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# THE IMPACT OF NEO-BROKERS ON THE OVERCONFIDENCE BIAS OF YOUNG RETAIL INVESTORS IN GERMANY

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**Abstract**

Neo-brokers play an essential role in the increase of young retail investors in Germany. Providing commission-free, low-cost trading and an engaging user experience, neo-brokers stimulate the investment behavior of young investors. By collecting data through an online survey, the impact of neo-brokers in Germany on the overconfidence bias of young retail investors will be examined. Setting up hierarchical binary logistic regression models, the study finds that young retail investors trade more frequently when investing through neo-brokers. However, there is no evidence that men trade more than women and thereby achieve lower returns when using neo-brokers.

Keywords (broker, Fintech, neo-broker, investment behavior, overconfidence, retail investors, online survey, hierarchical binary logistic regression)

**Abbreviations**

| | |
|---|---|
| CI | Confidence Interval |
| ETF | Exchange-traded Fund |
| OR | Odds ratio |

## 1. Introduction

Since 2019, many trading platforms offering commission-free and low-cost trading combined with a highly interactive and straightforward mobile app or website emerged in the German market (Fischer, Hübner, and Bulis 2020; Frölich and Lembach 2021). These so-called neo-brokers enabled the shift from wealthy and institutional investors to less affluent, young retail investors. However, critics claim that the friction management of neo-brokers aggravates retail investors' overconfidence bias (Ash et al. 2018; Chaudhry and Kulkarni 2021). In 2020, retail investors who are younger than 30 years experienced the highest increase in German stock market participation compared to other age groups (Deutsches Aktieninstitut, 2020). Thus, this directed research project focuses on retail investors aged 18 to 29 years, with 18 being the minimum age to be allowed to invest through neo-brokers (ibid.). By employing a deductive research approach including hierarchical binary logistic models, the following hypotheses based on the literature of Odean (1999) and Barber and Odean (2000, 2001, 2011) are tested. At first, the focus is on whether using neo-brokers increases young retail investors' trading frequency. Then, the focus is on validating that men trade more than women by executing trades through neo-brokers. Lastly, given trading through neo-brokers and having a higher trading frequency, it is tested whether male retail investors achieve lower portfolio returns than female retail investors.

This directed research project contributes to the existing literature in three ways. First, the research on the overconfident behavior of retail investors by Barber and Odean (2000, 2001, 2011) and Odean (1999) will be placed in the context of trading through neo-brokers versus online brokers. Second, the major determinants of investors' overconfidence bias identified by Kansal and Singh (2018) and Mishraa and Metildab (2015) will be reevaluated. Third, this thesis elaborates on additional indicators that impact investors' trading frequency and portfolio return. First, the literature review provides insights into the overconfidence bias of retail investors and the impact of neo-brokers on this cognitive bias by formulating three different hypotheses. Then, the methodology will be elaborated on, including the data generation process and hierarchical binary logistic regressions to analyze the hypotheses.

## 2. Literature review

The first section of the literature review covers the definition of the overconfidence bias, its impact on the investment behavior of retail investors, and its major determinants. Subsequently, the emergence of neo-brokers in Germany is discussed, followed by their impact on the overconfidence bias of young retail investors.

### 2.1 Overconfidence bias

According to Kahneman (2011), individuals rely on "System 1" and "System 2" thinking. Since the brain uses mental shortcuts by filtering out information in "System 1" thinking (heuristic simplification), individuals are more prone to cognitive biases, such as the overconfidence bias (Baker and Nofsinger 2002). Overconfidence bias is individuals' tendency to overestimate their abilities, knowledge, beliefs, and judgments and demonstrate more confidence than necessary in a given scenario (Gill et al. 2018). Moore and Healey (2008) distinguish between three separate phenomena of overconfidence: overestimation, overplacement, and overprecision. Overestimation refers to individuals being overconfident about their absolute competence or performance in an area, implying that they overestimate their outcome (Grieco and Hogarth 2009). On the other hand, overplacement is the inverse of overestimation in terms of relative comparisons within a group. This is also called the "better-than-average-effect" since individuals rate their skills and prospects as superior to their peers ( Barber and Odean 1999; Alicke and Govorun 2005). Lastly, overconfidence is demonstrated by individuals' tendency to overstate the precision of their knowledge by submitting far too narrow intervals for the evaluation of uncertain and unknown quantities, which is referred to as overprecision or miscalibration (Odean 1998; Klayman and Soll 2004; Glaser and Weber 2007).

### 2.1.1 Overconfidence bias and retail investment behavior

In contrast to traditional finance, which focuses on how retail investors should act, behavioral finance examines individuals' cognitive shortcuts and errors when conducting an investment decision (Statman 2019). Overestimation errors occur when investors overrate the precision of their knowledge about a financial instrument's value compared to the value indicated by publicly available information (Barber and Odean 2001; Kartini and Nahda 2021). Hence, overconfident investors disregard models and data in favor of their convictions. Overplacement errors are conducted when investors perceive their investment skills and performance as superior to other investors (Odean 1999). Finally, investors make overprecision errors when setting too narrow prediction intervals for the value of a financial instrument (ibid.).

The overconfidence bias inclines investors to trade more than rational investors, lowering their anticipated utility in the investment process (Odean 1998, 1999; Barber and Odean 2000, 2001, 2002, 2011). Overconfidence stimulates trading activity by causing investors to be overconfident in their judgments and underrate the opinions of others (Barber and Odean 1999; Riaz and Iqbal 2015). They perform worse than relevant benchmarks after accounting for trading expenses, and those who trade the most experience the lowest results (Barber and Odean 2000). Additionally, Odean (1999) found that the securities purchased by overconfident investors underperform those they sold. In general, male investors are more overconfident than female investors, resulting in increased trading activity and worse portfolio performance ( Barber and Odean 2001, 2011; Bakar and Yi 2016; Guddati and Bhat 2021). Because of limited predictability and abrasive input, it is challenging to choose common equities that will beat the market. Hence, stock selection is the stage of the investment process in which individuals tend to overestimate their capabilities (Barber and Odean 2001). If the actual return is less than predicted, overconfident investors will link it to an unlucky circumstance (Miller 1975).

### 2.1.2 Major determinants of retail investors' overconfidence bias

Besides the direct impact of the overconfidence bias on the investment behavior of retail investors, several researchers elaborate on the demographic and investment characteristics that positively correlate with investor overconfidence. These characteristics can reinforce the overconfidence bias regarding the phenomena mentioned above. Kansal and Singh (2018) identify that investors with a high income and many dependents, such as children and non-working spouses, are more susceptible to the overconfidence bias. Moreover, there is a positive correlation between high investment frequency, shorter investment time horizon, more investment experience, and investing in companies with a large market capitalization and investor overconfidence. Lastly, Mishraa and Metildab (2015) find that a higher degree of education and working in the financial sector positively impacts the overconfidence bias of retail investors.

## 2.2 Neo-brokers in Germany

Starting in 2019, neo-brokers such as Trade Republic, justTrade, and Scalable Capital have been launched in Germany, providing 24/7 commission-free and low-cost trading. This is achieved by offering an easy, straightforward, and seamless mobile app or website, which also enables purchasing partial stocks[1] ( Fischer, Hübner, and Bulis 2020; Frölich and Lembach 2021; Guddati and Bhat 2021). Trade Republic charges €1 for third-party costs per executed order, whereas justTrade provides free trading without third-party costs (Fischer, Hübner, and Bulis 2020; Trade Republic 2022b; JustTrade 2022). To facilitate low-cost capital market

[1] Investors can buy parts of a share

participation, innovation in very cost-effective IT infrastructure is combined with payment-for-order-flow business models, where all trading is routed through only one exchange venue (market maker)[2] (Fischer, Hübner, and Bulis 2020; Guddati and Bhat 2021). Market makers earn from the spread of bid and ask prices and neo-brokers receive a commission for each order. Therefore, critics claim that neo-brokers may not act in the investors' best interest. However, Meyer, Uhr, and Lutz (2021) prove that, on average, Trade Republic's execution prices are lower than those at Xetra[3] and are only higher on very rare occasions.

From a societal standpoint, the advent of neo-brokers in Germany addresses two critical issues. The first one is the shrinking generosity of Germany's public pension systems, which places a greater responsibility on households to supplement state pension payments. The second issue is the relatively low stock market participation (ibid.). Thus, neo-brokers have moved the stock market away from institutional and wealthy investors toward less affluent retail investors by aiming to "democratize investing" through no commission, low trading costs, and not requiring a minimum amount to invest[4], (Chaudhry and Kulkarni 2021).

### 2.2.1 The increase in young retail investors

Through their creative design, neo-brokers attract a young target group and elevate investments in financial instruments to a trendy activity (Chandar and Ferraioli 2021). In 2020, the German stock market experienced the highest increase in financial security holders in the last 20 years reaching 12.4 million. This increase was impacted by neo-brokers' surge in customer base during the Covid-19 pandemic (Tan 2021). Investors under 30 years were particularly active, with a growth rate of almost 70% to 1.4 million compared to 2019. Thus, this target group grew

[2] As of March 2022, Trade Republic solely offers trading through the electronic trading system Lang & Schwarz TradeCenter AG & Co. KG, operated by the Hamburg Stock Exchange (Trade Republic 2022a).
[3] Trading venue operated by Frankfurter Wertpapierbörse (FWB, the Frankfurt Stock Exchange)
[4] No minimum amount for the purchase of single stocks. The investment volume per execution of a savings plan purchase regarding ETF/stock ranges €10 to €10,000 (Trade Republic 2022b).

two times faster than other age groups. According to Deutsches Aktieninstitut (2020), most of this age cohort invests in single stocks instead of exchange-traded funds (ETFs), and the ratio of male investors to female investors is 2:1. In the further course of this thesis, retail investors are investors with German citizenship or German permanent residence permit who are between 18 and 29 years old.

### 2.2.2 Impact on overconfidence bias of young retail investors

Neo-brokers' overarching objective is to increase financial inclusion by encouraging and enabling more users, particularly younger people, to engage in the stock market. However, the trading applications' design choices and business models can potentially aggravate investors' inherent overconfidence bias (Guddati and Bhat 2021). Trading platforms can be conceived as technological and social decision systems that shape investor behavior because their design, structure, and features allow and restrain certain trading behaviors (Norman 2004; Chaudhry and Kulkarni 2021).

Neo-brokers simplify the trading process by eliminating frictions that interrupt, impede, or prevent users from carrying out a task in their digital interface, such as completing a trade. However, frictions are managed productively, encouraging their customers to continue interacting with the trading interface. This is achieved by triggering the users' spectrum of chemical, emotional, sensory, motor, and memory factors that struggle for control over how users think, feel, and ultimately determine how to respond in a situation (Ash et al. 2018). More specifically, neo-brokers use frictions such as sliders, buttons, and background data analytics to increase user engagement, resulting in a higher click-through rate (ibid.; Tan 2021). For instance, the essential design elements of "buy" and "sell" buttons are the size and color, the font and text inside the buttons, as well as the buttons' position on the interface (Ash et al. 2018). As can be seen in the case of Trade Republic, the "buy" and "sell" buttons are customized to the daily, weekly, monthly, yearly, and maximum return of a security. This is implemented by displaying a green background color when the security achieves a positive return and a red background when a negative return is performed in the given time frame (Appendix A). Trade Republic's interface designers aim to entice customers to execute a transaction through this interactive and changing design. Additionally, the friction management of German neo-brokers is reflected in the reduced number of clicks required to complete a transaction (Appendix B). As of 2022, Trade Republic maximizes transaction rates by enabling its customers to execute a trade within three clicks. With a conventional online broker, an average of twelve clicks is required (Jetter 2019).

In comparison to the dashboards of traditional investment platforms, neo-brokers' trading interface demonstrates the simplicity of information by solely presenting ten key indicators[6]. This reinforces the simplicity of trading financial instruments (Tan 2021). However, micro-interactions work as thresholds that reveal further information on the interface of neo-brokers' trading platforms. For instance, an interactive price chart is available for securities. A gray vertical line appears by dragging the finger over the chart, indicating the price, return rate, and total return at a particular time spot. Thus, the body's movement gets inextricably linked to the variable amount of the fluctuating stock price, which leads to increased user engagement (Ash et al. 2018; Tan 2021). Through the easy to navigate, engaging, and intuitive virtual trading platforms, investors are encouraged to trade more often, leading to poor financial outcomes ( Barber and Odean 2002; Barber et al. 2020; Tan 2021).

Overall, these platforms encourage young investors to depend more on intuition ("System 1" thinking) and less on critical thinking ("System 2" thinking) (Kahneman 2011). Given that individuals are more prone to rely on the intuitive "System 1" later in the day and that neo-brokers offer the opportunity to trade 24/7, substantial after-hour effects of neo-brokers' trading platforms on investors' overconfidence can be observed (Kahneman 2011; Kalda et al. 2021).

[6] See Trade Republic's application trading interface as of March 2022

Furthermore, the absence of commissions and the low trading costs exaggerate the active trading phenomenon among young and inexperienced investors, leading to lower portfolio returns (ibid.). As can be withdrawn from data of US neo-broker Robinhood, its customers "[…] traded nine times as many shares as E-Trade customers, and 40 times as many shares as Charles Schwab customers, per dollar in the average customer account […]", in the first quarter of 2020 (Popper 2020, n.p.).

## 3. Hypotheses development

As can be withdrawn from the literature review, neo-brokers engage in friction management, which impacts young investors to act toward certain behaviors (Norman 2004; Ash et al. 2018; Chaudhry and Kulkarni 2021). This is mainly reflected in the platforms' high user engagement, simple and seamless interface, and the reduced number of clicks for transaction completion. Hence, users are incentivized to execute an increased number of trades, ultimately leading to the following hypothesis:

*H1: German neo-brokers increase the trading frequency of young retail investors.*

When taking the German financial retail market into account, the ratio of male investors (0.93 million) to female investors (0.47 million) under 30 years is 2:1 (Deutsches Aktieninstitut 2020). Because the literature provides evidence that male investors are more confident than female investors and that a higher degree of overconfidence results in increased trading frequency (Barber and Odean 2001, 2011), the subsequent hypothesis will be tested:

*H2: Men trade more than women when investing through German neo-brokers.*

Furthermore, the literature presented several arguments supporting the notion that increased trading frequency is associated with poor portfolio performance (Barber and Odean 2000). This is justified by the trading costs and because securities purchased by overconfident investors underperform those sold (Odean 1999; Barber and Odean 2000). Considering these arguments, the following hypothesis will be analyzed:

*H3: Men decrease their portfolio's return more than women when investing through German neo-brokers and having a higher trading frequency.*

## 4. Data and Methodology

This section elaborates on the data and empirical methodology for testing the hypotheses. First, the approach for the data collection is revealed before describing the data set and variable selection. Lastly, the empirical methodology, including the construction of the variables for the hierarchical binary logistic regression models, is presented.

### 4.1 Data collection

An online survey was set up based on the literature review of young retail investors' investment behavior and overconfidence bias to analyze the hypotheses.

As shown in Appendix C, the survey was created with Qualtrics software consisting of two question blocks, which covered both demographic and investment characteristics of young German retail investors (Qualtrics 2022). The survey consisted of two different flows, one for individuals who are investing and the second one for individuals who are currently not investing in financial products. The first group answered 24, and the second group answered 14 questions. The information was collected through multiple-choice questions. Some allowed multiple answers, and text entry questions were used for trading frequency, return, expected return, and overprecision to ensure maximum accuracy for these indicators. The criterion set for sampling was as follows: (1) The respondent must have German citizenship or permanent German residency, and (2) the respondent is aged between 18 and 29. The survey was distributed on 09.04.2022 through three online channels (Linkedin, Facebook, and WhatsApp) in the personal network to ensure the generation of at least 200 observations. Through this self-selection sampling, 299 responses were received until 03.05.2022, which equals 25 days.

