to ignore.[187] In this context, Kumar (2009) classifies certain stocks as lottery-like, thus making a substantial contribution with regard to identifying stocks which exhibit lottery characteristics. These stocks are classified with regard to a benchmark and, within that benchmark, feature the following characteristics.

Below median price. Price refers to the stock price at the end of the previous month. Kumar (2009, p. 1899) phrases the rationale for using stock price as a criterion as follows: "I use stock price as one of the defining characteristics of lottery-type stocks because, like lotteries, if investors are searching for cheap bets, they should naturally gravitate toward low-priced stocks. Thus, stock price is likely to be an important characteristic of stocks that might be perceived as lotteries.".

[186] Even when assuming that there are no limitations on attention and the full range of available options is assessed, the so-called primary effect suggests that the first experience in a series will be cognitively privileged; that is, the first position has a substantial effect on preference and choice (see Carney and Banaji 2012).
[187] See for example Friedman and Savage (1948), Dorn and Sengmueller (2009), Dorn et al. (2015), and Arthur et al. (2016).

Above median idiosyncratic skewness. Idiosyncratic skewness is measured as the third moment of the residuals obtained by regressing daily stock returns of the previous six months on a two factor-model employing the market excess return and the square of the market excess return as respective factors.[188] For using idiosyncratic skewness, Kumar (2009, pp. 1899–1900) provides the following reasoning: "Within the set of low-priced stocks, investors are likely to be attracted more toward stocks that occasionally generate extreme positive returns that cannot be justified by the movements in the market. In other words, investors are likely to find stocks with high stock-specific or idiosyncratic skewness attractive.".

Above median idiosyncratic volatility. Idiosyncratic volatility is determined as the standard deviation of the residuals obtained by fitting a four-factor model – comprising the market, size, book-to-market, and momentum factors[189] – to a time-series of daily stock returns of the previous six months. Regarding the use of idiosyncratic volatility, Kumar's (2009, p. 1900) rationale is as follows: "Finally, within the set of stocks that have low prices and high idiosyncratic skewness, stocks with higher stock-specific volatility are more likely to be perceived as lotteries. When idiosyncratic volatility is high, investors might believe that the extreme return events observed in the past are more likely to be repeated.".

In accordance with the definition of lottery-like stocks, Kumar (2009) defines nonlottery-like stocks as stocks which exhibit above median price, below median idiosyncratic skewness, and below median idiosyncratic volatility.

Another definition for lottery-like stocks is introduced by Bali et al. (2011) who define stocks with extreme past daily returns as lottery-like. More specifically, Bali et al. (2011) sort stocks into decile portfolios based on the constituent maximum daily return over the previous month. Stocks within the highest decile portfolio, that is stocks exhibiting the highest constituent daily return over the previous month, are then categorized as lottery-like. As a variation, Bali et al. (2011) form decile portfolios based on the average comprising the five highest daily returns of the previous month. As before, stocks in the highest decile portfolio, that is stocks with the highest average

[188] See Harvey and Siddique (2000).
[189] The market, size, and book-to-market factor depict the three Fama and French (1993) asset pricing factors; adding the momentum factor identified by Jegadeesh and Titman (1993) provides Carhart's (1997) four factor model. Factor models are discussed in *Section 4.1*.

regarding the five highest daily returns over the previous month, are categorized as lottery-like. Accordingly, Bali et al. (2011) define stocks in the respective lowest decile as nonlottery-like.

Lottery-like stocks are shown to be popular among individual investors, that is, individual investors tend to overinvest in stocks with the aforementioned characteristics. Furthermore, empirical evidence suggests that lottery-like stocks generally underperform stocks that are not assigned to this particular category.[190] The underlying rationale being as follows: Preferences of individual investors for stocks with lottery features, that is high demand for such stocks, cause overpricing which subsequently results in lower returns.[191]

For European stocks, the results of Bali et al. (2011) are verified by Annaert et al. (2013). In contrast, Yuan et al. (2019) do not find evidence for a consistent mispricing of lottery-like stocks as defined by Bali et al. (2011) across different stock markets. For the US stock market, Yuan et al. (2019) find the mispricing reported by Bali et al. (2011) not to be stable over time. Nguyen and Truong (2018) provide evidence that extreme daily returns after quarterly earnings announcements neither entail lower future returns nor increase the probability of other future extreme positive short-term returns.

There are several studies which assess investor sentiment[192] with regard to lottery-like stocks. Fong (2013) argues that a subgroup of individual investors – denoted as risk seekers[193] – are prone to invest in lottery-like stocks (defined according to Kumar (2009)) during periods with high investor sentiment but when sentiment wanes reverse their preference. Fong's (2013) results are in line with De Long et al. (1990) and Shleifer and Summers (1990) who argue that investor sentiment can affect asset prices if there are noise traders, i.e. largely uninformed traders, and limits to arbitrage for rational market participants. Fong and Toh (2014) find that lottery-like stocks as defined by Bali et al. (2011) significantly underperform following states of high sentiment, but do not find a significant mispricing subsequent to states of low

[190] See Kumar (2009), Bali et al. (2011), Han and Kumar (2013), and Lin (2020).
[191] See Lin (2020).
[192] See Baker and Wurgler (2006), (2007) for studies on investor sentiment.
[193] Fong (2013) subdivides individual investors into risk averters and risk seekers. This is opposed to Neoclassical Finance Paradigm where all investors are assumed to be avers to risk, i.e. require a premium in order to be compensated for taking on additional risk (see Markowitz 1952a, 1952b, von Neumann and Morgenstern 1944).

sentiment. Lin (2020) shows that analysts are less likely to downgrade Kumar's (2009) lottery-like stocks, i.e. revise a respective recommendation from *buy* to *sell*, during periods of high investor sentiment. Furthermore, Lin (2020) provides empirical evidence that the negative price response to the downgrade of a lottery-like stock is more pronounced during periods of low investor sentiment.

There are numerous further studies which build on one of the two definitions of lottery-like stocks established by Kumar (2009) and Bali et al. (2011). Kumar et al. (2011) provide evidence that gambling attitudes induced by religious backgrounds impact investors' propensity to hold lottery-like stocks. Furthermore, Kumar et al. (2011) show that lottery-like stocks which correspond to companies located in areas with religion-induced lottery-like stock preferences exhibit a more pronounced negative lottery-stock premium. Doran et al. (2012) show that lottery-like stocks outperform their counterparts at the beginning of a New Year; subsequently, the observed outperformance is commonly reversed.[194] Doran et al. (2012) attribute their findings to gambling preference of individual investors which are more pronounced at the beginning of a New Year.[195] Further analyzing the performance of lottery-like stocks, Meng and Pantzalis (2018) provide evidence for a within-month cyclical pattern: Driven by the within-month cyclicality of individual investors' liquidity, the demand for stocks with lottery-like characteristics surges at the turn of the month which, in turn, boosts prices and returns.[196] In the context of informed trading, Kumar and Page (2014) find that institutions with a high degree of aversion towards gambling earn high abnormal returns when deciding to include lottery-like stocks in their portfolios. Lin (2020) finds that analyst downgrade revisions have a larger stock-price impact on lottery-like stocks than on nonlottery-like stocks. Differing market reactions suggest that downgrade recommendations are associated to different levels of information with regard to lottery-like and nonlottery-like stocks. In other terms, when analysts express that a respective lottery-like stock is not a good bet, investors strongly adjust

[194] Stock market seasonality, i.e. particularly large returns in the month of January, are discussed by Rozeff and Kinney (1976) and Ogden (1990).

[195] This effect is shown for US stocks in January and for Chinese stocks in the month following the Chinese New Year.

[196] Individual investors' liquidity – connected to income payments that are generally received at the turn of each calendar month – and corresponding surges in stock returns are, inter alia, discussed by Ogden (1990).

their expectations.[197] Agarwal et al. (2022) provide evidence that mutual fund managers hold lottery-like stocks in order to cater to investors' preferences.

3.4.2 Derivatives / CFDs

A most suitable definition for derivatives is provided by Oehler and Unser (2002, p. 17), who sum up the core concept of derivatives as follows:

A financial contract is a contract that primarily relates to the exchange of means of payment, or rather to the exchanges of claims to means of payment. The most important basic types of financial contracts are equity securities (e.g. shares) and debt securities (e.g. loans). In addition to claims to means of payment, these financial contracts are associated with information, design, and control rights; however, the monetary agreements are clearly prioritized. If such claims themselves become the subject of a contract, then such contracts are referred to as second order financial securities or derivatives, as they are derived from the original contracts or underlying securities (i.e. underlying), the first order financial securities. Higher-order financial instruments are therefore legal positions resulting from financial contracts. Due to the time lag between contract conclusion and contract settlement, derivatives are referred to as futures transactions and are traded on so-called futures markets, while underlying securities are traded as spot transactions on spot markets.

While in the context of risk management, the use of derivatives plays an essential role[198], individual investors may perceive and employ derivatives as purely speculative tools.[199] The speculative nature of derivatives is driven by their ability to allow investors – through leverage – to engage in major investments while only requiring limited expenditure.[200] In the context of leverage being used for speculative trading, Heimer and Simsek (2019, p. 2) note the following: “Leverage is a major catalyst of speculative trading, because it increases the scope for extreme returns, and enables investors to take larger positions than what they can afford with their own money.”.

[197] See Lin (2020).
[198] See Oehler and Unser (2002).
[199] For an overview and description of the various categories of derivatives see Bloss et al. (2008).
[200] See Bloss et al. (2008).

Within the extensive derivative universe, so-called contracts for difference (CFDs) are particularly popular among individual investors.[201] Lee and Choy (2014, p. 967) describe CFDs as a "financial derivative that allows an investor to pay the counterparty the difference between the current value of the contract and the value when entering the contract, with reference to an underlying security price (e.g. commodities, indices or shares). If the current value of the contract is higher (lower) than the value when entering the contract, the long (short) position holder receives (forgoes) the difference. Similar to futures, CFDs provide investors with the ability to hold leveraged long or short positions over the underlying asset by only requiring the holder to provide a portion of the open position as margin.".[202]

There are only a handful of empirical studies with regard to CFDs. Some empirical research addressing CFDs is provided by Brown et al. (2010), Lee and Choy (2014), Corbet and Twomey (2014), Twomey and Corbet (2014), and Arnold et al. (2022).

Previous research does not establish an explicit link between (financial market) gambling and CFD trading by individual investors. Yet, even in the absence of empirical evidence, it is possible to deduct that CFDs can be employed as lotteries. As CFDs are constructed to mirror – or amplify in the presence of leverage – the performance of the corresponding underlying asset, CFDs will resemble lotteries given the underlying asset possesses lottery-like features.[203] Furthermore, CFD investors can expose themselves to substantially more risk using leverage. Thus, in comparison to taking a regular long position in the underlying asset, employing levered CFDs will lead to higher profits in the case of a price movement in the anticipated direction, and higher (or even total) losses in case of a trend in the opposite direction. Yet, as lotteries are not only defined in terms of volatility, taking a levered position in an asset that does not exhibit lottery-like returns, will not necessarily result in a lottery-like return structure as described by Kumar (2009) and Bali et al. (2011).

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[201] See Brown et al. (2010), Corbet and Twomey (2014), and Arnold et al. (2022).
[202] For a more extensive description of CFDs see Brown et al. (2010).
[203] As stated by Kumar (2009), lotteries offer a large chance of a small loss and a small chance of a large gain. These features are then employed for Kumar's (2009) definition of lottery-like stocks. Thus, shorting lottery-like stocks via CFDs will result in a return structure that resembles a large probability of a small gain and a small probability of a large loss (large relative to the investment). If the mispricing, i.e. underperformance, with regard to lottery-like stocks is persisting (see *Section 3.4.1*), shorting lottery-like stocks via CFDs will result in abnormal positive returns.

3.4.3 Social Trading

This subsection describes social trading and assesses related academic research. Furthermore, the motivation to study gambling in the context of social trading is explored.

Social trading depicts the synthesis of social media and retail investor trading. FinTechs have long established a strong foothold in the retail investor market[204]; social trading is a FinTech-driven, platform-based innovation which facilitates the interaction among individual investors. There are several social trading vendors which respectively operate social trading platforms with a variety of platform-specific features (see *Section 4.2.3* and *Section 4.2.4* for a detailed description of two popular social trading platforms). Social trading as it is assessed in this dissertation does not only enable the communication among individual investors but furthermore allows for copy trading. That is, social trading entails a distinction between signal providers and signal followers. With regard to signal providers, social trading ensures visibility and (unedited) traceability, i.e. a signal provider account's strategy specifications, conducted transactions, and resulting returns are published.[205] Platform users can freely access all of the published information and may subsequently subscribe to the signal provider accounts of their choosing, thereby mirroring the corresponding accounts' returns. By delegating their investment decisions to a signal provider, i.e. another (mostly non-professional) trader operating on the platform, platform users become signal followers.[206]

Building on a concept initially introduced by Cetina Knorr (2003), Gemayel and Preda (2018a, 2018b) argue that social trading platforms reflect a *scopic regime* "which designates a state of permanent reciprocal observation and scrutiny among participants"[207].

There is a variety of studies assessing social trading. Returns on social trading platforms are assessed by Oehler et al. (2016a) and Dorfleitner et al. (2018). Analyzing portfolios on the *wikifolio* platform, Oehler et al. (2016a) find that, on

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[204] See Horn et al. (2020).
[205] Signal providers issue their corresponding data in an attempt to generate potential followers. A compensation only for their data publication – as discussed by Oehler (2016a) with regard to consumer data – is not part of social trading.
[206] See Oehler et al. (2016a) and Horn et al. (2020).
[207] See Gemayel and Preda (2018a, p. 176).

average, signal providers do not outperform the market. However, Oehler et al. (2016a) also provide empirical evidence that the best performing signal provider portfolios earn significant short-term excess returns. Dorfleitner et al. (2018) analyze the performance of hypothetical signal followers who select portfolios based on signal providers' previously realized performance and risk. In their study, Dorfleitner et al. (2018) find that simply selecting signal providers based on past returns leads to high losses. When selecting signal providers based on Sharpe ratios and thereby accounting for portfolio risk improves the achieved returns, however, signal followers still incur losses. Dorfleitner et al. (2018) conclude that, even when picking signal providers based on sophisticated selection strategies, no positive abnormal returns can be generated after taking into account transaction costs.

Lee and Ma (2018) assess the identification of so-called expert traders on social trading platforms; in this context, Lee and Ma (2018) suggest a ranking system which entails performance, risk, and consistency as corresponding measures. Studying signal followers' investment flows, Röder and Walter (2019) find that these follow past performance. In addition, Röder and Walter (2019) provide evidence that signal followers' funds follow raw returns rather than risk-adjusted returns obtained by applying factor models.

Wohlgemuth et al. (2016) find that in social trading, both cognition-based and affect-based signals of trustworthiness[208] can help signal providers to establish trust which, in turn, drives signal followers' investments. Within the continuum of affect-based and cognition-based signals, Kromidha and Li (2019) analyze the impact of the following four signal groups: Trader credentials, trading volume, performance, and risk. Kromidha and Li (2019) find that, for accumulating followers, trader credentials have a greater impact than performance, volume, or risk signals.[209] Erdős et al. (2022) provide evidence that, in addition, community-based signals (i.e. signals regarding the investment decisions of other platform users) can significantly impact signal followers' investment decisions.

[208] See McAllister (1995). See also Oehler et al. (2023) for a study with regard to the impact of trust on the willingness of individual investors to take financial risk.
[209] Kromidha and Li (2019) note that there are significant differences between virtual and real money traders.

In the context of social trading, the disposition effect[210] is assessed by Heimer (2016), Gemayel and Preda (2018a), Glaser and Risius (2018), Pelster and Hofmann (2018), and Liêu and Pelster (2020a, 2020b). Heimer (2016) studies retail traders before and after joining a social network which enables the visibility and traceability of transactions but does not entail copy trading.[211] In his study, Heimer (2016) provides empirical evidence that access to the social network significantly increases the disposition effect. Glaser and Risius (2018) find that the disposition effect intensifies with the amount of signal followers' capital entrusted to a signal provider. Pelster and Hofmann (2018) report an increasing disposition effect with the number of signal followers copying a signal provider's trading strategy. In contrast, Gemayel and Preda (2018a) find evidence of a weaker disposition effect among signal providers compared to traders in a traditional setting, i.e. an environment where participants are not subject to permanent scrutiny by their peers. Liêu and Pelster (2020a, 2020b) recognize the conflicting results of previous studies. In an experimental setting where the ranking of participants does not affect payoffs, Liêu and Pelster (2020a, 2020b) show that the applied (signal provider) ranking scheme has a significant impact on the disposition effect. That is, ranking traders (or signal providers in a social trading environment) with regard to the fraction of realized winning trades significantly drives the disposition effect.

Czaja and Röder (2020) use social trading to study the effects of overconfidence. In more detail, Czaja and Röder (2020) find that signal providers' self-enhancement bias leads to subsequent underperformance.[212]

Pelster and Breitmayer (2019) investigate how receiving attention from peers affects signal providers' trading patterns. In their study, Pelster and Breitmayer (2019) provide empirical evidence that signal providers who receive attention from their peers increase their trading activity and are more prone to take risks; Pelster and

[210] The disposition effect, first described by Shefrin and Statman (1985), is the tendency of (individual) investors to sell stocks with good performance (i.e. winners) too early and hold on to stocks with bad performance (i.e. losers) for too long. See also Heilmann et al. (2001) and Oehler et al. (2003) for studies with regard to the disposition effect.
[211] Heimer (2016) studies the platform *myforexbook* (www.myfxbook.com). The platform *myforexbook* facilitates the interaction of retail foreign exchange traders but does not entail typical social trading features like a distinction between signal providers and signal followers.
[212] The self-enhancement bias and the self-protection bias depict the two components of the self-attribution bias (see Gervais and Odean 2001, Miller and Ross 1975). The study conducted by Czaja and Röder (2020) is the first to provide empirical evidence for a link between the self-enhancement bias and overconfidence among nonprofessional traders (i.e. signal providers), thereby confirming the prior conjecture of Gervais and Odean (2001).

Breitmayer (2019) connect these trading behavior modifications to increased levels of excitement which, in turn, is driven by the elevated peer-attention.

Berger et al. (2018) argue that on social trading platforms through imitation private traders are able to achieve returns comparable to those generated by experienced investors. Berger et al. (2018, p. 325) conclude that "copy-trading is not more or less risky than other ways of making investments.". Social trading platforms may not have been designed with the intention to facilitate gambling. However, Social trading is subject to certain peculiarities that have to be discussed in the context of gambling.

Signal followers' motivation to use Social Trading. Individual investors have ventured into the digital world[213]; in this regard, social trading is a vehicle for the digital asset management of private investors. When participating in the financial market, individual investors face cognitive constraints[214], are subject to varying degrees of financial literacy[215], and, given the broad range of investment opportunities of modern financial markets, are confronted with a substantial search problem[216]. Thus, the motives to outsource investment decisions to more experienced market participants appear to be as prevailing in the digital world as in the analogous one. Motives for individual investors to use social trading may include the long-term accumulation of wealth[217], investing as a social activity[218], as well as entertainment purposes[219].

Incentive structure for signal providers on social trading platforms.[220] Social trading platforms offer remuneration for successful signal providers. In line with utility

[213] See Oehler et al. (2017c).
[214] Cognitive constraints of individual investors present limits with regard to the ability of perceiving and processing information; these limits substantially lead to the concept of bounded rationality (see Simon 1955, 1956) which, in turn, is a major buliding block of the behavioral finance paradigm (see *Section 2.5*). The terms cognitive constraints and limited cognitive capacities are used synonymously. For a discussion on limits with regard to the cognitive capacities of private investors see Kahneman (1973), Oehler (1992), (1995), (2013a), (2013d), and Shiller (1999).
[215] See, inter alia, Oehler and Werner (2008), Oehler et al. (2018f), (2019b), (2022b), and Oehler and Horn (2021b).
[216] See Barber and Odean (2008).
[217] For a more detailed overview of motives which are within the realm of capital accumulation see Oehler (1995), (1998b), (1999).
[218] Shiller (1984) notes that investing is a social activity which individuals enjoy discussing with their peers. This aspect is amplified by social trading which ensures the traceability of transactions and returns, as well as the communication among signal providers.
[219] Taffler (2018) points to excitement as a contributing factor with regard to stock market investing. Taking the perspective of signal providers, Pelster and Breitmayer (2019) analyze the impact of excitement in the context of social trading.
[220] The respective signal provider compensation schemes associated to the social trading platforms analyzed in the empirical part of this dissertation, *wikifolio* and *ZuluTrade*, are described in *Section*

maximizing individuals[221], it is reasonable to assume that the majority of signal providers is (at least partly) motivated by the prospect of receiving a monetary compensation. As detailed in *Section 4.2.3* and *Section 4.2.4*, signal providers only become eligible for compensation when having established a certain follower base. Thus, signal providers compete for signal followers. The competition for followers has two interrelated aspects. Signal followers need to be convinced to invest based on a signal provider's profile[222] as well as the corresponding performance track record[223]. Furthermore, in order to be able to convince signal followers, signal providers need to attract their attention. Given the wide selection of signal providers on social trading platforms, attracting attention is fundamental in order to be considered as an investment opportunity. As social trading platforms provide selection lists based on performance criteria, signal providers have to outperform (a sufficient number of) their peers in order to gain visibility. This setup introduces a quasi rank-dependent convex compensation[224] scheme. In other words, signal providers exhibiting a poor or rather average[225] performance in comparison to their peers are unlikely to gain signal followers and, thus, do not become eligible for compensation form the social trading platform. In contrast, signal providers who manage to outperform their peers may be able to gain visibility, establish a sufficient follower base and, subsequently, receive compensation via performance fees. This incentive structure may drive signal providers to increase risk after performing poorly. Convex incentives in social trading are discussed by Doering and Jonen (2018). In their study, Doering and Jonen (2018) provide empirical evidence that signal providers increase risk when approaching their high watermark. Kirchler et al. (2018) provide evidence that, even when removing monetary incentives, in a transparent tournament framework, underperformers still tend to increase risk. Connecting risk-shifting and financial market gambling, Agarwal

4.2.3 and *Section 2.2.4*. The incentive structure stemming from the respective compensation schemes is discussed in the course of this dissertation.

221 That is, individuals in accordance with the framework established by von Neumann and Morgenstern (1944).

222 See for example the impact of affect-based (see Wohlgemuth et al. 2016) and community-based (see Erdős et al. 2022) signals.

223 See Röder and Walter (2019) who discuss the performance characteristics that drive investment flows in social trading.

224 Convex or option-like incentives and risk taking are discussed by Ackermann et al. (1999), Carpenter (2000), and Brown et al. (2001). See also *Section 2.2*.

225 In social trading, average performance, i.e. accounts which do not explicitly underperform their peers but are far from occupying a top position, may not be sufficient to establish a desirable follower base and, in turn, become eligible for compensation.

et al. (2022) provide evidence that poorly performing mutual funds increase their lottery-like stock holdings towards the end of the year.

Signal providers triggering gambling for signal followers. So far, there is no concrete evidence that signal followers participate in social trading because they are driven by gambling motives. Yet, the desire of signal providers to receive compensation and the resulting competition among signal providers may drive those investors to participate in financial market gambling. Thus, in the context of social trading, the investment decisions of signal providers may trigger gambling for signal followers.

The described dynamics and associated signal provider incentives in social trading yield a strong motivation for explicitly studying gambling behavior in the context of social trading. Yet, respective (empirical) research combining social trading and financial market gambling, seems to be missing.

3.4.4 Sports Betting

Sports betting is more likely to be associated to traditional forms of gambling (see *Section 3.1*) than financial market gambling (see *Section 3.4.1* to *Section 3.4.3* and *Section 3.4.5*). Yet, due to its rich history, board availability and interesting portfolio implications, it will be discussed in this dissertation.[226]

Sports betting is an immensely popular form of gambling that has become a wide-spread and commonly accepted leisure activity.[227] McGee (2020) uses the term gamblification to describe the alignment of gambling with sporting activities enrooted into popular culture. Through the technology-driven rise of online gambling providers, sports betting has gained additional momentum.[228]

There is a body of empirical research addressing the efficiency of sports betting markets. Meta-analyses with regard market efficiency and sports betting are conducted by Sauer (1998) and Vaughan Williams (1999). Sauer (1998) concludes

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[226] For an historical overview on soccer betting see Forrest (2008). Combining the realms of sports and finance / financial economics, Herberger et al. (2019a), (2019b) discuss third party ownership agreements with regard to sports companies.
[227] Existing literature refers to a normalization of sports betting when describing how sports betting, as a subcategory of gambling, has become a societally accepted leisure activity (see Bunn et al. 2019, McGee 2020, Raymen and Smith 2020, Seal et al. 2022).
[228] See Deans et al. (2016), (2017), Killick and Griffiths (2022), and McGee (2020). For an examination of the characteristics of sports bettors see Humphreys and Perez (2020).

that market efficiency is generally satisfied. Vaughan Williams (1999) concludes that most of the reviewed studies provide evidence for semi-strong form market efficiency. Studying the National Football League (NFL)[229] sports betting market, Gray and Gray (1997) find evidence of some inefficiencies; however, Gray and Gray (1997) note that these observed inefficiencies tend to dissipate over time. Woodland and Woodland (1994) study the major league baseball (MLB)[230] betting market and find it to be highly efficient. Assessing the betting market for European soccer matches, Vlastakis et al. (2009) provide evidence of arbitrage opportunities that contradict weak-form market efficiency. Horse racing markets are generally found to exhibit high degrees of efficiency.[231]

While most studies conclude that sports betting markets are reasonably efficient[232], there are some notable exceptions. In particular, a well-documented phenomenon in sports betting which describes the tendency of gamblers to underbet favorites (i.e. understate the winning probability of favorites) and overbet underdogs (i.e. overstate the winning probability of underdogs) is labeled the favorite-longshot bias.[233]

Most studies that assess the rise, popularity, and societal acceptance of online sports betting focuses on the negative aspects for participants. For example, Raymen and Smith (2020, p. 384) argue that the acceptance of gambling as an everyday leisure activity and the resulting financial consequences have "contributed to strained personal relationships, family breakdown and prompted growing mental health issues […] including alcohol abuse, depression and anxiety that have in many cases resulted in the prescription of anti-depressants and antianxiety medications.".

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229 National Football League (NFL) refers to the top professional American Football league in the US (www.nfl.com).

230 Major League Baseball (MLB) refers to the top professional Baseball league in the US (www.mlb.com).

231 See Snyder (1978), Asch et al. (1982), Asch and Quandt (1987), and Swidler and Shaw (1995).

232 For an analysis of the determinants of betting market efficiency see Gramm and Owens (2005).

233 In the context of sports betting – especially horse racing – the favorite-longshot bias describes a mismatch between subjective and objective winning probabilities. Notable empirical studies on this phenomenon are provided by Ali (1977), Snyder (1978), Asch et al. (1982), Asch and Quandt (1987), and Woodland and Woodland (1994).

Yet, there has been no attempt to include returns form (non-pathological) sports betting into a behavioral portfolio framework where the high aspiration layer is "designed for a shot a riches."[234]. Such an approach is discussed in *Section 8*.

3.4.5 Other

In addition to social trading, crowdfunding is an innovation which is not specifically designed for gambling but may be perceived and employed as a gambling instrument by individual investors. Crowdfunding is a novel digital platform-based form of project financing that allows founders to fund their projects by raising relatively small amounts from a relatively large number of individuals. The Crowdfunding platform acts as a financial intermediary and thus may supplement – or even (partly) replace – traditional financial intermediaries like banks.[235] Demir et al. (2022) directly connect Crowdfunding to gambling: Their respective analyses suggest a negative relation between lottery jackpot size and crowdfunding contributions.[236] Building on their empirical findings, Demir et al. (2022) argue that playing the lottery satisfies the sensation seeking desires of individual investors participating in crowdfunding. Thus, according to Demir et al. (2022, p. 18) "both activities can produce the same thrill and excitement for some lenders who are sensation seekers, and those lenders will substitute between playing the lottery and lending in peer-to-peer markets.".

The argument could be made that there are many other financial instruments which share similarities with lotteries, i.e. offer a small probability of a huge reward and a large probability of a small loss.[237] Schneider and Oehler (2021) argue that certain currency pairs may be perceived and employed as lotteries – currency pairs as lotteries are in detail discussed in *Section 7*. Moreover, distressed debt securities are an asset class with potential for being perceived and employed as a gambling instrument. Bonds of companies in financial distress trade substantially below their face value. Given the recovery of the company, the corresponding securities

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[234] See Shefrin and Statman (2000, p. 141).
[235] See Mollick (2014), Oehler et al. (2018c), Oehler (2020), (2021b), and Horn et al. (2020). For further studies regarding crowdfunding see Ryu and Kim (2016), Freedman and Jin (2017), Hildebrand et al. (2017), Hornuf et al. (2018), Giudici et al. (2018), Viotto da Cruz (2018), Walthoff-Borm et al. (2018) and Grüner and Siemroth (2019).
[236] Demir et al. (2022) find a negative relation for lottery jackpot size and crowdlending (peer-to-peer lending) but not for reward-based crowdfunding. For a differentiation of the respective fundraising models which are encompassed under the umbrella term crowdfunding see Oehler et al. (2018c), and Oehler (2020), (2021b).
[237] See Kumar (2009).

experience a surge in market value.[238] However, due to the lack of concrete evidence that distressed debt securities are employed by individual investors as gambling instruments, this asset category is not further explored.

[238] See Anson (2002) and Lamm (2003).

4 Conceptual Foundations for the Empirical Analyses

4.1 Factor Models and Abnormal Returns

The empirical analyses in *Section 5*, *Section 6*, and *Section 8* involve assessing the performance of various portfolios; in this context, the factor models described in this section are applied.

"A security's price performance can only be considered 'abnormal' relative to a particular benchmark. Thus, it is necessary to specify a model generating 'normal' returns before abnormal returns can be measured."[239]. By applying factor models, it is possible to determine how a security, or a portfolio of securities, is impacted by one or several risk factors – the risk factor / factors being in turn representative of the selected benchmark.[240] This approach enables a comparison between the security's expected return – i.e. the return which is expected given the previously determined exposure to the corresponding risk factors – and the actual return that has been observed. The difference between expected return and actual return is designated the abnormal return.

The CAPM[241] serves as a basis for estimating expected returns; following the CAPM the expected return, $r_{i,t}$,of a security i at time t is composed as follows.

$$r_{i,t} = r_{f,t} + \beta_{1,i} \times (r_{M,t} - r_{f,t}), \tag{1}$$

where $r_{f,t}$ is the risk-free rate of return at time t and $r_{M,t}$ depicts the return of the market at time t, i.e. the applied (value-weighted) benchmark. The term $(r_{M,t} - r_{f,t})$ is the market risk premium at time t, i.e. the return of the benchmark net of the risk-free return (the market risk premium is in *Section 5*, *Section 6*, and *Section 8* also depicted as $RMRF$). $\beta_{1,i}$ is the coefficient associated to the market risk premium, that is, the exposure of security i to the market risk premium; $\beta_{1,i}$ is commonly referred to as market beta.

[239] See Brown and Warner (1980, p. 207).
[240] As portfolios are a collection of securities, the same rationale that applies to singular securities can be applied to portfolios.
[241] For a review of the CAPM, including its shortcomings, see Fama and French (2004). See also *Section 2.1*.

Based on the CAPM, Jensen (1968) derives a risk-adjusted performance measure that includes the exposure to the market risk as systematic risk factor. The corresponding one-factor model can be depicted as follows.

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_{1,i} \times (r_{M,t} - r_{f,t}) + \varepsilon_{i,t}, \tag{2}$$

where α_i is the risk-adjusted excess return, i.e. the return that is not captured by the systematic factor / factors. The term $\varepsilon_{i,t}$ depicts a random error with an expected value of zero.

The CAPM and, thus, Jensen's (1968) one-factor model, is challenged by the well-documented low-beta anomaly: Empirical tests show that, in contrast to what is predicted by the CAPM, the returns of portfolios composed of low-beta stocks are consistently higher and the returns of portfolios composed of high-beta stocks are consistently lower.[242]

Jensen's (1968) one-factor model is extended by Fama and French (1993) who identify two additional systematic risk factors. Empirical studies provide evidence that, in addition to the excess market return, factors based on firm size (i.e. the market value of equity), book-to-market equity (i.e. the book value of a firm's common stock in relation to its market value), leverage, and earnings-price ratio impact asset pricing.[243] In this context, Fama and French (1993) find that a three-factor model including the excess market return, size, and book-to-market (equity) factors, captures strong common stock return variation. The corresponding model is depicted as follows.

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_{1,i} \times (r_{M,t} - r_{f,t}) + \beta_{2,i} \times SMB_t + \beta_{3,i} \times HML_t + \varepsilon_{i,t}, \tag{3}$$

[242] See Friend and Blume (1970), Black et al. (1972), and Merton and Scholes (1972). The low-beta anomaly is closely related to the low-vola(tility) anomaly and fits into the broadly observed low-risk anomaly: Irrespective of the applied risk measure, low-risk stocks seem to perform better than predicted while their high-risk counterparts perform worse; see Black (1972), Haugen and Heins (1975), Haugen and Baker (1991), Chan et al. (1999), Jagannathan and Ma (2003), Ang et al. (2006), Blitz and van Vliet (2007), Ang et al. (2009), Baker et al. (2011), (2014), Baker and Haugen (2012), Leote de Carvalho et al. (2012), Blitz et al. (2013), Stambaugh et al. (2015), Bali et al. (2017), Beveratos et al. (2017), and Yin et al. (2019).
[243] See Banz (1981), Basu (1983), Rosenberg et al. (1985), and Bhandari (1988).

where SMB_t[244] and HML_t[245] depict the respective factors related to size and book-to-market equity; $\beta_{2,i}$, and $\beta_{3,i}$ depict the size and the book-to-market factors' corresponding coefficients, i.e. the risk exposure to these factors.

Carhart (1997) extends the Fama and French (1993) three-factor model by including a factor capturing momentum as described by Jegadeesh and Titman (1993); the corresponding model is depicted as follows.

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_{1,i} \times (r_{M,t} - r_{f,t}) + \beta_{2,i} \times SMB_t + \beta_{3,i} \times HML_t + \beta_{4,i} \times WML_t + \varepsilon_{i,t}, \tag{4}$$

where WML_t[246] presents the factor capturing momentum; $\beta_{4,i}$ depicts the momentum factor's corresponding coefficient, i.e. the risk exposure to momentum. Studies addressing momentum are, inter alia, provided by Oehler et al. (2003) and Herberger et al. (2011), (2020). The explanatory power of the factors relating to size, book-to-market, and momentum are discussed by Avramov and Chordia (2006) and Fama and French (2012).

Fama and French (2015) introduce a five-factor model where the Fama and French (1993) three-factor model is extended by two factors respectively reflecting profitability and investment. The model is depicted as follows.

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_{1,i} \times (r_{M,t} - r_{f,t}) + \beta_{2,i} \times SMB_t + \beta_{3,i} \times HML_t + \beta_{5,i} \times RMW_t + \beta_{6,i} \times CMA_t + \varepsilon_{i,t}, \tag{5}$$

where RMW_t[247] presents the factor capturing profitability and CMA_t[248] is the factor capturing investment; $\beta_{5,i}$, and $\beta_{6,i}$ depict the profitability and the investment factors'

244 The size factor, SMB_t (i.e. small minus big), "is the return on a diversified portfolio of small stocks minus the return on a diversified portfolio of big stocks" (see Fama and French 2015, pp. 2–3).

245 The book-to-market factor, HML_t (i.e. high minus low), "is the difference between the returns on diversified portfolios of high and low B/M [i.e. book-to-market] stocks" (see Fama and French 2015, p. 3).

246 The momentum factor, WML_t (i.e. winners minus losers), is the difference between the returns on portfolios consisting of stocks with high prior returns and portfolios composed with stocks exhibiting low prior returns (see Carhart 1997).

247 The profitability factor, RMW_t (i.e. robust minus weak), "is the difference between the returns on diversified portfolios of stocks with robust and weak profitability" (see Fama and French 2015, p. 3).

248 The investment factor, CMA_t (i.e. conservative minus aggressive), "is the difference between the returns on diversified portfolios of the stocks of low and high investment firms" (see Fama and French 2015, p. 3).

respective coefficients, i.e. the risk exposure to these factors. The five-factor model is further discussed by Fama and French (2016, 2017).

The Fama and French (2015) five-factor model is subsequently extended by the factor capturing momentum; the resulting Fama and French (2018) six-factor model is depicted as follows.

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_{1,i} \times \left(r_{M,t} - r_{f,t}\right) + \beta_{2,i} \times SMB_t + \beta_{3,i} \times HML_t$$
$$+ \beta_{5,i} \times RMW_t + \beta_{6,i} \times CMA_t + \beta_{4,i} \times WML_t + \varepsilon_{i,t}. \qquad (6)$$

As security returns and security prices are directly related, factor models are a convenient tool for identifying mispricing. If a security exhibits an alpha significantly different from zero, the security may potentially be overpriced / underpriced. That is, in comparison to the security's exposure to the applied risk factor / factors, the security offers too little / too much return compensation. To establish equilibrium conditions, its price needs to go down / up, thereby increasing / decreasing corresponding returns. The terms mispricing, abnormal return, under- and outperformance are always applied in the context of a chosen benchmark and a corresponding factor model.[249]

Factor models are frequently debated by researchers. Perhaps the best evidence for the ongoing debate and the associated uncertainty with regard to factor models is the continuing revision of old and emergence of new approaches.[250] Academic research has proposed a great variety of (potential) risk factors; this large selection of factors has been labeled as the factor zoo.[251] Nonetheless, when studying asset pricing, the models described in this section reflect the state of academic research and thus are an appropriate tool.

[249] See Brown and Warner (1980), Capon et al. (1990), Strong (1992), Armitage (1995), Doukas et al. (2010), van Ewijk et al. (2012), and Stambaugh and Yuan (2017) for the assessment of different factor models. See also the discussion of market efficiency and the corresponding implications for asset pricing of *Section 2.1*.

[250] See for example Neely et al. (2014) and Mohrschladt and Nolte (2018).

[251] See Cochrane (2011), Feng et al. (2020), and Bartram et al. (2021). See Barillas and Shanken (2018) for a comparison of asset pricing models.

4.2 Data Sources for the Empirical Analyses

4.2.1 Stock Market Data, Factors, and Foreign Exchange Rates

For the empirical analyses in this dissertation, stock market data which comprehensively mirror the corresponding stock market of different national economies are required.

Data mirroring the US stock market are obtained from the *Center for Research in Security Prices* (*CRSP*)[252], a survivorship bias-free database well-established among researchers.[253]

Data mirroring the stock markets of countries other than the US are obtained from *Thomson Reuters Datastream* (*Datastream*)[254]. When using *Datastream*, obtaining survivorship bias-free stock market data, which is representative of a national economy's stock market, takes several steps. First, an appropriate index has to be identified, which (roughly) covers all publicly traded stocks of the corresponding country. Subsequently, data on monthly index compositions, i.e. lists containing all of the stocks (identified by their *International Securities Identification Number* (*ISIN*)) assigned to the index, are obtained. All of the obtained stocks are consolidated; all duplicates are removed. Subsequently, after composing the survivorship bias-free index, *Datastream*'s *total return index* is queried for all corresponding stocks. Daily and monthly returns are calculated based on *total return index*. In addition, daily values for share price and market capitalization are queried from *Datastream*; monthly values are derived by applying means to the corresponding daily values. For mirroring the German stock market, the *CDAX* is applied.[255] The empirical analyses of *Section 6* include stock market indices for several more countries. The selected indices mirroring each country's stock market are listed in Appendix A6 Table 25.

In *Section 5*, the attempt to match German households' holding data to *CRSP* data produces poor results. *CRSP* includes a variety of securities that correspond to

252 See: www.crsp.org.

253 Although CRSP is generally accepted to be a complete database with accurate data records, there are some studies pointing to errors. See Rosenberg and Houglet (1974), Shumway (1997), and Shumway and Warther (1999).

254 Due to recent mergers / acquisitions, *Thomson Reuters Datastream* has been subject to a name change. *Datastream* is now operated by *Refinitive* (www.refinitiv.com) which is part of the *London Stock Exchange Group* (*LSEG*) (www.lseg.com).

255 For initial public offerings in Germany (IPOs) see Oehler et al. (2019a). See also Oehler (2000a), Herberger and Oehler (2011), Walker et al. (2011), and Oehler et al. (2017a) for further research on IPOs.

relatively unknown US companies; these are unlikely to be a relevant part of German private sector portfolio holdings. Thus, for the corresponding analyses in *Section 5*, the *S&P1500* is applied as an alternative proxy for the US stock market, resulting in vastly superior matching results. *S&P1500* data are in turn obtained from *Datastream* using the previously described multi-step approach.

The *wikifolio* social trading platform, analyzed in *Section 6*, issues a complete list of all assets – including the associated *ISINs* – that are available to *wikifolio* signal providers. This compilation of available assets is referred to as the *wikifolio* investment universe. For all stocks in the *wikifolio* investment universe, *total return index* data, share prices and firm market capitalizations are obtained from *Datastream*.

For each of the analyzed stock markets, regional (daily and monthly) factor data are obtained from the *Kenneth French Data Library* (*KFDL*)[256]. As there is an ongoing debate on whether the application of local factors is more appropriate than using regional factors[257], for robustness, some of the analyses of *Section 6* are re-estimated with local German factors obtained from *Richard Stehle*'s homepage[258]. As these data end in June 2016, for the remaining period, the regional European factors from the *KFDL* are applied. *KFDL* factors are denominated in USD while *Richard Stehle*'s factors are denominated in EUR; different currency denominations are accounted for in the analyses.

The focus of the *ZuluTrade* social trading platform – analyzed in *Section 7* – is on foreign exchange trading. That is, mostly currency pairs are traded by *ZuluTrade* signal providers. The empirical analyses in *Section 7* require daily exchange rates for currency pairs traded on *ZuluTrade*; these are obtained from the respective base currency's (or in some cases the quote currency's) national central bank / monetary authority. Provided that sufficient daily time series data is not available from the base currency's or the quote currency's national central bank / monetary authority, the required exchange rates are derived by applying corresponding EUR rates obtained

[256] See: *mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html*.
[257] See Hollstein (2022).
[258] See: *www.wiwi.hu-berlin.de/de/professuren/bwl/bb/data/fama-french-factors-germany/fama-french-factors-for-germany*.

from the *European Central Bank*. A detailed overview on the data sources of the analyses in *Section 7* is provided in Appendix A2 Table 17.

4.2.2 *Securities Holdings Statistics-Base plus* of *Deutsche Bundesbank*[259]

This section describes the *Securities Holdings Statistics-Base plus* (henceforth *SHS*-base) data which are applied in *Section 5* to mirror German aggregate private sector holdings. *SHS*-base data is aggregated and provided by the *Research Data and Service Centre* (*RDSC*) of *Deutsche Bundesbank*.[260]

SHS-base data as applied in the empirical analyses of this dissertation were obtained in the second half of 2017; thus, the corresponding data report at the time of data procurement is provided by Bade et al. (2017). As the *SHS*-base has been frequently updated, further data reports have been issued. The most recent data report before the submission of this dissertation is provided Blaschke et al. (2022). The *SHS*-base is a comprehensive and complete source of data as “all financial institutions domiciled in Germany report all securities they hold in save custody for domestic and foreign customers”[261] with no existent reporting limit.

SHS-base data, as applied in the empirical analyses of this dissertation, i.e. information on security holding positions on a security-by-security level, has been collected since December 2005. From 2005 to until the end of 2012, data were collected on a quarterly basis with each datapoint corresponding to end-of-quarter holdings (i.e. end-of-quarter holdings are equivalent to end-of-month holdings of the quarter’s last month). From the beginning of 2013, reporting frequency has changed from quarterly to monthly (each datapoint corresponding to end-of-months holdings). *SHS*-base data include three structural dimensions which are listed below.

Reporting financial institutions. Each reporting agent corresponds to a random ID. This dimension, i.e. information on the distribution of reporting agents, is not employed in the conducted empirical analyses as only aggregate holdings are

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[259] If not indicated otherwise, the description of the *Securities Holdings Statistics-Base plus* is obtained from Bade et al. (2017).
[260] The research project und which the data were requested and obtained corresponds to the following *RDSC* project-ID: *2018\0015*.
[261] See Bade et al. (2017, p. 4).

considered. Securities which are in a given quarter / month reported by less than three reporting agents, are (mandatorily) excluded from the data set.[262]

Holders. Each holding includes information on the sectoral classification[263] and the country of residence of the associated holder. For the empirical analyses in this dissertation, holding data corresponding to German households is considered.

Securities. All Securities are identified by their corresponding twelve-digit *ISIN*.

In addition to the identifying information (i.e. holder country and sector, reference month, reporting agent ID, and *ISIN*), *SH*S-base data include the number of units held, the corresponding nominal value in EUR (number of units held multiplied by the asset's book value), and the corresponding market value in EUR (number of units held multiplied by the asset's end-of-month market value). By aggregating data over all reporting agents, it is now possible to generate the overall number, nominal value, and market value of any given security in each quarter / month (over the observation period) that is held by the German household sector. This information allows an assessment regarding the representation of an asset among German households.

For example, consider any stock S in the German *CDAX* (benchmark mirroring the German stock market). Conventional stock market data allows for the determination of the market capitalization of the corresponding stock as well as the market capitalization of the overall benchmark. *SHS*-base data allows for the determination of the overall market value of stock S as well as the overall market value of the benchmark index as held by German households. By comparing the relative share of stock S as held by German households to the share of the stock within the benchmark index, it is possible to determine if the asset is over- or underrepresented.

Notable studies including *SHS*-base data are conducted by Fecht et al. (2018) and Oehler and Wanger (2020).

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[262] The mandatory exclusion of securities which are reported be less than three reporting agents is governed by *Deutsche Bundesbank*'s data privacy policy. For the conducted empirical analyses, this does not present a severe limitation as these securities "can barely be assumed to be representatively spread among German households." (see Oehler and Wanger 2020, p. 9).

[263] Holder sectors are classified according to the *European System of Accounts* (*ESA*). Holder sector classification followed the *ESA 95* scheme (see Statistical Office of the European Communities (Eurostat) 1996) until December 2012; since January 2013, the classification has followed the *ESA 2010* scheme (see Statistical Office of the European Communities (Eurostat) 2013).

4.2.3 Social Trading Data and Platform Design *wikifolio*[264]

In this section, the data and platform design for the *wikifolio* social trading platform[265], corresponding to the empirical analyses in *Section 6*, are described.

Signal providers on the *wikifolio* platform manage virtual portfolios – called *wikifolios* – that are (eventually) issued via certificates and thereby become available for investment. Generally, there is no restriction on who can become a signal provider on the *wikifolio* platform. The majority of signal providers is composed of private traders. Furthermore, there are labels indicating if an asset manager or a media company, i.e. a professional trader, is in charge of the *wikifolio*. Regarding private traders, the maximum number of simultaneously administered *wikifolios* is limited to eight, on the other hand, asset managers and media companies may simultaneously manage any given number.[266] The portfolios which underlie the *wikifolio* certificates, regardless of their assigned status, are purely virtual, i.e. signal providers do not actually hold the corresponding assets. In order to directly mirror the performance of their own administered *wikifolios*, signal providers need to buy corresponding *wikifolio* certificates (which is in accordance with the copy-trading approach of signal followers on the *wikifolio* platform). *Wikifolios* can obtain the label *Real Money* when a certain amount is invested in the corresponding *wikifolio* certificates by the administering signal provider. Signal providers are compensated via performance fees – ranging from five to 30 percent – which are self-imposed when creating the *wikifolio*. Receivable performance fees are calculated depending on the high watermark principle, meaning that signal providers only become eligible for remuneration if their corresponding *wikifolio* reaches a new high for the year, i.e. a new high watermark is set. The basis for calculating the performance fee is the return of the administered *wikifolio*, i.e. the difference between the current and the last peak of the *wikifolio* equivalent value.[267] High watermarks are reset to the current index level of each *wikifolio* at the end of each calendar year. Contingent on the amount of capital invested in a respective *wikifolio* certificates, signal providers are (only) entitled to

[264] The data and platform descriptions regarding the *wikifolio* social trading platform are substantially obtained from Oehler and Schneider (2023).
[265] See: www.wikifolio.com.
[266] *Wikifolios* may be closed – and potentially replaced – at any time by their corresponding signal provider.
[267] The *wikifolio* equivalent value is derived from the sum of cash and all other assets held. Daily closing prices (assessed by *Lang & Schwarz*) are applied for the high watermark calculation.

claim a pre-defined share of the amount derived from value appreciation and performance fee. The maximum share signal providers may receive is 50 percent.[268] Signal providers trading *wikifolios of wikifolios* are compensated differently – since their respective *wikifolios* are not included in the main empirical analyses, the corresponding approach is not elaborated.

Signal provider portfolio data are directly obtained from the *wikifolio* platform. For each *wikifolio* daily prices as well as transaction data regarding all conducted transactions are freely accessible. *Wikifolios* go through different life cycle stages: *Test*, *Published*, *Investable*, *Closing*, and *Closed*.[269] When reaching the status *Closed*, *wikifolios* remain visible on the profile of their corresponding signal provider, however, they no longer appear when using the platform's search function. Therefore, the names of all signal providers who manage *wikifolios* which appear on the dashboard, i.e. signal providers who can be found using the search function, are obtained. Afterwards, each signal provider's profile is assessed and data for all accessible *wikifolios* are downloaded. Thus, all *Closed wikifolios* associated to signal providers who manage at least one *wikifolio* exhibiting the status *Published*, *Investable*, or *Closing* are included. *Closed wikifolios* associated to signal providers who are not active anymore, i.e. all their corresponding *wikifolios* have all been closed, are not accessible and thus cannot be included in the analysis. *Wikifolio* data are obtained at the beginning of February 2019 which leads to a comprehensive dataset of 30,279 – divided by status into 15,341 *Published*, 7,696 *Investable*, 55 *Closing*, and 7,187 *Closed* – *wikifolios*. As data for signal providers who have completely disappeared from the platform is not available, the composed dataset is subject to a certain survivorship bias. When exhibiting good peer performance, there is no apparent incentive for signal providers to cease activities. Therefore, signal providers who have altogether vanished from the platform had likely been

[268] When less than 10,000 EUR are invested in the corresponding *wikifolio* certificate, signal providers are not compensated.

[269] Status *Test*: Only visible to the corresponding signal provider. Status *Published*: Released by the corresponding signal provider, i.e. transactions and returns are accessible for all registered platform users. Status *Investable*: An open-ended index certificate reflecting the underlying *wikifolio*'s price development has been issued by *Lang & Schwarz*, i.e. the *wikifolio* is available for investment. To attain this status, a minimum term of 21 days must have passed since the *wikifolio*'s creation, ten or more platform users have intended their willingness to invest, the indicated investment amount has exceeded 2,500 EUR, and the corresponding signal provider's personal data and trading approach specifications have been checked by the platform. Status *Closing*: Open positions are sold and fees are suspended. Investors may sell their corresponding *wikifolio* certificate at the last established price. Status *Closed*: There are no more outstanding *wikifolio* certificates.

administering underperforming *wikifolios*, placing them at the lower end of the performance spectrum.

For the empirical analysis, the dataset is limited to *wikifolios* which encompass data over at least six months; the dataset is thereupon reduced to 24,101 entities. The earliest data points go back to December 2011. Data after February 2019 are not included.

Signal providers can choose from an extensive investment universe. The main groups of tradable assets are stocks, funds, ETFs, investment certificates, and leverage products. When creating a *wikifolio*, signal providers can choose if they want to have access to the entire investment universe provided by the platform or exclude leverage products from their trading activities.[270] An overview of traded instrument categories is displayed in Appendix A2 Table 14. The number of conducted transactions is not evenly distributed among all administered *wikifolios*. There is a vast number of *wikifolios* where no transaction is conducted for several continuous months, indicating that the corresponding signal providers pursue a plain buy-and-hold strategy or have abandoned the administered *wikifolio* without closing. On the other hand, there are *wikifolios* continuously exhibiting a vast number of monthly transactions. To account for abandoned or inactive *wikifolios*, *wikifolio*-month observations are dropped after the signal provider has conducted the last transaction within a corresponding *wikifolio*. Table 1 provides an overview regarding the distribution of transactions after accounting for inactive entities.

For each transaction, the *ISIN*, the change in quantity, and the price of the respective traded asset is provided by the *wikifolio* platform. To provide an overview of signal providers' geographical preferences with regard to traded assets, we sort the obtained transaction data on the two initial letters of each transaction *ISIN* indicating the issuing country. The analysis reveals that signal providers strongly focus on assets which have been issued in Germany. Results are displayed in Appendix A2 Table 15. 70 percent of all transactions conducted by signal providers involve assets

[270] The tag *Attention: Might contain leverage products* – included in the summary information which appears when using the search function on the platform's front page as well as on the front page of the individual *wikifolio* – informs signal followers whether leverage products are potentially traded. There is ample research regarding the information content and suitability of (warning) lables for consumer / financial products; see Oehler (2013b), (2015d). See also Oehler (2021i), and Oehler et al. (2014a), (2018a).

issued in Germany. Regarding transaction volume, the focus on German assets is even more severe, accounting for a total share of 87 percent. The results indicate that, when considered together, *wikifolios* lack international diversification. However, missing spatial diversification might be caused by the peculiarities of the *wikifolio* platform; about 85 percent of assets which are available to signal providers have been issued in Germany. Thus, the selection process of signal providers might be biased by the (wide yet spatially pooled) range of available assets.

	$D1$	$D2$	$D3$	$D4$	$D5$	$D6$	$D7$	$D8$	$D9$	$D10$
Number	7	16	26	39	58	87	136	230	460	3,085
Volume	1	3	7	12	21	37	67	102	210	50,552

Table 1: Deciles Distribution Transactions *wikifolio* Platform

Notes: The table above reports deciles regarding the monthly number and volume of trades after accounting for inactive *wikifolios*. The data is listed according to deciles ($D1$ to $D10$). Volume is reported in thousand EUR.

By default, *wikifolios* are sorted on so-called *wikifolio points* which are calculated from twelve criteria. In addition to risk and return, the respective underlying criteria are meant to reflect the *wikifolio*'s popularity, as well as the corresponding signal provider's activity and commitment. A complete breakdown regarding the calculation method of *wikifolio points* as described on the *wikifolio* platform is provided in Appendix A2 Table 16. Furthermore, platform users may sort available *wikifolios* on the following 14 individual criteria: *Date created*, *Date of issuanc*e, *Performance ever*, *Performance since first issuance*, *Performance YTD*, *Performance 12 months*, *Performance 6 months*, *Performance 3 months*, *Performance 1 month*, *Sharpe Ratio (365 Days)*, *Maximum loss (to date)*, *Invested capital*, *Reservations*[271], and *Risk factor*[272].

[271] The criterion *Reservations* indicates the number of signal followers observing the *wikifolio*, i.e. keeping the *wikifolio* on their watchlist.

[272] The *Risk factor* is represented by the covariance of the respective *wikifolio* and the *Eurostoxx 50* index. Covariances are computed using daily closing price of the last two years. For each *wikifolio*, the highest covariance value of the last 200 days is displayed. This indicator is only provided for *wikifolios* which exclude leverage products.

4.2.4 Social Trading Data and Platform Design *ZuluTrade*[273]

In this section, the data and platform design for the *ZuluTrade* social trading platform[274], corresponding to the empirical analyses in *Section 7*, are described.

Transaction data is directly obtained from the *ZuluTrade* platform. Data for all accounts that can be grasped via the platform's search function are 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. All obtained accounts in the dataset are assessed to gather 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. Data are included until the end of January 2021 for the corresponding analyses.[275]

As data for accounts corresponding to signal providers which are now longer active on the platform are 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 superior performance in comparison to their peers, these traders had likely been located at the lower end of

[273] The data and platform descriptions regarding the *ZuluTrade* social trading platform are substantially obtained from Schneider and Oehler (2021).
[274] See: www.zulutrade.com.
[275] Signal provider trading data are 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.

the performance spectrum, at least towards the end of their involvement (see *Section 4.2.3*).

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[276]; 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.

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.[277] 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.

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 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

[276] 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.

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

recommend default options which signal followers may select to copy all trades with one micro lot (*Fixed*) / a 100 percent ratio (*Pro-Rata*) and a leverage of 100 to one. Those preset amounts are adjusted in accordance with the *Indicative Leverage*[278] ratio chosen by each signal follower when creating a *ZuluTrade* account. Summary statistics regarding signal provider trading data are displayed in Table 2.

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 2: Signal Provider Trading Data *ZuluTrade* Platform

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.

[278] 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.

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 Appendix A2 Table 17. 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.[279]

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.[280]

On the *ZuluTrade* platform, signal provider compensation depends on the account type of their corresponding *Real* investors (i.e. signal followers). 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

[279] All abbreviations relating to currencies are displayed and described in in the Appendix A2 Table 17.
[280] 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.

a previously set high watermark.[281] 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.

Thereafter, 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* (henceforth reserves). Each signal provider holds distinct reserves for all of her 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.[282] 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. The EU regulative framework imposes further restrictions on signal providers to be eligible for

[281] 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.
[282] Corresponding fees are calculated on a pro-rata basis.

EU-based signal followers.[283] 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.[284]

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)*[285], *Multiple Instruments Strategies*, and *Highest AUM – Amount Following*[286]. Only when selecting the tab captioned *All Traders*, the full range of available signal providers is displayed.

While all traders are displayed by default when the *All Traders* tab is selected, 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 followers' 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

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283 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 EU framework.
284 Each trader account displays pointers to corresponding accounts operated by the same signal provider.
285 On the *ZuluTrade* platform, *Winning* relates to the nominal amount a signal provider has generated for signal followers using *Real* accounts.
286 *ZuluTrade* defines the *Amount Following* as the invested funds of *Real* investors copying a signal provider's transactions.

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* (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.

