Good Peers, Good Apples?
Peer Effects in Portfolio Quality

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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

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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, 2021). 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), concurrent marketing campaigns or other financial advise provided by the bank. a. 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 the financial advice channel. 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. 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). 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 instead 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. Both these 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 matched 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. Using a decomposition of the return loss from

Calvet *et al.* (2007), we show that Followers have a higher risky share, a higher portfolio beta, and lower diversification loss than the matched sample of investors.

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 a matched sample of 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 and attention stocks, investments that are arguably detrimental to portfolio quality (Kumar, 2009; Bali *et al.*, 2011). We confirm that investing in lottery and attention stocks is associated with higher return losses. Defining lottery stocks as in (Kumar, 2009), we show that Followers are equally likely to invest in lottery stocks as the matched sample, both on the extensive and intensive margin. However, we find that Followers are more likely than average to invest in high-risk derivatives and structured retail products. While we do not price these securities, existing literature suggests that these are costly, generally underperform (Vokata, 2021), and thus also detrimental to individual investors' portfolios. On average, therefore, portfolios of Followers are of similar quality to other investors when we examine return loss, but also have lower diversification losses stemming from a higher likelihood of investing in funds.

However, the average investment performance of Followers hides considerable heterogeneity in portfolio composition and quality. Our second main result is that peer effects are responsible for a sizable portion of heterogeneity in portfolio quality. On average, the better quality of Followers' portfolios results from a "good" peer influence. On average, Recommender portfolios are of higher quality than the general population. Since Followers copy the portfolio of their Recommender, their portfolio quality is also higher. 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.

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.[1] 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.

[1] We note that this correlation stems from an overlap in the specific assets that Recommenders and Followers invest in.

Finally, we document that Recommenders hold portfolios that outperform the average investor in our sample. At the same time, we find that Follower portfolio overlap is increasing in Recommender performance. 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. This, however, stands in contrast to other studies examining malign outcomes in peer-effected portfolios (Heimer, 2016). This is likely due to the incentive structure of the investors in our sample. We argue that investors in our setting are characterized by interpersonal relationships and are motivated not by financial incentives, but by reputational costs, and thus are more likely to provide sound financial advice.

Is the peer effect that we uncover simply the result of pure imitation, or is there a transfer of knowledge and learning? The overlap analysis certainly suggest that peers are engaged in imitation, but a simple overlap does not rule out learning taking place. 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). The distinction between mindful and mindless learning is important for understanding the welfare of our study. 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. For mindful imitation, the welfare implications are clearer, and more likely to be positive. Being better informed presumably increases the chances that peers make informed decisions about their financial investments. Furthermore, the policy response to mindless imitation is to try to incentivize asset holdings among groups likely to act as Recommenders, whereas the policy respond to mindful learning is to encourage financial literacy and promote. Mindful learning in peer effects suggest a social multiplier to financial education that could potentially be studied empirically.

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 utility from owning the same mutual fund as their peers. Mutual funds are not fun. 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.

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).[2] 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 portfolio performance of peer effects.

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.

We also contribute to a large literature on retail investors' performance and investment

[2] 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).

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 and high skewness strategies, and to trading behavior (Balakina, 2022). Balakina (2022) study 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 their 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.[3]

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 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.

The data on customer referrals allow us to identify direct peers by linking referred customers with their recommenders. In total, we have a list of 4,011 customers who recommended someone and 4,011 customers who were referred.After matching the data on referrals to demographic data and cleaning it, we have 1,852 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 those Followers who had an account at the bank before the campaign started in 2012. Our final Follower sample consists of 533 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,

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

we chose the first twelve months of trading to avoid learning and luck from influencing portfolio choice (Anagol *et al.*, 2021). 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. Our main dataset contains the average values for each variable over the first 12 months of trading for Followers, Recommenders, and a large number of investors who have recently begun trading at the bank. 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 portfolio quality as detailed in Appendix A.1 and A.3.

2.1 Summary statistics

Table 1 provides demographic summary statistics for Recommenders, Followers and the general sample of investors who join the bank after 2012. We compute the average across monthly data for the first 12 months after opening a security account for all individuals. For Recommenders we calculate averages for the first 12 months after their matched Follower opens a security account, ensuring that the data for the Recommender comes from the same period as their Follower. Column 5 provides a t-test for differences in means across Follower and the general sample.

In general, Follower and the general sample are similar across most demographics. Followers are less likely to be male, are somewhat less likely to have a joint account, and have more total assets under management (AUM). Comparing Followers and Recommenders, we see that Recommenders are more likely male, are slightly older, are more likely to have our bank as their main bank, have higher income and have almost twice the amount held in total AUM. It therefore looks like Recommenders are positively selected.

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 individuals stocks and a greater weight on funds, compared to the general sample. When it comes to portfolio characteristics, 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. As we will explore in more detail later, the portfolio characteristics of Followers generally resemble those of the Recommenders.

