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## Good Peers, Good Apples? Peer Effects in Portfolio Quality

Olga Balakina, Claes Bäckman, Andreas Hackethal, Tobin Hanspal and Dominique M. Lammer

DEPARTMENT OF ECONOMICS
AND BUSINESS ECONOMICS
AARHUS UNIVERSITY

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# Peer Effects in Portfolio Quality

Olga Balakina, Claes Bäckman, Andreas Hackethal,

Tobin Hanspal and Dominique M. Lammer*

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**Abstract**

Peer effects can lead to better financial outcomes or help propagate financial mistakes across social networks. Using unique data on peer relationships and portfolio composition, we show considerable overlap in investment portfolios when an investor recommends their brokerage to a peer. We argue that this is strong evidence of peer effects and show that peer effects lead to better portfolio quality. Peers become more likely to invest in funds when their recommenders also invest, improving portfolio diversification compared to the average investor and various placebo counterfactuals. Our evidence suggests that social networks can provide good advice in settings where individuals are personally connected.

*JEL Classification:* D14, G11, G4

*Keywords:* Household finance, investment decisions, investment behavior, peer effects, social networks

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Balakina: Department of Economics and Business Economics, Aarhus University. Email: olga.balakina@econ.au.dk. Bäckman: Department of Economics and Business Economics, Aarhus University and Knut Wiksell Center for Financial Studies, Lund University. Email: claes.backman@econ.au.dk. Hackethal: Goethe University Frankfurt and Leibniz Institute for Financial Research SAFE Frankfurt. Email: hackethal@em.uni-frankfurt.de. Hanspal: Department of Finance, Vienna University of Business and Economics. Email: tobin.hanspal@wu.ac.at. Lammer: dominique.lammer@gmail.com. Support from the Danish Finance Institute (DFI) is gratefully acknowledged.

# 1 Introduction

Substantial evidence shows that social ties affect participation in the market for risky assets (Brown *et al.*, 2008; Kaustia & Knüpfer, 2012; Ouimet & Tate, 2019; Haliassos *et al.*, 2020; Maturana & Nickerson, 2019; Georgarakos *et al.*, 2013). Less is known, however, about whether social interactions propagate good or bad investment behavior. Do social connections spread information about the general benefits of participating in risky assets? Social connections would then increase stock market participation at the extensive margin, and reduce the costs of non-participation, an extensively studied mistake that many households make (Mehra & Prescott, 1985; Bach *et al.*, 2020; Gomes *et al.*, 2020). Or do social connections spread information about individual assets, as in Han *et al.* (2022) and Heimer (2014), making stock market participation a by-product of the advice to invest in specific assets? In this case, the quality of advice becomes paramount: bad advice could facilitate investments into specific assets or asset classes like cryptocurrencies or 'meme'-stocks, lead to investment mistakes at the individual level, and potentially asset bubbles at the macro-level (Pedersen, 2022). Alternatively, good advice could reduce idiosyncratic risk and improve portfolio quality, for example, by spreading information about investments in mutual funds or exchange traded funds (ETFs).

Despite the central importance of social networks for spreading information, there are several important challenges to overcome when studying whether social interactions propagate good or bad investment behavior. The first challenge is that social ties are often unobserved, forcing researchers to rely on assumptions about the nature of peer relationships, for example by grouping individuals based on working environment (Duflo & Saez, 2002, 2003; Ouimet & Tate, 2019), family ties (Li, 2014), or geography (Haliassos *et al.*, 2020; Hong *et al.*, 2004; Kaustia & Knüpfer, 2012). This makes it more challenging to separate the effect of social ties from the effects of selection and exposure to common shocks.

Our study takes advantage of a unique setting where we can observe direct links between individuals. Specifically, we make use of a referall campaign from an online brokerage, allowing us to observe peer relationships and the portfolio composition of a sample of German households. The peer relationship consists of individuals who recommend (Recommender) their bank and brokerage to an acquaintance (Follower). The bank incentivizes Recommenders with a cash bonus (20 EUR) or a non-cash bonus item from a variety of home appliances and electronics. In contrast to previous studies that have observed direct links between individuals, the relationships in our setting are likely to be more personal than in the kind of investment-specific social networks studied in Pelster & Gonzalez (2016) and Heimer (2016). The second challenge is that the quality of peer effects in investment behavior cannot be determined at the asset or even asset-class level. Rather, detailed portfolio composition is needed to evaluate the performance of the resultant portfolio and investment outcomes. As such, much of the existant literature has focused on *participation* in risky assets or specific investments. We link both Recommenders and Followers to detailed data on portfolio composition and study how the portfolios of the Recommender affect the *portfolio* of the Follower.

How do we identify peer effects in our setting? We argue that the overlap analysis helps separate the effect of social ties and peer effects from the effects of selection and exposure to common shocks. Most factors that would explain the correlation between investors who are connected, such as correlated risk aversion, background risk, or local bias, operate at the level of the portfolio, not at the level of individual securities (Knüpfer *et al.*, 2021). The investors in our sample have access to over 900,000 different assets, meaning that the likelihood that individual investors end up with the same portfolio by chance is minuscule, even when we condition on shared factors such as demographics, investor traits, or geography. We fix the Recommender portfolio one month before the Follower joins the bank to ensure that we capture the advice from Recommender to Follower. Our results show that Followers and Recommenders share approximately 20 percent of securities between them, a share that remains persistently high over a two-year period. For Followers with a positive overlap share, 30 percent of Followers share between 75 and 100 percent with their Recommender, indicating that the peer is the primary source of information about which assets to invest in within this group. We conduct several placebo tests to alleviate concerns that the overlap share does not occurs by chance or is driven by an omitted variable. The empirical concern is that investing in the same security may be driven by for example a local bias in asset choice, that Recommenders and Followers work at the same firm (Ouimet & Tate, 2019), similarity in consumption habits (see Keloharju *et al.*, 2012), or concurrent marketing campaigns and other financial advise provided by the bank. We confirm that Recommenders and Followers have a significantly larger overlap than several placebo samples. Even if we create placebo peers matched on year of investing, geographical location, age, assets under management, and risky share, the overlap share is always considerably higher than the placebo overlap. We also note that all investors in our sample all have the same bank and start trading in the same year, which helps rule out marketing and financial advice channels. Thus, the overlap between Recommenders and Followers is unlikely to be observed by chance.

We then move on to study the quality of peer advice. Specifically, we analyze the Return Loss and Relative Sharpe Ratio Loss for Followers during their first twelve months of trading. Both measures have previously been used to measure individual portfolio quality (Calvet *et al.*, 2007) and are useful as summary measures. We first document that Followers have better portfolio performance than the average investor over their first 12 months of trading after funding an account. Although we have a longer time series, we focus on the first twelve months of trading to avoid learning and luck from influencing portfolio choice (Anagol *et al.*, 2021). While the measured return loss of Followers is not statistically different from a general sample of investors that started trading in the same year, Followers with a positive overlap share with their Recommender, hold portfolios with a lower return loss. Decomposing the determinants of return loss, we show that Followers have a higher risky share, a higher portfolio beta, and lower diversification loss compared to other investors.

Importantly, the investment strategies of Followers are linked to their Recommenders' portfolios. We show a strong positive correlation between the ranking of Followers and Recommenders based on return loss and relative Sharpe ratio loss measures. Followers of bottom-decile Recommenders hold portfolios with significantly lower return losses than those recommended by peers at the other end of the distribution. In general, all measures of portfolio quality are highly correlated between Follower and Recommender. As Recommender portfolios are of higher quality than investors from general population, Followers who copy the portfolio of their Recommender also end up with higher quality portfolios. Thus, the better quality of Followers portfolios results from a "good" peer influence.

The lower diversification loss of Followers is rooted in their investment strategies. Followers are 4-6 percentage points more likely to invest in funds than other new investors, even after controlling for a wide range of individual and location-specific characteristics. We do not find any effects on the intensive margin (i.e., the share of funds invested into funds, given that the individual invests in funds). However, the average share invested in funds, given that an individual participates, is over 80 percent, thus providing little scope for additional investment. Since investing in funds is strongly correlated with lower return losses and a lower Sharpe ratio loss, higher participation in funds explains much of the lower diversification loss and improved performance for Followers. We then examine investment in lottery stocks, attention stocks, derivatives, and structured retail products. Such securities are arguably detrimental to portfolio quality (Kumar, 2009; Bali *et al.*, 2011; Vokata, 2021) and are associated with higher return losses. We show that Followers are equally likely to invest in lottery stocks as the general sample, both on the extensive and intensive margin. And are more likely than average to invest in high-risk derivatives and structured retail products.

We find that Followers investment choices are highly correlated with investments of Recommenders, and good investment strategies are more likely to be passed from Recommenders to Followers. The portfolio overlap is positively correlated with Recommender portfolio quality, suggesting that good advice is more likely to be accepted through social networks. We show that Followers are 50 percent more likely to invest in funds if their Recommenders invest in Funds. The positive correlation holds at the intensive margin as well: a one percent higher share of fund investment for the Recommender is associated with a 0.33 percent higher share of funds for the Follower. The correlations for investment strategies which decrease portfolio performance such as lottery and attention stocks are lower. The extensive margin correlation for lottery stocks is slightly above 30 percent unconditionally and decreases to 15 percent when we add relevant control variables. In addition, there is no positive correlation between the portfolio shares invested in the lottery stocks by Recommender and Follower. This relationship is robust to controlling for a wide range of Follower characteristics. Finally, we examine the investments strategies of Recommenders and Followers as drivers of portfolio performance. We find that Followers whose Recommenders invest in funds have lower return Loss, lower relative Sharpe ratio loss, lower portfolio beta, and lower diversification loss. Simultaneously, Recommenders participation in lottery stocks does not significantly affect any quality measure. Overall, therefore, we find evidence that the quality of advice depends on the quality of the person giving advice.

Is the peer effect that we uncover simply the result of pure imitation, or is there a transfer of knowledge and learning? Distinguishing between learning and pure imitation is important for undestanding the welfare effect of peer effects. With learning, Recommenders act as money doctors (Gennaioli *et al.*, 2015) and improve financial outcomes by helping Followers make more informed decisions about their financial investments. With (mindless) imitation, Followers simply copy the portfolio without regard to their preferences. The welfare implications of mindless imitation would also be unclear, as the preferences of Recommenders and Followers may differ (for a formal model, see Gagnon-Bartsch, 2017). What is right for the Recommenders may not be right for the Follower. With the (large) caveat that it is difficult to distinguish learning from imitation, we argue that our findings suggest that learning takes place. Given that Followers tilt their portfolios towards passive funds to a greater extent than lottery or attention stocks, it seems unlikely that this is done solely to generate social utility.

Our study improves our understanding of how social ties influence portfolio quality, and thereby complements the growing literature on peer effects and social networks (Bailey *et al.*, 2018; Cookson & Niessner, 2020; Siming, 2014; Hung, 2021) and the literature on peer effects in investment decisions and saving behavior (e.g., Beshears *et al.*, 2015;

Bursztyn *et al.*, 2014; Heimer, 2016; Kaustia & Knüpfer, 2012; Ouimet & Tate, 2019).[1] Our study is most similar to Knüpfer *et al.* (2021), who show that investors tend to hold the same securities as their parents. We differ by focusing closely on the portfolio performance of peer effects. Taken together, our findings suggest that higher quality investors tend to transfer quality advice on specific assets to their close peers, improving aggregate portfolio outcomes.

Although the effect we find in our setting is broadly positive, peer effects need not improve the efficiency of individuals portfolios. Heimer (2016) relates the influence of peers on a trading platform to investment performance by noting an increase in the disposition effect, arguably decreasing performance. These findings suggest that the increase is likely driven by investors attempting to maintain or create a good impression in front of their trading peers. Similarly, Cookson *et al.* (2021) shows that investors on a social network associate themselves with like-minded peers, which reduces performance. Our study complements these recent studies by showing that investors can largely benefit from the influence of a closely connected, non-random peer. Peer relationships in our setting are characterized by interpersonal relationships that are not likely motivated not by financial incentives, but instead by reputational costs. The different incentive structure of the investors in our sample thus make it more likely to provide sound financial advice.

We also contribute to a large literature on retail investors performance and investment behavior. This literature has documented that retail investors trade too much (Barber & Odean, 2000) or are too passive or inert (Bilias *et al.*, 2010; Calvet *et al.*, 2009), are under-diversified and expose themselves to idiosyncratic risk (Calvet *et al.*, 2007), chase trends or high attention stocks (Barber & Odean, 2008), and tilt their portfolios towards specific assets or asset classes, e.g., local stocks (Seasholes & Zhu, 2010), dividend-paying securities (Hartzmark & Solomon, 2019; Bräuer *et al.*, 2021), and cryptocurrencies or meme-stocks (Hackethal *et al.*, 2021; Hasso *et al.*, 2021). Several recent papers study have linked peer effects to the disposition effect (Heimer, 2016), investments in high-variance

[1] Outside of the finance literature, we also contribute to the work on word-of-mouth in marketing (e.g., Kumar *et al.*, 2010; Schmitt *et al.*, 2011; Lovett *et al.*, 2013; Baker *et al.*, 2016).

and high skewness strategies, and to trading behavior (Balakina, 2022). Balakina (2022) studies the effect of different social networks on trading behavior, finding that both homophily and learning is important for explaining the peer effect in trading behavior. Although we have chosen not to extend our results to financial mistakes such as the disposition effect or the effect on trading behavior, we complement these studies by examining how peers affect aggregate measures of portfolio quality. Our analysis provides a new and additional view on how external factors such as peer effects influence individual financial decision-making.

The remainder of our paper is structured as follows: Section 2 provides an overview of the data, the variables we use to measure portfolio quality, and the sample. Section 3 discusses the methodology and provides evidence on the overlap in portfolio composition. Section 4 provides our main results on whether peer effects are good or bad for portfolio quality. Section 5 concludes.

## 2 Data, variables and summary statistics

We use data from a large German online bank. The bank offers its clients a broad range of retail products, including checking and savings accounts, consumer loans and mortgages, brokerage services as well as robo- and telephone advice. The sample includes 258,000 randomly selected clients with socio-demographic and transaction data from January 2003 until September 2017. For consistency, we exclude all customers without a securities account or customers for whom certain values are missing.[2]

The dataset also contains data from 2012 to 2017 about a referral campaign the bank is constantly running, incentivized referrals with a cash bonus of 20 EUR or non-cash bonuses such as mixers, suitcases, headphones, or coffee machines. Customers can recommend a person via their online banking portal by sending a Facebook message or a link via email. Banks have such programs because referred customers have a higher

[2]See Hackethal *et al.* (2021) for additional discussion of this dataset.

contribution margin at the beginning of the relationship, higher retention, and are more valuable (Schmitt *et al.*, 2011). Referral programs are also important for banks, as the goods and services in banking are more experience goods rather than search goods (e.g. Bolton *et al.*, 2007; McKechnie, 1992), and recommenders help to reduce the uncertainty in choosing a new bank or product.[3]

The data on customer referrals allow us to identify direct peers by linking referred customers with their recommenders. We have a list of 4,011 customers who recommended someone and 4,011 customers who were referred. We observe multiple recommendations only on rare occasions. After matching the data on referrals to demographic data and cleaning it, we have 673 Followers remaining. We further restrict the sample by age, remove Followers who act as Recommenders, and remove Followers who do not open a security account or open a security account before the recommendation date. Finally, we remove Followers who had an account at the bank before the campaign started in 2012, and remove Followers with missing data. Our final Follower sample consists of 515 directly matched peer pairs. A full sample selection table is available in Table B1 in the appendix.

We make some further adjustments to the full dataset. We are interested in bank customers who have investments and who are active during the period when the Followers join the bank (after 2012). We therefore select customers who have non-zero assets under management and drop observations prior to when the customer opened a securities account at the bank. We also include only the first 12 months of trading activity and collapse the data to one observation per individual. Although we have a longer time series, we chose the first twelve months of trading to avoid learning and luck from influencing portfolio choice (Anagol *et al.*, 2021).

Our main dataset contains the average values for each variable over the first 12 months of

[3]It is important to note that the referral campaign is generic, in that it does not market specific assets or asset classes to customers. This would be problematic for our identification strategy if marketing messages encouraged correlated investment behavior. Such messages are used more frequently among Neo-brokers encouraging investors to recommend others where both parties can earn fractional shares or crytpocurrency tokens.

trading for Followers, Recommenders, and a large number of investors who have recently begun trading at the bank. Since Followers are all new investors, we also compare their behavior to other investors who recently joined the bank. In particular, we select new investors who joined after 2012 to form our control group. We do not observe investment or trading activity at other banks.

Finally, we merge asset price, characteristic, and return data from Eikon/Datastream at the ISIN-level to compute portfolio returns and measures of performance. Following Calvet *et al.* (2007), we use the CAPM model to calculate two measures of portfolio quality, the Relative Sharpe ratio loss and Return loss. We infer average returns based on a Capital Asset Pricing Model. Since German households mostly invest in German stock, we assume that the CAPM model holds for excess returns relative to German government bonds and that the benchmark portfolio is the German DAX index. Intuitively, the Relative Sharpe ratio loss is a measure of the loss from imperfect diversification, and the Return loss is a measure of how much individual loses by choosing their portfolio instead of a combination of the benchmark portfolio and cash to achieve the same risk level. The estimation procedure is described in detail in Appendix A.1. We define several investment strategies that may correlate with differences in realized returns and create a set of dummy variables that indicate whether an investors holds specific asset types. We also classify investments into Funds (ETFs and Active Funds), lottery stocks, attention stocks, and derivatives. We describe how we classify these assets in more detail in Appendix A.3.