4.2.5 Sports Betting Data[287]

In this section, the data that is used for mimicking sports betting returns are described; in *Section 8*, sports betting returns are analyzed within a multi-layer portfolio framework.

As there is a vast array of sports betting options, choosing representative bets and corresponding returns is rather difficult. This is addressed by following each signal of a sports betting signal provider. Signals are obtained from *90plusX*[288], a platform where specific recommendations for bets are issued on a daily basis. Betting recommendations relate to pairings of professional European soccer clubs. The vast majority of signals involves two pairings; these signals indicate the speculated winner, a draw, or whether or not both teams will score in the corresponding pairing. Occasionally signals refer to more specific options. In combination with each signal, the platform issues a recommendation with regard to the respective wager. Recommendations regarding wagers are provided in monetary units. One monetary unit may be transferred into the corresponding individual amount in national currency

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[287] The data and platform descriptions regarding the *90plusX* sports betting signal provider are substantially obtained from Schneider (2022).
[288] See: www.90plusx.com.

by dividing the total budget which has been assigned to gambling by 100. For example, if 1,000 EUR are designated to gambling and the platform recommends three monetary units in combination with a corresponding signal, the wager amounts to 30 EUR. The platform started publishing signals in December 2015. Up until December 2020, each historic signal, including the corresponding result, can be obtained from the platform. Data for 1,670 distinct signals is obtained. Platform users may access betting signals free of charge. The platform does not function as a bookmaker and has no direct financial stake in the outcome of each pairing or the success rate of its signals. Instead, the platform’s business model is based on recommending bookmakers for each of the issued signals. The platform receives remuneration if the bookmaker is assessed via a redirection link. The accessible data allows for constructing a return index, mirroring the value development of a strategy which is based on following all signals issued by *90plusX*.

In addition, two simple rule-based sports betting strategies are constructed to reflect potential sports betting returns. These strategies are based on German *Bundesliga* (German first league professional soccer) matches. The construction of those strategies requires the (a priori) odds for a victory for each team as well as all corresponding results. Data for each German *Bundesliga* match starting from season 2004/2005 to season 2020/2021 is obtained from *OddsPortal.com*[289]. The final dataset comprises 1,580 pairings.

[289] See: www.oddsportal.com.

5 Gambling with Lottery-like Stocks?[290]

5.1 Methodological Approach

5.1.1 Portfolio Construction

As basis for the empirical analyses, a dataset mirroring the German stock market (*CDAX*) and dataset mirroring the US stock market (*CRSP*) are obtained – only stocks with data for at least seven months were considered. Data on monthly *CDAX* index compositions is obtained from *Datastream* for the period from July 2000 to August 2020.[291] Subsequently, all *ISINs* are consolidated and duplicates are removed. The consolidation leads to 1,059 different *ISINs* for which stock market data, if available, is obtained between January 1990 to August 2020 – due to new listings and delistings, the included stocks may not have available data for the entire period. The dataset is merged with factor data corresponding to Europe form the *KFDL*. For the US stock market, survivorship bias-free *CRSP* data is applied. Factors for North America are, in turn, obtained from the *KFDL*. The market, size, and book-to-market factors are available from July 1990; data for the momentum factor starts in November 1990. Factor data availability marks the inception of the respective conducted analyses.[292]

As *CRSP* data were provided in USD, *CDAX* data are converted into USD to eliminate currency effects. As in Kumar (2009), each month three distinct portfolios based on idiosyncratic volatility, idiosyncratic skewness, and price are formed: $Lottery$ (comprising all lottery-like stocks), $NonLottery$ (comprising all nonlottery-like stocks), and $Others$ (comprising all stocks that are not assigned to the first two portfolios). Idiosyncratic volatility and idiosyncratic skewness are computed based on the daily stock returns of the previous six months (i.e. months $t-6$ to $t-1$), while price is measured as the average stock price over the previous month (i.e. month $t-1$). The $Lottery$ portfolio contains stocks in the lowest k^{th} price percentile, highest k^{th} idiosyncratic volatility percentile, and in the highest k^{th} idiosyncratic skewness percentile. As in Kumar (2009), $k = 50$ is chosen; that is, stocks exhibiting above median idiosyncratic volatility, above median idiosyncratic skewness, and below median price. In contrast, the $NonLottery$ portfolio is composed of stocks that are

[290] This section and the referred appendices are substantially obtained from Oehler and Schneider (2022).
[291] Before July 2000, *Datastream* did not provide data on the composition of the *CDAX*.
[292] See also *Section 4.2.1*.

assigned to the highest k^{th} stock price percentile, the lowest k^{th} idiosyncratic volatility percentile, and the lowest k^{th} idiosyncratic skewness percentile; that is, stocks featuring below median idiosyncratic volatility, below median idiosyncratic skewness, and above median price.[293]

Furthermore, another definition of lottery-like stocks, established by Bali et al. (2011), is applied: Stocks with extreme past daily returns are classified as lottery-like. Stocks are sorted based on the constituent maximum daily return over the previous month. Stocks in the highest k^{th} percentile, that is, stocks with the highest daily return over the previous month, are categorized as lottery-like. Similarly, stocks in the lowest k^{th} percentile are classified as nonlottery-like. The corresponding portfolios are labeled Max and $NonMax$. As a variation, decile portfolios are formed based on the average of the five highest daily returns in the previous month. Accordingly, stocks in the highest and lowest k^{th} percentiles are categorized as lottery-like ($Max5$) and nonlottery-like ($NonMax5$). In accordance with Bali et al. (2011), $k = 10$ is chosen.

In order to analyze the preferences of the German private sector regarding lottery-like characteristics on a broader level, several more portfolios are constructed and analyzed. In this context, portfolios are sorted on Kumar's (2009) constituent characteristics for lottery-like stocks. The resulting portfolios are as follows: low / high price ($LPrice$ / $HPrice$), high / low total volatility ($HTVol$ / $LTVol$), high / low idiosyncratic volatility ($HIVol$ / $LIVol$), high / low total skewness ($HTSkew$ / $LTSkew$), and high / low idiosyncratic skewness ($HISkew$ / $LISkew$). Stocks in the highest / lowest k^{th} percentile of each sorting criterion are assigned to the corresponding portfolio. When sorting portfolios on one criterion, $k = 10$ is chosen.[294]

Furthermore, portfolios are simultaneously sorted by using various combinations of the (constituent) characteristics of Kumar's (2009) lottery-like stocks. Hence, additional portfolios based on low / high price and high / low total volatility ($LPrice\&HTVol$ / $HPrice\&LTVol$), low / high price and high / low idiosyncratic volatility ($LPrice\&HIVol$ / $HPrice\&LIVol$), low / high price and high / low total skewness ($LPrice\&HTSkew$ / $HPrice\&LTSkew$), low / high price and high / low idiosyncratic volatility ($LPrice\&HISkew$ / $HPrice\&LISkew$), high / low total volatility and high / low

[293] For this paragraph, see also *Section 3.4.1*.
[294] For this paragraph, see also *Section 3.4.1*.

total skewness ($HTVol\&HTSkew$ / $LTVol\&LTSkew$), and high / low idiosyncratic volatility and high / low idiosyncratic skewness ($HIVol\&HISkew$ / $LIVol\&LISkew$) are constructed. Stocks in the highest or lowest k^{th} percentile are assigned to the corresponding portfolio. When sorting portfolios on two criteria, $k = 25$ is chosen.

Given this methodology, there are overlaps among several of the constructed portfolios in which stocks may be assigned to various portfolios at the same time. Summary statistics for all portfolios are displayed in Appendix A3 Table 18.

5.1.2 Performance Analysis and Weighting of Portfolios

For all portfolios, a performance analysis is conducted. In this context, mean monthly raw returns are computed by averaging the value-weighted monthly stock returns for each portfolio. Additionally, the performance is measured via risk-adjusted returns, which are calculated as the regression intercept alpha, α, from Carhart's (1997) four-factor model. The results for the portfolios sorted according to Kumar's (2009) and Bali et al.'s (2011) lottery-like stock definitions, as well as all other portfolios described in this section, are displayed in Appendix A3 Table 19, Table 20, and Table 21.

In order to assess the holdings of the German private sector with regard to the previously described portfolios, we merge *SHS*-base data (see *Section 4.2.2*) with the proxies for the German (*CDAX*) and the US (*CRSP*) stock markets. The *CRSP* data do not have security *ISINs*. Hence, *SHS*-base data cannot be directly merged with the *CRSP* dataset. Applying ticker symbols as common identifiers, *Datastream* is accessed to obtain *ISINs* for the corresponding *CRSP* securities. Matching *CRSP* securities with *ISINs* proves to be rather difficult. When merging the *CRSP* dataset – supplemented by all accessible *ISINs* – with *SHS*-base data, only about half of all security-month observations can be matched. The poor matching results are explained by the difficulties in acquiring *ISINs* for *CRSP* securities as well as the particular composition of the *CRSP* database. Regarding the latter, *CRSP* has a variety of securities that correspond to relatively unknown US companies that are unlikely to be a pertinent part of German private sector holdings.[295] Henceforth, this issue is addressed by using the *S&P1500* as an alternative proxy for the US stock

[295] As previously discussed, *Deutsche Bundesbank*'s data privacy protection policy only enables the usage of aggregated private sector data when a corresponding security is stored by at least three distinct reporting institutions.

market which leads to vastly superior matching results. *S&P1500* data are in turn obtained from *Datastream*.[296]

With the obtained data, it is assessed whether the German private sector, as mirrored by *SHS*-base data, disproportionally invests in any of the previously described portfolios. In this context, unexpected portfolio weights ($EW_{p,t}^{h}$) are constructed:

$$EW_{p,t}^{h} = \frac{w_{p,t}^{h} - w_{p,t}^{m}}{w_{p,t}^{m}} \times 100, \quad (7)$$

where $w_{p,t}^{h}$ is the relative weight of portfolio p held by the private sector in month t in relation to all corresponding private sector holdings; accordingly, $w_{p,t}^{m}$ is the relative market weight of portfolio p in month t. The unexpected portfolio weights are respectively composed for the proxies for the German (*CDAX*) and the US (*S&P1500*) stock markets. The relative private sector weight is constructed as the funds assigned to the respective portfolio that are divided by all funds assigned to German and US stocks for which *SHS*-base data are available. Accordingly, the relative market weight is constructed as the market value of the respective portfolio that is divided by the total market value of all German and US stocks; stock-month observations which cannot be matched to *SHS*-base data are not included when constructing the relative portfolio market weights with the available *SHS*-base data. The results are displayed in Table 3 and Appendix A4 Table 22.

5.1.3 Regression Analysis

Furthermore, a regression analysis is applied to assess the preferences of the private sector – derived from aggregate holding data – for lottery-like characteristics. Following Goetzmann and Kumar (2008) and Kumar (2009), we apply the unexpected weight allocated to each stock as the dependent variable. The measure is constructed as follows:

$$EW_{i,t}^{h} = \frac{w_{i,t}^{h} - w_{i,t}^{m}}{w_{i,t}^{m}} \times 100, \quad (8)$$

296 Data on monthly *S&P1500* compositions as well as daily time series data for individual stocks come from *Datastream* for the period covered by *SHS*-base data. See also *Section 4.2.1*.

where $w_{i,t}^{h}$ is the relative weight of stock i held by the private sector in month t in relation to all corresponding private sector holdings; $w_{i,t}^{m}$ depicts the relative market weight of stock i in month t.[297]

The corresponding baseline model for the regression analysis is as follows:

$$EW_{i,t}^{h} = \alpha + \beta_1 \times Vol + \beta_2 \times Skew + \beta_3 \times Price + \beta_4 \times DDomestic$$
$$+\beta_5 \times lnMCap + \beta_6 \times SSkew + \beta_7 \times RMax + \beta_8 \times R + \epsilon. \quad (9)$$

All dependent variables refer to stock-month observations. Vol / $Skew$ depicts (idiosyncratic) volatility / skewness that is measured using the daily returns of the previous month and previous six months, and $Price$ is the stock price during the previous month, $DDomestic$ is a dummy variable which equals one if the corresponding stock is listed in the *CDAX*, $lnMCap$ is the natural logarithm of a corresponding firm's market capitalization during the previous month, $SSkew$ is the systematic skewness that is measured by using the daily returns of the previous month and previous six months, $RMax$ is the maximum daily return attained in the previous month, and R is the monthly return over the previous month.

Furthermore, results for the following regression model are reported:

$$EW_{i,t}^{h} = \alpha + \beta_1 \times DVol + \beta_2 \times DSkew + \beta_3 \times DVolSkew + \beta_4 \times DPrice$$
$$+\beta_5 \times DPriceVol + \beta_6 \times DPriceSkew + \beta_7 \times DPriceVolSkew$$
$$+\beta_8 \times DDomestic \ + \beta_9 \times DRMax + \epsilon \quad (10)$$

where $DVol$ / $DSkew$ is a dummy variable that equals one if the corresponding stock's (idiosyncratic) volatility / skewness is measured by using the daily returns of the previous month and previous six months are within the highest k^{th} percentile of its domestic market; $DPrice$ depicts a dummy variable which equals one if the corresponding stock's price during the previous month is within the lowest k^{th} percentile. $DVolSkew$, $DPriceVol$, and $DPriceSkew$ depict dummy variables that

[297] In line with the previously described approach for constructing unexpected portfolio weights, unexpected stock weights are computed with regard to the proxies for the German (*CDAX*) and the US (*S&P1500*) stock markets. The relative private sector weight is constructed as the aggregated funds assigned to the respective stock i that are divided by all funds assigned to German and US stocks for which *SHS*-base data are available. Accordingly, the relative market weight is constructed as the market capitalization of stock i that is divided by the total market capitalization of all German and US stocks with available *SHS*-base data.

equal one if the corresponding stock is simultaneously within the highest k^{th} percentile with regard to the volatility and the skewness measure, or the lowest k^{th} percentile with regard to the price and the highest k^{th} percentile respectively with regard to the volatility or skewness measure. $DPriceVolSkew$ is a dummy variable which equals one if the corresponding stock is simultaneously in the lowest k^{th} price percentile, the highest k^{th} (idiosyncratic) volatility percentile, and the highest k^{th} (idiosyncratic) skewness percentile. $DRMax$ depicts a dummy variable equal to one if the stock is within the highest k^{th} percentile with regard to the maximum daily return of the previous month.

5.2 Results and Discussion

Considering all the constructed portfolios, statistically significant mispricing is rare. In contrast to Kumar (2009), this study does not find consistent evidence that the $Lottery$ portfolio statistically and significantly underperforms. The $Lottery$ portfolio of the US market shows an alpha of -.39 percent per month, however, with weak statistical significance at the five percent level (see Appendix A3 Table 19, *Panel°B*). For German lottery-like stocks, there is no evidence of any underperformance (see Appendix A3 Table 19, *Panel°A*). Pricing differentials are insignificant in both markets.

Regarding the Max and $Max5$ portfolios, the underperformance found by Bali et al. (2011) still prevails in both the US and the German stock markets.[298] Further evidence of mispricing for stocks with extreme maximum daily returns is provided by Annaert et al. (2013). Yet, in the US market the economic magnitude of the effect, as well as its statistical significance, is weaker as reported by Bali et al. (2011). For the decay in mispricing – instead of disappearing – after its publication, McLean and Pontiff (2016) point to frictions hindering arbitrage from completely eliminating the effect.[299] Max and $Max5$ stocks have very high levels of idiosyncratic risk represented by idiosyncratic volatility (see Appendix A3 Table 18). As reported in other research, idiosyncratic risk restrains the amount investors are willing to invest in mispriced

[298] In the US market, the Max portfolio does not significantly underperform its $NonMax$ counterpart.
[299] For limits to arbitrage see *Section 2.3*.

assets, thereby inhibiting arbitrage.[300] Thus, regarding the Max and $Max5$ portfolios, mispricing may be fairly persistent.[301]

Considering all other portfolios sorted, there is evidence of a statistically significant underperformance of high-risk stocks, that is, stocks with simultaneously high (idiosyncratic) volatility and high (idiosyncratic) skewness, in both markets. In this context, significant performance differentials may be attributed to the widely known low-volatility anomaly, which can be traced back to Black (1972) and Haugen and Heins (1975). Contradicting the CAPM, the low-volatility anomaly states that low-risk assets, irrespective of the applied risk measure, have superior returns.[302]

The results presented in Table 3 show that German private investors overinvest in stocks with lottery-like characteristics. This is in line with research that has reported that private investors have a strong preference for stocks with lottery-like features.[303] The German private sector overweights both domestic and foreign lottery-like stocks as defined by Kumar (2009). The exposure to domestic lottery-like stocks is 107 percent higher (see Table 3, column (7)) and the exposure to US lottery-like stocks is 25 percent higher (see Table 3, column (14)) than justified by the stocks' market capitalization. However, the households only overinvest in the domestic Max and $Max5$ portfolios as defined by Bali et al. (2011).

German private investors marginally overweight the domestic $NonLottery$ portfolio but seem to underinvest in the foreign $NonLottery$ portfolio. Furthermore, they underweight the domestic $NonMax$ and $NonMax5$ portfolios. Stocks with relatively low maximum daily returns, that is, stocks without large (positive) outliers, are unlikely to capture (extra) attention from private investors.[304] Thus, the underinvestment in stocks with low maximum daily returns may be driven by this lack of attention. As argued by Dorn and Sengmueller (2009), private investors to some extent consider trading as entertainment. Therefore, stocks assigned to the $NonMax$ and $NonMax5$

[300] See Treynor and Black (1973), Pontiff (1996), (2006), and McLean and Pontiff (2016). See also *Section 2.3*.
[301] See Annaert et al. (2013).
[302] For evidence on the low-volatility / low-risk anomaly see Haugen and Baker (1991), Jagannathan and Ma (2003), Ang et al. (2006), (2009), Blitz and van Vliet (2007), Baker and Haugen (2012), Leote de Carvalho et al. (2012), Blitz et al. (2013), and Bali et al. (2017). See also *Section 4.1*.
[303] See Kumar and Lee (2006), Kumar (2009), Doran et al. (2012), Han and Kumar (2013), and Bali et al. (2017). See also *Section 3.4.1*.
[304] See Odean (1999) and Barber and Odean (2008). See also *Section 3.3.3*.

portfolios may be unpopular choices as they do not trigger investors' excitement.[305] However, in contrast to their domestic equivalents, foreign $NonMax$ and $NonMax5$ stocks appear to be overweighted by private investors. For the German Max and $Max5$ portfolios, the mean of the relative market weight ($w_{p,t}^{m}$) exceeds the mean of the relative household portfolio weight ($w_{p,t}^{h}$), yet the mean of the excess weight ($EW_{p,t}^{h}$) indicates an average overinvestment (see Table 3, *Panel°A*). This can be attributed to two positive outliers in the excess market weight, yet the robustness of this pattern appears to be weak.

Differences with regard to relative weights assigned to a domestic portfolio and its foreign counterpart may be driven by the interrelation of familiarity and risk perception.[306] Studies have well-documented that investors are subject to ambiguity aversion.[307] In this context, due to their geographic remoteness, distant stocks correspond to a greater sense of unfamiliarity and thus investors perceive them as being riskier.[308] Thus, when investing aboard, investors may be drawn to stocks which have low levels of idiosyncratic risk.

Furthermore, when taking into account Shefrin and Statman's (2000) behavioral portfolio theory, investors who favor certain high-risk stocks as well as their low-risk counterparts do not pose a contradiction; as investors segregate their portfolios into mental accounts that correspond to different levels of aspiration, assets at both ends of the risk spectrum may appear as suitable investment choices.[309]

The results with regard to US stocks may be partly driven by the applied market proxy. As described, lottery-like stocks are defined in relative terms. While capturing a substantial portion of its market capitalization, the proxy for the US market – the *S&P1500* – only includes a fraction of available US equities. Hence, it is crucial to

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[305] See also *Section 3.3.3*.
[306] See Heath and Tversky (1991).
[307] See Fox and Tversky (1995), Bossaerts et al. (2010), Boyle et al. (2012), Ahn et al. (2014), and Baltzer et al. (2015).
[308] See Huberman (2001), Goetzmann and Kumar (2008), and Baltzer et al. (2015). As shown by some studies (see Baltzer et al. 2015, Huberman 2001, Oehler et al. 2008) ambiguity aversion and preferences for familiarity are driving forces behind the well-documented phenomenon that is labeled as home bias; see French and Poterba (1991), Tesar and Werner (1995), Cooper and Kaplanis (1994), Oehler (2001d), and Oehler et al. (2007), (2017e). For a comprehensive overview with regard to home and local bias see Oehler et al. (2008) as well as the therein cited literature.
[309] See Oehler et al. (2018b) and Oehler and Horn (2019), (2021a). See also *Section 3.3.1*.

acknowledge that with regard to the classification of US lottery-like stocks the applied benchmark may potentially lead to distortions.

Regarding disproportional investments, private investors substantially overinvest in low-priced stocks as well as in stocks with high levels of (idiosyncratic) volatility. In contrast, they underweight stocks with a high level of idiosyncratic skewness. The results are displayed in Appendix A4 Table 22.

Further, private investors overweight the portfolio that contains low-priced stocks which simultaneously have high levels of (idiosyncratic) volatility. Moreover, private investors overinvest in the portfolio that contains low-priced stocks which simultaneously have high levels of (idiosyncratic) skewness. They also overweight the domestic portfolio that contains high (idiosyncratic) volatility and high (idiosyncratic) skewness stocks; regarding its foreign counterpart, there is no evidence of a significant disproportional investment. These results are displayed in Appendix A4 Table 22.

The results of the regression analyses are displayed in Table 4. In line with Kumar (2009), this study provides evidence that private investors prefer low-priced stocks and stocks with high (idiosyncratic) volatility.

Running the regression of Equation 9 yields a statistically significant negative coefficient corresponding to the applied market capitalization measure. Therefore, this analysis confirms other studies reporting private investor preferences for small firms (i.e. firms with low market capitalizations).[310]

The regression model depicted in Equation 10 yields significantly positive coefficients for $DPriceVolSkew$ and $DRMax$ which respectively reflect lottery-like characteristics according to Kumar (2009) and Bali et al. (2011). They are evidence that private investors show preferences for the established definitions of lottery-like stocks.

Surprisingly, there is no consistent evidence that (idiosyncratic) skewness drives overinvestment in the private sector; the results are very consistent across the applied regression models. This is in contrast to the theoretical and empirical literature which

[310] See Barber and Odean (2000) (2001), (2008), Graham and Kumar (2006) and Kumar (2009). There is an extensive body of research assessing small- and mid-cap firms as well as their corresponding public equity; see, inter alia, Oehler et al. (2009), (2012b), (2013b), (2016f).

highlights the importance of skewness with regard to investors' preferences.[311] There are several factors which may drive the obtained results.[312] As individuals inherent limited capabilities to perceive and process information, the assumption that private investors are sufficiently able to assess a stock's corresponding (idiosyncratic) skewness appears to be rather pretentious. Even when financial literacy among investors is generally high, identifying and evaluating skewness may impose a challenge. In line with this argument, van Rooij et al. (2011) find that financial literacy is predominantly limited to basic knowledge of the concepts.[313] Share price and (idiosyncratic) volatility are features that may be identified much more easily by private investors. Accordingly, regarding the price and the idiosyncratic volatility feature, the conducted regression analysis yields unambiguous results. Furthermore, investors' expected skewness may not exactly match the applied skewness measures which are based on past daily returns.[314] Drerup et al. (2022) assess heterogeneity in skewness expectations, providing evidence that individuals disagree on the magnitude of skewness as well as on its sign.[315] In this study, past return skewness ($Skew_{t-1}$ / $Skew_{t-6}^{t-1}$) is extrapolate into the future.[316] While being a reasonable proxy, this approach may not directly capture private investor skewness expectations. Moreover, as skewness may not be persistent over time[317], investors potentially exhibit preferences for skewness when choosing stocks, but (at the aggregate level) do not rebalance their portfolios when stock and / or portfolio characteristics change.[318] The latter behavior might even be beneficial for households since excessive trading and rebalancing might considerably hamper their investment

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[311] See Kraus and Litzenberger (1976), Kane (1982), Mitton et al. (2018), Brunnermeier and Oehmke (2013), and Kumar et al. (2018). See also *Section 3.3.2*.

[312] Several studies challenge the prevailing narrative that investors strictly exhibit preferences for positive skewness. Yang and Nguyen (2019) provide empirical evidence that Japanese investors show preference for positively skewed assets, but do not dislike assets which are negatively skewed. Taking a theoretical approach, Brockett and Garven (1998) provide examples where a decision maker prefers the less skewed option when faced with the choice between two prospects with equal means and equal variances but different levels of skewness. That is, differences in higher moments can offset skewness preferences. Brünner et al. (2009) provide experimental evidence that skewness has an impact at the individual level, yet its direction is found to substantially differ across subjects.

[313] Financial Literacy in Germany is addressed by Oehler and Werner (2008), Oehler (2012e), Oehler et al. (2018f), (2019b), (2022b) and Oehler and Horn (2021b). An International comparative study on financial literacy is provided by OECD/INFE (2016). See also *Section 3.4.3*.

[314] In order to forecast skewness, Boyer et al. (2010) use lagged skewness as well as additional predictive variables.

[315] While being interpersonally stable, stock market expectations vary substantially in between individuals (see Dominitz and Manski 2011).

[316] See Kumar (2009) and Barberis et al. (2016).

[317] See Singleton and Wingender (1986), DeFusco et al. (1996), Harvey and Siddique (1999), and Adcock and Shutes (2005).

[318] See Calvet et al. (2009).

performance.[319] Finally, the observation period which coincides with the emergence of innovations in financial markets that are popular among private investors may have an impact on the reported results. These innovations include CFDs (see *Section 3.4.2*) as well as various forms of social trading (see *Section 3.4.3* as well as the empirical analyses of *Section 6* and *Section 7*). Given these new possibilities, private investors may no longer rely on stocks in order to include skewness into their overall portfolios.

[319] See Barber and Odean (2000), Anderson (2005), Bauer et al. (2007), and Horn and Oehler (2020).

	Panel°A – Germany (*CDAX*)							*Panel°B* – US (*CRSP*)						
	Mean	Median	SD	Mean	Median	SD	Mean	Mean	Median	SD	Mean	Median	SD	Mean
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Lottery														
$Lottery$	1.002	.955	.393	.536	.452	.293	106.543***	4.450	2.978	3.447	3.249	2.955	1.007	24.980***
							(22.59)							(4.78)
$NonLottery$	69.915	72.300	12.000	69.653	71.618	11.364	.243	35.397	36.342	8.333	37.878	37.460	5.296	-6.837***
							(.62)							(-4.93)
Max	.235	.080	.364	.372	.066	1.564	64.115***	2.824	2.052	2.201	2.793	2.640	1.271	-.135
							(7.25)							(-0.03)
$NonMax$	10.675	8.505	9.469	13.330	11.563	9.442	-28.922***	26.601	26.121	10.863	22.126	22.111	5.702	16.436***
							(-13.83)							(6.60)
$Max5$	.228	.074	.337	.313	.042	1.595	104.283***	2.299	1.749	1.820	2.166	1.810	1.185	7.636
							(12.56)							(1.43)
$NonMax5$	6.481	3.307	7.783	8.999	6.919	7.802	-39.514***	28.146	28.080	11.082	22.644	22.311	6.148	21.445***
							(-18.63)							(9.07)

Table 3: Portfolio Weights German Private Sector

Notes: The table presents the characteristics of the relative household portfolio weight ($w_{p,t}^{h}$), relative market weight ($w_{p,t}^{m}$), and the resulting unexpected or excess weight ($EW_{p,t}^{h}$) for six portfolios with lottery- and nonlottery-like features (see Bali et al. 2011, Kumar 2009). In Columns (1) and (8), (2) and (9), and (3) and (10) the Mean, Median, and standard deviation (SD) that correspond to the relative household portfolio weights are respectively reported. Columns (4) and (11), (5) and (12), and (6) and (13) respectively display the Mean, Median, and SD that correspond to the relative market weights of each portfolio. Columns (7) and (14) display the $Mean$ of the unexpected portfolio weight; one-sample t-tests are conducted in order to determine whether the underlying means are significantly different from zero. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively; t-statistics are displayed in parentheses. Columns (1) to (7) cover the holdings of the German private sector with regard to German stocks represented by the *CDAX*; columns (8) to (14) correspond to US stocks represented by the *S&P1500*. Data on aggregate private sector holdings come from *Deutsche Bundesbank*'s *SHS*-base.

Panel°A – Dependent Variable: Unexpected Stock Weight								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
α	-.0150	-.2208***	-.0060	-.2181***	-.0148	-.2149***	-.0116	-.2163***
	(-.92)	(-14.19)	(-.23)	(-14.12)	(-.92)	(-13.67)	(-.47)	(-14.27)
$TVol_{t-1}$	.3510***	.2679***	.3775***	.2994***				
	(19.27)	(7.81)	(11.15)	(6.63)				
$TSkew_{t-1}$	.0078	.0204***	.0056	.0236***				
	(1.40)	(3.36)	(.65)	(9.05)				
$IVol_{t-1}$					.3725***	.2541***	.3986***	.2695***
					(21.45)	(8.70)	(11.03)	(7.53)
$ISkew_{t-1}$					-.0029	.0157***	-.0036	.0172***
					(-.65)	(3.53)	(-.47)	(6.18)
$Price_{t-1}$	-.0898***	-.0236*	-.0886***	-.0277***	-.0855***	-.0252*	-.0841***	-.0287***
	(-5.62)	(-1.69)	(-17.61)	(-5.58)	(-5.53)	(-1.80)	(-17.34)	(-5.88)
$Domestic$		.7131***		.7036***		.6933***		.6841***
		(17.29)		(23.81)		(16.65)		(20.66)
$lnMCap$		-.2294***		-.2224***		-.2221***		-.2183***
		(-8.88)		(-8.87)		(-8.55)		(-9.03)
$SSkew_{t-1}$		-.0040		-.0189		-.0006		-.0112
		(-1.20)		(-1.58)		(-.19)		(-1.02)
$RMax$		-.1271***		-.1458***		-.1070***		-.1119***
		(-4.38)		(-4.62)		(-4.76)		(-5.01)
R		-.0048		-.0068**		-.0078		-.0101***
		(-.84)		(-2.04)		(-1.40)		(-2.93)
$Adj. R^2$	.1511	.3583	.1539	.3628	.1688	.3588	.1697	.3627

Table 4: Regression Analysis Unexpected Stock Weights

Notes: *Panel°A* displays the panel regression estimates for the regression model of Equation 9. In columns (1), (2), (3), (4), (9), (10), (11), and (12), the regression has been estimated using total volatility and total skewness measures; columns (5), (6), (7), (8), (13), (14), (15), and (16) depict regression specifications with idiosyncratic volatility and idiosyncratic skewness. Columns (1), (2), (5), (6), (9), (10), (13) and (14) depict panel regression estimates with time fixed effects and (accounting for potential serial and cross-correlations) stock-month clustered standard errors (see Petersen 2009). Columns (3), (4), (7), (8), (11), (12), (15), and (16) show the Fama and MacBeth (1973) cross-sectional regression estimates with Newey and West (1987) adjusted t-statistics. Following Kumar (2009), all variables are winsorized at their .5 and 99.5 percentile levels to ensure that extreme values are not affecting the results. Likewise, as in Kumar (2009), all variables (dependent and independent) are standardized (Mean set to zero and SD set to one); thus, the coefficient estimates may be directly compared within and across the depicted regression specifications. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively; t-statistics are displayed in parentheses.

Panel°A – continued								
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
α	-.0056	-.2185***	.0048	-.2183***	-.0055	-.2151***	.0007	-.2159***
	(-.34)	(-13.99)	(.16)	(-12.32)	(-.34)	(-13.75)	(.03)	(-12.24)
$TVol_{t-6}^{t-1}$	.3862***	.1614***	.4354***	.1854***				
	(18.35)	(7.59)	(8.38)	(10.29)				
$TSkew_{t-6}^{t-1}$	.0114	-.0302***	.0130	-.0288***				
	(1.41)	(-4.58)	(1.19)	(-3.20)				
$IVol_{t-6}^{t-1}$					.4095***	.1645***	.4611***	.1888***
					(19.63)	(7.48)	(8.38)	(10.56)
$ISkew_{t-6}^{t-1}$					-.0071	-.0256***	-.0074	-.0251***
					(-1.05)	(-4.27)	(-.81)	(-3.17)
$Price_{t-1}$	-.0825***	-.0229	-.0801***	-.0271***	-.0781***	-.0239	-.0753***	-.0277***
	(-5.04)	(-1.58)	(-19.23)	(-5.84)	(-4.89)	(-1.65)	(-18.55)	(-6.11)
$Domestic$		.7209***		.7149***		.7094***		.7028***
		(17.30)		(24.56)		(16.96)		(22.53)
$lnMCap$		-.2175***		-.2066***		-.2110***		-.2004***
		(-8.12)		(-9.38)		(-7.76)		(-9.55)
$SSkew_{t-6}^{t-1}$		-.0133**		-.0124**		-.0145**		-.0129**
		(-2.06)		(-2.33)		(-2.24)		(-2.44)
$RMax$		.0262***		.0287***		.0245***		.0271***
		(3.39)		(4.02)		(3.23)		(3.92)
R		-.0113**		-.0122***		-.0120**		-.0131***
		(-2.27)		(-3.60)		(-2.41)		(-3.66)
$Adj.R^2$	.1762	.3655	.1816	.3706	.1914	.3658	.1964	.3708

Table 4 – *continued*

Panel°B – Dependent Variable: Unexpected Stock Weight				
	(1)	(2)	(3)	(4)
α	-.4815***	-.4848***	-.4837***	-.4850***
	(-129.61)	(-117.10)	(-195.12)	(-99.20)
$DVol_{t-1}$	.0783***		.0890***	
	(7.20)		(5.40)	
$DSkew_{t-1}$	-.0212		-.0080	
	(-1.63)		(-.78)	
$DVolSkew_{t-1}$	-.0607***		-.0700***	
	(-4.33)		(-6.97)	
$DVol_{t-6}^{t-1}$		.1141***		.1251***
		(5.59)		(5.06)
$DSkew_{t-6}^{t-1}$		-.0121		-.0115
		(-.90)		(-.78)
$DVolSkew_{t-6}^{t-1}$		-.0543***		-.0764***
		(-3.77)		(-4.06)
$DPrice$	.2701***	.2074***	.2583***	.1981***
	(8.20)	(6.67)	(8.43)	(6.50)
$DPriceVol_{t-1}$	.1391***		.1674***	
	(6.23)		(8.19)	
$DPriceSkew_{t-1}$	-.0755***		-.0819***	
	(-4.30)		(-5.43)	
$DPriceVol_{t-6}^{t-1}$		.0944***		.1200***
		(5.14)		(4.13)
$DPriceSkew_{t-6}^{t-1}$		-.0555***		-.0609***
		(-3.53)		(-5.01)
$DPriceVolSkew_{t-1}$	.2735***		.2608***	
	(12.73)		(11.81)	
$DPriceVolSkew_{t-6}^{t-1}$		.4111***		.4078***
		(20.10)		(19.37)
$Domestic$	1.0932***	1.0801***	1.0916***	1.0793***
	(44.69)	(42.20)	(44.35)	(41.21)
$DRMax$	.1062***	.1034***	.0991***	.1051***
	(7.01)	(8.77)	(7.36)	(8.94)
$Adj.R^2$	.3222	.3283	.3229	.3286

Table 4 – *continued*

Notes: *Panel°B* presents the Fama and MacBeth (1973) cross-sectional regression estimates with Newey and West (1987) adjusted t-statistics; the regression model is depicted in Equation 10. In columns (1) and (2), dummy variables that correspond to total volatility and total skewness are employed; columns (3) and (4) display the results for dummy variables that correspond to idiosyncratic volatility and idiosyncratic skewness. Following Kumar (2009), $k = 50$ is chosen for all variables corresponding to price, volatility, and skewness, as well as for all variables corresponding to any combination of these measures. With regard to the $DMax$ variable, $k = 10$ is set. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively; t-statistics are displayed in parentheses.

Panel°C – Dependent Variable: Unexpected Stock Weight				
	(1)	(2)	(3)	(4)
α	-.4468***	-.4570***	-.4480***	-.4558***
	(-63.49)	(-63.21)	(-63.95)	(-62.11)
$DVol_{t-1}$	.1577***		.1594***	
	(6.22)		(6.68)	
$DSkew_{t-1}$	-.0644***		-.0602***	
	(-3.86)		(-3.78)	
$DVolSkew_{t-1}$	-.0486**		-.0387***	
	(-2.40)		(-3.17)	
$DVol_{t-6}^{t-1}$		.2491***		.2613***
		(6.22)		(7.93)
$DSkew_{t-6}^{t-1}$		-.0474***		-.0559***
		(-5.48)		(-3.71)
$DVolSkew_{t-6}^{t-1}$		-.0030		.0010
		(-.22)		(.06)
$DPrice$	.5726***	.4720***	.5594***	.4592***
	(10.64)	(10.17)	(10.96)	(10.36)
$DPriceVol_{t-1}$	.1677***		.1943***	
	(17.50)		(13.80)	
$DPriceSkew_{t-1}$	.0378**		.0210*	
	(2.35)		(1.74)	
$DPriceVol_{t-6}^{t-1}$		.1480***		.1574***
		(6.88)		(6.43)
$DPriceSkew_{t-6}^{t-1}$		.0653***		.0698***
		(3.99)		(3.17)
$DPriceVolSkew_{t-1}$	.1209***		.1250***	
	(8.42)		(7.66)	
$DPriceVolSkew_{t-6}^{t-1}$		.1419***		.1357***
		(7.80)		(7.32)
$Domestic$	1.0965***	1.0871***	1.0953***	1.0857***
	(46.82)	(46.84)	(46.80)	(45.90)
$DRMax$	.1107***	.0985***	.0981***	.0992***
	(4.35)	(6.27)	(4.48)	(5.62)
$Adj.R^2$	.3413	.3468	.3417	.3473

Table 4 – *continued*

Notes: *Panel°C* presents the Fama and MacBeth (1973) cross-sectional regression estimates with Newey and West (1987) adjusted t-statistics; the regression model is depicted in Equation 10. In columns (1) and (2), dummy variables correspond to total volatility and total skewness; columns (3) and (4) display the results for dummy variables that correspond to idiosyncratic volatility and idiosyncratic skewness. For the employed dummy variables, k is set as follows: $k = 10$ for $DPrice$, $DVol$, $DSkew$, and $DMax$; $k = 25$ for $DPriceVol$, $DPriceSkew$, and $DVolSkew$; $k = 50$ for $DPriceVolSkew$. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively; t-statistics are displayed in parentheses.

5.3 Recap and Conclusion

When assessing lottery-like stocks as defined by Kumar (2009), this study does not discover significant pricing differentials. This is not overly surprising as sophisticated investors acquire knowledge about mispricing through academic publications; as rational investors trade against mispricing, the effect decays or disappears.[320] In contrast, there is evidence that lottery-like stocks as defined by Bali et al. (2011) still tend to underperform their counterparts. As these stocks have high levels of idiosyncratic risk, for a potential explanation, repressed arbitrage and thus a more persistent mispricing are in line with existing studies.[321]

Taking into account aggregate private sector holdings (i.e. *SHS*-base data), this study provides evidence that German private investors overinvest in stocks with lottery-like characteristics as defined by Kumar (2009). Further, German private investors only overinvest in domestic lottery-like stocks as defined by Bali et al. (2011). The preferences for a subgroup of domestic stocks and the seemingly differing preferences for a similar subgroup in a foreign equity market may be attributed to the interrelation of familiarity and risk perception[322] as well as ambiguity aversion[323].

Regarding the aggregate overinvestment in stocks with lottery features, the statistical significance of the disproportional investment is high. Yet, due to the minor overall size of the $Lottery$, Max, and $Max5$ portfolios, the effect is not as severe. From October 2005 up until June 2017, the mean market value of the German $Lottery$ portfolio is 6.1 billion EUR or 7.8 billion USD. The German $Lottery$ portfolio, on average, accounts for 0.5 percent of the total market capitalization of the *CDAX*. Thus, on an aggregate level, investors should assign 0.5 percent of their funds designated for domestic equities to the $Lottery$ portfolio. Yet, the average weight assigned to the domestic $Lottery$ portfolio is 1.0 percent. As on the aggregate level German private investors have 145.2 billion EUR in domestic stocks; the expected aggregate investment in the German $Lottery$ portfolio is 726 million EUR. As the actual funds assigned to the $Lottery$ portfolio are about twice as high, the average aggregate overinvestment is 726 million EUR. Considering the entirety of German

320 See McLean and Pontiff (2016).
321 See Treynor and Black (1973), Pontiff (1996), (2006), and McLean and Pontiff (2016).
322 See Heath and Tversky (1991).
323 See Fox and Tversky (1995), Bossaerts et al. (2010), Boyle et al. (2012), Ahn et al. (2014), and Baltzer et al. (2015).

private investors, the corresponding aggregate overinvestment of 726 million EUR does not seem to be particularly relevant. Considering these results, one could make the argument that German private investors hold substantial parts of their public equity investments in foreign lottery-like stocks which are listed in a country other than the US. However, taking into account the previously discussed home bias phenomenon and the associated overall overinvestment in domestic assets, this does not seem to be likely. Thus, while in relative terms the aggregate overinvestment in stocks with lottery-like features may appear to be large, when considering the absolute invested funds, the effect appears relatively minor.

The regression analyses provide evidence that private investors prefer low-priced stocks and those with high (idiosyncratic) volatility. Furthermore, the results show that private investors gravitate to stocks with high maximum daily returns. As opposed to the literature, this study does not find evidence that (idiosyncratic) skewness drives the (over)investments of the private sector. Taking into account limited capabilities to perceive and process information, private investors may struggle to identify higher distribution moments like skewness. Features like price, (idiosyncratic) skewness, or maximum daily returns may be identified more easily and thus are reflected in the aggregate holdings of the private sector. Furthermore, private investors may be subject to heterogenous skewness expectations which are not captured by the applied proxies and / or are reluctant to rebalance their portfolios when skewness characteristics change. In addition, given the rise of financial innovations like CFDs and Social Trading which enjoy great popularity, private investors may no longer rely on stocks to include skewness into their overall portfolios.

6 Social Trading: Do Signal Providers Trigger Gambling?[324]

6.1 Characteristics and Performance *wikifolios*

Volatility and skewness characteristic of *wikifolios* included in the analysis are displayed in Appendix A5 Table 23. Idiosyncratic volatility ($IVol)$ and idiosyncratic skewness ($ISkew2F$) are computed following Kumar (2009) and Harvey and Siddique (2000). In addition, idiosyncratic skewness ($ISkew3F$) is computed following Boyer et al. (2010). For the computation of idiosyncratic volatility and idiosyncratic skewness, regional daily factors obtained from the *KFDL* are applied.[325]

Furthermore, monthly *wikifolio* alphas, α, are estimated using the Fama and French (1993) three-, the Carhart (1997) four-, the Fama and French (2015) five-, and the Fama and French (2018) six-factor model (see *Section 4.1*). As before, regional monthly factors are obtained from the *KFDL*. The results are displayed in Appendix A5 Table 24.

As the model fit is rather weak, the applied regional *KFDL* factors may not be an appropriate benchmark for analyzing *wikifolios*. Signal providers strongly focus on assets which have been issued in Germany (see *Section 4.2.3* and Appendix A5 Table 24). Thus, using local German factors may produce a sounder model.[326] Therefore, EUR-denominated *wikifolio* data are matched with local German factors obtained from *Richard Stehle*'s homepage.[327] As Dirkx and Peter (2020) conclude that the profitability and investment factor[328] have limited relevance with regard to the German market, alphas are estimated using the Fama and French (1993) three- and the Carhart (1997) four-factor model. The results are reported in Appendix A5 Table 24, *Panel°C* and *Panel°D*. Applying local German factors does not substantially

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[324] This section and the referred appendices are substantially obtained from Oehler and Schneider (2023).

[325] *Wikifolios* may include a label indicating a geographical focal point on Germany (*Focus GERMANY*), Europe (*Focus EUROPE*), or the US (*Focus USA*). *Wikifolios* focusing on Germany or Europe are merged with the European factors, while *wikifolios* focusing on the US are merged with the respective North American factors obtained from the *KFDL*. As in Oehler et al. (2016a), *wikifolios* which do not exhibit a label indicating a geographical focus are treated as if they follow a global investment strategy – correspondingly, the *KFDL* Developed factors are applied.

[326] See Hollstein (2022).

[327] See: *www.wiwi.hu-berlin.de/de/professuren/bwl/bb/daten/fama-french-factors-germany*.

[328] See Fama and French (2015). See also Section 4.1.

increase the model fit. The rather poor model fit is most likely caused by the variety of non-equity instruments which are included in the analyzed *wikifolios*.[329]

Contrary to Oehler et al. (2016a), the conducted performance analyses do not yield significantly negative alphas for the analyzed signal provider portfolios. The results suggest that *wikifolios* neither under- nor outperform the equity benchmark. Differences in the performance of *wikifolios* depicted in Oehler et al. (2016a) and the results reported in this study may be driven by a longer observation period as well as a much broader data pool.[330]

6.2 Methodological Approach Main Experiment

6.2.1 Selection of Independent Variables

Regarding signal providers, the incentive structure stems from the *wikifolio* platform's established incentive scheme. As described in *Section 4.2.3*, signal provider compensation depends on the success of the administered *wikifolio*, i.e. attainment of new high watermarks, and the amount of capital invested in the corresponding *wikifolio* certificate. In order to generate invested capital, *wikifolios* need to be visible, i.e. obtain good positions on the lists which are presented to signal followers. The default sorting criteria, as well as seven out of the 14 additional sorting options which may be selected, directly depend on past *wikifolio* performance (see *Section 4.2.3*). In this regard, it is interesting to assess if the number / volume of transactions conducted by signal providers is related to the past performance of their administered *wikifolios*. Additionally, within the elaborated conditions set by the *wikifolio* platform, past *wikifolio* returns may affect signal providers' intention to engage in gambling. In this context, this study analyzes whether the relative transaction number / volume with regard to lottery-like stocks relates to past *wikifolio* returns.

The *wikifolio* raw return of the previous month as well as the average monthly *wikifolio* raw returns over the previous six months are respectively employed as past performance measure. For these performance measures, each *wikifolio* is then

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329 Accordingly, the *wikifolio* characteristics reported in Appendix A5 Table 23 are re-estimated with local German factors.

330 Oehler et al. (2016a) analyze data corresponding to 1,084 *wikifolios*; the dataset for this analysis is extended to 24,101 entities.

assigned a number from one to ten, indicating its according relative monthly performance ranking.[331] The variables are depicted as follows:

$$RR_{i,t-1} \; / \; R\bar{R}_{i,t-6}^{t-1}. \tag{11}$$

The independent variable of interest, the relative performance ranking, is based on raw returns instead of abnormal returns (alphas). In the context of social trading, Röder and Walter (2019) provide evidence that investment flows follow raw returns instead of factor model alphas. Hence, basing the independent variable of interest on raw returns seems to be the coherent approach.

6.2.2 Absolute Number / Volume of Transactions

At first, it is assessed whether the monthly transaction volume generated by a signal provider for an administered *wikifolio*, as well as the corresponding number of transactions, depend on the *wikifolio*'s past performance. The according relevant dependent variables are the monthly number / volume of assets traded within each *wikifolio* ($T_{i,t}^{num}$ / $T_{i,t}^{vol}$). Even when eliminating abandoned or inactive *wikifolios*, there is a substantial number of *wikifolio*-month observations in the dataset where no transaction is conducted. Consequently, for these cases the respective variables take the value zero. Deriving from that, the dependent variables are highly positively skewed. Thus, for the regression analyses the dependent variables are transformed as follows:

$$lnT_{i,t}^{num} = \ln(1 + T_{i,t}^{num}) \; / \; lnT_{i,t}^{vol} = \ln(1 + T_{i,t}^{vol}). \tag{12}$$

By adding the constant one to the initial variables before applying the natural logarithm, it is assured that *wikifolio*-month observations with no respective transactions can be included into the regression analyses. As has been elaborated, relative past *wikifolio* performance ($RR_{i,t-1}$ / $R\bar{R}_{i,t-6}^{t-1}$) depicts the relevant independent variable. The baseline regression model is as follows:

$$DV = \alpha + \beta_1 \times IV + Controls + \epsilon. \tag{13}$$

[331] Monthly deciles with regard to the different past performance measures are employed as threshold values for the ranking procedure.

DV is a stand-in for the dependent variable reflecting the number ($T_{i.t}^{num}$) / volume ($T_{i,t}^{vol}$) of transactions conducted within *wikifolio* i in month t. IV is a stand-in for the independent variable of interest; that is, the relative past return variable of the *wikifolio*, measured over the previous month ($RR_{i,t-1}$) / previous six months ($R\bar{R}_{i,t-6}^{t-1}$). $Controls$[332] depicts a vector of control variables. The results are displayed in Appendix A7 Table 26.

6.2.3 Relative Number / Volume Lottery-like Transactions

As main analysis, the impact of past *wikifolio* performance on relative lottery-like stock transactions is assessed. Therefore, the relative monthly number / volume of lottery-like stocks traded ($RTL_{i,t}^{num}$ / $RTL_{i,t}^{vol}$) is set as dependent variable. The variables are defined as follows:

$$RTL_{i,t}^{num} = \frac{TL_{i,t}^{num}}{T_{i,t}^{num}} \; / \; RTL_{i,t}^{vol} = \frac{TL_{i,t}^{vol}}{T_{i,t}^{vol}}, \tag{14}$$

$TL_{i,t}^{num}$ / $TL_{i,t}^{vol}$ denote the monthly number / volume of lottery-like stocks traded. For the main analysis, Kumar's (2009) definition of lottery-like stocks is applied; all stocks in the *wikifolio* investment universe[333], i.e. all stocks that are available to signal providers, serve as a benchmark for classifying lottery-like stocks. Since relative shares of traded lottery-like stocks are employed, all *wikifolio*-month observations with no conducted transaction – indicating abandoned *wikifolios* or the implementation of a plain buy-and-hold strategy – are excluded. In order to establish coherence, the introduced dependent variables are transformed for the conducted

[332] Control variables include a dummy variable indicating if the *wikifolio*'s signal provider may trade leverage products ($Leverage_i$), a dummy variable indicating if the signal provider has invested a certain amount of his own money in certificates reflecting the corresponding *wikifolio*'s performance ($RealMoney_i$), dummy variables indicating the status of the *wikifolio* ($Investable_i$, $Closing_i$, and $Closed_i$), a dummy variable indicating if the corresponding signal provider only invests in other *wikifolios* (wow_i), dummy variables indicating if the *wikifolio* is administered by a professional asset manager ($Manager_i$), a media company ($Media_i$), or follows a predefined theme ($Theme_i$), a variable indicating the total number of *wikifolios* corresponding to each signal provider ($wikiNumber_i$), a variable indicating if the *wikifolio* has reached a new high watermark in month t ($HWM_{i,t}$), a variable indicating the level of the self-imposed performance fee of the *wikifolio* (Fee_i), and a variable indicating the *wikifolio*'s age in months ($Age_{i,t}$).

[333] For all stocks included in the *wikifolio* investment universe, the corresponding regional daily factors – the three Fama and French (1993) factors and the momentum factor (see Jegadeesh and Titman 1993) – are obtained from the *KFDL*; stocks issued from countries which cannot be sorted into regions with available factors are paired with the Developed ex US factors from the *KFLD*.

regression analyses by adding the constant one and then applying the natural logarithm:

$$lnRTL_{i,t}^{num} = ln\,(1 + RTL_{i,t}^{num}) \ / \ lnRTL_{i,t}^{vol} = ln\,(1 + RTL_{i,t}^{vol}). \tag{15}$$

As before, relative past *wikifolio* performance ($RR_{i,t-1}$ / $R\bar{R}_{i,t-6}^{t-1}$) depicts the relevant independent variable. The baseline regression model is depicted in Equation 13. DV is a stand-in for the dependent variable reflecting the relative number ($lnRTL_{i.t}^{num}$) / volume ($lnRTL_{i,t}^{vol}$) of lottery-like stock transactions conducted within *wikifolio* i in month t. IV is a stand-in for the relative past return variable of the *wikifolio*, measured over the previous month ($RR_{i,t-1}$) / previous six months ($R\bar{R}_{i,t-6}^{t-1}$). $Controls$[334] depicts a vector of control variables. Results are displayed in Table 5, *Panel°A* and *Panel°C*.

To gain further insights, it is assessed whether relative performance has a significant impact on the share of traded nonlottery-like stocks (classified according to Kumar (2009)). Therefore, the relative monthly number / volume of nonlottery-like stocks traded ($RTNL_{i,t}^{num}$ / $RTNL_{i,t}^{vol}$) is set as the according dependent variable:

$$RTNL_{i,t}^{num} = \frac{TNL_{i,t}^{num}}{T_{i,t}^{num}} \ / \ RTNL_{i,t}^{vol} = \frac{TNL_{i,t}^{vol}}{T_{i,t}^{vol}}, \tag{16}$$

$TNL_{i,t}^{num}$ / $TNL_{i,t}^{vol}$ denote the monthly number / volume of traded nonlottery-like stocks. As before, all *wikifolio*-month observations with no conducted transaction are excluded. The corresponding dependent variables are transformed for the constituent regression analyses by adding the constant one and then applying the natural logarithm:

$$lnRTNL_{i,t}^{num} = ln\,(1 + RTNL_{i,t}^{num}) \ / \ lnRTNL_{i,t}^{vol} = ln\,(1 + RTNL_{i,t}^{vol}). \tag{17}$$

[334] The control variables are those of the analysis where the the monthly number / volume of assets traded within each *wikifolio* is set as dependent variable. In addition, dummy variables indicating if an ETF, ETP, or Derivative is traded within *wikifolio* i in month t ($ETF_{i,t}$, $ETP_{i,t}$, or $Derivative_{i,t}$) are included. Furthermore, the natural logarithm of the number / volume ($lnT_{i,t}^{num}$ / $lnT_{i,t}^{vol}$) of assets traded within *wikifolio* i in month t is included as a control variable (previously employed as dependent variable).

As before, relative past *wikifolio* performance ($RR_{i,t-1}$ / $R\bar{R}_{i,t-6}^{t-1}$) is set as relevant independent variable. The previously described panel regression is applied. Results are reported in Table 5, *Panel°B* and *Panel°D*.

6.2.4 Net Lottery Flow

While the previously established regression models may provide an indication regarding the frequency of lottery-like stock trades, they do not allow to make a prediction about the net exposure towards risk induced by lottery-like stocks. Thus, in order to obtain an indication regarding the relation between the net exposure towards risk induced by lottery-like stocks and relative past performance, the cumulative net investment into lottery-like stocks is investigated.

In this context, the net lottery flow ($LF_{i,t=1}^{num,t}$ / $LF_{i,t=1}^{vol,t}$) – i.e. the difference between the cumulative number / volume of lottery-like stock purchases and the cumulative number / volume of lottery-like stock sales from the creation of *wikifolio* i to month t – is computed:

$$LF_{i,t=1}^{num,t} = \sum_{t=1}^{T} LI_{i,t}^{num} - \sum_{t=1}^{t} LS_{i,t}^{num} \text{ / } LF_{i,t=1}^{vol,t} = \ln\left(\sum_{t=1}^{t} LI_{i,t}^{vol}\right) - \ln\left(\sum_{t=1}^{t} LS_{i,t}^{vol}\right). \quad (22)$$

The initial panel regression is applied where the relative past *wikifolio* performance ($RR_{i,t-1}$ / $R\bar{R}_{i,t-6}^{t-1}$) depicts the primarily relevant independent variable. The corresponding results of the regression analysis are reported in Table 6.

6.3 Results

When the absolute number / volume of transactions within a *wikifolio* is set as the dependent variable, the initial results obtained from the regression analysis are ambiguous. The regression models where standard errors are simultaneously clustered by month and *wikifolio* as well as by month and signal provider do not indicate a statistically significant relationship between relative past performance and the number / volume of conducted transactions. When including fixed effects[335], all regression specifications yield significantly positive coefficients for the relative

[335] The following five distinct regression specifications including fixed effects are estimated: Time (i.e. month) fixed effects, portfolio-level (i.e. *wikifolio*-level) fixed effects, trader-level (i.e. signal provider-level) fixed effects, time and portfolio-level fixed effects, as well as time and trader-level fixed effects.

performance variable. In order to determine whether a non-linear model describes the relation between trading activity and relative past performance more appropriately, squared terms of the described relative return variables are included: $(RR_{i,t-1})^2$ and $(R\bar{R}_{i,t-6}^{t-1})^2$. Estimating regression models including squared terms indicates a U-shaped relation between relative past performance and trading activity which is statistically significant in the specifications including clustered standard errors and within the contrived fixed effects models. Regression results corresponding to the quadratic model are displayed in Appendix A7 Table 26.[336]

Regarding the upper end of the relative performance spectrum, i.e. signal providers who have previously outperformed their peers, an increase in trading activity seems to be in line with previous research. Gervais and Odean (2001), Odean (1999), and Statman et al. (2006) provide evidence that past returns have a positive impact on investor overconfidence, and thus on trading activity. Within the framework of a social trading platform, performing well relative to peers might induce a surge in signal provider overconfidence which causes increased trading activity. Since portfolios on the *wikifolio* platform are virtual, and thus there are no transaction costs for signal providers, the effect might be particularly pronounced.[337] As described, the considered independent variables, $RR_{i,t-1}$ and $R\bar{R}_{i,t-6}^{t-1}$, capture the relative performance of all *wikifolios* for which data could be attained; literature on overconfidence primarily focuses on absolute performance. Although based on performance relative to peers, it is reasonable to assume that outperforming peers is connected to generating net profits. Measuring relative performance over the previous month, in less than two percent of all *wikifolio*-month observations a negative return is generated when the *wikifolio* is assigned to one of the top three percentiles. Measuring relative performance over a six-month period leads to positive returns in more than 99.5 percent of all *wikifolio*-month observations when the *wikifolio* has outperformed 70 percent of its peers.