3 Identifying peer effects

This section presents the methodology of how we identify peer effects by examining overlap in portfolio composition. We then provide the results, and finally examine the determinants of the overlap share.

3.1 Methodology

There are three main challenges for our analysis. First, it is in general not clear who is influencing whom when documenting peer effects, meaning that we need to ensure that the *direction of causality* goes from Recommender to Follower. Second, we may observe the same behavior for Recommender and Followers because of some inherent characteristics, for example because of similar levels of risk aversion. We therefore need to account for *contextual effects* that may 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 shocks, for example local income shocks. Our analysis therefore need to account for *correlated effects* in terms of shocks. Note that we observe a direct link between peers that often has to be assumed in other studies. This helps us determine the direction of causality, as we can fix the Recommender portfolio a month before the Follower portfolio. For the first month of trading, the portfolio of the Recommender appears before the Follower even has a securities account. It is highly implausible that the Follower advised their Recommender on what assets to invest in, and then wait a month before opening their own account. We therefore assume that it is the Recommender who affects the Follower.

Our approach to identifying peer effects in portfolio composition and to solve the above issues is to 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 that German households could feasibly invest in. Even if two individuals are connected because of their level of risk aversion, it is unlikely that risk aversion alone would predict that they invest in the same assets. Similar logic applies to common shocks: even if a local newspaper or financial literacy program were to promote a specific asset class such as mutual funds or ETFs, there are still a wide range of specific funds for the individual investor to chose. Observing an overlap in the specific assets within a portfolios is therefore considerably more likely to be because of peer effects, compared to observing that two neighbors both participate in the stock market. This point is also made by Knüpfer *et al.* (2021), who examines inter-generational linkages in portfolio composition.

It is still possible, however, that preferences for popular or local stocks drives the portfolio composition for the Follower and Recommender. To account for these possibilities and to assess the rarity of the overlap, 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 setup for the Followers. Specifically, we select all new investors who join the bank after 2012. We then construct the matched pairs by i) randomly matching individual investors ii) matching each individual investors to other similar investors based on demographic characteristics, location, wealth and the risky share using the Coarsened Exact Matching of Iacus *et al.* (2012). 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, then we should observe a similar level of portfolio overlap between Follower and Placebo Followers. We conduct 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. Intuitively, this provides an estimate of the rarity of the specific portfolio composition of each Follower. 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.

3.2 Overlap results

The first set of results are presented in Figure 1. The figure plots the average value share and the number of stocks of the Follower portfolio that overlaps with the Recommender portfolio over time. The Recommender portfolio is fixed one month before and time is normalized to zero in the month of recommendation. 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 weight the number of overlapping assets by their share of the portfolio. The weighted overlap share is approximately 10 percent at time of recommendation, and the share increases over time. Note that at the time of recommendation, the Follower does not have a securities account at the bank by construction, but the Recommender does have an account. It is therefore highly likely that the direction of causality runs from the Recommender to the Follower.

In marked contrast, the overlap share for the placebo estimates in blue are 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. As these error bar shows, 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.

Figure 2 provides additional evidence on the overlap in portfolios. The figure plots the distribution of overlap for All Followers (orange bars) and for Followers with positive overlap (blue bars). While a majority of Followers have no overlap, among the 30 percent of Followers with positive overlap the share is considerable. 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 3 shows that the unweighted overlap share is around 50 percent after two years, decreasing from 70 percent at time of recommendation. The weighted overlap is more stable across time, fluctuating around 35 percent.

Figure 4 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 how little overlap there is on average 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 and 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.

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 3 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 is male, holds an academic degree, and if the bank is their main bank. Conversely, the overlap share is higher if the risky share if higher.

In contrast, assets under management (AUM), the number of securities, portfolio values, total average logins, or having a joint account predicts overlap. Finally, we also examine whether differences between the Follower and the Recommender predicts 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 in Table 3 for differences in age, income and gender already incorporate any effect of homophily on the propensity to become friends. The estimates should therefore be read as: given that you are friends, do proxies for homophily matter? In effect, this is the intensive margin of homophily, whereas the effect in Stolper & Walter (2019) is the extensive margin effect.

4 Main Results

This section provides the main results on whether peer effects are good or bad for portfolio quality. We begin by a brief overview of the methodology, and then provide results where we compare the return loss and relative Sharpe Ratio loss for Followers to a matched sample of other investors. We further show how Followers' portfolio quality is related to their investment strategies, and investigate how Follower and Recommender portfolio quality correlate.

4.1 Measuring portfolio quality

We measure the quality of peer advice by comparing the portfolios of the Followers to a control group. To identify a control group we apply the Coarsened Exact Matching of Iacus *et al.* (2012), and compare the measures of portfolio quality for Followers to the matched sample. The matched sample consists of investors who start investing in the same year, are the same age, and have similar income. In words, we compare portfolio quality of a Follower to the portfolio quality of an individual investor with the same age and income for the first twelve months of trading.