### 4.2 Data description

Out of the 299 responses received, 23 questionnaires are irrelevant since these individuals do not fulfill the relevant nationality and age criteria (cp. Appendix D). Hence, the valid number of survey respondents equals 276, of which 210 invest in financial instruments while 66 do not invest in financial instruments. Summary statistics of those currently not investing in the stock market are provided in Table 5.

The sample of young retail investors (n = 210) consists of 139 men and 71 women, and two-thirds are between 25 and 29 years old (cp. Table 1). Most of the survey respondents have at least a bachelor's degree (53.8%) or a master's degree (39.5%), and half of the sampled investors (52.4%) refer to their current employment status as a student. Gross income and net wealth fall below €40,000 and €30,000 respectively for half of the respondents, and 84.8% do not have any dependents, such as children or non-working spouse, to support financially.

At the beginning of the survey, the respondents were asked about the broker(s) they use to execute their investments. As shown in Figure 1, there is no clear pattern in the usage of specific brokers except for Trade Republic, which is used by 107 investors surveyed. Since one-third of survey participants do not use a neo-or crypto-broker but an online broker, the brokers were classified into neo-brokers, crypto-brokers, and online brokers (cp. Table 2). Accordingly, neo-brokers offer commission-free, low-cost (≤ €1/trade) trading, while crypto-brokers are those solely offering to trade crypto-currencies. On the other hand, online brokers charge their customers a commission and higher trading fees (>€1/trade). For the further course of this thesis, it is distinguished between retail investors using neo-brokers (including crypto-brokers and people using both neo- and online brokers) versus retail investors solely using online brokers. The gender distribution among the brokers reflects the ratio of male to female survey respondents (2:1) (cp. Table 1).

By asking the survey participants about their approach toward investing, most answered that they are willing to accept a moderate level of risk and expect their returns to be somewhere between the historical market returns (67.1%). Only 21.7% of investors highlighted that they take on significant risk and thereby expect to beat the market, of which 16.9% invest through neo-brokers and 4.8% through online brokers (cp. Table 3). Over 50% of investors across both types of brokers invest to accumulate net worth, save for retirement and generate additional income. The frequency of investors trading for entertainment and earning much money in a short time is higher for neo-broker investors (26.1% and 20.3%) as compared to online broker investors (11.1% and 5.6%) (cp. Figure 2). The sources of information for investing that are mostly used across both types of brokers are popular financial instruments listed in the broker's interface, recommendations of family and friends, and finance books (cp. Figure 3).

While more than half of the investors surveyed spend less than €250,00 per trade (57.6%), only one-tenth reveal that they aim to hold their investments for less than a year. Most of the sample has been investing for less than two years (38.6%) or two to five years (41.9%). However, of those investing in single stocks, only 15.7% of investors diversify their portfolio by holding at least 20 different stocks, while 84.3% of the portfolios are not diversified with less than 20 stocks (cp. Table 3). As can be withdrawn from Figure 4, users of neo-brokers show a higher preference for investing in large caps and midcaps than users of online brokers. The average neo-broker user trades 5.9 times per month, while users of online brokers display a less active trading behavior with an average of 2.5 times per month (cp. Table 4, Figure 5). Moreover, investors trading through neo-brokers did not only report a higher return[7] in 2021 ($\bar{x}$ = 49.0%) but are also more optimistic towards their expected return in 2022 ($\bar{x}$ = 45.8%) as compared to those trading through online brokers ($\bar{x}$ = 32.1% and $\bar{x}$ = 25.0% respectively) (cp. Table 4, Figure 6). Nonetheless, both groups expect less return in 2022 than in 2021, which may be due

[7] As part of this thesis, return is considered as return before inflation

to macroeconomic and political factors such as inflation and the Ukraine war (cp. Table 4). Considering the risk-return relationship of both neo-broker and online broker investors, users of neo-brokers on average invest a larger portion of their portfolio into higher risk-return financial instruments such as stocks and crypto. In contrast, users of online brokers show a higher tendency to invest in bonds and ETFs (cp. Figure 7). When asked about investment skills as compared to the peers, the return of the MDAX in 2021 and the expected return for the DAX in 2022, there is no clear difference to be observed between the investors of neo-brokers versus online brokers (cp. Figure 8, Figure 9, and Figure 10).

### 4.3 Variable Selection

Since 19 out of 26 variables are of categorical nature and many dichotomous variables would arise if the entire data collected were considered for the regression models, the data are grouped into categories. Then, they are looked at individually and filtered to prevent further analysis from multicollinearity and high degrees of freedom. A complete list of the evaluation of dependent and predictor variables and the decision criteria and reasoning is highlighted in Table 6. Because of the formulation of *H1 – H3*, the dependent variables trading frequency and return with the main predictors neo-broker versus online broker users and gender are considered for the regression models. Next, the major determinants of investors' overconfidence bias identified by Kansal and Singh (2018) and Mishraa and Metildab (2015) are investigated.

Due to the low data generated for the number of dependents larger than zero (n = 32) and respondents working in finance (n = 32), both variables will not be considered for further analysis. However, income and education are included in the regression models, as suggested by Kansal and Singh (2018). Moreover, the major determinants of investors' overconfidence bias investment horizon, investment experience, investing in large caps, and trading frequency are of further interest. Lastly, the number of stocks prove to be interesting due to the low portfolio diversification of young retail investors and trading volume which the emergence of neo-brokers impacts due to zero commission and low trading fees.

Based on the reasoning above, the following variables are considered for the regression models: neo_broker, trading_frequency, return, education, gender, income, invest_experience, invest_horizon, no_stocks, only_large_caps, trading_frequency, and trading_volume.

### 4.4 Empirical Methodology

This directed research project adopts a deductive approach by beginning with the literature review, deriving hypotheses from it, testing those hypotheses, and modifying the theory. Hence, the empirical methodology follows a process that moves from the general to the specific (Woiceshyn and Daellenbach 2018).

The complete inferential statistical analysis for dissecting the data and testing the hypotheses is carried out with IBM SPSS Statistics 28.0.1.1(14) statistic software package. First, all dependent and independent variables are tested for normal distribution using Kolmogorov-Smirnova and Shapiro-Wilk tests (cp. Table 7, Figure 11). Since the results with a p-value <.001 for each variable indicate a non-normal distribution, all variables are coded in a binary fashion. The category of most interest is coded as one while the other category is coded as reference (equal to zero). Table 8 highlights the definitions of all variables and the coding. The binary variables are tested for multicollinearity with Spearman's rank correlation coefficient to ensure no intercorrelations (cp. Table 9). Next, the influence of each independent variable on the dependent variables trading_frequency and return is tested individually with a binary logistic regression. The predictors that prove to be significant on a 95% confidence level are included in the hierarchical binary logistic regression models after applying different measures of model adequacy tests.

Given a collection of predictor variables, hierarchical binary logistic regression is a statistical approach for estimating the likelihood of an occurrence. As part of this directed research project, the random variable $y_i$ representing domestic retailers' trading frequency (1: >2 trades/month, 0: ≤ 2 trades/month) was considered for testing *H1* and *H2*. Besides, the random variable $y_i$ indicating the investors' return (before inflation) in 2021 (1: ≤ 11%, 0: >11%) is the dependent variable for the evaluation of *H3*. The primary predictor variable of interest is neo_broker, coded as one if retail investors use these platforms or zero if they solely use online brokers.

To test *H1*, stating that German neo-brokers increase domestic retailer investors' trading frequency, Model 1 is set up based on the results of the binary logistic regressions. With trading_frequency (1: >2 trades/month, 0: ≤2 trades/month) being the dependent variable, the predictor neo_broker (1: neo-broker, 0: online broker) is of particular interest followed by investment_horizon (1: <1year, 0: ≥1year), gender (1: male, 0: female), and trading volume (1: < €250, 0: ≥ €250) (cp. Table 8). If P(neo_broker = 1) takes on a value that is larger than one, Model 1 classifies that when using German neo-brokers, young retail investors execute on average more than two trades per month.

**Equation 1.** Model 1

$$\mathrm{P}\,(y_i = 1) = \frac{\exp\,(\beta_0 + \beta_1 \text{neo\_broker} + \beta_2 \text{invest\_horizon} + \beta_3 \text{gender} + \beta_4 \text{trading\_volume})}{1 + \exp\,(\beta_0 + \beta_1 \text{neo\_broker} + \beta_2 \text{invest\_horizon} + \beta_3 \text{gender} + \beta_4 \text{trading\_volume})} \tag{1}$$

$$\begin{aligned} y_i &= 1 \; if \; \beta_i x_i + \varepsilon_i > 0 \; (> 2 \; trades \; per \; month) \\ y_i &= 0 \; if \; \beta_i x_i + \varepsilon_i \leq 0 \; (\leq 2 \; trades \; per \; month) \end{aligned} \tag{2}$$

Based on the results of the binary logistic regressions, the same predictors are chosen to validate *H2* as for Model 1. However, gender is prioritized because the focus is on analyzing whether male investors trade more frequently than female investors, given the fact that they invest through neo-brokers. If P(neo_broker = 1) takes on a value that is larger than one, Model 2 classifies that when using German neo-brokers, young male retail investors trade more frequently than young female retail investors.

**Equation 2.** Model 2

$$P\,(y_i = 1) = \frac{\exp\,(\beta_0 + \beta_1 \text{neo\_broker} + \beta_2 \text{gender} + \beta_3 \text{invest\_horizon} + \beta_4 \text{trading\_volume})}{1 + \exp\,(\beta_0 + \beta_1 \text{neo\_broker} + \beta_2 \text{gender} + \beta_3 \text{invest\_horizon} + \beta_4 \text{trading\_volume})} \quad (1)$$

$$y_i = 1\ if\ \beta_i x_i + \varepsilon_i > 0\ (men\ trade\ more\ than\ women)$$
$$y_i = 0\ if\ \beta_i x_i + \varepsilon_i \leq 0\ (\ men\ trade\ less\ than\ women) \quad (2)$$

Lastly, Model 3 tests the assumption that when investing through neo-brokers and trading more frequently, men experience lower returns than women. Hence, the dependent variable of interest is return (1: ≤11%, 0: >11%) and the predictor variables are neo_broker (1: neo-broker, 0: online broker), gender (1: male, 0: female), trading_frequency (1: >2 trades/month, 0: ≤ 2 trades/month), and invest_inexperience (1: <2 years, 0: ≥2 years). If P(return = 1) takes on a value that is larger than one, Model 3 classifies that when using German neo-brokers and trading more frequently, young male investors achieve lower portfolio returns than young female investors.

**Equation 3.** Model 3

$$P\,(y_i = 1) = \frac{\exp\,(\beta_0 + \beta_1 \text{neo\_broker} + \beta_2 \text{gender} + \beta_3 \text{trading\_frequency} + \beta_4 \text{invest\_inexperience})}{1 + \exp\,(\beta_0 + \beta_1 \text{neo\_broker} + \beta_2 \text{gender} + \beta_3 \text{trading\_frequency} + \beta_4 \text{invest\_inexperience})} \quad (1)$$

$$y_i = 1\ if\ \beta_i x_i + \varepsilon_i > 0\ (\leq 11\%\ gross\ return\ in\ 2021)$$
$$y_i = 0\ if\ \beta_i x_i + \varepsilon_i \leq 0\ (> 11\%\ gross\ return\ in\ 2021) \quad (2)$$

## 5. Hierarchical binary logistic regressions results

In the following, the hierarchical binary logistic regression results for Model 1 to Model 3 will be highlighted. To evaluate hypothesis *H1*, all variables of interest are looked at individually by running binary logistic regressions with trading_frequency as the dependent variable and each of the predictors neo_broker, education, gender, income, invest_inexperience, invest_horizon, no_stocks, and only_large_caps, overconfidence, trading_volume.

As highlighted in Table 10, these initial screenings show that the predictors neo_broker, invest_horizon, gender, and trading_volume, increase the likelihood of trading more than twice per month. However, invest_inexperience increases the likelihood of trading twice or less per month on a 5% significance level. In the next step, the predictors are prioritized according to the odds ratios (OR) after considering the primary predictor variable neo_broker (cp. Table 12). Then, a hierarchical binary logistic regression is run. Table 12 illustrates the estimated coefficients, odds ratios with 95% confidence intervals (CI), and each predictor's significance obtained from Model 1.

With a $\chi^2$ value of 7.304 and p-value of 0.504, the Hosmer-Lemeshow test statistic proves the goodness of fit for Model 1. The omnibus test ($\chi^2$: 26.113, p-value: <.001) reveals that Model 1 provides an explanatory contribution by adding the predictors compared to the modal prediction. Hence, Model 1 is analyzed in the following. The odds ratio for neo-brokers is 1.989 (CI: 1.018 – 3.885, p-value: .044), indicating that the likelihood of the executing more than two trades per month is almost twice as high for users of neo-brokers as compared to users of online brokers, having allowed for invest_horizon, gender, trading_volume, and invest_inexperience. Further, Model 1 illustrates that individual investors who plan to hold their financial instruments for less than a year are 2.428 times more likely (CI: 1.250 – 4.716, p-value: .009) to exhibit frequent trading behavior (>2 trades /month) than those having a holding period of one year or more. Nonetheless, gender does not show significance in conjunction with the other explanatory variables in Model 1. The odds for investors who spend an average of less than €250 per trade is 1.982 (CI: 1.055 – 3.726, p-value: .034) as compared to the reference group (≥€250 /trade), adjusted for the other predictors. In contrast, the odds for inexperienced investors having less than two years of investment experience is .459 (CI: .234 – .902, p-value: .024) compared to those who have been investing for two years or more, allowed for the other independent variables. Thus, the likelihood of frequent trading increases by 98.2% if investors have a low trading volume and decreases by 54.1% if investors have less than two years of investment experience.

As an approximation of the percentage of explained variance, Nagelkerke $R^2$ is employed, which has a value of 0.166. Overall, 68.7% of investors can be classified by the model to their actual responses compared to 58.1% when considering trading frequency alone (cp. Table 12). As P(neo_broker = 1) takes on a value that is larger than one (OR: 1.989), *H1* can be accepted.

For testing *H2,* the same sequence of steps is used as for the analysis of *H1*. Since both models have the same dependent variable, the model remains the same except that gender is prioritized. It is the major predictor of interest after considering neo_broker (cp. Table 14). The investigation into gender alone revealed that men are twice more prone to frequent trading than women (OR: 2,014, CI: 1.102 – 3.681, p-value: .023), but the variable no longer reaches the level of statistical significance in conjunction with neo_broker, investment_horizon, trading_volume, and investment_inexperience (cp. Table 13, Table 15). Hence, the second hypothesis that men trade more than women cannot be accepted.

Equivalent to the procedures mentioned above, binary logistic regressions are set up with return as the dependent variable and the predictors neo_broker, education, gender, income, invest_inexperience, invest_horizon, no_stocks, only_large_caps, trading_frequency, and trading_volume for testing *H3* (cp. Table 16). A total of three predictors out of ten were significant at a 95% confidence level, changing the probability of trading more than twice a month. The predictors gender, invest_inexperience, and trading_frequency have a negative coefficient (OR < 1) which implies a decreasing likelihood of low portfolio returns (cp. Table 16). Even though the variable neo_broker does not show statistical significance at a 5% confidence level (OR: .630, CI: .355 – 1.117, p-value: .114), it is considered for Model 3 because it is the main predictor for the validation of *H3*. After prioritizing the predictors based on their contribution to answering the hypothesis and on the values of their odds ratios, the hierarchical binary logistic model for testing *H3* was set up (cp. Table 17, Table 18Table 17). As can be revealed by the Hosmer and Lemeshow test statistic, the goodness of fit for Model 3 is achieved ($\chi 2$: 11.246, p-value: .128). Furthermore, the model contributes to explaining return (Omnibus test $\chi 2$: 30.628, p-value: <.001) which indicates its validity. However, controlling the effect of other predictors, gender, and trading_frequency no longer reach statistical significance at a 95% confidence level. The model shows that investors with less than two years of investment experience are 3.265 (CI: 1.732 – 6.155, p-value: <.001) times more likely to achieve portfolio returns of 11% or less than more experienced investors. The predictors neo_broker (OR: .574, p-value: .090, CI: .303 – 1.090), trading_frequency (OR: .591, p-value: .090, CI: .321 – 1.086) and gender (OR: .580, p-value: .094, CI: .306 – 1.098) are valid on a 90% confidence level. Nonetheless, the results cannot be of further consideration as the threshold value for this directed research project is a 95% confidence level.