[336] When measuring relative past performance over the previous six months, there are two specifications where the quadratic regression model does not yield corresponding statistically significant coefficients. However, measuring relative past performance over the previous three months (in order to check for robustness) yields corresponding significant coefficients within all specifications.
[337] It is well established, that individual investors severely reduce their returns by (excessive) trading (see Barber and Odean 2000, 2001, Odean 1999). In this context, not being subject to transaction costs might have an impact on signal provider trading behavior.

Apart from overconfidence, excitement and entertainment may be considered as an explanation for the reported results (see *Section 3.3.3*). In the context of social trading, Pelster and Breitmayer (2019) show that signal providers who receive attention (from signal followers) increase their trading activity due to increased levels of excitement. Furthermore, Pelster and Breitmayer (2019) provide evidence, that past performance is the main determinant for a signal provider to be followed. Performing well relative to peers might boost signal provider attractiveness which will lead to a larger number of signal followers investing in the corresponding *wikifolio*. The enhanced excitement which is caused by additional followers may encourage signal providers to be more active, i.e. increase their trading activity.

Regarding the lower end of the relative performance spectrum, i.e. underperforming signal providers, an increase in trading activity may be caused by traders trying to restructure their losing *wikifolios*. The incentive to restructure a losing entity might be amplified by the lack of transaction costs and the limited monetary downside risk for signal providers. Restructuring a *wikifolio* may be implemented by including new assets. Furthermore, contrary to what is suggested by the disposition effect[338], signal providers may decide to get rid of losing positions.

As depicted in *Section 6.2.3*, regression analyses for dependent variables reflecting the relative share of transactions involving lottery-like stocks are conducted; that is, the monthly relative number of traded lottery-like stocks ($lnRTL_{i.t}^{num}$) and monthly relative volume of traded lottery-like stocks ($lnRTL_{i.t}^{vol}$) are respectively set as the dependent variable. The initial regression analysis does not yield a statistically significant relation between relative past *wikifolio* performance and the traded share of lottery-like stocks. In order to determine whether there is a non-linear relation between the relative share of transactions involving lottery-like stocks and previous performance, squared terms of the performance measures are included: $(RR_{i,t-1})^2$ and $(R\bar{R}_{i,t-6}^{t-1})^2$. Results are displayed in Table 5.

The results suggest a highly significant quadratic relation between the traded share of lottery-like stocks and past *wikifolio* performance. The regression coefficients relating to the employed *wikifolio* performance measures are significant throughout

338 For a discussion of the disposition effect (see Shefrin and Statman 1985) in social trading see *Section 3.4.3*.

all conducted analyses. The considered coefficients remain statistically significant when computing standard errors simultaneously clustered by month and *wikifolio*, as well as when computing standard errors simultaneously clustered by month and trader. Moreover, all models including fixed effects yield statistically significant coefficients corresponding to the relative performance variables. The sign of the respective coefficients – negative sign of the past performance measure and positive sign for the squared term – suggest a U-shaped relationship, i.e. signal providers increase the traded share of lottery-like stocks when exhibiting relatively good or relatively bad performance.

The dummy variable indicating whether signal providers have invested their own money in a corresponding *wikifolio* certificate ($RealMoney_i$) is significantly positive in all regression specifications, i.e. signal providers with an investment in their own *wikifolio* are more likely to trade a higher share of lotteries. The dummy variables indicating whether an ETF ($ETF_{i,t}$), ETP ($ETP_{i,t}$) or derivative ($Derivative_{i,t}$) is traded within *wikifolio* i in month t are significantly negative in all conducted regressions. Signal providers trading ETFs, ETPs, or Derivatives may, on average, be less likely to trade stocks due to their pursued trading strategy focusing on non-stock instruments. Furthermore, signal providers trading derivatives do not depend on stocks when intending to trade assets with lottery-like payoffs. Although not significant in all models, the regression analyses yield positive coefficients relating to the variable depicting the levels of a *wikifolio*'s performance fee (Fee_i). As described, performance fees are determined by signal providers when creating the *wikifolio*. In this context, the following applies: The higher the performance fee, the better the prospect of high compensation. Signal providers with self-selected high performance fees might have a stronger focus on receiving a certain level of benefits from the *wikifolio* platform, and thus try to substantially exceed previous high watermarks by trading lottery-like stocks more frequently.

Regarding nonlottery-like stocks, the results indicate an inverse U-shaped quadratic relationship, i.e. signal providers administering *wikifolios* with more moderate peer performance are more likely to trade nonlottery-like stocks. The coefficients corresponding to relative past performance are highly significant within all model specifications.

The regression model where the net lottery flow is set as the dependent variable suggests a linear rather than a quadratic relationship. That is, the obtained results indicate a negative linear relationship between the net lottery flow and relative past *wikifolio* performance. When the net lottery flow variable is based on volume ($LF_{i,t=1}^{vol,T}$), the performance measure is not statistically significant in all regression specifications. However, when *wikifolio*-level fixed effects are included, the performance measure is statistically significant at the per mill level. The obtained results suggest that signal providers increase the net position of lottery-like stocks when underperforming their peers. Results are depicted in Table 6.

Panel°A – Dependent Variable: Relative Number Lottery Transactions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
α	.0541***	.0541***	.0551***	.0319***	.0362***	.0352***	.0383***
	(19.42)	(17.75)	(63.40)	(37.16)	(33.56)	(44.59)	(34.01)
$RR_{i,t-1}$	-.0098***	-.0098***	-.0095***	-.0006**	-.0031***	-.0006**	-.0030***
	(-13.43)	(-12.23)	(-34.49)	(-2.13)	(-11.02)	(-2.20)	(-10.88)
$(RR_{i,t-1})^2$	.0009***	.0009***	.0009***	.0001***	.0003***	.0001***	.0003***
	(14.19)	(12.94)	(36.96)	(3.36)	(12.40)	(3.45)	(12.34)
$Leverage$	.0023*	.0023*	.0027***		-.0024***		-.0025***
	(1.90)	(1.80)	(5.00)		(-3.25)		(-3.40)
$RealMoney$	.0081***	.0081***	.0080***		.0074***		.0075***
	(3.01)	(2.65)	(9.86)		(5.26)		(5.36)
$Investable$	-.0034***	-.0034***	-.0020***		-.0002		.0009
	(-3.46)	(-3.01)	(-4.64)		(-.21)		(1.27)
$Closing$	-.0133**	-.0133**	-.0132***		-.0125***		-.0116***
	(-2.58)	(-2.48)	(-4.37)		(-3.11)		(-2.88)
$Closed$	-.0078***	-.0078***	-.0050***		-.0024***		-.0008
	(-6.14)	(-5.44)	(-7.67)		(-2.79)		(-.87)
Fee	.0106*	.0106	.0109***		.0221***		.0213***
	(1.76)	(1.47)	(4.25)		(4.95)		(4.78)
$Media$	-.0143***	-.0143**	-.0140***				
	(-2.86)	(-2.16)	(-6.21)				
$Manager$	-.0106***	-.0106**	-.0101***				
	(-2.70)	(-2.28)	(-5.71)				
$Theme$	.0285	.0285***	.0282**				
	(.79)	(13.46)	(2.27)				
$wikiNumber$	-.0001	-.0001	-.0001**				
	(-.71)	(-.44)	(-2.01)				
lnT^{num}	.0042***	.0042***	.0040***	.0016***	.0026***	.0016***	.0026***
	(12.84)	(11.01)	(27.02)	(8.15)	(14.15)	(7.92)	(14.11)
ETF	-.0195***	-.0195***	-.0187***	-.0100***	-.0137***	-.0101***	-.0137***
	(-24.19)	(-20.87)	(-46.33)	(-17.79)	(-28.69)	(-18.03)	(-28.59)
ETP	-.0040***	-.0040***	-.0027***	-.0091***	-.0083***	-.0074***	-.0065***
	(-3.25)	(-2.98)	(-2.70)	(-8.36)	(-7.94)	(-6.74)	(-6.24)
$Derivative$	-.0332***	-.0332***	-.0330***	-.0192***	-.0250***	-.0180***	-.0243***
	(-22.91)	(-21.38)	(-55.74)	(-23.41)	(-35.83)	(-22.00)	(-34.83)
HWM	-.0013***	-.0013	-.0023***	.0012***	.0002	.0010**	-.0002
	(-.98)	(-.98)	(-5.29)	(3.37)	(.69)	(2.54)	(-.49)
Age	.0001*	.0001	-.0001***	.0002***	.0001***		-.0000
	(1.79)	(1.63)	(-5.08)	(13.61)	(11.35)		(-.27)
R^2	.0294	.0294	.0353	.3015	.2104	.3048	.2140

Table 5: Regression Results Relative Share Lottery-like Stocks and Past Performance

Notes: In *Panel°A*, the monthly share regarding the number of traded lottery-like stocks relative to all traded assets ($lnRTL_{i,t}^{num}$) is set as dependent variable. In specification (1) to (7) relative performance is measured over the previous month ($RR_{i,t-1}$); in specification (8) to (14) relative performance is measured over the previous six months ($R\bar{R}_{i,t-6}^{t-1}$). In specification (1) and (8) t-statistics correspond to *wikifolio* and month-clustered standard errors; in specification (2) and (9), t-statistics correspond to signal provider and month-clustered standard errors (see Petersen 2009). Specifications (3) and (10) include time fixed effects; specifications (4) and (11) include *wikifolio*-level fixed effects; (5) and (12) include signal provider-level fixed effects. Specification (6) and (13) simultaneously include time and *wikifolio*-level fixed effects. Specification (7) and (14) simultaneously include time and signal provider-level fixed effects. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively; t-statistics are displayed in parentheses.

Panel°A – continued							
	(8)	(9)	(10)	(11)	(12)	(13)	(14)
α	.0589***	.0589***	.0593***	.0330***	.0389***	.0363***	.0408***
	(19.97)	(18.03)	(67.42)	(36.96)	(35.32)	(43.64)	(35.56)
$R\bar{R}_{i,t-6}^{t-1}$	-.0116***	-.0116***	-.0112***	-.0010***	-.0040***	-.0010***	-.0039***
	(-14.18)	(-12.79)	(-39.95)	(-3.41)	(-13.75)	(-3.37)	(-13.46)
$(R\bar{R}_{i,t-6}^{t-1})^2$	.0010***	.0010***	.0010***	.0001***	.0004***	.0001***	.0004***
	(14.81)	(13.43)	(41.48)	(4.11)	(14.23)	(4.11)	(14.04)
$Leverage$	.0018	.0018	.0022***		-.0027***		-.0028***
	(1.53)	(1.45)	(4.20)		(-3.62)		(-3.74)
$RealMoney$	.0079***	.0079**	.0077***		.0072***		.0073***
	(2.92)	(2.58)	(9.51)		(5.15)		(5.23)
$Investable$	-.0035***	-.0035***	-.0021***		-.0002		.0008
	(-3.51)	(-3.06)	(-4.96)		(-.33)		(1.11)
$Closing$	-.0136***	-.0136**	-.0136***		-.0127***		-.0118***
	(-2.68)	(-2.58)	(-4.51)		(-3.15)		(-2.93)
$Closed$	-.0078***	-.0078***	-.0051***		-.0025***		-.0009
	(-6.07)	(-5.38)	(-7.84)		(-2.90)		(-1.01)
Fee	.0098	.0098	.0101***		.0215***		.0208***
	(1.64)	(1.37)	(3.94)		(4.82)		(4.66)
$Media$	-.0135***	-.0135**	-.0133***				
	(-2.73)	(-2.07)	(-5.88)				
$Manager$	-.0101**	-.0101**	-.0096***				
	(-2.60)	(-2.18)	(-5.43)				
$Theme$	.0295	.0295***	.0287**				
	(.81)	(16.29)	(2.31)				
$wikiNumber$	-.0001	-.0001	-.0001**				
	(-.98)	(-.61)	(-2.59)				
lnT^{num}	.0042***	.0042***	.0040***	.0016***	.0026***	.0016***	.0026***
	(12.81)	(10.98)	(26.85)	(8.15)	(14.22)	(7.91)	(14.14)
ETF	-.0194***	-.0194***	-.0186***	-.0100***	-.0137***	-.0102***	-.0137***
	(-23.98)	(-20.68)	(-45.92)	(-17.81)	(-28.70)	(-18.05)	(-28.60)
ETP	-.0040***	-.0040***	-.0026***	-.0091***	-.0082***	-.0074***	-.0064***
	(-3.24)	(-2.98)	(-2.65)	(-8.36)	(-7.89)	(-6.73)	(-6.19)
$Derivative$	-.0336***	-.0336***	-.0333***	-.0192***	-.0250***	-.0180***	-.0244***
	(-22.80)	(-21.28)	(-56.31)	(-23.43)	(-35.95)	(-22.02)	(-34.95)
HWM	-.0007	-.0007	-.0016***	.0015***	.0007**	.0014***	.0003
	(-.50)	(-.50)	(-3.81)	(4.32)	(2.01)	(3.51)	(.85)
Age	.0001**	.0001**	.0000***	.0002***	.0001***		.0000
	(2.58)	(2.33)	(-2.66)	(13.82)	(11.85)		(.17)
R^2	.0307	.0307	.0364	.3015	.2104	.3048	.2140

Table 5 – *continued*

Panel°B – Dependent Variable: Relative Number Nonlottery Transactions							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
α	.1484***	.1484***	.1487***	.1484***	.1521***	.1512***	.1504***
	(29.40)	(26.96)	(85.83)	(91.84)	(71.94)	(101.74)	(68.18)
$RR_{i,t-1}$	.0377***	.0377***	.0375***	.0064***	.0178***	.0064***	.0177***
	(30.25)	(27.89)	(68.35)	(12.05)	(32.72)	(12.05)	(32.64)
$(RR_{i,t-1})^2$	-.0034***	-.0034***	-.0034***	-.0006***	-.0016***	-.0006***	-.0016***
	(-30.14)	(-27.81)	(-70.96)	(-13.67)	(-34.36)	(-13.68)	(-34.36)
$Leverage$	-.0138***	-.0138***	-.0141***		-.0331***		-.0330***
	(-5.00)	(-4.45)	(-13.23)		(-22.94)		(-22.93)
$RealMoney$	-.0168***	-.0168***	-.0171***		-.0200***		-.0201***
	(-3.05)	(-2.86)	(-10.61)		(-7.30)		(-7.36)
$Investable$	-.0055**	-.0055**	-.0052***		.0016		.0011
	(-2.37)	(-2.12)	(-6.25)		(1.14)		(.80)
$Closing$	-.0138	-.0138	-.0137**		-.0210***		-.0205**
	(-.91)	(-.88)	(-2.27)		(-2.66)		(-2.60)
$Closed$	-.0109***	-.0109***	-.0100***		-.0069***		-.0075***
	(-3.30)	(-2.96)	(-7.65)		(-4.08)		(-4.31)
Fee	-.1543***	-.1543***	-.1521***		-.0694***		-.0683***
	(-10.73)	(-9.00)	(-29.75)		(-7.93)		(-7.83)
$Media$	.0258	.0258	.0246***				
	(1.62)	(1.49)	(5.46)				
$Manager$	-.0289**	-.0289**	-.0296***				
	(-2.52)	(-2.23)	(-8.40)				
$Theme$	-.0433	-.0433***	-.0434*				
	(-1.13)	(-11.11)	(-1.75)				
$wikiNumber$	-.0013***	-.0013***	-.0013***				
	(-7.19)	(-5.19)	(-19.22)				
lnT^{num}	.0210***	.0210***	.0209***	.0204***	.0243***	.0205***	.0243***
	(26.29)	(21.71)	(70.19)	(54.60)	(68.41)	(54.99)	(68.63)
ETF	-.1090***	-.1090***	-.1090***	-.0528***	-.0879***	-.0535***	-.0885***
	(-43.09)	(-35.16)	(-135.08)	(-49.77)	(-93.64)	(-50.46)	(-94.28)
ETP	-.0326***	-.0326***	-.0337***	-.0254***	-.0333***	-.0263***	-.0345***
	(-10.44)	(-8.96)	(-17.15)	(-12.33)	(-16.32)	(-12.77)	(-16.89)
$Derivative$	-.1456***	-.1456***	-.1464***	-.0836***	-.1197***	-.0835***	-.1198***
	(-46.99)	(-39.37)	(-123.87)	(-54.17)	(-87.70)	(-54.23)	(-87.66)
HWM	.0038	.0038	.0068***	-.0025***	-.0002	-.0018**	.0013*
	(1.51)	(1.50)	(7.95)	(-3.83)	(-.24)	(-2.40)	(1.66)
Age	.0001	.0001	.0000	.0002***	.0002***		.0003***
	(.79)	(.71)	(.30)	(6.69)	(8.07)		(5.72)
R^2	.1871	.1871	.1918	.4770	.3616	.4808	.3655

Table 5 – *continued*

Notes: In *Panel°B*, the monthly share regarding the number of traded nonlottery-like stocks relative to all traded assets ($lnRTNL_{i,t}^{num}$) is set as dependent variable. In specification (1) to (7) relative performance is measured over the previous month ($RR_{i,t-1}$); in specification (8) to (14) relative performance is measured over the previous six months ($R\bar{R}_{i,t-6}^{t-1}$). In specification (1) and (8) t-statistics correspond to *wikifolio* and month-clustered standard errors; in specification (2) and (9), t-statistics correspond to signal provider and month-clustered standard errors (see Petersen 2009). Specifications (3) and (10) include time fixed effects; specifications (4) and (11) include *wikifolio*-level fixed effects; (5) and (12) include signal provider-level fixed effects. Specification (6) and (13) simultaneously include time and *wikifolio*-level fixed effects. Specification (7) and (14) simultaneously include time and signal provider-level fixed effects. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively; t-statistics are displayed in parentheses.

Panel°B – continued							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
α	.1409***	.1409***	.1407***	.1492***	.1468***	.1511***	.1449***
	(27.82)	(25.26)	(80.27)	(88.57)	(68.01)	(96.51)	(64.58)
$R\bar{R}_{i,t-6}^{t-1}$	.0405***	.0405***	.0406***	.0061***	.0196***	.0063***	.0197***
	(30.97)	(27.97)	(73.01)	(10.72)	(34.67)	(11.12)	(34.90)
$(R\bar{R}_{i,t-6}^{t-1})^2$	-.0036***	-.0036***	-.0036***	-.0006***	-.0018***	-.0006***	-.0018***
	(-28.31)	(-25.94)	(-74.75)	(-12.15)	(-35.54)	(-12.46)	(-35.79)
$Leverage$	-.0126***	-.0126***	-.0129***		-.0321***		-.0321***
	(-4.59)	(-4.09)	(-12.12)		(-22.25)		(-22.25)
$RealMoney$	-.0159***	-.0159***	-.0162***		-.0193***		-.0194***
	(-2.90)	(-2.74)	(-10.05)		(-7.03)		(-7.09)
$Investable$	-.0054**	-.0054**	-.0048***		.0020		.0017
	(-2.33)	(-2.08)	(-5.77)		(1.41)		(1.17)
$Closing$	-.0131	-.0131	-.0127**		-.0204**		-.0197**
	(-.86)	(-.84)	(-2.12)		(-2.58)		(-2.50)
$Closed$	-.0112***	-.0112***	-.0097***		-.0067***		-.0070***
	(-3.37)	(-3.02)	(-7.44)		(-3.95)		(-4.04)
Fee	-.1537***	-.1537***	-.1508***		-.0675***		-.0663***
	(-10.75)	(-9.01)	(-29.51)		(-7.72)		(-7.60)
$Media$	.0234	.0234	.0221***				
	(1.50)	(1.37)	(4.90)				
$Manager$	-.0302***	-.0302**	-.0310***				
	(-2.63)	(-2.37)	(-8.83)				
$Theme$	-.0476	-.0476***	-.0464*				
	(-1.23)	(-11.06)	(-1.88)				
$wikiNumber$	-.0013***	-.0013***	-.0013***				
	(-6.91)	(-4.99)	(-18.42)				
lnT^{num}	.0211***	.0211***	.0210***	.0204***	.0242***	.0206***	.0243***
	(26.81)	(22.08)	(70.49)	(54.66)	(68.31)	(55.03)	(68.54)
ETF	-.1093***	-.1093***	-.1092***	-.0528***	-.0878***	-.0534***	-.0885***
	(-42.83)	(-35.09)	(-135.11)	(-49.70)	(-93.57)	(-50.40)	(-94.20)
ETP	-.0332***	-.0332***	-.0343***	-.0255***	-.0337***	-.0264***	-.0349***
	(-10.54)	(-9.07)	(-17.46)	(-12.40)	(-16.55)	(-12.84)	(-17.09)
$Derivative$	-.1449***	-.1449***	-.1457***	-.0838***	-.1197***	-.0837***	-.1198***
	(-46.70)	(-39.17)	(-123.41)	(-54.31)	(-87.73)	(-54.36)	(-87.68)
HWM	.0029	.0029	.0058***	-.0028***	-.0008	-.0022***	.0005
	(1.09)	(1.08)	(6.87)	(-4.37)	(-1.21)	(-2.99)	(.64)
Age	.0000	.0000	-.0001***	.0001***	.0002***		.0002***
	(-.36)	(-.33)	(-3.86)	(6.15)	(6.89)		(4.69)
R^2	.1885	.1885	.1933	.4769	.3617	.4807	.3657

Table 5 – *continued*

Panel°C – Dependent Variable: Relative Volume Lottery Transactions							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
α	.0603***	.0603***	.0642***	.0411***	.0457***	.0435***	.0487***
	(17.07)	(15.52)	(53.82)	(27.85)	(31.06)	(30.73)	(31.74)
$RR_{i,t-1}$	-.0098***	-.0098***	-.0095***	-.0008***	-.0032***	-.0008***	-.0032***
	(-13.40)	(-12.30)	(-34.94)	(-2.82)	(-11.66)	(-2.86)	(-11.52)
$(RR_{i,t-1})^2$	.0009***	.0009***	.0009***	.0001***	.0003***	.0001***	.0003***
	(14.20)	(13.05)	(37.58)	(4.21)	(13.26)	(4.26)	(13.20)
$Leverage$	.0020*	.0020	.0023***		-.0017**		-.0019**
	(1.73)	(1.65)	(4.38)		(-2.38)		(-2.55)
$RealMoney$	.0077***	.0077***	.0076***		.0054***		.0056***
	(3.25)	(2.86)	(9.50)		(3.87)		(4.00)
$Investable$	-.0017*	-.0017	-.0002		.0004		.0015**
	(-1.81)	(-1.57)	(-.57)		(.61)		(2.06)
$Closing$	-.0100*	-.0100*	-.0098***		-.0105***		-.0095**
	(-1.86)	(-1.79)	(-3.28)		(-2.61)		(-2.38)
$Closed$	-.0061***	-.0061***	-.0034***		-.0023***		-.0007
	(-5.24)	(-4.63)	(-5.27)		(-2.74)		(-.83)
Fee	.0116**	.0116*	.0129***		.0225***		.0219***
	(2.03)	(1.71)	(5.07)		(5.06)		(4.93)
$Media$	-.0135***	-.0135**	-.0133***				
	(-3.28)	(-2.47)	(-5.94)				
$Manager$	-.0102***	-.0102**	-.0094***				
	(-2.71)	(-2.34)	(-5.40)				
$Theme$	.0391	.0391***	.0389***				
	(1.08)	(18.82)	(3.16)				
$wikiNumber$	.0000	.0000	.0000				
	(.33)	(.21)	(.60)				
lnT^{vol}	-.0002	-.0002	-.0005***	-.0007***	-.0006***	-.0008***	-.0007***
	(-.86)	(-.72)	(-5.55)	(-5.91)	(-6.07)	(-6.13)	(-6.88)
ETF	-.0189***	-.0189***	-.0179***	-.0105***	-.0137***	-.0106***	-.0136***
	(-24.71)	(-21.44)	(-44.96)	(-18.76)	(-28.78)	(-18.95)	(-28.45)
ETP	-.0024**	-.0024*	-.0011	-.0076***	-.0066***	-.0061***	-.0050***
	(-2.16)	(-1.95)	(-1.16)	(-7.01)	(-6.37)	(-5.58)	(-4.80)
$Derivative$	-.0278***	-.0278***	-.0276***	-.0166***	-.0212***	-.0156***	-.0206***
	(-21.03)	(-19.57)	(-48.08)	(-20.48)	(-30.93)	(-19.22)	(-29.99)
HWM	-.0008	-.0008	-.0017***	.0015***	.0007**	.0014***	.0003
	(-.63)	(-.63)	(-3.92)	(4.34)	(1.99)	(3.36)	(.70)
Age	.0000	.0000	-.0001***	.0001***	.0001***		-.0001***
	(.12)	(.11)	(-10.27)	(8.92)	(6.14)		(-2.92)
R^2	.0266	.0266	.0320	.2873	.1996	.2900	.2026

Table 5 – *continued*

Notes: In *Panel°C*, the monthly share regarding the volume of traded lottery-like stocks relative to all traded assets ($lnRTL_{i,t}^{vol}$) is set as dependent variable. In specification (1) to (7) relative performance is measured over the previous month ($RR_{i,t-1}$); in specification (8) to (14) relative performance is measured over the previous six months ($R\bar{R}_{i,t-6}^{t-1}$). In specification (1) and (8) t-statistics correspond to *wikifolio* and month-clustered standard errors; in specification (2) and (9), t-statistics correspond to signal provider and month-clustered standard errors (see Petersen 2009). Specifications (3) and (10) include time fixed effects; specifications (4) and (11) include *wikifolio*-level fixed effects; (5) and (12) include signal provider-level fixed effects. Specification (6) and (13) simultaneously include time and *wikifolio*-level fixed effects. Specification (7) and (14) simultaneously include time and signal provider-level fixed effects. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively; t-statistics are displayed in parentheses.

Panel°C – continued							
	(8)	(9)	(10)	(11)	(12)	(13)	(14)
α	.0650***	.0650***	.0682***	.0426***	.0483***	.0449***	.0511***
	(18.56)	(16.75)	(57.42)	(28.73)	(32.73)	(31.56)	(33.24)
$R\bar{R}_{i,t-6}^{t-1}$	-.0116***	-.0116***	-.0112***	-.0014***	-.0042***	-.0014***	-.0041***
	(-14.56)	(-13.17)	(-40.40)	(-4.58)	(-14.63)	(-4.56)	(-14.37)
$(R\bar{R}_{i,t-6}^{t-1})^2$	.0010***	.0010***	.0010***	.0001***	.0004***	.0001***	.0004***
	(15.04)	(13.71)	(41.99)	(5.42)	(15.32)	(5.43)	(15.16)
$Leverage$	.0015	.0015	.0019***		-.0020***		-.0021***
	(1.36)	(1.28)	(3.60)		(-2.79)		(-2.92)
$RealMoney$	.0075***	.0075***	.0073***		.0052***		.0053***
	(3.15)	(2.78)	(9.13)		(3.72)		(3.84)
$Investable$	-.0017*	-.0017	-.0004		.0003		.0014*
	(-1.88)	(-1.64)	(-.94)		(.46)		(1.87)
$Closing$	-.0103*	-.0103*	-.0103***		-.0107***		-.0098**
	(-1.95)	(-1.87)	(-3.43)		(-2.66)		(-2.44)
$Closed$	-.0061***	-.0061***	-.0035***		-.0024***		-.0009
	(-5.19)	(-4.59)	(-5.47)		(-2.83)		(-.97)
Fee	.0107*	.0107	.0121***		.0219***		.0213***
	(1.89)	(1.60)	(4.74)		(4.92)		(4.79)
$Media$	-.0128***	-.0128**	-.0126***				
	(-3.14)	(-2.37)	(-5.61)				
$Manager$	-.0097**	-.0097**	-.0089***				
	(-2.60)	(-2.23)	(-5.12)				
$Theme$	.0401	.0401***	.0394***				
	(1.11)	(23.49)	(3.21)				
$wikiNumber$	.0000	.0000	.0000				
	(.06)	(.04)	(.00)				
lnT^{vol}	-.0001	-.0001	-.0005***	-.0007***	-.0006***	-.0008***	-.0007***
	(-.82)	(-.68)	(-5.30)	(-5.87)	(-5.78)	(-6.11)	(-6.61)
ETF	-.0188***	-.0188***	-.0178***	-.0105***	-.0137***	-.0106***	-.0136***
	(-24.32)	(-21.14)	(-44.62)	(-18.78)	(-28.81)	(-18.97)	(-28.48)
ETP	-.0024**	-.0024*	-.0011	-.0076***	-.0065***	-.0061***	-.0049***
	(-2.16)	(-1.95)	(-1.13)	(-7.00)	(-6.33)	(-5.57)	(-4.76)
$Derivative$	-.0282***	-.0282***	-.0280***	-.0166***	-.0213***	-.0156***	-.0207***
	(-21.10)	(-19.61)	(-48.71)	(-20.50)	(-31.09)	(-19.25)	(-30.15)
HWM	-.0001	-.0001	-.0010**	.0018***	.0012***	.0018***	.0008**
	(-.09)	(-.09)	(-2.34)	(5.38)	(3.36)	(4.42)	(2.08)
Age	.0000	.0000	-.0001***	.0001***	.0001***		-.0001**
	(.89)	(.81)	(-7.79)	(9.18)	(6.72)		(-2.40)
R^2	.0279	.0279	.0330	.2872	.1996	.2900	.2027

Table 5 – *continued*

Panel°D – Dependent Variable: Relative Volume Nonlottery Transactions							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
α	.1240***	.1240***	.1239***	.0922***	.1016***	.0935***	.0933***
	(18.68)	(16.44)	(49.64)	(31.43)	(33.57)	(33.31)	(29.57)
$RR_{i,t-1}$	.0390***	.0390***	.0388***	.0075***	.0188***	.0075***	.0187***
	(30.01)	(27.47)	(67.90)	(13.43)	(33.10)	(13.42)	(32.97)
$(RR_{i,t-1})^2$	-.0035***	-.0035***	-.0035***	-.0007***	-.0017***	-.0007***	-.0017***
	(-30.37)	(-27.70)	(-70.49)	(-15.11)	(-34.78)	(-15.10)	(-34.73)
$Leverage$	-.0114***	-.0114***	-.0116***		-.0322***		-.0316***
	(-4.11)	(-3.62)	(-10.55)		(-21.39)		(-21.01)
$RealMoney$	-.0041	-.0041	-.0045***		-.0076***		-.0082***
	(-.76)	(-.71)	(-2.68)		(-2.67)		(-2.87)
$Investable$	.0031	.0031	.0029***		.0097***		.0076***
	(1.31)	(1.16)	(3.36)		(6.61)		(5.11)
$Closing$	-.0124	-.0124	-.0124**		-.0138*		-.0158*
	(-.87)	(-.81)	(-1.97)		(-1.68)		(-1.91)
$Closed$	-.0058*	-.0058	-.0058***		-.0028		-.0064***
	(-1.74)	(-1.55)	(-4.29)		(-1.57)		(-3.51)
Fee	-.1697***	-.1697***	-.1689***		-.0775***		-.0770***
	(-11.52)	(-9.51)	(-31.65)		(-8.49)		(-8.45)
$Media$	.0297**	.0297**	.0287***				
	(2.14)	(2.09)	(6.12)				
$Manager$	-.0459***	-.0459***	-.0463***				
	(-4.00)	(-3.75)	(-12.67)				
$Theme$	-.0690*	-.0690***	-.0695***				
	(-1.90)	(-15.50)	(-2.70)				
$wikiNumber$	-.0012***	-.0012***	-.0012***				
	(-6.37)	(-4.62)	(-16.46)				
lnT^{vol}	.0060***	.0060***	.0060***	.0099***	.0096***	.0100***	.0098***
	(13.84)	(11.65)	(33.62)	(39.32)	(43.65)	(39.78)	(44.57)
ETF	-.1118***	-.1118***	-.1123***	-.0582***	-.0922***	-.0588***	-.0934***
	(-41.90)	(-33.84)	(-134.55)	(-52.31)	(-94.22)	(-52.94)	(-95.26)
ETP	-.0228***	-.0228***	-.0236***	-.0217***	-.0263***	-.0226***	-.0277***
	(-6.55)	(-5.56)	(-11.61)	(-10.04)	(-12.36)	(-10.43)	(-13.02)
$Derivative$	-.1320***	-.1320***	-.1324***	-.0727***	-.1066***	-.0726***	-.1062***
	(-42.45)	(-34.97)	(-110.05)	(-45.18)	(-75.62)	(-45.16)	(-75.32)
HWM	.0043*	.0043*	.0071***	-.0018***	.0010	-.0014*	.0022***
	(1.68)	(1.67)	(8.04)	(-2.64)	(1.34)	(-1.74)	(2.65)
Age	.0001*	.0001	.0001***	.0001***	.0002***		.0005***
	(1.66)	(1.50)	(3.98)	(4.98)	(6.72)		(10.58)
R^2	.1732	.1732	.1775	.4540	.3433	.4576	.3472

Table 5 – *continued*

Notes: In *Panel°D*, the monthly share regarding the volume of traded nonlottery-like stocks relative to all traded assets ($lnRTNL_{i,t}^{vol}$) is set as dependent variable. In specification (1) to (7) relative performance is measured over the previous month ($RR_{i,t-1}$); in specification (8) to (14) relative performance is measured over the previous six months ($R\bar{R}_{i,t-6}^{t-1}$). In specification (1) and (8) t-statistics correspond to *wikifolio* and month-clustered standard errors; in specification (2) and (9), t-statistics correspond to signal provider and month-clustered standard errors (see Petersen 2009). Specifications (3) and (10) include time fixed effects; specifications (4) and (11) include *wikifolio*-level fixed effects; (5) and (12) include signal provider-level fixed effects. Specification (6) and (13) simultaneously include time and *wikifolio*-level fixed effects. Specification (7) and (14) simultaneously include time and signal provider-level fixed effects. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively; t-statistics are displayed in parentheses.

Panel°D – continued							
	(8)	(9)	(10)	(11)	(12)	(13)	(14)
α	.1183***	.1183***	.1184***	.0937***	.0984***	.0942***	.0901***
	(18.56)	(16.11)	(47.68)	(31.85)	(32.42)	(33.35)	(28.56)
$R\bar{R}_{i,t-6}^{t-1}$	.0415***	.0415***	.0415***	.0069***	.0203***	.0071***	.0203***
	(31.11)	(27.81)	(71.75)	(11.58)	(34.31)	(11.99)	(34.43)
$(R\bar{R}_{i,t-6}^{t-1})^2$	-.0037***	-.0037***	-.0037***	-.0007***	-.0018***	-.0007***	-.0018***
	(-28.75)	(-26.00)	(-73.54)	(-13.08)	(-35.23)	(-13.40)	(-35.37)
$Leverage$	-.0103***	-.0103***	-.0105***		-.0313***		-.0307***
	(-3.72)	(-3.28)	(-9.51)		(-20.75)		(-20.39)
$RealMoney$	-.0030	-.0030	-.0035**		-.0068**		-.0073**
	(-.56)	(-.53)	(-2.08)		(-2.38)		(-2.56)
$Investable$	.0032	.0032	.0034***		.0101***		.0082***
	(1.38)	(1.23)	(3.93)		(6.89)		(5.50)
$Closing$	-.0115	-.0115	-.0112*		-.0132		-.0149*
	(-.81)	(-.76)	(-1.79)		(-1.60)		(-1.81)
$Closed$	-.0061*	-.0061	-.0055***		-.0026		-.0059***
	(-1.81)	(-1.62)	(-4.05)		(-1.46)		(-3.26)
Fee	-.1691***	-.1691***	-.1674***		-.0757***		-.0750***
	(-11.53)	(-9.51)	(-31.37)		(-8.28)		(-8.23)
$Media$	.0274**	.0274*	.0261***				
	(2.01)	(1.94)	(5.59)				
$Manager$	-.0472***	-.0472***	-.0477***				
	(-4.10)	(-3.89)	(-13.06)				
$Theme$	-.0735**	-.0735***	-.0727***				
	(-2.03)	(-14.80)	(-2.83)				
$wikiNumber$	-.0011***	-.0011***	-.0011***				
	(-6.08)	(-4.40)	(-15.62)				
lnT^{vol}	.0059***	.0059***	.0058***	.0099***	.0094***	.0100***	.0097***
	(13.65)	(11.45)	(32.80)	(39.18)	(42.91)	(39.61)	(43.79)
ETF	-.1121***	-.1121***	-.1123***	-.0581***	-.0920***	-.0587***	-.0932***
	(-41.46)	(-33.67)	(-134.35)	(-52.20)	(-94.03)	(-52.83)	(-95.05)
ETP	-.0234***	-.0234***	-.0242***	-.0218***	-.0267***	-.0227***	-.0281***
	(-6.68)	(-5.68)	(-11.90)	(-10.10)	(-12.56)	(-10.49)	(-13.20)
$Derivative$	-.1312***	-.1312***	-.1316***	-.0729***	-.1066***	-.0728***	-.1062***
	(-41.99)	(-34.66)	(-109.46)	(-45.31)	(-75.60)	(-45.27)	(-75.29)
HWM	.0035	.0035	.0063***	-.0021***	.0003	-.0018**	.0014*
	(1.31)	(1.31)	(7.21)	(-3.12)	(.46)	(-2.27)	(1.73)
Age	.0000	.0000	.0000	.0001***	.0001***		.0005***
	(.42)	(.38)	(-.21)	(4.38)	(5.45)		(9.46)
R^2	.1743	.1743	.1788	.4539	.3433	.4574	.3472

Table 5 – *continued*

Panel°A – Dependent Variable: Number Net Lottery Flow							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
α	-4.5640***	-4.5640***	-4.2017***	1.0087***	-1.5981***	3.3079***	-.5286***
	(-4.35)	(-3.20)	(-26.90)	(10.04)	(-8.61)	(37.89)	(-2.67)
$RR_{i,t-1}$	-.1035***	-.1035***	-.0938***	-.0387***	-.0637***	-.0381***	-.0621***
	(-3.11)	(-2.76)	(-6.27)	(-4.51)	(-5.44)	(-4.40)	(-5.24)
$Leverage$	.5396	.5396	.5359***		-1.6622***		-1.7998***
	(1.27)	(1.17)	(4.17)		(-11.09)		(-11.99)
$RealMoney$	.0872	.0872	.0636		4.5005***		4.5585***
	(.05)	(.04)	(.33)		(15.74)		(15.96)
$Investable$	.0020	.0020	.3219***		1.5727***		2.0198***
	(.01)	(.00)	(3.17)		(10.65)		(13.49)
$Closing$	-2.9027**	-2.9027*	-2.8246***		.8062		1.4067*
	(-2.04)	(-1.86)	(-3.86)		(.98)		(1.71)
$Closed$	-2.1418***	-2.1418***	-1.5415***		-.0237		.7035***
	(-3.38)	(-2.74)	(-9.70)		(-.13)		(3.86)
Fee	-.1397	-.1397	.2659		2.0995**		2.0850**
	(-.04)	(-.03)	(.43)		(2.30)		(2.29)
$Media$	-3.7821	-3.7821	-3.8566***				
	(-1.14)	(-.97)	(-7.05)				
$Manager$	-1.2542**	-1.2542*	-1.3173***				
	(-2.29)	(-1.66)	(-3.09)				
$Theme$	-3.3909***	-3.3909**	-2.8959				
	(-3.31)	(-2.53)	(-.96)				
$wikiNumber$	.1952***	.1952**	.1913***				
	(3.27)	(2.18)	(23.10)				
lnT^{num}	2.7015***	2.7015***	2.6709***	.0557*	.9408***	.0421	.9427***
	(6.55)	(5.37)	(73.88)	(1.83)	(25.45)	(1.38)	(25.45)
ETF	.0637	.0637	.2838***	-.0195	-.3403***	-.0637	-.2671***
	(.14)	(.11)	(2.91)	(-.23)	(-3.48)	(-.74)	(-2.72)
ETP	.2359	.2359	.3975	-1.7177***	-1.4457***	-1.4610***	-1.1645***
	(.34)	(.28)	(1.67)	(-10.25)	(-6.80)	(-8.69)	(-5.46)
$Derivative$	-2.6168***	-2.6168***	-2.7520***	.1732	-.4819***	.2515**	-.5855***
	(-4.76)	(-3.98)	(-19.29)	(1.38)	(-3.39)	(2.00)	(-4.11)
HWM	-.8213***	-.8213***	-.8903***	-.1092**	-.2143***	-.0546	-.1771*
	(-3.48)	(-3.52)	(-8.65)	(-2.05)	(-2.97)	(-.88)	(-2.13)
Age	.0954***	.0954***	.0648***	.1136***	.1167***		.0475***
	(5.69)	(4.77)	(21.48)	(59.67)	(46.88)		(9.61)
R^2	.0315	.0315	.0336	.7206	.4384	.7212	.4394

Table 6: Regression Results Net Lottery Flow and Past Performance

Notes: In *Panel°A*, the net flow into lottery-like stocks based on transaction numbers, $LF_{i,t=1}^{num,t}$, is set as dependent variable. In specification (1) to (7) relative performance is measured over the previous month ($RR_{i,t-1}$); in specification (8) to (14) relative performance is measured over the previous six months ($R\bar{R}_{i,t-6}^{t-1}$). In specification (1) and (8) t-statistics correspond to *wikifolio* and month-clustered standard errors; in specification (2) and (9), t-statistics correspond to signal provider and month-clustered standard errors (see Petersen 2009). Specifications (3) and (10) include time fixed effects; specifications (4) and (11) include *wikifolio*-level fixed effects; (5) and (12) include signal provider-level fixed effects. Specification (6) and (13) simultaneously include time and *wikifolio*-level fixed effects. Specification (7) and (14) simultaneously include time and signal provider-level fixed effects. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively; t-statistics are displayed in parentheses.

Panel°A – continued							
	(8)	(9)	(10)	(11)	(12)	(13)	(14)
α	-4.0821***	-4.0821***	-3.7665***	1.2987***	-1.2855***	3.5761***	-.2279
	(-3.94)	(-2.86)	(-23.85)	(12.59)	(-6.86)	(39.76)	(-1.14)
$R\bar{R}_{i,t-6}^{t-1}$	-.1930***	-.1930***	-.1797***	-.0965***	-.1254***	-.0944***	-.1238***
	(-3.16)	(-2.90)	(-12.02)	(-10.23)	(-10.12)	(-9.91)	(-9.89)
$Leverage$	.5243	.5243	.5230***		-1.6725***		-1.8090***
	(1.23)	(1.14)	(4.07)		(-11.16)		(-12.06)
$RealMoney$	.1850	.1850	.1530		4.5623***		4.6184***
	(.10)	(.09)	(.78)		(15.96)		(16.16)
$Investable$	.0180	.0180	.3354***		1.5921***		2.0391***
	(.05)	(.04)	(3.30)		(10.79)		(13.62)
$Closing$	-2.7708*	-2.7708*	-2.7028***		.7995		1.3995*
	(-1.95)	(-1.78)	(-3.70)		(.97)		(1.70)
$Closed$	-2.1782***	-2.1782***	-1.5769***		-.0641		.6660***
	(-3.43)	(-2.78)	(-9.93)		(-.36)		(3.66)
Fee	-.2781	-.2781	.1422		2.0198**		2.0115**
	(-.08)	(-.06)	(.23)		(2.22)		(2.21)
$Media$	-3.7576	-3.7576	-3.8354***				
	(-1.13)	(-.97)	(-7.01)				
$Manager$	-1.2691**	-1.2691*	-1.3330***				
	(-2.31)	(-1.70)	(-3.12)				
$Theme$	-3.1293***	-3.1293**	-2.6392				
	(-3.09)	(-2.37)	(-.88)				
$wikiNumber$	.1957***	.1957**	.1918***				
	(3.28)	(2.19)	(23.16)				
lnT^{num}	2.7113***	2.7113***	2.6796***	.0689**	.9562***	.0543*	.9571***
	(6.56)	(5.38)	(74.12)	(2.26)	(25.84)	(1.78)	(25.82)
ETF	-.0087	-.0087	.2156**	-.0241	-.3627***	-.0677	-.2886***
	(-.02)	(-.02)	(2.20)	(-.28)	(-3.71)	(-.78)	(-2.94)
ETP	.1999	.1999	.3622	-1.7183***	-1.4541***	-1.4625***	-1.1741***
	(.29)	(.24)	(1.52)	(-10.26)	(-6.84)	(-8.70)	(-5.51)
$Derivative$	-2.6339***	-2.6339***	-2.7684***	.1787	-.4815***	.2561***	-.5862***
	(-4.77)	(-3.98)	(-19.41)	(1.42)	(-3.39)	(2.04)	(-4.11)
HWM	-.6806***	-.6806***	-.7112***	-.0553	-.1484**	.0185	-.0847
	(-2.80)	(-2.81)	(-6.94)	(-1.05)	(-2.08)	(.30)	(-1.03)
Age	.0952***	.0952***	.0649***	.1133***	.1164***		.0473***
	(5.70)	(4.78)	(21.53)	(59.50)	(46.78)		(9.57)
R^2	.0319	.0319	.0340	.7207	.4385	.7213	.4395

Table 6 – *continued*

Panel°B – Dependent Variable: Volume Net Lottery Flow							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
α	1.8221***	1.8221***	1.9495***	1.2794***	1.3006***	1.0103***	1.3396***
	(17.73)	(16.62)	(60.12)	(42.09)	(34.13)	(34.84)	(33.36)
$RR_{i,t-1}$	-.0008	-.0008	-.0014	-.0043***	-.0032**	-.0052***	-.0040**
	(-.27)	(-.27)	(-.71)	(-3.44)	(-2.00)	(-4.08)	(-2.42)
$Leverage$	.0035	.0035	-.0012		-.0897***		-.0916***
	(.06)	(.06)	(-.07)		(-4.31)		(-4.40)
$RealMoney$	.3413***	.3413***	.3430***		.1216***		.1247***
	(3.17)	(3.02)	(13.38)		(3.07)		(3.15)
$Investable$	-.1800***	-.1800***	-.1448***		-.1307***		-.1214***
	(-3.72)	(-3.63)	(-10.99)		(-6.42)		(-5.87)
$Closing$	-.0103	-.0103	-.0036		-.1979*		-.1844
	(-.02)	(-.02)	(-.04)		(-1.73)		(-1.61)
$Closed$	-.2579***	-.2579***	-.1831***		-.1824***		-.1583***
	(-4.13)	(-4.03)	(-8.80)		(-7.46)		(-6.27)
Fee	-.5521*	-.5521*	-.4264***		.5731***		.5845***
	(-1.86)	(-1.67)	(-5.23)		(4.53)		(4.62)
$Media$	.0993	.0993	.0897				
	(.38)	(.57)	(1.25)				
$Manager$	.2937	.2937	.2825***				
	(1.15)	(1.01)	(5.05)				
$Theme$	.9473	.9473***	.9733**				
	(1.06)	(15.67)	(2.47)				
$wikiNumber$	-.0084**	-.0084**	-.0085***				
	(-2.59)	(-2.31)	(-7.88)				
lnT^{vol}	-.0328***	-.0328***	-.0436***	-.0223***	-.0116***	-.0218***	-.0128***
	(-3.93)	(-3.64)	(-16.04)	(-7.90)	(-3.83)	(-7.69)	(-4.18)
ETF	-.3721***	-.3721***	-.3276***	-.0093	-.1568***	-.0057	-.1493***
	(-10.88)	(-10.06)	(-25.70)	(-.74)	(-11.57)	(-.45)	(-10.97)
ETP	-.0132	-.0132	-.0257	.0183	.0191	.0050	.0088
	(-.25)	(-.24)	(-.83)	(.75)	(.65)	(.20)	(.30)
$Derivative$	-.3610***	-.3610***	-.3841***	-.0459**	-.2650***	-.0431**	-.2685***
	(-7.50)	(-7.19)	(-20.94)	(-2.52)	(-13.60)	(-2.37)	(-13.74)
HWM	.0714***	.0714***	.0984***	.0600***	.0669***	.0756***	.0820***
	(3.40)	(3.36)	(7.28)	(7.73)	(6.70)	(8.36)	(7.09)
Age	-.0157***	-.0157***	-.0193***	-.0128***	-.0125***		-.0144***
	(-12.99)	(-12.26)	(-47.56)	(-45.91)	(-36.00)		(-20.79)
R^2	.0178	.0178	.0202	.6452	.3601	.6456	.3606

Table 6 – *continued*

Notes: In *Panel°B*, the net flow into lottery-like stocks based on transaction volumes, $LF_{i,t=1}^{vol,t}$, is set as dependent variable. In specification (1) to (7) relative performance is measured over the previous month ($RR_{i,t-1}$); in specification (8) to (14) relative performance is measured over the previous six months ($R\bar{R}_{i,t-6}^{t-1}$). In specification (1) and (8) t-statistics correspond to *wikifolio* and month-clustered standard errors; in specification (2) and (9), t-statistics correspond to signal provider and month-clustered standard errors (see Petersen 2009). Specifications (3) and (10) include time fixed effects; specifications (4) and (11) include *wikifolio*-level fixed effects; (5) and (12) include signal provider-level fixed effects. Specification (6) and (13) simultaneously include time and *wikifolio*-level fixed effects. Specification (7) and (14) simultaneously include time and signal provider-level fixed effects. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively; t-statistics are displayed in parentheses.

Panel°B – continued							
	(8)	(9)	(10)	(11)	(12)	(13)	(14)
α	1.8243***	1.8243***	1.9494***	1.2857***	1.3022***	1.0162***	1.3414***
	(18.11)	(16.92)	(60.36)	(42.29)	(34.22)	(35.07)	(33.44)
$R\bar{R}_{i,t-6}^{t-1}$	-.0014	-.0014	-.0014	-.0065***	-.0040**	-.0075***	-.0049***
	(-.38)	(-.37)	(-.73)	(-4.72)	(-2.34)	(-5.39)	(-2.84)
$Leverage$	.0034	.0034	-.0013		-.0899***		-.0919***
	(.06)	(.06)	(-.07)		(-4.32)		(-4.41)
$RealMoney$	.3421***	.3421***	.3436***		.1235***		.1270***
	(3.18)	(3.03)	(13.40)		(3.12)		(3.21)
$Investable$	-.1799***	-.1799***	-.1447***		-.1300***		-.1206***
	(-3.72)	(-3.63)	(-10.98)		(-6.39)		(-5.83)
$Closing$	-.0094	-.0094	-.0028		-.1979*		-.1846
	(-.02)	(-.02)	(-.03)		(-1.73)		(-1.61)
$Closed$	-.2581***	-.2581***	-.1833***		-.1833***		-.1595***
	(-4.13)	(-4.02)	(-8.81)		(-7.50)		(-6.31)
Fee	-.5533*	-.5533*	-.4273***		.5706***		.5816***
	(-1.86)	(-1.68)	(-5.24)		(4.51)		(4.60)
$Media$	.0995	.0995	.0898				
	(.38)	(.57)	(1.25)				
$Manager$	.2934	.2934	.2823***				
	(1.15)	(1.01)	(5.04)				
$Theme$	.9491	.9491***	.9753**				
	(1.06)	(15.84)	(2.47)				
$wikiNumber$	-.0084**	-.0084**	-.0085***				
	(-2.59)	(-2.31)	(-7.88)				
lnT^{vol}	-.0327***	-.0327***	-.0435***	-.0217***	-.0113***	-.0210***	-.0123***
	(-3.90)	(-3.62)	(-15.98)	(-7.64)	(-3.70)	(-7.40)	(-4.03)
ETF	-.3727***	-.3727***	-.3280***	-.0097	-.1574***	-.0061	-.1502***
	(-10.95)	(-10.12)	(-25.66)	(-.77)	(-11.62)	(-.49)	(-11.03)
ETP	-.0134	-.0134	-.0259	.0183	.0189	.0049	.0085
	(-.25)	(-.24)	(-.83)	(.75)	(.64)	(.20)	(.29)
$Derivative$	-.3611***	-.3611***	-.3842***	-.0454**	-.2649***	-.0426**	-.2684***
	(-7.51)	(-7.20)	(-20.94)	(-2.50)	(-13.59)	(-2.34)	(-13.73)
HWM	.0723***	.0723***	.0984***	.0608***	.0669***	.0767***	.0824***
	(3.42)	(3.38)	(7.32)	(7.92)	(6.77)	(8.60)	(7.20)
Age	-.0157***	-.0157***	-.0193***	-.0128***	-.0125***		-.0144***
	(-12.99)	(-12.27)	(-47.56)	(-46.00)	(-36.03)		(-20.79)
R^2	.0178	.0178	.0202	.6452	.3601	.6457	.3606

Table 6 – *continued*

6.4 Robustness Checks

6.4.1 Definition for Lottery-like Stocks

In order to test the robustness of the obtained results, a definition of lottery-like stocks that differs from Kumar's (2009) classification is selected. Therefore, using all stocks from the *wikifolio* investment universe as benchmark, lottery-like stocks are classified in accordance with the definition introduced by Bali et al. (2011) – stocks with extreme past daily returns are identified as lottery-like (see *Section 3.4.1* and *Section 5.1.1*).[339]

Signal providers on the *wikifolio* platform are mostly individual investors. Assuming limited cognitive processing capabilities and, in this context, limited investor attention[340], signal providers may select lottery-like assets solely based on maximum past (daily) returns. Kumar (2009) argues that investors are searching for cheap bets and thus should tend towards low-priced stocks. Consequently, Kumar (2009) employs stock price as one of the defining criteria for lottery-like stocks. However, since signal provider portfolios on the *wikifolio* platform are purely virtual, i.e. signal providers simply chose their starting capital when creating a *wikifolio*, the price criterion might not be as relevant.

Employing Bali et al.'s (2011) definitions of lottery-like stocks (Max / $Max5$) leads to results which are similar to those described in the main experiment.

6.4.2 Benchmarks for Lottery-like Stocks

Furthermore, the robustness of the results from the main experiment is evaluated by categorizing lottery-like stocks with regard to a different benchmark. As previously described, signal providers can choose from a broad investment universe including stocks, funds, ETFs, investment certificates, and leverage products. Available assets are selected by the *wikifolio* platform. Hence, within the previous analyses, certain stocks may have been defined as lottery-like, which would not be categorized as such, if a comprehensive country-specific stock index was employed as benchmark

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339 Stocks are sorted into decile portfolios based on the constituent maximum daily return over the past month. Stocks in the highest decile portfolio (Max), i.e. stocks exhibiting the highest constituent daily return over the previous month, are categorized as lottery-like. As a variation, decile portfolios are formed based on the average comprising the five highest returns of the previous month. Accordingly, stocks in the highest decile portfolio ($Max5$), i.e. stocks exhibiting the highest average regarding the five highest daily returns over the previous month, are categorized as lottery-like. See also *Section 3.4.1*.

340 See Kahneman (1973), Odean (1999), and Barber and Odean (2008). See also *Section 3.3.3*.

and vice versa. Based on the number and volume of transactions by issuing country (see Appendix A2 Table 15), ten comprehensive country-specific stock indices are selected.[341]

The employed indices are displayed in Appendix A6 Table 25. Lottery-like stocks are identified within each index by applying Kumar's (2009) classification method.[342] Subsequently, the information if a stock is categorized as lottery-like during a respective month is merged to the transaction dataset.

Sorting stocks with regard to comprehensive national stock indices leads to results which are very similar to those of the main experiment.

6.4.3 Idiosyncratic Skewness Computation

In the main experiment, lottery-like stocks are defined according to Kumar (2009). Therefore, idiosyncratic skewness is computed following Harvey and Siddique (2000). However, idiosyncratic skewness computed according to Harvey and Siddique (2000) is under debate for not being a robust measured variable.[343] Therefore, in addition, idiosyncratic skewness is measured according to Boyer et al. (2010) as the skewness of regression residuals obtained from applying the Fama and French (1993) three-factor model. As before, lottery-like stocks as stocks are characterized as stocks with below median price, above median idiosyncratic volatility, and above median idiosyncratic skewness – idiosyncratic skewness now being measured by applying a three-factor ($ISkew3F$) instead of a two-factor ($ISkew2F$) model.

The main experiment is re-estimated with idiosyncratic skewness calculated according to Boyer et al. (2010). The obtained results are not fundamentally different than those previously reported. The U-shaped quadratic relationship between the traded share of lottery-like stocks and relative past *wikifolio* performance is still

341 Many ETFs and investment funds are issued in Luxembourg, however, there are barley any corresponding listed stocks with available price data on *Datastream*. Thus, even though assets issued in Luxembourg are third most frequently traded by signal providers, a respective country-specific stock index is not employed for the analysis.
342 As before, the corresponding regional Fama and French (1993) factors and the momentum (see Jegadeesh and Titman 1993) factor for computing idiosyncratic volatility and idiosyncratic skewness are obtained from the *KFDL*.
343 See Hou et al. (2020).

consistently significant. Likewise, the inverse U-shaped quadratic relationship between nonlottery-like stocks and relative past *wikifolio* performance remains its significance. Finally, as before, there is evidence for a negative linear relationship between the net lottery flow and relative past *wikifolio* performance. When the dependent variable is based on volume, the coefficient of the variable reflecting relative performance is not statistically significant in all of the applied regression specifications. Yet, in each specification where *wikifolio* or trader fixed-effects are included, the coefficient corresponding to past performance is statistically significant at the per mill level.

6.5 Recap, Discussion, and Conclusion

To sum up, the results of the main experiment indicate a quadratic relationship between the primarily examined independent variable, relative past *wikifolio* performance, and the traded share of lottery-like stocks: Signal providers exhibiting relatively bad past performance and signal providers exhibiting relatively good past performance seem to trade a higher share of lottery-like stocks.

The observed results might be explained by several well-documented behavioral phenomena as well as peculiarities of the social trading platform and the established signal provider compensations scheme.