We first examine several measures of portfolio quality for Recommenders and compare them to the portfolio quality in the matched sample. Specifically, we calculate the Return Loss and the Relative Sharpe Ratio loss for the Follower portfolio and for the overlap portfolio. We construct the matched sample based on demographic characteristics, location, wealth and the risky share, and compare the Return Loss and the Relative Sharpe Ratio loss between Followers and Placebo Followers. Similar to before, we collapse the first 12 months of trading to isolate the peer effect from any learning by the Follower.

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 is only recommending 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. No overlap in portfolios is then consistent with no peer effects. We believe that this is unlikely to be true, however, for several reasons. First, the Follower overall portfolio could be influenced by the Recommender 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 construct their portfolio with this recommendation in mind. This would be the case if the Recommender encourages investments into mutual funds, for example, and would imply a peer effect even if the overlap share is zero. We will examine this effect directly. Second, portfolio composition is not independent from the single assets in the portfolio. If the Follower purchases an asset because of a recommendation, they should also adjust the rest of their portfolio. This implies that the non-overlap is 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, in general showing stronger results than what we provide below. This suggests that including all Followers likely biases our estimates towards zero.

4.2 Baseline results

This section presents our baseline results for portfolio quality. We compare Followers to a matched 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:

$$y_{i,k} = \alpha + \gamma Follower_{i,k} + \mathbf{X'_{i,k}}\beta + \delta_i + \delta_k. + \epsilon_{i,k} \tag{2}$$

where y_i is the main dependent variable, measured for individual i living in region k during the first twelve months after opening their securities account. We focus on log Return Loss and log Sharpe Ratio loss. α is a constant, $Follower_i$ 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 $\mathbf{X}'$, for example including age, income, education level and gender. In most regression we also include a year δ_t and region fixed effect. Finally, we use robust standard errors.

Table 4 provides our first main results. In the first three columns the dependent variable is log Return Loss, and in the last three columns the dependent variable is the log relative Sharpe ratio loss. Column 1 and 4 provide results without control variables, column 2 and 5 adds separate region and year fixed effects, and column 3 and 6 adds further control variables based on individual Follower characteristics.

The results in the first three columns show that Followers have lower Return Loss, but also that the coefficients are not statistically significant. Compared to the general sample of investors, Followers do not have either better or worse portfolios. In columns 4-6 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, all results for the RSRL are economically and statistically significant, and show that Followers have more diversified portfolios. The coefficient in column 4 is -0.15, which is around 10 percent of the average relative Sharpe ratio loss. The coefficient decreases to -0.14 when we add fixed effects for region, age and years, and is further decreased to -0.12 in column 6.

Table **??** provides a simple heterogeneity analysis. In the table we interact the Follower dummy variable with dummies for age, income, high number of transactions and male, and also control independently for these dummies. In column 1, for example, *Age dummy* $\times$ *Follower* examines the return loss for young Followers, while controlling for both Follower and Age dummy separately. The results show that young investor generally have higher return loss, as indicated by the positive and significant coefficient on *Age dummy*. The coefficient on *Age dummy* $\times$ *Follower*, however, is negative, showing that young Followers have a lower return loss. Our interpretation is that while young investors generally hold worse portfolios, this effect is mitigated by the presence of a Recommender. In column 5 we also see that similar results hold for the relative Sharpe ratio loss. The coefficient on *Income dummy* $\times$ *Follower* and *Male* $\times$ *Follower* are similarly negative, but are not statistically significant.

Table 5 presents results for the decomposition of return loss into its components, described in Equation (9) in Appendix A.1. We regress return loss (the same results as Column 3 of Table 4) and each component of return loss on a dummy for Follower as well as on demographic and financial variables. As before, the return loss is not significantly lower for Followers. However, the rest of the results reveal that Followers have a higher risky share, i.e. that they invest a larger share of their portfolio into risky assets. Moreover, they have a higher portfolio beta, and a lower diversification loss. Followers are more aggressive in their risk taking (as measured by a higher portfolio beta and a higher risky share), and less more efficient in their portfolio choices. Since each term is additive in Equation (9), the higher portfolio beta and higher risky share cancel out the lower diversification loss.

4.3 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 matched sample and whether that difference can explain the gap in diversification loss. We start by defining several investment strategies that may correlate with differences in realized returns. We create a set of dummy variables that indicate whether an investors holds specific asset types. We 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.

Our analysis is motivated by Han *et al.* (2022), who provides a model where stocks with high volatility and high skewness are more likely to be recommended by peers in a social network. In our empirical setup, these types of 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 be inclined 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 well recommend investments with lower volatility and fees, and higher expected returns (e.g., diversified passive funds). In what follows, we show that Followers generally invest more into passive funds, and that their investments in lottery and attention stocks are not generally higher than the general sample.