## 6. Discussion

Based on the hierarchical binary logistic regression results, *H1* can be accepted while *H2* and *H3* cannot be accepted. Previous researchers (Mishraa and Metildab 2015; Kansal and Singh 2018) reveal a significant impact of high levels of education, working in finance, having dependents, high investment frequency, shorter investment horizon, greater investment expertise, and investing in companies with large market capitalization on the overconfidence bias. However, not all of these predictors reached a 5% level of significance in the regression models of this directed research project.

Due to a lack of data, working in finance and having dependents were excluded from further analysis. Education (OR: 1.157, CI: .658 – 2.034, p-value: .613), income (OR: 1.321, CI: .737 – 2.367, p-value: .349), and only_large_caps (OR: 1.455, CI: .765 – 2.767, p-value: .253), did not reach the level of significance when running the binary logistic regressions with trading_frequency as the dependent variable (cp. Table 10). Nonetheless, the results of the binary logistic regression with gender as the predictor were equivalent to the findings of Barber and Odean (2000, 2001, 2002, 2011), who state that male investors are more prone to frequent trading than female investors. In particular, the data highlights that the likelihood for men to trade more than two times a month is twice as high (OR: 2.014, CI: 1.102 – 3.681, p-value: .023) as compared to women. Moreover, the significant relationship of a short investment horizon and greater trading experience on a higher trading frequency can be proved. According to the sample data, investors with an investment horizon of less than a year are 2.562 times more likely to trade more than twice a month (CI: 1.388 – 4.729, p-value: .003). In addition, experienced investors (≥2 years) are 1.795 times more likely (CI: .313 – .992, p-value: .047) to exhibit frequent trading behavior than inexperienced investors. Importantly, the likelihood for users of neo-brokers to trade frequently is 2.292 (CI: 1.248 – 4.209, p-value: .008) higher than those using online brokers. This can be linked to the fact that neo-brokers' business model enables commission-free, low-cost trading. The investigation into the number of stocks in the investors' portfolios alone did not reveal a significant relationship. Still, a trading volume of less than €250 per trade increases the likelihood of frequent trading by a factor of two (CI: 1.060 – 3.483, p-value: .031) (cp. Table 10).

When the significant predictors are looked at in conjunction with each other, the variable gender no longer reaches statistical significance (cp Table 12). However, the odds ratios of the other predictors remain approximately the same and hence show that investors who trade through neo-brokers are twice more likely (CI: 1.018 – 3.885, p-value: .044) to trade frequently than those using online brokers, having allowed for invest_horizon, gender, trading_volume, and invest_inexperience. These results correspond to Ash et al. (2018), stating that the friction management of neo-brokers, which is reflected in high user engagement, simple and seamless interface, and the reduced number of clicks for transaction completion, leads to a higher trading frequency. Moreover, the frequent trading phenomenon can be explained by the fact that neo-brokers do not require a minimum amount to invest and offer commission-free, low-cost trading fees and free saving plan execution (Trade Republic 2022b). Out of the seven determinants of the overconfidence bias presented by Kansal and Singh (2018) and Mishraa and Metildab (2015), only two – short investment horizon and greater investment experience – can be validated by Model 1. Nonetheless, the model provides other significant indicators that were not yet addressed by other researchers, such as the significant relationship between low trading volume and investing through neo-brokers with trading frequency.

As the results of Model 2 do not show a significant relationship between gender and trading_frequency at a 95% confidence level, having allowed for neo.broker, invest_horizon, trading_volume, invest_inexperience*, H2* cannot be accepted (cp. Table 15). However, the analysis of gender alone is consistent with Barber and Odean (2001, 2011) in that men show more frequent trading behavior than women due to a higher degree of overconfidence. This complements previous research that men are twice as likely to trade more than twice a month (OR: 2.014, CI: 1.102 – 3.681, p-value: .023) as compared to women (cp. Table 13).

All the predictors tested for *H1* and *H2* individually were also looked at for *H3* with the addition of trading_frequency. This is because a higher trading frequency leads to an increased degree of overconfidence and lower portfolio returns (Kansal and Singh 2018). The predictors education (OR: .671, CI: .382 – 1.179, p-value: .165), income (OR: 761, CI: 429 – 1.350, p-value: .351), invest_horizon (OR: .898, CI: .491 – 1.641, p-value: .726), and only_large_caps (OR: .982, CI: .516 – 1.868, p-value: .956) do not reach the level of statistical significance. This is in contrast to the findings of Kansal and Singh (2018) findings and Mishraa and Metildab (2015). The p-values of invest_horizon and only_large_caps are close to one, indicating that the observed effects are almost equal to the null hypothesis values.

Consequently, only investment experience and trading frequency reach the 5% significance level. As opposed to Odean's (1999) and Barber and Odean (2000) research, both predictors show an inverse relationship with portfolio return. Investors with less than two years of related experience are 3.586 (CI: 2.001 – 6.427, p-value: <.001) times more likely to achieve a portfolio return of 11% or less than those with two years or more of investment experience. This can be explained by the following factors. First, the binary logistic regression only controls for invest_inexperience but does not consider trading_frequency and gender, representing implicit measures of the overconfidence bias. However, Glaser and Weber (2007) illustrate that investors are rarely capable of estimating their prior portfolio performance accurately. Even though experienced investors having five or more years of investment experience are more able to do so, the mean of retail investors' perceived return minus actual return is 10.32% compared to 13.18% for investors with less than five years of investment experience. Nonetheless, experienced investors may have learned from previous mistakes and adjusted their investment strategy and portfolio and thus outperform less experienced investors. Lastly, investors with two or more years of investment experience may behave more rationally and are less prone to "System 1" thinking and the overconfidence bias.

An inverse relationship also accounts for trading_frequency with an odds ratio of .454 (CI: .257 – .799, p-value: .006). This shows that those who trade more than twice a month are 54.6% less likely to achieve a portfolio return of 11% or less. This is not in line with Odean (1999) and Barber and Odean (2000) who state that increased trading frequency is linked to poor portfolio performance due to trading costs and the underperformance of securities purchased by those sold. However, investors trading more frequently might have a different risk-return relationship than those trading less frequently. Higher risks can be taken by investing in stocks that require constant hold or sell evaluation. On the other hand, less frequent traders may be inclined to invest in bonds and ETFs. Based on the regression results, no conclusion can be drawn on the risk-return relationship of the investors as the generated data does not differentiate between buy and sell. Since the return is measured by asking the survey participants how much portfolio return (before inflation) they achieved in 2021, the variable return is solely based on the results of 2021. The S&P 500 achieved a return (before inflation) of 26.89% in 2021. Suppose this is taken as a benchmark for the market return and the assumption that the average retail investor is unlikely to beat the market, investors may have beaten historical market returns due to the stock market's solid performance in 2021 (Hajric and Graffeo 2022).

Moreover, gender is significant at a 95% confidence level but shows the opposite impact on return, than explained by Barber and Odean (2000, 2001, 2002, 2011). Male investors are 61.1% (CI: .216 – .700, p-value: .002) less likely to achieve low portfolio returns in comparison to female investors. This can be justified because men are more experienced and rational investors. Another explanation can be that men answered the survey questionnaire according to social desirability, presenting themselves in a generally favorable fashion. The main predictor of interest, neo_broker (OR: .630, CI: .355 – 1.117, p-value: .114), trading_volume (OR: 1.471, CI: .832 – 2.600, p-value: .180) and no_stocks (OR: 1.474 , CI: .590 – 3.684, p-value: .407) do not show statistical significance.

When taking all significant predictors for the hierarchical binary logistic regression into account, including the main independent variable of interest neo_broker, only the variable invest_inexperience remains significant (cp: Table 18). Hence, the influence of trading_frequency and gender on return is impacted by the addition or removal of other variables. As the remaining predictors can only provide significance on a 90% confidence level, *H3* cannot be accepted. In contrast to previous research, the data shows a tendency for an inverse relationship between return and the predictors. More specifically, when trading through neo-brokers, having a higher trading frequency, being male, and having investment experience, a portfolio return of more than 11% is achieved. If these variables would be significant at a 95%

confidence level, the inverse relationship of the predictors with return could be proved. As the stock market showed a solid performance in 2021, the investors surveyed may not show overconfidence in terms of overestimating their own returns or answeing the survey according to social desirability. Rather, the investor in the sample but may have profited from the upward trend in the stock market in 2021.

## 7. Limitations and Future Research

The following section focuses on the limitations of this directed research project and topics for future research. Besides the data that has been collected through the online survey, insightful information would have been gathered by including questions about the importance of certain features, such as the seamless and interactive design and the reduced number of clicks to complete a trade. This could have validated the specific driving forces for increased overconfidence identified by Ash et al. (2018). Information on how much time investors spend on trading platforms daily, the average time frame for completing trades (morning, noon, afternoon, evening), and the average time for making an investment decision would have been interesting. Hence, information on how neo-brokers' friction management impacts the overconfident behavior of young investors could have been collected. As the survey was distributed in the personal network, including fellow students from Nova School of Business and Economics, Zeppelin University, and previous contacts from internships, the survey results are subject to the self-selection bias. Therefore, specific demographics fail to respond to the survey, which is displayed in the high level of education and social class affiliation. It can be assumed that survey respondents who are business administration students or professionals with business administration backgrounds are predominant in the sample. Thus, the findings from the sample cannot be generalized to the entire population.

Consequently, future research should survey people who know less about investments and do not have a business administration or finance background. Portfolio returns should be measured through longer time horizons to not only rely on the returns of one year. As existing studies do not consider the risk-return relationship of financial instruments with reference to the overconfidence bias, considering a classification of investors' portfolios would reveal relevant information about the return of risk-taking versus risk-averse investors. Lastly, future research should focus on an overconfidence index consisting of overprecision, overestimation, and overplacement to directly evaluate differences in overconfidence among neo-brokers, crypto-brokers, and online brokers.

## 9. Conclusion

The business model of neo-brokers centered on providing 24/7 commission-free and low-cost trading by offering an easy, straightforward, and seamless mobile app or website, attracted many new German retail investors, especially those that are younger than 30 years. Previous literature elaborates on the overconfidence bias of retail investors, stating that it leads to an increased trading frequency and lower returns, especially for male investors. Through productive friction management, neo-brokers encourage their investors to depend more on intuition and less on "System 2" thinking, increasing the overconfidence bias. Hence, this directed research project tested whether using neo-brokers increases the overconfidence bias of young retail investors in Germany. By collecting data through an online survey distributed among fellow students and the broader personal network, the hypotheses were tested using hierarchical binary logistic regressions. It could be proven that the odds of trading more than twice a month increases by a factor of two if investors trade through neo-brokers' platforms. However, the hypotheses that men trade more than women and decrease their portfolio return when using neo-brokers and having a high trading frequency could not be accepted. The sampled data is subject to the self-selection bias because it predominantly consists of a distinct level of education and social class affiliation. Thus, future research should consider sampling a broader range of respondents regarding socio-demographic characteristics.

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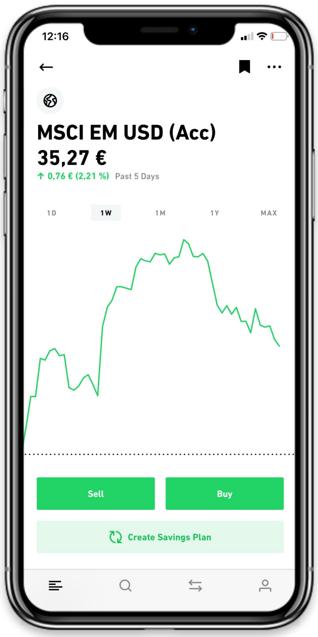
## Appendix

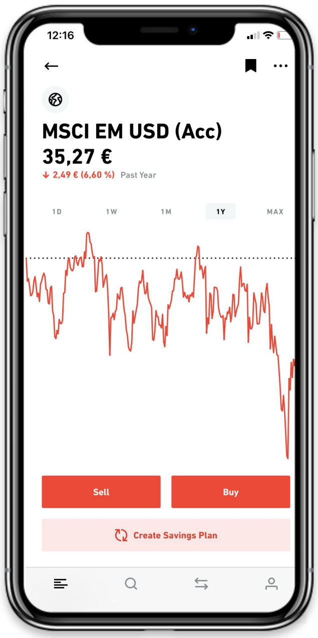
*Appendix A: Changing colors of sell and buy buttons at Trade Republic*


**Daily overview**




**Weekly overview**

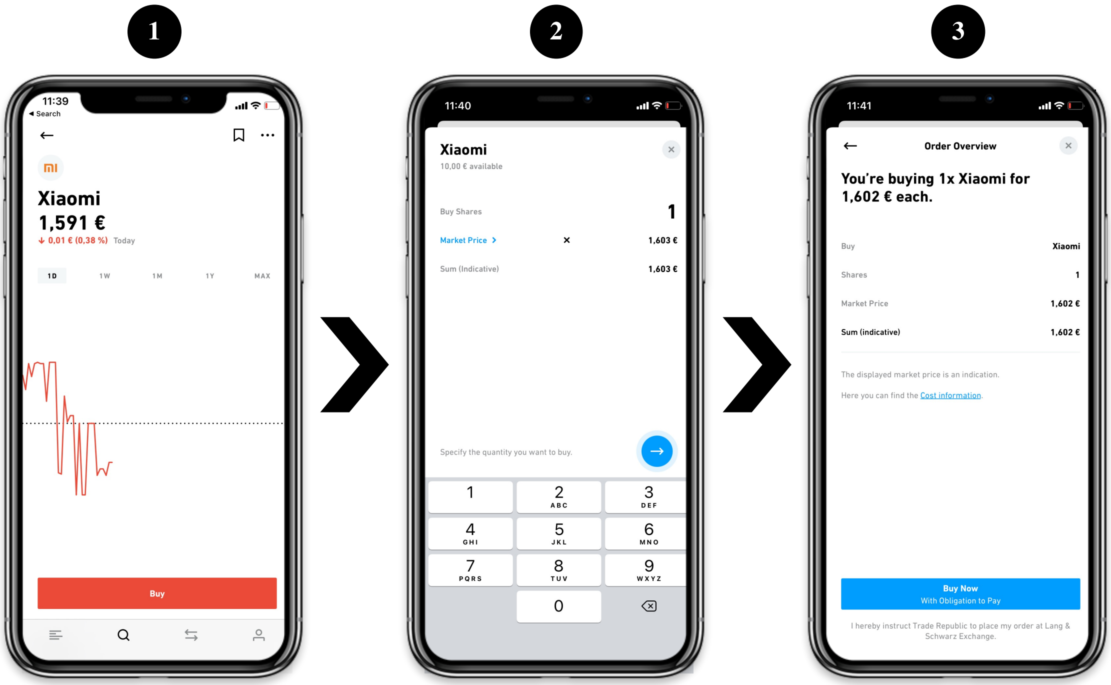

**Monthly overview**




**Yearly overview**


**Max overview**

*Appendix B: Three-click trading flow at Trade Republic*




**Stock overview**

**Selection of quantity and price**

**Trade overview and confirmation**

*Appendix C: Survey questionnaire*

<u>Introduction</u>

As part of my directed research project for my Master's studies at Nova School of Business and Economics, I am analyzing the investment behavior of German retail investors who are younger than 30 years.