Regarding signal providers at the lower end of the performance spectrum, i.e. signal providers administering underperforming *wikifolios*, there are several factors which may induce lottery trading. Underperforming *wikifolios* are unlikely to generate – or maintain – a desirable base of signal followers. Considering the limited monetary downside risk, signal providers corresponding to *wikifolios* at the lower end of the relative performance spectrum have little to lose. Due to their specific return characteristics, i.e. high idiosyncratic volatility and positive idiosyncratic skewness, lottery-like stocks may be particularly appealing to signal providers looking to improve the positioning of an underperforming *wikifolio*.

Hoping for an exceptionally high positive return, previously underperforming signal providers may include lottery-like stocks more frequently into their corresponding *wikifolios*. In turn, when included lottery-like stocks fail to deliver the desired return, signal providers may shortly thereafter replace the corresponding assets.

With regard to signal providers operating *wikifolios* at the upper end of the peer performance range, overconfidence (see *Section 2.5.3*) might be a suitable explanation for the observed results. De Long et al. (1991), Odean (1999), Barber and Odean (2001), and Broihanne et al. (2014) document a positive relation between overconfidence and risk taking. When their overconfidence is increased due to good relative past performance[344], signal providers might be drawn to assets exhibiting more risk and thus increase the proportion of traded lottery-like stocks. Furthermore, overconfident traders overestimate the precision of their information[345], and thus may severely overestimate their ability to make profits by timing the market. When believing to have precise or superior information, signal providers may increase trading with regard to stocks where major (positive) price movements are more likely, i.e. stocks exhibiting high idiosyncratic volatility and high idiosyncratic skewness – lottery characteristics.

Furthermore, *wikifolio* signal providers who have outperformed their peers may be inclined to accept gambles – i.e. trade lottery-like stocks – for a chance of being listed among the top-performing accounts (on the platform's front page). For professionally managed funds, Chevalier and Ellison (1997) find that managers being well ahead of the market are strongly inclined to gamble; an effect they suggest may perhaps be driven by the attempt to attain a position on listings of top-performing funds.

The obtained results indicate an inverted U-shape quadratic relationship between relative past performance and the traded share of nonlottery-like stocks. Hence, signal providers administering *wikifolios* with more moderate peer performance are more likely to trade low idiosyncratic volatility and low idiosyncratic skewness stocks. Signal providers located somewhere in the middle of the relative performance spectrum may pursue an investment strategy focusing on feasible long-term returns – instead of speculating on potential (short-term) extreme returns. Thus, those signal providers may be more prone to invest in stocks exhibiting low levels of (idiosyncratic) volatility and (idiosyncratic) skewness.

Addressing the net exposure towards risk induced by lottery-like stocks, the conducted analysis provides evidence of a negative linear relation between net lottery flow and the applied relative performance variables. In addition to trading lottery-like

344 See Odean (1999), Gervais and Odean (2001), and Statman et al. (2006).
345 See Benos (1998), Daniel et al. (1998), and Odean (1998), (1999).

stocks more frequently, the results indicate that signal providers administering underperforming *wikifolios* increase their net exposure towards lottery-like stocks. Even though signal provider compensation is not directly linked to a corresponding administered *wikifolio*'s ranking, the platform's compensation scheme (see *Section 4.2.3*) indirectly imposes tournament incentives as signal providers must achieve a position reasonably suited for generating attention from signal followers.[346] The obtained results are related to research on the flow-performance relationship of professionally managed funds (see *Section 2.2*) – it has been well established that professional asset managers are concerned about their ranking. The results of the conducted experiment are in line Agarwal et al. (2022) who provide evidence that poorly performing mutual funds increase their lottery-like stock holdings.

Allowing signal providers to simultaneously operate more than one account, a feature common to social trading platforms, may further help to explain why underperforming signal providers exhibit an increased preference for lottery-like stocks. The *wikifolio* platform enables signal providers to operate up to eight *wikifolios* at the same time with no or limited exposure to their generated returns.[347] As unsuccessful *wikifolios* may be closed – and potentially replaced – at any time, signal providers incur limited costs when abandoning unsuccessful projects. Hence, signal providers with underperforming *wikifolios* may be particularly inclined to employ lottery-like characteristics – speculating on the unlikely but possible event of an extreme positive return – in an attempt to turn around a fruitless portfolio.

In brief, the results suggest that peer performance on the *wikifolio* platform is a significant factor with regard to signal provider gambling behavior. Attaining a position at the upper or at the lower end of the performance spectrum may induce signal providers to trade lottery-like stocks more frequently. Furthermore, signal providers operating *wikifolios* which have previously underperformed increase their net exposure towards lottery-like stocks, exposing their followers to lottery-like return characteristics.

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[346] With regard to social trading, Röder and Walter (2019) provide evidence that investment flows follow past performance reflected by raw returns; thus, competition most likely relates to rae instead of risk adjusted performance (see the selected performance variable employed in the conducted regression analyses). For tournament incentives, see Ehrenberg and Bognanno (1990a), (1990b), Knoeber and Thurman (1994), Taylor (2003), and Kirchler et al. (2018). See also *Section 3.4.3*.

[347] Only when acquiring issued certificates associated to their administered *wikifolios*, signal providers gain exposure to their generated returns.

7 Competition for Visibility: When do (FX) Signal Providers employ Lotteries?[348]

7.1 Methodological Approach

7.1.1 Definition of Lottery-like assets

As described in *Section 4.2.4*, *ZuluTrade* mainly serves as a platform for foreign exchange trading. Due to the absence of an established method that identifies currency pairs with lottery-like features, i.e. an approach categorizing lottery-like and nonlottery-like currency pairs, Bali et al.'s (2011) definition for lottery-like stocks is transferred to the foreign exchange market.[349]

The reasoning is as follows: Similar to stocks, currency pairs exhibiting extreme positive daily returns during 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.[350] 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.

Motivated by Bali et al. (2011), daily exchange rates are applied to calculated the maximum daily return for each currency pair and each month included in the dataset (see *Section 4.2.1* and *Section 4.2.4*).[351] Accordingly, for commodities included in the dataset, daily prices are employed to compose maximum daily returns; regarding

[348] This section and the referred appendices are substantially obtained from Schneider and Oehler (2021).
[349] As previously discussed, Bali et al. (2011) 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. See also *Section 3.4.1*.
[350] There is a comprehensive body of literature which links extreme daily price movements of a respective currency (currency crashes / currency crisis) to speculative attacks (see Connolly 1986, Eichengreen et al. 1995, Krugman 1979, Krugman and Rotemberg 1992) as well as a wide variety of political and economic factors (see Balima 2020, Chiu and Willett 2009, Frankel and Rose 1996, Leblang and Satyanath 2006, 2008, Obstfeld 1996, Steinberg et al. 2015). This study, however, does not cover the underlying causes for occurring extreme currency price movements.
[351] As described in *Section 4.2.1*, daily exchange rates for currency pairs in the 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, the required exchange rates are derived by applying corresponding EUR rates obtained from the *European Central Bank*.

equity indices and individual equities, the corresponding *Datastream* return index (in USD) is applied. Subsequently, monthly decile portfolios based on the maximum daily return of the previous month are formed. Assets assigned to the highest decile portfolio are defined as lotteries. For categorizing lotteries, corresponding assets are included one month prior to their initial signal provider trade in the composed dataset.[352]

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[353], in the context of this analysis, crypto currencies are by default categorized as lottery-like.[354]

In accordance with Bali et al. (2011), lotteries have been defined in relative terms. In the context of this analysis, categorizing lotteries in dependence upon available assets seems to be the most appropriate approach. In periods where all tradable assets exhibit relatively smooth daily price fluctuations, i.e. periods where extreme daily returns are less pronounced, signal providers are still subject to the predetermined investment universe. Therefore, when making investment decisions, certain options will appear more attractive to signal providers with the intention to gamble. Among all available choices, assets would be perceived as functional lotteries in month t, even if they didn't make the cut during previous or subsequent periods. Furthermore, as the social trading platform provides relative performance-based selection lists, signal providers may be focused on outperforming peers rather than attaining absolute target values. In periods where the magnitude of the highest daily returns is less pronounced across all assets, more moderate outcomes may be sufficient for achieving superior peer performance. After the introduction of crypto currencies, signal providers have access to an entire asset category which exhibits highly speculative characteristics and may generally be perceived as a suitable

[352] The first crypto currency in the dataset is traded in November 2017. Individual equities are not traded until the very end of the observation period.
[353] See Chimienti et al. (2019) and Giudici et al. (2020).
[354] See also Horn and Wendt (2021) and Wendt and Horn (2021) who argue that investments in crypto currencies and initial coin offerings (ICOs) are of a highly speculative nature and, thus, should only be employed as a part of (very) high aspiration portfolio layers.

gambling instrument. Therefore, crypto currencies are excluded from the relative lottery categorization approach.

Summary statistics with regard to all assets included in the dataset, as well as the subcategory of sorted lotteries, are displayed in Appendix A8 Table 27.

7.1.2 Selection of Independent Variables

As described, 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(see *Section 4.2.4*).

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.[355] 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.[356]

On *ZuluTrade*, as is customary on social trading platforms, almost all sorting criteria relate to past signal provider performance. Thus, the main independent variables for this analysis are based on past win ratios as well as past net profits to broadly mirror signal provider trading merit. Each account is considered separately.

More precisely, the win ratio of account i covering the previous month $(t-1)$ is selected as a performance measure:

$$Win_{i,t-1} = \frac{NWin_{i,t-1}}{NClose_{i,t-1}}, \tag{23}$$

[355] See Odean (1999) and Barber and Odean (2008). See also *Section 3.3.3*.
[356] See also the descriptions relating to the *wikifolio* social trading platform.

$NWin_{i,t-1}$ 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, the average win ratio over the previous six months ($t-6$ to $t-1$) is computed:

$$\overline{Win}_{i,t-6}^{t-1} = \frac{\sum_{n=1}^{6} Win_{i,t-n}}{6}. \tag{24}$$

In addition, the net profit of the previous month is employed as a signal provider account performance measure:

$$Profit_{i,t-1} = \sum_{n=1}^{m} SProfit_{i,t-1}^{n}, \tag{25}$$

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:

$$\overline{Profit}_{i,t-6}^{t-1} = \frac{\sum_{n=1}^{6} Profit_{i,t-n}}{6}. \tag{26}$$

Subsequently, each performance measure is employed to generate monthly deciles. Using the respective deciles as thresholds, each account-month observation is then assigned a number from one to ten, indicating the according relative monthly performance ranking with regard to the different performance measures (this approach is in line with the analyses concerning the *wikifolio* platform describe in *Section 6*). The variables referring to relative past performance based on win ratios are depicted as

$$RWin_{i,t-1} \;/\; R\overline{Win}_{i,t-6}^{t-1}, \tag{27}$$

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

$$RProfit_{i,t-1} \;/\; R\overline{Profit}_{i,t-6}^{t-1}. \tag{28}$$

7.1.3 Absolute Number Transactions

First, the relationship between the monthly number of conducted trades and the relative past performance indicators is assessed. The according dependent variable, the number of conducted trades (opening and closing of positions) by signal provider i in month t, is depicted as follows:

$$T_{i,t}. \tag{29}$$

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

$$lnT_{i,t} = \ln(1 + T_{i,t}). \tag{30}$$

The resulting baseline regression model is as follows:

$$\begin{aligned} lnT_{i,t} &= \alpha + \beta_1 \times IV + \beta_2 \times Lots_{i,t} + \beta_3 \times Open_{i,t} + \beta_4 \times Long_{i,t} \\ &+ \beta_5 \times Age_{i,t} + \beta_6 \times Crypto_{i,t} + \beta_7 \times Commodity_{i,t} + \beta_8 \times Index_{i,t} + \varepsilon. \end{aligned} \tag{31}$$

IV 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 ($RProfit_{i,t-1}$ / $R\overline{Profit}_{i,t-6}^{t-1}$). In addition, a variety of control variables is included: $Lots_{i,t}$ 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 one when a crypto currency, commodity, or index is traded in signal provider account i in month t.

7.1.4 Relative Number Lottery Transactions

In the main analysis, the impact of the previously described relative past performance indicators on the monthly share of lottery-like trades is assessed. The share of lottery-like assets traded by signal provider account i in month t is employed as dependent variable:

$$RTL_{i,t}^{Max} = \frac{TL_{i,t}^{Max}}{T_{i,t}}, \tag{34}$$

where $TL_{i,t}^{Max}$ is the number of trades of signal provider i in month t involving lottery assets. Since the dependent variable, $RTL_{i,t}^{Max}$, is positively skewed, the following transformation using the natural logarithm is conducted:

$$lnRTL_{i,t}^{Max} = \ln\left(1 + RTL_{i,t}^{Max}\right). \tag{35}$$

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

$$\begin{aligned} lnRTL_{i,t}^{Max} &= \alpha + \beta_1 \times IV + \beta_2 \times Lots_{i,t} + \beta_3 \times Open_{i,t} + \beta_4 \times Long_{i,t} \\ &+ \beta_5 \times Age_{i,t} + \beta_6 \times Commodity_{i,t} + \beta_7 \times Index_{i,t} + \beta_8 \times RNum_{i,t} + \varepsilon. \end{aligned} \tag{36}$$

As in the regression analysis in the previous section, IV represents the independent variable of interest which respectively reflects signal provider win ratios and profits. Furthermore, a variable reflecting relative past performance jointly based on win rations and net profits is introduced:

$$RComb_{i,t-1} = (RWin_{i,t-1} + RProfit_{i,t-1})/2, \tag{37}$$

$$\overline{RComb}_{i,t-6}^{t-1} = (\overline{RWin}_{i,t-6}^{t-1} + \overline{RProfit}_{i,t-6}^{t-1})/2. \tag{38}$$

The dependent variable reflecting the share of lottery-like trades, $lnRTL_{i,t}^{Max}$, 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 exhibit, on average, more than twelve trades per month (see Appendix A8 Table 28). Thus, it is rarely the case that not at least one monthly trade is conducted within any of the included signal provider accounts.

7.2 Results

Regarding the initial results from the regression analysis where the absolute number of transactions depicts the dependent variable ($T_{i,t}$), there is no evidence of 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, the squares of the respective win ratio variables are included into the regression analysis.[357] 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 to 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. That is, 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 one or zero. 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.

Therefore, the relative win ratio variables are adjusted as follows:

$$RWinAdj_{i,t-1} = (RWin_{i,t-1} + RNWin_{i,t-1})/2, \tag{39}$$

[357] Including squared terms of the relative performance variables is motivated by the approach and the corresponding results relating to the *wikifolio* platform (see *Section 6*).

$$R\overline{WinAdj}_{i,t-6}^{t-1} = (R\overline{Win}_{i,t-6}^{t-1} + RN\overline{Win}_{i,t-6}^{t-1})/2, \quad (40)$$

where $RNWin_{i,t-1}$ / $RN\overline{Win}_{i,t-6}^{t-1}$ reflect the ranking of signal provider account i with regard to the total 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 one to ten; 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 Appendix A9 Table 29.

Regarding the main experiment where the share of traded lottery-like assets depicts the dependent variable, the initial results obtained from applying the regression model depicted in Equation 36 do not indicate a significant relation between the composed relative performance measures and the conducted lottery trades. As these results are of limited informative value, squared terms of the employed relative performance measures are included in order to obtain a more comprehensive picture. Panel regression results including squared terms are displayed in Table 7.

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.[358] The relationship is consistent over all of the applied relative performance measures; that is, performance based on net profits ($RProfit_{i,t-1}$ / $R\overline{Profit}_{i,t-6}^{t-1}$), win ratios ($RWin_{i,t-1}$ / $R\overline{Win}_{i,t-6}^{t-1}$), as well as the combined measure ($RComb_{i,t-1}$ / $R\overline{Comb}_{i,t-6}^{t-1}$).

Applying adjusted win ratios composed over the previous month (see Equation 39) 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 (see Equation 40), however, the statistical significance of the effect disappears. In this context, to get further insights

[358] These results are therefore in line with the results discussed in *Section 6* with regard to the *wikifolio* social trading platform.

regarding the impact of win ratios and the absolute number of won transactions, the adjusted win ratio variable is composed as follows:

$$R\overline{Win}Adj_{i,t-x}^{t-1} = (RWin_{i,t-1} + R\overline{NWin}_{i,t-x}^{t-1})/2, \quad (41)$$

where x may take the value of two, three, four, five, or six. Combining the win ratio measure of the previous month with the variable corresponding to the average monthly number of positions closed at a net profit over a two- to six-month period yields statistically significant coefficients (although the statistical significance for x equal to four, five, and six is rather weak in some of the regression specifications). The obtained results provide further evidence for the stated line of argumentation: Instead of being caused by trading activity and the corresponding impact on win ratio computation, the U-shaped relationship between win ratios and lottery trades is driven by relative signal provider performance.

Furthermore, one could argue that signal providers are subject to the disposition effect and, thus, close positions as soon as they yield a (marginal) profit.[359] In this context, an increase in trading activity could (potentially) be related to a higher net profit as depicted by the second employed performance measure. Hence, an adjusted performance measure relating to profits is introduced; by incorporating the average profit per transaction, a potential effect of the transaction number on total monthly profits should be mitigated. The adjusted profit variables are composed as follows:

$$RProfitAdj_{i,t-1} = (RProfit_{i,t-1} + RAvgProfit_{i,t-1})/2, \quad (42)$$

$$R\overline{Profit}Adj_{i,t-6}^{t-1} = (R\overline{Profit}_{i,t-6}^{t-1} + RAvg\overline{Profit}_{i,t-6}^{t-1})/2\,, \quad (43)$$

where $RAvgProfit_{i,t-1}$ / $RAvg\overline{Profit}_{i,t-6}^{t-1}$ reflect the ranking of signal provider account i with regard to the average profit per transaction in month $t-1$ / the average of monthly average profits per transaction covering $t-6$ to $t-1$. The ranking is expressed in a number from one to ten; monthly deciles based on all accounts in the dataset are employed as threshold values. Including average profits per transaction yields highly statistically significant results, the respective signs of the coefficients further indicating a U-shaped relation between past performance and traded lotteries.

359 For a discussion of the disposition effect (see Shefrin and Statman 1985) in social trading see *Section 3.4.3*.

Panel°A – Dependent Variable: Relative Number Lottery Trades					
	(1)	(2)	(3)	(4)	(5)
α	.0309***	.0309***	.0315***	.0343***	.0350***
	(3.84)	(3.61)	(14.03)	(12.83)	(13.42)
$RWin_{i,t-1}$	-.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)
$Lots_{i,t}$	.0000***	.0000***	.0000***	.0000***	.0000***
	(4.34)	(4.41)	(9.43)	(8.47)	(8.31)
$Age_{i,t}$	-.0000	-.0000	-.0000*	-.0003***	-.0003***
	(-.90)	(-.79)	(-1.78)	(-13.06)	(-12.51)
$Open_{i,t}$	.0104	.0104	.0031	.0043	.0044
	(1.06)	(1.08)	(1.20)	(1.61)	(1.64)
$Long_{i,t}$	.0111**	.0111*	.0131***	.0077***	.0081***
	(2.59)	(1.96)	(10.38)	(5.33)	(5.68)
$Commodity_{i,t}$	.0602***	.0602***	.0589***	.0562***	.0575***
	(6.05)	(5.90)	(46.75)	(31.61)	(34.01)
$Index_{i,t}$	.0889***	.0889***	.0922***	.0590***	.0702***
	(4.08)	(4.06)	(45.35)	(18.84)	(25.05)
$RNum_{i,t}$	-.0030***	-.0030***	-.0027***	-.0020***	-.0023***
	(-3.13)	(-2.80)	(-9.92)	(-5.27)	(-6.30)
R^2	.0720	.0720	.1499	.2133	.1856

Table 7: Regression Results Relative Share Lottery Trades and Past Performance

This table (*Panel°A*) displays regression estimates obtained by applying the regression model of Equation 36; the share of lottery-like trades as defined in *Section 7.1.4* is set as dependent variable ($lnRTL_{i,t}^{Max}$). *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 specifications (1), (6), and (11), t-statistics correspond to month and signal provider account-clustered standard errors; in specifications (2), (7), and (12) standard errors are clustered by month and signal provider (see 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). 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; t-statistics are displayed in parentheses.

Panel°A – continued					
	(6)	(7)	(8)	(9)	(10)
α	.0430***	.0430***	.0429***	.0364***	.0373***
	(5.42)	(4.76)	(18.80)	(13.54)	(14.17)
$RProfit_{i,t-1}$	-.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)
$Lots_{i,t}$	.0000	.0000	.0000***	.0000***	.0000***
	(1.34)	(1.35)	(5.98)	(4.70)	(4.75)
$Age_{i,t}$	-.0001***	-.0001**	-.0001***	-.0004***	-.0003***
	(-2.67)	(-2.54)	(-6.40)	(-14.01)	(-13.56)
$Open_{i,t}$	.0093	.0093	.0026	.0058**	.0059**
	(1.05)	(1.09)	(1.03)	(2.32)	(2.36)
$Long_{i,t}$	.0096**	.0096*	.0120***	.0068***	.0072***
	(2.27)	(1.78)	(9.65)	(4.81)	(5.17)
$Commodity_{i,t}$	.0587***	.0587***	.0573***	.0571***	.0585***
	(5.90)	(5.76)	(45.86)	(32.56)	(35.01)
$Index_{i,t}$	.0881***	.0881***	.0914***	.0593***	.0703***
	(4.03)	(4.01)	(45.12)	(19.00)	(25.14)
$RNum_{i,t}$	-.0043***	-.0043***	-.0039***	-.0026***	-.0029***
	(-4.95)	(-4.52)	(-14.78)	(-6.97)	(-8.19)
R^2	.0737	.0737	.1508	.2089	.1813

Table 7 – *continued*

Panel°A – continued					
	(11)	(12)	(13)	(14)	(15)
α	.0449***	.0449***	.0454***	.0371***	.0382***
	(5.10)	(4.51)	(18.49)	(13.05)	(13.66)
$RComb_{i,t-1}$	-.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***
	(4.28)	(4.34)	(9.39)	(8.50)	(8.34)
$Age_{i,t}$	-.0001**	-.0001**	-.0001***	-.0003***	-.0003***
	(-2.31)	(-2.18)	(-5.48)	(-13.52)	(-13.06)
$Open_{i,t}$	.0110	.0110	.0038	.0043	.0045*
	(1.12)	(1.15)	(1.45)	(1.64)	(1.68)
$Long_{i,t}$	.0103**	.0103*	.0124***	.0077***	.0080***
	(2.45)	(1.87)	(9.81)	(5.30)	(5.66)
$Commodity_{i,t}$	.0591***	.0591***	.0578***	.0562***	.0575***
	(5.97)	(5.83)	(45.91)	(31.59)	(33.98)
$Index_{i,t}$	.0891***	.0891***	.0924***	.0591***	.0703***
	(4.10)	(4.08)	(45.53)	(18.84)	(25.09)
$RNum_{i,t}$	-.0033***	-.0033***	-.0030***	-.0021***	-.0024***
	(-3.73)	(-3.37)	(-11.25)	(-5.56)	(-6.64)
R^2	.0751	.0751	.1529	.2135	.1857

Table 7 – *continued*

Panel°B – Dependent Variable: Relative Number Lottery Trades					
	(1)	(2)	(3)	(4)	(5)
α	.0302***	.0302***	.0311***	.0370***	.0382***
	(4.18)	(3.89)	(14.06)	(12.63)	(13.61)
$R\overline{Win}_{i,t-6}^{t-1}$	-.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)
$Lots_{i,t}$	.0000***	.0000***	.0000***	.0000***	.0000***
	(4.37)	(4.44)	(9.36)	(8.43)	(8.26)
$Age_{i,t}$	-.0000	-.0000	-.0000*	-.0003***	-.0003***
	(-.61)	(-.53)	(-1.04)	(-12.95)	(-12.43)
$Open_{i,t}$	.0097	.0097	.0025	.0041	.0042
	(.99)	(1.01)	(.97)	(1.56)	(1.58)
$Long_{i,t}$	.0111***	.0111**	.0132***	.0077***	.0081***
	(2.61)	(1.98)	(10.41)	(5.36)	(5.69)
$Commodity_{i,t}$	.0602***	.0602***	.0589***	.0564***	.0577***
	(6.05)	(5.91)	(46.74)	(31.71)	(34.10)
$Index_{i,t}$	.0885***	.0885***	.0918***	.0590***	.0700***
	(4.06)	(4.05)	(45.11)	(18.82)	(24.98)
$RNum_{i,t}$	-.0033***	-.0033***	-.0029***	-.0021***	-.0024***
	(-3.97)	(-3.56)	(-10.91)	(-5.62)	(-6.69)
R^2	.0719	.0719	.1499	.2134	.1857

Table 7 – *continued*

This table (*Panel°B*) displays regression estimates obtained by applying the regression model of Equation 36; the share of lottery-like trades as defined in *Section 7.1.4* is set as dependent variable ($lnRTL_{i,t}^{Max}$). *Panel°B* reports the results relating to the relative performance variables – win ratio ($R\overline{Win}_{i,t-6}^{t-1}$), net profit ($R\overline{Profit}_{i,t-6}^{t-1}$), and the combined term ($R\overline{Comb}_{i,t-6}^{t-1}$) – measured over the previous six months. In specifications (1), (6), and (11), t-statistics correspond to month and signal provider account-clustered standard errors; in specifications (2), (7), and (12) standard errors are clustered by month and signal provider (see 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). 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; t-statistics are displayed in parentheses.

Panel°B – continued					
	(6)	(7)	(8)	(9)	(10)
α	.0512***	.0512***	.0512***	.0377***	.0392***
	(5.96)	(5.05)	(22.28)	(13.59)	(14.52)
$R\overline{Profit}_{i,t-6}^{t-1}$	-.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)
$Lots_{i,t}$	.0000	.0000	.0000***	.0000***	.0000***
	(1.32)	(1.33)	(5.73)	(4.59)	(4.65)
$Age_{i,t}$	-.0002***	-.0002***	-.0001***	-.0003***	-.0003***
	(-3.12)	(-3.01)	(-7.88)	(-13.24)	(-12.90)
$Open_{i,t}$	.0103	.0103	.0036	.0061**	.0062**
	(1.17)	(1.22)	(1.44)	(2.44)	(2.46)
$Long_{i,t}$	.0091**	.0091*	.0115***	.0067***	.0071***
	(2.19)	(1.72)	(9.25)	(4.74)	(5.07)
$Commodity_{i,t}$	.0575***	.0575***	.0560***	.0570***	.0584***
	(5.84)	(5.71)	(44.77)	(32.48)	(34.91)
$Index_{i,t}$	.0881***	.0881***	.0914***	.0595***	.0707***
	(4.04)	(4.03)	(45.16)	(19.06)	(25.29)
$RNum_{i,t}$	-.0040***	-.0040***	-.0036***	-.0023***	-.0026***
	(-4.51)	(-4.17)	(-13.81)	(-6.09)	(-7.18)
R^2	.0756	.0756	.1526	.2089	.1814

Table 7 – *continued*

Panel°B – continued					
	(11)	(12)	(13)	(14)	(15)
α	.0492***	.0492***	.0493***	.0430***	.0432***
	(5.76)	(5.00)	(19.34)	(13.80)	(14.34)
$R\overline{Comb}_{i,t-6}^{t-1}$	-.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***
	(4.33)	(4.40)	(9.13)	(8.38)	(8.21)
$Age_{i,t}$	-.0001*	-.0001	-.0001***	-.0003***	-.0003***
	(-1.77)	(-1.58)	(-3.77)	(-13.28)	(-12.72)
$Open_{i,t}$	.0099	.0099	.0028	.0043	.0043
	(1.03)	(1.05)	(1.09)	(1.61)	(1.63)
$Long_{i,t}$	.0106**	.0106*	.0127***	.0076***	.0080***
	(2.55)	(1.95)	(10.06)	(5.29)	(5.61)
$Commodity_{i,t}$	.0592***	.0592***	.0578***	.0562***	.0575***
	(6.04)	(5.90)	(45.94)	(31.64)	(34.02)
$Index_{i,t}$	.0888***	.0888***	.0921***	.0589***	.0702***
	(4.09)	(4.08)	(45.36)	(18.81)	(25.07)
$RNum_{i,t}$	-.0033***	-.0033***	-.0029***	-.0020***	-.0023***
	(-3.88)	(-3.52)	(-11.11)	(-5.45)	(-6.46)
R^2	.0752	.0752	.1530	.2137	.1860

Table 7 – *continued*

7.3 Robustness Checks

7.3.1 Independent Variable / Performance Measure

First, the robustness of the obtained results is tested 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, the net gain in profit pips of the previous month are employed as signal provider trading performance measure:

$$Pips_{i,t-1} = \sum_{n=1}^{m} SPips_{i,t-1}^{n}, \tag{44}$$

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:

$$\overline{Pips}_{i,t-6}^{t-1} = \frac{\sum_{n=1}^{6} Pips_{i,t-n}}{6}. \tag{45}$$

As before, the computed performance measures are employed to generate monthly deciles. Using deciles as thresholds, each account-month observation is assigned a number from one to ten, indicating its according relative monthly performance ranking. The corresponding variables referring to relative past performance based on profit pips are depicted as follows:

$$RPips_{i,t-1} \;/\; R\overline{Pips}_{i,t-6}^{t-1}. \tag{46}$$

The regression model from Equation 36 is applied with the performance measures based on profit pips. The corresponding results are displayed in Appendix A10 Table 30.

The obtained results are similar to those depicted in Table 7 where net profits are employed as the respective performance measure. There is consistent empirical evidence for a quadratic U-shaped relationship between past relative profit pips and the traded lottery share.

7.3.2 Definition for Lottery-like Assets

Further, the robustness of the obtained results is assessed by applying a different lottery definition. Once again following Bali et al. (2011), decile portfolios are formed based on an average comprising the five highest daily returns of the previous month.[360] Accordingly, 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:

$$RTL_{i,t}^{Max5} = \frac{TL_{i,t}^{Max5}}{T_{i,t}}, \tag{47}$$

where $TL_{i,t}^{Max5}$ is the number of lottery trades conducted within signal provider account i in month t. As the variable is positively skewed, the natural logarithm is applied:

$$lnRTL_{i,t}^{Max5} = \ln\left(1 + TL_{i,t}^{Max5}\right). \tag{48}$$

The regression model from Equation 36 is applied; results are displayed in Appendix A10 Table 31.

Applying an alternative lottery definition yields results that are 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.

7.4 Recap, Discussion, and Conclusion

To sum up, this study provides evidence for a statistically significant positive relationship between the applied relative performance measures and the conducted number of trades.[361] Although the number of investors copying a corresponding signal provider account is not directly observed, 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

[360] Bali et al.'s (2011) approach where lottery-like stocks are identified based on the five highest daily returns of the previous month is detailed in *Section 3.4.1*.

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

performance as decisive factor when allocating funds. In the context of this 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*. Thus, visibility is increased which in turn leads to more followers.

The 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.[362] The enhanced excitement caused by additional followers may encourage signal providers to be more active, i.e. increase their trading activity.[363]

Furthermore, performing well relative to peers, might additionally boost signal provider overconfidence which causes a surge in trading activity.[364]

Regarding the main experiment (see *Section 7.1.4*), the obtained results indicate a quadratic relationship between the primarily examined independent variables, relative win ratios and relative profits (as well as the combined measure), 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.

These results are in line with the results obtained with regard to the *wikifolio* platform and the traded share of lottery-like stocks. Underlying effects for the relationship between the traded share of lottery-like stocks and prior peer performance are elaborated in *Section 6.3*. Nonetheless, it is crucial to point to some differences. Due to the extensive investment universe available to signal providers on the *wikifolio*

362 See Dorn and Sengmueller (2009) and Taffler (2018). See also *Section 3.3.3*.
363 See Pelster and Breitmayer (2019).
364 See Odean (1999), Gervais and Odean (2001), and Statman et al. (2006). See also Section 2.5.3 as well as the corresponding discussion in *Section 6.3*.

platform, there may be portfolio effects which are not accounted for in the conducted analysis. Furthermore, stocks may be bought because of the corresponding firms' business models and an associated (rather subjective) expectation about (long-term) value development. Induced by the wide variety of available assets, attention (as previously discussed) may be a driver with regard to certain stock purchases. Given the nature of currency pairs (i.e. no business model where subjective expectations are likely to be influential) and the relative narrow selection of available options for signal providers on the *ZuluTrade* platform, it seems reasonable to assume that *ZuluTrade* signal providers select assets (solely) based on their risk and return characteristics. Hence, an increased trading frequency of lottery-like assets on the *ZuluTrade* platform is assumed to be equivalent to an increase in risk-taking, or more specifically, gambling.

In this context, the results reported with regard to the *ZuluTrade* platform are related to two behavioral effects initially documented by Thaler and Johnson (1990) – the house money and the break effect (see *Section 2.5.2*). 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"[365], making up for incurred losses entirely. Regarding the *house money effect*, Thaler and Johnson (1990, p. 657) 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.".

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 the applied performance variables capture the relative performance of *ZuluTrade* 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

[365] See Thaler and Johnson (1990, p. 658).

variable reflecting relative profits of the previous month ($RProfit_{i,t-1}$) takes a value of five; when taking a value of six, 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 eight, 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.[366]

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 study, gambles. In the context of social trading, signal providers compete for visibility. Underperforming accounts are unlikely to generate (or maintain) followers who 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.[367] 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.
The effect might be further facilitated by certain platform design features common to social trading. Similar to the *wikifolio* platform, *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) without affecting 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

[366] See also the *Section 6.5*.
[367] For tournament incentives, see Ehrenberg and Bognanno (1990a), (1990b), Knoeber and Thurman (1994), Taylor (2003), and Kirchler et al. (2018). See also *Section 3.4.3*.

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 simply turn their focus to accounts with better prospects.

In addition, signal providers might be subject to the gambler's fallacy: 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 reoccurrence of an extreme daily price movement in the anticipated direction.[368]

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 risk. 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 4.2.4*), 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, similar to the results from the *wikifolio* platform, the observed results regarding *ZuluTrade* may be partly explained by the well-documented relationship between overconfidence and risk taking (see *Section 2.5.3*). 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[369], signal providers might be inclined to take more risk and thus increase the share of traded lotteries. Moreover, overconfident traders

[368] See Tversky and Kahneman (1974). For the gambler's fallacy see also Oehler (1992, p. 103), (1995, p. 29).
[369] See Odean (1999), Gervais and Odean (2001), and Statman et al. (2006). See also *Section 2.5.3*.

tend to overestimate the precision of their information.[370] Therefore, 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.

Moreover, outperformeing signal providers may gamble in an attempt to attain a position among top-performers. As on the *wikifolio* platform, corresponding rankings / lists are maintained by *ZuluTrade*.[371]

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 generate profits with issued trading signals. 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-like return characteristics, particularly positive skewness, as explicitly appealing.

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 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 trade lotteries.

[370] See Benos (1998), Daniel et al. (1998), and Odean (1998), (1999). See also *Section 2.5.3*.
[371] See Chevalier and Ellison (1997). See also *Section 2.2* and the discussion in *Section 6.3*.

8 Sports Betting vs. Lottery-like Stock Investing: Evidence from Germany[372]

8.1 Methodological Approach

8.1.1 Multi-layer Portfolio Approach

It is a prevalent finding in the context of behavioral finance that (private) investors display fundamentally differing risk attitudes for different mental accounts and corresponding portfolios.[373]

Shefrin and Statman (2000) connect different portfolio layers with aspiration; in their study, a two-layer portfolio is explored. The portfolio layer which is associated with low aspiration is designed to avoid poverty. The high aspiration layer caters to a potential shot at riches. Building on that, it is assumed that investors use the main part of their available funds for long-term oriented capital accumulation in a basic portfolio layer[374], while a minor share is used for high-risk investments, i.e. gambling. In this context, each overall portfolio starts with 90 percent of all funds invested in the relatively save layer (following base layer) while ten percent are assigned to the speculative layer (following gambling layer).

For the base layer, an investment in an ETF which mirrors the performance of the German stock market is employed. More specifically, the *iShares MSCI Germany ETF*[375] is selected; return data is obtained from *Datastream* for the period May 2000 to August 2020.

The construction of the overall portfolios is described in the following sections. Transaction costs are taken into consideration for each multi-layer strategy. Thus, each portfolio is implemented with and without taking into account transaction costs. Following Oehler and Wanger (2020), proportional transaction costs are assumed to amount to 0.25 percent of the order value.[376] Oehler and Wanger (2020) assume fixed transaction costs of ten EUR per transaction. This study differs from their approach as fixed transaction costs are set to one EUR per transaction which is in line with popular discount brokers like *Trade Republic*[377]. In order to accurately account for fixed transaction costs, an initial total portfolio value of 100,000 EUR is

[372] This section and the referred appendices are substantially obtained from Schneider (2022).
[373] See *Section 3.3.1*.
[374] See Oehler and Horn (2019).
[375] *ISIN*: US4642868065.
[376] See Lynch and Balduzzi (2000).
[377] See: www.traderepublic.com.

assumed. That is, initially, 90,000 EUR are invested in the *base layer*, while 10,000 EUR are available for gambling. These amounts are then scaled back to a return index starting at 100.

8.1.2 High Aspiration / Gambling Layer Portfolios with Sports Betting

Based on the accessible sports betting signals (see *Section 4.2.5*), a return index (*RI*) mirroring the value development of a strategy which is based on following all signals issued by *90plusX* is constructed. The development of the return index is visualized in Figure 1. Furthermore, risk factors based on realized daily returns are computed; these are displayed in Table 8.

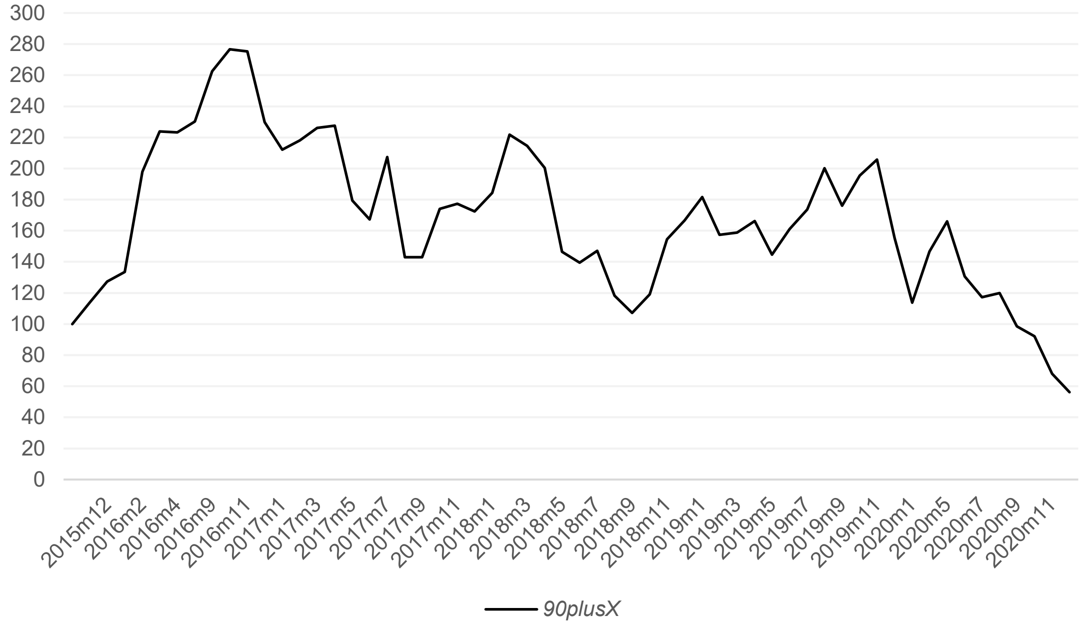

Figure 1: Return Index *90plusX*

Notes: The graph above depicts the return index of a strategy which is based on following all signals issued by the sports betting signal provider *90plusX*. Signals (including suggested wagers) and actual results are obtained directly from the *90plusX* platform; the obtained signals cover the period from December 2015 to December 2020. Overall, 1,670 distinct signals are considered.

In addition, two simple rule-based strategies are modeled for German *Bundesliga* soccer matches (see *Section 4.2.5*): *Favorite Strategy* and *Underdog Strategy*. For the first strategy, for each pairing, the odds for winning of both competitors are compared. A decision is then made for the team that is considered to be more likely to win, i.e. the team with the smaller relative payoff to a gambler in case of a victory. For the second strategy, as before, the odds for winning of both competitors are compared. In the context of this strategy, the team that is considered to be less likely to win, i.e. the team with the higher relative payoff to a gambler in case of a victory, is picked.

Regarding the corresponding wagers for each pairing, it is assumed that each month the budget designated for gambling is evenly distributed among all *Bundesliga* pairings. For example, if 1,000 EUR are designated to gambling and there are 30 pairings in a respective month, the wager for each match amounts to 33.33 EUR. Return indices mirroring the value development of the two rule-based strategies are respectively displayed in Figure 2 and Figure 3. Furthermore, risk factors based on realized daily returns are computed; these are displayed in Table 8.

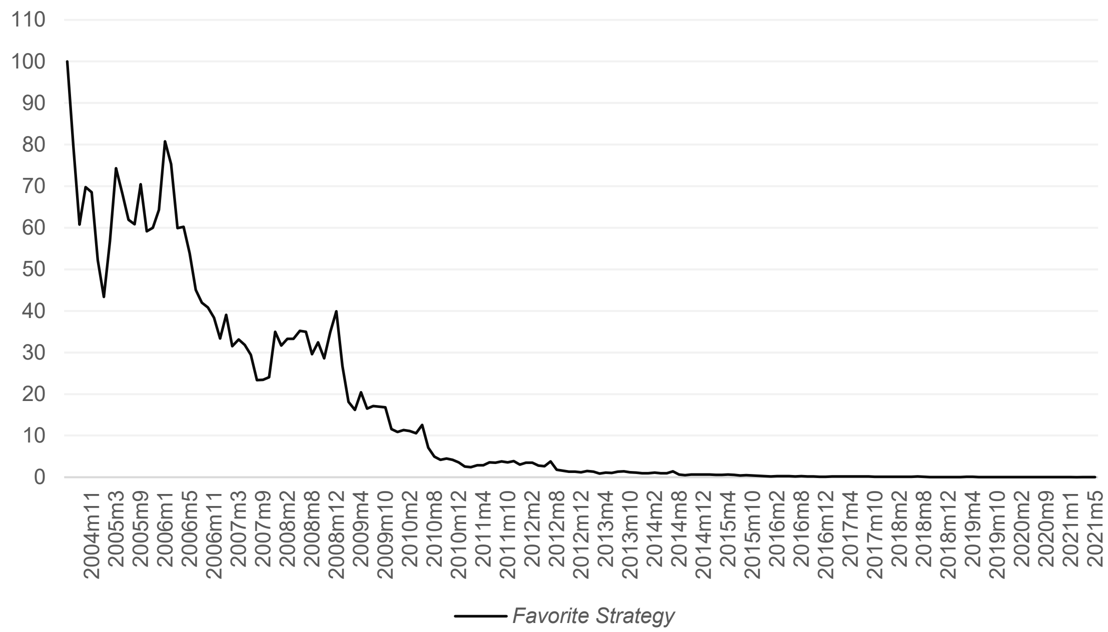

Figure 2: Return Index *Favorite Strategy*

Notes: The graph above depicts the return index of a simple rule-based betting strategy for German *Bundesliga* soccer games: For each pairing, the odds for winning of both competitors are compared and a bet is placed on the team considered to be more likely to win by the bookmakers. Data from season 2004/2005 to season 2020/2021 is included which corresponds to 1,580 distinct pairings.

The *Favorite Strategy* exhibits a rather poor performance. The *Underdog Strategy* features a few steep upticks which are subsequently reversed. Towards the end of the observation period, the *Underdog Strategy* has several extremely high positive returns catapulting the return index to over 1,600 points. The exceptional positive returns are, however, followed by a month where the identified underdog does not win a single game; in consequence, the return index drops to zero.

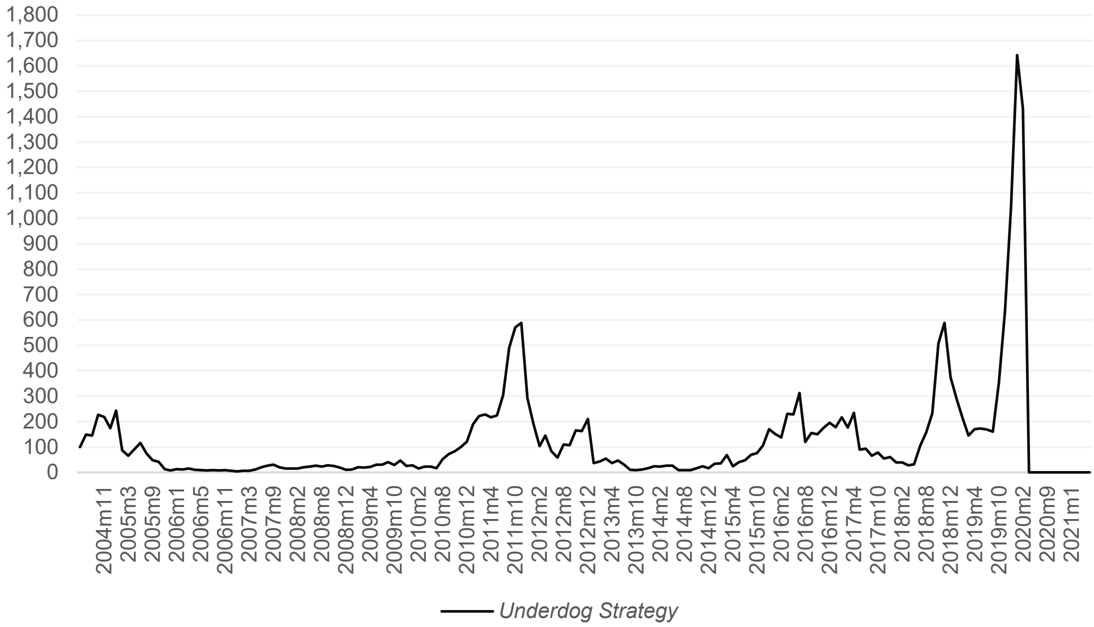

Figure 3: Return Index *Underdog Strategy*

Notes: The graph above depicts the return index of a simple rule-based betting strategy for German *Bundesliga* soccer games: For each pairing, the odds for winning of both competitors are compared and a bet is placed on the team considered to be less likely to win by the bookmakers. Data from season 2004/2005 to season 2020/2021 is included which corresponds to 1,580 distinct pairings.

				TVol		TSkew	
	R	$RMax$	$RMax5$	$1M$	$6M$	$1M$	$6M$
90PlusX							
Mean	.243	7.226	4.461	3.696	3.724	.207	.335
Median	1.815	6.533	3.929	3.238	3.528	.298	.341
SD	15.917	4.029	2.732	1.481	.890	.512	.208
Favorite Strategy							
Mean	-3.827	9.085	3.186	6.499	6.582	.007	-.126
Median	-4.944	8.055	3.654	5.623	6.395	.061	-.118
SD	18.871	6.275	5.776	3.839	1.194	.624	.868
Underdog Strategy							
Mean	10.792	31.614	8.175	16.311	16.341	.870	1.877
Median	5.982	23.737	8.961	12.362	14.552	.836	1.455
SD	47.470	29.673	12.851	12.778	5.202	.821	1.320

Table 8: Return and Risk Characteristics Sports Betting

Notes: The table above displays return characteristics and risk factors corresponding to the three sports betting strategies *90plusX*, *Favorite Strategy*, and *Underdog Strategy*. R is the monthly return which is generated by each strategy. $RMax$ / $RMax5$ denotes the maximum daily return / the average of the five highest daily returns generated in month t. $TVol$ and $TSkew$ respectively depict total volatility and skewness, measured with the daily returns of the previous month, $1M$ $(t-1)$, and the previous six months, $6M$ $(t-6$ to $t-1)$.

All three sports betting strategies exhibit a return index below 100 at the end of their corresponding observation period, i.e. effectively lose money. Nonetheless, these are not excluded – and labeled as failures – from the following portfolio considerations. When the overall portfolio is frequently rebalanced, intertemporal winnings from one portfolio component are reallocated. Thus, incorporating the described betting strategies as the high-risk component into a diversified portfolio promises to yield interesting implications.

8.1.3 ETF and Sports Betting

Regarding the combination of the base layer with *90plusX* signals (i.e. gambling layer), two routes of overall portfolio construction are explored. First, it is assumed that the initial allocation of funds between the base layer and the gambling layer will remain unchanged. That is, there will be no reallocation of funds, i.e. rebalancing, during the observation period, even in the face of substantial changes of the initial relative weights. The corresponding strategy is labeled $ETF\&90plusX$ without Rebalancing ($ETF\&90plusX\ w/o\ RB$).

As an alternative, a strategy is implemented where the relative weights of both portfolio layers are held constant. In this context, at the beginning of each month, the total portfolio value is assessed; accordingly, 90 percent of the total portfolio value are invested in the ETF, while ten percent are employed for following signals from *90plusX*. For this strategy, the amount corresponding to one monetary unit (recommended by *90plusX* in connection with each signal) is recalculated on a monthly basis. The corresponding strategy is labeled $ETF\&90plusX$ Rebalancing ($ETF\&90plusX\ RB$).

Furthermore, the base layer is respectively combined with one of the rule-based sports betting strategies. As in the previous section, for each of the two betting strategies, two routes of overall portfolio construction are explored.

First, it is assumed that the initial allocation of funds between the base layer and the gambling layer will remain unchanged. That is, there will be no rebalancing, during the observation period. The corresponding strategies are labeled $ETF\&Favorite$ without Rebalancing ($ETF\&Favorite\ w/o\ RB$) and $ETF\&Underdog$ without Rebalancing ($ETF\&Underdog\ w/o\ RB$). In addition, a strategy is executed where the relative weights of the two portfolio layers are held constant. In this regard, at the beginning of each month, the total portfolio value is assessed; accordingly, 90 percent of the total portfolio value is invested in the ETF, while 10 percent is employed for respectively implementing one of the two rule-based sports betting strategies. The strategies are labeled $ETF\&Favorite$ Rebalancing ($ETF\&Favorite\ RB$) and $ETF\&Underdog$ Rebalancing ($ETF\&Underdog\ RB$).

The return index development of the overall portfolios is visualized in Appendix A11 Figure4, Figure 5, and Figure 6.

8.1.4 ETF and Lottery-like Stocks

In this section, the gambling layer of the portfolio is represented by lottery-like stocks. Lottery-like stocks are defined using the previously employed definition by Kumar (2009) (i.e. $Lottery$) as well as the two previously utilized definitions by Bali et al. (2011) (i.e. Max and $Max5$). The *CDAX* is selected as the corresponding benchmark for categorizing lottery-like stocks,

Regarding the multi-layer portfolios where the gambling layer is represented by lottery-like stocks, three different approaches are explored. For all three approaches, it is assumed that a potential investor with stock market gambling intentions will focus on a portfolio with a convenient number of stocks, rather than investing in all available lottery-like stocks. This assumption is based on research addressing investors' limited cognitive processing capabilities.[378] Thus, for the gambling layer, portfolios that include ten lottery-like stocks, selected according to their market capitalization, are constructed.[379]

First, for combining the gambling layer and the base layer, an approach without any rebalancing is selected. Therefore, it is assumed that neither the lottery-like stocks which form the gambling layer, nor the distribution of funds between the two layers, are rebalanced. This approach is conducted for the all three definitions of lottery-like

[378] Empirical evidence for (private) investors' limitations and their consequential focus of a subset of assets – instead of focusing on the entire available investment universe – is inter alia provided by Barber and Odean (2008) and Jacobs and Hillert (2016). The impact of attention in the context of choosing among a wide variety of available options is discussed in *Section 3.3.3*.

[379] That is, the ten lottery-like stocks which exhibit the highest market capitalization when the portfolio is formed are selected. As it is assumed that portfolios are formed at the beginning of a corresponding month, market capitalization in month t (rather than in month $t-1$) is applied.

stocks. The overall portfolio resulting from combining the base layer and the gambling layer is labeled $ETF\&Lottery$ without Rebalancing ($ETF\&Lottery\ w/o\ RB$). Accordingly, the overall portfolio resulting from combining the base layer and the Max / $Max5$ gambling layer is denoted as $ETF\&Max$ without Rebalancing ($ETF\&Max\ w/o\ RB$) / $ETF\&Max5$ without Rebalancing ($ETF\&Max5\ w/o\ RB$). The development of the return indices corresponding to those three portfolios is visualized in Appendix A11 Figure 7 (equally-weighted lottery-like stocks) and Figure 8 (value-weighted lottery-like stocks).

Second, portfolios are modeled where (only) the gambling layer is readjusted on a monthly basis. That is, at the beginning of each month, ten lottery-like stocks with the highest market capitalization are selected for investment. However, the distribution of total funds between the base layer and the gambling layer is not rebalanced, i.e. the relative weights imposed at the start are not readjusted and, thus, may change substantially. Once again, the approach is conducted for the all three definitions of lottery-like stocks. The overall portfolios resulting from combining the base layer and the gambling layer are labeled $ETF\&Lottery$ Rebalancing Gambling ($ETF\&Lottery\ RB\ Gambling$), $ETF\&Max$ Rebalancing Gambling ($ETF\&Max\ RB\ Gambling$), and $ETF\&Max5$ Rebalancing Gambling ($ETF\&Max5\ RB\ Gambling$). The development of the return indices corresponding to those three portfolios is depicted in Appendix A11 Figure 9, Figure 10, and Figure 11.

Finally, an approach is explored where total funds are rebalanced between the base layer and the gambling layer on a monthly basis. That is, the relative weights selected at the beginning are held constant throughout the entire study period. In addition to rebalancing the two portfolio layers, the gambling layer on is readjusted on a monthly basis (i.e. the gambling layer reflects an investment in the ten lottery-like stocks with the highest market capitalization in each month). As before, the approach is conducted for all three definitions of lottery-like stocks. The overall portfolios are labeled $ETF\&Lottery$ Rebalancing All ($ETF\&Lottery\ RB\ All$), $ETF\&Max$ Rebalancing All ($ETF\&Max\ RB\ All$), and $ETF\&Max5$ Rebalancing All ($ETF\&Max5\ RB\ All$). The development of the return indices corresponding to those portfolios is visualized in Appendix A11 Figure 12, Figure 13 and Figure 14.

8.2 Results and Discussion

For each of the multi-layer portfolios, risk factors are calculated based on realized returns. These risk factors are displayed in Table 9 and Table 10. Furthermore, performance key figures are computed; these are depicted in Appendix A13, Table 33.

Considering the performance of the portfolios incorporating sports betting, only the $ETF\&Underdog$ portfolio that is rebalanced on a monthly basis outperforms the market. This outperformance may be attributed to occasional major positive returns generated by the *Underdog* betting strategy which are mostly followed by similar declines (see Figure 3). However, due to monthly rebalancing, temporal winnings from this betting strategy are partly reallocated to the base layer, i.e. the ETF investment. Regarding the different combinations of the ETF investment and lottery-like stocks, the $ETF\&Lottery$ portfolio where only the gambling layer is readjusted ($ETF\&Lottery\ RB\ Gambling$) yields statistically significant positive alphas. This outperformance is driven by major positive returns of the monthly adjusted gambling layer which contains lottery-like stocks as defined by Kumar (2009).

Regarding raw returns, the $ETF\&Underdog$ portfolio exhibits substantially higher means than the $ETF\&Favorite$ and the $ETF\&90plusX$ portfolio. In turn, these higher mean values correspond to a higher standard deviation. The mean raw returns of the $ETF\&Lottery$, $ETF\&Favorite$, and $ETF\&Underdog$ portfolios with no rebalancing are relatively similar. When the gambling layer is readjusted on a monthly basis, mean returns of the $ETF\&Lottery$ portfolio increase substantially, even when transaction costs are taken into consideration. These mean values see a decrease when, in addition to readjusting the gambling layer on a monthly basis, the overall portfolio is rebalanced. Yet, the mean returns of the $ETF\&Lottery$ portfolio remain on a higher level in comparison to those of its $ETF\&Max$ and $ETF\&Max5$ counterparts.