## 2.1 Summary statistics

Table 1 and Table 2 provides demographic and portfolio summary statistics for Recommenders, Followers, and a general sample of investors. We compute the average across monthly data for the first 12 months after opening a security account for both Followers and the general sample. For Recommenders, we calculate averages for the first 12 months after their Follower opens a security account, ensuring that the data for the Recommender comes from the same period as their Follower. Column 4 provides a t-test for differences in means across Follower and the general sample.

Followers and the general sample are similar across most demographics. There are no statistical differences in age, academic titles, or in having our bank as their main bank. Followers are less likely than the general sample to be male, are somewhat less likely to have a joint account, and have more total assets under management (AUM). Examining Recommenders, we see that they are older are more likely to use this account as their main bank, are more active as measured by total logins, and that they are typically wealthier and have higher income.

Table 2 report summary statistics for portfolio characteristics. Followers are less likely to be stock market participants, have a higher risky share, a lower weight on individual stocks, and a greater weight on funds than the general sample. Followers have a higher portfolio Beta, a higher expected return, and a higher Sharpe ratio. Finally, Followers also have a lower relative Sharpe ratio loss. We leave the discussion over differences in investment styles to our main results in Section 4.

How does the performance of the portfolios of Recommenders compare to the general population? Panel A) of Figure 1 plots the distribution of log return loss for Recommenders and all other investors in our sample. Recall that a *lower* value of log Return Loss indicates a *better* outcome. The figure shows that the distribution of log Return Loss for Recommenders is shifted more towards the left, indicating that their portfolios generally are of better quality. Panel B) plots the distribution of Log Relative Sharpe Ratio loss, again showing a similar pattern.

# 3 Identifying peer effects

This section discusses how we identify peer effects by examining overlap in portfolio composition. The section begins with a description of the methodology and then provides results that show that the overlap between Followers and Recommenders is considerably higher than for any placebo match. We end the section by showing correlates of the overlap share.

## 3.1 Methodology

There are three main challenges for our analysis. First, we need to ensure that the *direction of causality* goes from Recommender to Follower. Second, we may observe the same behavior for Recommenders and Followers because of some inherent characteristics, such as similar levels of risk aversion. We therefore need to account for *contextual effects* that may simultaneously inform the portfolio decisions of both Follower and Recommender. Third, we may observe the same behavior because both the Recommender and Follower are exposed to the same external factors, for example, local income shocks. Our analysis therefore needs to account for *correlated effects*.

Our empirical approach fixes the Recommender portfolio one month before the Follower portfolio to help determine the direction of causality. For the first month of trading, the portfolio of the Recommender appears before the Follower even has a securities account. It seems highly implausible that the Follower would *advise their Recommender* on what assets to invest in, and then wait a month before opening an account.

To address the second and third challenges outlined above, we examine the *overlap* between the portfolios of the Recommender and the Follower. We calculate portfolio overlap $Overlap_i^F$ as the value of securities that are present in both the Recommender portfolio and the Follower portfolio divided by the value of the Follower portfolio:

$$Overlap_i^F = \frac{\sum_{k=1}^{K} V_k \mathbb{1}_{k=m}}{\sum_{k=1}^{K} V_k} \tag{1}$$

where $V_k$ is the value of asset $k$ in the portfolio of Follower $i$, $\mathbb{1}_{k=m}$ is an indicator equal to one if asset $k$ is in both the Follower and the Recommender portfolio. We also calculate an unweighted overlap as $UnweightedOverlap_i^F = \frac{\sum_{k=1}^{K} \mathbb{1}_{k=m}}{K}$. This measure is simply the number of individual assets $k$ that are shared between the Recommender and the

Follower divided by the number of assets in the Follower portfolio.

To see how the overlap in portfolios helps solve the challenges described above, it is worth comparing peer effects in portfolio composition to peer effects in stock market participation, the standard outcome variable in most of the literature. Contextual effects and correlated shocks likely predict participation in financial markets, but it is less clear that they would predict portfolio composition. We observe over 900,000 different assets available to the investors in our sample. Even highly correlated risk aversion among peers is unlikely to lead to investments in identical assets. A similar logic applies to common shocks: even if a local newspaper or financial literacy program promotes a specific asset class such as mutual funds or ETFs, there is still a wide range of specific funds available to the individual investor. Observing an overlap in the specific assets within a portfolio is considerably more likely to be because of peer effects than observing that two neighbors participate in the stock market. Knüpfer *et al.* (2021) makes this point when they examine inter-generational linkages in portfolio composition.

However, it is still possible that preferences for popular or local stocks drive the portfolio composition for the Follower and Recommender. To account for these possibilities, we start our analysis by comparing the overlap in portfolios between Followers and Recommenders to the overlap for matched pairs, which we call Placebo pairs. We construct Placebo pairs by first limiting the sample to new investors to match our sample construction of Followers. Specifically, we select all new investors who join the bank after 2012. We then create the matched pairs by i) randomly matching individual investors ii) matching each investor to other similar investors based on demographic characteristics, location, wealth, and risky share. This approach allows us to further control for contextual effects and common shocks. If contextual effects or common shocks drive the decision to invest in certain stocks, we should observe a similar portfolio overlap between Followers and Placebo Followers. We re-run the placebo exercise 100 times to attain a measure of uncertainty in the Placebo overlap share.

We also conduct an exercise where we match each Follower to all other investors with active portfolios over the same 12-month window. For each Follower $i \in F$, we calculate the portfolio overlap between Follower $i$ in and all investors $j \in G, j \notin F$ in the general sample $G$. Intuitively, this provides an estimate of the rarity of the specific portfolio composition of each Follower.

### 3.2 Overlap results

Figure 2 presents the first set of results. The figure plots the average value share and the number of stocks of the Follower portfolio that overlaps with the Recommender portfolio over time. We fix the Recommender portfolio one month before the Follower joins the bank and normalize time to zero in the month of recommendation. We also ensure that the Follower does not have a securities account at the bank at the time of recommendation and remove assets that the Followers bring from other banks in the overlap analysis. Therefore, it is highly likely that the direction of causality runs from the Recommender to the Follower. Panel a) plots the unweighted overlap (the number of assets that overlap between the Follower and the Recommender). At the time of recommendation, the unweighted overlap is close to 20 percent, decreasing to approximately 16 percent two years after the recommendation date. In panel b), we weigh the number of overlapping assets by their portfolio share. The weighted overlap share is approximately 10 percent at the time of recommendation, and the share increases over time.

In marked contrast, the overlap share for the placebo estimates in blue is close to zero. The blue line marks the average overlap share for the Placebo Followers, and the blue error bar represents the 99th and 1st percentile of the draws from the population. The average overlap is close to zero percent, indicating that the considerably higher overlap that we observe for Followers is unlikely to occur by chance. Table 3 summarizes several different placebo groups, showing that the average overlap is always below 5 percent. Including more precise matching does not overly affect these estimates, showing the rarity of the overlap.

Figure 3 provides additional evidence on the overlap in portfolios. The figure plots the overlap distribution for All Followers (orange bars) and Followers with positive overlap (blue bars). While most Followers have no overlap, the share is considerable among the 30 percent of Followers with positive overlap. Around 30 percent of Followers with positive overlap share between 75 and 100 percent of their portfolio with their Recommender. Examining the overlap for Followers with a non-zero overlap over time, Figure 4 shows that the unweighted overlap share is around 50 percent after two years, decreasing from 70 percent at the time of the recommendation. The weighted overlap is more stable across time, fluctuating around 35 percent.

Figure 5 provides an alternative illustration. In the figure, we match each Follower portfolio to the portfolio of *all* investors active over the same 12-month window. For each Follower, we have approximately 90,000 portfolios. The figure shows little overlap between investor portfolios, reflecting the dizzying number of assets that investors could potentially choose. For more than 80 percent of the sample, the overlap is zero. Moreover, the average overlap for the Placebo sample is again close to zero. The average overlap in Follower-Recommender portfolios of 20 percent is larger than the 95th percentile of the Placebo portfolios. To observe such a large share of Followers having a non-zero overlap is thus highly unlikely to happen by chance.

How should we think about these statistics? Based on Panel B in Table 3, it is unlikely that the overlap with placebo portfolios across all Follower is as high as we observe by chance. Put differently, the probability of one Follower having a positive overlap with other investors is small, making the probability that many Followers have a positive overlap by chance negligible. In total, 199 out of 515 Followers have an overlap with their Recommender which is higher than the mean overlap of 2.3 percent for the direct matches, and 117 Followers have an overlap greater than the 95th percentile value of 0.135. We interpret these results as evidence that Recommenders provide advice about portfolio composition that Followers use to form their portfolios. For a substantial fraction of all Followers, their peer provides a substantial part of the information Followers use to form their portfolios.

### 3.3 Determinants of overlap

Before moving on to understand if this results in better or worse portfolio outcomes, we briefly provide evidence on the determinants of the overlap share. Table 4 performs an exploratory analysis using Follower characteristics. The dependent variable is the average overlap share for the first 12 months of trading, and the independent variables are related to either demographic characteristics (column 1), portfolio characteristics (column 2), or bank characteristics (column 3). The table shows that overlap is lower if the Follower holds an academic degree and is younger. Conversely, the overlap share is higher if the risky share is higher. Moving on, we also examine whether differences between the Follower and the Recommender predict overlap. Stolper & Walter (2019) find that homophily (an individual's affinity for socializing with others like them) predicts whether they listen to financial advice. However, we do not find statistically or economically significant evidence that the overlap share in portfolios is larger if the Follower and the Recommender are more similar in either age, income, or gender. Moreover, the adjusted $R^2$ value for all regression is low, showing that demographic characteristics generally do not explain much of the variation in overlap share.

Why do we not find any effects of homophily? The relationships defined in our data are not random: one person has recommended their bank to their friend. The estimates for differences in age, income, and gender already incorporate any effect of homophily on the propensity to become friends. In effect, this is the intensive margin of homophily, whereas the effect in Stolper & Walter (2019) is the extensive margin effect. Therefore, the estimates should be read as: given that you are friends, do proxies for homophily matter for overlap in portfolios? The answer in Table 4 is no.

Finally, Table 5 show that the portfolio quality of the Recommenders has a strong impact on the overlap share. The two main dependent variables are Return Loss and Relative Sharpe Ratio Loss (Calvet *et al.*, 2007) for Followers during their first twelve months of trading. We construct these measures at the individual level using a standard single-index model for expected returns, following the approach in Calvet *et al.* (2007). Recall that the relative Sharpe ratio loss compares the Sharpe ratio of the individual investor to the Sharpe ratio of a benchmark index, in our case, the German DAX index, and measures the diversification loss achieved by the risky portfolio. The return loss measures the average return the investor foregoes by choosing their portfolio instead of a position that combines the benchmark index with cash to achieve the same risk level. Therefore, a higher value entails a larger loss. Both these measures have previously been used to measure individual portfolio quality (Calvet *et al.*, 2007) and are useful as summary measures. The results show that a lower Return loss and lower Relative Sharpe ratio loss both predict *higher* overlap. Followers copy more of the portfolio when the quality of the Recommender portfolio is higher.

# 4 Main Results

This section provides the main results on how peer effects affect portfolio quality. We first show how Follower portfolio quality compares to the portfolio quality for other investors. We collapse the first 12 months of trading after joining the bank for both Followers and a general sample of similar investors. Our baseline results show that all Followers have similar Return loss to other investors, whereas Followers with a strictly positive overlap with their Recommender, have lower Return loss. Decomposing the Return loss into its various components, we show that Followers have a higher risky share and a higher portfolio beta and lower diversification losses. Moreover, we show that Followers have a higher propensity to invest in funds and a similar propensity to invest in lottery or attention stocks. Finally, we investigate how and why Follower and Recommender portfolio quality correlates. Specifically, we examine how the Recommender's portfolio transmits to the Follower's portfolio in terms of overall quality and asset allocation.

In our empirical exercise, we have chosen to examine the full portfolio of the Follower instead of examining the portfolio that overlaps between Follower and Recommender. If the peer only recommends certain assets, and the Follower constructs the rest of the portfolio on their own without taking the recommended assets into account, examining only the overlap portfolio is appropriate. A lack of overlap in portfolios is then consistent with a lack of peer effects. However, we believe this is unlikely to be true for several reasons. First, the Recommender could influence the Follower's overall portfolio even if no assets overlap. One can imagine, for instance, that the Recommender advises the Follower to invest in a certain asset or asset class and that the Follower constructs their portfolio with this recommendation in mind. For example, the Recommender could encourage investments into mutual funds, which would imply a peer effect even if the overlap share is zero. We will examine this effect directly. Second, portfolio composition is not independent of the single assets in the portfolio. If the Follower purchases an asset because of a recommendation, they should adjust the rest of their portfolio. The non-overlap is likely a function of the overlap portfolio share, making it appropriate to examine the full portfolio instead of just the overlapping assets. In Appendix C, we provide selected results for the sample of Follower with positive overlap, showing stronger results than what we provide below. Including all Followers likely biases our estimates towards zero.

## 4.1 Baseline results

This section presents our baseline results for portfolio quality. We compare Followers to a sample of other investors who are in their first year of trading. Specifically, we estimate the following equation to examine the portfolio quality of Followers:

$$y_{i,k,t} = \alpha + \gamma Follower_{i,k,t} + \mathbf{X'_{i,k,t}}\beta + \delta_{i,k} + \epsilon_{i,k,t} \tag{2}$$

where $y_{i,k,t}$ is the main dependent variable, measured for individual $i$ living in region $k$ in year $t$ during the first twelve months after opening their securities account. $\alpha$ is a constant, $Follower_{i,k,t}$ is a dummy variable equal to one for Followers and zero for placebo Followers. We include a vector of demographic and financial control variables in $\mathbf{X'_{i,k,t}}$, including age, age squared, income, education level, and gender. We also include two bank-level controls: a dummy equal to one if the bank is the main bank of the individual and a dummy equal to one for having a joint account. We also include a year × region fixed effect in most regressions. Finally, we use robust standard errors.

Table 6 provides our first main results. The dependent variable in the first four columns is log Return Loss, and the dependent variable in the last four columns is the log relative Sharpe ratio loss. The results in the first three columns show that Followers have lower Return Loss but the coefficients are not statistically or economically significant after adding controls. In column 4, we show that Followers with a positive overlap have lower Return loss. The coefficient on Follower × Positive Overlap of -0.20 is approximately 3 percent of the average Return loss or 15 percent of the dependent variable standard deviation.

In columns 5-8, we examine the Relative Sharpe Ratio loss. Recall that the relative Sharpe ratio loss measures loss from diversification and that a higher value entails a larger loss. In contrast to the previous results for Return loss, the results for the RSRL are economically and statistically significant, showing that Followers have more diversified portfolios. The coefficient in column 5 is -0.28, approximately 20 percent of the average relative Sharpe ratio loss and 33 percent of a standard deviation. When we add controls the coefficient is reduced but remains significant. The coefficient on Follower is -0.10 when we add region × year fixed effect in Column 6 and is -0.09 in column 7 when we add individual-level controls. These coefficients correspond to 6 percent of the dependent variable mean. Column 8 shows that Followers with a positive overlap have larger estimated coefficient, although it is not statistically significant.

Why do we find insignificant effects for Return loss but significant effects for the Relative Sharpe ratio loss? There is a natural correspondence between the two measures that we use to examine this question. Following Calvet *et al.* (2007), the relationship can be written as:

$$RL_i = (Er_m^e)w_i\beta_i(\frac{RSRL_i}{1-RSRL_i}). \tag{3}$$

The return loss is a function of the expected excess return on the mean-variance efficient market portfolio ($Er_m^e$), the household's weight in risky assets $w_i$, the beta of household portfolio, and a transformation of the household's relative Sharpe ratio loss. Taking logs of equation (3):

$$\ln RL_i = \ln(Er_m^e) + \ln w_i + \ln \beta_i + \ln\left(\frac{RSRL_i}{1 - RSRL_i}\right). \tag{4}$$

The decomposition relates the return loss to the log equity premium, which is constant across individuals, to two measures of how aggressive the individual portfolio is (the share invested in risky assets and the beta of the individual portfolio), and to a measure of portfolio inefficiency (the transformation of the Sharpe ratio loss). We can use this decomposing to examine why we have an insignificant effect on Return loss. Table 7 presents the results. We present results for return loss (the same results as Column 3 of Table 6) and each component of return loss. The empirical setup corresponds to (2). The decomposition reveals that Followers are more aggressive in their risk-taking, as measured by a higher risky share and a higher portfolio beta, and more efficient in their portfolio choices, as measured by the lower diversification loss. The coefficient on Follower is 0.17 and 0.07 for the log risky share and log portfolio beta, respectively. Both coefficients are statistically significant at conventional levels. The coefficient on Follower is -0.16 for diversification loss, again significant at the 1 percent level. Since each term is additive in Equation (4), the higher risky share and portfolio beta cancel out the lower diversification loss.

## 4.2 Investment style

What accounts for the lower diversification loss for Followers? To answer this question, we investigate whether Followers' investment styles are different from the general sample of investors, and whether that difference can explain the gap in diversification loss. Our analysis is motivated by Han *et al.* (2022), who provides a model where stocks with high volatility and skewness are more likely to be recommended by peers in a social network. In our empirical setup, these recommendations would be captured by a higher share invested in lottery and attention stocks. Sui & Wang (2022) show that investors tend to post more on social media about their better-performing stocks and that this leads to the spread of high-variance, high-skewness stocks. On the other hand, investors may want to recommend assets with desirable characteristics to their friends, especially as they do not have monetary incentives to provide biased advice. In that case, experienced investors may recommend investments with lower volatility, fees, and higher expected returns (e.g., diversified passive funds). In what follows, we show that Followers generally invest more into funds, and that their investments in lottery and attention stocks are not generally higher than the general sample.