The survey will take less than 5 minutes to complete, and all responses are kept anonymous and confidential.

If you have any questions about the survey, please email me: 45656@novasbe.pt. Thank you very much for your time and for contributing to my Master's thesis!

<u>Survey flow 1: People who invest in financial instruments</u>

1. Are you currently investing in some financial instruments?
   - ○ Yes
   - ○ No

2. Why do you invest in financial instruments? (multiple answers are possible)
   - ☐ Additional source of income
   - ☐ Accumulate net worth
   - ☐ Earn a lot of money in a short time
   - ☐ Entertainment
   - ☐ Save for retirement
   - ☐ Other, please specify: ________________

3. Which of the following statements best describes your approach toward investment decisions?
   - ○ I try to minimize risk and the possibility of any loss while accepting lower rates of return.
   - ○ I am willing to accept a moderate level of risk and tolerate losses, but I expect my returns to be somewhere between the historical market returns.
   - ○ I typically take on significant risk and am willing to tolerate large losses, but I expect my returns to be higher than the historical market returns.
   - ○ None of the above

4. What financial instruments do you invest in and what percentage of your total portfolio do they represent? (percentages must sum up to 100%)
   - ☐ _______ Stocks
   - ☐ _______ Bonds
   - ☐ _______ ETFs
   - ☐ _______ Mutual funds
   - ☐ _______ Crypto
   - ☐ _______ Derivatives
   - ☐ _______ Other, please specify

   4.1. If you invest in single stocks, how many stocks do you hold in your portfolio?

- ○ less than 5
- ○ 5 – 9
- ○ 10 – 19
- ○ 20 – 29
- ○ 30 – 39
- ○ 40 – 59
- ○ 60 or more

4.2. If you invest in single stocks, in which type of stocks do you invest? (multiple answers are possible)

- ○ Smaller-sized companies with a market capitalization less than $2 billion
- ○ Medium-sized companies with a market capitalization between $2 billion and $10 billion
- ○ Large-sized companies with a market capitalization larger than $10 billion

5. Which of the criteria below have an impact on the selection of the financial instruments you invest in? (multiple answers are possible)
   - ☐ Finance books
   - ☐ News in broker's interface
   - ☐ Online forums (Example: Reddit)
   - ☐ Popular stocks / ETFs / crypto / derivatives listed in broker's interface
   - ☐ Recommendations of bank advisor
   - ☐ Recommendations of family and friends
   - ☐ Social media
   - ☐ "Top Mover List" by broker
   - ☐ Traditional media (newspapers, radio, magazines, and television)
   - ☐ Other, please specify: ________________

6. Which broker/s do you use for your investments? (multiple answers are possible)
   - ☐ Comdirect
   - ☐ DKB
   - ☐ Finanzen.net zero
   - ☐ ING
   - ☐ justTrade
   - ☐ Scalable Capital
   - ☐ Onvista
   - ☐ Smartbroker
   - ☐ Trade Republic
   - ☐ Other, please specify: ________________

7. What percentage of your total net worth (investments, cash, savings account, real estate less loans and debts) is invested in financial instruments?
   - ○ Less than 25%

- 25% – 50%
- 51% – 75%
- More than 75%
- Prefer not to say

8. On average, how many trades do you execute per month?

   ________________

9. On average, how much money do you invest per trade?
   - €49.99 or less
   - €50.00 – €99.99
   - €100.00 – €249.99
   - €250.00 – €499.99
   - €500 – €999.99
   - €1,000 – €1,999
   - €2,000 – €4,999
   - €5,000 – €9,999
   - €10,000 or more
   - Prefer not to say

10. What was your portfolio return (before taxes and inflation) in 2021?
    ________________%

11. What portfolio return (before taxes and inflation) do you expect to achieve in 2022?
    ________________%

12. When making an investment, for how long do you plan to keep the money invested?
    - Less than 1 day
    - Less than 1 week
    - Less than 1 month
    - Less than 1 year
    - 1 – 2 years
    - 3 – 5 years
    - 6 – 10 years
    - More than 10 years

13. For how long have you been investing in the stock market?
    - Less than 2 years
    - 2 – 5 years
    - 6 – 10 years
    - More than 10 years

14. How do you assess your investment knowledge and skills in comparison to your fellow students, friends and family?
    - ○ Significantly better
    - ○ Better
    - ○ Equal
    - ○ Worse
    - ○ Significantly worse

15. To your best recollection, how much return did the MDAX achieve in 2021?
    - ○ 6% – 10%
    - ○ 11% – 15%
    - ○ 16% – 20%
    - ○ More than 20%

15.1. How confident are you that your answer is correct?

| | 0 | 10 | 20 | 30 | 40 | 50 | 60 | 70 | 80 | 90 | 100 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Level of confidence (%) | | | | | | | | | | | |

16. Please make three estimates of the DAX return (%) until the end of this year.

Your best estimate should be your best guess of the DAX return in 2022.
Your high estimate should very rarely be lower than the actual outcome of the DAX return in 2022 (only a 5% chance that the actual return falls above it).
Your low estimate should very rarely be higher than the actual outcome of the DAX return in 2022 (only a 5% chance that the actual return falls below it)

- ○ Best estimate (%) ________________
- ○ High estimate (%) ________________
- ○ Low estimate (%) ________________

16.1. How confident are you that your answer is correct?

| | 0 | 10 | 20 | 30 | 40 | 50 | 60 | 70 | 80 | 90 | 100 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Level of confidence (%) | | | | | | | | | | | |

17. German Are you a German citizen and/or have a German permanent residence permit?
    - ○ Yes
    - ○ No

18. What is your gender?
    - ○ Female
    - ○ Male
    - ○ Other

19. How old are you?
    - ○ 18 – 24

- ○ 25 – 29
- ○ 30 – 39
- ○ 40 – 65
- ○ Older than 65

20. What is the highest level of school you have completed or the highest degree you have received?
    - ○ Less than high school degree
    - ○ High school degree or equivalent
    - ○ Technical or occupational certificate
    - ○ Bachelor's degree
    - ○ Master's degree
    - ○ Doctorate

21. Which of the following categories best describes your employment status?
    - ○ Apprentice
    - ○ Student
    - ○ Employed, not working in Finance or R&D
    - ○ Employed, working in Finance
    - ○ Employed, working in R&D
    - ○ Entrepreneur
    - ○ Other, please specify: ________________

22. Having in mind income from all sources - work, investment, family and government - into which income bracket does your personal before-tax income fall?
    - ○ €0 – €9,999
    - ○ €10,000 – €19,999
    - ○ €20,000 – €29,999
    - ○ €30,000 – €39,999
    - ○ €40,000 – €59,999
    - ○ €60,000 – €79,999
    - ○ €80,000 – €99,999
    - ○ €100,000 or more
    - ○ Prefer not to say

23. Into which of the following brackets does the value of your total net worth (investments, cash, savings account, real estate less loans and debts) fall?
    - ○ Less than €0 (negative net worth)
    - ○ €0 – €9,999
    - ○ €10,000 – €29,999
    - ○ €30,000 – €69,999
    - ○ €70,000 – €99,999
    - ○ €100,000 – €299,999

- €300,000 – €499,999
- €500,000 – €999,999
- €1,000,000 or more
- Prefer not to say

24. How many people do you fully or partially support financially in your family (besides yourself)? Examples: children, elderly, non-working spouse, etc.
    - 0
    - 1 – 3
    - more than 3

---

End of survey

Survey flow 2: People who invest in financial instruments

1. Why are you not investing in financial instruments? (multiple answers are possible)
    - Bad experience in the past
    - Know too little about investments
    - No money for investments at the moment
    - No time to invest
    - No trust in brokers
    - Prefer to invest in hard assets, such as real estate and gold
    - Prefer to keep my money in bank accounts
    - Too complicated
    - Too risky
    - Waiting for certain market conditions to start investing
    - Other, please specify: ________________

2. Which opportunity(s) do you see in investing in financial instruments? (multiple answers are possible)
    - Additional source of income
    - Accumulate net worth
    - Earn a lot of money in a short time
    - Save for retirement
    - Other, please specify: ________________

3. Do you plan to invest in financial instruments in near future?
    - Yes
    - No

3.1. What financial instruments would you invest in and what percentage of your total portfolio would they represent? (percentages must sum up to 100%)

- ☐ _______ Stocks
- ☐ _______ Bonds
- ☐ _______ ETFs
- ☐ _______ Mutual funds
- ☐ _______ Crypto
- ☐ _______ Derivatives
- ☐ _______ Other, please specify

3.2. If you would invest in single stocks, how many stocks would you hold in your portfolio?

- ○ Less than 5
- ○ 5 – 9
- ○ 10 – 19
- ○ 20 – 29
- ○ 30 – 39
- ○ 40 – 59
- ○ 60 or more
- ○ Don't know

3.3. If you would invest in single stocks, in which type of stocks would you invest? (multiple answers are possible)

- ☐ Smaller-sized companies with a market capitalization less than $2 billion
- ☐ Medium-sized companies with a market capitalization between $2 billion and $10 billion
- ☐ Large-sized companies with a market capitalization larger than $10 billion
- ☐ Don't know

3.4. Which of the criteria below would have an impact on your selection of financial instruments? (multiple answers are possible)

- ☐ Finance books
- ☐ Online forums (Example:  Reddit)
- ☐ Recommendations of bank advisor
- ☐ Recommendations of family and friends
- ☐ Social media
- ☐ Traditional media (newspapers, radio, magazines, and television)
- ☐ Other, please specify: _________________

3.5. If you know any of the brokers below, which one would you choose for your future investments?

- ☐ Comdirect
- ☐ DKB

- ☐ Finanzen.net zero
- ☐ ING
- ☐ justTrade
- ☐ Scalable Capital
- ☐ Onvista
- ☐ Smartbroker
- ☐ Trade Republic
- ☐ Other, please specify: ________________

3.6. What percentage of your total net worth (investments, cash, savings account, real estate less loans and debts) would you invest in financial instruments?

- ○ Less than 25%
- ○ 25% – 50%
- ○ 51% – 75%
- ○ More than 75%
- ○ Prefer not to say

3.7. What portfolio return (before taxes and inflation) would you expect to achieve in your first year?

________________%

4. How do you assess your investment knowledge and skills in comparison to your fellow students, friends and family?

- ○ Significantly better
- ○ Better
- ○ Equal
- ○ Worse
- ○ Significantly worse

5. To your best recollection, how much return did the MDAX achieve in 2021?

- ○ 6% – 10%
- ○ 11% – 15%
- ○ 16% – 20%
- ○ More than 20%

5.1. How confident are you that your answer is correct?

| | 0 | 10 | 20 | 30 | 40 | 50 | 60 | 70 | 80 | 90 | 100 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Level of confidence (%) | | | | | | | | | | | |

6. Please make three estimates of the DAX return (%) until the end of this year.
Your best estimate should be your best guess of the DAX return in 2022.
Your high estimate should very rarely be lower than the actual outcome of the DAX return in 2022 (only a 5% chance that the actual return falls above it).

Your low estimate should very rarely be higher than the actual outcome of the DAX return in 2022 (only a 5% chance that the actual return falls below it)

- Best estimate (%) ________________
- High estimate (%) ________________
- Low estimate (%) ________________

6.1. How confident are you that your answer is correct?

| | 0 | 10 | 20 | 30 | 40 | 50 | 60 | 70 | 80 | 90 | 100 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Level of confidence (%) | | | | | | | | | | | |

7. German Are you a German citizen and/or have a German permanent residence permit?
   - Yes
   - No

8. What is your gender?
   - Female
   - Male
   - Other

9. How old are you?
   - 18 – 24
   - 25 – 29
   - 30 – 39
   - 40 – 65
   - Older than 65

10. What is the highest level of school you have completed or the highest degree you have received?
    - Less than high school degree
    - High school degree or equivalent
    - Technical or occupational certificate
    - Bachelor's degree
    - Master's degree
    - Doctorate

11. Which of the following categories best describes your employment status?
    - Apprentice
    - Student
    - Employed, not working in Finance or R&D
    - Employed, working in Finance
    - Employed, working in R&D
    - Entrepreneur

- ○ Other, please specify: ________________

12. Having in mind income from all sources - work, investment, family and government - into which income bracket does your personal before-tax income fall?
    - ○ €0 – €9,999
    - ○ €10,000 – €19,999
    - ○ €20,000 – €29,999
    - ○ €30,000 – €39,999
    - ○ €40,000 – €59,999
    - ○ €60,000 – €79,999
    - ○ €80,000 – €99,999
    - ○ €100,000 or more
    - ○ Prefer not to say

13. Into which of the following brackets does the value of your total net worth (investments, cash, savings account, real estate less loans and debts) fall?
    - ○ Less than €0 (negative net worth)
    - ○ €0 – €9,999
    - ○ €10,000 – €29,999
    - ○ €30,000 – €69,999
    - ○ €70,000 – €99,999
    - ○ €100,000 – €299,999
    - ○ €300,000 – €499,999
    - ○ €500,000 – €999,999
    - ○ €1,000,000 or more
    - ○ Prefer not to say

14. How many people do you fully or partially support financially in your family (besides yourself)? Examples: children, elderly, non-working spouse, etc.
    - ○ 0
    - ○ 1 – 3
    - ○ more than 3

---

End of survey

*Appendix D: Sample construction*

| | |
|---|---|
| **Total number of survey participants with complete responses** | **299** |
| - non-German nationality | 14 |
| - respondents older than 29 years | 9 |
| **= Final sample of valid observations** | **276** |
| - individuals who are not investing | 66 |
| **= Final sample of retail investors** | **210** |

*Table 1: Socio-demographic characteristics of survey participants*

| | | invest = yes (1) | | neo_broker = yes (1) | | neo_broker = no (0) | |
|---|---|---|---|---|---|---|---|
| **Variable** | **Description** | **Frequency** | **Percentage** | **Frequency** | **Percentage** | **Frequency** | **Percentage** |
| Gender | Female | 71 | 33.8% | 44 | 21.0% | 27 | 12.8% |
| | Male | 139 | 66.2% | 94 | 44.8% | 45 | 21.4% |
| Age | 18 – 24 | 66 | 31.4% | 48 | 22.9% | 18 | 8.5% |
| | 25 – 29 | 144 | 68.6% | 90 | 42.9% | 54 | 25.7% |
| Education | Less than high school degree | 1 | 0.5% | 1 | 0.5% | | 0.0% |
| | High school degree or equivalent | 7 | 3.3% | 4 | 1.9% | 3 | 1.4% |
| | Technical or occupational certificate | 2 | 1.0% | 1 | 0.5% | 1 | 0.5% |
| | Bachelor's degree | 113 | 53.8% | 77 | 36.7% | 36 | 17.1% |
| | Master's degree | 83 | 39.5% | 54 | 25.7% | 29 | 13.8% |
| | Doctorate | 4 | 1.9% | 1 | 0.5% | 3 | 1.4% |
| Employment | Apprentice | 3 | 1.4% | 1 | 0.5% | 2 | 0.9% |
| | Student | 110 | 52.4% | 75 | 35.7% | 35 | 16.7% |

| | | invest = yes (1) | | neo_broker = yes (1) | | neo_broker = no (0) | |
|---|---|---|---|---|---|---|---|
| **Variable** | **Description** | **Frequency** | **Percentage** | **Frequency** | **Percentage** | **Frequency** | **Percentage** |
| | Employed. working in Finance | 32 | 15.2% | 22 | 10.5% | 10 | 4.7% |
| | Entrepreneur | 11 | 5.2% | 7 | 3.3% | 4 | 1.9% |
| | Employed. working in R&D | 7 | 3.3% | 3 | 1.4% | 4 | 1.9% |
| | Employed. not working in Finance or R&D | 47 | 22.4% | 30 | 14.3% | 17 | 8.1% |
| Gross income | €0 – €9.999 | 46 | 21.9% | 29 | 13.8% | 17 | 8.1% |
| | €10.000 – €19.999 | 40 | 19.0% | 26 | 12.4% | 14 | 6.6% |
| | €20.000 – €29.999 | 14 | 6.7% | 11 | 5.3% | 3 | 1.4% |
| | €30.000 – €39.999 | 9 | 4.3% | 8 | 3.8% | 1 | 0.5% |
| | €40.000 – €59.999 | 34 | 16.2% | 23 | 11.0% | 11 | 5.2% |
| | €60.000 – €79.999 | 31 | 14.8% | 20 | 9.6% | 11 | 5.2% |
| | €80.000 – €99.999 | 10 | 4.8% | 5 | 2.4% | 5 | 2.4% |
| | €100.000 or more | 8 | 3.8% | 4 | 1.9% | 4 | 1.9% |
| Net wealth | €0 – €9.999 | 37 | 17.6% | 22 | 10.5% | 15 | 7.1% |

| | | invest = yes (1) | | neo_broker = yes (1) | | neo_broker = no (0) | |
|---|---|---|---|---|---|---|---|
| **Variable** | **Description** | **Frequency** | **Percentage** | **Frequency** | **Percentage** | **Frequency** | **Percentage** |
| | €10.000 – €29.999 | 60 | 28.6% | 46 | 21.9% | 14 | 6.7% |
| | €30.000 – €69.999 | 50 | 23.8% | 32 | 15.2% | 18 | 8.6% |
| | €70.000 – €99.999 | 10 | 4.8% | 5 | 2.4% | 5 | 2.4% |
| | €100.000 – €299.999 | 14 | 6.7% | 10 | 4.8% | 4 | 1.9% |
| | €300.000 – €499.999 | 4 | 1.9% | 3 | 1.4% | 1 | 0.5% |
| | €500.000 – €999.999 | 5 | 2.4% | 2 | 1.0% | 3 | 1.4% |
| | €1.000.000 or more | 1 | 0.5% | 1 | 0.5% | | 0.0% |
| | 0 | 178 | 84.8% | 117 | 55.7% | 61 | 29.1% |
| Dependents | 1 – 3 | 30 | 14.3% | 20 | 9.5% | 10 | 4.8% |
| | more than 3 | 2 | 1.0% | 1 | 0.5% | 1 | 0.5% |