	W/o Transaction Costs						With Transaction Costs					
	W/o Rebalancing			With Rebalancing			W/o Rebalancing			With Rebalancing		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Measured over Previous Month ($1M$, $t-1$)												
$TVol$												
Mean	.9838	1.1455	1.2502	.9803	1.1042	1.3062	.9839	1.1455	1.2506	.9803	1.1042	1.3063
Median	.8458	.9555	1.0574	.8144	.9646	1.1211	.8456	.9555	1.0575	.8144	.9646	1.1212
$IVol$												
Mean	.5975	.6170	.8062	.5476	.6605	.9312	.5979	.6170	.8068	.5476	.6605	.9313
Median	.5179	.5157	.6497	.4801	.5527	.7739	.5187	.5157	.6503	.4801	.5527	.7739
$TSkew$												
Mean	-.1128	-.0399	.1059	-.1251	-.0811	.3508	-.1125	-.0399	.1064	-.1251	-.0811	.3508
Median	-.0943	-.1110	.0060	-.2552	-.0927	.1321	-.0944	-.1110	.0072	-.2552	-.0927	.1324
$ISkew2F$												
Mean	-.0056	.0433	.3448	-.0558	-.0836	.6423	-.0052	.0432	.3453	-.0558	-.0836	.6423
Median	-.0056	.0018	.2115	-.0268	-.0683	.4153	-.0065	.0018	.2116	-.0267	-.0683	.4154
$ISkew3F$												
Mean	-.0006	.0744	.3412	-.0008	-.1177	.6450	-.0005	.0744	.3417	-.0008	-.1178	.6450
Median	.0542	.0723	.2369	.0233	-.0909	.4034	.0545	.0722	.2381	.0232	-.0909	.4037
$RMax$												
Mean	2.0850	2.5370	2.9684	2.1056	2.3706	3.3493	2.0854	2.5369	2.9703	2.1056	2.3706	3.3495
Median	1.8026	2.1453	2.3089	1.8609	2.0000	2.5551	1.8047	2.1452	2.3123	1.8611	1.9997	2.5551
$RMax5$												
Mean	1.3197	1.6187	1.7545	1.3201	1.5271	1.8730	1.3200	1.6187	1.7550	1.3201	1.5271	1.8731
Median	1.1945	1.3741	1.4654	1.1760	1.3468	1.6284	1.1948	1.3741	1.4660	1.1760	1.3468	1.6284
Measured over Previous Six Months ($6M$, $t-6$ to $t-1$)												
$TVol$												
Mean	1.0196	1.2077	1.3238	1.0208	1.1562	1.3920	1.0196	1.2077	1.3243	1.0208	1.1562	1.3920
Median	.8338	1.0441	1.1452	.8420	1.0149	1.2721	.8338	1.0441	1.1457	.8420	1.0149	1.2721
$IVol$												
Mean	.7551	.9579	.9132	.8024	.8708	.8667	.7548	.9578	.9131	.8024	.8708	.8667
Median	.6136	.7856	.7720	.6382	.7129	.7247	.6134	.7856	.7720	.6382	.7129	.7247
$TSkew$												
Mean	-.4490	-.2648	.0846	-.5069	-.2300	.9753	-.4484	-.2649	.0856	-.5069	-.2300	.9754
Median	-.4146	-.2052	-.0862	-.4932	-.1870	.3603	-.4136	-.2052	-.0851	-.4931	-.1870	.3603
$ISkew2F$												
Mean	-.0053	-.0120	.4268	-.0034	-.0681	1.7235	-.0050	-.0120	.4278	-.0034	-.0681	1.7236
Median	-.0502	.0640	.2096	-.0592	-.0021	.8986	-.0496	.0640	.2096	-.0592	-.0021	.8987
$ISkew3F$												
Mean	-.0279	-.0223	.4785	-.0454	-.1043	1.7762	-.0275	-.0224	.4794	-.0454	-.1043	1.7762
Median	.0299	.0284	.2396	-.0393	-.0460	.9815	.0303	.0284	.2397	-.0393	-.0460	.9816

Table 9: Risk Factors Portfolios $ETF\&90plusX$, $ETF\&Favorite$, and $ETF\&Underdog$

Notes: The table above displays portfolio risk factors for different two-layer portfolios; these portfolios contain a base layer and a gambling layer. Funds corresponding to the base layer of each portfolio are invested in an ETF (*iShares MSCI Germany*) which is chosen to mirror the German stock market. The gambling layer comprises returns from sports betting. Column (1), (4), (7), and (10) correspond to the $ETF\&90plusX$ portfolio, columns (2), (5), (8), and (11) correspond to the $ETF\&Favorite$ portfolio, and columns (3), (6), (9), and (12) correspond to the $ETF\&Underdog$ portfolio. Columns (1) to (6) refer to portfolios without transaction costs. Columns (7) to (12) refer to portfolios where transaction costs are considered. Columns (1) to (3) and (7) to (9) present portfolios without monthly rebalancing. Columns (4) to (6) and (10) to (12) refer to portfolios with monthly rebalancing.

	W/o Rebalancing			Rebalancing Gambling Layer			Rebalancing All		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel°A: Equally-weighted Lottery-like stocks (w/o Transaction Costs)									
Measured over Previous Month ($1M$, $t-1$)									
$TVol$									
Mean	1.3261	1.3627	1.3660	1.2754	1.3707	1.3742	1.3271	1.3157	1.3330
Median	1.1527	1.1882	1.1900	1.1082	1.2012	1.1976	1.1606	1.1701	1.1853
$IVol$									
Mean	.6572	.6879	.6918	.6130	.6926	.6919	.6475	.6544	.6564
Median	.5551	.5781	.5825	.5315	.5841	.5851	.5567	.5565	.5490
$TSkew$									
Mean	-.0323	-.0382	-.0374	-.0357	-.0366	-.0383	-.0444	-.0396	-.0457
Median	-.0727	-.0763	-.0702	-.0452	-.0762	-.0597	-.0873	-.0630	-.0631
$ISkew2F$									
Mean	-.0061	-.0075	-.0049	.0359	-.0136	-.0157	.0033	-.0193	-.0218
Median	-.0080	-.0515	-.0341	.0588	-.0231	-.0354	.0048	-.0627	-.0488
$ISkew3F$									
Mean	-.0153	-.0083	-.0067	-.0125	-.0076	-.0092	-.0068	-.0049	-.0119
Median	-.0168	-.0409	-.0366	-.0093	-.0415	-.0378	-.0097	-.0149	.0016
$RMax$									
Mean	2.6284	2.6993	2.7066	2.4898	2.7170	2.7219	2.6195	2.5965	2.6271
Median	2.2128	2.3170	2.3247	2.0622	2.3082	2.3354	2.1898	2.1676	2.2068
$RMax5$									
Mean	1.6763	1.7206	1.7250	1.6322	1.7292	1.7347	1.6785	1.6586	1.6799
Median	1.4291	1.4613	1.4648	1.3835	1.4618	1.4703	1.4344	1.4159	1.4186
Measured over Previous Six Months ($6M$, $t-6$ to $t-1$)									
$TVol$									
Mean	1.3785	1.4164	1.4197	1.3254	1.4246	1.4279	1.3799	1.3675	1.3845
Median	1.2251	1.2531	1.2552	1.1694	1.2614	1.2691	1.2272	1.2122	1.2327
$IVol$									
Mean	.7705	.8089	.8131	.7174	.8134	.8129	.7622	.7667	.7691
Median	.6483	.6783	.6838	.5980	.6856	.6874	.6495	.6581	.6554
$TSkew$									
Mean	-.1953	-.1950	-.1939	-.2205	-.1923	-.1927	-.2112	-.1971	-.2005
Median	-.1508	-.1559	-.1551	-.2344	-.1591	-.1637	-.1863	-.1686	-.1742
$ISkew2F$									
Mean	-.1264	-.1148	-.1134	-.0956	-.1166	-.1203	-.1171	-.1133	-.1260
Median	-.0208	-.0129	-.0122	-.0353	-.0052	-.0029	-.0331	-.0304	-.0173
$ISkew3F$									
Mean	-.1077	-.0988	-.0994	-.0463	-.1001	-.1000	-.0877	-.0698	-.0845
Median	-.0294	-.0243	-.0244	-.0137	-.0358	-.0302	-.0427	-.0360	-.0267

Table 10: Risk Factors Portfolios $ETF\&Lottery$, $ETF\&Max$, and $ETF\&Max5$

Notes: The table above displays portfolio risk factors for different two-layer portfolios; these portfolios contain a base layer and a gambling layer. Funds corresponding to the base layer of each portfolio are invested in an ETF (*iShares MSCI Germany*) which is chosen to mirror the German stock market. The gambling layer comprises returns from lottery-like stocky. In *Panel°A*, the lottery-like stocks within the gambling layer are equally-weighted; *Panel°B* depicts results for value-weighted lottery-like stocks. Columns (1), (4), and (7) correspond to the $ETF\&Lottery$ portfolio, columns (2), (5), and (8) correspond to the $ETF\&Max$ portfolio, and columns (3), (6), and (9) correspond to the $ETF\&Max5$ portfolio. For this subset of results, transaction costs are not taken into account.

	W/o Rebalancing			Rebalancing Gambling Layer			Rebalancing All		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel°B: Value-weighted Lottery-like Stocks (w/o Transaction Costs)									
Measured over Previous Month ($1M$, $t-1$)									
$TVol$									
Mean	1.3820	1.3876	1.3857	1.3462	1.3502	1.3604	1.3327	1.3219	1.3438
Median	1.2072	1.2120	1.2102	1.1645	1.1834	1.1859	1.1712	1.1698	1.1843
$IVol$									
Mean	.7049	.7104	.7091	.6891	.6777	.6877	.6542	.6600	.6669
Median	.5969	.6038	.6023	.6061	.5750	.5836	.5593	.5671	.5747
$TSkew$									
Mean	-.0342	-.0344	-.0348	.0062	-.0353	-.0329	-.0320	-.0373	-.0424
Median	-.0694	-.0760	-.0757	-.0050	-.0809	-.0259	-.0961	-.0522	-.0509
$ISkew2F$									
Mean	-.0028	-.0024	-.0024	.0795	-.0065	-.0081	.0250	-.0014	-.0146
Median	-.0061	-.0092	-.0098	.1012	-.0270	-.0037	.0164	-.0244	-.0155
$ISkew3F$									
Mean	-.0049	-.0036	-.0038	.0248	.0048	-.0023	.0142	.0130	.0025
Median	-.0378	-.0372	-.0378	.0728	.0005	-.0129	.0125	-.0021	-.0133
$RMax$									
Mean	2.7443	2.7554	2.7512	2.6754	2.6817	2.6907	2.6365	2.6222	2.6585
Median	2.3526	2.3644	2.3647	2.2802	2.2736	2.3214	2.2272	2.1900	2.2395
$RMax5$									
Mean	1.7470	1.7538	1.7513	1.7403	1.7015	1.7197	1.6888	1.6646	1.6962
Median	1.4813	1.4842	1.4819	1.5104	1.4392	1.4751	1.4412	1.4248	1.4518
Measured over Previous Six Months ($6M$, $t-6$ to $t-1$)									
$TVol$									
Mean	1.4360	1.4418	1.4398	1.3950	1.4042	1.4126	1.3845	1.3754	1.3973
Median	1.2757	1.2822	1.2801	1.2382	1.2435	1.2576	1.2293	1.2190	1.2432
$IVol$									
Mean	.8279	.8345	.8330	.8069	.7966	.8044	.7699	.7751	.7823
Median	.7002	.7072	.7059	.7307	.6758	.6818	.6588	.6740	.6814
$TSkew$									
Mean	-.1897	-.1893	-.1897	-.1278	-.1866	-.1750	-.1981	-.1833	-.1797
Median	-.1522	-.1542	-.1541	-.1221	-.1748	-.1582	-.1574	-.1688	-.1589
$ISkew2F$									
Mean	-.1112	-.1094	-.1092	-.0202	-.1076	-.1103	-.0975	-.0918	-.1109
Median	.0025	.0004	-.0005	.0378	-.0028	.0011	.0010	-.0075	-.0250
$ISkew3F$									
Mean	-.1010	-.0998	-.0996	.0055	-.0797	-.0626	-.0734	-.0490	-.0554
Median	-.0353	-.0318	-.0321	.0003	-.0020	-.0191	-.0236	-.0031	-.0178

Table 10 – *continued*

Horn and Oehler (2020) find that households generally do not benefit from (automated) portfolio rebalancing. This may not apply when assets with a lottery-like return structure are included into a multi-layer portfolio as major intertemporal winnings from the gambling layer are reallocated to the steadier base layer. While not all of the considered multi-layer portfolios with rebalancing are superior, some of them perform substantially better than the strategies where no rebalancing is undertaken.

Furthermore, correlation coefficients with the stock market ($\rho_{P,M}$) are computed for each of the composed portfolios; these are displayed in Table 11. As investors may hold other assets with some degree of market correlation[380], reducing the market correlation of the multi-layer investment portfolio will be beneficial. Considering that labor income itself correlates with the market[381], even in the case of no further investments reducing exposure towards market risk adds value. To proxy for the stock market, monthly value-weighted *CDAX* returns are employed. With the exception of the $ETF\&Lottery\ RB\ Gambling$ portfolio, all portfolios where the gambling layer is composed of lottery-like stocks exhibit very high correlation coefficients with the market. In comparison, correlation of the $ETF\&90plusX$, $ETF\&Favorite$ and $ETF\&Underdog$ portfolios with the market is lower. Exhibiting a correlation coefficient between 0.73 and 0.78, the $ETF\&Underdog$ portfolio shows the lowest correlation with market returns. The correlation coefficient of the $ETF\&90plusX$ portfolio takes values between 0.85 and 0.93; for the $ETF\&Favorite$ portfolio, correlation coefficients between 0.93 and 0.98 are obtained. The $ETF\&Lottery\ RB\ Gambling$ portfolio exhibits correlation coefficients between 0.87 and 0.94. All other portfolios where the gambling layer presents a lottery-like stock investment exhibit correlation coefficients between 0.96 and 0.98.

Finally, risk factors for the overall portfolios including sports betting and the portfolios including lottery-like stocks are compared.[382] The respective results are displayed in Table 12. Regarding the comparative analysis, the respective time horizon is limited by *90plusX* and *Bundesliga* data availability. That is, when comparing the $ETF\&90plusX$ portfolio with the $ETF\&Lottery$, $ETF\&Max$, and $ETF\&Max5$ portfolios,

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[380] See Oehler and Wanger (2020).
[381] See Jagannathan and Wang (1996) and Jagannathan et al. (1998).
[382] The results in Table 12 do not include transaction costs. The analysis has been conducted for portfolios where transaction costs are taken into account. The obtained results do not substantially differ from those depicted in Table 12.

only risk factors starting in December 2015 can be applied. Accordingly, when assessing risk factor differences for the $ETF\&Favorite$ and $ETF\&Underdog$ portfolios, the comparative analysis starts in August 2004.

	W/o Rebalancing			With Rebalancing		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel°A: Multi-layer Portfolios with Sports Betting						
W/o Transaction Costs						
Returns *CDAX*	.8546	.9796	.7783	.9295	.9303	.7266
	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)
With Transaction Costs						
Returns *CDAX*	.8541	.9796	.7777	.9295	.9303	.7265
	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)

Table 11: Correlation Market Returns and Multi-layer Portfolios

Notes: This table (*Panel°A*) displays correlation coefficients ($\rho_{P,M}$) where monthly returns of the $ETF\&90plusX$, $ETF\&Favorite$, and $ETF\&Underdog$ portfolio are respectively correlated with the market. Columns (1) and (4) correspond to the $ETF\&90plusX$ portfolio, columns (2) and (5) correspond to the $ETF\&Favorite$ portfolio, and columns (3) and (6) correspond to the $ETF\&Underdog$ portfolio. As a proxy for the market, value-weighted *CDAX* returns are applied. Below the correlation coefficients, the corresponding significance level is reported in parentheses.

In Table 12 *Panel°A* and *Panel°B*, the $ETF\&90plusX$ portfolio constitute the benchmark. The results indicate that, in comparison to portfolios where the gambling layer represents an investment in lottery-like stocks, investors can significantly reduce total volatility by following sports betting signals. Idiosyncratic volatility measured over the previous six months appears to be significantly higher for the $ETF\&90plusX$ portfolio – although the trend is less persistent. This is not overly surprising as the gambling layer of the $ETF\&90plusX$ portfolio will not exhibit any comovement with market returns. The exception is the $ETF\&Lottery\ RB\ Gambling$ portfolio with value-weighted lottery-like stocks which has lower levels of idiosyncratic volatility in comparison to the $ETF\&90plusX\ w/o\ RB$ and the $ETF\&90plusX\ RB$ portfolios. Regarding the employed skewness measures, the analysis does not yield a clear trend.

	W/o Rebalancing			Rebalancing Gambling Layer			Rebalancing All		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel°B: Multi-layer Portfolios with Lottery-like Stocks									
Equally-weighted Lottery-like Stocks, w/o Transaction Costs									
Returns *CDAX*	.9828	.9827	.9826	.9338	.9815	.9830	.9815	.9783	.9802
	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)
Value-weighted Lottery-like Stocks, w/o Transaction Costs									
Returns *CDAX*	.9830	.9825	.9827	.8674	.9778	.9564	.9771	.9772	.9780
	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)
Equally-weighted Lottery-like Stocks, with Transaction Costs									
Returns *CDAX*	.9828	.9827	.9826	.9446	.9819	.9827	.9816	.9783	.9802
	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)
Value-weighted Lottery-like Stocks, with Transaction Costs									
Returns *CDAX*	.9830	.9825	.9827	.8885	.9817	.9795	.9772	.9772	.9781
	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)

Table 11 – *continued*

Notes: This table (*Panel°B*) displays correlation coefficients ($\rho_{P,M}$) where monthly returns of the $ETF\&Lottery$, $ETF\&Max$, and $ETF\&Max5$ portfolio are respectively correlated with the market. Columns (1), (4), and (7) correspond to the $ETF\&Lottery$ portfolio, columns (2), (5), and (8) correspond to the $ETF\&Max$ portfolio, and columns (3), (6), and (9) correspond to the $ETF\&Max5$ portfolio. As a proxy for the market, value-weighted *CDAX* returns are employed. Below the correlation coefficients, the corresponding significance level is reported in parentheses.

In Table°12 *Panel°C* and *Panel°D*, the $ETF\&Favorite$ portfolio presents the benchmark. As for the $ETF\&90plusX$ portfolio, total volatility is significantly reduced by contrast with all portfolios where lottery-like stocks are included. When measured over the previous six months, idiosyncratic volatility is significantly higher for the $ETF\&Favorite$ portfolio in all pairings. Again, as the sports betting returns which represent the gambling layer of the $ETF\&Favorite$ portfolio will not exhibit any stock market correlation, this is not surprising. With very few exceptions, in comparison to all portfolios with lottery-like stock gambling layers, idiosyncratic skewness is higher for the $ETF\&Favorite\ w/o\ RB$ portfolio; the $ETF\&Favorite\ RB$ portfolio does not display a similar trend. For most pairings, the $ETF\&Favorite\ w/o\ RB$ portfolio exhibits significantly higher maximum daily returns. By contrast, regarding the $ETF\&Favorite\ RB$ portfolio, maximum daily returns are significantly lower.

In *Panel°E* and *Panel°F* of Table 12, the $ETF\&Underdog$ portfolio is set as the benchmark. For the $ETF\&Underdog\ RB$ portfolio, total volatility is significantly higher in comparison to all portfolios where lottery-like stocks form the gambling layer. For the $ETF\&Underdog\ w/o\ RB$ portfolio, there is no clear trend with regard to total volatility. Idiosyncratic volatility is much higher for the portfolios where the *Underdog Strategy* is employed for the gambling layer; this trend is highly significant with regard to all pairings. For all pairings, the $ETF\&Underdog$ portfolio exhibits significantly higher maximum daily returns. Finally, total and idiosyncratic skewness is much higher for the $ETF\&Underdog$ portfolio over all pairings and irrespective of the applied measure. The composed risk factor differentials are particularly pronounced for idiosyncratic skewness - measured over the previous six months – corresponding to the $ETF\&Underdog\ RB$ portfolio.

To sum up, following signals in sports betting does not lead to an overall portfolio outperformance. Only the $ETF\&Underdog\ RB$ and the $ETF\&Lottery\ RB\ Gambling$ portfolios manage to outperform the market. As the outperformance is driven by particularly high returns of the gambling layer, which may as well be arbitrary, these results must be considered curiously. Overall market correlation is lower for the portfolios where sports betting returns constitute the gambling layer. When following sports betting signals as well as when implementing the *Favorite Strategy*, total volatility is reduced in comparison to the portfolios which include lottery-like stocks. With regard to skewness, the $ETF\&Underdog$ portfolio yields substantial higher values than all of its $ETF\&Lottery$, $ETF\&Max$, and $ETF\&Max5$ counterparts.

	Min	Mean	Max	Min	Mean	Max
	Panel°A: $ETF\&90plusX\ w/o\ RB$			*Panel°B*: $ETF\&90plusX\ RB$		
Measured over Previous Month ($1M$, $t-1$)						
$TVol$	-.3297***	-.1432	-.0964***	-.3334***	-.1470	-.1001***
	(-7.90)		(-3.61)	(-7.94)		(-3.69)
$IVol$	-.1502***	.0349	.0706***	-.2040***	-.0189	.0169
	(-5.03)		(4.46)	(-6.80)		(1.64)
$TSkew$	-.0850	.0206	.0465	-.1002	.0053	.0313
	(-.90)		(.79)	(-1.04)		(.68)
$ISkew2F$	-.1103	.0700	.1131*	-.1670*	.0133	.0563
	(-1.11)		(1.68)	(-1.78)		(1.11)
$ISkew3F$	-.0442	-.0243	.0657	-.0449	-.0249	.0651
	(-.51)		(.64)	(-.71)		(.68)
$RMax$	-.4887***	-.1166	.0199	-.4728***	-.1007	.0358
	(-4.53)		(.30)	(-4.43)		(.55)
$RMax5$	-.4040***	-.0647	-.0073	-.4091***	-.0697	-.0123
	(-6.86)		(-.27)	(-7.36)		(-.69)
Measured over Previous Six Months ($6M$, $t-6$ to $t-1$)						
$TVol$	-.3331***	-.1571	-.1006***	-.3349	-.1589	-.1024***
	(-18.84)		(-7.96)	(-18.36)		(-7.93)
$IVol$	-.1341***	.0770	.1148***	-.0867**	.1245	.1623***
	(-3.33)		(4.92)	(-2.02)		(6.21)
$TSkew$	-.1824***	.0376	.0824***	-.2451***	-.0251	.0197
	(-3.04)		(3.75)	(-3.61)		(1.31)
$ISkew2F$	-.0042	.0721	.0967**	-.0064	.0699	.0945***
	(-.08)		(2.59)	(-.11)		(3.44)
$ISkew3F$	-.0375	.0623	.0983*	-.0587	.0411	.0771*
	(-.62)		(1.76)	(-1.02)		(1.84)

Table 12: Comparison Risk Factors Multi-layer Portfolios

Notes: The table above (*Panel°A* and *Panel°B*) depicts risk factor differentials with regard to the $ETF\&90plusX$ portfolio and the multi-layer portfolios where the gambling layer is represented by lottery-like stocks (i.e. $ETF\&Lottery$, $ETF\&Max$, and $ETF\&Max5$). In *Panel°A*, the $ETF\&90plusX$ portfolio without rebalancing is set as benchmark; the results depicted in *Panel°B* correspond to differentials with regard to the $ETF\&90plusX$ portfolio with monthly rebalancing. Each risk factor of the benchmark portfolio is compared with the corresponding risk factors of all multi-layer portfolios with lottery-like stocks; the values for the pairing with the minimum (Min) and maximum (Max) difference is reported. Furthermore, the simple mean of the differences for all considered pairings is reported. For this analysis, transaction costs are not taken into account. Differences in risk factors (between two portfolios) are tested for statistical significance using two-sample t-tests; t-statistics are displayed in parentheses. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Min	Mean	Max	Min	Mean	Max
	Panel°C: $ETF\&Favorite\ w/o\ RB$			*Panel°D*: $ETF\&Favorite\ RB$		
Measured over Previous Month ($1M$, $t-1$)						
$TVol$	-.1421***	-.1033	-.0225*	-.1836***	-.1454	-.0639***
	(-14.14)		(-1.71)	(-11.81)		(-4.81)
$IVol$	-.0579***	-.0256	.0433***	-.0127	.0192	.0885***
	(-8.90)		(3.89)	(-1.04)		(8.42)
$TSkew$	-.0057	.0463	.0573***	-.0487	.0031	.0143
	(-.14)		(2.95)	(-1.14)		(.56)
$ISkew2F$	-.0358	.0560	.0755***	-.1633***	-.0724	-.0520
	(-.70)		(2.54)	(-2.83)		(-1.18)
$ISkew3F$	.0545	.0791	.1004**	-.1411**	-.1172	-.0951
	(1.04)		(2.07)	(-2.26)		(-1.58)
$RMax$	-.0168**	.0648	.2621***	-.1841***	-.1043	.0949**
	(-2.01)		(6.13)	(-7.25)		(2.48)
$RMax5$	-.0194	.0374	.1179***	-.1105***	-.0543	.0267
	(-.63)		(5.84)	(-3.84)		(1.46)
Measured over Previous Six Months ($6M$, $t-6$ to $t-1$)						
$TVol$	-.1535***	-.1130	-.0285***	-.2031***	-.1633	-.0782***
	(-21.64)		(-4.16)	(-16.86)		(-11.42)
$IVol$	.1607***	.1997	.2836***	.0743***	.1128	.1972***
	(8.23)		(13.29)	(4.05)		(10.45)
$TSkew$	-.0794***	.0016	.0341	-.0480*	.0323	.0654***
	(-2.89)		(1.51)	(-1.72)		(2.78)
$ISkew2F$	-.0609*	.0401	.0619***	-.1181***	-.0182	.0047
	(-1.65)		(5.00)	(-2.86)		(.16)
$ISkew3F$	-.0579	.0381	.0687***	-.1456***	-.0505	-.0190
	(-1.37)		(4.87)	(-3.21)		(-.57)

Table 12 – *continued*

Notes: The table above (*Panel°C* and *Panel°D*) depicts risk factor differentials with regard to the $ETF\&Favorite$ portfolio and the multi-layer portfolios where the gambling layer is represented by lottery-like stocks (i.e. $ETF\&Lottery$, $ETF\&Max$, and $ETF\&Max5$). In *Panel°C*, the $ETF\&Favorite$ portfolio without rebalancing is set as benchmark; the results depicted in *Panel°D* correspond to differentials with regard to the $ETF\&Favorite$ portfolio with monthly rebalancing. Each risk factor of the benchmark portfolio is compared with the corresponding risk factors of all multi-layer portfolios with lottery-like stocks; the values for the pairing with the minimum (Min) and maximum (Max) difference is reported. Furthermore, the simple mean of the differences for all considered pairings is reported. For this analysis, transaction costs are not taken into account. Differences in risk factors (between two portfolios) are tested for statistical significance using two-sample t-tests; t-statistics are displayed in parentheses. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Min	Mean	Max	Min	Mean	Max
	Panel°E: $ETF\&Underdog\ w/o\ RB$			*Panel°F*: $ETF\&Underdog\ RB$		
Measured over Previous Month $(1M,\ t-1)$						
$TVol$	-.0325	.0057	.0872***	.0306	.0688	.1503***
	(-1.39)		(3.35)	(.99)		(5.04)
$IVol$	.1402***	.1721	.2414***	.2741***	.3060	.3753***
	(4.57)		(7.62)	(8.10)		(12.06)
$TSkew$	.1470**	.1988	.2100***	.5916***	.6826	.7029***
	(2.43)		(3.78)	(6.38)		(7.26)
$ISkew2F$	.2798***	.3708	.3912***	.6520***	.6759	.6980***
	(3.68)		(5.31)	(6.60)		(7.06)
$ISkew3F$	.3338***	.3576	.3797***	1.2207***	1.3010	1.3342***
	(4.14)		(4.89)	(9.59)		(10.48)
$RMax$	.4347***	.5144	.7137***	.8425***	.9222	1.1215***
	(3.93)		(6.27)	(5.09)		(6.77)
$RMax5$	.1228***	.1790	.2600***	.2533***	.3095	.3906***
	(3.03)		(7.79)	(5.06)		(8.76)
Measured over Previous Six Months $(1M,\ t-6$ to $t-1)$						
$TVol$	-.0356**	.0042	.0894***	.0450**	.0848	.1699***
	(-2.08)		(4.75)	(2.08)		(10.27)
$IVol$	.1135***	.1519	.2363***	.0694***	.1079	.1923***
	(6.31)		(11.93)	(3.66)		(9.73)
$TSkew$	.2933***	.3736	.4068***	.4036***	.4554	.4665***
	(4.07)		(5.78)	(5.11)		(6.01)
$ISkew2F$	.4172***	.5172	.5400***	1.7588***	1.8587	1.8816***
	(4.07)		(5.55)	(10.78)		(11.93)
$ISkew3F$	.4843***	.5794	.6109***	1.8280***	1.9231	1.9546***
	(4.25)		(5.70)	(10.45)		(11.66)

Table 12 – *continued*

Notes: The table above (*Panel°E* and *Panel°F*) depicts risk factor differentials with regard to the $ETF\&Underdog$ portfolio and the multi-layer portfolios where the gambling layer is represented by lottery-like stocks (i.e. $ETF\&Lottery$, $ETF\&Max$, and $ETF\&Max5$). In *Panel°E*, the $ETF\&Underdog$ portfolio without rebalancing is set as benchmark; the results depicted in *Panel°F* correspond to differentials with regard to the $ETF\&Underdog$ portfolio with monthly rebalancing. Each risk factor of the benchmark portfolio is compared with the corresponding risk factors of all multi-layer portfolios with lottery-like stocks; the values for the pairing with the minimum (Min) and maximum (Max) difference is reported. Furthermore, the simple mean of the differences for all considered pairings is reported. For this analysis, transaction costs are not taken into account. Differences in risk factors (between two portfolios) are tested for statistical significance using two-sample t-tests; t-statistics are displayed in parentheses. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

8.3 Conclusion

Within the framework of behavioral portfolio theory, Shefrin and Statman (2000) describe a two-layer portfolio: While the low aspiration layer is designed for avoiding poverty, the high aspiration layer serves as a vehicle for shots at riches.

The analyses of *Section 8* add to this framework by exploring the characteristics of several realistic multi-layer portfolios where the high aspiration layer respectively mirrors different gambling approaches. As lottery-like stocks and sports betting enjoy great popularity among private investors[383], these seem to be appropriate instruments for modeling realistic gambling layers. Analyzing the performance and characteristics of the overall two-layer portfolios indicates that maintaining a high aspiration portfolio layer which is used for following signals in sports betting ($ETF\&90plusX$) does not lead to an overall outperformance. However, when following these sports betting signals, or when implementing the *Favorite Strategy* ($ETF\&Favorite$), total volatility is reduced while idiosyncratic volatility increases in comparison to the portfolios where the high aspiration layer consists of lottery-like stocks. Investors aiming to increase overall portfolio skewness benefit from using their gambling layer to execute the *Underdog Strategy* ($ETF\&Underdog$). Finally, market correlation is lower for the portfolios where sports betting returns constitute the gambling layer.

The conducted study in this section helps individual investors to better understand their overall portfolio risk-return characteristics when funds are split between a long-term oriented broadly diversified portfolio layer and a speculative layer serving as a vehicle for gambling.

[383] For the popularity of lottery-like stocks among private investors see, inter alia, Kumar (2009) and Bali et al. (2011); see also *Section 3.4.1* and *Section 5*. For the popularity of sports betting see, inter alia, Seal et al. (2022); see also *Section 3.4.4*.

9 Discussion and Overview of Results

At the beginning of this dissertation, the following aims have been established:

- To assess the preferences of the German private sector for stocks with lottery features.
- Given the design features of social trading, to study the factors that induce signal providers to trade lottery assets.
- To model and compare realistic multi-layer portfolios with a speculative high aspiration layer that is used for gambling.

Along those aims, this dissertation has made several contributions. First, the analyses performed within the scope of this dissertation are the first to analyze individual investor preferences for stocks with lottery features using aggregate private sector holdings instead of brokerage data (see *Section 5*). Second, in the context of social trading, this dissertation is the first to explicitly study signal provider gambling behavior, adding a novel aspect to a growing body of literature (see *Section 6* and *Section 7*). Third, building on the multi-layer portfolio framework, the analyses in *Section 8* are the first to model two-layer portfolios where the high aspiration layer respectively mirrors gambling with lottery-like stocks and gambling via sports betting.

The first aim has been assessed with the questions formulated in *RQ1* and *RQ2*. Subsequently, the second aim is covered by *RQ3* and *RQ4*. Lastly, *RQ5* tackles the third formulated aim.

RQ1: Do German private investors, on an aggregate level, display preferences for lottery-like stocks?

This dissertation provides evidence that German private investors significantly overinvest in stocks with lottery-like characteristics as defined by Kumar (2009). However, German private investors only overinvest in German lottery-like stocks as defined by Bali et al. (2011). In this context, private investors' preferences for a subgroup of domestic (i.e. German) stocks with seemingly different preferences for a similar subgroup in a foreign (i.e. US) equity market may be reconciled by pointing to the interrelation of familiarity and risk perception[384] as well as ambiguity aversion[385]. The statistical significance of the reported overinvestment in lottery-like stocks is high. Yet, due to the minor overall size of the $Lottery$, Max, and $Max5$ portfolios, the economic significance of the aggregate overinvestment is not as substantial.

RQ2: Are there certain lottery characteristics that drive an aggregate overinvestment of German private investors?

Using the dataset with German and US stocks, the results from the conducted analyses show that German private investors have preferences for low-priced stocks as well as for stocks with high (idiosyncratic) volatility. Furthermore, there is evidence that private investors gravitate toward stocks with high maximum daily returns. In conflict with other studies, the analyses of this dissertation do not yield consistent evidence that (idiosyncratic) skewness drives private sector investments.[386] As private investors are subject to limited capabilities in regards to perceiving and processing information[387], they may struggle to identify higher distribution moments like skewness. In turn, they may more easily identify features like price or maximum daily returns and thus these are reflected in their aggregate holdings.

RQ3: Are signal provider transactions with lottery-like stocks driven by the prior peer performance?

The results from the empirical analyses of *Section 6* indicate that signal providers tend to increase the traded relative share of lottery-like stocks within an administered account when being placed at one of the extreme ends of the relative performance spectrum. Furthermore, there is evidence that signal providers administering accounts with more moderate peer performance are more likely to trade nonlottery stocks, i.e. stocks exhibiting low idiosyncratic volatility and low idiosyncratic skewness. With regard to the net exposure towards lottery-like return characteristics, the empirical results suggest that underperforming signal providers increase the net

[384] See Heath and Tversky (1991). See also Fischer and Frewer (2009) and Song and Schwarz (2009).
[385] See Fox and Tversky (1995), Bossaerts et al. (2010), Boyle et al. (2012), Ahn et al. (2014), and Baltzer et al. (2015).
[386] See Kane (1982), Mitton and Vorkink (2007), Brunnermeier and Oehmke (2013), and Kumar et al. (2018).
[387] See Kahneman (1973), Oehler (1992), (1995), (2013a), (2013d), and Shiller (1999).

position of lottery-like stocks and therefore trigger gambling for their corresponding followers.

Underperforming signal providers may be attracted to stocks with high idiosyncratic volatility and positive idiosyncratic skewness as these offer the potential to improve the positioning of a failing account. Speculating on exceptionally high positive returns, underperforming signal providers may include lottery-like stocks more frequently into a corresponding account. In turn, when the selected lottery-like stocks fail to deliver the desired result, they may be substituted shortly after their inclusion. For signal providers at the upper end of the peer performance range, overconfidence may explain the increase in traded lottery-like stocks. When overconfidence is increased by favorable past performance[388], signal providers may start favoring riskier assets[389] and, thus, increase the proportion of traded lottery-like stocks. Furthermore, as overconfident traders overestimate the precision of their information[390], signal providers with good peer performance may overestimate their ability to time the market and therefore increase trading lottery-like stocks as these are more likely to be subject to major price movements. Moreover, in line with Chevalier and Ellison (1997), outperformers may gamble in an attempt to attain a position among top-performing signal providers – corresponding rankings / lists are maintained by (the analyzed) social trading platforms.

The increased net exposure to lottery-like stocks reported for underperformers is in line with literature on tournament incentives. Even though signal provider compensation is not directly linked to an account's ranking, the precondition to generate followers in order to become eligible for compensation indirectly imposes tournament incentives as signal providers must achieve a position reasonably suited for generating attention.[391] Finally, allowing signal providers to simultaneously operate more than one account with limited exposure to their own generated

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[388] For the relationship between performance and overconfidence see Odean (1999), Gervais and Odean (2001), and Statman et al. (2006). See also *Section 2.5.3*.
[389] For the positive relationship between overconfidence and risk taking see De Long et al. (1991), Odean (1999), Barber and Odean (2001), and Broihanne et al. (2014). See also *Section 2.5.3*.
[390] See Benos (1998), Daniel et al. (1998), and Odean (1998), (1999).
[391] Those results are in line with Kirchler et al. (2018), who provide evidence that tournament incentives increase risk-taking among underperforming traders. Furthermore, with regard to mutual funds, Agarwal et al. (2022) provide evidence that underperformers increase their lottery-like stock holdings. See also *Section 2.2*.

returns[392] may drive the observed effect. As unsuccessful accounts can be closed (and potentially replaced) at any time with limited costs, signal providers with underperforming accounts may be particularly inclined to employ lottery features – speculating on the unlikely but possible event of an extreme positive return in an attempt to turn around a failing portfolio.

RQ4: Are signal provider transactions with lottery-like currencies driven by the prior peer performance?

In line with the results of *Section 6*, the results obtained from the empirical analyses of *Section 7* suggest a quadratic relationship between relative signal provider performance and the traded share of lotteries – represented by lottery-like currency pairs. That is, signal providers with comparatively good and signal providers with comparatively bad past performance trade a higher share of lottery currency pairs. When assuming that an increased trading frequency of lottery-like currency pairs translates into an increase in risk-taking – or more specifically gambling – the previously discussed explanatory approaches may likewise be applied. Again, briefly summarized, signal providers who have outperformed their peers may suffer from (an increase) in overconfidence and may aim at attaining a listing position among top-performing accounts. On the other end of the peer performance spectrum, signal providers have little to lose; thus lottery-like return characteristics may seem particularly appealing.

RQ5: Are there substantial differences between multi-layer portfolios with a lottery-like stock gambling layer and multi-layer portfolios including a sports betting gambling layer?

Maintaining a high aspiration portfolio layer which is used for following signals in sports betting (i.e. for this analysis signals from *90plusX* that relate to major European soccer matches) does not lead to an overall portfolio outperformance. Yet, when following the respective sports betting signals, total volatility is reduced in comparison to the assessed portfolios where the high aspiration layer consists of lottery-like stocks. Idiosyncratic volatility, in contrast, is higher in the portfolio with signal-based sports betting. Likewise, portfolios where the gambling layer mirrors a rule-based

[392] See the discussed asymmetries regarding the distribution of economic consequences between signal providers and signal followers in *Section 2.2*.

Bundesliga soccer sports betting strategy which always wagers on the team that is perceived to be more likely to win (i.e. favorite), yield lower levels of total volatility and higher levels of idiosyncratic volatility in comparison to the portfolios with lottery-like stocks as gambling component. Regarding portfolios including the rule-based sports betting strategy where the wager is always placed on the team that is perceived to be less likely to win (i.e. underdog), in comparison to portfolios with lottery-like stock gambling components, skewness is substantially increased. These results suggested that investors, aiming to use the high aspiration gambling layer for including high levels of idiosyncratic volatility into their overall portfolios, can benefit from substituting lottery-like stocks for the signal-based or favorite-based betting approach. Furthermore, rather than investing in lottery-like stocks, investors who aspire high levels of (idiosyncratic) skewness are better off when the gambling layer is employed for implementing the underdog-based betting strategy. Overall (and unsurprisingly) market correlation is lower for the portfolios where sports betting returns form the gambling layer. As investors may hold additional assets with some degree of market correlation[393], it is desirable to reduce the respective market correlation of a multi-layer investment portfolio. Considering that labor income itself correlates with the market[394], even in the case of no further investments, reducing exposure towards market risk is beneficial.

[393] See, inter alia, Oehler and Horn (2019), (2021a), Oehler and Wanger (2020), and Horn and Oehler (2020).
[394] See Jagannathan and Wang (1996) and Jagannathan et al. (1998). See also Ha and Fabozzi (2022) for an integarted portfolio approach that takes into consideration human capital.

10 Critical Appraisal and Implications

As previously discussed, *SHS*-base data presents a selection bias-free[395] source for studying aggregate private sector holdings. Nonetheless, when using *SHS*-base data, certain effects which may have a systematic impact on aggregate holdings have to be acknowledged. In the context of making investment decisions, many private investors rely on the counsel of financial advisors.[396] In this context, Foerster et al. (2017) provide evidence that financial advisors predominantly compose very similar portfolios instead of tailoring portfolios in accordance with individual households' characteristics. Thus, it is difficult to differentiate between aggregate holdings that may be the result of (customary) investment advice and aggregate holdings that are driven by return distribution preferences of private investors. A similar argument can be made with regard to employer stock compensation programs which may likewise be reflected in aggregate private sector holdings.

Moreover, taking into account the cognitive constraints of private investors[397], attention – that is not driven by stock returns – may impact private sector holdings.[398] Likewise related to the inability of private investors to perceive and correctly process all available information, rather subjective expectations regarding the success probability of certain business models may have an impact on the allocation of funds. Moreover, in order specifically attract private investors, listed firms may use social media channels for the communication of capital market-relevant corporate information[399] – firms that are overrepresented in private sector holdings may be more active with regard to those (novel) communication channels in comparison to their peers. Finally, investment decisions reflected in aggregate private sector holdings may be partly driven by sustainability considerations.[400] Studying aggregate private sector holdings while accounting for those factors is left to future research.

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395 For a discussion of the impact of the so-called selection bias see Heckman (1990).

396 See Oehler and Wanger (2020) as well as the therein cited literature. See also Oehler and Kohlert (2009).

397 See Kahneman (1973), Oehler (1992), (1995), (2013a), (2013d), and Shiller (1999).

398 See Barber and Odean (2008) and Hillert et al. (2014).

399 See Herberger and Oehler (2020).

400 See, inter alia, Oehler et al. (2011b), (2012a), (2014b), (2018e), and Oehler and Wendt (2016b). In this regard, see also the literature assessing sin stocks (see Blitz and Fabozzi 2017, Fabozzi et al. 2008) and literature assessing environmental, social, and governance (ESG) firm ratings that aim at faciliating sustainability-based investment decisions (see Horn 2023, Horn and Oehler 2022, and Oehler and Horn, 2022).

The aggregate overinvestment in lottery-like stocks is rather marginal. However, the collective private sector investments in assets, especially stocks, with lottery features should be monitored on a regular basis. If at some point the overinvestment in such assets becomes more substantial, researchers should try to explore the underlying effects. Potentially, given such a future development, regulators and policymakers need to take action. Even in the absence of significant mispricing, private investors should be aware of the implications associated with lottery-like return distributions – private sector financial literacy may then be an appropriate starting point.[401]

The *wikifolio* and the *ZuluTrade* platform offer comprehensive datasets. Although an effort is taken to reduce the survivorship bias in those datasets (see the corresponding elaborations of *Section 4.2.3* and *Section 4.2.4*), collecting data for accounts corresponding to signal providers who have completely disappeared from the platform is not possible. As there is no sound reason why signal providers should lose interest and disappear from the platform when (consistently) outperforming peers, it is assumed that the majority of the unobserved accounts were located at the lower end of the performance spectrum. In line with the previously submitted arguments, those signal providers would have had an incentive to take gambles at the end of the lifecycle of a corresponding account. Including such accounts might have potentially increased the magnitude of the documented effects in *Section 6* and *Section 7*. However, due to the lack of data, assumptions regarding signal providers who have disappeared from the studied social trading platforms remain speculative.

The design features of social trading involve severe asymmetries regarding the distribution of economic consequences between signal providers and signal followers. In short, when a portfolio performs well, the administering signal provider can (potentially) receive (extensive) remuneration via performance fees (that are tied to high watermarks). On the other hand, a poorly performing portfolio barely brings any (monetary) consequences for the signal provider. In this context, this dissertation provides extensive empirical evidence that signal provider gambling transactions are driven by prior signal provider peer performance. Social trading platform vendors and signal followers should be aware of those effects. Unless an incentive structure can be established that rewards steady long-term performance – and likewise erases the

[401] See Oehler et al. (2018f), (2019b), (2022b), Oehler and Horn (2021b), and Oehler and Werner (2008). See also *Section 5.2*.

attractiveness of taking gambles – social trading may be employed as a part of a speculative high aspiration portfolio layer but should be avoided in other portfolio layers that, for example, involve retirement savings.[402] For social trading to become more than a speculative investment, adequate testing – resulting in an evaluation comprehensible for consumers / investors – of social trading platforms and signal providers has to be established.[403] In dependence of the overall development and prevalence of social trading, regulators may potentially have to take action to ensure consumer / investor protection.[404]

Due to the wide variety of available options[405], modeling common sports betting returns is rather difficult; an attempt has been made in *Section 8*. However, the composed sports betting strategies do not mirror effects which may be induced by bettors' preferences for certain supported teams or even individual players. Future research may address sports betting on the level of the individual bettor and derive stylized sports bettors with common observable preferences to gain further insights.

In regards of existing literature on (individual) investor decision making[406], constructing mulit-layer portfolios with a basic low aspiration layer and a speculative high aspiration layer may be in line with the asset management approach of many real-world market participants. Investors maintaining a highly speculative high aspiration layer that includes assets subject to a lottery-like return structure (e.g. lottery-like stocks and sports betting), may benefit from rebalancing. That is, reallocating (temporal) winnings from the gambling layer to the base layer may benefit overall portfolio performance. However, for obvious reasons, investors should be cautious with regard to shifting funds from the base layer to the gambling layer.

This dissertation is finished with a reference to the following anecdotal evidence: Never bet more than you are willing to lose.

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402 A similar conclusion is reached by Horn and Wendt (2021) and Wendt and Horn (2021) in the context of investments in cryptyo currencies and ICOs.
403 See Oehler (2014a), (2017d).
404 The essentail features of consumer protection are, inter alia, discussed by Oehler (2005c), (2006b), (2011), (2012a), (2012c), (2013a), (2013c), (2013d), (2014b), (2014c), (2015a), (2015b), (2016b), (2016c), (2017b), (2017e), (2018), (2021a), (2021b), (2021d), (2021e), (2021g), (2021i). See also Kohlert and Oehler (2009), Oehler and Reisch (2012), Strünck et al. (2012), (2013), Brönneke and Oehler (2013), Hagen et al. (2013), Oehler et al. (2013a), Oehler and Kenning (2013), Kenning and Oehler (2017), and Wendt et al. (2021).
405 See Deans et al. (2016).
406 See Oehler (1995), Shefrin and Statman (2000), and Oehler and Horn (2021a).

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Appendix

A1 Employed Variables and Portfolio Abbreviations

Panel°A – Factor Model Variables	
$R_{i,t}$	Raw return of stock / portfolio i on day / in month t.
$R_{F,t}$	Risk-free return on day / in month t.
$RMRF_t$	Return of the market portfolio net of the risk-free return on day / in month t.
SMB_t	Small minus big; factor reflecting performance differences between small and large firms on day / in month t as described by Fama and French (1993).
HML_t	High minus low; factor reflecting performance differences between firms with a low price-to-book ratio and firms with a high price-to-book on day / in month t as describes by Fama and French (1993).
WML_t	Winners minus losers; factor reflecting momentum on day / in month t as identified by Jegadeesh and Titman (1993), that is, persistence of stocks' historical over- and underperformance.
RMW_t	Robust minus weak; factor reflecting performance differences between firms with a robust (high) operating profitability and firms with a weak (low) operating profitability on day / in month t (see Fama and French 2015).
CMA_t	Conservative minus aggressive; factor reflecting performance differences between firms which invest conservatively and firms which invest aggressively on day / in month t (see Fama and French 2015).
Panel°B – Risk Measures	
$TVol$	Total volatility; standard deviation in the daily returns measured over the previous month ($TVol_{t-1}$) / previous six months ($TVol_{t-6}^{t-1}$).
$IVol$	Idiosyncratic volatility; standard deviation in the residual obtained by fitting Carhart's (1997) four-factor model to the daily returns of the previous month ($IVol_{t-1}$) / previous six months ($IVol_{t-6}^{t-1}$).
$TSkew$	Total skewness; scaled by the third moment of daily returns measured over the previous month ($TSkew_{t-1}$) / previous six months ($TSkew_{t-6}^{t-1}$).
$ISkew2F$	Idiosyncratic skewness; scaled by the third moment of the residual obtained by following Harvey and Siddique (2000): fitting a two-factor model – $RMRF$ and $RMRF^2$ – to daily returns of the previous month ($ISkew2F_{t-1}$) / previous six months ($ISkew2F_{t-6}^{t-1}$).
$ISkew3F$	Idiosyncratic skewness; scaled measure of the third moment of the residual obtained by following Boyer et al. (2010): Fitting the Fama and French (1993) three-factor model to daily returns of the previous month ($ISkew3F_{t-1}$) / previous six months ($ISkew3F_{t-6}^{t-1}$).
$SSkew$	Systematic skewness / co-skewness; coefficient of the $RMRF^2$-variable is obtained by fitting a two-factor model (see Harvey and Siddique 2000) – $RMRF$ and $RMRF^2$ – to daily returns of the previous month ($SSkew_{t-1}$) / previous six months ($SSkew_{t-6}^{t-1}$).
Panel°C – Stand-ins	
$DV_{i,t}$	Stand-in for dependent variable.
$IV_{i,t}$	Stand-in for independent variable of interest.
$Controls$	Vector of control variables.

Table 13: Employed Variables and Portfolio Abbreviations

Notes: The table above depicts and describes all (regression) variables and portfolios of this dissertation.

Panel°D – Portfolios	
$LPrice$ / $HPrice$	Portfolio containing low / high price stocks, that is, stocks within the lowest / highest k^{th} percentile with regard to the corresponding stock price in the previous month.
$HTVol$ / $LTVol$	Portfolio containing high / low total volatility stocks, that is, stocks within the highest / lowest k^{th} percentile with regard to total volatility measured using daily returns of the previous six months.
$HIVol$ / $LIVol$	Portfolio containing high / low idiosyncratic volatility stocks, that is, stocks within the highest / lowest k^{th} percentile with regard to idiosyncratic volatility measured using daily returns of the previous six months.
$HTSkew$ / $LTSkew$	Portfolio containing high / low total skewness stocks, that is, stocks within the highest / lowest k^{th} percentile with regard to total skewness measured using daily returns of the previous six months.
$HISkew$ / $LISkew$	Portfolio containing high / low idiosyncratic skewness stocks, that is, stocks within the highest / lowest k^{th} percentile with regard to idiosyncratic skewness measured using daily returns of the previous six months.
$LPrice\&HTVol$ / $HPrice\&LTVol$	Portfolio containing stocks simultaneously exhibiting low / high price and high / low total volatility, that is, stocks within the lowest / highest k^{th} percentile with regard to stock price as well as the highest / lowest k^{th} percentile with regard to total volatility.
$LPrice\&HIVol$ / $HPrice\&LIVol$	Portfolio containing stocks simultaneously exhibiting low / high price and high / low idiosyncratic volatility, that is, stocks within the lowest / highest k^{th} percentile with regard to stock price as well as the highest / lowest k^{th} percentile with regard to idiosyncratic volatility.
$LPrice\&HTSkew$ / $HPrice\&LTSkew$	Portfolio containing stocks simultaneously exhibiting low / high price and high / low total skewness, that is, stocks within the lowest / highest k^{th} percentile with regard to stock price as well as the highest / lowest k^{th} percentile with regard to total skewness.
$LPrice\&HISkew$ / $HPrice\&LISkew$	Portfolio containing stocks simultaneously exhibiting low / high price and high / low idiosyncratic skewness, that is, stocks within the lowest / highest k^{th} percentile with regard to stock price as well as the highest / lowest k^{th} percentile with regard to idiosyncratic skewness.
$HTVol\&HTSkew$ / $LTVol\&LTSkew$	Portfolio containing stocks simultaneously exhibiting high / low total volatility and high / low total skewness, that is, stocks within the highest / lowest k^{th} percentile with regard to total volatility as well as the highest / lowest k^{th} percentile with regard to total skewness.
$HIVol\&HISkew$ / $LIVol\&LISkew$	Portfolio containing stocks simultaneously exhibiting high / low idiosyncratic volatility and high / low idiosyncratic skewness, that is, stocks within the highest / lowest k^{th} percentile with regard to idiosyncratic volatility as well as the highest / lowest k^{th} percentile with regard to idiosyncratic skewness.
$Lottery$ / $NonLottery$	Portfolio containing lottery-like / nonlottery-like stocks as defined by Kumar (2009): Stocks within the lowest / highest k^{th} price percentile, highest / lowest k^{th} idiosyncratic volatility percentile, and highest / lowest k^{th} idiosyncratic skewness percentile.
Max / $NonMax$	Portfolio containing lottery-like stocks according to Bali et al. (2011): Stocks are sorted into decile portfolios based on the constituent maximum daily return over the previous month; stocks in the highest / lowest decile portfolio – stocks exhibiting the highest / lowest maximum daily return – are assigned to the Max / $NonMax$ portfolio.
$Max5$ / $NonMax5$	Portfolio containing lottery-like stocks according to Bali et al. (2011): Decile portfolios are formed based on the average comprising the five highest daily returns of the previous month; stocks in the highest / lowest decile portfolio are assigned to the $Max5$ / $NonMax5$ portfolio.
$ETF\&Lottery$	Portfolio presenting a mixture of an ETF mirroring the German stock market and Kumar's (2009) definition of lottery-like stocks – see $Lottery$ portfolio.
$ETF\&Max$	Portfolio presenting a mixture of an ETF mirroring the German stock market and Bali et al.'s (2011) definition of lottery-like stocks – see Max portfolio.
$ETF\&Max5$	Portfolio presenting a mixture of an ETF mirroring the German stock market and Bali et al.'s (2011) definition of lottery-like stocks – see $Max5$ portfolio.

Table 13 – *continued*

Panel°D – continued	
$ETF\&90plusX$	Portfolio presenting a mixture of an ETF mirroring the German stock market and returns from signals corresponding to the sports betting signal provider *90plusX*.
$ETF\&Favorite$	Portfolio presenting a mixture of an ETF mirroring the German stock market and returns corresponding to the *Favorite* sports betting strategy.
$ETF\&Underdog$	Portfolio presenting a mixture of an ETF mirroring the German stock market and returns corresponding to the *Underdog* sports betting strategy.
Panel°E – Variables / Regression Variables *Section 5*	
$w_{p,t}^{m}$	Relative weight of portfolio p held by the German private sector in month t (Kumar, 2009) based on *SHS*-base data. Measured as the sum of funds assigned to portfolio p, divided by the sum of funds assigned to the respective benchmark (*CDAX* and *S&P1500*).
$w_{p,t}^{h}$	Relative market weight of portfolio p in month t (Kumar, 2009). Measured as the market capitalization of portfolio p that is divided by the total market capitalization of the respective benchmark (*CDAX* and *S&P1500*).
$EW_{p,t}^{h}$	Unexpected portfolio weight following Kumar (2009); disproportional investment of German private sector – mirrored by *SHS*-base data – in portfolio p measured in month *t*.
$w_{i,t}^{m}$	Relative weight of stock i held by the German private sector in month t (see Kumar 2009) based on *SHS*-base data. Measured as the sum of funds assigned to stock i that is divided by the sum of funds assigned to the respective benchmark (*CDAX* and *S&P1500*).
$w_{i,t}^{h}$	Relative market weight of stock i in month t (see Kumar 2009). Measured as the market capitalization of stock i that is divided by the total market capitalization of the respective benchmark (*CDAX* and *S&P1500*).
$EW_{i,t}^{h}$	Unexpected stock weight following Kumar (2009); disproportional investment of German private sector – mirrored by *SHS*-base data – in stock i measured in month *t*.
$Price$	Price of stock i measured over the previous month.
$lnMCap$	Natural logarithm of the market capitalization that corresponds to stock i and is measured over the previous month.
$RMax$	Maximum daily return of stock i measured during the previous month.
$DDomestic$	Dummy variable; equals one if stock i is of German origin (listed in *CDAX*).
$DVol$	Dummy variable; equals one if stock i is within the highest k^{th} total / idiosyncratic volatility percentile in the previous month.
$DSkew$	Dummy variable; equals one if stock i is within the highest k^{th} total / idiosyncratic skewness percentile in the previous month.
$DPrice$	Dummy variable; equals one if stock i is within the lowest k^{th} price percentile in the previous month.
$DPriceVol$	Dummy variable; equals one if stock i is simultaneously within the lowest k^{th} price percentile and the highest total / idiosyncratic volatility percentile in the previous month.
$DPriceSkew$	Dummy variable; equals one if stock i is simultaneously within the lowest k^{th} price percentile and the highest total / idiosyncratic skewness percentile in the previous month.
$DVolSkew$	Dummy variable; equals one if stock i is simultaneously within the highest k^{th} total / idiosyncratic volatility percentile and the highest total / idiosyncratic skewness percentile in the previous month.
$DPriceVolSkew$	Dummy variable; equals one if stock i is simultaneously within the lowest k^{th} price percentile, the highest k^{th} total / idiosyncratic volatility percentile, and the highest total / idiosyncratic skewness percentile in the previous month.
$DRMax$	Dummy variable; equals one if stock i, based on the maximum daily return of the previous month, is within the highest k^{th} percentile.