We now show how investments in different asset classes correlate with portfolio quality. Note that these results are not specific to Followers or Recommenders but instead use all the investors in our sample. In Figure 6 and Table 8 we report how each investment style is related to return loss and relative Sharpe ratio loss, our measures of "good" and "bad" portfolio quality. The variable of interest is *Participation*, a dummy variable equal to one if the investor invests in the specific asset class. Participation in funds is generally associated with lower Log Return loss and log relative Sharpe ratio loss. In contrast, participation in lottery and attention stocks generally reduces Log Return loss and log relative Sharpe ratio loss. We note that we cannot include the portfolio performance stemming from derivatives participation as return data on options, certificates, structured retail products, and warrants is unavailable in our setting. However, a large literature suggests that these and other structured retail products tend to underperform (Célérier & Vallée, 2017; Vokata, 2021).

Table 9 shows the difference in participation rates between Followers and the general sample for different investment styles. Figure 7 provide a graphical representation of the table. Panel A examines the participation rate (extensive margin), while Panel B states the conditional investment in each specific asset type. The table shows that Followers are 5.8 percent more likely to invest in funds. However, there is no statistical difference for the fund portfolio share. Within the fund category, Followers are 7.0 pp. more likely to invest in passive funds and 6.7 pp. more likely to invest in active funds. At the intensive margin, Followers invest a lower share in both active and passive funds. Moving on to lottery and attention stock investments, we find no statistical difference between Followers and the general sample at the extensive margin. On the intensive margin, Followers invest less in several types of lottery stocks. For instance, Column 7 in Panel B shows that Followers invest 3.4 pp. lower share in high skewness stocks compared to other investors. We find little evidence that Followers are more attracted to Attention stocks. Of particular interest is Column 12, where we examine the participation rate of high-risk derivative instruments. Derivatives include investments in structured retail products such as certificates, warrants, and various types of options. We note that Followers are 3.8 p.p more likely than the general sample to invest in such assets, but that Followers also invest 4.5 p.p.less in these products conditional on participation. Note that these investments are not included in our Return loss and Relative Sharpe ratio loss calculation, as they are not priced in our data.

Our evidence shows that participation in certain asset classes is correlated with portfolio quality and that Followers are more likely to invest in asset classes that correlate with better portfolio quality. In sum, Followers invest more into funds, leading to better portfolio quality. We do not find evidence that Followers invest more in lottery or attention type stocks, in contrast to the theoretical predictions in Han *et al.* (2022) and the empirical results in Sui & Wang (2022), Heimer (2016) and Cookson *et al.* (2021). Our study complements these recent studies by showing that investors can largely benefit from the influence of a closely connected, non-random peer. The results are consistent with Recommenders being inclined to recommend assets with desirable characteristics to their friends, especially as they do not have monetary incentives to provide biased advice.

## 4.3 What determines Follower portfolio quality?

In this section, we test the relevant mechanisms which underlie our results. Specifically, we test if the better quality of Followers' portfolios and their choice of investment strategies are related to peer effects or some other characteristic of the Follower. Intuitively, if the higher quality of Follower portfolios is due to peer effects, we should see a positive correlation in measures of portfolio quality between Followers and Recommenders. This is indeed what we find.

Panel A of Figure 8 plots the log Return Loss and the Log Relative Sharpe Ratio Loss for the Follower against Recommender rank over each variable. We sort Recommenders into deciles by log Return loss and the log Relative Sharpe ratio loss and then compare the portfolio quality for Followers across deciles. There is a strong linear relationship between Recommender rank and Follower portfolio quality for both measures. Followers log Return Loss increases from -7.8 to -5.8 between the top and bottom decile. In Panel B of Figure 8 we instead plot the log Relative Sharpe ratio loss, again showing an almost linear relationship between Recommender rank and the value for the Follower.

Figure 9 then shows that the above results are robust to controlling for various Follower characteristics and using continuous values for the Recommender. The figure provides binscatter plots of Follower and Recommender portfolio characteristics. All figures control for region $\times$ year fixed effects, a dummy for male, income proxy, academic title, age, and age squared, as well as controls for having our bank as the main bank and a dummy equal to one if the account is a joint account. The figure demonstrates additional results for portfolio beta, risky share, portfolio value, and weight in funds. All figures control for a wide range of Follower characteristics and plot the Follower variable on the $y$-axis and the corresponding variable for the Recommender over the same period on the $x$-axis. Table B3 in Appendix B provides estimates in table form. Overall, the results indicate that there is a strong correlation between the portfolio characteristics of the Follower and the Recommender. For example, a 1 percent higher Return Loss for the Recommender is associated with a 0.48 percent higher Return Loss for the Follower. All these estimates are statistically significant at the 1 percent level and are robust to including control for Follower characteristics.

How do Recommenders transmit the quality of their portfolios to Followers? Table 10 shows a high and significant correlation between most investment strategies of Recommender and Follower both at the extensive and intensive margins. For example, a Follower is 57 percentage points more likely to invest in funds if the Recommender him or herself invests in funds. At the intensive margin, a one percent point increase in fund share of the Recommender is associated with a 0.638 percent increase in fund share in the Follower's portfolio. The correlation between Recommender and Follower among alternative investment strategies such as lottery stocks or derivative investments is lower. At the extensive margin, a Follower is from 13 (column 4) to 36 (column 5) percentage points percent more likely to invest in lottery stocks if the Recommender invests. The equivalent coefficient for derivative participation is 0.24. At the intensive margin the correlation at the intensive margin is statistically significant and comparable to the results for funds.

Moreover, Table C2 shows that Recommender participation in specific asset classes generally imply that participation in *other* asset classes is lower. Each cell in the table represents a separate regression, where the dependent variables are listed in columns and the independent variables are listed in rows. For instance, in the first row the independent variable of interest is a dummy variable equal to one if the Recommender invests in funds (Recommender: Funds), and the first column is a dummy variable equal to one if the Follower invests in funds. The coefficient indicates that Follower are 54.6 percent more likely to invest in funds if the Recommender invests in funds. In column 2, we see that the Follower is 22.9 percent *less* likely to invest in Lottery stocks if the Recommender invests in funds. Overall, the table indicates that there is substition between asset classes. If the Recommender invests in funds, the Followers more invests in funds and less in lottery stocks.

Finally, the investment strategies of the Recommender has a strong impact on the portfolio quality of the Follower. Table 12 regresses the participation decisions of Followers (columns marked with " Fol." ) and Recommender (columns marked with " Rec." ) on portfolio quality measures for the Follower.

## 4.4 Welfare impliciations

Are Followers better off because of the peer effect in portfolio composition that we uncover? The higher risky share and portfolio betas imply that Followers are taking more risk, moving to the right in an Expected return-volatility framework. At the same time, the lower diversification loss implies that Followers have a higher ex-ante expected return for the same level of volatility, moving them upwards in an Expected return-volatility framework. Whether more risk is appropriate for Followers is less clear and depends on whether the Followers are learning from their peers or simply imitating them. We can distinguish between mindful learning, where the investor learns from an informed peer, and mindless imitation, where the investor derives utility from similarity in choices (see Ambuehl *et al.*, 2018, for experimental evidence). For mindful imitation, the welfare implications are clearer, and more likely to be positive. With mindful learning, Recommenders act as money doctors (Gennaioli *et al.*, 2015) and improve financial outcomes by helping Followers make more informed decisions about their financial investments. For mindless imitation, Followers simply copy the portfolio without regard to their preferences. The welfare implications of mindless imitation would also be unclear, as the preferences of Recommenders and Followers may differ (for a formal model, see Gagnon-Bartsch, 2017). What is right for the Recommenders may not be right for the Follower.

The overlap analysis suggests that peers are engaged in imitation, but a simple overlap does not rule out learning taking place. To distinguish between these two types of imitation, it is useful to think about the positive relationship between the overlap share and the Recommender portfolio quality. Higher quality portfolios are more likely to spread, which implies that the overlap we observe is likely due to learning. If it was instead a case of simple mindless imitation, investors would copy the portfolios regardless of quality. Moreover, that funds is more likely to be passed from Recommender to Follower than lottery or attention stocks is informative. Bluntly put, we find it unlikely that individuals derive social utility (Bursztyn *et al.*, 2014) from owning the same mutual fund as their peers. It instead seems more plausible that investors derive utility from owning the same *stock* as their peer, which is contrary to what we find. Lottery or attention stocks are passed to a much lower extent than funds, which is again suggestive of learning.

# 5 Conclusion

In this paper, we use administrative data from a German online bank to analyze peer effects based on a direct recommender-referral relationship. We provide evidence of considerable overlap between the portfolios of Recommenders and Followers, which we use as our main evidence of peer effects in portfolio composition. The evidence suggests that social ties help spread information about individual assets, making it important to study the quality of the advice. Second, we find that investors that follow peer advice have better portfolios than investors with the same demographic characteristics, measured as a lower relative Sharpe Ratio loss and lower diversification loss (Calvet *et al.*, 2007). The quality of the portfolios are driven by the investment in funds. On average, the quality of financial advice shared between subjects in our setting is high. Third, we find that the quality of the Followers portfolio is highly correlated with the quality of his or her Recommenders portfolio. The correlation in portfolio performance stems from a high correlation in asset class participation between Recommender and Follower. Investors are more likely to invest in good asset classes such as mutual funds when their peers invest in funds. A similar relationship holds for asset classes which reduce performance, such as structured retail products, derivatives, and lottery stocks, but to a lesser extent. The results suggest that social connections can propagate both good and bad investment behavior, depending on the quality of advice given. Finally, we find that the positive overlap in portfolios is strongly correlated with Recommender portfolio quality, suggesting that Recommenders are positively selected. We conclude that in our setting, the "good" investment advice of the peers outweighs "bad" investment spillovers and leads to higher quality portfolios for the followers.

The question we ask in this paper is whether peer effects lead to better portfolios. The answer, as with much else in finance and economics, is that it depends. We provide evidence that peer effects in finance derive from overlap in portfolio composition: friends recommend specific assets to another, resulting in an overlap between their portfolios. In our setting it turns out that this leads to better outcomes. However, in our case Recommenders had better portfolios than the average investor, which is not necessarily the case in all situations. Our setting also potentially differs in other dimensions. Recommenders are provided a small cash bonus if friends and family members fund a bank account. This incentive is unrelated to the performance of their own or referred portfolios and unconditional on (quality) advice shared between Recommender and Follower. Recommenders are neither certified financial advisors nor anonymous social media 'analysts,' each with their own set of incentives and pitfalls. For example, the former is often characterized as a credence relationship where principal-agent conflicts arise due to information asymmetry, and incentives may exacerbate advice quality. The latter may be biased by confirmatory information (Cookson *et al.*, 2022), have competitive or even malign incentives (Frydman, 2015), or extrapolate from past returns (Dim, 2021). Rather, Recommenders-Follower pairs are characterized by a personal relationship that likely precedes the observed financial advice. And given that Recommenders are wealthy, it seems unlikely they would do this for the small monetary or token prize provided. Thus, Recommenders may be incentivized to provide sound financial advice by reputational costs, social utility (Bursztyn *et al.*, 2014), or 'warm glow.'[4]

The key overall message from our results is instead that peer effects lead to similarity in portfolio composition. Whether peer effects are good or bad for individual portfolios then depend on how good your friends are and who you listen to. While in our case the friends turned out to be quite good for portfolio composition, primarily due to a higher propensity to invest in stocks, it is reasonable to believe that this will not be the case in all situations. Indeed, if peer effects in stock market participation arises due to overlaps in portfolio composition it is natural to assume that this will spread investment mistakes too, provided that the peer makes such mistakes.

[4]An existing literature examines moral behavior and incentives in sender-receiver games and most relevant is the link to credence good markets such as financial advice (Kerschbamer & Sutter, 2017), (Inderst *et al.*, 2019), and (Chen & Gesche, 2017) and sources therein.

Finally, we note that the results should be interpreted with care, both due to the sample and methodological challenges in peer research. The external validity is limited, as the sample only consists of data from one German online bank. The choice of this bank is not exogenously given, and the generalization of the findings is therefore limited. In addition, peer pairs have not been randomly assigned, and there might be issues due to the simultaneity problem.

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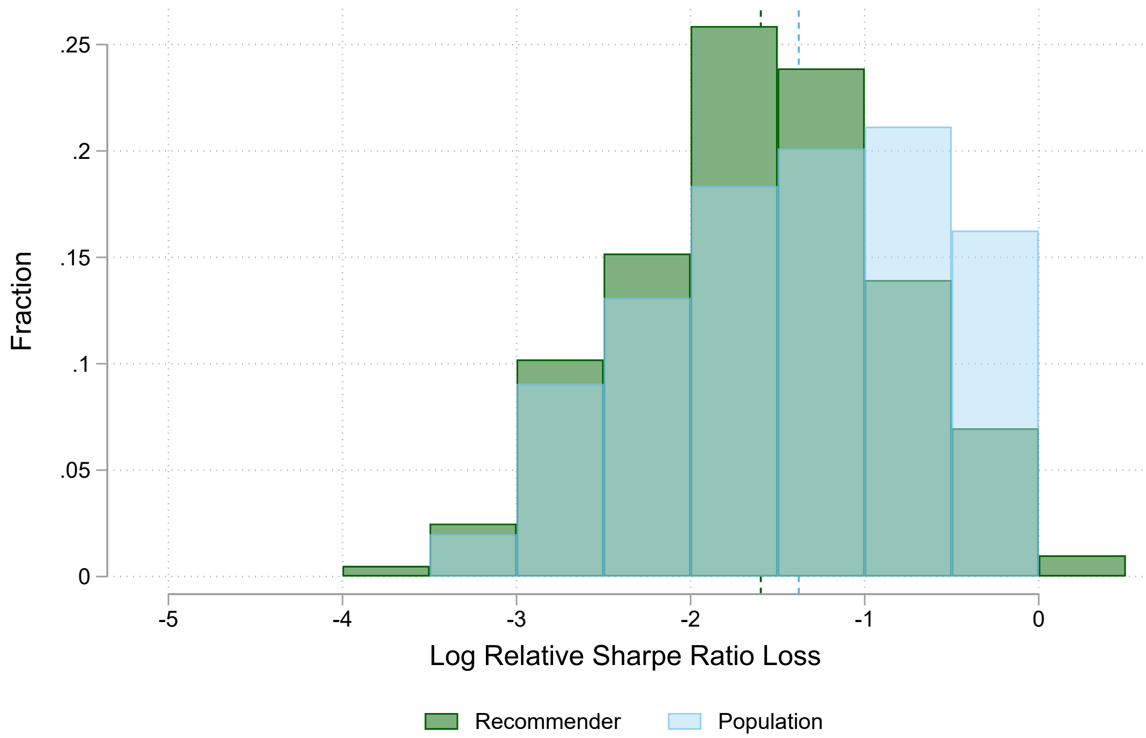
# 6 Figures


A) Log Return Loss

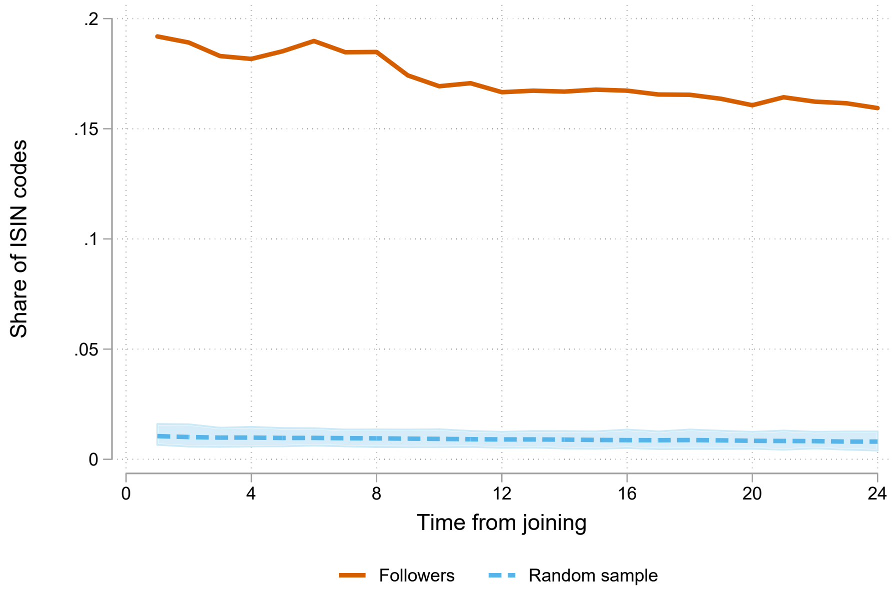



B) Log Relative Sharpe Ratio loss

Figure 1: Histogram of portfolio quality for Recommenders and the population

*Notes:* Panel A plots the distribution of log return loss for Recommenders and all other investors in our sample. Panel B plots the distribution of Log Relative Sharpe Ratio loss for Recommenders and all other investors in our sample.

a) Overlap in number of assets




b) Overlap in share of portfolio

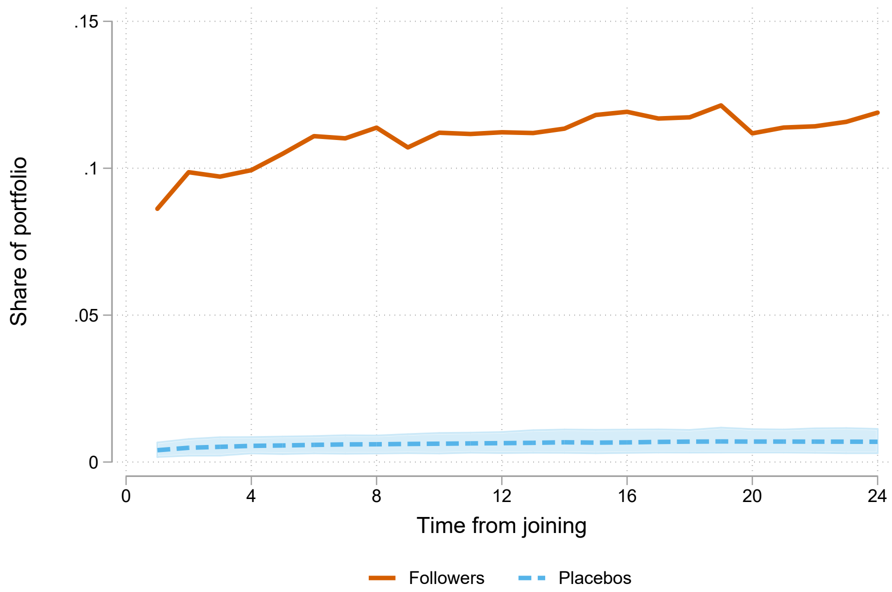



Figure 2: Overlap in number of assets and share of portfolio

*Notes:* Panel a) show the unweighted overlap share, the overlap in number of assets. Panel b) shows the portfolio overlap, where the overlap in assets is weighted by their value in the portfolio. For both figures the orange line shows the development of peer-determined number of shares in the Followers' portfolios from 0 to 24 months after the referral date. The portfolio for the Recommender is lagged one month relative to the Follower. The blue line shows the peer-determined share for Placebo Followers. Placebo Followers are defined as individuals who begin trading during one of the years where we observe Followers. Placebo Recommender are matched to a Follower based on age, portfolio value, total wealth, gender, experience, stock participation, risky share and German federal states. The blue confidence intervals mark the 1 and 99th percentile of the distribution of placebo overlap shares.