*Figure 1: Type of broker/s used for investments (multiple response question)*

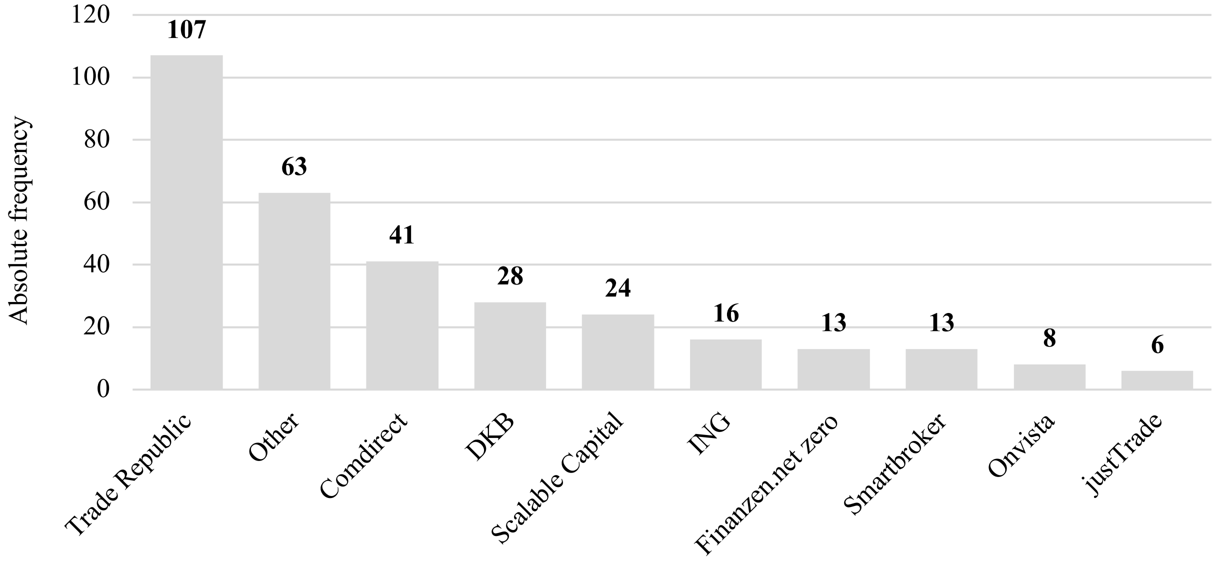



*Table 2: Broker classification*

| **Neo-broker**<br>no commission. trading fee per trade ≤ €1 | **Crypto-broker**<br>only possible to trade crypto-currencies | **Online broker**<br>commission fee. trading fee per trade > €1 |
|---|---|---|
| Bitpanda | Binance | 1822direkt |
| Finanzen.net zero | Bison | Bankhaus Metzler |
| justTrade | Bitstamp | BW-Bank |
| Scalable Capital | Coinbase | Comdirect |
| Smartbroker | Etoro | Commerzbank |
| Trade Republic | Kraken | Consorsbank |
| | Pionex | Degiro |

| **Neo-broker**<br>no commission. trading fee per trade ≤ €1 | **Crypto-broker**<br>only possible to trade crypto-currencies | **Online broker**<br>commission fee. trading fee per trade > €1 |
|---|---|---|
| | | Deka |
| | | Deutsche Bank |
| | | DKB |
| | | Ebase |
| | | FFB |
| | | Flatex |
| | | IG |
| | | ING |
| | | Interactive Brokers |
| | | Libertex |
| | | Main Bank |
| | | Morgan Stanley |
| | | N26 |
| | | Onvista |
| | | OpenSea |
| | | Oskar |
| | | Postbank |
| | | Quirion |
| | | Sparkasse |
| | | Schwab |
| | | TauRes |
| | | Union Investment |
| | | Vanguard |

*Table 3: Categorical investment characteristics of survey participants (invest = yes)*

| | | invest = yes (1) | | neo_broker = yes (1) | | neo_broker = no (0) | |
|---|---|---|---|---|---|---|---|
| **Variable** | **Description** | **Frequency** | **Percentage** | **Frequency** | **Variable** | **Description** | **Frequency** |
| Investment approach | I try to minimize risk and the possibility of any loss while accepting lower rates of return. | 23 | 11.1% | 13 | 6.3% | 10 | 4.8% |
| | I am willing to accept a moderate level of risk and tolerate losses, but I expect my returns somewhere between the historical market returns. | 139 | 67.1% | 87 | 42.0% | 52 | 25.1% |
| | I typically take on significant risk and are willing to tolerate large losses, but I expect my returns to be higher than the historical market returns. | 45 | 21.7% | 35 | 16.9% | 10 | 4.8% |
| Percentage of net worth invested | Less than 25% | 66 | 31.6% | 42 | 20.1% | 24 | 11.5% |
| | 25% – 50% | 53 | 25.4% | 34 | 16.3% | 19 | 9.1% |
| | 51% – 75% | 51 | 24.4% | 38 | 18.2% | 13 | 6.2% |
| | More than 75% | 39 | 18.7% | 23 | 11.0% | 16 | 7.7% |
| | €49.99 or less | 25 | 12.6 | 19 | 9.6% | 6 | 3.0% |

| | | invest = yes (1) | | neo_broker = yes (1) | | neo_broker = no (0) | |
|---|---|---|---|---|---|---|---|
| **Variable** | **Description** | **Frequency** | **Percentage** | **Frequency** | **Variable** | **Description** | **Frequency** |
| Trading volume | €50.00 – €99.99 | 39 | 19.7 | 30 | 15.2% | 9 | 4.5% |
| | €100.00 – €249.99 | 50 | 25.3 | 33 | 16.7% | 17 | 8.6% |
| | €250.00 – €499.99 | 31 | 15.7 | 23 | 11.6% | 8 | 4.0% |
| | €500 – €999.99 | 24 | 12.1 | 14 | 7.1% | 10 | 5.1% |
| | €1.000 – €1.999 | 8 | 4.0 | 5 | 2.5% | 3 | 1.5% |
| | €2.000 – €4.999 | 13 | 6.6 | 3 | 1.5% | 10 | 5.1% |
| | €5.000 – €9.999 | 3 | 1.5 | 0 | 0.0% | 3 | 1.5% |
| | €10.000 or more | 5 | 2.5 | 3 | 1.5% | 2 | 1.0% |
| Investment horizon | Less than 1 day | 1 | 0.5 | 0 | 0.0% | 1 | 0.5% |
| | Less than 1 week | 5 | 2.4 | 4 | 1.9% | 1 | 0.5% |
| | Less than 1 month | 5 | 2.4 | 5 | 2.4% | 0 | 0.0% |
| | Less than 1 year | 24 | 11.4 | 20 | 9.5% | 4 | 1.9% |
| | 1 – 2 years | 25 | 11.9 | 17 | 8.1% | 8 | 3.8% |

| | | invest = yes (1) | | neo_broker = yes (1) | | neo_broker = no (0) | |
|---|---|---|---|---|---|---|---|
| **Variable** | **Description** | **Frequency** | **Percentage** | **Frequency** | **Variable** | **Description** | **Frequency** |
| | 3 – 5 years | 47 | 22.4 | 27 | 12.9% | 20 | 9.5% |
| | 6 – 10 years | 40 | 19.0 | 27 | 12.9% | 13 | 6.2% |
| | More than 10 years | 63 | 30.0 | 38 | 18.1% | 25 | 11.9% |
| Investment experience | Less than 2 years | 81 | 38.6 | 59 | 28.1% | 22 | 10.5% |
| | 2 – 5 years | 88 | 41.9 | 58 | 27.6% | 30 | 14.3% |
| | 6 – 10 years | 35 | 16.7 | 19 | 9.0% | 16 | 7.6% |
| | More than 10 years | 6 | 2.9 | 2 | 1.0% | 4 | 1.9% |
| Number of stocks in portfolio | less than 5 | 47 | 30.1 | 27 | 17.3% | 20 | 12.8% |
| | 5 – 9 | 40 | 25.6 | 30 | 19.2% | 10 | 6.4% |
| | 10 – 19 | 45 | 28.8 | 35 | 22.4% | 10 | 6.4% |
| | 20 – 29 | 10 | 6.4 | 7 | 4.5% | 3 | 1.3% |
| | 30 – 39 | 7 | 4.5 | 6 | 3.8% | 1 | 0.7% |
| | 40 – 59 | 1 | .6 | 1 | 0.7% | 0 | 0.9% |

| | | invest = yes (1) | | neo_broker = yes (1) | | neo_broker = no (0) | |
|---|---|---|---|---|---|---|---|
| **Variable** | **Description** | **Frequency** | **Percentage** | **Frequency** | **Variable** | **Description** | **Frequency** |
| | 60 or more | 6 | 3.8 | 3 | 1.9% | 3 | 1.9% |

*Figure 2: Reasons for investing neo-broker vs. online broker users (multiple response question)*

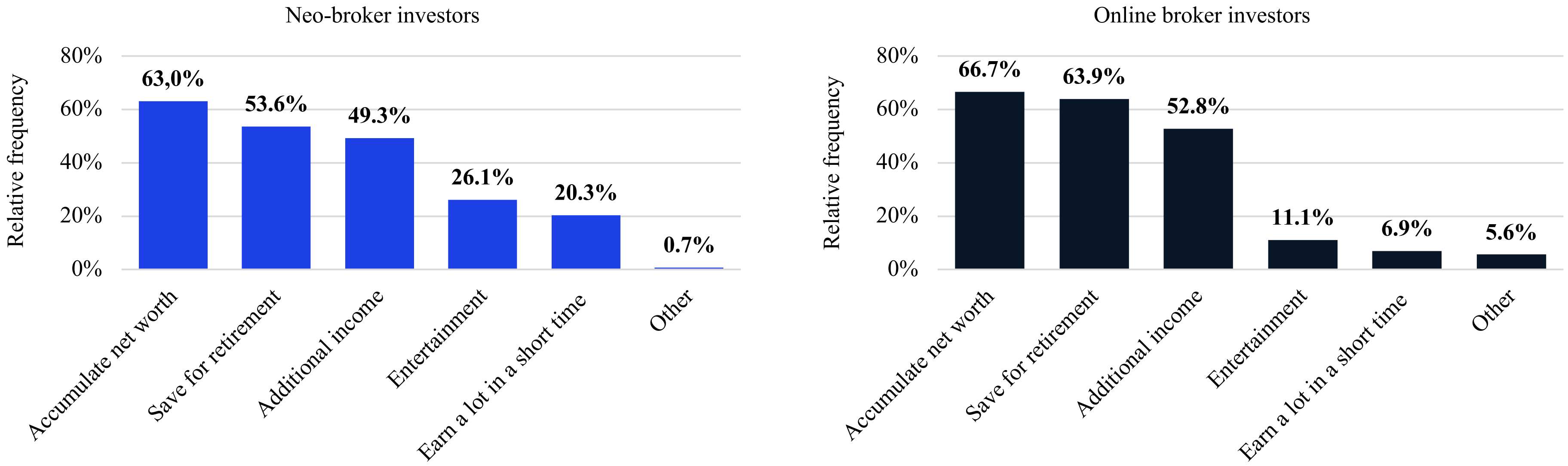


*Figure 3: Sources of information for investing neo-broker vs. online broker users (multiple response question)*

**Labels: 1**) Popular financial instruments listed in broker's interface, **2**) Recommendations of family and friends, **3**) Finance books, **4**) News in broker's interface, **5**) Online forums, **6**) Traditional media, **7**) Social media, **8**) Recommendations of bank advisor, **9**) "Top Mover List" by broker, **10**) Other: Own research and analysis, financial podcasts