Table 13 – *continued*

Panel°F – Variables / Regression Variables *Section 6*	
$T_{i,t}^{num}$ / $T_{i,t}^{vol}$	Number / volume of assets traded within *wikifolio* i in month t.
$lnT_{i,t}^{num}$ / $lnT_{i,t}^{vol}$	Number / volume of assets traded within *wikifolio* i in month t as employed in the regression analysis. Obtained by adding the constant one to the number / volume of assets traded and then applying the natural logarithm.
$I_{i,t}^{num}$ / $I_{i,t}^{vol}$	Number / volume of assets purchased within *wikifolio* i in month t.
$S_{i,t}^{num}$ / $S_{i,t}^{vol}$	Number / volume of assets sold within *wikifolio* i in month t.
$lnI_{i,t}^{num}$ / $lnI_{i,t}^{vol}$	Number / volume of assets purchased within *wikifolio* i in month t as employed in the regression analysis. Obtained by adding the constant one to the number / volume of assets purchased and then applying the natural logarithm.
$lnS_{i,t}^{num}$ / $lnS_{i,t}^{vol}$	Number / volume of assets sold within *wikifolio* i in month t as employed in the regression analysis. Obtained by adding the constant one to the number / volume of assets sold and then applying the natural logarithm.
$TL_{i,t}^{num}$ / $TL_{i,t}^{vol}$	Number / volume of traded lottery-like stocks within *wikifolio* i in month t.
$TNL_{i,t}^{num}$ / $TNL_{i,t}^{vol}$	Number / volume of traded nonlottery-like stocks within *wikifolio* i in month t.
$RTL_{i,t}^{num}$ / $RTL_{i,t}^{vol}$	Share regarding number / volume of traded lottery-like stocks relative to number / volume of all traded assets within *wikifolio* i in month t.
$RTNL_{i,t}^{num}$ / $RTNL_{i,t}^{vol}$	Share regarding number / volume of traded nonlottery-like stocks relative to number / volume of all traded assets within *wikifolio* i in month t.
$lnRTL_{i,t}^{num}$ / $lnRTL_{i,t}^{vol}$	Share regarding number / volume of traded lottery-like stocks relative to number / volume of all traded assets within *wikifolio* i in month t as employed in the regression analysis. Obtained by adding the constant one to the lottery-like stock share (number / volume) of assets traded and then applying the natural logarithm.
$lnRTNL_{i,t}^{num}$ / $lnRTNL_{i,t}^{vol}$	Share regarding number / volume of traded nonlottery-like stocks relative to number / volume of all traded assets within *wikifolio* i in month t as employed in the regression analysis. Obtained by adding the constant one to the nonlottery-like stock share (number / volume) of assets traded and then applying the natural logarithm.
$IL_{i,t}^{num}$ / $IL_{i,t}^{vol}$	Number / volume of purchased lottery-like stocks within *wikifolio* i in month t.
$SL_{i,t}^{num}$ / $SL_{i,t}^{vol}$	Number / volume of sold lottery-like stocks within *wikifolio* i in month t.
$INL_{i,t}^{num}$ / $INL_{i,t}^{vol}$	Number / volume of purchased nonlottery-like stocks within *wikifolio* i in month t.
$SNL_{i,t}^{num}$ / $SNL_{i,t}^{vol}$	Number / volume of sold nonlottery-like stocks within *wikifolio* i in month t.
$RIL_{i,t}^{num}$ / $RIL_{i,t}^{vol}$	Share regarding number / volume of purchased lottery-like stocks relative to number / volume of all purchased assets within *wikifolio* i in month t.
$RSL_{i,t}^{num}$ / $RSL_{i,t}^{vol}$	Share regarding number / volume of sold lottery-like stocks relative to number / volume of all purchased assets within *wikifolio* i in month t.
$lnRIL_{i,t}^{num}$ / $lnRIL_{i,t}^{vol}$	Share regarding number / volume of purchased lottery-like stocks relative to number / volume of all purchased assets within *wikifolio* i in month t as employed in the regression analysis. Obtained by adding the constant one to the lottery-like stock share (number / volume) of assets purchased and then applying the natural logarithm.
$lnRSL_{i,t}^{num}$ / $lnRSL_{i,t}^{vol}$	Share regarding number / volume of sold lottery-like stocks relative to number / volume of all sold assets within *wikifolio* i in month t as employed in the regression analysis. Obtained by adding the constant one to the lottery-like stock share (number / volume) of assets sold and then applying the natural logarithm.

Table 13 – *continued*

Panel°F – continued	
$LF_{i,t=1}^{num,t}$ / $LF_{i,t=1}^{vol,t}$	Net flow into lottery-like stocks; computed as the difference between the cumulative number / volume of lottery-like stock purchases and the cumulative number / volume of lottery-like stock sales from the creation of *wikifolio* i to month t.
$R_{i,t-1}$	Raw return of *wikifolio* i in month $t-1$.
$\bar{R}_{i,t-6}^{t-1}$	Average raw return of *wikifolio* i over the previous six months.
$RR_{i,t-1}$	Relative performance ranking of *wikifolio* i with regard to the raw return of the previous month ($t-1$). The ranking is expressed in a number from one to ten. Monthly deciles involving all *wikifolios* in the dataset are employed as threshold values.
$R\bar{R}_{i,t-6}^{t-1}$	Relative performance ranking of *wikifolio* i with regard to average monthly *wikifolio* raw returns over the previous six months ($t-6$ to $t-1$). The ranking is expressed in a number from one to ten. Monthly deciles involving all *wikifolios* in the dataset are employed as threshold values.
$Age_{i,t}$	Months since creation of *wikifolio* i at month t.
$Fee_{i,t}$	Performance fee set by the signal provider when creating *wikifolio* i. Performance fees may range from five to 30 percent.
$wikiNumber_i$	Number of *wikifolios* which are administered by the signal provider corresponding to *wikifolio* i.
$HWM_{i,t}$	Dummy variable; equals one if wi*kifolio* i reaches a new yearly high watermark in month t.
$Leverage_i$	Dummy variable; equals one if signal provider administering *wikifolio* i does not categorically exclude leverage products from trading activities. The *wikifolio* shows the associated status *Attention: Might contain leverage products*.
$Real_i$	Dummy variable; equals one if the corresponding signal provider has invested at least 5.000 EUR/CHF in the administered *wikifolio*. The *wikifolio* shows the associated status *Real Money* which is updated every 90 days. Due to the peculiarities of our dataset, we only obtain information about this status at the time the data is downloaded. We treat *wikifolios* as if the status displayed at the time of the download is applicable for their entire existence.
$Media_i$	Dummy variable; equals one if *wikifolio* i is administered by a media company. The *wikifolio* shows the associated label *Media wikifolio*.
$Manager_i$	Dummy variable; equals one if *wikifolio* i is administered by a professional asset manager. The *wikifolio* shows the associated label *Asset manager wikifolio*.
$Theme_i$	Dummy variable; equals one if *wikifolio* i is a theme-specific *wikifolio*, i.e. only securities that can be assigned to a specific industry or a specific investment theme are included. The *wikifolio* shows the associated label *Theme wikifolio*.
wow_i	Dummy variable; equals one if *wikifolio* i is a *wikifolio* of *wikifolios*, i.e. it is only invested in *wikifolio* certificates. The *wikifolio* shows the associated label *wikifolio of wikifolio*.
$Investable_i$	Dummy variable; equals one if *wikifolio* i is investable, i.e. open-ended index certificates have been issued and are available to signal followers. The *wikifolio* shows the associated status *Investable*.
$Closing_i$	Dummy variable; equals one if *wikifolio* i is in the process of closing (only relevant when *wikifolio* certificates have been issued). All corresponding open positions are sold and *wikifolio* fees are suspended (no further price changes) while signal followers are able to sell their certificates. The *wikifolio* shows the associated status *Closing*.
$Closed_i$	Dummy variable; equals one if *wikifolio* i is closed. Closed *wikifolio*s remain visible on the profile of the corresponding signal provider, however, they can no longer be found using the search function on the *wikifolio* platform. The *wikifolio* shows the associated status *Closed*.

Table 13 – *continued*

Panel°F – continued	
$ETF_{i,t}$	Dummy variable; equals one if at least one ETF is traded within *wikifolio* i in month t.
$ETP_{i,t}$	Dummy variable; equals one if at least one Exchange Traded Product (ETP) is traded within *wikifolio* i in month t. Exchange Traded Products include Exchange Traded Commodities (ETC) as well as Exchange Traded Notes (ETN).
$Derivative_{i,t}$	Dummy variable; equals one if at least one derivative is traded within *wikifolio* i in month t.
Panel°G – Variables / Regression Variables *Section 7*	
$NClose_{i,t-1}$	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 $t-1$.
$\overline{Profit}_{i,t-6}^{t-1}$	Average profit; average monthly net profit / loss obtained within signal provider account i, covering months $t-6$ to $t-1$.
$SPips_{i,t-1}^{n}$	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 $t-1$.
$RWin_{i,t-1}$	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 one to ten. 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 one to ten. 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 one to ten. 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 one to ten. 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 one to ten. Monthly deciles covering the profit pips balances of all signal provider accounts in the dataset are employed as threshold values.

Table 13 – *continued*

Panel°G – continued	
$RNWin_{i,t-1}$	Ranking of signal provider account i with regard to the total number of positions closed in month $t-1$ with a net profit. The ranking is expressed in a number from one to ten. Monthly deciles covering the total 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 the obtained average monthly number of positions closed with a net profit, covering months $t-6$ to $t-1$. The ranking is expressed in a number from one to ten. Monthly deciles covering average monthly numbers of closed positions with a net profit of all signal provider accounts in the dataset are employed as threshold values.
$RWinAdj_{i,t-1}$	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 monthly win ratio variable ($R\overline{Win}_{i,t-6}^{t-1}$) and variable corresponding to the average monthly number of positions closed with a net profit ($R\overline{NWin}_{i,t-6}^{t-1}$).
$RAvgProfit_{i,t-1}$	Ranking of signal provider account i with regard to the average profit per transaction in month $t-1$. The ranking is expressed in a number from one to ten. Monthly deciles covering all signal provider accounts in the dataset are employed as threshold values.
$RAvg\overline{Profit}_{i,t-6}^{t-1}$	Ranking of signal provider account i regarding the average of monthly average profits per transaction covering months $t-6$ to $t-1$. The ranking is expressed in a number from 1 to 10. Monthly deciles covering average profits of all signal provider accounts in the dataset are employed as threshold values.
$RProfitAdj_{i,t-1}$	Adjusted profit; mean of total monthly profit variable ($RProfit_{i,t-1}$) and variable corresponding to the monthly profit per transaction ($RAvgProfit_{i,t-1}$).
$R\overline{Profit}Adj_{i,t-6}^{t-1}$	Average adjusted profit; mean of average monthly profit ($R\overline{Profit}_{i,t-6}^{t-1}$) variable and variable corresponding to the average of monthly average profits per transaction ($RAvg\overline{Profit}_{i,t-6}^{t-1}$).
$RComb_{i,t-1}$	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.
$Lots_{i,t}$	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 one 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 one if a commodity is traded within signal provider account i in month t.
$Index_{i,t}$	Dummy variable; equals one if an index is traded by signal provider i in month t.
$T_{i,t}$	Number of trades (opened and closed positions) conducted within signal provider account i in month t.
$lnT_{i,t}$	Number of conducted trades within signal provider account i in month t as employed in the regression analysis; obtained by adding the constant one to the number of trades and then applying the natural logarithm.
$TL_{i,t}^{Max}$	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): Assets 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.

Table 13 – *continued*

Panel°G – continued	
$TL_{i,t}^{Max5}$	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): Assets 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.
$RTL_{i,t}^{Max}$	Share of lottery trades to all trades conducted within signal provider account i in month t.
$RTL_{i,t}^{Max5}$	Share of lottery trades to all trades conducted within signal provider account i in month t.
$lnRTL_{i,t}^{Max}$	Share of lottery trades within signal provider account i in month t as employed in the regression analysis; obtained by adding the constant one to the traded lottery share and then applying the natural logarithm.
$lnRTL_{i,t}^{Max5}$	Share of lottery trades within signal provider account i in month t as employed in the regression analysis; obtained by adding the constant one to the traded lottery share and then applying the natural logarithm.

Table 13 – *continued*

A2 Social Trading Data and Platform Design (*Section 4*)

Instrument	All		*Published*		*Investable*		*Closing*		*Closed*	
Panel°A – Number Transactions (in thousands)										
Derivative	3,697	36.97%	433	24.87%	2,387	35.39%	158	90.95%	719	53.66%
ETF	827	8.27%	162	9.30%	564	8.36%	5	2.74%	97	7.22%
Stock	4,805	48.06%	1,005	57.74%	3,360	49.82%	9	4.92%	432	32.22%
wikifolio	282	2.82%	68	3.91%	186	2.75%	0	.00%	28	2.10%
ETC	18	.18%	3	.16%	11	.17%	0	.01%	4	.29%
ETN	5	.05%	1	.06%	3	.04%	0	.04%	1	.07%
ETP	34	.34%	5	.31%	21	.32%	1	.58%	7	.50%
Other	330	3.30%	64	3.65%	212	3.15%	1	0.77%	53	3.93%
Total	9,998	100%	1,740	100%	6,744	100%	173	100%	1,341	100%
Panel°B – Volume Transactions (in million EUR)										
Derivative	426,602.9	62.59%	62,135.0	55.08%	290,794.9	61.11%	3,493.0	95.06%	70,180.0	78.66%
ETF	45,210.7	6.63%	12,226.0	10.84%	26,948.3	5.66%	28.9	.79%	6,007.5	6.73%
Stock	85,654.8	12.57%	32,465.0	28.78%	44,077.9	9.26%	129.9	3.53%	8,982.1	10.07%
wikifolio	112,492.7	16.51%	3,171.0	2.81%	107,675.8	22.63%	.0	.00%	1,646.0	1.84%
ETC	656.8	.10%	94.3	.08%	85.1	.02%	.0	.00%	477.5	.54%
ETN	235.9	.03%	35.2	.03%	59.3	.01%	1.7	.05%	139.7	.16%
ETP	1,159.6	.17%	437.0	.39%	361.6	.08%	5.5	.15%	355.4	.40%
Other	9,533.8	1.40%	2,243.2	1.99%	5,846.8	1.23%	15.6	.43%	1,428.2	1.60%
Total	681,547	100%	112,807	100%	475,850	100%	3,675	100%	89,216	100%

Table 14: Traded Instruments *wikifolio* Platform

Notes: The table above reports the number (*Panel°A*) and volume (*Panel°B*) of transactions – conducted by signal providers within their corresponding *wikifolios* – subdivided by instrument category. Transaction numbers are depicted in thousands, transaction volumes in millions. ETF, ETP, ETC, and ETN respectively denote Exchange Traded Funds, Exchange Traded Products, Exchange Traded Commodities, and Exchange Traded Notes.

Country		All		*Published*		*Investable*		*Closing*		*Closed*	
Panel°A – Number Transactions (in thousands)											
Germany	DE	6,809.1	70.08%	999.3	59.75%	4,640.4	70.8%	164.4	94.90%	1,005.1	76.58%
US	US	1,223.2	12.59%	303.2	18.13%	790.5	12.05%	3.1	1.80%	126.3	9.62%
Luxembourg	LU	388.9	4.00%	67.4	4.03%	274.9	4.19%	1.1	.63%	45.5	3.46%
Canada	CH	183.9	1.89%	46.0	2.75%	112.1	1.71%	.7	.43%	25.1	1.91%
Switzerland	CA	187.9	1.93%	41.1	2.46%	125.9	1.92%	.2	.11%	20.7	1.58%
France	FR	148.7	1.53%	33.8	2.02%	98.5	1.50%	.7	.41%	15.6	1.19%
UK	GB	128.5	1.32%	29.8	1.78%	86.7	1.32%	.3	.18%	11.6	.89%
Austria	AT	107.6	1.11%	18.2	1.09%	81.4	1.24%	.2	.13%	7.7	.59%
Ireland	IE	87.8	.90%	24.5	1.47%	54.2	.83%	1.0	.57%	8.1	.62%
Netherlands	NL	77.1	.79%	18.2	1.09%	51.7	.79%	.2	.14%	6.9	.53%
Japan	JP	37.3	.38%	9.8	.59%	23.4	.36%	.1	.03%	4.0	.31%
Sweden	SE	35.3	.36%	8.6	.52%	23.8	.36%	.4	.22%	2.5	.19%
Others		301.0	3.10%	72.5	4.33%	194.4	2.96%	.8	.44%	33.3	2.54%
Europe		8,142.8	83.81%	1,286.2	76.91%	5,538.6	84.45%	169.4	97.78%	1,148.6	87.51%
EU		7,912.7	81.44%	1,230.1	73.55%	5,394.7	82.26%	168.5	97.29%	1,119.4	85.28%
Europe ex DE		1,333.7	13.73%	287.0	17.16%	898.2	13.70%	5.0	2.87%	143.5	10.93%
EU ex DE		1,103.5	11.36%	230.8	13.80%	754.3	11.50%	4.1	2.39%	114.3	8.71%
Total		9,716.4	100%	1,672.5	100%	6,558.1	100%	173.2	100%	1,312.6	100%
Panel°B – Volume Transactions (in million EUR)											
Germany	DE	488,315	85.81%	83,431	76.14%	324,286	88.08%	3,546	96.49%	77,052	88.08%
US	US	29,285	5.15%	10,312	9.41%	15,306	4.16%	40	1.08%	3,627	4.15%
Luxembourg	LU	18,321	3.22%	4,294	3.92%	10,442	2.84%	15	.41%	3,570	4.08%
Switzerland	CH	6,824	1.20%	1,781	1.63%	4,349	1.18%	27	.73%	668	.76%
France	FR	4,883	.86%	1,675	1.53%	2,637	.72%	15	.41%	557	.64%
Canada	CA	3,571	.63%	910	.83%	2,384	.65%	2	.05%	275	.31%
Sweden	SE	3,018	.53%	284	.26%	2,699	.73%	1	.02%	35	.04%
Ireland	IE	2,919	.51%	1,562	1.43%	1,236	.34%	5	.12%	117	.13%
UK	GB	2,105	.37%	1,211	1.11%	701	.19%	6	.16%	187	.21%
Netherlands	NL	2,029	.36%	1,100	1.00%	828	.22%	3	.08%	98	.11%
Austria	AT	1,589	.28%	439	.40%	896	.24%	2	.06%	252	.29%
Japan	JP	870	.15%	449	.41%	296	.08%	1	.03%	124	.14%
Others		5,324	.94%	2,125	1.94%	2,113	.57%	14	.37%	922	1.05%
Europe		533,124	93.69%	97,093	88.61%	349,219	94.85%	3,628	98.72%	83,185	95.09%
EU		525,559	92.36%	95,022	86.72%	344,591	93.59%	3,600	97.96%	82,347	94.13%
Europe ex DE		44,809	7.87%	13,662	12.47%	24,933	6.77%	82	2.23%	6,133	7.01%
EU ex DE		37,244	6.54%	11,590	10.58%	20,305	5.52%	54	1.47%	5,295	6.05%
Total		569,055	100%	109,571	100%	368,174	100%	3,675	100%	87,484	100%

Table 15: Transactions *wikifolio* Platform by *ISIN* Country Code

Notes: The table above reports the number (*Panel°A*) and volume (*Panel°B*) of transactions – conducted by signal providers within their corresponding *wikifolios* – subdivided by *ISIN* country identifier. Transaction numbers are depicted in thousands, transaction volumes in millions. Certain signal providers limit themselves to investing into other issued *wikifolio* certificates, their corresponding *wikifolios* are tagged *wikifolio of wikifolios*. Since *wikifolio* certificates are issued by *Lang & Schwarz*, they receive *ISINs* with German country identifiers. In order to obtain unbiased results, *wikifolios of wikifolios* are not included in the table above.

Criteria	Calculation	Min	Max
Track record	1 at 6 months; 1.5 after 2 years.	.00	1.50
Risk factor	.8 with a risk factor of 1.3 or above or no available risk factor (e.g. *wikifolios* including leverage products); 1.1 with a risk factor of 1; 1.25 with a risk factor of .6 or below.	.80	1.25
Maximum loss (until now)	.1 with more than 60 percent loss; 0.6 to 1 with a loss between 60 and 10 percent (linear); 1 with a loss below 10 percent.	.00	3.00
Last login	0 after 3 months; 1.2 with login at current day.	.00	1.20
Trading activity	0 with 4 trades; 1 with 25 trades; 1.2 with 100 trades.	.00	1.20
Average monthly return	0 the weakest *wikifolio*; 1.5 the best *wikifolio*.	.00	1.50
Invested capital	.25 with no invested capital; 1 with invested capital of 10,000 EUR/CHF; 1.5 with invested capital of 100,000 EUR/CHF; 2 with invested capital of 1,000,000 EUR/CHF.	.25	2.00
Bestseller (ranked by number of buy orders)	1 with rank not in top 25; 1.25 with rank in top 25.	1.00	1.25
Watchlistings	1 with 10 watchlistings; 1.5 with 100 watchlistings.	.00	1.50
Share performance since initial offering	.8 the weakest *wikifolio*; 1.3 the best *wikifolio*.	.80	1.30
Media Reputation	1 with no or average media reputation; 1.25 above average media reputation.	1.00	1.25

Table 16: Criteria *wikifolio* Points

Notes: The table above defines the constituent criteria which are the computation base for *wikifolio points*, the default *wikifolio* sorting criterion. The information is obtained from the *wikifolio* 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

Table 17: Traded Assets *ZuluTrade* Platform

Notes: The table above displays all assets which have been traded by signal providers in the obtained *ZuluTrade* 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.

Symbol	Meaning	Source	Round Trips	Buy	Sell
Currencies					
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
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

Table 17 – *continued*

Symbol	Meaning	Source	Round Trips	Buy	Sell
Currencies					
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
Crypto Currencies					
ADA/BTC	Cardano/Bitcoin	*investing.com*	3	2	1
BCH/USD	Bitcoin Cash/US Dollar	*Datastream*	110	65	45
BTC/EUR	Bitcoin/Euro	*Datastream*	1	1	0
BTC/USD	Bitcoin/US Dollar	*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	*Datastream*	235	185	50
LTC/USD	Litecoin/US Dollar	*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	*Datastream*	163	129	34
Commodities					
Copper/USD	Copper/US Dollar	*Datastream*	1,216	604	612
XAG/EUR	Silver/Euro	*Datastream*	46	38	8
XAG/USD	Silver/US Dollar	*Datastream*	6,328	5,309	1,019
XAU/EUR	Gold/Euro	*Datastream*	443	173	270
XAU/USD	Gold/US Dollar	*Datastream*	143,214	74,184	69,030
XBR/USD	Brent Crude Oil/US Dollar	*Datastream*	7,171	5,590	1,581
XNG/USD	Natural Gas/US Dollar	*Datastream*	912	570	342
XPT/USD	Platin/US Dollar	*Datastream*	1	0	1
XTI/USD	West Texas Intermediate Crude Oil/US Dollar	*Datastream*	10,547	6,214	4,333
SOY/USD	Soya Beans/USD	*Datastream*	1	1	0
Indices					
ASX 200	Australian Stock Index	*Datastream*	718	388	330
CAC 40	French Stock Index	*Datastream*	1,249	823	426
DAX 30	German Stock Index	*Datastream*	22,187	13,800	8,387
Dow Jones	US Stock Index	*Datastream*	18,338	9,093	9,245
Euro Stoxx 50	European Stock Index	*Datastream*	595	392	203
FTSE 100	British Stock Index	*Datastream*	2,232	1,394	838
FTSE China A50	Chinese Stock Index	*Datastream*	112	87	25
FTSE MIB	Italian Stock Index	*Datastream*	59	30	29
HSI	Hong Kong Stock Index	*Datastream*	51	32	19
IBEX 35	Spanish Stock Index	*Datastream*	829	507	322
NASDAQ-100	US Stock Index	*Datastream*	11,311	6,611	4,700
Nikkei 225	Japanese Stock Index	*Datastream*	1,595	671	924
Russell 2000	US Stock Index	*Datastream*	2	0	2
S&P 500	US Stock Index	*Datastream*	16,465	7,811	8,654
SMI	Swiss Stock Index	*Datastream*	28	24	4
Stocks					
@AAL	American Airlines Group	*Datastream*	4	4	0
@AAPL	Apple	*Datastream*	5	4	1
@AMZN	Amazon	*Datastream*	11	8	3
U:BA	Boeing	*Datastream*	1	1	0

Table 17 – *continued*

Symbol	Meaning	Source	Round Trips	Buy	Sell
Stocks					
U:CRM	Salesforce	*Datastream*	2	2	0
U:CVX	Chevron	*Datastream*	2	2	0
@EBAY	EBAY	*Datastream*	2	2	0
@FB	Facebook	*Datastream*	1	0	1
@GILD	Gilead Sciences	*Datastream*	2	2	0
@GOOGL	Alphabet	*Datastream*	13	7	6
U:KO	Coca Cola	*Datastream*	1	1	0
@MSFT	Microsoft	*Datastream*	1	1	0
@NFLX	Netflix	*Datastream*	5	5	0
U:PFE	Pfizer	*Datastream*	1	1	0
U:T	AT&T	*Datastream*	1	1	0
@TSLA	Tesla	*Datastream*	5	3	2
U:WMT	Walmart	*Datastream*	2	2	0
U:XOM	ExxonMobile	*Datastream*	7	6	1
Others					
@QQQ	Invesco QQQ Trust	*Datastream*	3	2	1
Bund/EUR	Euro-Bund-Future	*Datastream*	479	225	254
Unidentified					
NA	NA	*NA*	8	4	4

Table 17 – *continued*

A3 Summary Statistics and Performance Portfolios (*Section 5*)

Panel°A – Germany (*CDAX*)

			TVol		IVol		TSkew		ISkew	
	$Price$	$MCap$	$1M$	$6M$	$1M$	$6M$	$1M$	$6M$	$1M$	$6M$
Price										
$LPrice$	1.21	54.26	10.45	12.66	9.34	12.54	.47	1.53	.42	1.56
$HPrice$	453.10	7,269.77	2.06	2.18	1.64	1.94	.17	.42	.17	.49
Volatility										
$HTVol$	40.42	121.66	12.81	16.34	11.42	16.16	.62	2.29	.54	2.33
$LTVol$	120.04	4,973.95	1.03	1.07	.80	.93	.12	.18	.12	.23
$HIVol$	39.24	81.80	12.94	16.50	11.46	16.18	.62	2.35	.53	2.33
$LIVol$	115.45	8,842.26	1.07	1.12	.77	.90	.11	.13	.11	.21
Skewness										
$HTSkew$	61.66	486.51	9.26	12.72	8.24	12.59	.81	4.02	.70	4.04
$LTSkew$	85.37	2,296.39	2.55	2.65	2.14	.46	-.39	-1.66	-.29	-1.56
$HISkew$	60.86	576.00	9.30	12.81	8.20	12.53	.80	4.02	.72	4.09
$LISkew$	85.44	2,394.03	2.59	2.68	2.18	2.49	-.37	-1.57	-.34	-1.68
Price and Volatility										
$LPrice\&HTVol$	2.63	74.82	9.21	11.05	8.21	10.92	.46	1.55	.41	1.58
$HPrice\&LTVol$	235.76	7,764.37	1.32	1.38	1.02	1.19	.12	.19	.13	.26
$LPrice\&HIVol$	2.57	58.59	9.23	11.08	8.17	10.84	.46	1.56	.40	1.56
$HPrice\&LIVol$	218.80	9,027.80	1.37	1.43	1.01	1.18	.12	.16	.13	.23
Price and Skewness										
$LPrice\&HTSkew$	2.77	93.62	9.65	12.07	8.61	11.95	.70	2.69	.62	2.70
$HPrice\&LTSkew$	213.14	6,703.72	1.91	1.99	1.49	1.72	-.20	-.81	-.12	-.69
$LPrice\&HISkew$	2.65	105.07	9.98	12.53	8.83	12.26	.71	2.74	.64	2.77
$HPrice\&LISkew$	216.55	6,476.71	1.92	1.99	1.50	1.73	-.17	-.72	-.17	-.79
Volatility and Skewness										
$HTVol\&LTVol$	43.48	169.42	9.62	12.25	8.56	12.09	.72	2.87	.62	2.86
$LTVol\&LTSkew$	102.13	5,873.73	1.35	1.41	1.05	1.22	-.20	-.76	-.13	-.66
$HIVol\&HISkew$	43.26	139.90	9.85	12.59	8.70	12.31	.72	2.94	.64	2.96
$LIVol\&LISkew$	96.93	6,541.75	1.38	1.44	1.04	1.21	-.16	-.64	-.16	-.71
Lottery										
$Lottery$	5.30	127.07	7.20	8.77	6.33	8.54	.56	1.88	.51	1.92
$NonLottery$	117.13	5,577.12	1.69	1.76	1.31	1.51	-.03	-.23	-.02	-.22
Max	44.62	200.78	14.04	12.60	12.46	12.46	1.42	1.96	1.23	1.99
$NonMax$	99.61	2,434.23	1.04	2.73	.82	2.60	-.61	.51	-.51	.56
$Max5$	45.66	206.82	14.13	12.63	12.53	12.48	1.10	1.79	.96	1.82
$NonMax5$	103.05	1,766.23	1.05	2.89	.84	2.78	-.55	.56	-.48	.61

Table 18: Summary Statistics Portfolios

Notes: This table reports summary statistics for the portfolios of *Section 5*. $Price$ refers to the mean monthly stock price; $MCap$ depicts the mean monthly market capitalization (in million USD). $TVol$ and $TSkew$ respectively depict the mean monthly values for total volatility and skewness, measured with the daily returns of the previous month, $1M$ $(t-1)$, and the previous six months, $6M$ $(t-6$ to $t-1)$. $IVol$ depicts the mean monthly idiosyncratic volatility computed as the standard deviation in the residuals obtained by fitting Carhart's (1997) four-factor model to a time-series of daily stock returns that cover the previous month, $1M$ $(t-1)$, and the previous six months, $6M$ $(t-6$ to $t-1)$. $ISkew$ is the mean monthly idiosyncratic skewness that is measured as the third moment of the residuals obtained by regressing the daily stock returns for the previous month, $1M$ $(t-1)$, and the previous six months, $6M$ $(t-6$ to $t-1)$, on a two factor-model, where the two factors are the market excess return and the squared of the market excess return (see Harvey and Siddique 2000). The analysis is conducted for the German (*Panel°A*) and the US (*Panel°B*) stock market. The *CDAX* is a proxy for the German stock market. For the US stock market, all common *CRSP* shares are employed.

Panel°B – US (*CRSP*)										
			TVol		IVol		TSkew		ISkew	
	$Price$	$MCap$	$1M$	$6M$	$1M$	$6M$	$1M$	$6M$	$1M$	$6M$
Price										
$LPrice$	1.19	44.53	7.30	7.52	6.43	7.30	.34	.83	.31	.83
$HPrice$	369.92	16,633.97	2.04	2.12	1.48	1.73	.16	.30	.16	.39
Volatility										
$HTVol$	4.15	141.12	8.80	9.49	7.65	9.14	.50	1.41	.45	1.40
$LTVol$	305.40	12,435.56	1.22	1.27	.94	1.08	.06	.10	.08	.16
$HIVol$	3.89	112.53	8.73	9.42	7.67	9.18	.51	1.44	.45	1.42
$LIVol$	321.06	15,542.93	1.29	1.34	.90	1.03	.06	.08	.08	.15
Skewness										
$HTSkew$	23.47	1,502.51	5.36	6.12	4.60	5.87	.77	3.14	.68	3.25
$LTSkew$	29.52	3,028.04	3.24	3.36	2.66	3.07	-.36	-1.78	-.27	-1.89
$HISkew$	23.49	2,192.38	5.10	5.85	4.35	5.57	.75	3.06	.69	3.34
$LISkew$	39.77	3,664.30	3.22	3.34	2.61	3.03	-.33	-1.65	-.31	-2.00
Price and Volatility										
$LPrice\&HTVol$	2.25	77.99	7.14	7.50	6.21	7.20	.38	.91	.34	.91
$HPrice\&LTVol$	283.25	14,517.31	1.53	1.59	1.12	1.30	.09	.15	.11	.21
$LPrice\&HIVol$	2.27	72.56	7.01	7.36	6.14	7.13	.38	.90	.34	.89
$HPrice\&LIVol$	272.89	15,216.98	1.59	1.65	1.12	1.30	.09	.14	.11	.21
Price and Skewness										
$LPrice\&HTSkew$	2.43	84.68	7.02	7.61	6.13	7.35	.65	2.00	.57	1.98
$HPrice\&LTSkew$	134.73	10,909.84	2.05	2.13	1.51	1.77	-.19	-.75	-.13	-.82
$LPrice\&HISkew$	2.49	92.95	7.04	7.68	6.17	7.44	.67	2.10	.60	2.13
$HPrice\&LISkew$	97.12	11,028.43	2.06	2.15	1.52	1.78	-.16	-.66	-.18	-.93
Volatility and Skewness										
$HTVol\&LTVol$	6.72	263.22	7.31	8.04	6.31	7.71	.69	2.24	.61	2.26
$LTVol\&LTSkew$	127.65	10,163.93	1.54	1.59	1.17	1.35	-.22	-.66	-.15	-.65
$HIVol\&HISkew$	6.84	253.48	7.23	8.00	6.29	7.72	.71	2.36	.64	2.42
$LIVol\&LISkew$	84.66	11,311.64	1.58	1.63	1.15	1.32	-.18	-.51	-.20	-.74
Lottery										
$Lottery$	4.84	182.99	5.76	6.18	4.98	5.91	.51	1.39	.47	1.44
$NonLottery$	91.26	8,336.62	1.96	2.03	1.45	1.68	-.05	-.26	-.05	-.37
Max	8.05	410.26	9.37	7.72	8.13	7.38	1.26	1.32	1.11	1.35
$NonMax$	191.40	8,592.51	1.17	1.86	.92	1.64	-.44	.33	-.33	.40
$Max5$	6.53	273.99	9.60	8.05	8.32	7.71	.91	1.19	.81	1.20
$NonMax5$	218.40	8,177.53	1.18	1.89	.93	1.69	-.33	.37	-.25	.44

Table 18 – *continued*

Panel°A – Lottery-like Stock Portfolios Germany (*CDAX*)															
	Lottery					Max					Max5				
	(1)	(2)	(3)	(1)-(2)	(1)-(3)	(4)	(5)	(6)	(4)-(5)	(4)-(6)	(7)	(8)	(9)	(7)-(8)	(7)-(9)
Mean	.6682	.5585	.4420	.1096	.2262	-.6245	.3116	.5337	-.9362	-1.1582	-.7244	.3947	.5165	-1.1192	-1.2409
SD	8.0814	5.9789	5.6090	5.7070	5.7655	10.2542	4.7029	5.8996	9.8213	8.7260	10.8363	4.5385	5.8831	10.6961	9.3000
α	.4363	.0459	-.0549	.3903	.4912	-1.2638***	-.1226	.0462	-1.1412**	-1.3100***	-1.2197**	-.0072	.0341	-1.2126**	-1.2538**
	(1.46)	(.35)	(-.36)	(1.31)	(1.64)	(-2.61)	(-.65)	(.39)	(-2.15)	(-2.73)	(-2.38)	(-.04)	(.29)	(-2.13)	(-2.46)
$MktRf$	1.1781***	1.1212***	1.0280***	.0569	.1500**	1.1887***	.6655***	1.1153***	.5233***	.0735	1.2275***	.5699***	1.1103***	.6576***	.1172
	(19.05)	(40.66)	(32.56)	(.92)	(2.42)	(11.71)	(16.76)	(44.55)	(4.71)	(.73)	(11.45)	(13.60)	(44.50)	(5.53)	(1.10)
SMB	.8253***	-.1134*	-.0520	.9386***	.8773***	.5805***	.1877**	-.0811	.3928*	.6616***	.5645**	.2468***	-.0947*	.3176	.6591***
	(6.23)	(-1.92)	(-.77)	(7.11)	(6.60)	(2.69)	(2.22)	(-1.52)	(1.66)	(3.09)	(2.48)	(2.77)	(-1.78)	(1.26)	(2.91)
HML	-.4589***	-.0822	-.1872***	-.3767***	-.2717**	-.5194***	.1400*	-.1339***	-.6593***	-.3854**	-.8093***	.1552*	-.1281***	-.9644***	-.6812***
	(-3.84)	(-1.54)	(-3.07)	(-3.17)	(-2.27)	(-2.64)	(1.82)	(-2.76)	(-3.06)	(-1.98)	(-3.89)	(1.91)	(-2.65)	(-4.19)	(-3.30)
WML	-.3685***	-.0506	.0005	-.3179***	-.3691***	.1078	.0789	-.0362	.0289	.1440	.0065	.0784	-.0397	-.0718	.0462
	(-4.64)	(-1.43)	(.01)	(-4.02)	(-4.63)	(.83)	(1.55)	(-1.13)	(.20)	(1.12)	(.05)	(1.46)	(-1.24)	(-.47)	(.34)
$Adj. R^2$	.5761	.8460	.7706	.1558	.1616	.2832	.4670	.8643	.0671	.0336	.2828	.3687	.8646	.1016	.0438

Table 19: Value-weighted Returns Lottery-like Stock Portfolios

Notes: This table reports the key figures for performance, including performance differentials, for the value-weighted portfolios described in *Section 5.1*. Columns (1) and (2) respectively display the results for the $Lottery$ and $NonLottery$ portfolios sorted according to Kumar (2009). Columns (4) / (7) and (5) / (8) show the results for the Max / $Max5$ and $NonMax$ / $NonMax5$ portfolios that are sorted according to Bali et al. (2011). Columns (3), (6), and (9) respectively display the results for portfolios that contain stocks which, regarding the corresponding sorting approach, have not been assigned to any of the previous categories. The analysis contains the value-weighted mean monthly portfolio return (Mean), the respective standard deviation (SD), as well as the regression intercept alpha (α) from Carhart's (1997) four-factor model as performance measures. Furthermore, the exposure to the market ($RMRF$), size (SMB), value (HML), and momentum (WML) factor is reported. The analysis is conducted for the German (*Panel°A*) as well as the US (*Panel°B*) stock market. The *CDAX* is used as a proxy for the German stock market. Regarding the US, the analysis contains all common shares of the *CRSP* universe. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively; t-statistics are displayed in parentheses.

Panel°B – Lottery-like Stock Portfolios US (*CRSP*)															
	Lottery					Max					Max5				
	(1)	(2)	(3)	(1)-(2)	(1)-(3)	(4)	(5)	(6)	(4)-(5)	(4)-(6)	(7)	(8)	(9)	(7)-(8)	(7)-(9)
Mean	.3512	.6153	.4946	-.2641	-.1435	.3644	.4138	.6412	-.0494	-.2768	.1850	.4862	.6213	-.3012	-.4363
SD	8.9982	4.0259	4.9268	6.7338	5.5672	9.2822	3.3441	4.6673	8.1767	6.1537	10.6735	3.3694	4.6551	9.7261	7.7548
α	-.3861**	-.0490	-.2204***	-.3371	-.1657	-.5488**	-.1219	-.1304***	-.4269	-.4184*	-.8249***	.0154	-.1560***	-.8403**	-.6689**
	(-2.00)	(-1.52)	(-3.88)	(-1.64)	(-0.87)	(-2.27)	(-1.55)	(-4.74)	(-1.53)	(-1.76)	(-2.70)	(0.17)	(-5.47)	(-2.47)	(-2.20)
$MktRf$	1.2995***	.9488***	1.0518***	.3506***	.2477***	1.3746***	.7355***	1.0591***	.6391***	.3156***	1.4622***	.7018***	1.0609***	.7604***	.4014***
	(27.72)	(121.43)	(76.29)	(7.04)	(5.34)	(23.30)	(38.22)	(157.69)	(9.38)	(5.43)	(19.65)	(32.36)	(152.33)	(9.15)	(5.42)
SMB	1.4614***	-.1558***	.1680***	1.6171***	1.2934***	1.0623***	-.2313***	.0470***	1.2936***	1.0152***	1.3478***	-.2085***	.0364***	1.5563***	1.3115***
	(20.97)	(-13.41)	(8.20)	(21.85)	(18.75)	(12.13)	(-8.10)	(4.72)	(12.79)	(11.77)	(12.21)	(-6.48)	(3.52)	(12.62)	(11.94)
HML	-.4693***	.0414***	-.1455***	-.5107***	-.3238***	-.7489***	.2368***	-.0456***	-.9857***	-.7033***	-.8594***	.2542***	-.0340***	-1.1136***	-.8254***
	(-7.81)	(4.13)	(-8.23)	(-8.00)	(-5.44)	(-9.87)	(9.57)	(-5.28)	(-11.25)	(-9.41)	(-8.98)	(9.12)	(-3.80)	(-10.42)	(-8.67)
WML	-.3867***	.0168**	-.0344***	-.4035***	-.3523***	-.2574***	.0312*	-.0075	-.2886***	-.2499***	-.2081***	-.0144	-.0003	-.1937**	-.2078***
	(-9.01)	(2.35)	(-2.73)	(-8.85)	(-8.29)	(-4.76)	(1.77)	(-1.22)	(-4.62)	(-4.68)	(-3.05)	(-0.73)	(-0.04)	(-2.54)	(-3.06)
$Adj.R^2$	.8485	.9790	.9563	.6947	.6121	.7729	.8108	.9883	.6093	.4982	.7258	.7618	.9874	.5908	.4867

Table 19 – *continued*

Panel°A – Portfolios Sorted on One Criterion Germany (*CDAX*)															
	Price			TVol			IVol			TSkew			ISkew		
	(1)	(2)	(1)-(2)	(3)	(4)	(3)-(4)	(5)	(6)	(5)-(6)	(7)	(8)	(7)-(8)	(9)	(10)	(9)-(10)
Mean	2.6574	.1850	2.4723	-.6733	.5260	-1.1993	-.5743	.6586	-1.2330	.1216	.3722	-.2506	.0029	.2826	-.2797
SD	20.1288	6.1211	19.5813	12.1211	4.3250	12.0257	12.2926	5.1505	11.8656	5.8421	5.9842	5.5930	6.3856	6.2152	6.3039
α	2.8182**	-.3482*	3.1665***	-.9145	.0035	-.9179	-.7974	.0853	-.8827	-.3806	.0080	-.3886	-.5854**	-.2303	-.3551
	(2.59)	(-1.88)	(2.91)	(-1.51)	(.02)	(-1.42)	(-1.30)	(.49)	(-1.37)	(-1.50)	(.04)	(-1.32)	(-2.13)	(-1.05)	(-1.03)
$MktRf$	.9772***	1.0448***	-.0676	1.1200***	.6523***	.4677***	1.1342***	.8300***	.3042**	.7533***	.9405***	-.1872***	.8863***	.9699***	-.0837
	(4.30)	(26.92)	(-.30)	(8.86)	(19.02)	(3.45)	(8.86)	(22.73)	(2.26)	(14.21)	(23.73)	(-3.04)	(15.56)	(21.29)	(-1.17)
SMB	.9606**	-.1670**	1.1276**	.4016	.2099***	.1917	.4967*	.1144	.3823	.5470***	.2475***	.2995**	.5775***	.0792	.4983***
	(1.99)	(-2.02)	(2.33)	(1.49)	(2.88)	(.66)	(1.81)	(1.46)	(1.33)	(4.85)	(2.94)	(2.29)	(4.73)	(.81)	(3.25)
HML	-.8876**	-.0819	-.8057**	-.9463***	.2387***	-1.1850***	-.9213***	.2790***	-1.2003***	-.0405	.1816**	-.2221*	-.1269	.1919**	-.3188**
	(-2.01)	(-1.09)	(-1.83)	(-3.86)	(3.59)	(-4.51)	(-3.71)	(3.94)	(-4.60)	(-.39)	(2.36)	(-1.86)	(-1.15)	(2.18)	(-2.31)
WML	-.5391*	.0361	-.5752**	-.1761	.1579***	-.3340*	-.2306	.0810*	-.3116*	.1118	-.1592***	.2710***	.1053	-.0430	.1483
	(-1.85)	(.73)	(-1.97)	(-1.09)	(3.59)	(-1.92)	(-1.41)	(1.73)	(-1.81)	(1.65)	(-3.14)	(3.44)	(1.44)	(-.73)	(1.61)
$Adj.R^2$	.0685	.6959	.0183	.2025	.5330	.0727	.2073	.6329	.0593	.3795	.6734	.1185	.4241	.6111	.0652

Table 20: Value-weighted Returns Portfolios Sorted on One Criterion

Notes: This table reports the key figures for performance, including performance differentials, for the value-weighted portfolios described in *Section 5.1*. Columns (1) and (2) respectively display the results for the low price, $LPrice$, and high price, $HPrice$, portfolios. Columns (3) / (7) and (4) / (8) show the results for the high total volatility / skewness, $HTVol$ / $HTSkew$, and low total volatility / skewness, $LTVol$ / $LTSkew$, portfolios. Columns (5) / (9) and (6) / (10) present the results for the high idiosyncratic volatility / skewness, $HIVol$ / $HISkew$, and low idiosyncratic volatility / skewness, $LIVol$ / $LISkew$, portfolios. The analysis contains the value-weighted mean monthly portfolio return (Mean), the respective standard deviation (SD), and the regression intercept alpha (α) from Carhart's (1997) four-factor model as performance measures. Furthermore, the exposure to the market ($RMRF$), size (SMB), value (HML), and momentum (WML) factor is reported. The analysis is conducted for the German (*Panel°A*) as well as the US (*Panel°B*) stock market. The *CDAX* is used as a proxy for the German stock market. Regarding the US, the analysis contains all common shares of the *CRSP* universe. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively; t-statistics are displayed in parentheses.

Panel°B – Portfolios Sorted on One Criterion US (*CRSP*)															
	Price			TVol			IVol			TSkew			ISkew		
	(1)	(2)	(1)-(2)	(3)	(4)	(3)-(4)	(5)	(6)	(5)-(6)	(7)	(8)	(7)-(8)	(9)	(10)	(9)-(10)
Mean	.3541	.6205	-.2664	-.0968	.4953	-.5921	-.0145	.5473	-.5618	.9147	.7226	.1922	.8187	.6717	.1471
SD	11.9796	4.1069	10.4650	11.7700	3.2269	11.1147	11.5052	3.6120	10.4425	5.2296	4.6194	3.5223	5.0793	4.6905	3.4318
α	-.2005	-.1060***	-.0944	-.9318**	-.0652	-.8666**	-.9023**	-.1064*	-.7959**	.1401	.0972	.0428	.0650	.0956	-.0307
	(-0.46)	(-3.25)	(-0.22)	(-2.51)	(-0.87)	(-2.16)	(-2.44)	(-1.83)	(-2.02)	(0.96)	(1.08)	(0.24)	(0.49)	(1.09)	(-0.18)
$MktRf$	1.2023***	.9503***	.2520**	1.3648***	.7256***	.6392***	1.3771***	.8567***	.5204***	.9758***	.9679***	.0079	.9787***	.9730***	.0057
	(11.43)	(119.45)	(2.36)	(15.09)	(39.47)	(6.53)	(15.31)	(60.55)	(5.42)	(27.54)	(44.09)	(0.18)	(30.69)	(45.61)	(0.14)
SMB	1.7801***	-.1741***	1.9542***	1.6532***	-.3042***	1.9574***	1.6530***	-.3047***	1.9577***	.2484***	.0174	.2310***	.2400***	.0035	.2365***
	(11.41)	(-14.75)	(12.36)	(12.32)	(-11.15)	(13.48)	(12.39)	(-14.52)	(13.76)	(4.72)	(0.53)	(3.60)	(5.06)	(0.11)	(3.81)
HML	-.6027***	-.0830***	-.5198***	-1.0315***	.2586***	-1.2901***	-.8350***	.2085***	-1.0435***	-.1329***	.0182	-.1512***	-.1046**	-.0611**	-.0436
	(-4.46)	(-8.11)	(-3.79)	(-8.87)	(10.94)	(-10.26)	(-7.23)	(11.48)	(-8.47)	(-2.92)	(0.65)	(-2.72)	(-2.56)	(-2.23)	(-0.81)
WML	-.6990***	.1354***	-.8343***	-.4076***	.0776***	-.4851***	-.3540***	.0766***	-.4305***	.0738**	-.1324***	.2063***	.0949***	-.1568***	.2517***
	(-7.24)	(18.55)	(-8.53)	(-4.91)	(4.60)	(-5.41)	(-4.29)	(5.90)	(-4.89)	(2.27)	(-6.58)	(5.20)	(3.25)	(-8.03)	(6.58)
$Adj.R^2$	.5669	.9785	.4195	.6674	.8171	.5642	.6573	.9140	.5268	.7417	.8726	.1563	.7799	.8846	.1739

Table 20 – *continued*

Panel°A – Portfolios Sorted on Two Criteria Germany (*CDAX*)									
	Price and TVol			Price and TSkew			TVol and TSkew		
	(1)	(2)	(1)-(2)	(3)	(4)	(3)-(4)	(5)	(6)	(5)-(6)
Mean	.5629	.4119	.1510	.6727	.2668	.4059	-.4717	.5759	-1.0476
SD	11.4702	5.0999	10.4364	8.4434	6.3187	7.3890	8.5279	5.1709	7.6759
α	1.0809**	-.1272	1.2081**	.6621**	-.2673	.9294**	-.7191*	.0352	-.7544*
	(2.27)	(-.79)	(2.36)	(1.84)	(-1.37)	(2.35)	(-1.91)	(.22)	(-1.84)
$MktRf$	1.1805***	.8840***	.2965***	.9726***	1.0783***	-.1057	1.0436***	.8940***	.1496*
	(11.83)	(26.13)	(2.76)	(12.89)	(26.33)	(-1.28)	(13.24)	(26.98)	(1.74)
SMB	1.0325***	.0553	.9772***	.8338***	.1196	.7142***	.6156***	.0270	.5886***
	(4.86)	(.77)	(4.28)	(5.20)	(1.37)	(4.06)	(3.67)	(.38)	(3.22)
HML	-.8448***	.0627	-.9075***	-.4506***	.0157	-.4663***	-.6792***	.1360**	-.8152***
	(-4.37)	(.96)	(-4.37)	(-3.08)	(.20)	(-2.91)	(-4.44)	(2.12)	(-4.90)
WML	-1.0497***	.1034**	-1.1531***	-.4741***	-.0116	-.4624***	-.2074**	.0845**	-.2918***
	(-8.21)	(2.39)	(-8.39)	(-4.90)	(-.22)	(-4.36)	(-2.05)	(1.99)	(-2.65)
$Adj. R^2$	.4434	.6757	.2288	.4119	.6885	.0862	.3704	.6965	.0836
	Price and IVol			Price and ISkew			IVol and ISkew		
	(7)	(8)	(7)-(8)	(9)	(10)	(9)-(10)	(11)	(12)	(11)-(12)
Mean	.5703	.5180	.0523	.6727	.2668	.1747	-.6296	.6519	-1.2815
SD	11.3717	5.9472	10.0416	8.4434	6.3187	7.2802	8.4762	6.0495	8.1173
α	.9306*	.0270	.9036*	.6621*	-.2673	.6548*	-.8314**	.1401	-.9715***
	(1.90)	(.16)	(1.77)	(1.84)	(-1.37)	(1.66)	(-2.03)	(.75)	(-2.23)
$MktRf$	1.1508***	1.0335***	.1172	.9726***	1.0783***	-.1632**	.8853***	1.0069***	-.1217
	(11.27)	(29.07)	(1.11)	(12.89)	(26.33)	(-1.99)	(10.41)	(26.06)	(-1.34)
SMB	1.1741***	-.1718**	1.3459***	.8338***	.1196	.7671***	.5682***	-.1292	.6974***
	(5.37)	(-2.26)	(5.92)	(5.20)	(1.37)	(4.38)	(3.12)	(-1.56)	(3.59)
HML	-.8313***	.0003	-.8315***	-.4506***	.0157	-.3907**	-.6923***	.1676**	-.8598***
	(-4.20)	(.00)	(-4.04)	(-3.08)	(.20)	(-2.47)	(-4.22)	(2.25)	(-4.92)
WML	-.9337***	-.0339	-.8998***	-.4741***	-.0116	-.3869***	-.1707	-.0414	-.1294
	(-7.13)	(-.74)	(-6.62)	(-4.90)	(-.22)	(-3.68)	(-1.56)	(-.83)	(-1.11)
$Adj. R^2$	.4106	.7388	.1844	.4119	.6885	.0858	.2709	.7045	.0984

Table 21: Value-weighted Returns Portfolios Sorted on Two Criteria

Notes: This table reports the key figures for performance, including performance differentials, for the value-weighted portfolios described in *Section 5.1*. Columns (1) / (3) and (2) / (4) respectively display the results for the portfolios that are jointly sorted on price and total volatility / skewness ($HTVol\&LP$ / $HTSkew\&LP$ and $LTVol\&HP$ / $LTSkew\&HP$). Columns (5) and (6) display the results for the portfolios that are jointly sorted on total volatility and total skewness ($HTVol\&HTSkew$ and $LTVol\&LTSkew$). In columns (7) / (9) and (8) / (11) respectively, we report the results for the portfolios that are jointly sorted on price and idiosyncratic volatility / skewness ($HIVol\&LP$ / $HISkew\&LP$ and $LIVol\&HP$ / $LISkew\&HP$). Columns (11) and (12) depict the results for the portfolios that are jointly sorted on idiosyncratic volatility and idiosyncratic skewness ($HIVol\&HISkew$ and $LIVol\&LISkew$). The analysis contains the value-weighted mean monthly portfolio return (Mean), the respective standard deviation (SD), and the regression intercept alpha (α) from Carhart's (1997) four-factor model as performance measures. Furthermore, the exposure to the market ($RMRF$), size (SMB), value (HML), and momentum (WML) factor is reported. The analysis is conducted for the German (*Panel°A*) as well as the US (*Panel°B*) stock market. The *CDAX* is used as a proxy for the German stock market. Regarding the US, the analysis contains all common shares of the *CRSP* universe. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively; t-statistics are displayed in parentheses.

Panel°B – Portfolios Sorted on Two Criteria US (*CRSP*)									
	Price and TVol			Price and TSkew			TVol and TSkew		
	(1)	(2)	(1)-(2)	(3)	(4)	(3)-(4)	(5)	(6)	(5)-(6)
Mean	.1075	.5900	-.4825	.2198	.7576	-.5378	.3876	.6739	-.2863
SD	11.4387	3.5505	10.3843	.6790	4.1676	8.3876	10.1253	3.7431	8.8280
α	-.5924*	-.0460	-.5464	-.4789	.0394	-.5184	-.6678**	.0295	-.6973**
	(-1.74)	(-0.81)	(-1.48)	(-1.53)	(0.63)	(-1.58)	(-2.42)	(0.40)	(-2.25)
$MktRf$	1.3209***	.8418***	.4791***	1.1955***	.9566***	.2390***	1.4364***	.8606***	.5758***
	(15.94)	(61.01)	(5.33)	(15.65)	(62.55)	(2.98)	(21.33)	(47.19)	(7.62)
SMB	1.8481***	-.2854***	2.1335***	1.5736***	-.1602***	1.7339***	1.2043***	-.2614***	1.4657***
	(15.04)	(-13.94)	(16.00)	(13.89)	(-7.06)	(14.56)	(12.05)	(-9.66)	(13.07)
HML	-.6938***	.2097***	-.9035***	-.6035***	.0037	-.6072***	-.8938***	.2236***	-1.1174***
	(-6.51)	(11.82)	(-7.82)	(-6.15)	(0.19)	(-5.89)	(-10.32)	(9.54)	(-11.50)
WML	-.6451***	.0684***	-.7135***	-.4639***	.0712***	-.5351***	-.1172*	.0625***	-.1797**
	(-8.49)	(5.41)	(-8.65)	(-6.62)	(5.08)	(-7.27)	(-1.90)	(3.74)	(-2.59)
$Adj.R^2$	.7046	.9148	.5791	.6790	.9238	.4868	.7517	.8657	.5895
	Price and IVol			Price and ISkew			IVol and ISkew		
	(7)	(8)	(7)-(8)	(9)	(10)	(9)-(10)	(11)	(12)	(11)-(12)
Mean	.1813	.5758	-.3945	.2339	.6868	-.4530	.3078	.6803	-.3725
SD	11.2483	3.7531	9.8238	10.1595	4.0964	8.4232	9.3446	3.8256	7.9440
α	-.4989	-.0939**	-.4051	-.3981	.0193	-.4174	-.5259**	.0388	-.5646**
	(-1.50)	(-2.28)	(-1.16)	(-1.28)	(0.36)	(-1.28)	(-2.03)	(0.61)	(-1.98)
$MktRf$	1.3022***	.9007***	.4015***	1.2098***	.9413***	.2685***	1.2537***	.8913***	.3624***
	(16.04)	(89.86)	(4.71)	(16.02)	(71.40)	(3.39)	(19.91)	(57.33)	(5.24)
SMB	1.8308***	-.2564***	2.0872***	1.6146***	-.1784***	1.7930***	1.2644***	-.2498***	1.5142***
	(15.20)	(-17.25)	(16.49)	(14.38)	(-9.10)	(15.23)	(13.51)	(-10.81)	(14.74)
HML	-.6668***	.1281***	-.7950***	-.6096***	-.0286*	-.5811***	-.8125***	.1528***	-.9653***
	(-6.39)	(9.95)	(-7.26)	(-6.29)	(-1.69)	(-5.72)	(-10.06)	(7.66)	(-10.89)
WML	-.6396***	.0511***	-.6907***	-.4573***	.0400***	-.4973***	-.1270**	.0437***	-.1708***
	(-8.59)	(5.56)	(-8.83)	(-6.61)	(3.31)	(-6.85)	(-2.20)	(3.07)	(-2.70)
$Adj.R^2$	.7078	.9600	.5770	.6915	.9422	.5061	.7465	.9078	.5774

Table 21 – *continued*

A4 Portfolio Weights German Private Sector (*Section 5*)

Panel°A – Portfolios Sorted on One Criterion							
	Germany (*CDAX*)						
	Mean	Median	SD	Mean	Median	SD	Mean
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Price							
$LPrice$	.019	.016	.011	.005	.004	.003	309.923***
							(28.57)
$HPrice$	41.752	42.426	6.913	46.213	45.742	6.618	-9.663***
							(-16.69)
Volatility							
$HTVol$	.100	.021	.222	.485	.012	2.191	104.313***
							(10.57)
$LTVol$	23.383	23.336	13.887	27.576	28.853	12.781	-22.164***
							(-12.80)
$HIVol$	.053	.021	.090	.027	.012	.036	123.947***
							(10.89)
$LIVol$	56.368	59.066	10.670	56.774	57.720	9.682	-1.025*
							(-1.78)
Skewness							
$HTSkew$	.741	.432	1.030	1.835	.847	2.926	-29.354***
							(-6.30)
$LTSkew$	15.292	10.54	12.667	14.211	11.934	10.153	4.079**
							(1.96)
$HISkew$	1.272	.803	1.481	2.464	1.206	3.027	-25.052***
							(-5.75)
$LISkew$	15.429	14.160	7.164	15.399	14.400	6.376	.278
							(0.15)

Table 22: Portfolio Weights German Private Sector

Notes: the table presents the characteristics regarding the relative household portfolio weight ($w_{p,t}^{h}$), relative market weight ($w_{p,t}^{m}$), and the resulting unexpected or excess weight ($EW_{p,t}^{h}$) for the portfolios described in *Section 5*. *Panel°A* presents the results for the portfolios respectively sorted on one of the three constituent lottery-like features identified by Kumar (2009). *Panel°B* presents the results for the portfolios respectively sorted on two of Kumar’s (2009) three constituent lottery-like features. Columns (1) and (8), (2) and (9), and (3) and (10) respectively report the Mean, Median, and standard deviation (SD) that correspond to the relative household portfolio weights. Columns (4) and (11), (5) and (12), and (6) and (13) respectively display the Mean, Median, and SD that correspond to the relative market weights of each portfolio. Columns (7) and (14) display the $Mean$ of the unexpected portfolio weight (see *Section 5.1*); in order to determine whether underlying means are significantly different from zero, one-sample t-tests are conducted. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively; t-statistics are displayed in parentheses. Columns (1) to (7) cover German private sector holdings with regard to German stocks represented by the *CDAX*; columns (8) to (14) correspond to US stocks represented by the *S&P1500*. Data on aggregate private sector holdings come from the *Deutsche Bundesbank*’s *SHS*-base (see *Section 4.2.2*).