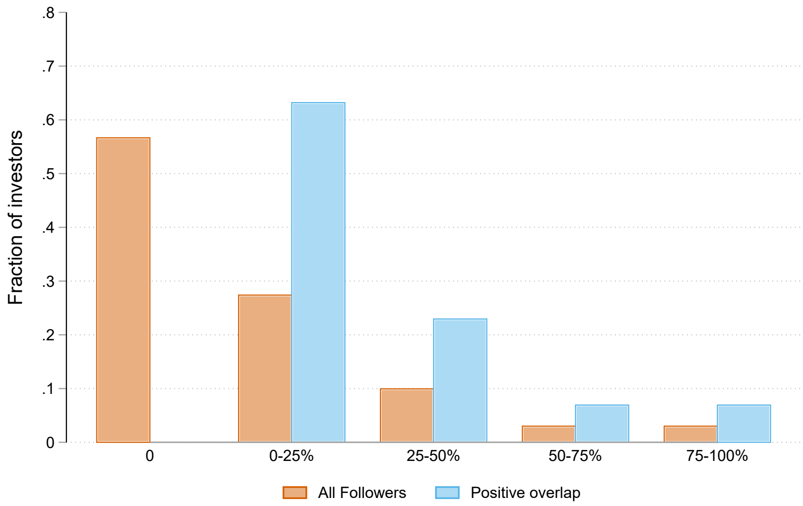



Figure 3: Distribution of overlap share

*Notes:* The figure shows the distribution of the number of investors by the average share of peer-determined securities in their accounts. The portfolio for the Recommender is lagged one month relative to the Follower.

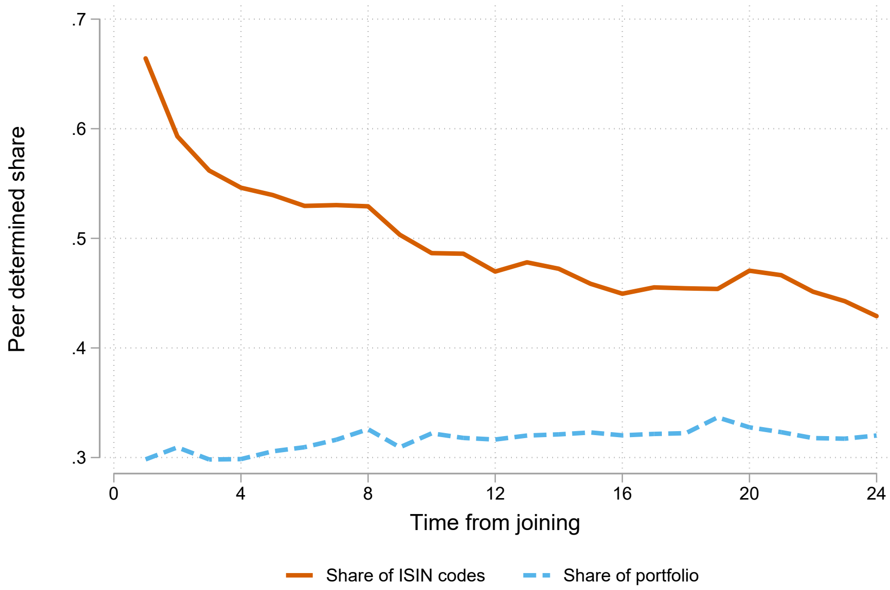



Figure 4: Overlap and unweighted overlap for Followers with positive overlap

*Notes:* The orange line shows the development of peer-determined shares in the Followers' portfolios from 0 to 24 months after the referral date. The portfolio for the Recommender is lagged one month relative to the Follower. The blue line shows the peer-determined share for Placebo Followers. Placebo Followers are defined as individuals who begin trading during one of the years where we observe Followers. Placebo Recommender are matched to a Follower based on age, portfolio value, total wealth, gender, experience, stock participation, risky share and German federal states. The blue confidence intervals mark the 1 and 99th percentile of the random draw of the overlap share .

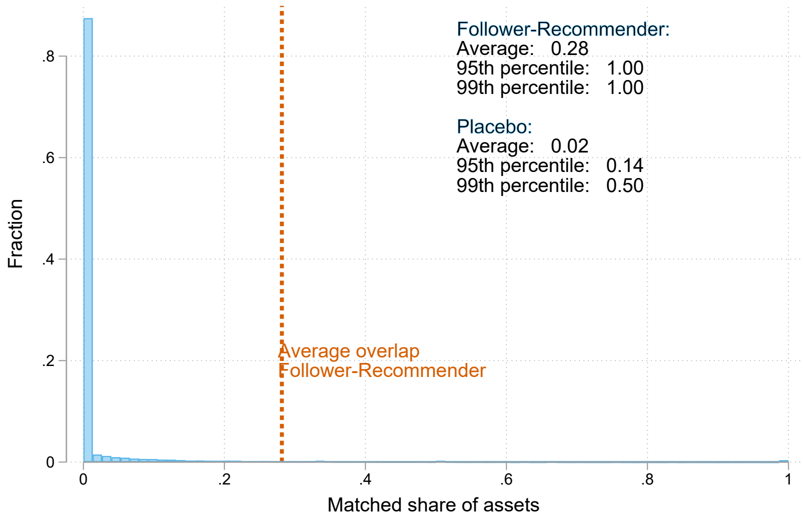



Figure 5: Overlap with all investors

*Notes:* The dashed red line shows the average portfolio overlap between followers and recommenders while the blue histogram bars show the matched share of assets for all investors in the sample.

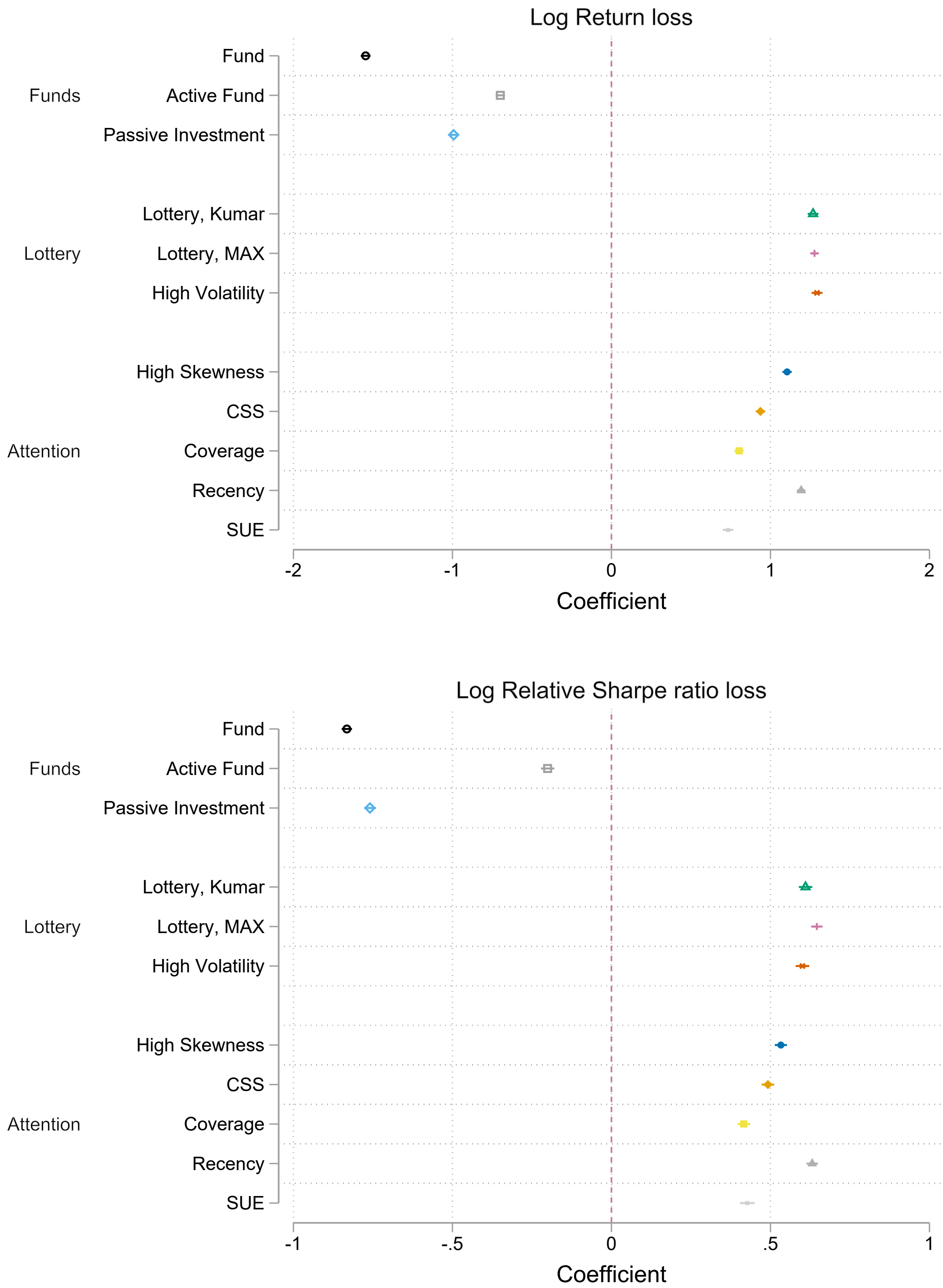



Figure 6: Asset type participation and portfolio performance

*Notes:* The figure presents results for comparison of the correlations between investment in asset type, such as mutual funds in general, and active, passive funds and ETFs specifically, lottery stocks and high attention stocks for Followers and the matched sample.

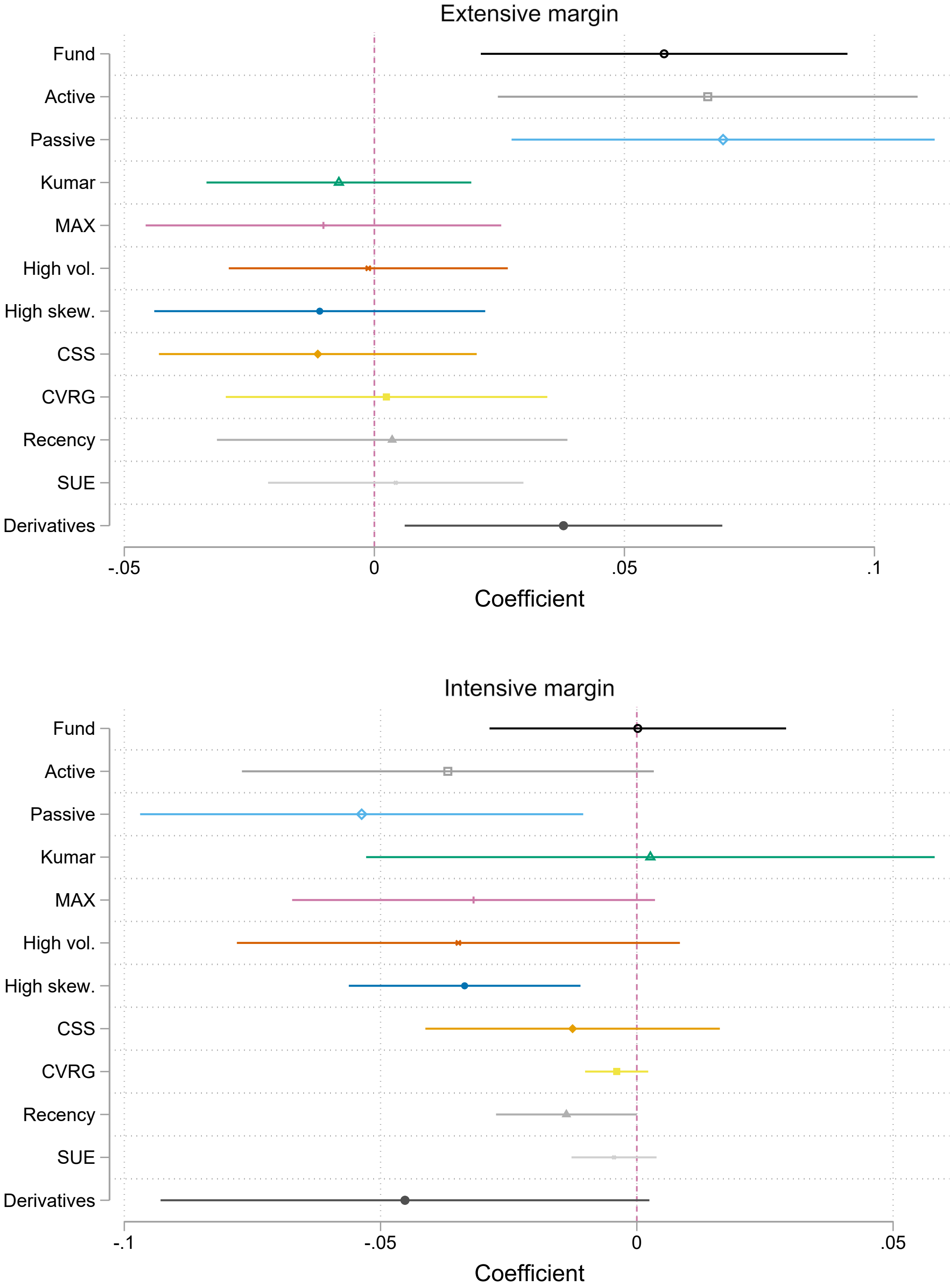
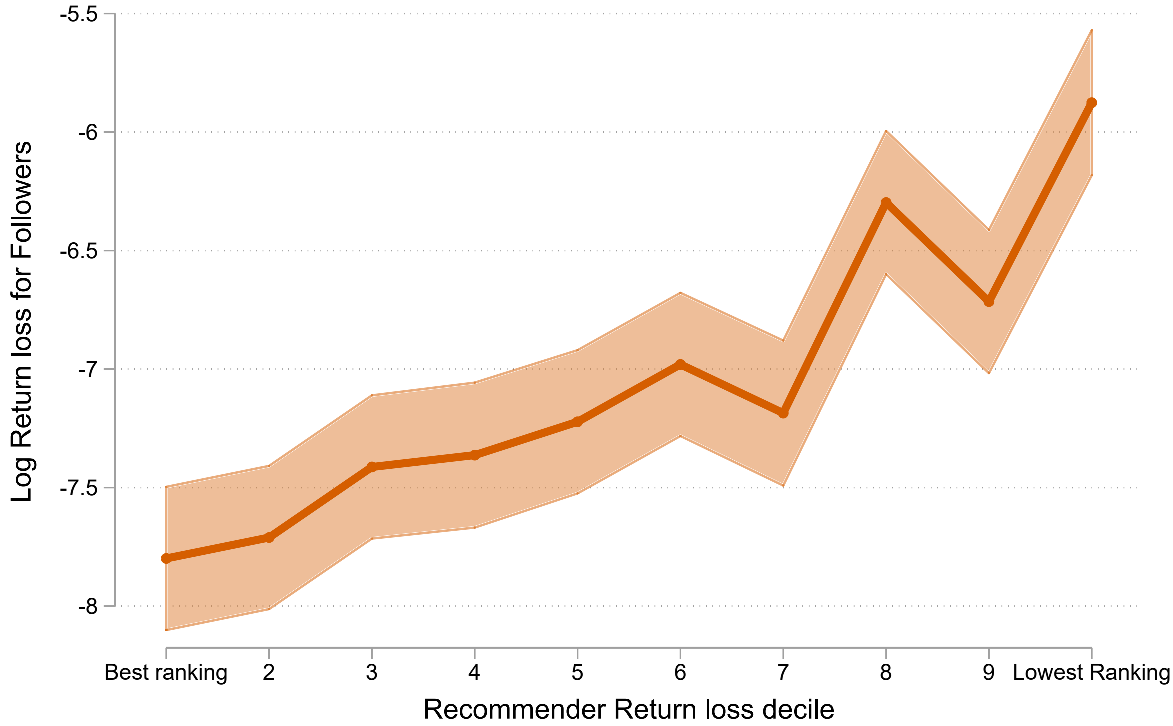
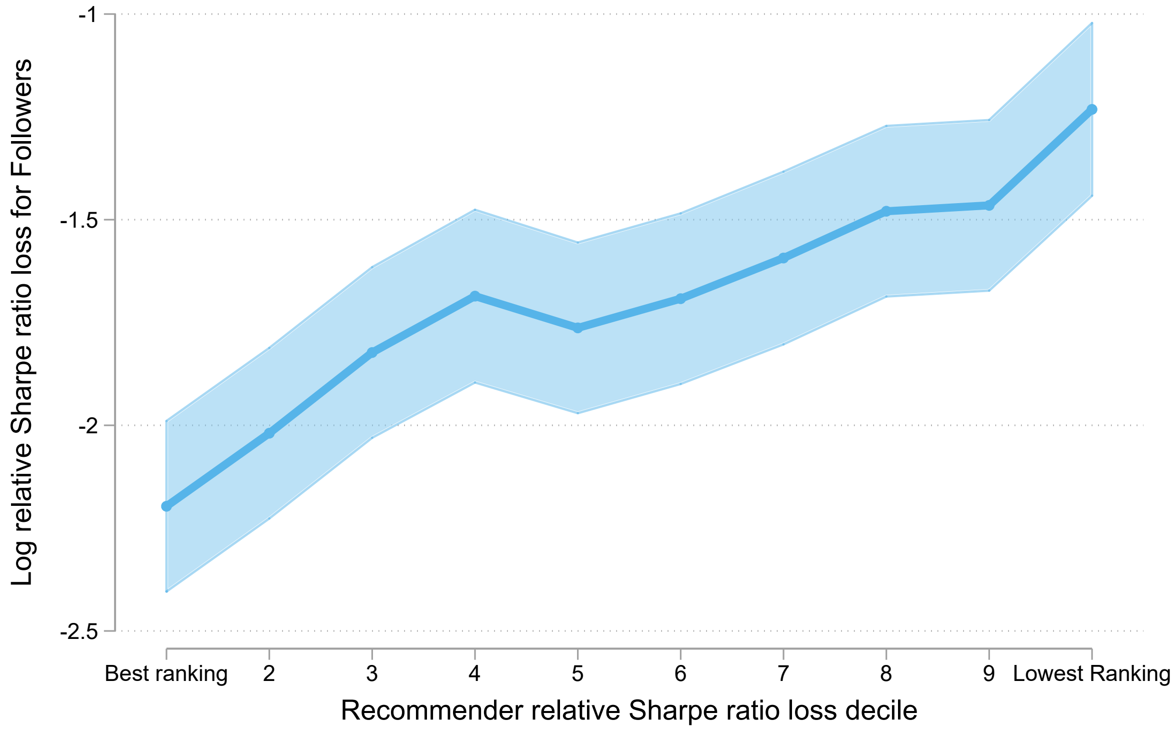