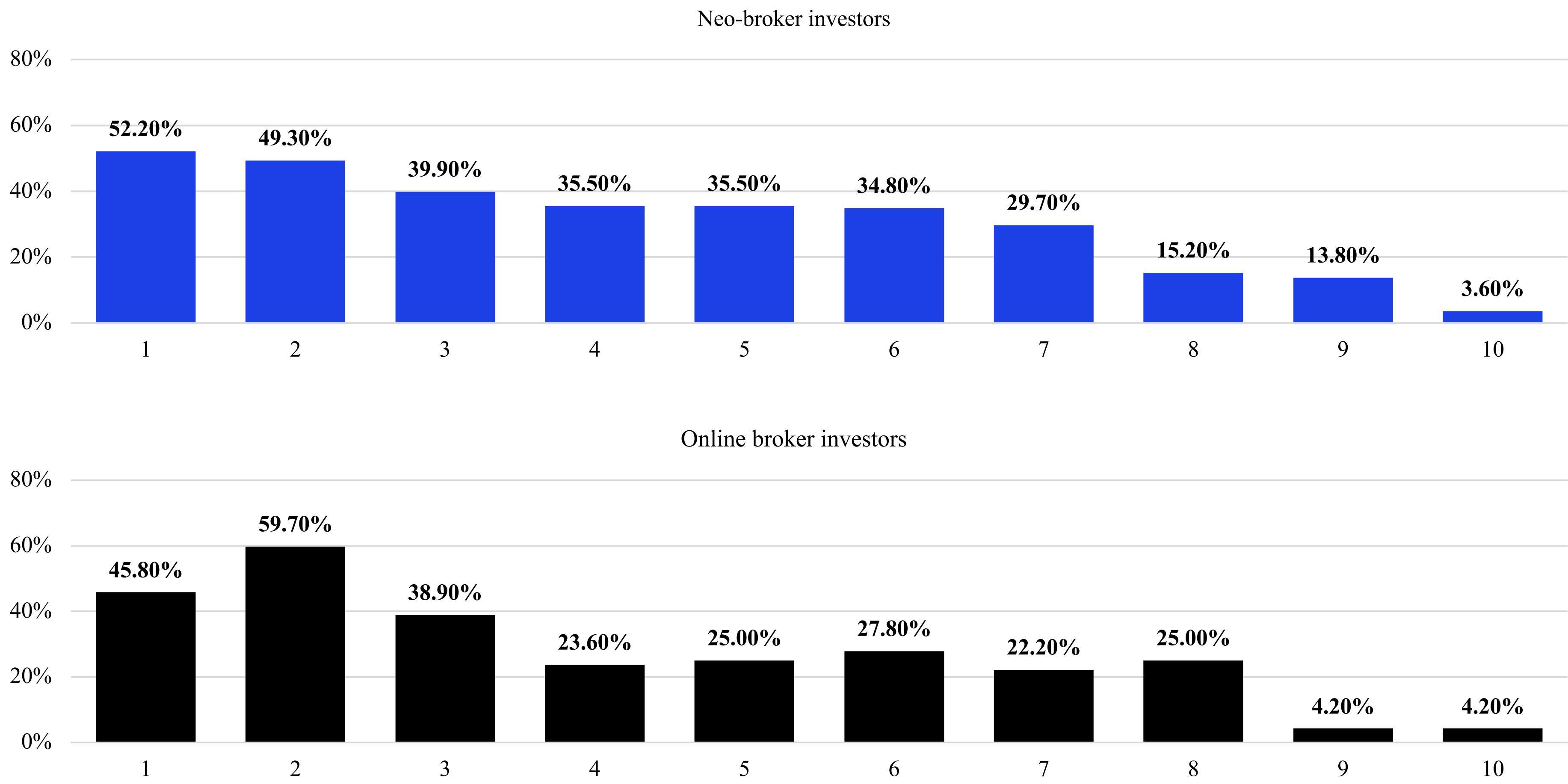


*Table 4: Numeric investment characteristics of survey participants (invest = yes)*

| | **invest = yes (1)** | | | **neo_broker = yes (1)** | | | **neo_broker = no (0)** | | |
|---|---|---|---|---|---|---|---|---|---|
| **Variable** | **Mean** | **Median** | **Sd** | **Mean** | **Median** | **Sd** | **Mean** | **Median** | **Sd** |
| Average trades / month | 4.8 | 2.0 | 19.6 | 5.9 | 2.0 | 24.0 | 2.5 | 2.0 | 3.4 |
| Return (before inflation) 2021 | 43.2 | 12.0 | 138.7 | 49.0 | 13.0 | 147.8 | 32.1 | 10.0 | 119.5 |
| Expected return (before inflation) 2022 | 38.7 | 8.0 | 150.6 | 45.8 | 10.0 | 164.7 | 25.1 | 7.0 | 119.0 |
| Types of financial instruments as % of portfolio: | | | | | | | | | |
| Stocks | 32.1 | 25.5 | 29.7 | 35.0 | 29.0 | 29.4 | 26.6 | 19.5 | 29.5 |
| Bonds | 4.3 | 0.0 | 9.3 | 4.7 | 0.0 | 10.1 | 3.5 | 0.0 | 7.6 |
| ETFs | 41.6 | 36.0 | 34.2 | 37.8 | 30.0 | 31.5 | 49.0 | 49.0 | 38.1 |
| Mutual funds | 7.3 | 0.0 | 20.9 | 5.3 | 0.0 | 17.1 | 11.1 | 0.0 | 26.5 |
| Crypto | 11.1 | 0.0 | 20.9 | 13.6 | 5.0 | 22.7 | 6.2 | 0.0 | 15.9 |
| Derivatives | 2.1 | 0.0 | 8.7 | 1.8 | 0.0 | 8.0 | 2.5 | 0.0 | 10.0 |
| Other (P2P) | 1.5 | 0.0 | 8.5 | 1.7 | 0.0 | 9.0 | 1.2 | 0.0 | 7.4 |

*Figure 4: Market capitalization of stocks invested in neo-broker vs. online broker users (multiple response question)*

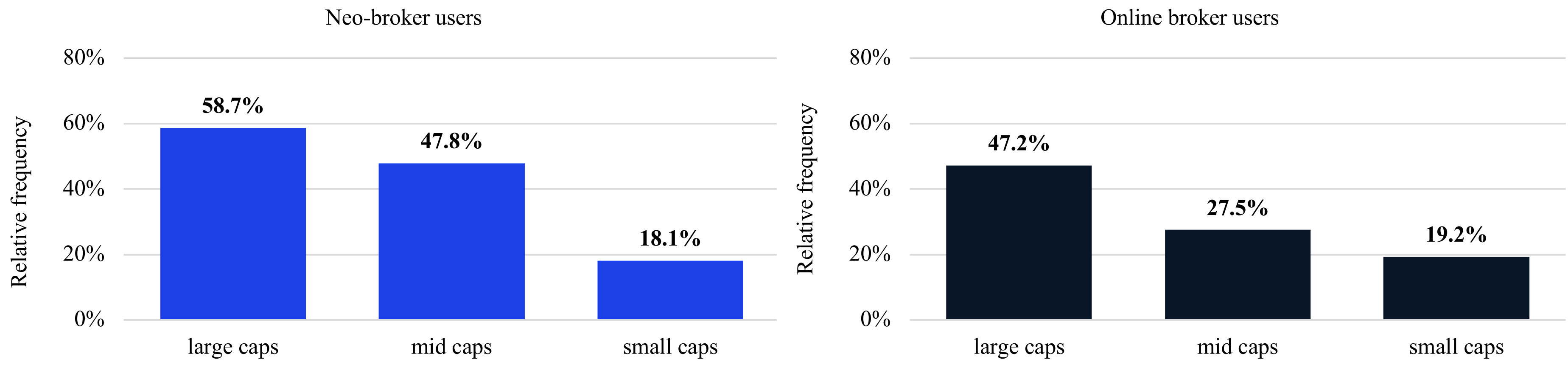



*Figure 5: Trading frequency neo-broker vs. online broker investors*

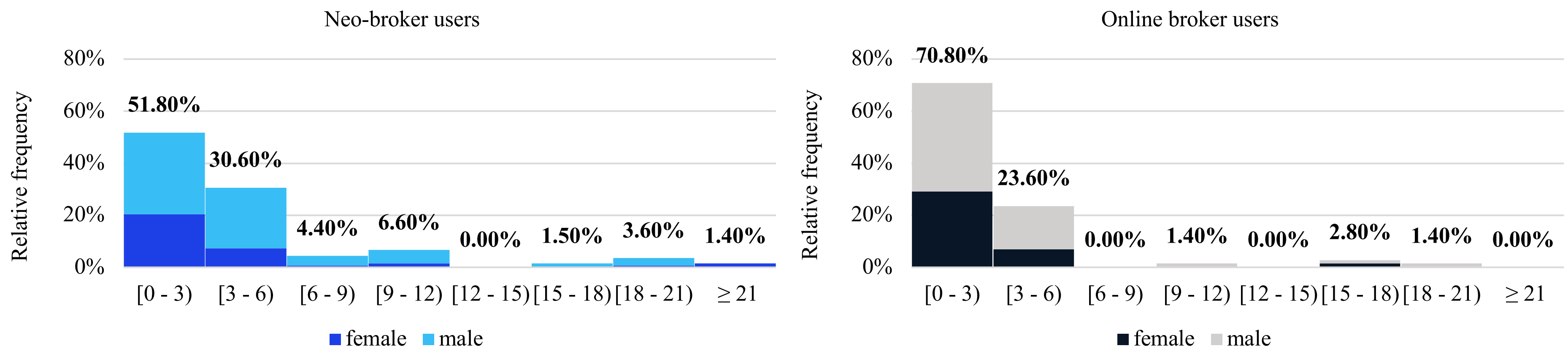


*Figure 6: Return (before inflation) 2021 neo-broker vs. online broker users*

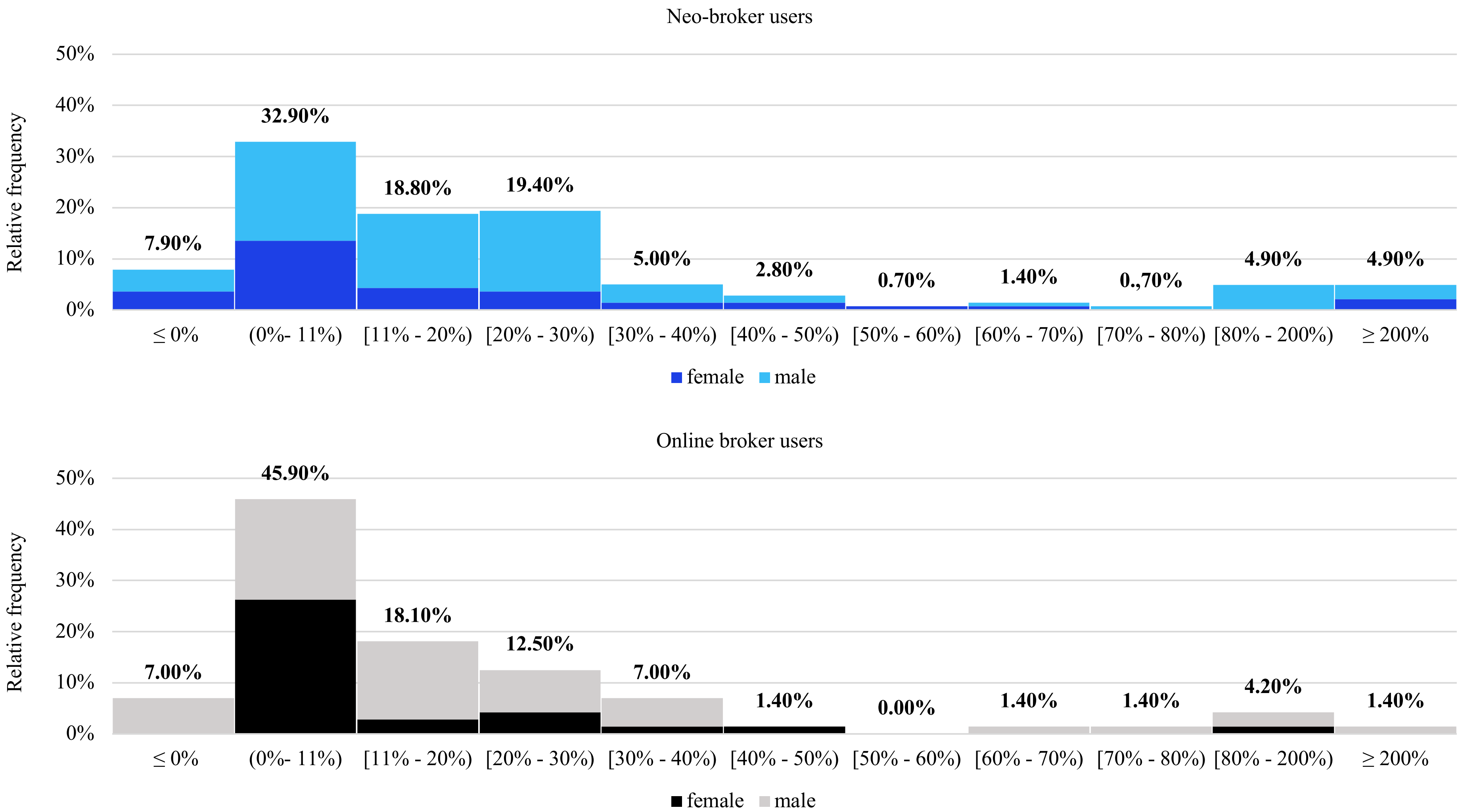


*Figure 7: Financial instruments invested in neo-broker vs. online broker users*

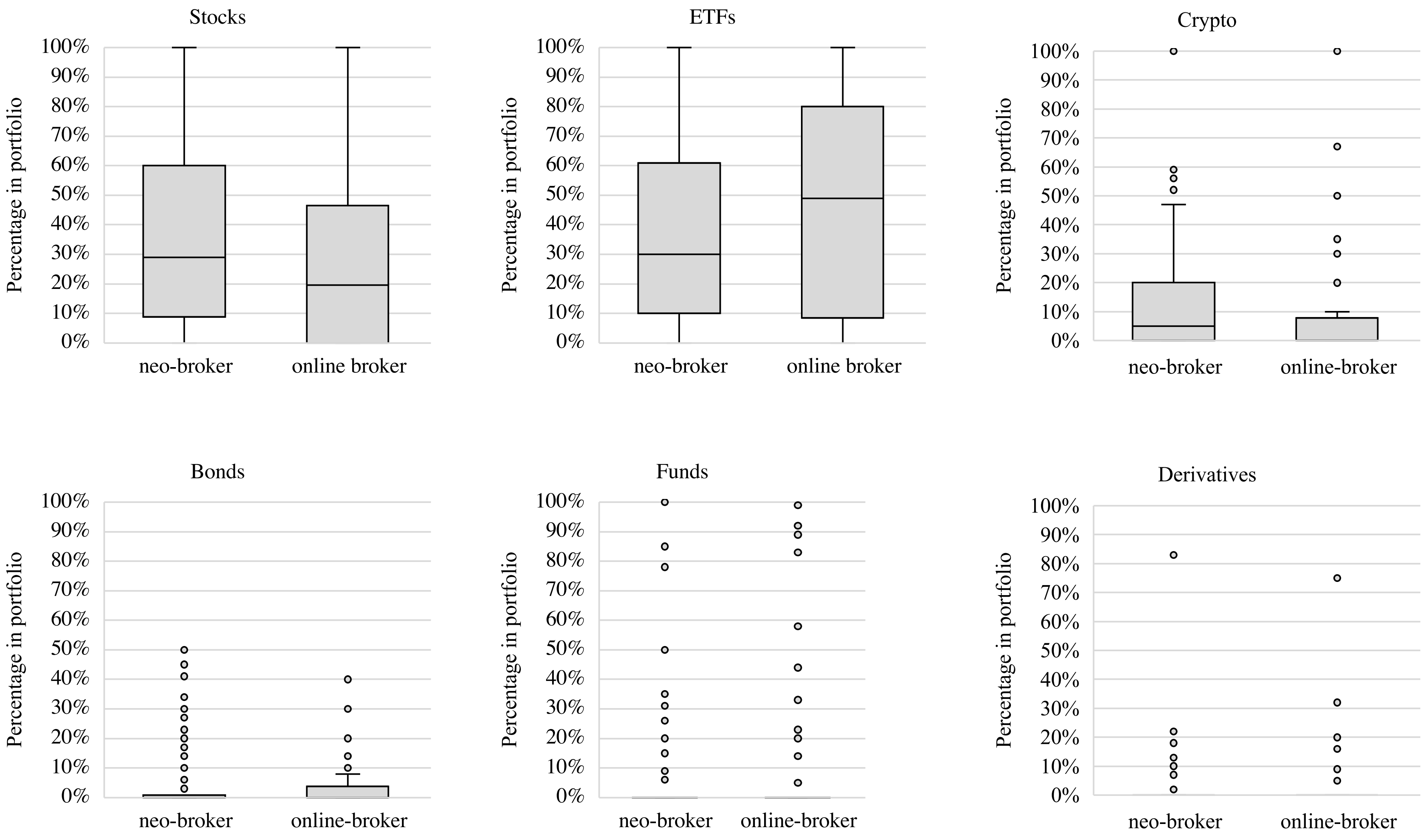


*Figure 8: Overplacement ("Better-than-average-effect") neo-broker vs. online broker users*