Panel°A – continued							
	US (*S&P1500*)						
	Mean	Median	SD	Mean	Median	SD	Mean
	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Price							
$LPrice$	2.489	1.450	2.102	1.178	.928	.571	85.934***
							(11.70)
$HPrice$	30.655	30.436	4.494	27.200	27.071	2.753	12.573***
							(13.09)
Volatility							
$HTVol$	1.709	1.443	1.150	1.322	1.228	.704	36.510***
							(6.44)
$LTVol$	38.120	37.317	9.215	30.509	30.892	5.234	24.228***
							(18.40)
$HIVol$	1.604	1.461	.964	1.071	1.046	.282	59.245***
							(6.27)
$LIVol$	41.207	40.628	9.251	34.150	34.012	5.321	19.900***
							(15.03)
Skewness							
$HTSkew$	5.850	4.815	3.694	5.869	5.423	2.199	-3.650
							(-1.06)
$LTSkew$	8.221	7.462	4.631	7.007	6.965	1.857	12.077***
							(3.01)
$HISkew$	6.636	5.684	3.605	6.820	6.478	1.993	-5.761**
							(-2.04)
$LISkew$	9.912	9.134	5.123	7.931	7.629	1.860	19.891***
							(5.39)

Table 22 – *continued*

Panel°B – Portfolios Sorted on Two Criteria							
	Germany (*CDAX*)						
	Mean	Median	SD	Mean	Median	SD	Mean
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Price and Volatility							
$LPrice\&HTVol$	.152	.139	.093	.068	.060	.039	133.614***
							(25.55)
$HPrice\&LTVol$	50.902	56.022	15.089	55.306	60.376	14.546	-9.606***
							(-12.08)
$LPrice\&HIVol$	.150	.137	.082	.068	.060	.035	131.560***
							(25.40)
$HPrice\&LIVol$	66.025	67.204	4.721	69.599	71.535	5.476	-4.973***
							(-13.51)
Price and Skewness							
$LPrice\&HTSkew$	.126	.128	.045	.062	.051	.030	125.374***
							(18.15)
$HPrice\&LTSkew$	35.321	36.186	15.648	35.264	34.775	14.149	-2.471*
							(1.88)
$LPrice\&HISkew$	.127	.120	.053	.061	.050	.033	131.090***
							(18.37)
$HPrice\&LISkew$	33.192	34.442	12.175	33.718	33.492	10.747	-2.816*
							(-2.00)
Volatility and Skewness							
$HTVol\&HTSkew$	.346	.253	.302	.668	.148	2.237	71.444***
							(9.10)
$LTVol\&LTSkew$	31.593	32.661	15.456	31.690	34.194	13.532	-4.958***
							(-3.54)
$HIVol\&HISkew$	.318	.240	.245	.657	.146	2.224	71.365***
							(8.92)
$LIVol\&LISkew$	37.073	38.087	13.041	37.334	37.491	11.534	-1.908*
							(-1.72)

Table 22 – *continued*

Panel°B – continued							
	US (*S&P1500*)						
	Mean	Median	SD	Mean	Median	SD	Mean
	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Price and Volatility							
$LPrice\&HTVol$	1.857	1.555	1.455	1.144	1.102	.453	53.893***
							(11.97)
$HPrice\&LTVol$	34.104	34.238	4.723	32.452	32.675	3.076	5.204***
							(5.50)
$LPrice\&HIVol$	1.953	1.585	1.544	1.114	1.024	.470	63.740***
							(12.86)
$HPrice\&LIVol$	33.541	33.861	5.287	33.785	34.037	3.349	-.680
							(-0.64)
Price and Skewness							
$LPrice\&HTSkew$	1.755	1.119	1.696	1.179	.993	.600	32.470***
							(5.53)
$HPrice\&LTSkew$	11.615	10.663	5.631	12.905	12.430	3.571	-11.147***
							(-3.77)
$LPrice\&HISkew$	1.931	1.165	2.033	1.275	1.034	.707	31.921***
							(5.43)
$HPrice\&LISkew$	13.562	13.486	5.757	12.900	12.717	2.795	3.665
							(1.20)
Volatility and Skewness							
$HTVol\&HTSkew$	1.991	1.591	1.114	2.171	1.817	1.127	-1.765
							(-0.43)
$LTVol\&LTSkew$	15.064	14.372	7.599	13.863	13.708	4.657	6.784**
							(2.04)
$HIVol\&HISkew$	1.885	1.624	1.074	1.878	1.797	.653	4.047
							(0.92)
$LIVol\&LISkew$	16.917	15.829	7.392	13.722	12.852	4.215	21.396***
							(7.15)

Table 22 – *continued*

A5 Characteristics and Performance *wikifolios* (*Section 6*)

	$1M$					$6M$				
	TVol	IVol	TSkew	ISkew2F	ISkew3F	TVol	IVol	TSkew	ISkew2F	ISkew3F
Panel°A – Mean *wikifolio* Characteristics USD										
All *wikifolios*	1.688	1.301	-.032	.012	-.004	1.891	1.703	-.072	.044	.026
Leverage	2.978	2.347	-.014	.017	.002	3.608	3.352	-.048	.040	.013
w/o Leverage	1.177	.887	-.039	.010	-.006	1.231	1.069	-.081	.045	.031
Published	1.523	1.179	-.022	.025	.007	1.725	1.562	-.050	.070	.042
Investable	1.598	1.223	-.048	-.003	-.020	1.836	1.640	-.098	.020	.004
Closing	3.241	2.560	-.008	.036	.003	3.404	3.059	.083	.165	.173
Closed	2.764	2.153	.010	.043	.035	2.911	2.672	-.001	.082	.093
Panel°B – Monthly Mean *wikifolio* Characteristics USD										
All *wikifolios*	1.574	1.200	.015	.062	.045	1.725	1.540	-.046	.065	.055
Leverage	2.598	2.019	.030	.062	.045	3.017	2.788	.029	.109	.093
w/o Leverage	1.186	.888	.007	.059	.042	1.242	1.076	-.060	.059	.051
Published	1.445	1.101	.026	.066	.049	1.590	1.422	-.040	.079	.059
Investable	1.469	1.114	.002	.064	.038	1.652	1.464	-.045	.071	.060
Closing	2.606	2.044	.017	.065	.032	2.784	2.479	.023	.150	.145
Closed	2.678	2.128	.019	.066	.058	3.189	2.958	-.023	.050	.058
Panel°C – Mean wikifolio Characteristics EUR										
All *wikifolios*	1.496	1.132	-.089	-.048	-.020	1.710	1.513	-.221	-.061	-.053
Leverage	2.801	2.197	-.087	-.059	-.027	3.453	3.200	-.202	-.084	-.072
w/o Leverage	.979	.710	-.089	-.044	-.018	1.040	.865	-.229	-.053	-.045
Published	1.322	1.002	-.091	-.055	-.020	1.535	1.362	-.212	-.056	-.046
Investable	1.411	1.059	-.089	-.043	-.019	1.661	1.457	-.235	-.064	-.056
Closing	3.084	2.464	-.042	-.009	.012	3.260	2.907	-.067	.047	.090
Closed	2.573	1.987	-.079	-.052	-.029	2.731	2.481	-.177	-.070	-.066
Panel°D – Monthly Mean wikifolio Characteristics EUR										
All *wikifolios*	1.401	1.028	-.041	-.022	.006	1.562	1.346	-.178	-.051	-.042
Leverage	2.423	1.861	-.078	-.060	-.027	2.855	2.617	-.115	-.026	-.012
w/o Leverage	1.008	.710	-.041	-.019	.008	1.072	.872	-.190	-.051	-.043
Published	1.269	.922	-.041	-.028	.004	1.423	1.218	-.184	-.065	-.053
Investable	1.297	.942	-.037	-.017	.010	1.492	1.274	-.163	-.010	-.010
Closing	2.438	1.893	-.015	.025	.011	2.622	2.279	-.139	-.013	.011
Closed	2.512	1.946	-.052	-.036	-.006	3.032	2.791	-.178	-.095	-.080

Table 23: Characteristics *wikifolios*

Notes: The table above reports monthly volatility and skewness characteristics with regard to the *wikifolios* in the employed dataset. Total volatility ($TVol$), idiosyncratic volatility ($IVol$), total skewness ($TSkew$), and idiosyncratic skewness ($ISkew2F$ / $ISkew3F$) are computed using daily *wikifolio* returns of the previous month, $1M$ $(t-1)$, and the previous six months, $6M$ $(t-6$ to $t-1)$. $IVol$ and $ISkew2F$ are computed following Kumar (2009) and Harvey and Siddique (2000). $ISkew3F$ is computed following Boyer et al. (2010). *Leverage* refers to the subgroup of *wikifolios* that do not generally exclude leverage products from their trading activities; *w/o Leverage* represents the subgroup of *wikifolios* where leverage products are generally excluded. *Published*, *Investable*, *Closing*, and *Closed* refer to the *wikifolios*' corresponding life cycle status. For *Panel°A* and *Panel°B*, regional factor data for the computation of idiosyncratic volatility and idiosyncratic skewness are obtained from the *KFDL*. Following Oehler et al. (2016), daily *wikifolio* returns are converted into USD. In *Panel°C* and *Panel°D*, idiosyncratic volatility and idiosyncratic skewness are computed using local factor data for Germany obtained from *Richard Stehle*'s homepage; as these local factor data are provided in EUR, *wikifolio* returns – provided by the *wikifolio* platform denominated in EUR – are not further adjusted. However, as local German factor data end in June 2016, for the remaining period, European factors from the *KFDL* – converted into EUR – are applied. *Panel°A* and *Panel°C* report the mean values for all available *wikifolio*-month observations. *Panel°B* and *Panel°D* report mean values based on equally weighted monthly means.

Panel°A – Raw Returns USD		*Panel°B* – Panel Regression Estimates USD							
		α	$RMRF$	SMB	HML	RMW	CMA	WML	R^2
All *wikifolios*									
Mean	.5076	.0948	.5543***	-.0836	-.2484				.0013
Median	.2083	(.28)	(6.51)	(-.48)	(-1.30)				
SD	51.0441	.1151	.5470***	-.0821	-.2782			-.0489	.0013
		(.35)	(6.47)	(-.47)	(-1.40)			(-.38)	
		.1520	.5225***	-.1589	-.2943	-.2792	-.1515		.0014
		(.43)	(5.33)	(-.95)	(-1.30)	(-.93)	(-.56)		
		.1787	.5144***	-.1590	-.3434	-.2952	-.1340	-.0581	.0014
		(.54)	(5.34)	(-.95)	(-1.49)	(-1.00)	(-.48)	(-.44)	
Leverage									
Mean	.3756	.0085	.5749***	-.1450	-.0435				.0004
Median	-.0364	(.02)	(6.16)	(-.59)	(-.17)				
SD	95.2699	.0224	.5676***	-.1437	-.0703			-.0400	.0004
		(.05)	(6.08)	(-.58)	(-.28)			(-.22)	
		.1267	.5352***	-.2840	-.2789	-.5917	.0032		.0004
		(.26)	(5.08)	(-1.44)	(-1.13)	(-1.14)	(.01)		
		.1556	.5225***	-.2846	-.3434	-.6124	.0220	-.0724	.0004
		(.32)	(4.87)	(-1.44)	(-1.13)	(-1.14)	(.06)	(-.37)	
w/o Leverage									
Mean	.5600	.1306	.5492***	-.0623	-.3254				.0971
Median	.3042	(.39)	(6.02)	(-.37)	(-1.70)				
SD	6.0386	.1507	.5428***	-.0608	-.3522			-.0457	.0974
		(.47)	(5.85)	(-.36)	(-1.78)			(-.34)	
		.1681	.5203***	-.1168	-.3063	-.1715	-.2047		.0988
		(.48)	(5.10)	(-.67)	(-1.28)	(-.60)	(-.77)		
		.1907	.5143***	-.1167	-.3448	-.1841	-.1901	-.0466	.0990
		(.58)	(5.06)	(-.67)	(-1.50)	(-.67)	(-.70)	(-.35)	
Published									
Mean	.3981	-.0025	.5256***	-.0854	-.2730				.0204
Median	.1904	(-.01)	(5.86)	(-.50)	(-1.44)				
SD	12.4578	.0090	.5216***	-.0845	-.2896			-.0277	.0204
		(.03)	(5.60)	(-.49)	(-1.45)			(-.20)	
		.0229	.4957***	-.1307	-.2078	-.1054	-.2510		.0208
		(.07)	(4.95)	(-.76)	(-.85)	(-.36)	(-.95)		
		.0339	.4924***	-.1307	-.2276	-.1118	-.2445	-.0241	.0208
		(.11)	(4.86)	(-.76)	(-.96)	(-.39)	(-.92)	(-.18)	

Table 24: Performance *wikifolios*

Notes: This table (*Panel°A* and *Panel°B*) reports performance characteristics with regard to the *wikifolios* in the employed dataset. *Panel°A* reports monthly raw return characteristics. *Panel°B* reports panel regression estimates with standard errors clustered by month and *wikifolio* (see Petersen 2009); alphas, α, are estimated by applying the Fama and French (1993) three-, the Carhart (1997) four-, the Fama and French (2015) five- and the Fama and French (2018) six-factor model. $RMRF$, SMB, HML, RMW, CMA and WML respectively denote the exposure to the market, size, value, profitability, investment, and momentum factor. *Leverage* refers to the subgroup of *wikifolios* that do not generally exclude leverage products from their trading activities; *w/o Leverage* represents the subgroup of *wikifolios* where leverage products are generally excluded. *Published*, *Investable*, *Closing*, and *Closed* refer to the *wikifolios*' corresponding life cycle status. Following Oehler et al. (2016a), monthly *wikifolio* returns are converted into USD. Regional factor data are obtained from the *KFDL*. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively; t-statistics are displayed in parentheses.

Panel°A – continued		*Panel°B – continued*							
		α	$RMRF$	SMB	HML	RMW	CMA	WML	R^2
Investable									
Mean	.5917	.1516	.5824***	-.1387	-.3405*				.0018
Median	.2536	(.44)	(7.05)	(-.82)	(-1.79)				
SD	48.0254	.1537	.5816***	-.1385	-.3435*			-.0052	.0018
		(.47)	(7.27)	(-.82)	(-1.71)			(-.04)	
		.1977	.5661***	-.1924	-.4328*	-.2496	-.0162		.0018
		(.57)	(5.91)	(-1.16)	(-1.96)	(-.93)	(-.06)		
		.2056	.5636***	-.1925	-.4470*	-.2544	-.0116	-.0177	.0018
Closing									
Mean	.4536	-.2782	1.2438***	.6929	.1242				.0188
Median	.4765	(-.35)	(4.27)	(1.28)	(.26)				
SD	31.2105	.0118	1.1162***	.7405	-.4283			-.8894	.0217
		(.02)	(4.67)	(1.38)	(-.81)			(-1.64)	
		-.5721	1.2280***	.9744	1.4049	1.7762	-1.2576		.0214
		(-.71)	(3.87)	(1.57)	(1.26)	(1.14)	(-1.02)		
		-.2797	1.1191***	.9869	.7512	1.5678	-1.0808	-.7902	.0236
		(-.38)	(3.98)	(1.65)	(.77)	(1.04)	(-.91)	(-1.60)	
Closed									
Mean	.5162	.1909	.5003***	.1765	.4884				.0002
Median	.0361	(.26)	(3.27)	(.39)	(.81)				
SD	117.6044	.3020	.4579***	.1852	.3036			-.2295	.0002
		(.37)	(3.04)	(.40)	(.64)			(-.80)	
		.6669	.3302**	-.3856	-.0727	-1.7022	-.0681		.0004
		(.65)	(2.26)	(-1.25)	(-.22)	(-1.16)	(-.13)		
		.8442	.2834*	-.3832	-.4516	-1.8187	.1367	-.3282	.0004
		(.73)	(1.72)	(-1.24)	(-.82)	(-1.18)	(.19)	(-.85)	

Table 24 – *continued*

Panel°C – Raw Returns EUR		*Panel°D* – Panel Regression Estimates EUR					
		α	$RMRF$	SMB	HML	WML	R^2
All *wikifolios*							
Mean	.3788	.1530	.4264***	-.1439*	-.0956		.0013
Median	.2127	(.65)	(7.18)	(-1.86)	(-.58)		
SD	51.7708	.3004	.4584***	-.0801	-.1036	-.1657**	.0014
		(1.21)	(7.57)	(-.99)	(-.66)	(-2.09)	
Leverage							
Mean	.2571	.0300	.3990***	-.1560	.0985		.0004
Median	-.0487	(.08)	(4.43)	(-1.13)	(.29)		
SD	96.7035	.1658	.4317***	-.0822	.0892	-.1735	.0004
		(.40)	(5.22)	(-.67)	(.27)	(-1.32)	
w/o Leverage							
Mean	.4272	.2003	.4374***	-.1389*	-.1741		.1134
Median	.3292	(.91)	(7.37)	(-1.89)	(-1.56)		
SD	5.6197	.3532	.4695***	-.0781	-.1816*	-.1643**	.1184
		(1.56)	(7.74)	(-.99)	(-1.73)	(-2.25)	
Published							
Mean	.2701	.0728	.4201***	-.1388*	-.1738		.0220
Median	.1700	(.34)	(7.36)	(-1.78)	(-1.47)		
SD	12.2547	.2187	.4530***	-.0729	-.1817	-.1673**	.0231
		(.97)	(7.79)	(-.89)	(-1.62)	(-2.38)	
Investable							
Mean	.4812	.2332	.4854***	-.1051	-.2065*		.0018
Median	.2997	(1.02)	(7.83)	(-1.34)	(-1.76)		
SD	48.5424	.3348	.5080***	-.0560	-.2107*	-.1223	.0019
		(1.45)	(7.73)	(-.65)	(-1.87)	(-1.49)	
Closing							
Mean	.3622	.0489	1.0187***	-.3227	-.6806*		.0193
Median	.4191	(.06)	(4.12)	(-1.03)	(-1.74)		
SD	31.0383	.8001	1.2253***	.2611	-.7041**	-1.1890**	.0268
		(1.12)	(4.52)	(.63)	(-2.02)	(-2.08)	
Closed							
Mean	.2913	.0581	.1423	-.3639	.8070		.0004
Median	-.0287	(.09)	(.83)	(-1.61)	(1.06)		
SD	119.7828	.3622	.1901	-.2997	.7743	-.2340	.0004
		(.45)	(1.30)	(-1.52)	(1.05)	(-1.26)	

Table 24 – *continued*

Notes: This table (*Panel°C* and *Panel°D*) reports performance characteristics with regard to the *wikifolios* in the employed dataset. *Panel°C* reports monthly raw return characteristics. *Panel°D* reports panel regression estimates with standard errors clustered by month and *wikifolio* (see Petersen 2009); alphas, α, are estimated by applying the Fama and French (1993) three-, the Carhart (1997) four-, the Fama and French (2015) five- and the Fama and French (2018) six-factor model. $RMRF$, SMB, HML, and WML respectively denote the exposure to the market, size, value, and momentum factor. *Leverage* refers to the subgroup of *wikifolios* that do not generally exclude leverage products from their trading activities; *w/o Leverage* represents the subgroup of *wikifolios* where leverage products are generally excluded. *Published*, *Investable*, *Closing*, and *Closed* refer to the *wikifolios*' corresponding life cycle status. Monthly *wikifolio* returns are, as provided by the *wikifolio* platform, denominated in EUR. Local factor data for Germany are obtained from *Richard Stehle*'s homepage; as these data end in June 2016, for the remaining period the *KFDL* European factors, converted into EUR, are applied. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively; t-statistics are displayed in parentheses.

A6 Characteristics Lottery and Nonlottery Benchmark Portfolios (*Section 6*)

		$1M$					$6M$				
		TVol	IVol	TSkew	ISkew		TVol	IVol	TSkew	ISkew	
Benchmark	Portfolio	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
wikifolio	$Lottery$	6.16	5.33	.52	.48	.43	8.28	8.00	1.55	1.61	1.53
Investment	$NonLottery$	1.62	1.10	-.09	-.10	-.08	1.69	1.27	-.34	-.45	-.35
Universe	Max	13.81	12.36	1.25	1.09	.98	10.15	9.87	1.59	1.61	1.56
Stocks:7,308	$NonMax$	1.14	.89	-.60	-.47	-.41	4.04	3.81	.24	.31	.27
	$Max5$	13.88	12.40	.97	.86	.77	10.16	9.87	1.46	1.46	1.42
	$NonMax5$	1.16	.92	-.50	-.41	-.36	4.21	3.99	.29	.35	.31
Germany	$Lottery$	11.03	9.77	.66	.59	.53	14.15	13.87	2.26	2.26	2.20
CDAX	$NonLottery$	1.75	1.32	-.00	.01	.01	1.82	1.51	-.16	-.14	-.15
Stocks: 778	Max	23.61	20.99	1.49	1.27	1.14	22.75	22.36	2.73	2.69	2.64
	$NonMax$	1.10	.89	-.65	-.52	-.47	4.25	4.09	.68	.72	.68
	$Max5$	23.69	21.05	1.28	1.11	.99	22.49	22.11	2.58	2.55	2.49
	$NonMax5$	1.13	.93	-.59	-.49	-.44	4.59	4.45	.75	.79	.75
US	$Lottery$	5.87	4.85	.47	.46	.41	10.49	9.96	1.42	1.59	1.48
MSCI USA	$NonLottery$	1.44	.95	-.15	-.14	-.12	1.51	1.11	-.44	-.57	-.42
All Cap	Max	14.58	12.87	1.34	1.21	1.09	10.82	10.32	1.28	1.39	1.31
Stocks: 6,122	$NonMax$	.78	.60	-.39	-.29	-.25	4.86	4.61	.30	.39	.35
	$Max5$	14.71	12.93	.97	.88	.79	9.75	9.30	1.12	1.20	1.15
	$NonMax5$	.78	.61	-.27	-.21	-.18	8.76	8.38	.36	.45	.40
Sweden	$Lottery$	4.73	3.98	.56	.53	.47	7.53	7.18	1.37	1.50	1.39
OMX All Share	$NonLottery$	1.72	1.18	-.04	-.05	-.03	1.80	1.35	-.25	-.32	-.27
Stocks: 418	Max	8.23	7.00	1.35	1.20	1.07	7.44	7.12	1.25	1.33	1.26
	$NonMax$	1.25	.95	-.55	-.41	-.34	7.12	6.68	.27	.40	.30
	$Max5$	8.29	7.04	1.01	.91	.80	7.53	7.20	1.11	1.17	1.11
	$NonMax5$	1.26	.97	-.42	-.33	-.28	7.21	6.79	.29	.41	.32
Canada	$Lottery$	4.59	3.75	.42	.41	.36	5.73	5.27	.98	1.11	.99
S&P/TSX	$NonLottery$	1.39	1.04	-.09	-.08	-.06	1.46	1.20	-.31	-.32	-.30
Composite	Max	7.50	6.28	1.07	.95	.84	6.89	6.42	.86	.94	.86
Stocks: 371	$NonMax$	1.07	.82	-.44	-.34	-.29	2.45	2.24	.20	.29	.22
	$Max5$	7.62	6.34	.72	.65	.57	7.20	6.68	.71	.78	.71
	$NonMax5$	1.07	.82	-.33	-.27	-.24	2.47	2.27	.22	.30	.23
UK	$Lottery$	4.86	4.13	.43	.41	.36	6.39	6.08	1.13	1.28	1.18
FTSE All Share	$NonLottery$	1.59	1.10	-.08	-.10	-.08	1.67	1.26	-.34	-.40	-.35
Stocks: 603	Max	7.90	6.74	1.18	1.03	.92	7.62	7.25	.64	.73	.68
	$NonMax$	1.07	.82	-.48	-.36	-.30	3.50	3.25	.26	.39	.32
	$Max5$	8.01	6.79	.81	.73	.65	7.79	7.38	.52	.61	.56
	$NonMax5$	1.08	.84	-.38	-.31	-.26	3.55	3.31	.31	.43	.36

Table 25: Characteristics Lottery and Nonlottery Benchmark Portfolios

Notes: The table above reports monthly volatility and skewness characteristics with regard to all stocks included in the *wikifolio* investment universe as well as different comprehensive country stock market indices. Total volatility ($TVol$), idiosyncratic volatility ($IVol$), total skewness ($TSkew$) and idiosyncratic skewness ($ISkew2F$ / $ISkew3F$) are computed using daily stock returns of the previous month, $1M$ ($t-1$), and the previous six months, $6M$ ($t-6$ to $t-1$). $IVol$ and $ISkew2F$ are computed following Kumar (2009) and Harvey and Siddique (2000). $ISkew3F$ is computed following Boyer et al. (2010). All daily stock returns are measured in USD. Data from January 2010 to September 2020 are employed. Regional factor data are obtained from the *KFDL*. The $Lottery$ ($NonLottery$) portfolio includes all stocks with above (below) median idiosyncratic volatility, above (below) median idiosyncratic skewness, and below (above) median price. Max ($NonMax$) and $Max5$ ($NonMax5$) are portfolios containing lottery-like stocks in accordance with Bali et al.'s (2011) definition.

		$1M$					$6M$				
		TVol	IVol	TSkew	ISkew		TVol	IVol	TSkew	ISkew	
Benchmark	Portfolio	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Austria	$Lottery$	2.61	2.17	.34	.34	.31	2.78	2.54	.90	1.05	.94
ATX Prime	$NonLottery$	1.59	1.14	-.03	-.03	-.01	1.65	1.29	-.16	-.17	-.17
Stocks: 47	Max	3.47	2.84	.86	.76	.96	3.00	2.72	.53	.60	.54
	$NonMax$	1.13	.88	-.51	-.39	-.33	1.57	1.37	.23	.30	.27
	$Max5$	3.54	2.84	.59	.53	.47	3.05	2.70	.48	.52	.48
	$NonMax5$	1.12	.89	-.40	-.35	-.29	1.62	1.43	.20	.25	.24
France	$Lottery$	3.42	2.90	.56	.55	.49	3.90	3.66	1.78	1.95	1.83
CAC All Share	$NonLottery$	1.55	1.06	-.02	-.02	-.01	1.61	1.22	-.19	-.23	-.20
Stocks: 471	Max	5.88	5.06	1.36	1.20	1.10	4.91	4.66	1.55	1.64	1.56
	$NonMax$	.94	.73	-.48	-.37	-.32	1.77	1.61	.53	.65	.57
	$Max5$	5.94	5.08	1.06	.95	.86	4.96	4.67	1.44	1.53	1.46
	$NonMax5$	.94	.74	-.40	-.32	-.28	1.81	1.66	.58	.68	.61
Japan	$Lottery$	2.98	2.35	.40	.43	.39	3.24	2.88	1.04	1.35	1.14
TOPIX	$NonLottery$	1.55	1.06	-.05	-.07	-.06	1.60	1.22	-.22	-.26	-.18
Composite	Max	4.49	3.65	1.20	1.09	.99	3.67	3.27	1.00	1.20	1.07
Stocks: 2,301	$NonMax$	1.10	.82	-.56	-.41	-.34	1.75	1.50	.04	.20	.10
	$Max5$	4.57	3.68	.86	.81	.74	3.73	3.31	.91	1.10	.99
	$NonMax5$	1.10	.83	-.41	-.32	-.26	1.79	1.54	.08	.22	.13
Ireland	$Lottery$	5.41	4.75	.46	.41	.37	6.08	5.90	1.76	1.78	1.72
ISEQ All Share	$NonLottery$	1.69	1.28	-.01	-.02	-.02	1.78	1.47	-.19	-.19	-.17
Stocks: 65	Max	8.90	7.83	1.10	.92	.84	7.62	7.41	1.42	1.40	1.37
	$NonMax$	1.22	1.01	-.86	-.73	-.68	2.29	2.16	.17	.25	.21
	$Max5$	8.87	7.79	.92	.78	.70	7.54	7.32	1.33	1.31	1.28
	$NonMax5$	1.24	1.04	-.87	-.75	-.69	2.38	2.27	.20	.28	.25
Netherlands	$Lottery$	3.64	3.10	.47	.46	.41	4.32	4.08	1.52	1.67	1.56
AEX All Share	$NonLottery$	1.48	.99	-.07	-.10	-.08	1.56	1.14	-.29	-.36	-.33
Stocks: 160	Max	7.04	6.13	1.25	1.09	.98	5.86	5.62	1.22	1.29	1.24
	$NonMax$	1.08	.84	-.69	-.55	-.47	2.44	2.25	.32	.40	.34
	$Max5$	7.06	6.10	1.00	.88	.78	5.83	5.56	1.10	1.16	1.11
	$NonMax5$	1.08	.85	-.62	-.50	-.44	2.53	2.36	.41	.49	.43
Switzerland	$Lottery$	3.20	2.75	.44	.39	.36	3.54	3.36	1.21	1.30	1.22
Swiss All Share	$NonLottery$	1.21	.91	-.06	-.07	-.05	1.26	1.05	-.27	-.32	-.29
Stocks: 268	Max	5.23	4.55	1.11	.97	.87	4.48	4.30	1.06	1.10	1.05
	$NonMax$	.83	.67	-.53	-.44	-.39	1.53	1.42	.28	.28	.26
	$Max5$	5.27	4.56	.80	.72	.64	4.51	4.30	.93	.96	.92
	$NonMax5$	.83	.68	-.43	-.38	-.33	1.57	1.47	.34	.34	.33

Table 25 – *continued*

A7 Regression Results Number / Volume Transactions (*Section 6*)

Panel°A – Dependent Variable: Number Transactions							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
α	.804***	.804***	.865***	1.474***	.897***	1.238***	.836***
	(20.74)	(17.42)	(91.74)	(227.98)	(96.03)	(208.77)	(84.11)
$RR_{i,t-1}$	-.103***	-.103***	-.100***	-.019***	-.060***	-.021***	-.062***
	(-9.86)	(-8.22)	(-31.87)	(-7.49)	(-22.10)	(-8.19)	(-22.86)
$(RR_{i,t-1})^2$	.010***	.010***	.009***	.003***	.006***	.003***	.006***
	(9.81)	(8.29)	(33.90)	(11.78)	(26.59)	(12.28)	(27.12)
$Leverage$	.525***	.525***	.493***		.289***		.306***
	(20.74)	(17.51)	(107.57)		(48.29)		(50.76)
$RealMoney$	.698***	.698***	.675***		.734***		.721***
	(10.71)	(8.42)	(63.11)		(49.98)		(49.21)
$Investable$	.660***	.660***	.677***		.580***		.561***
	(28.39)	(23.11)	(150.37)		(87.17)		(83.60)
$Closing$	.465***	.465*	.449***		.707***		.681***
	(2.66)	(1.95)	(12.53)		(16.86)		(16.28)
$Closed$	.432***	.432***	.498***		.292***		.254***
	(12.48)	(9.95)	(66.00)		(34.67)		(29.44)
Fee	1.278***	1.278***	1.376***		1.814***		1.731***
	(9.10)	(6.79)	(48.40)		(46.28)		(44.15)
$Media$	.037	.037	.005				
	(.20)	(.18)	(.19)				
$Manager$	-.263***	-.263	-.282***				
	(-2.83)	(-1.61)	(-13.33)				
$Theme$	-1.613***	-1.613***	-1.575***				
	(-15.04)	(-27.36)	(-21.05)				
$wikiNumber$	.030***	.030***	.029***				
	(14.16)	(8.00)	(69.83)				
HWM	.253***	.253***	.280***	.258***	.269***	.273***	.285***
	(8.06)	(7.99)	(56.67)	(81.63)	(77.75)	(74.27)	(71.37)
Age	-.010***	-.010***	-.014***	-.011***	-.010***		-.006***
	(-9.12)	(-8.69)	(-101.20)	(-99.28)	(-84.48)		(-26.58)
R^2	.1176	.1176	.1325	.5861	.4734	.5893	.4775

Table 26: Regression Results Number / Volume Transactions and Past Performance

Notes: This table (*Panel°A*), reports the coefficients for the regression assessing the relation between trading activity and relative past *wikifolio* performance. The monthly number of assets traded ($T_{i,t}^{num}$) is employed as dependent variable. Relative performance is measured over the previous month ($RR_{i,t-1}$) and the previous six months ($\bar{RR}_{i,t-6}^{t-1}$). In specification (1) and (8), t-statistics correspond to *wikifolio* and month-clustered standard errors; in specification (2) and (9), standard errors are clustered by month and signal provider (see Petersen 2009). Specifications (3) and (10) include time fixed effects. Fixed effects on the *wikifolio*-level are included in specifications (4) and (11). Trader-level fixed effects, i.e. for each identified signal provider, are included in specifications (5) and (12). In specification (6) and (13) time and *wikifolio*-level fixed effects are simultaneously included; in specification (7) and (14), time and signal provider-level fixed effects are simultaneously included. Below the regression coefficients, t-statistics are displayed in parentheses. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively. The obtained data covers the period from December 2011 to February 2019. Only *wikifolios* with available return data for at least six months are included in the analysis.

Panel°A – continued							
	(8)	(9)	(10)	(11)	(12)	(13)	(14)
α	.770***	.770***	.811***	1.379***	.808***	1.143***	.743***
	(19.82)	(16.28)	(85.31)	(200.95)	(84.74)	(178.50)	(73.71)
$R\bar{R}_{i,t-6}^{t-1}$	-.099***	-.099***	-.087***	-.001	-.042***	.000***	-.043***
	(-8.16)	(-6.99)	(-27.34)	(-.21)	(-15.06)	(-.12)	(-15.17)
$(R\bar{R}_{i,t-6}^{t-1})^2$	.010***	.010***	.009***	.003***	.006***	.003***	.006***
	(9.56)	(8.18)	(32.20)	(10.66)	(25.77)	(10.55)	(25.90)
$Leverage$	.522***	.522***	.493***		.291***		.308***
	(20.84)	(17.51)	(106.97)		(48.60)		(51.13)
$RealMoney$	.688***	.688***	.666***		.716***		.703***
	(10.58)	(8.32)	(62.18)		(48.84)		(48.08)
$Investable$	.658***	.658***	.675***		.573***		.554***
	(28.48)	(23.09)	(149.82)		(86.25)		(82.57)
$Closing$	.456**	.456*	.442***		.708***		.681***
	(2.60)	(1.91)	(12.33)		(16.91)		(16.31)
$Closed$	.435***	.435***	.501***		.301***		.262***
	(12.55)	(10.01)	(66.35)		(35.82)		(30.35)
Fee	1.286***	1.286***	1.389***		1.811***		1.726***
	(9.17)	(6.84)	(48.86)		(46.29)		(44.11)
$Media$	.040	.040	.008				
	(.21)	(.20)	(.28)				
$Manager$	-.257***	-.257	-.277***				
	(-2.76)	(-1.58)	(-13.10)				
$Theme$	-1.618***	-1.618***	-1.580***				
	(-14.97)	(-26.96)	(-21.12)				
$wikiNumber$	.030***	.030***	.029***				
	(14.14)	(7.96)	(69.69)				
HWM	.240***	.240***	.260***	.239***	.245***	.245***	.252***
	(7.43)	(7.38)	(52.64)	(76.59)	(71.60)	(67.81)	(63.61)
Age	-.010***	-.010***	-.014***	-.011***	-.010***		-.006***
	(-9.01)	(-8.58)	(-99.50)	(-98.90)	(-83.88)		(-25.82)
R^2	.1182	.1182	.1328	.5878	.4754	.5909	.4794

Table 26 – *continued*

Panel°B – Dependent Variable: Volume Transactions							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
α	4.640***	4.640***	4.973***	6.237***	4.772***	5.523***	4.900***
	(29.38)	(26.95)	(147.77)	(235.66)	(130.85)	(227.51)	(126.35)
$RR_{i,t-1}$	-.383***	-.383***	-.359***	-.099***	-.218***	-.106***	-.224***
	(-10.39)	(-9.16)	(-32.06)	(-9.39)	(-20.60)	(-10.14)	(-21.26)
$(RR_{i,t-1})^2$	.036***	.036***	.034***	.012***	.023***	.012***	.023***
	(10.59)	(9.38)	(34.15)	(12.68)	(24.28)	(13.42)	(24.91)
$Leverage$	1.411***	1.411***	1.233***		.649***		.638***
	(18.85)	(16.45)	(75.37)		(27.74)		(27.14)
$RealMoney$	1.723***	1.723***	1.613***		1.701***		1.691***
	(11.73)	(9.62)	(42.24)		(29.65)		(29.59)
$Investable$	1.895***	1.895***	1.988***		1.531***		1.571***
	(23.15)	(19.85)	(123.71)		(58.92)		(59.93)
$Closing$	1.193**	1.193***	1.091***		1.702***		1.779***
	(2.43)	(1.97)	(8.53)		(10.39)		(10.90)
$Closed$	1.249***	1.249***	1.610***		.886***		.949***
	(10.49)	(8.94)	(59.81)		(26.97)		(28.15)
Fee	4.382***	4.382***	4.971***		5.250***		5.220***
	(10.69)	(8.29)	(48.99)		(34.30)		(34.11)
$Media$	-.145	-.145	-.299***				
	(-.29)	(-.26)	(-3.02)				
$Manager$	.690*	.690	.589***				
	(1.87)	(1.24)	(7.81)				
$Theme$	-5.901***	-5.901***	-5.681***				
	(-11.29)	(-33.15)	(-21.27)				
$wikiNumber$	.084***	.084***	.080***				
	(13.75)	(7.38)	(53.07)				
HWM	1.009***	1.009***	1.082***	1.038***	1.066***	1.045***	1.084***
	(6.88)	(6.85)	(61.36)	(80.29)	(79.02)	(69.62)	(69.48)
Age	-.044***	-.044***	-.066***	-.034***	-.034***		-.041***
	(-8.92)	(-8.68)	(-132.34)	(-75.13)	(-73.51)		(-43.99)
R^2	.0890	.0890	.1169	.4451	.3578	.4499	.3635

Table 26 – *continued*

Notes: This table (*Panel°A*), reports the coefficients for the regression assessing the relation between trading activity and relative past *wikifolio* performance. The monthly volume of assets traded ($T_{i,t}^{vol}$) is employed as dependent variable. Relative performance is measured over the previous month ($RR_{i,t-1}$) and the previous six months ($R\bar{R}_{i,t-6}^{t-1}$). In specification (1) and (8), t-statistics correspond to *wikifolio* and month-clustered standard errors; in specification (2) and (9), standard errors are clustered by month and signal provider (see Petersen 2009). Specifications (3) and (10) include time fixed effects. Fixed effects on the *wikifolio*-level are included in specifications (4) and (11). Trader-level fixed effects, i.e. for each identified signal provider, are included in specifications (5) and (12). In specification (6) and (13) time and *wikifolio*-level fixed effects are simultaneously included; in specification (7) and (14), time and signal provider-level fixed effects are simultaneously included. Below the regression coefficients, t-statistics are displayed in parentheses. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively. The obtained data covers the period from December 2011 to February 2019. Only *wikifolios* with available return data for at least six months are included in the analysis.

Panel°B – continued							
	(8)	(9)	(10)	(11)	(12)	(13)	(14)
α	4.396***	4.396***	4.630***	5.846***	4.394***	5.118***	4.494***
	(27.16)	(24.76)	(136.46)	(208.01)	(118.01)	(195.32)	(114.14)
$R\bar{R}_{i,t-6}^{t-1}$	-.334***	-.334***	-.265***	-.016	-.137***	-.013***	-.130***
	(-7.81)	(-6.97)	(-23.32)	(-1.45)	(-12.47)	(-1.16)	(-11.90)
$(R\bar{R}_{i,t-6}^{t-1})^2$	.035***	.035***	.030***	.011***	.022***	.011***	.021***
	(9.85)	(8.75)	(29.78)	(10.76)	(22.52)	(10.74)	(22.24)
$Leverage$	1.410***	1.410***	1.246***		.660***		.653***
	(19.02)	(16.55)	(75.72)		(28.20)		(27.72)
$RealMoney$	1.677***	1.677***	1.569***		1.635***		1.625***
	(11.43)	(9.36)	(41.05)		(28.54)		(28.48)
$Investable$	1.885***	1.885***	1.979***		1.505***		1.543***
	(23.25)	(19.86)	(123.14)		(58.03)		(58.95)
$Closing$	1.154**	1.154*	1.058***		1.708***		1.782***
	(2.36)	(1.89)	(8.28)		(10.44)		(10.94)
$Closed$	1.267***	1.267***	1.628***		.922***		.980***
	(10.63)	(9.05)	(60.46)		(28.10)		(29.11)
Fee	4.440***	4.440***	5.058***		5.250***		5.216***
	(10.86)	(8.41)	(49.85)		(34.35)		(34.14)
$Media$	-.137	-.137	-.295***				
	(-.28)	(-.25)	(-2.99)				
$Manager$	.711*	.711	.605***				
	(1.92)	(1.28)	(8.02)				
$Theme$	-5.931***	-5.931***	-5.712***				
	(-11.29)	(-31.99)	(-21.39)				
$wikiNumber$	.084***	.084***	.080***				
	(13.77)	(7.37)	(53.07)				
HWM	.930***	.930***	.967***	.958***	.969***	.932***	.947***
	(6.22)	(6.20)	(54.92)	(75.08)	(72.53)	(62.91)	(61.27)
Age	-.043***	-.043***	-.066***	-.034***	-.034***		-.040***
	(-8.83)	(-8.59)	(-130.88)	(-74.72)	(-73.01)		(-43.37)
R^2	.0898	.0898	.1174	.4469	.3600	.4518	.3657

Table 26 – *continued*

A8 Characteristics and Performance ZuluTrade Accounts (*Section 7*)

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	.03	1.11	.07
Currencies	-.77	-.35	.35	.79	.03	.71	.02	.73	.07
Crypto Currencies	-5.27	-2.41	1.79	5.47	.15	5.47	.40	5.56	1.29
Crypto Currency/Fiat Money	-5.63	-2.35	2.01	5.87	.03	5.10	.16	5.44	.76
Crypto Currency/Crypto Currency	-4.97	-2.44	1.64	5.15	.24	5.83	.64	5.68	1.83
Commodities	-1.89	-.76	.85	1.93	.05	1.70	-.01	1.78	.03
Indices	-1.52	-.62	.73	1.54	.03	1.27	.00	1.32	-.13
Stocks	-2.09	-.83	.96	2.17	.08	1.90	.09	1.96	.11
Assets categorized as lottery-like									
Lottery	-3.01	-1.23	1.24	3.00	.17	3.40	.49	3.16	.52
Other	-.93	-.39	.42	.98	.02	.79	-.03	.86	.01

Table 27: Summary Statistics Traded Assets

Notes: This table displays return characteristics for all assets included in the 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 mean monthly returns by category (*Panel°C*), the 10th ($P10$), 25th ($P25$), 75th ($P75$), and 90th ($P90$) percentiles as well as mean values are reported. Furthermore, *Panel°A* reports 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 (see Bali et al. 2011). Crypto currencies are by default categorized as lotteries (not included into the sorting procedure). Remaining assets are denoted as others.

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 27 – *continued*

	$D1$	$D2$	$D3$	$D4$	$D5$	$D6$	$D7$	$D8$	$D9$	$D10$
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 28: 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.

A9 Regression Results Number Trades (*Section 7*)

Panel°A – Dependent Variable: Number Trades										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
α	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

Table 29: Regression Results Number Transactions and Past Performance

Notes: This table (*Panel°A*) displays panel regression estimates obtained by applying the regression model in Equation 31. The number of conducted trades of signal provider account i in month t ($T_{i,t}$) is set as dependent variable. In *Panel°A*, results relate to relative performance variables measured over the previous month. In (1) and (6), t-statistics correspond to month and signal provider account-clustered standard errors; in (2) and (7), standard errors are clustered by month and signal provider (see Petersen 2009). (3) and (8) include time fixed effects. Fixed effects on the portfolio-level (i.e. each signal provider account) are included in (4) and (9). Trader-level fixed effects (i.e. each signal provider) are included in (5) and (10). Data is obtained from *ZuluTrade* for the period October 2008 to January 2021. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively; t-statistics are displayed in parentheses.

Panel°B – Dependent Variable: Number Trades										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
α	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

Table 29 – *continued*

Notes: This table (*Panel°B*) displays panel regression estimates obtained by applying the regression model in Equation 31. The number of conducted trades of signal provider account i in month t ($T_{i,t}$) is set as dependent variable. In *Panel°B*, results relate to relative performance variables measured over the previous six months. In (1) and (6), t-statistics correspond to month and signal provider account-clustered standard errors; in (2) and (7), standard errors are clustered by month and signal provider (see Petersen 2009). (3) and (8) include time fixed effects. Fixed effects on the portfolio-level (i.e. each signal provider account) are included in (4) and (9). Trader-level fixed effects (i.e. each signal provider) are included in (5) and (10). Data is obtained from *ZuluTrade* for the period October 2008 to January 2021. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively; t-statistics are displayed in parentheses.

A10 Regression Results Robustness Checks (*Section 7*)

Panel°A – Dependent Variable: Relative Number Lottery Trades										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
α	.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

Table 30: Regression Results Relative Share Lottery Trades and Past Performance

Notes: Panel°A displays results for the regression model of Equation 36. The share of lottery-like assets traded ($lnRTL_{i,t}^{Max}$) is the dependent variable. Relative performance is measured over the previous month. In (1) and (6) / (2) and (7), t-statistics correspond to month and signal provider account-clustered / signal provider-cluster standard errors (see Petersen 2009). (3) and (8) include time fixed effects. Fixed effects on the portfolio-level (i.e. each signal provider account) are included in (4) and (9). Trader-level fixed effects (i.e. each signal provider) are included in (5) and (10). Data is obtained from *ZuluTrade* from October 2008 to January 2021. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively; t-statistics are displayed in parentheses.

Panel°B – Dependent Variable: Relative Number Lottery Trades										
	(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

Table 30 – *continued*

Notes: This table (*Panel°B*) displays results for the regression model of Equation 36. The share of lottery-like assets traded ($lnRTL_{i,t}^{Max}$) is the dependent variable. Relative performance is measured over the previous six months. In (1) and (6), t-statistics correspond to month and signal provider account-clustered standard errors; in (2) and (7), standard errors are clustered by month and signal provider (see Petersen 2009). (3) and (8) include time fixed effects. Fixed effects on the portfolio-level (i.e. each signal provider account) are included in (4) and (9). Trader-level fixed effects (i.e. each signal provider) are included in (5) and (10). Data is obtained from *ZuluTrade* for the period October 2008 to January 2021. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively; t-statistics are displayed in parentheses.

Panel°A – Dependent Variable: Relative Number Lottery Trades					
	(1)	(2)	(3)	(4)	(5)
α	.0349***	.0349***	.0362***	.0361***	.0378***
	(5.33)	(5.07)	(17.20)	(15.08)	(16.14)
$RWin_{i,t-1}$	-.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)
$Lots_{i,t}$	.0000***	.0000***	.0000***	.0000***	.0000***
	(6.22)	(6.39)	(10.99)	(10.82)	(10.49)
$Age_{i,t}$	-.0001*	-.0001	-.0001***	-.0003***	-.0003***
	(-1.79)	(-1.51)	(-3.18)	(-13.38)	(-14.01)
$Open_{i,t}$	-.0038	-.0038	-.0083***	-.0127***	-.0123***
	(-.39)	(-.41)	(-3.39)	(-5.34)	(-5.18)
$Long_{i,t}$	.0042	.0042	.0053***	.0006	.0014
	(.96)	(.68)	(4.50)	(.45)	(1.13)
$Commodity_{i,t}$	.0656***	.0656***	.0655***	.0581***	.0605***
	(6.00)	(5.89)	(55.42)	(36.47)	(39.80)
$Index_{i,t}$	.1003***	.1003***	.1036***	.0637***	.0795***
	(5.19)	(5.16)	(54.30)	(22.70)	(31.59)
$RNum_{i,t}$	-.0031***	-.0031***	-.0031***	-.0013***	-.0019***
	(-4.03)	(-3.42)	(-12.12)	(-3.85)	(-5.72)
R^2	.1001	.1001	.1300	.2658	.2359

Table 31: Regression Results Relative Share Lottery Trades and Past Performance

Notes: This table (*Panel°A*) displays regression estimates obtained by applying the regression model of Equation 36; the share of lottery-like trades as defined in *Section 7.3.2* is set as dependent variable ($lnRTL_{i,t}^{Max5}$). *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 specifications (1), (6), and (11), t-statistics correspond to month and signal provider account-clustered standard errors; in specifications (2), (7), and (12) standard errors are clustered by month and signal provider (see 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). 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; t-statistics are displayed in parentheses.

Panel°A – continued					
	(6)	(7)	(8)	(9)	(10)
α	.0429***	.0429***	.0436***	.0337***	.0358***
	(6.61)	(5.58)	(20.20)	(13.89)	(14.99)
$RProfit_{i,t-1}$	-.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)
$Lots_{i,t}$	.0000	.0000	.0000***	.0000***	.0000***
	(1.58)	(1.59)	(6.85)	(5.71)	(5.72)
$Age_{i,t}$	-.0001***	-.0001***	-.0001***	-.0003***	-.0003***
	(-4.00)	(-3.45)	(-7.68)	(-13.64)	(-14.29)
$Open_{i,t}$	-.0028	-.0028	-.0072***	-.0088***	-.0087***
	(-.28)	(-.29)	(-3.09)	(-3.89)	(-3.79)
$Long_{i,t}$	.0038	.0038	.0050***	.0001	.0008
	(.88)	(.64)	(4.30)	(.05)	(.60)
$Commodity_{i,t}$	.0644***	.0644***	.0642***	.0583***	.0608***
	(5.88)	(5.78)	(54.33)	(36.73)	(40.11)
$Index_{i,t}$	.1000***	.1000***	.1031***	.0649***	.0799***
	(5.16)	(5.12)	(53.80)	(22.98)	(31.50)
$RNum_{i,t}$	-.0046***	-.0046***	-.0045***	-.0018***	-.0024***
	(-5.55)	(-4.94)	(-18.25)	(-5.37)	(-7.46)
R^2	.0999	.0999	.1298	.2588	.2297

Table 31 – *continued*

Panel°A – continued					
	(11)	(12)	(13)	(14)	(15)
α	.0447***	.0447***	.0456***	.0354***	.0372***
	(6.36)	(5.58)	(19.78)	(13.87)	(14.80)
$RComb_{i,t-1}$	-.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***
	(6.12)	(6.29)	(10.96)	(10.84)	(10.51)
$Age_{i,t}$	-.0001***	-.0001***	-.0001***	-.0003***	-.0003***
	(-3.49)	(-3.04)	(-6.61)	(-13.48)	(-14.18)
$Open_{i,t}$	-.0034	-.0034	-.0079***	-.0127***	-.0124***
	(-.36)	(-.37)	(-3.24)	(-5.36)	(-5.19)
$Long_{i,t}$	.0035	.0035	.0047***	.0006	.0014
	(.82)	(.58)	(3.93)	(.44)	(1.12)
$Commodity_{i,t}$	.0647***	.0647***	.0645***	.0581***	.0605***
	(5.93)	(5.83)	(54.65)	(36.48)	(39.80)
$Index_{i,t}$	.1006***	.1006***	.1038***	.0637***	.0796***
	(5.21)	(5.18)	(54.53)	(22.69)	(31.62)
$RNum_{i,t}$	-.0035***	-.0035***	-.0035***	-.0014***	-.0020***
	(-4.69)	(-4.08)	(-14.08)	(-4.20)	(-6.15)
R^2	.1028	.1028	.1327	.2657	.2358

Table 31 – *continued*

Panel°B – Dependent Variable: Relative Number Lottery Trades					
	(1)	(2)	(3)	(4)	(5)
α	.0346***	.0346***	.0356***	.0398***	.0412***
	(5.45)	(5.16)	(17.15)	(15.16)	(16.36)
$R\overline{Win}_{i,t-6}^{t-1}$	-.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)
$Lots_{i,t}$	.0000***	.0000***	.0000***	.0000***	.0000***
	(6.36)	(6.57)	(10.92)	(10.78)	(10.44)
$Age_{i,t}$	-.0000	-.0000	-.0000**	-.0003***	-.0003***
	(-1.36)	(-1.13)	(-2.26)	(-13.32)	(-13.95)
$Open_{i,t}$	-.0044	-.0044	-.0088***	-.0128***	-.0125***
	(-.46)	(-.48)	(-3.61)	(-5.37)	(-5.22)
$Long_{i,t}$	.0042	.0042	.0054***	.0006	.0015
	(.97)	(.69)	(4.53)	(.48)	(1.14)
$Commodity_{i,t}$	.0657***	.0657***	.0655***	.0582***	.0606***
	(6.00)	(5.90)	(55.43)	(36.56)	(39.89)
$Index_{i,t}$	.0999***	.0999***	.1032***	.0637***	.0793***
	(5.18)	(5.15)	(54.06)	(22.69)	(31.52)
$RNum_{i,t}$	-.0033***	-.0033***	-.0033***	-.0014***	-.0019***
	(-4.74)	(-4.11)	(-13.27)	(-4.11)	(-6.04)
R^2	.1001	.1001	.1300	.2659	.2360

Table 31 – *continued*

Notes: This table (*Panel°B*) displays regression estimates obtained by applying the regression model of Equation 36; the share of lottery-like trades as defined in *Section 7.3.2* is set as dependent variable ($lnRTL_{i,t}^{Max5}$). In *Panel°B*, relative performance variables – win ratio ($R\overline{Win}_{i,t-6}^{t-1}$), net profit ($R\overline{Profit}_{i,t-6}^{t-1}$), and the combined term ($R\overline{Comb}_{i,t-6}^{t-1}$) – are measured over the previous month. In specifications (1), (6), and (11), t-statistics correspond to month and signal provider account-clustered standard errors; in specifications (2), (7), and (12) standard errors are clustered by month and signal provider (see 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). 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; t-statistics are displayed in parentheses.

Panel°B – continued					
	(6)	(7)	(8)	(9)	(10)
α	.0539***	.0539***	.0546***	.0388***	.0410***
	(7.46)	(6.00)	(25.12)	(15.48)	(16.75)
$R\overline{Profit}_{i,t-6}^{t-1}$	-.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)
$Lots_{i,t}$	.0000	.0000	.0000***	.0000***	.0000***
	(1.55)	(1.56)	(6.59)	(5.63)	(5.65)
$Age_{i,t}$	-.0002***	-.0002***	-.0002***	-.0003***	-.0003***
	(-4.76)	(-4.10)	(-9.96)	(-13.60)	(-14.26)
$Open_{i,t}$	-.0015	-.0015	-.0059**	-.0085***	-.0083***
	(-.15)	(-.16)	(-2.53)	(-3.74)	(-3.65)
$Long_{i,t}$	.0032	.0032	.0044***	-.0000	.0007
	(.74)	(.54)	(3.74)	(-.02)	(.52)
$Commodity_{i,t}$	.0627***	.0627***	.0626***	.0582***	.0607***
	(5.79)	(5.68)	(52.91)	(36.64)	(40.00)
$Index_{i,t}$	.0998***	.0998***	.1030***	.0650***	.0801***
	(5.17)	(5.13)	(53.81)	(23.02)	(31.61)
$RNum_{i,t}$	-.0044***	-.0044***	-.0043***	-.0016***	-.0022***
	(-5.30)	(-4.80)	(-17.62)	(-4.77)	(-6.75)
R^2	.1032	.1032	.1330	.2568	.2299

Table 31 – *continued*

Panel°B – continued					
	(11)	(12)	(13)	(14)	(15)
α	.0496***	.0496***	.0493***	.0406***	.0412***
	(6.64)	(5.96)	(20.60)	(14.56)	(15.23)
$R\overline{Comb}_{i,t-6}^{t-1}$	-.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***
	(6.48)	(6.72)	(10.70)	(10.75)	(10.43)
$Age_{i,t}$	-.0001***	-.0001***	-.0001**	-.0003***	-.0003***
	(-2.66)	(-2.24)	(-4.92)	(-13.45)	(-14.02)
$Open_{i,t}$	-.0043	-.0043	-.0086***	-.0127***	-.0124***
	(-.45)	(-.47)	(-3.51)	(-5.35)	(-5.21)
$Long_{i,t}$	.0037	.0037	.0049***	.0005	.0014
	(.88)	(.63)	(4.16)	(.41)	(1.07)
$Commodity_{i,t}$	.0647***	.0647***	.0645***	.0581***	.0605***
	(5.96)	(5.86)	(54.65)	(36.49)	(39.80)
$Index_{i,t}$	.1004***	.1004***	.1036***	.0636***	.0795***
	(5.22)	(5.19)	(54.40)	(22.67)	(31.61)
$RNum_{i,t}$	-.0034***	-.0034***	-.0034***	-.0014***	-.0019***
	(-4.76)	(-4.18)	(-13.84)	(-4.02)	(-5.92)
R^2	.1032	.1032	.1328	.2659	.2361

Table 31 – *continued*

A11 Return Index Development Multi-layer Portfolios (*Section 8*)

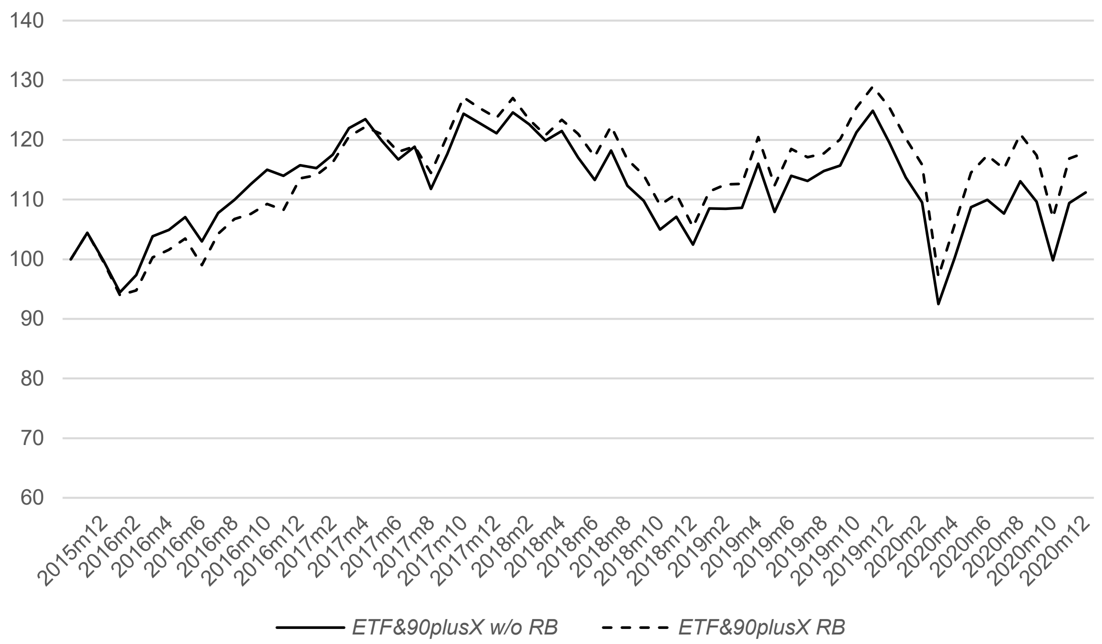

Figure 4: Return Index Portfolio ETF and Sports Betting Signals

Notes: The graph above depicts the return indices of two two-layer portfolios. At the beginning, the base layer each portfolio constitutes for 90 percent of all funds; these funds are invested in an ETF (*iShares MSCI Germany*) which is chosen to mirror the German stock market. The gambling layer of the portfolios, respectively accounting for ten percent of the initial portfolio value, is used for following sports betting signals issued by *90plusX*. The displayed return indices respectively correspond to a portfolio without rebalancing ($ETF\&90PlusX\ w/o\ RB$) and a portfolio with monthly rebalancing so that relative weights of the two layers are held constant ($ETF\&90PlusX\ RB$). In accordance with the availability of signals, period from December 2015 to December 2020 is covered. Due to only marginal differences, this graph does not include the return indices where transaction costs are taken into consideration.