Figure 7: Asset type participation and portfolio performance

*Notes:* This figure presents results comparing investments in specific asset classes for Follower and the general sample. The figure plots the coefficient on Follower along with 95 percent confidence intervals. Control variables include a dummy for male, income proxy, academic title, age and age squared, as well as controls for having our bank as the main bank and a dummy equal to one if the account is a joint account.



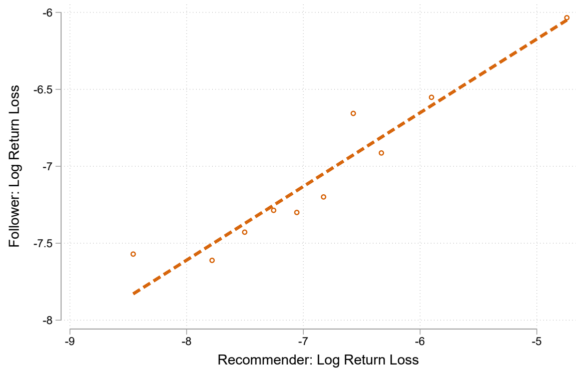

A) Return Loss



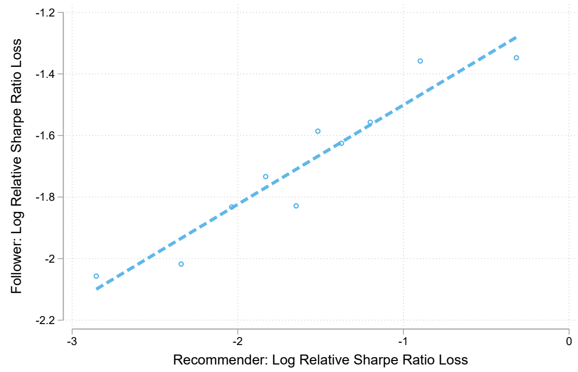

B) Relative Sharpe Ratio loss

Figure 8: Follower portfolio quality conditional on Recommender portfolio quality

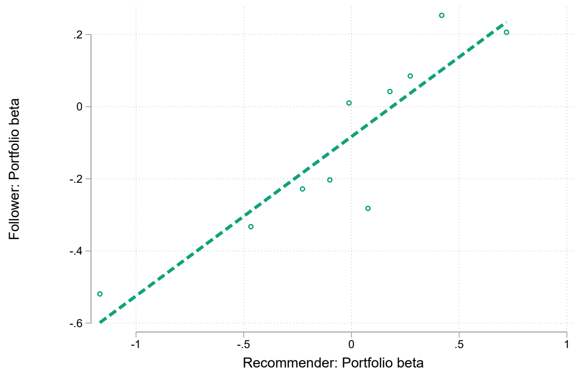
*Notes:* The figure plots the log Return Loss (Panel A) and the Log Relative Sharpe Ratio Loss (Panel B) for the Follower against Recommender rank. Recommenders are sorted into deciles by log Return loss and the Log Relative Sharpe Ratio Loss, and the average value for Followers is shown on the $y$-axis. 95% confidence intervals are provided.



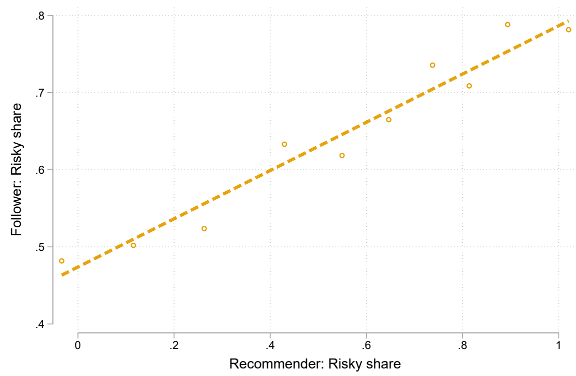

Return Loss



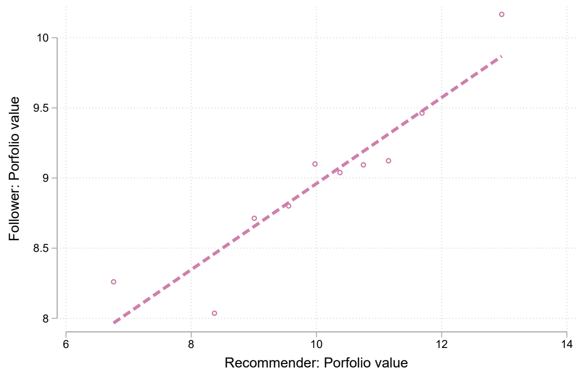

Relative Sharpe Ratio loss



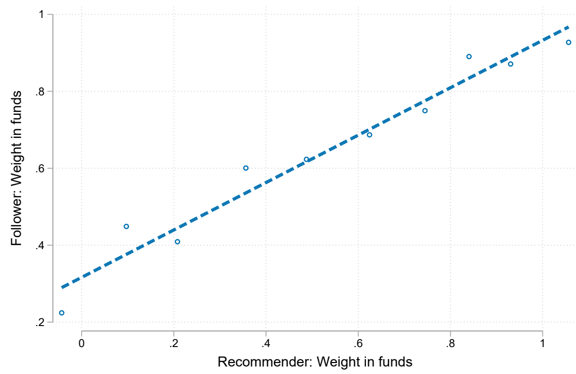

Portfolio Beta




Risky Share




Portfolio value




Weight in funds

Figure 9: Follower and Recommender Portfolio composition

*Notes:* The figure provides binscatter plots of Follower and Recommender portfolio characteristics. The figure demonstrates additional results for portfolio beta, risky share, portfolio value and weight in funds. All figures controls for region $\times$ year fixed effects, a dummy for male, income proxy, academic title, age and age squared, as well as controls for having our bank as the main bank and a dummy equal to one if the account is a joint account. We plot the Follower values on the y-axis and the corresponding variable for the Recommender over the same time period on the x-axis.

# 7 Tables

Table 1: Descriptive Statistics

*Notes:* This table reports the descriptive statistics of the customer demographics and the characteristics of the recommenders and the referrals of the full sample. The last column presents the differences in means between both groups, where t-statistics are reported in brackets. Total AUM is assets under management, including risky assets and cash. Income proxy is the monthly average difference between the high and low balances in the checking account. Geo wealth proxy is measured on a scale from 1-9 and indicates the average wealth level of individuals within a micro-geographical area. I: Main bank is an indicator equal to one if a customer allocates at least half of the tax exemption limit to this bank. The reported values are calculated by first computing the cross-annual average for the last 12 observations and then taking the cross-sectional average of these values across all investors. Standard deviations are in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

| | (1)<br>Follower | (2)<br>General sample | (3)<br>Recommender | (4)<br>T-test (2) - (1) |
|---|---|---|---|---|
| **A. Demographic characteristics** | | | | |
| Male | 0.52 | 0.72 | 0.77 | 0.20*** |
| | (0.50) | (0.45) | (0.42) | [9.86] |
| Age | 41.32 | 41.73 | 43.15 | 0.41 |
| | (15.58) | (13.79) | (14.35) | [0.67] |
| Academic title | 0.06 | 0.06 | 0.05 | -0.00 |
| | (0.23) | (0.23) | (0.22) | [-0.06] |
| Joint account | 0.10 | 0.15 | 0.15 | 0.05*** |
| | (0.29) | (0.36) | (0.36) | [3.38] |
| Main bank | 0.31 | 0.29 | 0.49 | -0.02 |
| | (0.46) | (0.45) | (0.50) | [-1.03] |
| Total logins | 24.26 | 32.02 | 50.23 | 7.76* |
| | (90.09) | (90.12) | (114.88) | [1.93] |
| **B. Wealth and income** | | | | |
| Total AUM (EUR) | 34,228 | 29,481 | 61,217 | -4,747** |
| | (47,568) | (46,513) | (75,541) | [-2] |
| Income proxy | 2,702 | 2,991 | 4,259 | 289 |
| | (6,138) | (10,043) | (7,893) | [1] |
| Portfolio value (EUR) | 24,340 | 23,887 | 92,916 | -453 |
| | (44,515) | (110,399) | (202,798) | [-0] |
| Observations | 515 | 25,090 | 515 | 25,605 |

## Table 2: Portfolio descriptive Statistics

*Notes:* The reported values are calculated by first computing the cross-annual average for the last 12 observations and then taking the cross-sectional average of these values across all investors. Standard deviations are in parentheses and t-statistics are brackets. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

| | (1) Follower | (2) General sample | (3) Recommender | (4) T-test (2) - (1) |
|---|---|---|---|---|
| **A. Portfolio composition** | | | | |
| Number of securities | 4.965 | 4.695 | 13.025 | -0.269 |
| | (4.388) | (5.837) | (13.601) | [-1.04] |
| Number of trades | 1.770 | 2.015 | 3.356 | 0.246 |
| | (2.097) | (4.581) | (7.845) | [1.21] |
| Stock market participant | 0.503 | 0.568 | 0.751 | 0.065*** |
| | (0.500) | (0.495) | (0.433) | [2.93] |
| Risky share | 0.644 | 0.577 | 0.543 | -0.066*** |
| | (0.296) | (0.315) | (0.368) | [-4.73] |
| Weight stocks | 0.315 | 0.399 | 0.378 | 0.083*** |
| | (0.416) | (0.440) | (0.375) | [4.26] |
| Weight bonds | 0.028 | 0.024 | 0.024 | -0.004 |
| | (0.138) | (0.125) | (0.100) | [-0.71] |
| Weight funds | 0.625 | 0.541 | 0.530 | -0.084*** |
| | (0.427) | (0.448) | (0.390) | [-4.20] |
| **B. Portfolio quality measures** | | | | |
| Portfolio beta | 1.320 | 1.103 | 1.094 | -0.217** |
| | (5.053) | (2.251) | (0.582) | [-2.08] |
| Portfolio expected return | 0.005 | 0.004 | 0.004 | -0.001** |
| | (0.018) | (0.008) | (0.002) | [-2.08] |
| Standard deviation of returns | 0.087 | 0.061 | 0.065 | -0.025 |
| | (0.676) | (0.896) | (0.306) | [-0.64] |
| Sharpe ratio | 0.091 | 0.080 | 0.089 | -0.011*** |
| | (0.023) | (0.029) | (0.026) | [-8.34] |
| Return loss | 0.006 | 0.003 | 0.004 | -0.002 |
| | (0.075) | (0.108) | (0.036) | [-0.48] |
| Relative Sharpe Ratio loss | 0.248 | 0.338 | 0.265 | 0.090*** |
| | (0.191) | (0.243) | (0.212) | [8.34] |
| Trade risk | 1.836 | 1.901 | 1.900 | 0.065 |
| | (1.424) | (1.456) | (1.639) | [1.00] |
| Herfindahl-Hirschman-Index | 0.203 | 0.265 | 0.148 | 0.062*** |
| | (0.304) | (0.341) | (0.238) | [4.09] |
| **C. Investment Styles** | | | | |
| I: Active Fund Investment | 0.400 | 0.345 | 0.551 | -0.055*** |
| | (0.490) | (0.475) | (0.498) | [-2.62] |
| Passive Investment | 0.559 | 0.437 | 0.668 | -0.122*** |
| | (0.497) | (0.496) | (0.471) | [-5.52] |
| Warrants and Options | 0.159 | 0.141 | 0.356 | -0.018 |
| | (0.366) | (0.348) | (0.479) | [-1.19] |
| I: Lottery Investment, Kumar | 0.107 | 0.151 | 0.246 | 0.045*** |
| | (0.309) | (0.358) | (0.431) | [2.80] |
| I: High Volatility Investment | 0.122 | 0.152 | 0.239 | 0.030* |
| | (0.328) | (0.359) | (0.427) | [1.88] |
| I: High Skewness Investment | 0.204 | 0.250 | 0.371 | 0.046** |
| | (0.403) | (0.433) | (0.484) | [2.41] |
| I: Attention Investment, CSS | 0.184 | 0.228 | 0.346 | 0.044** |
| | (0.388) | (0.420) | (0.476) | [2.34] |
| I: Attention Investment, Coverage | 0.183 | 0.213 | 0.298 | 0.030* |
| | (0.387) | (0.409) | (0.458) | [1.66] |
| I: Attention Investment, Recency | 0.285 | 0.341 | 0.432 | 0.055*** |
| | (0.452) | (0.474) | (0.496) | [2.62] |
| I: Lottery Investment, MAX | 0.307 | 0.373 | 0.466 | 0.066*** |
| | (0.462) | (0.484) | (0.499) | [3.06] |
| I: Attention Investment, SUE | 0.107 | 0.133 | 0.171 | 0.027* |
| | (0.309) | (0.340) | (0.377) | [1.76] |
| Observations | 515 | 25,090 | 515 | 25,605 |

## Table 3: Overlap and placebo overlap

*Notes:* Panel A plots the mean, 5th percentile and 95th percentile for portfolio Overlap for Followers and for various placebo samples. The portfolio for the Recommender is lagged one month relative to the Follower. Follower-Recommender is the actual overlap between Follower-Recommender pairs in our sample. Random sample are constructed by randomly matching non-Followers to other non-Followers. CEM samples restrict the sample to individuals who match certain criteria listed in Appendix A.2.1. CEM1 is the least strict match and CEM 4 is the most strict match. CEM1 restricts the sample so that the distribution of Followers is the same in age groups, gender, German states and first year of trading. CEM2 matches on exact age, gender, state, and year of trading. CEM3 matches on exact age, gender, first year of trading, value of assets under management and risky share. CEM4 is the same as CEM3 except for also including German state. More details on the matching procedure is available in Appendix A.2. In Panel B, the table states the mean portfolio overlap, and the standard deviation, 95th percentile, and number of observations for directly matching all active investors to each follower.