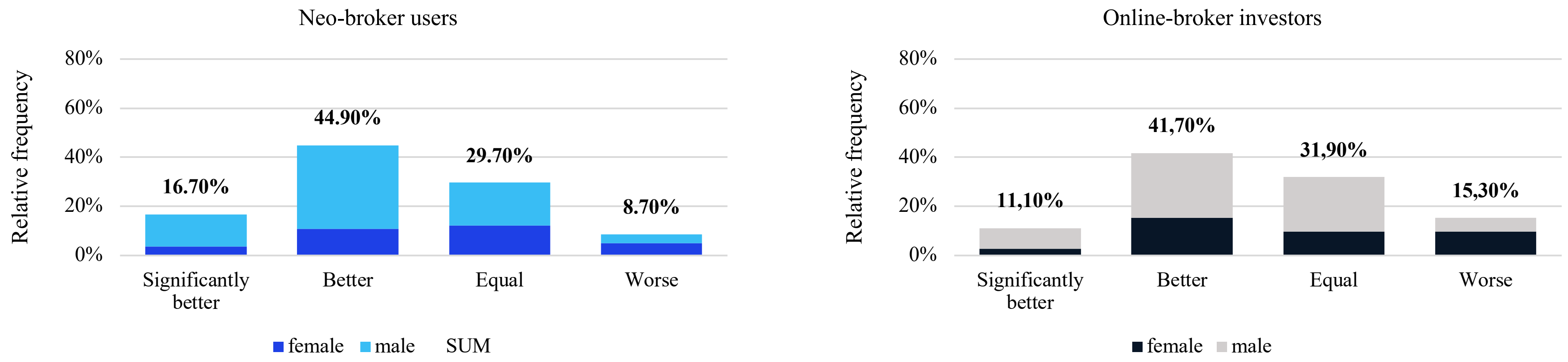
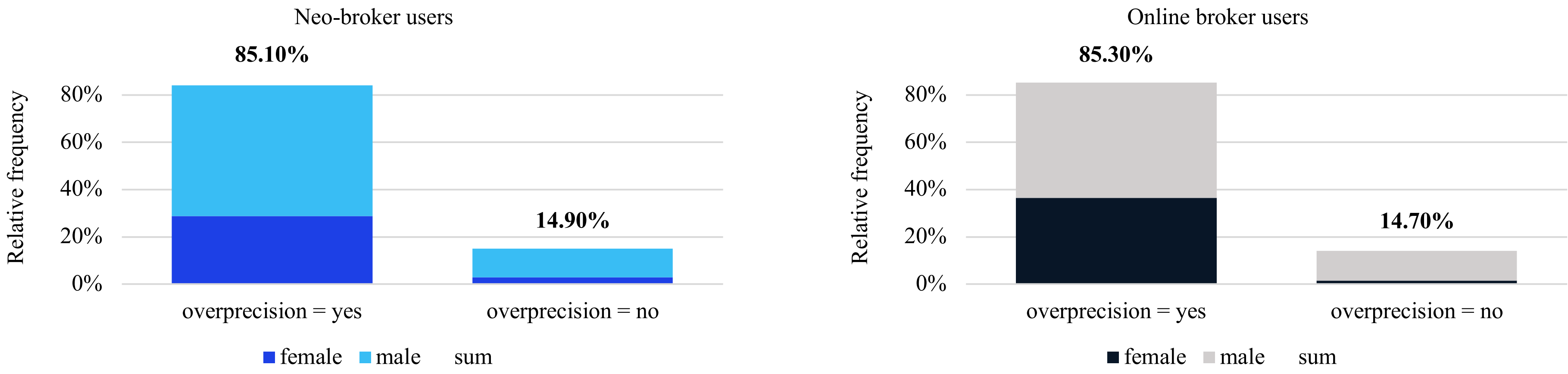
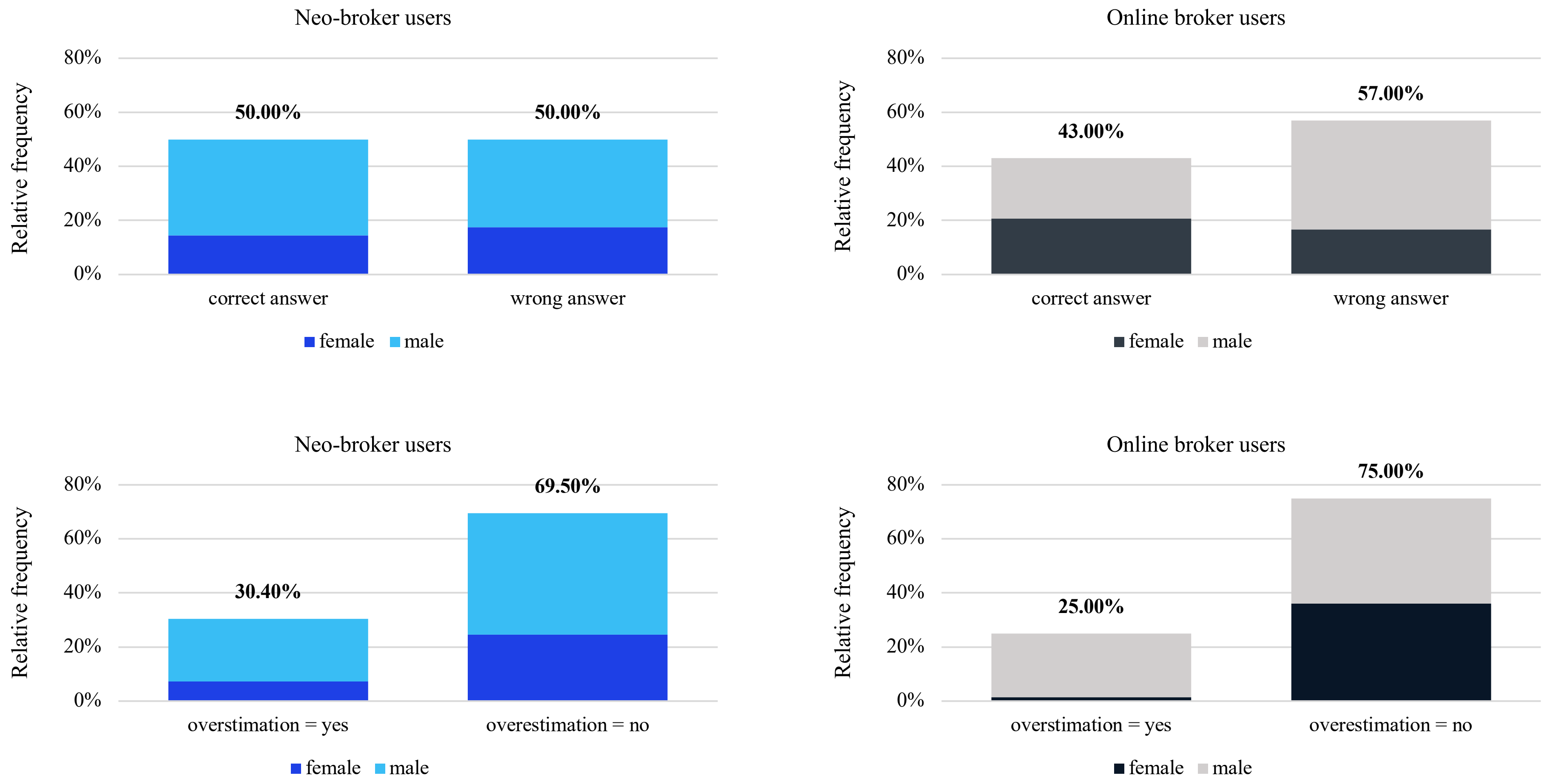



*Figure 9: Overprecision* neo-broker vs. online broker users*




* Overprecision is defined as providing a lower width of the predicted confidence intervals for the DAX than 22.68%- points (20-year standard deviation of DAX returns)

*Figure 10: Overestimation* neo-broker vs. online broker users*




* Overestimation is defined as giving a wrong answer and be 50% or more confident that the answer is correct

*Table 5: Categorical and numeric investment characteristics of survey participants (invest = no)*

| Variable | Description | Frequency | Percentage |
|---|---|---|---|
| Invest future | Yes | 52 | 78.8 |
| | No | 14 | 21.2 |
| Percentage of net worth future | Less than 25% | 26 | 51.0 |
| | 25% – 50% | 21 | 41.2 |
| | 51% – 75% | 4 | 7.8 |
| | More than 75% | - | - |
| Number of stocks in portfolio future | less than 5 | 1 | 2.9 |
| | 5 – 9 | 16 | 45.7 |
| | 10 – 19 | 13 | 37.1 |
| | 20 – 29 | 3 | 8.6 |
| | 30 – 39 | 2 | 5.7 |
| | 40 – 59 | - | - |
| | More than 60 | - | - |
| | Significantly better | 3 | 4.5 |

| Variable | Description | Frequency | Percentage |
|---|---|---|---|
| Overplace-ment | Better | 7 | 10.6 |
| | Equal | 21 | 31.8 |
| | Worse | 29 | 43.9 |
| | Significantly worse | 6 | 9.1 |

| Variable | Mean | Median | Std Dev. |
|---|---|---|---|
| Expected return Y1 | 7.71 | 5 | 6.44 |
| Types of financial instruments as % of future portfolio: | | | |
| Stocks | 26.81 | 23.50 | 23.19 |
| Bonds | 11.23 | 0.00 | 15.87 |
| ETFs | 49.10 | 50.00 | 29.92 |
| Mutual funds | 4.54 | 0.00 | 13.58 |
| Crypto | 4.87 | 0.00 | 8.32 |
| Derivatives | 3.46 | 0.00 | 7.78 |

*Table 6: Variable selection*

| Category | Nature | Variable | Decision criteria and reasoning |
|---|---|---|---|
| Dependent variables | numeric | - Trading frequency, return | Both variables will be considered since these are essential for testing *H1 – H3*. |
| Main predictors | categorical | - Brokers (multiple response), gender | Both variables will be considered since these are essential for testing *H1 – H3*.. |
| Demographics | categorical | - Income<br>- Wealth<br>- Education<br>- Employment status<br>- Number of dependents | Since there is a significant relationship between income and net worth, the latter will not be considered for further analysis and only income will be included in the regression models as suggested by Kansal and Singh (2018).<br>Due to the low data generated for the number of dependents >0 (n = 32) and respondents working in finance (n = 32), both variables will not be considered for further analysis.<br>Even though the sample shows a clear tendency towards respondents with a high academic background, education will be considered to evaluate the difference between investors obtaining a master's degree versus those with a lower educational level (cp. Mishraa and Metildab 2015). |
| Investment characteristics | categorical | - Investment horizon<br>- Investment experience<br>- Trading volume<br>- Risk tolerance/ willingness to take risks<br>- Types of stocks invested in (multiple response) | While investment horizon, investment experience, and types of stocks invested in (large caps) are proven to be essential with regards to the overconfidence bias in the literature (cp. Kansal and Singh 2018), the percentage of net worth invested, and risk tolerance do not reveal any further insights. However, number of stocks proved to be interesting due to the low diversification of the survey respondents as well as |

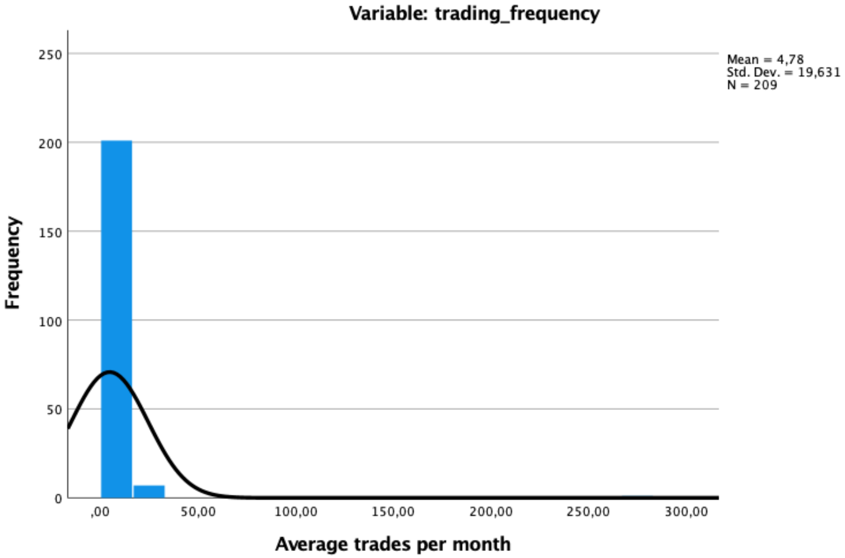
| Category | Nature | Variable | Decision criteria and reasoning |
|---|---|---|---|
| | numeric | - Number of stocks<br>- Percentage of net worth invested<br>- Types of instruments invested in | trading volume which might be highly impacted by the emergence of neo-brokers due to the low trading fees.<br>According to the literature, the lower portfolio return of overconfident investors is due to higher trading expenses and underperformance of securities purchased by those sold and not due to different risk-return relationships (cp. Barber and Odean 2000, Odean 1999). Hence, the types of instruments invested in will not be considered for further analysis. |
| Overconfidence indicators | categorical<br>numeric | - Financial knowledge<br>- Estimated return of MDAX 2021<br>- Estimated return of DAX until end of 2022<br>- Confidence level of estimated return of MDAX 2021<br>- Confidence level of DAX until end of 2022<br>- Expected return in 2022 | As an increased trading frequency as well as lower return is the consequence of overconfident investors (cp. Barber and Odean 2000, 2001, 2002, 2011), these overconfidence indicators are not relevant as predictors for the regression models since their impact is already proven.<br>Moreover, the focus of this directed research project is on explaining how neo-brokers impact the trading frequency and return of retail investors, which is the consequence of overconfident behavior. |
| Other | categorical | - Reasons for investing (multiple response)<br>- Sources of information (multiple response) | Sources of information are not relevant in terms of further analysis because the data is quite evenly distributed among both brokers and previous literature does not provide any proof of correlation with the overconfidence bias.<br>Reasons for investing is reflected in other variables, such as investment horizon and risk tolerance. |