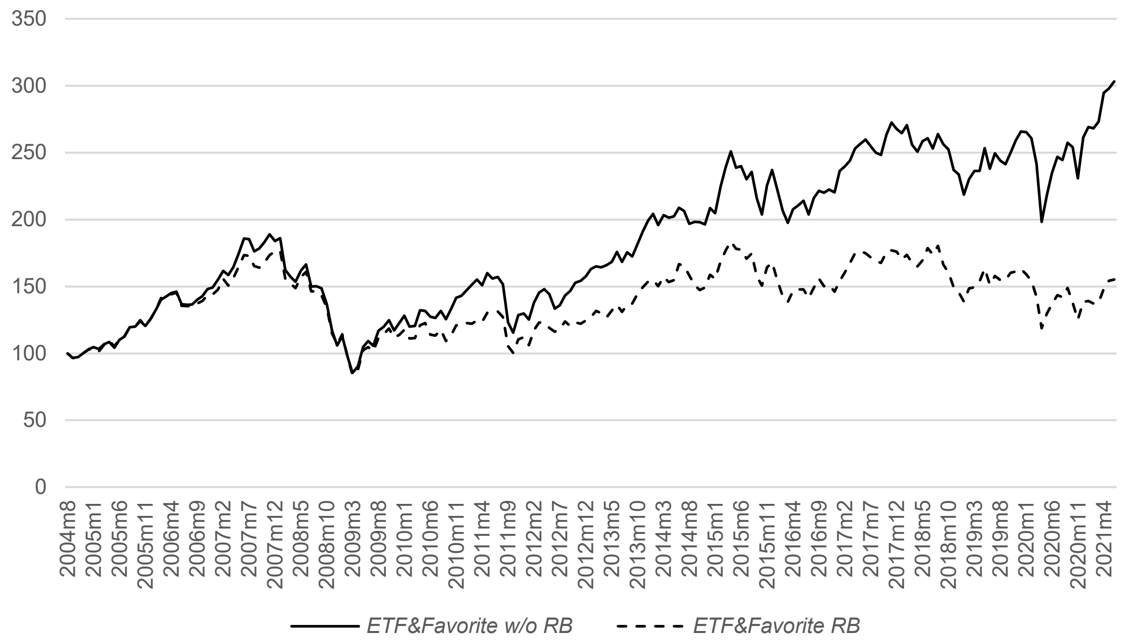

Figure 5: Return Index Portfolio ETF and *Favorite Strategy*

Notes: The graph above depicts the return indices of two two-layer portfolios. At the beginning, the base layer of each portfolio constitutes for 90 percent of all funds; these funds are invested in an ETF (*iShares MSCI Germany*) which is chosen to mirror the German stock market. The gambling layer of the portfolios, respectively accounting for ten percent of the total portfolio value, is used for implementing a simple rule-based sports betting strategy (*Favorite Strategy*) with regard to German *Bundesliga* soccer matches. The displayed return indices respectively correspond to a portfolio without rebalancing ($ETF\&Favorite\ w/o\ RB$) and a portfolio with monthly rebalancing so that relative weights of the two layers are held constant ($ETF\&Favorite\ RB$). In accordance with the availability of historic *Bundesliga* data, i.e. pairings, results, and odds, the period from season 2004/2005 to season 2020/2021 is covered. Due to only marginal differences, this graph does not include the return indices where transaction costs are taken into consideration.

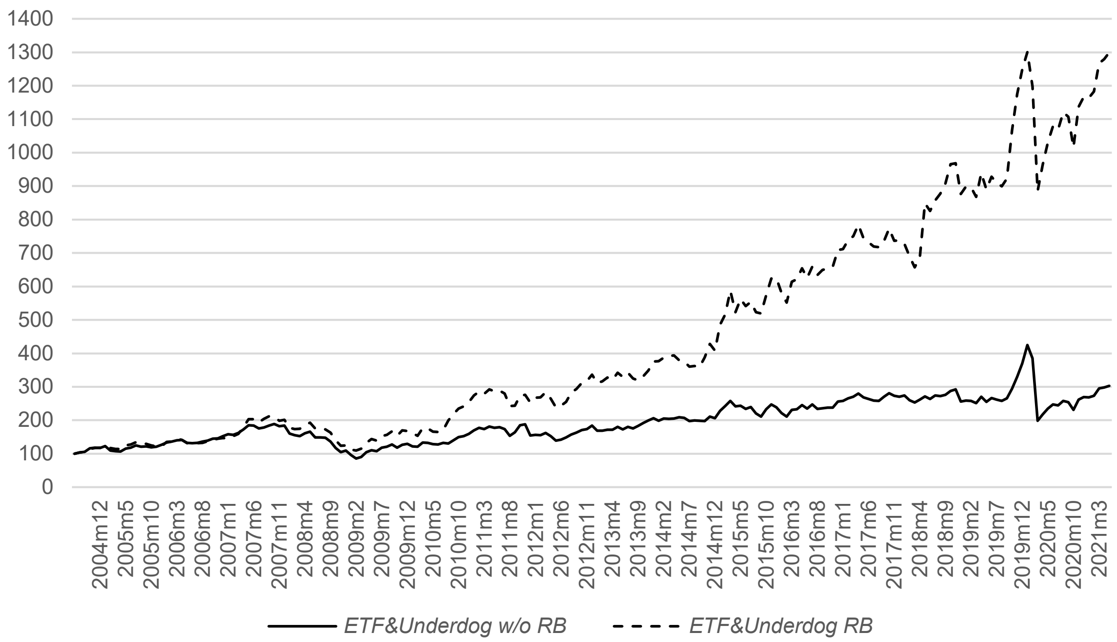

Figure 6: Return Index Portfolio ETF and *Underdog Strategy*

Notes: The graph above depicts the return indices of two two-layer portfolios. At the beginning, the base layer of each portfolio constitutes for 90 percent of all funds; these funds are invested in an ETF (*iShares MSCI Germany*) which is chosen to mirror the German stock market. The gambling layer of the portfolios, respectively accounting for ten percent of the total portfolio value, is used for implementing a simple rule-based sports betting strategy (*Underdog Strategy*) with regard to German *Bundesliga* soccer matches. The displayed return indices respectively correspond to a portfolio without rebalancing ($ETF\&Underog\ w/o\ RB$) and a portfolio with monthly rebalancing so that relative weights of the two layers are held constant ($ETF\&Underdog\ RB$). In accordance with the availability of historic *Bundesliga* data, i.e. pairings, results, and odds, the period from season 2004/2005 to season 2020/2021 is covered. Due to only marginal differences, this graph does not include the return indices where transaction costs are taken into consideration.

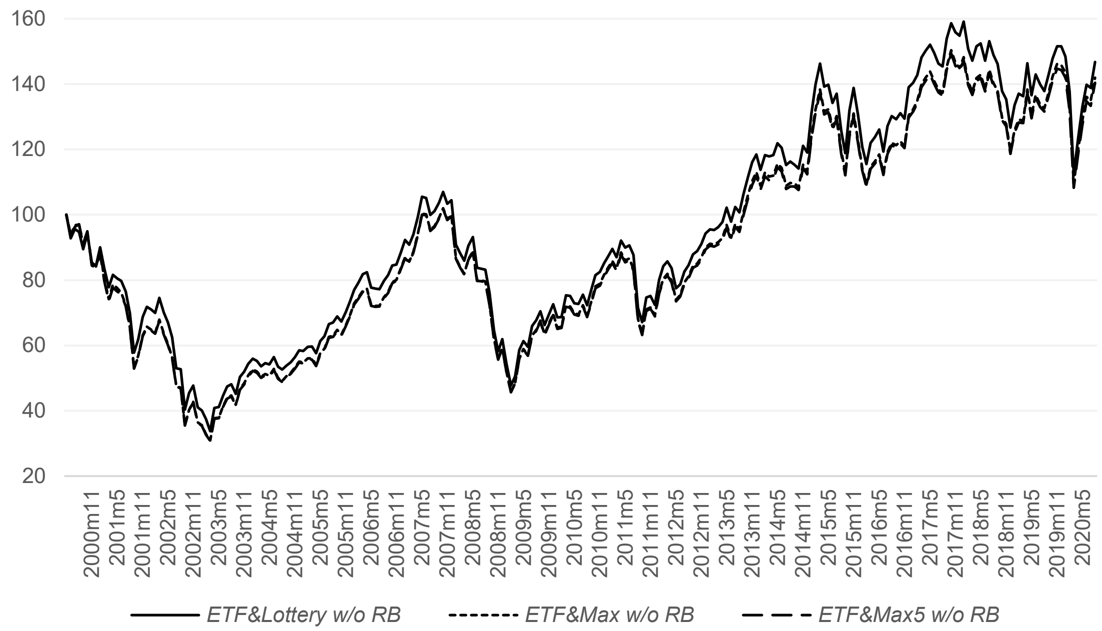

Figure 7: Return Index Portfolios ETF and Equally-weighted Lottery-like Stocks without Rebalancing

Notes: The graph above depicts the return indices of three two-layer portfolios. At the beginning, the base layer each portfolio constitutes for 90 percent of all funds; these funds are invested in an ETF (*iShares MSCI Germany*) which is chosen to mirror the German stock market. The gambling layer of the portfolios, respectively accounting for ten percent of the total portfolio value, comprises ten equally-weighted lottery-like stocks (see Kumar 2009, Bali et al. 2011) which are selected according to their market capitalization. The *CDAX* is employed as the benchmark for lottery-like stock selection. The displayed return indices correspond to portfolios without rebalancing: $ETF\&Lottery\ w/o\ RB$, $ETF\&Max\ w/o\ RB$, and $ETF\&Max5\ w/o\ RB$. The period from June 2000 to August 2020 is covered. Due to only marginal differences, return indices where transaction costs are taken into consideration are not displayed.

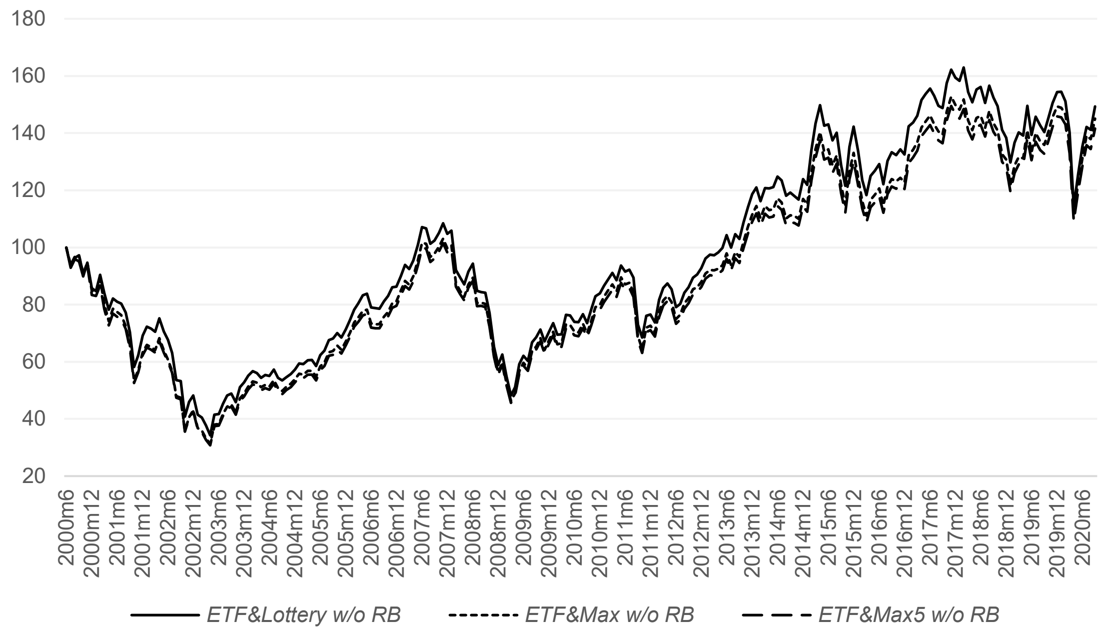

Figure 8: Return Index Portfolios ETF and Value-weighted Lottery-like Stocks without Rebalancing

Notes: The graph above depicts the return indices of three two-layer portfolios. At the beginning, the base layer each portfolio constitutes for 90 percent of all funds; these funds are invested in an ETF (*iShares MSCI Germany*) which is chosen to mirror the German stock market. The gambling layer of the portfolios, respectively accounting for ten percent of the total portfolio value, comprises ten value-weighted lottery-like stocks (Kumar, 2009, Bali et al. 2011) which are selected according to their market capitalization. The *CDAX* is employed as the benchmark for lottery-like stock selection. The displayed return indices correspond to portfolios without rebalancing: $ETF\&Lottery\ w/o\ RB$, $ETF\&Max\ w/o\ RB$, and $ETF\&Max5\ w/o\ RB$. The period from June 2000 to August 2020 is covered. Due to only marginal differences, return indices where transaction costs are taken into consideration are not displayed.

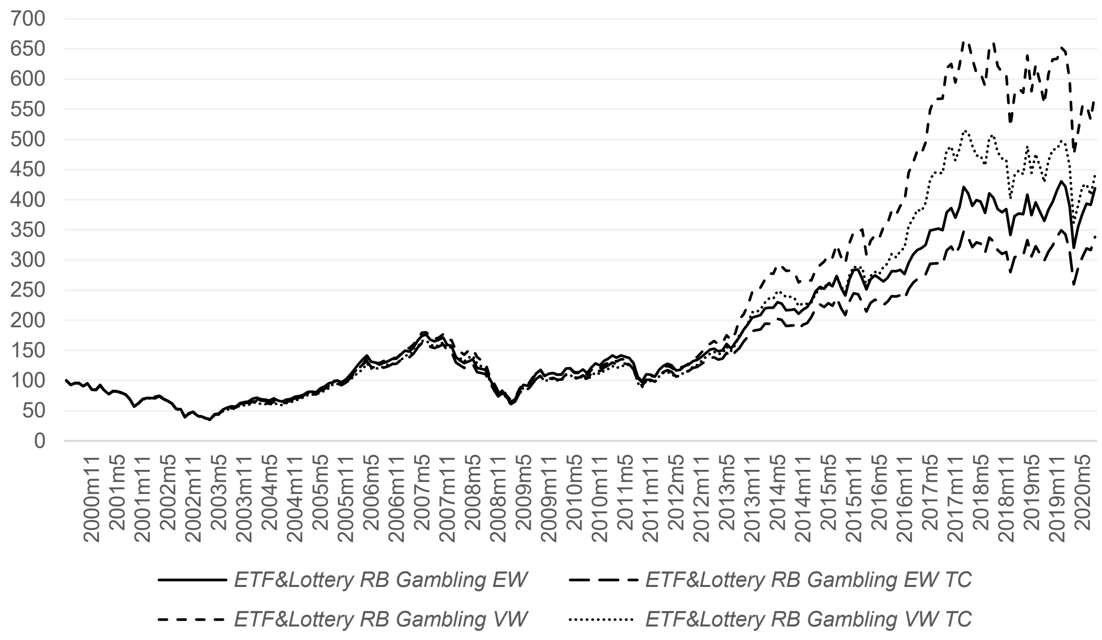

Figure 9: Return Index Portfolios ETF and Lottery-like Stocks ($Lottery$) with Gambling Layer Rebalancing

Notes: The graph above depicts the return indices of four two-layer portfolios. At the beginning, the base layer each portfolio constitutes for 90 percent of all funds; these funds are invested in an ETF (*iShares MSCI Germany*) which is chosen to mirror the German stock market. The gambling layer of the portfolios, respectively accounting for ten percent of the total portfolio value, comprises ten lottery-like stocks as defined by Kumar (2009) which are selected according to their market capitalization. The *CDAX* is employed as the benchmark for lottery-like stock selection. The composition of the gambling layer is readjusted at the beginning of each month (based on the market capitalization of identified lottery-like stocks); there is no rebalancing (i.e. no reallocation of funds) between the base layer and the gambling layer. $ETF\&Lottery\ RB\ Gambling\ EW$ and $ETF\&Lottery\ RB\ Gambling\ VW$ respectively present portfolios with equally-weighted and value-weighted lottery-like stocks (gambling layer) and no transaction costs. $ETF\&Lottery\ RB\ Gambling\ EW\ TC$ and $ETF\&Lottery\ RB\ Gambling\ VW\ TC$ respectively present portfolios with equally-weighted and value-weighted lottery-like stocks where transaction costs are taken into account. The period from June 2000 to August 2020 is covered.

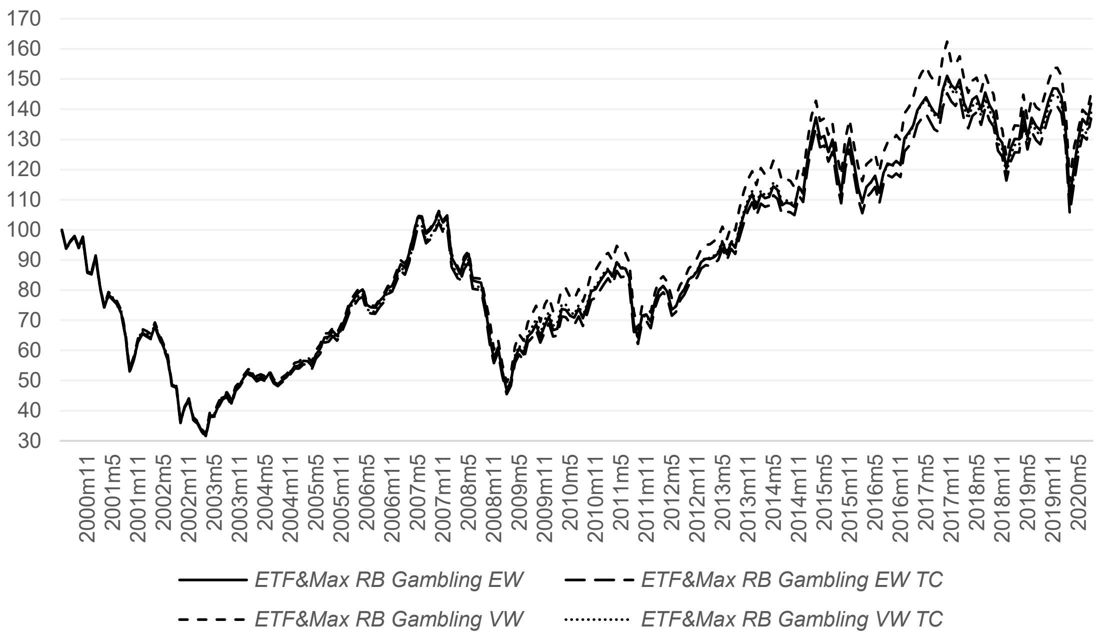

Figure 10: Return Index Portfolios ETF and Lottery-like Stocks (Max) with Gambling Layer Rebalancing

Notes: The graph above depicts the return indices of four two-layer portfolios. At the beginning, the base layer each portfolio constitutes for 90 percent of all funds; these funds are invested in an ETF (*iShares MSCI Germany*) which is chosen to mirror the German stock market. The gambling layer of the portfolios, respectively accounting for ten percent of the total portfolio value, comprises ten lottery-like stocks as defined by Bali et al. (2011), i.e. stocks with the highest maximum daily return over the previous month. The ten lottery-like stocks with the respective highest market capitalization are selected for the gambling layer. which are selected according to their market capitalization. The *CDAX* is employed as the benchmark for lottery-like stock selection. The composition of the gambling layer is readjusted at the beginning of each month (based on the market capitalization of identified lottery-like stocks); there is no rebalancing (i.e. no reallocation of funds) between the base layer and the gambling layer. $ETF\&Max\ RB\ Gambling\ EW$ and $ETF\&Max\ RB\ Gambling\ VW$ respectively present portfolios with equally-weighted and value-weighted lottery-like stocks (gambling layer) and no transaction costs. $ETF\&Max\ RB\ Gambling\ EW\ TC$ and $ETF\&Max\ RB\ Gambling\ VW\ TC$ respectively present portfolios with equally-weighted and value-weighted lottery-like stocks where transaction costs are taken into account. The period from June 2000 to August 2020 is covered.

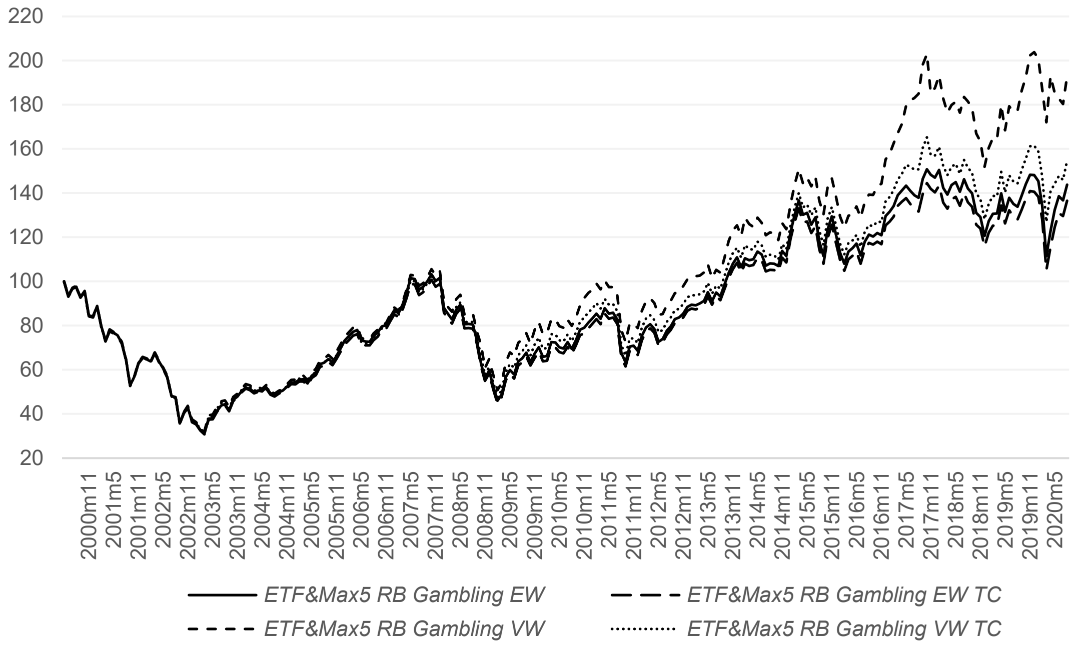

Figure 11: Return Index Portfolios ETF and Lottery-like Stocks ($Max5$) with Gambling Layer Rebalancing

Notes: The graph above depicts the return indices of four two-layer portfolios. At the beginning, the base layer each portfolio constitutes for 90 percent of all funds; these funds are invested in an ETF (*iShares MSCI Germany*) which is chosen to mirror the German stock market. The gambling layer of the portfolios, respectively accounting for ten percent of the total portfolio value, comprises ten lottery-like stocks as defined by Bali et al. (2011), i.e. stocks with the highest average comprising the five highest daily returns of the previous month. The ten lottery-like stocks with the respective highest market capitalization are selected for the gambling layer. The *CDAX* is employed as the benchmark for lottery-like stock selection. The composition of the gambling layer is readjusted at the beginning of each month (based on the market capitalization of identified lottery-like stocks); there is no rebalancing (i.e. no reallocation of funds) between the base layer and the gambling layer. $ETF\&Max\ RB\ Gambling\ EW$ and $ETF\&Max\ RB\ Gambling\ VW$ respectively present portfolios with equally-weighted and value-weighted lottery-like stocks (gambling layer) and no transaction costs. $ETF\&Max\ RB\ Gambling\ EW\ TC$ and $ETF\&Max\ RB\ Gambling\ VW\ TC$ respectively present portfolios with equally-weighted and value-weighted lottery-like stocks where transaction costs are taken into account. The period from June 2000 to August 2020 is covered.

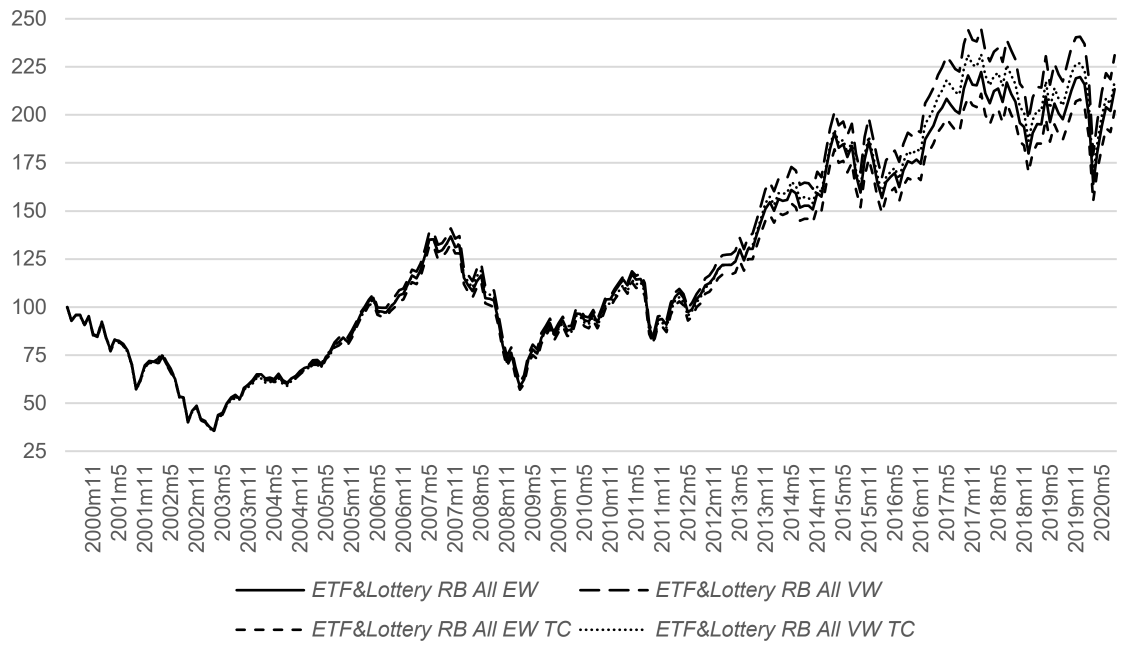

Figure 12: Return Index Portfolios ETF and Lottery-like Stocks ($Lottery$) with Rebalancing

Notes: The graph above depicts the return indices of four two-layer portfolios. At the beginning, the base layer each portfolio constitutes for 90 percent of all funds; these funds are invested in an ETF (*iShares MSCI Germany*) which is chosen to mirror the German stock market. The gambling layer of the portfolios, respectively accounting for ten percent of the total portfolio value, comprises ten lottery-like stocks as defined by Kumar (2009) which are selected according to their market capitalization. The *CDAX* is employed as the benchmark for lottery-like stock selection. The initial relative weights of the two layers are held constant, i.e. total funds are reallocated (i.e. rebalanced) at the beginning of each month. Furthermore, the composition of the gambling layer is readjusted at the beginning of each month (based on the market capitalization of identified lottery-like stocks) $ETF\&Lottery\ RB\ All\ EW$ and $ETF\&Lottery\ RB\ All\ VW$ respectively present portfolios with equally-weighted and value-weighted lottery-like stocks (gambling layer) and no transaction costs. $ETF\&Lottery\ RB\ All\ EW\ TC$ and $ETF\&Lottery\ RB\ All\ VW\ TC$ respectively present portfolios with equally-weighted and value-weighted lottery-like stocks where transaction costs are taken into account. The period from June 2000 to August 2020 is covered.

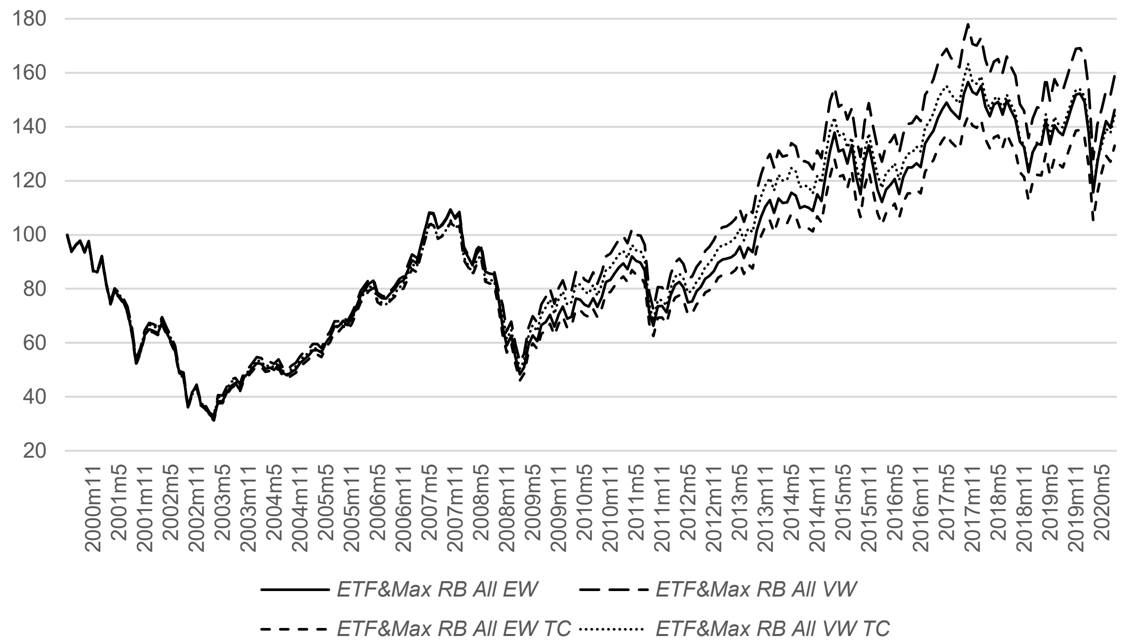

Figure 13: Return Index Portfolios ETF and Lottery-like Stocks (Max) with Rebalancing

Notes: The graph above depicts the return indices of four two-layer portfolios. At the beginning, the base layer each portfolio constitutes for 90 percent of all funds; these funds are invested in an ETF (*iShares MSCI Germany*) which is chosen to mirror the German stock market. The gambling layer of the portfolios, respectively accounting for ten percent of the total portfolio value, comprises ten lottery-like stocks as defined by Bali et al. (2011), i.e. stocks with the highest maximum daily return over the previous month, which are selected according to their market capitalization. The *CDAX* is employed as the benchmark for lottery-like stock selection. The initial relative weights of the two layers are held constant, i.e. total funds are reallocated (i.e. rebalanced) at the beginning of each month. Furthermore, the composition of the gambling layer is readjusted at the beginning of each month (based on the market capitalization of identified lottery-like stocks) $ETF\&Max\ RB\ All\ EW$ and $ETF\&Max\ RB\ All\ VW$ respectively present portfolios with equally-weighted and value-weighted lottery-like stocks (gambling layer) and no transaction costs. $ETF\&Max\ RB\ All\ EW\ TC$ and $ETF\&Max\ RB\ All\ VW\ TC$ respectively present portfolios with equally-weighted and value-weighted lottery-like stocks where transaction costs are taken into account. The period from June 2000 to August 2020 is covered.

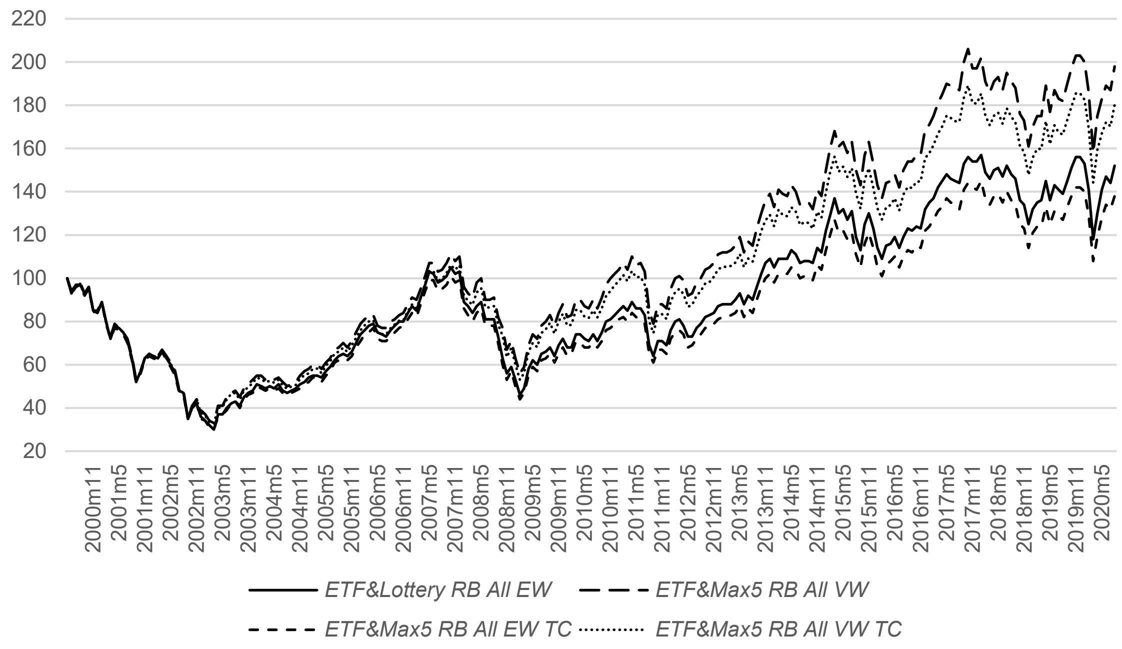

Figure 14: Return Index Portfolios ETF and Lottery-like Stocks ($Max5$) with Rebalancing

Notes: The graph above depicts the return indices of four two-layer portfolios. At the beginning, the base layer each portfolio constitutes for 90 percent of all funds; these funds are invested in an ETF (*iShares MSCI Germany*) which is chosen to mirror the German stock market. The gambling layer of the portfolios, respectively accounting for ten percent of the total portfolio value, comprises ten lottery-like stocks as defined by Bali et al. (2011), i.e. stocks with the highest average comprising the five highest daily returns of the previous month. The ten lottery-like stocks with the respective highest market capitalization are selected for the gambling layer. The *CDAX* is employed as the benchmark for lottery-like stock selection. The initial relative weights of the two layers are held constant, i.e. total funds are reallocated (i.e. rebalanced) at the beginning of each month. Furthermore, the composition of the gambling layer is readjusted at the beginning of each month (based on the market capitalization of identified lottery-like stocks) $ETF\&Max5\ RB\ All\ EW$ and $ETF\&Max5\ RB\ All\ VW$ respectively present portfolios with equally-weighted and value-weighted lottery-like stocks (gambling layer) and no transaction costs. $ETF\&Max5\ RB\ All\ EW\ TC$ and $ETF\&Max5\ RB\ All\ VW\ TC$ respectively present portfolios with equally-weighted and value-weighted lottery-like stocks where transaction costs are taken into account. The period from June 2000 to August 2020 is covered.

A12 Risk Factors Multi-layer Portfolios ($ETF\&90plusX$, $ETF\&Favorite$, and $ETF\&Underdog$) with Transaction Costs (*Section 8*)

	W/o Rebalancing			Rebalancing Gambling Layer			Rebalancing All		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel°A: Equally-weighted Lottery-like stocks (with Transaction Costs)									
Measured over Previous Month ($1M$, $t-1$)									
Total Volatility									
Mean	1.3262	1.3627	1.3660	1.2631	1.3747	1.3849	1.3272	1.3159	1.3331
Median	1.1527	1.1882	1.1900	1.0873	1.2076	1.2096	1.1607	1.1702	1.1851
Idiosyncratic Volatility									
Mean	.6572	.6879	.6918	.6061	.6957	.7019	.6476	.6545	.6565
Median	.5551	.5782	.5825	.5259	.5875	.5930	.5568	.5565	.5492
Total Skewness									
Mean	-.0323	-.0382	-.0374	-.0320	-.0365	-.0359	-.0444	-.0396	-.0457
Median	-.0728	-.0763	-.0703	-.0340	-.0736	-.0568	-.0871	-.0636	-.0635
Idiosyncratic Skewness (ISkew2F)									
Mean	-.0061	-.0074	-.0049	.0442	-.0129	-.0138	.0032	-.0192	-.0217
Median	-.0078	-.0515	-.0341	.0683	-.0202	-.0160	.0049	-.0627	-.0488
Idiosyncratic Skewness (ISkew3F)									
Mean	-.0153	-.0083	-.0067	.0002	-.0078	-.0086	-.0068	-.0049	-.0119
Median	-.0168	-.0406	-.0365	-.0048	-.0429	-.0321	-.0098	-.0144	.0018
Maximum Daily Return									
Mean	2.6285	2.6993	2.7066	2.4592	2.7252	2.7466	2.6198	2.5969	2.6275
Median	2.2132	2.3170	2.3247	2.0321	2.3180	2.3670	2.1901	2.1687	2.2068
Average of 5 highest Daily Returns									
Mean	1.6764	1.7206	1.7250	1.6200	1.7345	1.7485	1.6786	1.6589	1.6801
Median	1.4292	1.4613	1.4648	1.3822	1.4664	1.4814	1.4345	1.4161	1.4188
Measured over Previous Six Months ($6M$, $t-6$ to $t-1$)									
Total Volatility									
Mean	1.3786	1.4164	1.4197	1.3131	1.4287	1.4391	1.3800	1.3677	1.3846
Median	1.2251	1.2531	1.2552	1.1738	1.2623	1.2712	1.2273	1.2125	1.2328
Idiosyncratic Volatility									
Mean	.7706	.8089	.8131	.7084	.8171	.8250	.7623	.7669	.7693
Median	.6484	.6783	.6838	.5940	.6868	.6966	.6496	.6582	.6555
Total Skewness									
Mean	-.1953	-.1950	-.1939	-.2205	-.1922	-.1892	-.2111	-.1970	-.2005
Median	-.1508	-.1559	-.1551	-.2037	-.1583	-.1570	-.1863	-.1688	-.1742
Idiosyncratic Skewness (ISkew2F)									
Mean	-.1264	-.1148	-.1134	-.0826	-.1162	-.1169	-.1171	-.1133	-.1260
Median	-.0208	-.0129	-.0122	-.0137	-.0057	-.0041	-.0330	-.0303	-.0169
Idiosyncratic Skewness (ISkew3F)									
Mean	-.1077	-.0988	-.0994	-.0280	-.1027	-.1029	-.0877	-.0699	-.0846
Median	-.0294	-.0243	-.0244	.0093	-.0390	-.0385	-.0426	-.0359	-.0269

Table 32: Risk Factors Portfolios $ETF\&Lottery$, $ETF\&Max$, and $ETF\&Max5$ with Transaction Costs

The table above displays portfolio risk factors for different two-layer portfolios; these portfolios contain a base layer and a gambling layer. Funds corresponding to the base layer of each portfolio are invested in an ETF (*iShares MSCI Germany*) which is chosen to mirror the German stock market. The gambling layer comprises returns from lottery-like stocky. In *Panel°A*, the lottery-like stocks within the gambling layer are equally-weighted; *Panel°B* depicts results for value-weighted lottery-like stocks.

	W/o Rebalancing			Rebalancing Gambling Layer			Rebalancing All		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel°B: Value-weighted Lottery-like stocks (with Transaction Costs)									
Measured over Previous Month ($1M$, $t-1$)									
Total Volatility									
Mean	1.3821	1.3857	1.3877	1.3457	1.3572	1.3604	1.3328	1.3221	1.3439
Median	1.2072	1.2103	1.2120	1.1607	1.1849	1.1885	1.1713	1.1700	1.1844
Idiosyncratic Volatility									
Mean	.7050	.7091	.7104	.6979	.6825	.6831	.6543	.6601	.6670
Median	.5970	.6023	.6038	.6192	.5797	.5832	.5593	.5671	.5749
Total Skewness									
Mean	-.0342	-.0348	-.0344	.0112	-.0352	-.0380	-.0320	-.0374	-.0424
Median	-.0695	-.0756	-.0759	.0018	-.0874	-.0342	-.0963	-.0525	-.0514
Idiosyncratic Skewness (ISkew2F)									
Mean	-.0028	-.0024	-.0024	.0843	-.0051	-.0138	.0250	-.0014	-.0146
Median	-.0061	-.0098	-.0091	.0845	-.0244	-.0211	.0163	-.0247	-.0158
Idiosyncratic Skewness (ISkew3F)									
Mean	-.0049	-.0038	-.0036	.0306	.0039	-.0007	.0141	.0130	.0024
Median	-.0379	-.0378	-.0372	.0745	-.0315	-.0104	.0125	-.0031	-.0120
Maximum Daily Return									
Mean	2.7445	2.7513	2.7554	2.6825	2.6962	2.6912	2.6367	2.6226	2.6587
Median	2.3527	2.3647	2.3644	2.2888	2.2905	2.3026	2.2271	2.1909	2.2406
Average of 5 highest Daily Returns									
Mean	1.7471	1.7513	1.7538	1.7434	1.7112	1.7181	1.6890	1.6648	1.6963
Median	1.4814	1.4819	1.4842	1.5284	1.4500	1.4500	1.4413	1.4244	1.4515
Measured over Previous Six Months ($6M$, $t-6$ to $t-1$)									
Total Volatility									
Mean	1.4361	1.4398	1.4418	1.3949	1.4111	1.4143	1.3846	1.3756	1.3974
Median	1.2758	1.2801	1.2823	1.2367	1.2528	1.2594	1.2294	1.2193	1.2435
Idiosyncratic Volatility									
Mean	.8280	.8331	.8346	.8168	.8022	.8010	.7700	.7753	.7824
Median	.7003	.7060	.7073	.7417	.6813	.6812	.6588	.6742	.6815
Total Skewness									
Mean	-.1897	-.1897	-.1893	-.1119	-.1878	-.1838	-.1981	-.1834	-.1797
Median	-.1522	-.1541	-.1542	-.1299	-.1722	-.1594	-.1572	-.1693	-.1588
Idiosyncratic Skewness (ISkew2F)									
Mean	-.1111	-.1092	-.1093	.0095	-.1090	-.1176	-.0975	-.0919	-.1110
Median	.0026	-.0005	.0004	.0707	-.0057	-.0085	.0010	-.0077	-.0257
Idiosyncratic Skewness (ISkew3F)									
Mean	-.1010	-.0996	-.0998	.0333	-.0852	-.0752	-.0735	-.0492	-.0556
Median	-.0353	-.0321	-.0317	.0074	-.0129	-.0250	-.0232	-.0030	-.0183

Table 32 – *continued*

A13 Performance Multi-layer Portfolios (*Section 8*)

	Raw Return			Time Series Regression					
	Mean	Median	SD	α	$RMRF$	SMB	HML	WML	R^2
Panel°A: Multi-layer Portfolios ETF and Sports Betting									
W/o Rebalancing, w/o Transaction Costs									
$ETF\&90plusX$	.2780	1.0925	4.6165	.0784	.6530***	-.2042	-.2238	-.3409***	.6032
				(.19)	(7.47)	(-1.05)	(-1.53)	(-2.91)	
$ETF\&Favorite$	.6891	1.1949	5.2198	.0424	.8881***	-.3341***	-.1410***	-.1964***	.8951
				(.33)	(33.29)	(-7.92)	(-3.10)	(-6.59)	
$ETF\&Underdog$	.7999	1.5046	6.6126	.1441	.8624***	-.2769**	.0373	-.2217***	.5538
				(.43)	(12.39)	(-2.52)	(.32)	(-2.85)	
W/o Rebalancing, with Transaction Costs									
$ETF\&90plusX$	.2778	1.0878	4.6168	.0784	.6526***	-.2040	-.2236	-.3408***	.6025
				(.19)	(7.46)	(-1.05)	(-1.53)	(-2.91)	
$ETF\&Favorite$	.6890	1.1946	5.2198	.0423	.8881***	-.3341***	-.1410***	-.1964***	.8950
				(.33)	(33.29)	(-7.92)	(-3.10)	(-6.59)	
$ETF\&Underdog$	.8002	1.4965	6.6168	.1444	.8623***	-.2768**	.0376	-.2218***	.5530
				(.43)	(12.37)	(-2.51)	(.32)	(-2.85)	
With Rebalancing, w/o Transaction Costs									
$ETF\&90plusX$	.3700	.8323	4.5540	.1763	.6977***	-.2667	-.2543**	-.3487***	.6867
				(.50)	(9.11)	(-1.57)	(-1.98)	(-3.40)	
$ETF\&Favorite$	.3497	.6853	5.0949	-.2276	.8104***	-.3310***	-.1214**	-.2019***	.8107
				(-1.34)	(23.19)	(-5.99)	(-2.04)	(-5.17)	
$ETF\&Underdog$	1.4806	1.1705	6.3873	.9884***	.7507***	-.3878***	-.1839	-.2117***	.4680
				(2.77)	(10.22)	(-3.34)	(-1.47)	(-2.58)	
With Rebalancing, with Transaction Costs									
$ETF\&90plusX$	.3664	.8297	4.5545	.1729	.6978***	-.2669	-.2542**	-.3486***	.6867
				(.49)	(9.11)	(-1.57)	(-1.98)	(-3.40)	
$ETF\&Favorite$	.3458	.6811	5.0947	-.2315	.8104***	-.3309***	-.1214**	-.2019***	.8107
				(-1.36)	(23.19)	(-5.99)	(-2.04)	(-5.17)	
$ETF\&Underdog$	1.4741	1.1580	6.3866	.9819***	.7505***	-.3876***	-.1836	-.2117**	.4679
				(2.75)	(10.22)	(-3.34)	(-1.47)	(-2.58)	

Table 33: Performance Multi-layer Portfolios

Notes: This table (*Panel°A*) reports performance key figures for multi-layer portfolios: $ETF\&90plusX$, $ETF\&Favorite$, and $ETF\&Underdog$. These portfolios contain a base layer and a gambling layer. The Mean, Median, and standard deviation (SD) of monthly portfolio returns are reported. Furthermore, time-series regression estimates from Carhart's (1997) four-factor model are reported. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively; t-statistics are displayed in parentheses.

	Raw Return			Time Series Regression					
	Mean	Median	SD	α	$RMRF$	SMB	HML	WML	R^2
Panel°B: Multi-layer Portfolios ETF and Lottery-like Stocks									
W/o Rebalancing, w/o Transaction Costs									
Equally-weighted Lottery-like Stocks									
$ETF\&Lottery$	.3573	1.0410	5.8780	-.1152	.9539***	-.2071***	-.0216	-.1381***	.9159
				(-1.00)	(40.34)	(-5.83)	(-.60)	(-6.49)	
$ETF\&Max$	.3334	.9118	5.9871	-.1306	.9716***	-.2058***	-.0487	-.1416***	.9167
				(-1.12)	(40.54)	(-5.71)	(-1.34)	(-6.57)	
$ETF\&Max5$	.3296	.9282	5.9794	-.1397	.9710***	-.2105***	-.0459	-.1387***	.9168
				(-1.20)	(40.59)	(-5.86)	(-1.26)	(-6.45)	
Value-weighted Lottery-like Stocks									
$ETF\&Lottery$	.3623	.9403	5.8796	-.1101	.9543***	-.2045***	-.0185	-.1390***	.9160
				(-.95)	(40.37)	(-5.76)	(-.51)	(-6.54)	
$ETF\&Max$	.3383	.9748	5.9403	-.1299	.9669***	-.2033***	-.0452	-.1369***	.9174
				(-1.12)	(40.83)	(-5.71)	(-1.26)	(-6.43)	
$ETF\&Max5$	.3299	.9484	5.9590	-.1460	.9707***	-.2136***	-.0464	-.1332***	.9182
				(-1.27)	(41.06)	(-6.01)	(-1.29)	(-6.27)	
Rebalancing Gambling Layer, w/o Transaction Costs									
Equally-weighted Lottery-like Stocks									
$ETF\&Lottery$	.8011	1.1793	6.4318	.4015**	1.0247***	.1128**	.0816	-.2110***	.8605
				(2.47)	(30.76)	(2.25)	(1.61)	(-7.04)	
$ETF\&Max$	.3279	1.1273	5.9858	-.1230	.9713***	-.1884***	-.0624*	-.1440***	.9145
				(-1.04)	(40.03)	(-5.17)	(-1.69)	(-6.60)	
$ETF\&Max5$	.3341	1.1012	5.9959	-.1217	.9749***	-.1996***	-.0677*	-.1412***	.9187
				(-1.05)	(41.13)	(-5.60)	(-1.88)	(-6.63)	
Value-weighted Lottery-like Stocks									
$ETF\&Lottery$	.9486	1.4700	6.6338	.6035***	.9653***	.1603**	.1131	-.2379***	.7451
				(2.66)	(20.78)	(2.30)	(1.60)	(-5.70)	
$ETF\&Max$	.3350	1.1403	5.9492	-.1215	.9631***	-.1801***	-.0610	-.1346***	.9003
				(-.96)	(36.98)	(-4.60)	(-1.54)	(-5.75)	
$ETF\&Max5$	.4509	1.0118	5.9403	.0230	.9429***	-.1807***	-.1154**	-.1295***	.8700
				(.16)	(31.75)	(-4.05)	(-2.56)	(-4.85)	
Rebalancing All, w/o Transaction Costs									
Equally-weighted Lottery-like Stocks									
$ETF\&Lottery$	.4998	.8468	6.0544	.0763	.9789***	-.1304***	-.0245	-.1754***	.9172
				(.65)	(40.52)	(-3.59)	(-.67)	(-8.07)	
$ETF\&Max$	.3382	1.0264	5.9529	-.0971	.9671***	-.1425***	-.0593	-.1484***	.9073
				(-.79)	(38.46)	(-3.77)	(-1.55)	(-6.56)	
$ETF\&Max5$	.3551	1.2653	5.9824	-.0783	.9758***	-.1450***	-.0782**	-.1465***	.9132
				(-.66)	(39.91)	(-3.95)	(-2.10)	(-6.66)	
Value-weighted Lottery-like Stocks									
$ETF\&Lottery$	.5284	1.3020	5.9821	.1103	.9633***	-.1173***	-.0230	-.1718***	.9056
				(.89)	(37.78)	(-3.06)	(-.59)	(-7.50)	
$ETF\&Max$	.3706	1.1215	5.9247	-.0812	.9575***	-.1685***	-.0593	-.1350***	.8951
				(-.63)	(35.99)	(-4.22)	(-1.47)	(-5.65)	
$ETF\&Max5$	.4640	1.1041	5.9679	.0196	.9682***	-.1679***	-.0957**	-.1310***	.8993
				(.15)	(36.87)	(-4.25)	(-2.40)	(-5.55)	

Table 33 – *continued*

Notes: *Panel°B* reports performance key figures for multi-layer portfolios: $ETF\&Lottery$, $ETF\&Max$, and $ETF\&Max5$. The portfolios contain a base and a gambling layer. The Mean, Median, and standard deviation (SD) of monthly portfolio returns are reported. Furthermore, time-series regression estimates from Carhart's (1997) four-factor model are reported. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively; t-statistics are displayed in parentheses.

	Raw Return			Time Series Regression					
	Mean	Median	SD	α	$RMRF$	SMB	HML	WML	R^2
Panel°B – continued									
W/o Rebalancing, with Transaction Costs									
Equally-weighted Lottery-like Stocks									
$ETF\&Lottery$	.3573	1.0414	5.8780	-.1152	.9539***	-.2072***	-.0217	-.1381***	.9159
				(-1.00)	(40.34)	(-5.83)	(-.60)	(-6.49)	
$ETF\&Max$	.3334	.9119	5.9871	-.1306	.9716***	-.2058***	-.0487	-.1416***	.9167
				(-1.12)	(40.54)	(-5.71)	(-1.34)	(-6.57)	
$ETF\&Max5$	.3296	.9282	5.9794	-.1397	.9710***	-.2105***	-.0459	-.1387***	.9168
				(-1.20)	(40.59)	(-5.86)	(-1.26)	(-6.45)	
Value-weighted Lottery-like Stocks									
$ETF\&Lottery$	.3624	.9402	5.8797	-.1101	.9544***	-.2045***	-.0185	-.1390***	.9160
				(-.95)	(40.37)	(-5.76)	(-.51)	(-6.54)	
$ETF\&Max$	.3384	.9748	5.9403	-.1299	.9669***	-.2033***	-.0452	-.1369***	.9174
				(-1.12)	(40.83)	(-5.71)	(-1.26)	(-6.43)	
$ETF\&Max5$	.3300	.9471	5.9590	-.1460	.9707***	-.2137***	-.0464	-.1332***	.9182
				(-1.27)	(41.06)	(-6.01)	(-1.29)	(-6.27)	
Rebalancing Gambling Layer, with Transaction Costs									
Equally-weighted Lottery-like Stocks									
$ETF\&Lottery$	.7085	1.2755	6.3450	.3038**	1.0181***	.0776*	.0669	-.2046***	.8738
				(1.99)	(32.56)	(1.65)	(1.41)	(-7.28)	
$ETF\&Max$	.3157	.9907	6.0094	-.1405	.9733***	-.2035***	-.0611*	-.1437***	.9152
				(-1.19)	(40.12)	(-5.58)	(-1.66)	(-6.59)	
$ETF\&Max5$	.3151	.9540	6.0139	-.1463	.9754***	-.2130***	-.0628*	-.1411***	.9179
				(-1.25)	(40.81)	(-5.93)	(-1.73)	(-6.56)	
Value-weighted Lottery-like Stocks									
$ETF\&Lottery$	.8291	1.2268	6.4914	.4723**	.9655***	.1208*	.0961	-.2285***	.7746
				(2.26)	(22.58)	(1.88)	(1.48)	(-5.94)	
$ETF\&Max$	.3197	1.1522	5.9768	-.1410	.9696***	-.1974***	-.0603	-.1373***	.9109
				(-1.17)	(39.19)	(-5.31)	(-1.60)	(-6.17)	
$ETF\&Max5$	.3610	1.0150	5.9342	-.0881	.9621***	-.1988***	-.0869**	-.1339***	.9106
				(-.73)	(39.11)	(-5.38)	(-2.32)	(-6.05)	
Rebalancing All, with Transaction Costs									
Equally-weighted Lottery-like Stocks									
$ETF\&Lottery$	.4772	.8271	6.0521	.0534	.9787***	-.1305***	-.0246	-.1749***	.9172
				(.45)	(40.54)	(-3.60)	(-.67)	(-8.06)	
$ETF\&Max$	.2999	.9902	5.9495	-.1355	.9666***	-.1427***	-.0593	-.1481***	.9073
				(-1.11)	(38.48)	(-3.78)	(-1.55)	(-6.56)	
$ETF\&Max5$	.3176	1.2282	5.9790	-.1160	.9753***	-.1452***	-.0781	-.1461***	.9132
				(-.97)	(39.92)	(-3.95)	(-2.10)	(-6.65)	
Value-weighted Lottery-like Stocks									
$ETF\&Lottery$	.5043	1.2793	5.9804	.0860	.9632***	-.1173***	-.0230	-.1715***	.9056
				(.69)	(37.81)	(-3.06)	(-.59)	(-7.49)	
$ETF\&Max$	.3315	1.0833	5.9215	-.1203	.9571***	-.1686***	-.0592	-.1348***	.8952
				(-.93)	(36.01)	(-4.22)	(-1.47)	(-5.64)	
$ETF\&Max5$	.4258	1.0672	5.9646	-.0187	.9678***	-.1680***	-.0956**	-.1307***	.8994
				(-.15)	(36.90)	(-4.26)	(-2.40)	(-5.54)	

Table 33 – *continued*