| | | Average overlap | 5th percentile | 95th percentile |
|---|---|---|---|---|
| Follower-Recommender | | 0.17 | 0.00 | 1.00 |
| **Panel A: Random matches** | | | | |
| Random sample | | 0.01 | 0.01 | 0.01 |
| CEM1 | | 0.01 | 0.01 | 0.01 |
| CEM2 | | 0.01 | 0.01 | 0.01 |
| CEM3 | | 0.01 | 0.01 | 0.01 |
| CEM4 | | 0.01 | 0.01 | 0.01 |
| Exact | | 0.03 | 0.02 | 0.04 |
| | Mean | Standard deviation | 95th percentile | N |
| **Panel B: Direct matches across all investors** | | | | |
| All investors | 0.023 | 0.097 | 0.135 | 42,965,024 |
| Demographics | 0.024 | 0.095 | 0.146 | 3,851,766 |
| Location | 0.024 | 0.102 | 0.167 | 1,027,400 |
| AUM | 0.023 | 0.091 | 0.155 | 74,986 |
| Risky share | 0.025 | 0.100 | 0.157 | 38,830 |
| Total | 0.023 | 0.097 | 0.137 | 47,958,006 |

Table 4: Overlap share and Follower Characteristics

*Notes:* The dependent variable is the average overlap share for the first 12 months of trading, and the independent variables are related to demographic characteristics (column 1), portfolio characteristics (column 2) and bank characteristics (column 3), and differences between the Follower and Recommender (column 4). Column (5) includes all variables. Robust standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

| | (1) Demographics | (2) Portfolio | (3) Bank | (4) Differences | (5) All |
|---|---|---|---|---|---|
| Male | -0.020 | | | | -0.029 |
| | (0.019) | | | | (0.027) |
| Academic title | -0.062*** | | | | -0.075*** |
| | (0.021) | | | | (0.024) |
| Age | -0.001 | | | | -0.002** |
| | (0.001) | | | | (0.001) |
| Income proxy | -0.000* | | | | -0.000 |
| | (0.000) | | | | (0.000) |
| Total AUM (EUR) | | -0.000 | | | 0.000 |
| | | (0.000) | | | (0.000) |
| Risky share | | 0.109*** | | | 0.141*** |
| | | (0.034) | | | (0.042) |
| Number of securities | | 0.001 | | | -0.002 |
| | | (0.002) | | | (0.003) |
| Portfolio value (EUR) | | 0.000 | | | -0.000 |
| | | (0.000) | | | (0.000) |
| Main bank | | | -0.025 | | -0.025 |
| | | | (0.020) | | (0.021) |
| Total logins | | | 0.000** | | 0.000** |
| | | | (0.000) | | (0.000) |
| Joint account | | | -0.044 | | -0.026 |
| | | | (0.030) | | (0.031) |
| Number of trades | | | 0.003 | | 0.003 |
| | | | (0.004) | | (0.005) |
| Robo-trade | | | 0.008 | | 0.018 |
| | | | (0.025) | | (0.026) |
| Age difference | | | | 0.000 | 0.001* |
| | | | | (0.000) | (0.001) |
| Different gender | | | | 0.012 | -0.001 |
| | | | | (0.019) | (0.028) |
| Income difference | | | | -0.000 | -0.000 |
| | | | | (0.000) | (0.000) |
| Constant | 0.146*** | 0.038* | 0.118*** | 0.098*** | 0.140*** |
| | (0.031) | (0.020) | (0.016) | (0.015) | (0.050) |
| Observations | 515 | 515 | 467 | 515 | 467 |
| Adjusted $R^2$ | 0.004 | 0.018 | -0.002 | -0.004 | 0.023 |

## Table 5: Overlap and Recommender portfolio quality

*Notes:* The dependent variable is the average overlap share for the first 12 months of trading for the Follower. The independent variables of interest is *Rec: log Return loss* and *Rec: log RSRL*, the log Return loss and log Relative Sharpe ratio loss for the Recommender. Control variables for the Follower include dummy for male, income proxy, academic title, age and age squared, as well as controls for having our bank as the main bank and a dummy equal to one if the account is a joint account. Control variables include Age, academic title, a dummy for gender and income proxy. Specifications with region× year fixed effects are indicated in the bottom row. Robust standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

| | Return loss | | | | Relative Sharpe ratio loss | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Rec: log Return loss | -0.070*** | -0.069*** | -0.050** | -0.054** | | | | |
| | (0.023) | (0.023) | (0.025) | (0.025) | | | | |
| Rec: log RSRL | | | | | -0.109*** | -0.105*** | -0.067* | -0.071** |
| | | | | | (0.031) | (0.032) | (0.035) | (0.035) |
| **Follower controls** | | | | | | | | |
| Male | | -0.004 | -0.054 | -0.032 | | 0.000 | -0.052 | -0.034 |
| | | (0.051) | (0.057) | (0.059) | | (0.051) | (0.057) | (0.059) |
| Income proxy (std) | | -0.001 | -0.021 | -0.016 | | -0.001 | -0.022 | -0.018 |
| | | (0.037) | (0.048) | (0.050) | | (0.037) | (0.047) | (0.049) |
| Academic title | | -0.129 | -0.198** | -0.155 | | -0.128 | -0.200* | -0.158 |
| | | (0.100) | (0.101) | (0.100) | | (0.103) | (0.103) | (0.101) |
| Age | | 0.007 | 0.010 | 0.009 | | 0.009 | 0.011 | 0.010 |
| | | (0.010) | (0.011) | (0.011) | | (0.010) | (0.011) | (0.011) |
| Age squared | | -0.000 | -0.000 | -0.000 | | -0.000 | -0.000 | -0.000 |
| | | (0.000) | (0.000) | (0.000) | | (0.000) | (0.000) | (0.000) |
| Main bank | | -0.006 | 0.031 | 0.029 | | -0.009 | 0.028 | 0.026 |
| | | (0.053) | (0.063) | (0.062) | | (0.053) | (0.063) | (0.062) |
| Joint account | | -0.118 | -0.092 | -0.078 | | -0.098 | -0.078 | -0.062 |
| | | (0.081) | (0.088) | (0.087) | | (0.085) | (0.091) | (0.090) |
| **Recommender controls** | | | | | | | | |
| Rec: age | | | | 0.004** | | | | 0.004** |
| | | | | (0.002) | | | | (0.002) |
| Rec: Academic title | | | | -0.172* | | | | -0.175* |
| | | | | (0.096) | | | | (0.097) |
| Rec: Male | | | | 0.093 | | | | 0.078 |
| | | | | (0.074) | | | | (0.073) |
| Rec: Income proxy | | | | -0.000 | | | | -0.000 |
| | | | | (0.000) | | | | (0.000) |
| Region#Year fixed effect | No | No | Yes | Yes | No | No | Yes | Yes |
| Observations | 407 | 407 | 395 | 395 | 407 | 407 | 395 | 395 |
| Adjusted $R^2$ | 0.024 | 0.017 | 0.061 | 0.073 | 0.025 | 0.017 | 0.058 | 0.071 |

Table 6: Log Return Loss and Relative Sharpe Ratio Loss

*Notes:* In the first four columns the dependent variable is log Return Loss, and in the last four columns the dependent variable is the log relative Sharpe ratio loss. Column 1 and 5 provide results with no control variables, column 2 and 6 adds separate region× year fixed effects, and column 3 and 7 adds further control variables based on individual characteristics. Control variables include a dummy for male, income proxy, academic title, age and age squared, as well as controls for having our bank as the main bank and a dummy equal to one if the account is a joint account. Column 4 and 8 adds an interaction Follower and Positive Overlap, where Positive Overlap is a dummy variable equal to one if we observe a positive overlap between the Recommender and Follower. The unconditional mean of the dependent variable is listed in the table footer. Robust standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

| | Log Return loss | | | | Log Relative Sharpe ratio loss | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Follower | -0.27*** | -0.11** | -0.08 | -0.00 | -0.28*** | -0.10*** | -0.09*** | -0.05 |
| | (0.05) | (0.05) | (0.05) | (0.07) | (0.03) | (0.03) | (0.03) | (0.04) |
| Follower × Positive Overlap | | | | -0.20* | | | | -0.11 |
| | | | | (0.11) | | | | (0.07) |
| Male | | | 0.23*** | 0.23*** | | | 0.07*** | 0.07*** |
| | | | (0.02) | (0.02) | | | (0.01) | (0.01) |
| Income proxy (std) | | | 0.03*** | 0.03*** | | | 0.02*** | 0.02*** |
| | | | (0.01) | (0.01) | | | (0.00) | (0.00) |
| Academic title | | | -0.26*** | -0.26*** | | | -0.09*** | -0.09*** |
| | | | (0.04) | (0.04) | | | (0.02) | (0.02) |
| Age | | | -0.02*** | -0.02*** | | | -0.01*** | -0.01*** |
| | | | (0.00) | (0.00) | | | (0.00) | (0.00) |
| Age squared | | | 0.00*** | 0.00*** | | | 0.00*** | 0.00*** |
| | | | (0.00) | (0.00) | | | (0.00) | (0.00) |
| Main bank | | | 0.12*** | 0.12*** | | | 0.06*** | 0.06*** |
| | | | (0.02) | (0.02) | | | (0.01) | (0.01) |
| Joint account | | | -0.10*** | -0.10*** | | | -0.05*** | -0.05*** |
| | | | (0.02) | (0.02) | | | (0.01) | (0.01) |
| Region#Year fixed effect | No | Yes | Yes | Yes | No | Yes | Yes | Yes |
| Dep. var. mean | -6.73 | -6.73 | -6.73 | -6.73 | -1.39 | -1.39 | -1.39 | -1.39 |
| Dep. var. std. dev | 1.31 | 1.31 | 1.31 | 1.31 | 0.83 | 0.83 | 0.83 | 0.83 |
| Number of Followers | 515 | 515 | 515 | 515 | 515 | 515 | 515 | 515 |
| Observations | 25605 | 25605 | 25605 | 25605 | 25605 | 25605 | 25605 | 25605 |
| Adjusted $R^2$ | 0.001 | 0.055 | 0.071 | 0.071 | 0.002 | 0.212 | 0.217 | 0.217 |

Table 7: Decomposition of return loss

*Notes:* This table presents results for the decomposition of return loss into its components from equation 4. We regress return loss (the same results as Column 3 of Table 6) and each component of return loss on a dummy for Follower as well as on demographic and financial variables. Control variables include a dummy for male, income proxy, academic title, age and age squared, as well as controls for having our bank as the main bank and a dummy equal to one if the account is a joint account. Robust standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

| | Return loss $\ln(RL_i)$ | Risky share $\ln w_i$ | Risky portfolio beta $\ln \beta_i$ | Diversification loss $\ln\left(\frac{RSRL_i}{1-RSRL_i}\right)$ |
|---|---|---|---|---|
| Follower | -0.08 | 0.17*** | 0.07** | -0.16*** |
| | (0.05) | (0.04) | (0.03) | (0.05) |
| Male | 0.23*** | 0.10*** | 0.12*** | 0.10*** |
| | (0.02) | (0.01) | (0.02) | (0.02) |
| Income proxy (std) | 0.03*** | -0.05*** | -0.01 | 0.03*** |
| | (0.01) | (0.02) | (0.01) | (0.01) |
| Academic title | -0.26*** | 0.08*** | -0.11*** | -0.14*** |
| | (0.04) | (0.03) | (0.04) | (0.03) |
| Age | -0.02*** | -0.02*** | -0.00 | -0.02*** |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Age squared | 0.00*** | 0.00*** | -0.00 | 0.00*** |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Main bank | 0.12*** | 0.06*** | 0.05*** | 0.05*** |
| | (0.02) | (0.01) | (0.01) | (0.02) |
| Joint account | -0.10*** | -0.18*** | -0.04** | -0.06*** |
| | (0.02) | (0.02) | (0.02) | (0.02) |
| Region#Year fixed effect | Yes | Yes | Yes | Yes |
| Dep. var. mean | -6.73 | -0.85 | -0.26 | -0.86 |
| Dep. var. std. dev | 1.31 | 1.02 | 1.15 | 1.35 |
| Number of Followers | 515 | 515 | 515 | 515 |
| Observations | 25605 | 25587 | 25605 | 25605 |
| Adjusted $R^2$ | 0.071 | 0.041 | 0.128 | 0.236 |

## Table 8: Asset type participation and portfolio performance

*Notes:* This table presents results for comparison of the correlations between investment in asset type, such as mutual funds in general, and active, passive funds and ETFs specifically, lottery stocks and high attention stocks for Followers and the matched sample. Robust standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

| **Panel A: Log Return Loss** | Funds | | | Lottery | | | | Attention | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Fund | Active | Passive | Kumar | MAX | High Volatility | High Skewness | CSS | CVRG | Recency | —SUE— |
| Participation | -1.546*** | -0.699*** | -0.992*** | 1.268*** | 1.277*** | 1.293*** | 1.105*** | 0.937*** | 0.802*** | 1.193*** | 0.733*** |
| | (0.016) | (0.015) | (0.015) | (0.017) | (0.014) | (0.017) | (0.015) | (0.015) | (0.015) | (0.014) | (0.017) |
| Constant | -5.663*** | -6.484*** | -6.289*** | -6.916*** | -7.200*** | -6.922*** | -7.001*** | -6.938*** | -6.896*** | -7.131*** | -6.823*** |
| | (0.014) | (0.011) | (0.011) | (0.009) | (0.010) | (0.009) | (0.009) | (0.009) | (0.010) | (0.010) | (0.009) |
| Observations | 25605 | 25605 | 25605 | 25605 | 25605 | 25605 | 25605 | 25605 | 25605 | 25605 | 25605 |
| Adjusted $R^2$ | 0.301 | 0.065 | 0.142 | 0.120 | 0.223 | 0.126 | 0.134 | 0.090 | 0.063 | 0.187 | 0.036 |

| **Panel B: Log Relative Sharpe ratio Loss** | Funds | | | Lottery | | | | Attention | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Fund | Active | Passive | Kumar | MAX | High Volatility | High Skewness | CSS | CVRG | Recency | —SUE— |
| Participation | -0.832*** | -0.201*** | -0.759*** | 0.610*** | 0.646*** | 0.601*** | 0.533*** | 0.492*** | 0.417*** | 0.631*** | 0.427*** |
| | (0.008) | (0.011) | (0.009) | (0.011) | (0.009) | (0.011) | (0.010) | (0.010) | (0.010) | (0.009) | (0.012) |
| Constant | -0.820*** | -1.323*** | -1.058*** | -1.484*** | -1.632*** | -1.484*** | -1.525*** | -1.504*** | -1.481*** | -1.607*** | -1.449*** |
| | (0.005) | (0.007) | (0.006) | (0.006) | (0.007) | (0.006) | (0.006) | (0.006) | (0.006) | (0.007) | (0.006) |
| Observations | 25605 | 25605 | 25605 | 25605 | 25605 | 25605 | 25605 | 25605 | 25605 | 25605 | 25605 |
| Adjusted $R^2$ | 0.216 | 0.013 | 0.206 | 0.069 | 0.141 | 0.067 | 0.077 | 0.062 | 0.042 | 0.130 | 0.030 |

# Table 9: Participation in asset types compared to general sample

*Notes:* This table presents results for the correlation between investment in asset type, such as mutual funds in general, and active, passive funds and ETFs specifically, lottery stocks and high attention stocks. Control variables include a dummy for male, income proxy, academic title, age and age squared, as well as controls for having our bank as the main bank and a dummy equal to one if the account is a joint account. Robust standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

| **Panel A: Extensive margin** | Funds | | | Lottery | | | | Attention | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) Fund | (2) Active | (3) Passive | (4) Kumar | (5) MAX | (6) High Volatility | (7) High Skewness | (8) CSS | (9) CVRG | (10) Recency | (11) —SUE— | (12) Derivatives |
| Follower | 0.058*** | 0.067*** | 0.070*** | -0.007 | -0.010 | -0.001 | -0.011 | -0.011 | 0.002 | 0.004 | 0.004 | 0.038** |
| | (0.019) | (0.021) | (0.022) | (0.014) | (0.018) | (0.014) | (0.017) | (0.016) | (0.016) | (0.018) | (0.013) | (0.016) |
| Region#Year fixed effect | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 25605 | 25605 | 25605 | 25605 | 25605 | 25605 | 25605 | 25605 | 25605 | 25605 | 25605 | 25605 |
| Adjusted $R^2$ | 0.044 | 0.028 | 0.126 | 0.085 | 0.234 | 0.075 | 0.130 | 0.125 | 0.110 | 0.217 | 0.116 | 0.021 |

| **Panel B: Intensive margin** | Funds | | | Lottery | | | | Attention | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) Fund | (2) Active | (3) Passive | (4) Kumar | (5) MAX | (6) High Volatility | (7) High Skewness | (8) CSS | (9) CVRG | (10) Recency | (11) —SUE— | (12) Derivatives |
| Follower | 0.000 | -0.037* | -0.054** | 0.003 | -0.032* | -0.035 | -0.034*** | -0.013 | -0.004 | -0.014** | -0.004 | -0.045* |
| | (0.015) | (0.020) | (0.022) | (0.028) | (0.018) | (0.022) | (0.012) | (0.015) | (0.003) | (0.007) | (0.004) | (0.024) |
| Region#Year fixed effect | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 17599 | 8849 | 11256 | 3839 | 9502 | 3874 | 6374 | 5813 | 5422 | 8688 | 3387 | 3602 |
| Adjusted $R^2$ | 0.041 | 0.045 | 0.093 | 0.063 | 0.176 | 0.057 | 0.033 | 0.027 | 0.022 | 0.055 | 0.035 | 0.013 |