*Table 7: Distribution of dependent and independent variables – Test of normality*

| | Kolmogorov-Smirnov[a] | | | Shapiro-Wilk | | |
|---|---|---|---|---|---|---|
| | **Statistic** | **df** | **Sig.** | **Statistic** | **df** | **Sig.** |
| neo_broker | .446 | 136 | <.001 | .572 | 136 | <.001 |
| trading_frequency | .359 | 136 | <.001 | .634 | 136 | <.001 |
| return | .367 | 136 | <.001 | .633 | 136 | <.001 |
| education | .386 | 136 | <.001 | .625 | 136 | <.001 |
| gender | .467 | 136 | <.001 | .538 | 136 | <.001 |
| income | .356 | 136 | <.001 | .635 | 136 | <.001 |
| invest_inexperience | .438 | 136 | <.001 | .581 | 136 | <.001 |
| invest_horizon | .427 | 136 | <.001 | .593 | 136 | <.001 |
| no_stocks | .513 | 136 | <.001 | .422 | 136 | <.001 |
| only_large_caps | .431 | 136 | <.001 | .589 | 136 | <.001 |
| trading_volume | .371 | 136 | <.001 | .631 | 136 | <.001 |

a. Lilliefors Significance Correction

Figure 11: Distribution of trading frequency and return



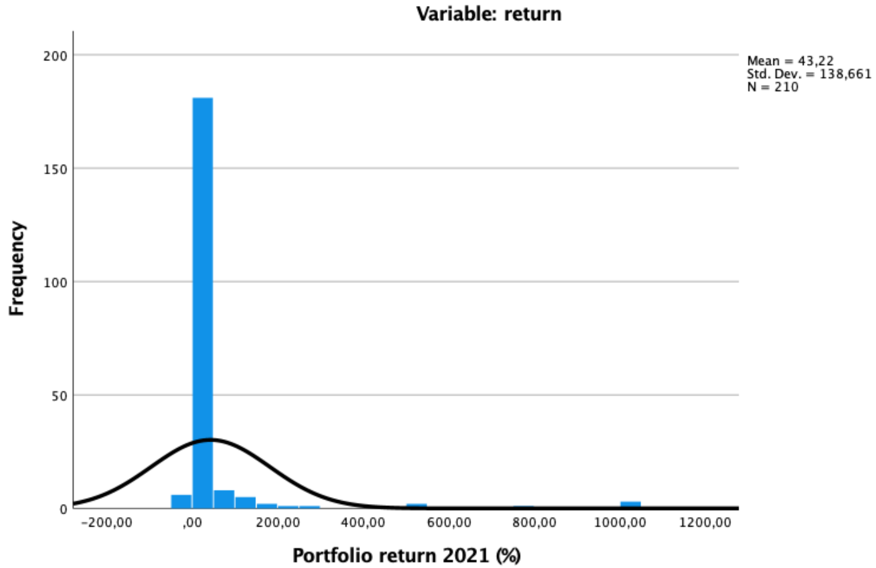



*Table 8: Variable construction and definition*

| **Variable** | **Description** |
|---|---|
| neo_broker | Survey participants were asked which broker/s they use for their investments. The variable was coded in a binary fashion identifying investors who trade through neo- or crypto brokers (1) or solely through online brokers (0). |
| trading_frequency | Survey participants were asked how many trades on average they execute per month. Based on previous data by (Meyer, Uhr, and Lutz 2021), the responses were transformed into a dichotomous variable for either on average executing >2 trades per month (1) or 2 trades or less per month (0). |
| return | By responding to how much return (before inflation) the survey participants achieved in 2021, a binary variable was created distinguishing between a gross return of 11% or less (1) and more than 11% (0).<br>This differentiation is based on the previous market return (before inflation), estimated with the S&P 500 over the last 30 years (10.79%). |
| education | This variable measures the different educational levels by comparing those survey participants that have a master's degree (1) with those that have a bachelor's degree or lower educational status (0). This differentiation was chosen because there were only 4 observations obtaining a doctorate and a clear tendency of survey participants have a high academic background by either having a bachelor's or a master's degree. |
| gender | Binary variable that differentiates between male (1) and female (0). Survey participants identifying themselves as "other" were excluded from analysis due to the low number of observations (N = 4). |
| income | The variable assesses the participants' annual gross income and was recoded into a dichotomous variable of either earning €40.000+ (1) or less than €40.000 (0) which was based on the distribution of income of the survey participants. |
| invest_inexperience | Based on the reported investment experience in the online survey, the variable was recoded into investors with less than 2 years of experience (1) and more than 2 years of experience (0).This is |

| Variable | Description |
|---|---|
| | because the total number of German retail investors who are 29 years old or less especially increased since 2020. |
| invest_horizon | By asking survey respondents on how long they are planning to hold their financial instruments. the variable identifies investors with a holding period of less than 1 day to less than a year (1) and of larger than a year (0), thereby considering short-term investors vs. medium- and long-term investors. |
| no_stocks | The retail investors who hold stocks in their portfolio were asked about the number to identify diversified and less diversified portfolios. Accordingly, the binary variable distinguishes between less than 20 stocks (1) and 20+ stocks or no stocks (0) because previous literature suggests that a portfolio considering of 20-30 different stocks can be considered as diversified. |
| only_large_caps | The retail investors who hold stocks in their portfolio were asked about the companies' market capitalization (small, mid, large cap). The variable was dichotomized by differentiating between investing in large caps only (1) or investing in small, mid and/or large caps or if they do not invest in stocks at all (0). |
| trading_volume | Survey participants were asked how much money they on average invest per trade. The binary variable identifies investors with a trading volume of less than €250 per trade (1) and of €250 or more per trade (0). This is because neo-brokers enable to trade with lower amounts which is reinforced by the low trading fees. |

*Table 9: Spearman's rank correlation coefficient*

| | V1 | V2 | V3 | V4 | V5 | V6 | V7 | V8 | V9 | V10 | V11 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **V1** | 1.000 | | | | | | | | | | |
| **V2** | .186** | 1.000 | | | | | | | | | |
| **V3** | -.109 | -.190** | 1.000 | | | | | | | | |
| **V4** | -.025 | .035 | -.097 | 1.000 | | | | | | | |
| **V5** | .056 | .158* | -.220** | .096 | 1.000 | | | | | | |
| **V6** | -.055 | .068 | -.067 | .539** | .087 | 1.000 | -.070 | | | | |
| **V7** | .119 | -.138* | .302** | -.086 | -.302** | -.070 | 1.000 | | | | |
| **V8** | .146* | .211** | -.024 | .014 | .095 | .203** | .062 | 1.000 | | | |
| **V9** | -.009 | -.148 | .067 | .047 | .006 | -.050 | .159* | .108 | 1.000 | | |
| **V10** | .066 | .079 | -.004 | .039 | .156* | .077 | .002 | .025 | .097 | 1.000 | |
| **V11** | .154* | .149* | .094 | -.082 | -.113 | -.208** | .114 | .023 | .128 | .009 | 1.000 |

*. Correlation is significant at the 0.05 level (2-tailed)
**. Correlation is significant at the 0.01 level (2-tailed)

**V1** = neo_broker, **V2** = trading = frequency, **V3** = return, **V4** = education, **V5** = gender, **V6** = income, **V7** = invest_inexperience, **V8** = invest_horizon, **V9** = no_stocks, **V10** = only_large_caps, **V11** = trading_volume

*Table 10: Binary logistic regression models for explaining trading_frequency (H1, step 1)*

| **Variable** | **Coefficient (B)** | **SE (B)** | **p-value** | **Odds Ratio** | **95% Confidence Interval** | |
|---|---|---|---|---|---|---|
| | | | | | **Lower** | **Upper** |
| neo_broker<br>0 : online<br>1 : neo/crypto | .829* | .310 | .008 | 2.292 | 1.248 | 4.209 |
| education<br>0 : other (excl. doctorate)<br>1 : master | .146 | .288 | .613 | 1.157 | .658 | 2.034 |
| gender<br>0 : female<br>1 : male | .700* | .308 | .023 | 2.014 | 1.102 | 3.681 |
| income<br>0 : < €40k<br>1 : ≥ €40k | .279 | .298 | .349 | 1.321 | .737 | 2.367 |
| invest_inexperience<br>0 : ≥2 years<br>1 : <2 years | -.585* | .294 | .047 | .557 | .313 | .992 |
| invest_horizon<br>0 : ≥ 1year<br>1 : < 1year | .941* | .313 | .003 | 2.562 | 1.388 | 4.729 |
| no_stocks<br>0 : ≥20<br>1 : <20 | -.845 | .467 | .070 | .430 | .172 | 1.073 |
| only_large_caps<br>0 : other<br>1 : only large caps | .375 | .328 | .253 | 1.455 | .765 | 2.767 |
| trading_volume<br>0 : ≥ €250<br>1 : < €250 | .653* | .303 | .031 | 1.922 | 1.060 | 3.483 |

* Significant at a 95% confidence level

*Table 11: Priorization of independent variables based on odds ratio after considering neo_broker (H1, step 2)*

| Priorization | Independent variables |
|---|---|
| 1 | neo_broker |
| 2 | invest_horizon |
| 3 | gender |
| 4 | trading_volume |
| 5 | invest_inexperience |
| 6 | only_large_caps |
| 7 | income |
| 8 | education |
| 9 | no_stocks |

*Table 12: Hierarchical binary logistic regression model based on prioritized predictors (H1, step 3)*

| | | | Model 1 | | | |
|---|---|---|---|---|---|---|
| **Variable** | **Coefficient (B)** | **SE (B)** | **p-value** | **Odds Ratio** | **95% Confidence Interval** | |
| | | | | | **Lower** | **Upper** |
| neo_broker<br>0 : online<br>1 : neo/crypto | .688* | .342 | 1.989 | .044 | 1.018 | 3.885 |
| invest_horizon<br>0 : ≥ 1year<br>1 : < 1year | .887* | .339 | 2.428 | .009 | 1.250 | 4.716 |

| Model 1 | | | | | | |
|---|---|---|---|---|---|---|
| Variable | Coefficient (B) | SE (B) | p-value | Odds Ratio | 95% Confidence Interval | |
| | | | | | Lower | Upper |
| gender<br>0 : female<br>1 : male | .452 | .356 | 1.571 | .204 | .782 | 3.155 |
| trading_volume<br>0 : ≥ €250<br>1 : < €250 | .684* | .322 | 1.982 | .034 | 1.055 | 3.726 |
| invest_inexperience<br>0 : ≥2 years<br>1 : <2 years | -.778* | .344 | .459 | .024 | .234 | .902 |
| Omnibus Test | Chi square: 26.113, df: 5, sig: <.001 | | | | | |
| Hosmer and Lemeshow Test | Chi square: 7.304, df: 8, sig: .504 | | | | | |
| Nagelkerke | .166 | | | | | |
| Classification table | 58.1% | | | | | |
| Classification table model 1 | 68.7% | | | | | |

* Significant at a 95% confidence level

*Table 13: Binary logistic models for explaining trading_frequency (H2, step 1)*

| Variable | Coefficient (B) | SE (B) | p-value | Odds Ratio | 95% Confidence Interval | |
|---|---|---|---|---|---|---|
| | | | | | Lower | Upper |
| neo_broker<br>0 : online<br>1 : neo/crypto | .829* | .310 | .008 | 2.292 | 1.248 | 4.209 |
| education<br>0 : other (excl. doctorate)<br>1 : master | .146 | .288 | .613 | 1.157 | .658 | 2.034 |
| gender<br>0 : female<br>1 : male | .700* | .308 | .023 | 2.014 | 1.102 | 3.681 |
| income<br>0 : < €40k<br>1 : ≥ €40k | .279 | .298 | .349 | 1.321 | .737 | 2.367 |
| invest_inexperience<br>0 : ≥2 years<br>1 : <2 years | -.585* | .294 | .047 | .557 | .313 | .992 |
| invest_horizon<br>0 : ≥ 1year<br>1 : < 1year | .941* | .313 | .003 | 2.562 | 1.388 | 4.729 |
| no_stocks<br>0 : ≥20<br>1 : <20 | -.845 | .467 | .070 | .430 | .172 | 1.073 |
| only_large_caps<br>0 : other<br>1 : only large caps | .375 | .328 | .253 | 1.455 | .765 | 2.767 |
| trading_volume<br>0 : ≥ €250<br>1 : < €250 | .653* | .303 | .031 | 1.922 | 1.060 | 3.483 |

* Significant at a 95% confidence level

*Table 14: Priorization of independent variables based on odds ratio (after considering neo_broker and gender) (H2, step 2)*

| **Priorization** | **Independent variables** |
|---|---|
| 1 | neo_broker |
| 2 | gender |
| 3 | invest_horizon |
| 4 | trading_volume |
| 5 | invest_inexperience |
| 6 | only_large_caps |
| 7 | income |
| 8 | education |
| 9 | no_stocks |

*Table 15: Hierarchical binary logistic regression model based on prioritized independent variables (H2, step 3)*

| | | | **Model 2** | | | |
|---|---|---|---|---|---|---|
| **Variable** | **Coefficient (B)** | **SE (B)** | **p-value** | **Odds Ratio** | **95% Confidence Interval** | |
| | | | | | **Lower** | **Upper** |
| neo_broker<br>0 : online<br>1 : neo/crypto | .688* | .342 | 1.989 | .044 | 1.018 | 3.885 |
| gender<br>0 : female<br>1 : male | .452 | .356 | 1.571 | .204 | .782 | 3.155 |

| | | | **Model 2** | | | |
|---|---|---|---|---|---|---|
| **Variable** | **Coefficient (B)** | **SE (B)** | **p-value** | **Odds Ratio** | **95% Confidence Interval** | |
| | | | | | **Lower** | **Upper** |
| invest_horizon<br>0 : ≥ 1year<br>1 : < 1year | .887* | .339 | 2.428 | .009 | 1.250 | 4.716 |
| trading_volume<br>0 : ≥ €250<br>1 : < €250 | .684* | .322 | 1.982 | .034 | 1.055 | 3.726 |
| invest_inexperience<br>0 : ≥2 years<br>1 : <2 years | -.778* | .344 | .459 | .024 | .234 | .902 |
| Omnibus Test | Chi square: 26.113, df: 5, sig: <.001 | | | | | |
| Hosmer and Lemeshow Test | Chi square: 7.304, df: 8, sig: .504 | | | | | |
| Nagelkerke | .166 | | | | | |
| Classification table | 58.1% | | | | | |
| Classification table model 1 | 68.7% | | | | | |

* Significant at a 95% confidence level

*Table 16: Binary logistic regression models for explaining the return (H3, step 1)*

| **Variable** | **Coefficient (B)** | **SE (B)** | **p-value** | **Odds Ratio** | **95% Confidence Interval** | |
|---|---|---|---|---|---|---|
| | | | | | **Lower** | **Upper** |
| neo_broker<br>0 : online<br>1 : neo/crypto | -.463 | .293 | .114 | .630 | .355 | 1.117 |
| education<br>0 : other (excl. doctorate)<br>1 : master | -.399 | .288 | .165 | .671 | .382 | 1.179 |
| gender<br>0 : female<br>1 : male | -.944* | .299 | .002 | .389 | .216 | .700 |
| income<br>0 : < €40k<br>1 : ≥ €40k | -.273 | .292 | .351 | .761 | .429 | 1.350 |
| invest_inexperience<br>0 : ≥2 years<br>1 : <2 years | 1.277* | .298 | <.001 | 3.586 | 2.001 | 6.427 |
| invest_horizon<br>0 : ≥1year<br>1 : <1year | -.108 | .308 | .726 | .898 | .491 | 1.641 |
| no_stocks<br>0 : ≥20<br>1 : <20 | .388 | .467 | .407 | 1.474 | .590 | 3.684 |
| only_large_caps<br>0 : other<br>1 : only large caps | -.018 | .328 | .956 | .982 | .516 | 1.868 |
| trading_frequency<br>0 : ≤ 2 trades/month<br>1 : >2 trades/month | -.791* | .289 | .006 | .454 | .257 | .799 |

| Variable | Coefficient (B) | SE (B) | p-value | Odds Ratio | 95% Confidence Interval | |
|---|---|---|---|---|---|---|
| | | | | | Lower | Upper |
| trading_volume<br>0 : ≥ €250<br>1 : < €250 | .386 | .291 | .185 | 1.471 | .832 | 2.600 |

* Significant at a 95% confidence level

*Table 17: Priorization of independent variables based on odds ratio (after considering neo_broker. gender. and trading_frequency) (H3, step 2)*

| Priorization | Independent variables |
|---|---|
| 1 | neo_broker |
| 2 | trading_frequency |
| 3 | gender |
| 4 | invest_inexperience |
| 5 | invest_horizon |
| 6 | trading_volume |
| 7 | only_large_caps |
| 8 | Income |
| 9 | education |
| 10 | no_stocks_low |

*Table 18: Hierarchical binary logistic regression model for explaining return (H3. step 3)*

| | Model 3 | | | | | |
|---|---|---|---|---|---|---|
| **Variable** | **Coefficient (B)** | **SE (B)** | **p-value** | **Odds Ratio** | **95% Confidence Interval** | |
| | | | | | **Lower** | **Upper** |
| neo_broker<br>0 : online<br>1 : neo/crypto | -,554 | ,327 | .574 | .090 | .303 | 1.090 |
| trading_frequency<br>0 : ≤ 2 trades/month<br>1 : >2 trades/month | -,527 | ,311 | .591 | .090 | .321 | 1.086 |
| gender<br>0 : female<br>1 : male | -,545 | ,326 | .580 | .094 | .306 | 1.098 |
| invest_inexperience<br>0 : ≥2 years<br>1 : <2 years | 1,183* | ,323 | 3.265 | <.001 | 1.732 | 6.155 |
| Omnibus Test | Chi square: 30.628, df: 4, sig: <.001 | | | | | |
| Hosmer and Lemeshow Test | Chi square: 11.246, df: 7, sig: .128 | | | | | |
| Nagelkerke | .181 | | | | | |
| Classification table | 54.8% | | | | | |
| Classification table model 2 | 67.6% | | | | | |

* Significant at a 95% confidence level