## Table 10: Recommender and Follower participation in asset classes

*Notes:* This table presents results for the correlation between investment in asset type, such as mutual funds in general, and active, passive funds and ETFs specifically, lottery stocks and high attention stocks for Followers and Recommenders. Control variables include a dummy for male, income proxy, academic title, age and age squared, as well as controls for having our bank as the main bank and a dummy equal to one if the account is a joint account. Robust standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

| **Panel A: Extensive margin** | Funds | | | Lottery | | | | Attention | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| | Fund | Active | Passive | Kumar | Max | High Volatility | High Skewness | CSS | Coverage | Recency | SUE | Derivatives |
| Recommender Participation | 0.548*** | 0.404*** | 0.451*** | 0.135** | 0.357*** | 0.210*** | 0.202*** | 0.252*** | 0.298*** | 0.292*** | 0.262*** | 0.222*** |
| | (0.062) | (0.049) | (0.054) | (0.054) | (0.057) | (0.060) | (0.060) | (0.053) | (0.053) | (0.062) | (0.068) | (0.046) |
| Region#Year fixed effect | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 398 | 398 | 398 | 398 | 398 | 398 | 398 | 398 | 398 | 398 | 398 | 398 |
| Adjusted $R^2$ | 0.284 | 0.232 | 0.219 | 0.078 | 0.291 | 0.087 | 0.098 | 0.175 | 0.194 | 0.243 | 0.190 | 0.124 |

| **Panel B: Intensive margin** | Funds | | | Lottery | | | | Attention | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| | Fund | Active | Passive | Kumar | Max | High Volatility | High Skewness | CSS | Coverage | Recency | SUE | Derivatives |
| Recommender Portfolio weight | 0.623*** | 0.402*** | 0.636*** | 0.734*** | 0.497*** | 0.334*** | 0.234** | 0.641*** | 0.416*** | 0.578*** | 0.657*** | 0.197*** |
| | (0.046) | (0.081) | (0.059) | (0.249) | (0.085) | (0.121) | (0.119) | (0.169) | (0.128) | (0.097) | (0.202) | (0.075) |
| Region#Year fixed effect | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 398 | 398 | 398 | 398 | 398 | 398 | 398 | 398 | 398 | 398 | 398 | 398 |
| Adjusted $R^2$ | 0.363 | 0.170 | 0.294 | 0.395 | 0.482 | 0.305 | 0.192 | 0.236 | 0.136 | 0.336 | 0.201 | 0.075 |

## Table 11: Recommender participation and Follower participation across asset classes

*Notes:* This table presents results for comparison of the correlations between investment in asset type, such as mutual funds in general, and active, passive funds and ETFs specifically, lottery stocks and high attention stocks for Followers and the matched sample. Robust standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

| | (1)<br>Fund | (2)<br>Lottery | (3)<br>Attention | (4)<br>Derivatives |
|---|---|---|---|---|
| Recommender: Funds | 0.546***<br>(8.83) | -0.229***<br>(-3.60) | -0.219***<br>(-3.44) | 0.086**<br>(2.01) |
| Recommender: Lottery | -0.270***<br>(-5.79) | 0.338***<br>(5.60) | 0.358***<br>(6.10) | -0.052<br>(-0.99) |
| Recommender: Attention | -0.279***<br>(-5.98) | 0.337***<br>(5.66) | 0.331***<br>(5.60) | -0.049<br>(-0.93) |
| Recommender: Derivatives | 0.044<br>(1.02) | 0.005<br>(0.10) | -0.011<br>(-0.24) | 0.222***<br>(4.76) |
| Controls | Yes | Yes | Yes | Yes |

Table 12: Portfolio Quality and Recommender Investment Style

*Notes:* This table examines the correlations between Recommender investment style and Follower's portfolio quality characteristics. Recommenders are classified into categories based on their investment in funds, lottery stock (MAX), and high attention stocks (CSS). We create three dummy variables equal to one if Recommender invests in an asset type, and zero otherwise. Log Return Loss, log Sharpe Ratio loss, log portfolio beta, log risk share, and log diversification loss are the dependent variables. Control variables include a dummy for male, income proxy, academic title, age and age squared, as well as controls for having our bank as the main bank and a dummy equal to one if the account is a joint account. Robust standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% levels.

| | Return loss | | Risky Share | | Beta | | Diversification Loss | |
|---|---|---|---|---|---|---|---|---|
| | (1) Fol. | (2) Rec. | (3) Fol. | (4) Rec. | (5) Fol. | (6) Rec. | (7) Fol. | (8) Rec. |
| **Funds** | | | | | | | | |
| Fund | -1.41*** | -1.04*** | 0.22* | 0.01 | -0.45*** | -0.33*** | -0.95*** | -0.63*** |
| | (0.17) | (0.17) | (0.13) | (0.12) | (0.10) | (0.10) | (0.15) | (0.13) |
| **Lottery** | | | | | | | | |
| MAX | 0.76*** | 0.32 | 0.34** | 0.15 | 0.02 | 0.13 | 0.60** | 0.13 |
| | (0.20) | (0.23) | (0.16) | (0.16) | (0.12) | (0.15) | (0.23) | (0.22) |
| High Volatility | 0.50*** | 0.12 | -0.10 | 0.11 | 0.13 | 0.13 | 0.32* | -0.03 |
| | (0.15) | (0.18) | (0.12) | (0.12) | (0.12) | (0.12) | (0.18) | (0.17) |
| High Skewness | -0.08 | 0.11 | -0.01 | -0.03 | 0.16 | -0.08 | -0.18 | 0.16 |
| | (0.19) | (0.23) | (0.13) | (0.18) | (0.13) | (0.17) | (0.22) | (0.22) |
| **Attention** | | | | | | | | |
| CSS | -0.15 | 0.18 | 0.07 | 0.09 | -0.00 | 0.04 | -0.11 | 0.15 |
| | (0.16) | (0.19) | (0.13) | (0.15) | (0.12) | (0.13) | (0.19) | (0.18) |
| Age | -0.01 | -0.02 | -0.02 | -0.02 | -0.02 | -0.02 | 0.01 | 0.01 |
| | (0.02) | (0.02) | (0.02) | (0.02) | (0.01) | (0.01) | (0.02) | (0.02) |
| Age squared | 0.00 | 0.00 | 0.00* | 0.00* | 0.00 | 0.00 | -0.00 | -0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Region#Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 398 | 398 | 398 | 398 | 398 | 398 | 398 | 398 |
| Adjusted $R^2$ | 0.455 | 0.208 | 0.025 | 0.013 | 0.098 | 0.042 | 0.253 | 0.096 |

FOR ONLINE PUBLICATION

# A Online Appendix: Variable definitions

## A.1 Calculating risk and performance of individual portfolios

This section describes how we calculate risk and returns for individual portfolios, following Calvet *et al.* (2007). Our approach is intended to allow us to examine individual portfolio returns in a systematic manner. Since we observe all trading within the portfolio, we can compute portfolio returns for each individual in our sample directly. However, given the generally large standard deviations of annual returns and the short time dimension, we chose to infer the average return based on an asset-pricing model. The Capital Asset Pricing Model (CAPM) is the natural starting point, which captures how the excess return for a stock or portfolio varies with the equity market. Since German households mostly invest in German stock, we assume that the CAPM model holds for excess returns relative to German government bonds:

$$r^e_{j,t} = \beta_j r^e_{m,t} + \epsilon_{j,t} \tag{5}$$

where $r^e_{j,t}$ is the expected excess return on asset $j$, and $r^e_{m,t}$ is the excess return of the German DAX index. Both returns are calculated as the excess return over the German short-term government bond, the Bund. For each asset $j$, we then estimate its beta coefficient $\beta_j$ by regressing the excess return $r_{j,t} - r_{f,t}$ on the index $r_{m,t} - r_{f,t}$ using monthly data in a 24 month rolling window.

We use the above measures from the CAPM estimation to calculate the losses from suboptimal portfolio choice. For each individual, we compare the Sharpe ratio of their portfolio to the Sharpe ratio of the benchmark index. Specifically, we calculate the mean $\mu_i$ and standard deviation $\sigma_i^2$ of the excess return and the Sharpe ratio for the individual portfolio as $S_i = \mu_i/\sigma_i^2$. The Sharpe ratio for the index is then simply $S_B = \mu_B/\sigma_B^2$, and the loss from poor diversification relative to the benchmark can be quantified by the relative Sharpe ratio loss $RSRL_i$:

$$RSRL_i = 1 - \frac{S_i}{S_B}. \tag{6}$$

The relative Sharpe ratio loss measures loss from diversification in an intuitive manner. The ratio depends on the portfolio's mean return, standard deviation, and benchmark. However, the RSRL does not require that we compute the aggregate equity premium or that the benchmark portfolio is mean-variance efficient. If the benchmark index is mean-variance efficient, then the relative Sharpe ratio loss is related to the share of idiosyncratic volatility:

$$(1 - RSRL_i)^2 = 1 - \frac{\sigma_{k,i}^2}{\sigma_i^2}. \tag{7}$$

A higher share of idiosyncratic volatility $\sigma_{k,i}^2$ implies a higher relative Sharpe ratio loss. Moreover, when the benchmark portfolio is mean-variance efficient, the RSRL equals 1 minus the correlation between the individual and benchmark portfolio.

We also calculate a measure of return loss. Where the RSRL quantifies the diversification level of the household portfolio, the return loss also considers how much the investor allocates to the risky share. Intuitively, the return loss is equal to the average return the individual loses by choosing their portfolio instead of a combination of the benchmark portfolio and cash to achieve the same risk level:

$$RL_i = w_i(S_B\sigma_i - \mu_i) \tag{8}$$

where $w_i$ is the weight allocated to risky assets. In brief, the return loss is a function of the expected excess return on the market portfolio. The return loss quantifies the cost in return units, i.e., relative to the size of the portfolio. A small portfolio will generally lead to a small or even negligible loss.

There is a natural correspondence between the return loss and the relative Sharpe ratio loss. Following Calvet *et al.* (2007), the relationship can be written as:

$$RL_i = (Er_m^e)w_i\beta_i(\frac{RSRL_i}{1 - RSRL_i}). \tag{9}$$

The return loss is a function of the expected excess return on the mean-variance efficient market portfolio ($Er_m^e$), the household's weight in risky assets $w_i$, the beta of household portfolio, and a transformation of the household's relative Sharpe ratio loss. The decomposition shows that the return loss is related to the expected excess return on the market portfolio. In our main results, we assume that the monthly expected excess return is 0.36408% following Jacobs *et al.* (2014). It is trivial to rescale the return loss estimate using another assumption about the expected excess return on the market portfolio. We then use this relationship to decompose the return loss into different components. Taking logs of equation (9):

$$\ln RL_i = \ln(Er_m^e) + \ln w_i + \ln \beta_i + \ln\left(\frac{RSRL_i}{1 - RSRL_i}\right). \tag{10}$$

The decomposition relates the return loss to the log equity premium, which is constant across individuals, two measures of how aggressive the individual portfolio is (the share invested in risky assets and the beta of the individual portfolio), and to a measure of portfolio inefficiency (the transformation of the Sharpe ratio loss). We will use this decomposition to examine sources of inefficiency in individual portfolios.

## A.2 Detail on matching procedure and placebo group construction

### A.2.1 Placebo groups

To construct placebo groups, we use coarsened exact matching method (CEM) described in Iacus *et al.* (2008). We start by focusing on the sample of existing brokerage clients of the bank and restrict the sample to the ages between 18 and 75 and exclude the followers and recommenders from the referral campaign. We then continue by matching placebo followers to the selected sample of investors (e.g., placebo recommenders) in four ways:

1. Matching on observable characteristics (CEM1):

   – Age intervals (18-30, 31-40, 41-50, 51-60, and 61-75);

   – Gender (male, female )

   – Geographical location at the German state bundesland - level (Baden-Wrttemberg, Bayern, Berlin, Brandenburg, Bremen, Hamburg, Hessen, Mecklenburg-Vorpommern, Niedersachsen, Nordrhein-Westfalen, Rheinland-Pfalz, Saarland, Sachsen, Sachsen-Anhalt, Schleswig-Holstein, Thringen, Abroad (Ausland));

   – Year of the first trade (2012, 2013, 2014, 2015, 2016, 2017).

2. Matching on observable characteristics (CEM2):

   – Exact age in years;

   – Gender;

   – German state;

   – Year of the first trade.

3. Matching on observable characteristics (CEM3):

   – Exact age in years;

- Gender;
- Year of the first trade;
- Value of assets under management in Euro (quartiles);
- Risky share in percentages (quartiles).

4. Matching on observable characteristics (CEM4):
   - Exact age in years;
   - Gender;
   - German state;
   - Year of the first trade;
   - Value of assets under management in Euro (quartiles);
   - Risky share in percentages (quartiles).

Table A1 presents the CEM matching methods description.

Table A1: CEM Matching

| **Matching criteria** | **CEM1** | **CEM2** | **CEM3** | **CEM4** |
|---|---|---|---|---|
| Age intervals: 18-30, 31-40, 41-50, 51-60, 61-75 | Yes | No | No | No |
| Exact age in years | No | Yes | Yes | Yes |
| Gender: male, female | Yes | Yes | Yes | Yes |
| Address: German state | Yes | Yes | No | Yes |
| Year of the first trade: 2012, 2013, 2014, 2015, 2016, 2017 | Yes | Yes | Yes | Yes |
| Value AUM, in Euro: quartiles | No | No | Yes | Yes |
| Risky share, %: quartiles | No | No | Yes | Yes |

Each CEM matching generates stratums and weights. The weight assigned to the observation's stratum equals 0 if the observation is unmatched and one if the observation is a resultant match. Procedure CEM3 is the preferred placebo group that we employ across analyses and the main text, and weights from this group are used across regression specifications.

### A.2.2 Matching procedure used in Overlap analysis

In the overlap comparison exercise (e.g., Figure 2), we construct placebo Recommender-Follower pairs and estimate the portfolio overlap for those pairs. We first define a sample of placebo Recommenders, i.e., bank clients who funded an investment account before 2012, and a sample of placebo Followers, i.e., bank clients who founded an account after 2012.

Second, we create pairs of placebo Recommenders and Followers using three selection methods: 1) random Recommender and random Follower, 2) random Recommender and matched Follower, and 3) matched Recommender and matched Follower. We describe these three selection methods below.

For the random Recommender - random Follower pair, we randomly select 1000 Recommenders (investors in the sample pre-2012) and 1000 followers (investors who funded an account post-2012) and randomly pair them according to the randomization order. Once placebo Recommenders and placebo Followers are paired, we construct the overlap portfolios for each pair and calculate the average overlap in the number of assets and value-weighted overlap. We repeat the pair-simulations 100 times.

For the random Recommender  matched Follower, we first select 1000 Recommenders randomly, following the same procedure described above. The Followers are restricted to a sample of potential placebo Followers. We remove from the sample all individuals with CEM weight equal to zero, i.e., individuals that were not matched to any follower. We randomly choose 1000 Followers from the resulting sample and pair them with previously selected Recommenders. We repeat the procedure for all CEM methods described in subsection A.2.1.

Finally, for the matched Recommender  matched Follower, we restrict both samples of placebo Recommenders and Followers. We exclude all individuals with CEM weights equal to zero and select 1000 individuals to construct pairs. In this selection method, placebo Recommenders are therefore matched based on observable characteristics to investors in the referral campaign that we study following CEM3 criteria described in A1. As previously, we repeat the procedure for all CEM methods described in subsection A.2.1.

We calculate the average overlap in the number of assets and the value-weighted portfolio for each pair-simulation method. We compare these overlap measures for the placebo pairs with the overlap measures we observe for actual Recommender-Follower pairs from the referral campaigns. The two panels in Figure 2 present the results.

## A.3 Classification of asset types

We define several investment strategies that are associated with "good" and "bad" investment behavior as *investment styles*. Using ISIN-level assets, we create a set of dummy variables that signify whether an individual invests in an asset type. We now describe how we classify assets in more detail.

First, we identify individuals who generally invest in mutual funds, specifically in active, passive, or ETF funds. Fund investment boosts individual portfolio diversification and improves portfolio performance. We use internal bank reporting to define funds that divides assets into categories. The definition of active funds and ETFs comes from Morningstar database. [5] Table 8 reports that participation in funds generally reduces Log Return loss and log relative Sharpe ratio loss, and we hence refer to this asset types as good investments.

Second, Kumar (2009) and Bali *et al.* (2011) find that lottery stocks are overpriced, and that individual portfolios with large lottery stock investments underperform. We use two different approaches to define lottery stocks. The first approach is proposed by Kumar

[5] Each fund's investment strategy can be found under Fund Investment Orientation. We define ETF funds as funds whose Asset Category Description are listed as Alternative, Bond, Commodity, Equity, Mixed Asset, Money Market, Other ETF.

(2009) and defines lottery stocks as stocks in the lowest $k^{th}$ stock price percentile, the highest $k^{th}$ idiosyncratic volatility percentile, and the highest $k^{th}$ idiosyncratic skewness percentile.[6] The second approach defines lottery stocks as stocks from the top $25^{th}$ decile of the maximum daily return within the previous month (MAX) (Bali *et al.*, 2011). The third approach uses that high volatility and high skewness are characteristics of lottery-like stocks and are linked to the worse portfolio performance Kumar (2009). High volatility stocks are the stocks in the highest $25^{th}$ idiosyncratic volatility percentile. High skewness stocks are the stocks in the highest $25^{th}$ idiosyncratic skewness percentile. Both idiosyncratic volatility and skewness are measures of volatility and scaled skewness of the residual obtained by fitting a three-factor model to the daily stock returns last six-month time series (Kumar, 2009; Han *et al.*, 2022). Table 8 reports that participation in lottery stocks is associated with worse portfolio quality as proxied by higher return loss and higher relative Sharpe ratio loss, and we, therefore, refer to these assets as bad investments.

Third, investors may be attracted to volatile and positively skewed stocks due to disproportional high reporting of extremely high returns (Han *et al.*, 2022). We identify individuals who invest in high attention stocks. We use four proxies to define high attention stocks. First, following Hackethal *et al.* (2021), we define high attention stocks as stocks in the $25^th$ highest percentile of the monthly average Composite Sentiment Score (CSS) from RavenPack.[7] The second proxy, following Bali *et al.* (2021), is analyst coverage (CVRG), which shows whether a firm has a high profile in public discussion. If the firm is in the public spotlight, more investors learn about its characteristics, including lottery-like characteristics, such as extreme returns. We use the number of different earnings forecasts for a stock in a month from the Institutional Brokers' Estimate System (I/B/E/S) database. A high attention stock has a number of forecasts in the $25^th$ percentile.

[6] We investigate both $k = 50$. The results are independent of the choice of the percentile cut-off

[7] The CSS is determined using different textual analysis methods applied to emotionally charged words and phrases in media articles. Based on the mood in those articles, a sentiment score between 0 and 100 is computed where a value of 50 indicates a neutral sentiment level and values above (below) 50 indicate positive (negative) sentiment levels.

The third attention proxy is based on the magnitude of news events, measured by the absolute value of a stock's latest standardized quarterly earnings surprises ($|SUE|$) from I/B/E/S (Bernard & Thomas, 1990; Bali *et al.*, 2021). Finally, the fourth attention proxy, RECENCY, captures the recency of a high attention event and therefore reflects the dynamic decay of attention over time (Bali *et al.*, 2021). RECENCY measure is equal to the inverse of one plus the number of trading days between the MAX day, the day of the maximum return in the previous month, and the last trading day in the portfolio formation month. We conjecture that investor attention is greater for the more recent events and define high attention stocks as stocks with RECENCY measure in the $25^th$ percentile.

**FOR ONLINE PUBLICATION**

# B Online Appendix: Tables

Table B1: Sample selection

The table reports the sample selection procedure, and how many individuals and observation we remove at each step.

| | Individuals | | Observations | |
|---|---|---|---|---|
| | Remaining | Dropped | Remaining | Dropped |
| Initial sample | 673 | | 13,061 | |
| Age $< 18$ or age $> 75$ | 579 | 94 | 11,092 | 1,969 |
| Both follower and recommender | 558 | 21 | 10,670 | 422 |
| Do not open securities account | 558 | 0 | 10,670 | 0 |
| Security account before recommendation | 543 | 15 | 10,367 | 303 |
| Open account before 2012 | 536 | 7 | 10,217 | 150 |
| Missing data | 515 | 21 | 9,840 | 377 |
| Final sample | 515 | | 9,840 | |

Table B2: Log Return Loss and Relative Sharpe Ratio Loss for different time horizons

*Notes:* The table replicates Table 6 for different time horizons. Panel A uses data for 6 months, Panel B uses data for 12 months, and Panel C uses data for 24 months. In the first four columns the dependent variable is log Return Loss, and in the last four columns the dependent variable is the log relative Sharpe ratio loss. Column 1 and 5 provide results with no control variables, column 2 and 6 adds separate region× year fixed effects, and column 3 and 7 adds further control variables based on individual characteristics. Control variables include a dummy for male, income proxy, academic title, age and age squared, as well as controls for having our bank as the main bank and a dummy equal to one if the account is a joint account. Column 4 and 8 adds an interaction Follower and Positive Overlap, where Positive Overlap is a dummy variable equal to one if we observe a positive overlap between the Recommender and Follower. The unconditional mean of the dependent variable is listed in the table footer. Robust standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

| | Log Return loss | | | | Log Relative Sharpe ratio loss | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| **6 months** | | | | | | | | |
| Follower | -0.26*** | -0.09* | -0.06 | 0.02 | -0.31*** | -0.09** | -0.08** | -0.04 |
| | (0.05) | (0.05) | (0.05) | (0.07) | (0.03) | (0.03) | (0.03) | (0.04) |
| Follower × Positive Overlap | | | | -0.22** | | | | -0.11 |
| | | | | (0.10) | | | | (0.07) |
| Region#Year fixed effect | No | Yes | Yes | Yes | No | Yes | Yes | Yes |
| Controls | No | No | Yes | Yes | No | No | Yes | Yes |
| Observations | 25370 | 25370 | 25370 | 25370 | 25370 | 25370 | 25370 | 25370 |
| Adjusted $R^2$ | 0.001 | 0.064 | 0.078 | 0.078 | 0.003 | 0.259 | 0.263 | 0.263 |
| **12 months** | | | | | | | | |
| Follower | -0.27*** | -0.11** | -0.08 | -0.00 | -0.28*** | -0.10*** | -0.09*** | -0.05 |
| | (0.05) | (0.05) | (0.05) | (0.07) | (0.03) | (0.03) | (0.03) | (0.04) |
| Follower × Positive Overlap | | | | -0.20* | | | | -0.11 |
| | | | | (0.11) | | | | (0.07) |
| Region#Year fixed effect | No | Yes | Yes | Yes | No | Yes | Yes | Yes |
| Controls | No | No | Yes | Yes | No | No | Yes | Yes |
| Observations | 25605 | 25605 | 25605 | 25605 | 25605 | 25605 | 25605 | 25605 |
| Adjusted $R^2$ | 0.001 | 0.055 | 0.071 | 0.071 | 0.002 | 0.212 | 0.217 | 0.217 |
| **24 months** | | | | | | | | |
| Follower | -0.21*** | -0.08 | -0.05 | 0.01 | -0.21*** | -0.07** | -0.06* | -0.03 |
| | (0.05) | (0.05) | (0.05) | (0.07) | (0.03) | (0.03) | (0.03) | (0.04) |
| Follower × Positive Overlap | | | | -0.14 | | | | -0.08 |
| | | | | (0.10) | | | | (0.06) |
| Region#Year fixed effect | No | Yes | Yes | Yes | No | Yes | Yes | Yes |
| Controls | No | No | Yes | Yes | No | No | Yes | Yes |
| Observations | 25823 | 25823 | 25823 | 25823 | 25823 | 25823 | 25823 | 25823 |
| Adjusted $R^2$ | 0.000 | 0.042 | 0.059 | 0.059 | 0.001 | 0.150 | 0.156 | 0.156 |

Table B3: Follower and Recommender portfolio composition

*Notes:* This table provides the regressions from binscatter figures in Figure 9. Robust standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Recommender: Log Return Loss | 0.48*** | | | | |
| | (0.08) | | | | |
| Recommender: Log relative Sharpe Ratio loss | | 0.32*** | | | |
| | | (0.05) | | | |
| Recommender: Risky share | | | 0.31*** | | |
| | | | (0.04) | | |
| Recommender: Log Beta | | | | 0.44*** | |
| | | | | (0.11) | |
| Recommender: Share of funds | | | | | 0.62*** |
| | | | | | (0.05) |
| **Control variables (Recommender)** | | | | | |
| Academic title | -0.31 | -0.15 | 0.06 | -0.04 | 0.05 |
| | (0.19) | (0.13) | (0.05) | (0.16) | (0.07) |
| Age | -0.01 | -0.00 | -0.01 | -0.01 | -0.01 |
| | (0.02) | (0.01) | (0.01) | (0.01) | (0.01) |
| Age squared | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Male | 0.20* | 0.07 | 0.03 | 0.17** | -0.13*** |
| | (0.11) | (0.08) | (0.03) | (0.07) | (0.04) |
| Income proxy (std) | -0.01 | 0.05 | -0.06** | -0.00 | -0.00 |
| | (0.06) | (0.04) | (0.02) | (0.04) | (0.03) |
| Main bank | 0.24* | 0.07 | -0.02 | 0.12 | -0.04 |
| | (0.13) | (0.09) | (0.03) | (0.08) | (0.04) |
| Joint account | -0.18 | -0.01 | -0.01 | -0.09 | 0.06 |
| | (0.16) | (0.13) | (0.04) | (0.12) | (0.07) |
| Constant | -3.77*** | -1.26*** | 0.53*** | 0.14 | 0.50*** |
| | (0.68) | (0.31) | (0.12) | (0.25) | (0.17) |
| Region#Year fixed effect | Yes | Yes | Yes | Yes | Yes |
| Observations | 395 | 395 | 502 | 391 | 398 |
| Adjusted $R^2$ | 0.269 | 0.141 | 0.176 | 0.159 | 0.363 |

# C Online Appendix: Results for Positive Overlap sample

Table C1: **Followers with positive overlap**
Log Return Loss and relative Sharpe Ratio Loss

Notes:

| | Log Return loss | | | Log Relative Sharpe ratio loss | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Follower | -0.40*** | -0.24*** | -0.20** | -0.35*** | -0.16*** | -0.16*** |
| | (0.08) | (0.08) | (0.08) | (0.05) | (0.05) | (0.05) |
| Male | | | 0.22*** | | | 0.07*** |
| | | | (0.02) | | | (0.01) |
| Income proxy (std) | | | 0.03*** | | | 0.02*** |
| | | | (0.01) | | | (0.00) |
| Academic title | | | -0.27*** | | | -0.09*** |
| | | | (0.05) | | | (0.02) |
| Age | | | -0.02*** | | | -0.01*** |
| | | | (0.00) | | | (0.00) |
| Age squared | | | 0.00*** | | | 0.00*** |
| | | | (0.00) | | | (0.00) |
| Main bank | | | 0.12*** | | | 0.06*** |
| | | | (0.02) | | | (0.01) |
| Joint account | | | -0.10*** | | | -0.05*** |
| | | | (0.02) | | | (0.01) |
| Region#Year fixed effect | No | Yes | Yes | No | Yes | Yes |
| Dep. var. mean | -6.72 | -6.72 | -1.39 | -1.39 | -1.39 | -1.39 |
| Dep. var. std. dev | 1.31 | 1.31 | 0.83 | 0.83 | 0.83 | 0.83 |
| Number of Followers | 207 | 207 | 207 | 207 | 207 | 207 |
| Observations | 25297 | 25297 | 25297 | 25297 | 25297 | 25297 |
| Adjusted $R^2$ | 0.001 | 0.055 | 0.071 | 0.001 | 0.213 | 0.218 |

## Table C2: Recommender participation and Follower participation across asset classes

*Notes:* This table presents results for comparison of the correlations between investment in asset type, such as mutual funds in general, and active, passive funds and ETFs specifically, lottery stocks and high attention stocks for Followers and the matched sample. Robust standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

| | Funds | | | Lottery | | | | Attention | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) Fund | (2) Active | (3) Passive | (4) Kumar | (5) Max | (6) High Volatility | (7) High Skewness | (8) CSS | (9) Coverage | (10) Recency | (11) SUE | (12) Derivatives |
| Recommender: Funds | 0.546*** | 0.264*** | 0.363*** | -0.156*** | -0.234*** | -0.138** | -0.188*** | -0.282*** | -0.108* | -0.201*** | -0.098** | 0.086** |
| | (8.83) | (4.14) | (5.78) | (-3.09) | (-3.68) | (-2.49) | (-3.00) | (-4.55) | (-1.76) | (-3.18) | (-2.00) | (2.01) |
| Recommender: Active Funds | 0.278*** | 0.405*** | 0.071 | -0.081** | -0.136*** | -0.102*** | -0.088* | -0.139*** | -0.079* | -0.130*** | -0.039 | 0.022 |
| | (6.18) | (8.26) | (1.29) | (-2.51) | (-2.96) | (-2.95) | (-1.96) | (-3.34) | (-1.90) | (-2.85) | (-1.20) | (0.53) |
| Recommender: Passive Investments | 0.362*** | 0.074 | 0.453*** | -0.055 | -0.124** | -0.053 | -0.058 | -0.133*** | -0.068 | -0.089* | -0.034 | 0.094** |
| | (6.73) | (1.23) | (8.32) | (-1.48) | (-2.25) | (-1.30) | (-1.17) | (-2.66) | (-1.41) | (-1.66) | (-0.89) | (2.31) |
| Recommender: Lottery, Kumar | -0.165*** | -0.043 | -0.141** | 0.134** | 0.221*** | 0.144** | 0.139** | 0.204*** | 0.106* | 0.212*** | 0.103** | -0.016 |
| | (-2.87) | (-0.64) | (-2.10) | (2.52) | (3.37) | (2.57) | (2.11) | (3.25) | (1.81) | (3.18) | (2.13) | (-0.32) |
| Recommender: Lottery, MAX | -0.266*** | -0.091 | -0.225*** | 0.150*** | 0.359*** | 0.184*** | 0.222*** | 0.249*** | 0.252*** | 0.320*** | 0.156*** | -0.031 |
| | (-5.67) | (-1.39) | (-3.24) | (3.73) | (6.30) | (4.05) | (4.10) | (5.04) | (4.81) | (5.60) | (4.62) | (-0.60) |
| Recommender: High Volatility | -0.172*** | -0.058 | -0.166** | 0.126** | 0.261*** | 0.204*** | 0.178*** | 0.177*** | 0.063 | 0.238*** | 0.084* | -0.012 |
| | (-2.74) | (-0.85) | (-2.53) | (2.30) | (3.88) | (3.41) | (2.66) | (2.72) | (1.02) | (3.52) | (1.71) | (-0.24) |
| Recommender: High Skewness | -0.197*** | -0.002 | -0.182*** | 0.104** | 0.274*** | 0.147*** | 0.200*** | 0.213*** | 0.192*** | 0.242*** | 0.154*** | -0.062 |
| | (-3.78) | (-0.02) | (-2.78) | (2.37) | (4.26) | (2.86) | (3.38) | (3.70) | (3.34) | (3.82) | (3.71) | (-1.28) |
| Recommender: High Attention, CSS | -0.152*** | 0.011 | -0.184*** | 0.121*** | 0.265*** | 0.132*** | 0.169*** | 0.250*** | 0.191*** | 0.263*** | 0.138*** | -0.006 |
| | (-2.88) | (0.17) | (-2.90) | (2.90) | (4.41) | (2.83) | (2.95) | (4.72) | (3.64) | (4.33) | (3.24) | (-0.13) |
| Recommender: High Attention, CVRG | -0.148*** | -0.080 | -0.143** | 0.089* | 0.284*** | 0.116** | 0.272*** | 0.187*** | 0.301*** | 0.254*** | 0.153*** | -0.015 |
| | (-2.83) | (-1.24) | (-2.30) | (1.91) | (4.77) | (2.34) | (4.64) | (3.33) | (5.71) | (4.27) | (3.43) | (-0.35) |
| Recommender: Highattention, Recency | -0.251*** | -0.123* | -0.231*** | 0.097** | 0.316*** | 0.111** | 0.181*** | 0.249*** | 0.249*** | 0.298*** | 0.104*** | -0.040 |
| | (-5.33) | (-1.80) | (-3.40) | (2.28) | (5.34) | (2.14) | (3.11) | (4.79) | (4.46) | (4.94) | (2.62) | (-0.78) |
| Recommender: HighAttention, SUE | -0.193*** | -0.095 | -0.131* | 0.055 | 0.285*** | 0.136** | 0.220*** | 0.237*** | 0.220*** | 0.272*** | 0.257*** | -0.013 |
| | (-3.00) | (-1.33) | (-1.77) | (0.90) | (3.81) | (2.06) | (2.79) | (3.12) | (3.03) | (3.51) | (3.85) | (-0.24) |
| Recommender: Derivatives | 0.044 | 0.053 | 0.054 | -0.056 | -0.001 | 0.002 | 0.013 | -0.065 | 0.008 | 0.000 | 0.036 | 0.222*** |
| | (1.02) | (0.96) | (0.97) | (-1.59) | (-0.02) | (0.06) | (0.29) | (-1.59) | (0.18) | (0.00) | (1.00) | (4.76) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

Table C3: **Followers with positive overlap**
Decomposition of return loss

Notes:

| | Return loss $\ln(RL_i)$ | Risky share $\ln w_i$ | Risky portfolio beta $\ln \beta_i$ | Diversification loss $\ln\left(\frac{RSRL_i}{1-RSRL_i}\right)$ |
|---|---|---|---|---|
| Follower | -0.20** | 0.30*** | 0.02 | -0.25*** |
| | (0.08) | (0.06) | (0.05) | (0.08) |
| Male | 0.22*** | 0.10*** | 0.12*** | 0.10*** |
| | (0.02) | (0.01) | (0.02) | (0.02) |
| Income proxy (std) | 0.03*** | -0.05*** | -0.01 | 0.03*** |
| | (0.01) | (0.02) | (0.01) | (0.01) |
| Academic title | -0.27*** | 0.08*** | -0.12*** | -0.14*** |
| | (0.05) | (0.03) | (0.04) | (0.03) |
| Age | -0.02*** | -0.02*** | -0.00 | -0.02*** |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Age squared | 0.00*** | 0.00*** | -0.00 | 0.00*** |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Main bank | 0.12*** | 0.06*** | 0.05*** | 0.06*** |
| | (0.02) | (0.01) | (0.01) | (0.02) |
| Joint account | -0.10*** | -0.18*** | -0.04** | -0.06*** |
| | (0.02) | (0.02) | (0.02) | (0.02) |
| Region#Year fixed effect | Yes | Yes | Yes | Yes |
| Dep. var. mean | -6.72 | -0.85 | -0.26 | -0.86 |
| Dep. var. std. dev | 1.31 | 1.03 | 1.16 | 1.35 |
| Number of Followers | 207 | 207 | 207 | 207 |
| Observations | 25297 | 25279 | 25297 | 25297 |
| Adjusted $R^2$ | 0.071 | 0.041 | 0.128 | 0.237 |

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