Table 7 shows the difference in participation rates between Followers and their matched counterparts, for each investment style. Panel A examiens the participation rate (extensive margin), while Panel B states the conditional investment in each specific asset type. The table shows that Followers, compared to the matched sample, are 5.5% more likely to invest in funds. However, there is no statistical difference for the fund portfolio share. Within fund category, Followers are 6.1 pp. more likely to invest in ETFs and passive funds and 5.2 pp. more likely in invest in active trading strategies. At the intensive margin, Followers invest a lower share in ETFs compared to the matched sample, however insignificant at conventional levels.

Moving on to lottery and attention stock investments, Table 7 shows no statistical difference between Followers and the matched sample at the extensive margin. On the intensive margin, Followers appear to invest less in High Skewness and Recency stocks, conditional on investing. Column 7 in Panel B shows that Followers invest 2.3 pp. lower share in high skewness stocks compared to the matched sample. Except for the Recency measure of attention, the results show that Followers have a lower share of assets with recent maximum return events compared to the matched sample.

Of particular interest is Column 12, where we examine the participation rate of high-risk derivative instruments. Derivatives include investments in structure retail products such as certificates, warrants, and various types of options. We note that Followers are 3.4 p.p more likely than the general sample to invest in such assets, however invest less in these products conditional on participation (Panel B).

In Table 6 we report how each investment style is related to return loss and relative Sharpe ratio loss, our measures of "good" and "bad" portfolio quality. Participation in funds is generally associated with lower Log Return loss and log relative Sharpe ratio loss, whereas participation in lottery stocks 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 derivative participation as return data on options, and certificates 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).

Overall, the results show that Followers compared to a matched investor are more likely invest in good investments, and are more prudent with their investments in lottery stocks.

4.4 What determines Follower portfolio quality?

In the previous section we showed that overall, portfolio quality is higher among Followers than a comparable sample of matched investors. 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 due to some other characteristic of the Follower. Intuitively, if the higher quality of Follower portfolios is due to peer effects, we should see that a positive correlation in measures of portfolio quality between Followers and Recommenders.

Panel A of Figure 5 plots the log Return Loss and the Log Relative Sharpe Ratio Loss for the Follower against Recommender rank over the 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 5 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 6 then shows that the above results are robust to controlling for various characteristics of the Follower and to using continuous values for the Recommender. 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 a wide range of Follower characteristics, and plots the Follower variable on the y-axis and the corresponding variable for the Recommender over the same time period on the x-axis. Table B5 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 higher Return Loss for the Recommender is associated with a 0.51 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.

Table **??** provides an alternative estimate of the determinant of Follower portfolio quality. The table regresses portfolio characteristics on a dummy variable, *Good Recommender* equal to one if the Recommender has an below median return loss. Good Recommenders are associated with a lower Return Loss, a lower Sharpe Ratio loss, a lower risky beta and a higher weight in funds.

How do Recommenders transmit the quality of their portfolios to Followers? Table 8 shows that there is high and significant correlation between almost all investment strategies of Recommender and Follower both at the extensive and intensive margins. For example, a Follower is 55 percentage points more likely to invest in funds if the Recommender him or herself invests in funds, and at the intensive margin, a one percent point increase in fund share of the Recommender is associated with 0.64 percentage point increase in fund share in Follower's portfolio. In comparison, the correlation between Recommender and Follower among alternative investment strategies such as lottery stocks or derivative investments is much lower. At the extensive margin, a Follower is from 11 to 33 percentage points percent more likely to invest in lottery stocks if the Recommender invests. The correlation with derivative participation is similarly, close to 24 percentage points. At the intensive margin, the correlation at the intensive margin is statistically significant and comparable to the results for funds. The correlation between high attention stock and derivative investments and is also statistically significant, however substantially lower than the correlation for fund investment.

Finally, we examine the relationship between Recommender investment style and Follower's portfolio quality characteristics. We determine if a Recommender invests in one of the asset categories, such as funds, lottery stocks, and attention stocks categories based on their investment in funds and lottery stock. We create two dummy variables equal to one if Recommender invests in funds/lottery stocks, and zero otherwise. We estimate equation (3):

$$y_{i,k} = \alpha + \sum_{j=1}^{S} \gamma_j RecommenderInvest_{i,j} + \mathbf{X'_{i,k}}\beta + \delta_{i,k} + \epsilon_{i,k} \tag{3}$$

where y_i is the main dependent variable, measured for individual i living in region k during the first twelve months after opening their securities account: log Return Loss, log Sharpe Ratio loss, log portfolio beta, log risk share, and log diversification loss. α is a constant, $RecommenderInvest_{i,j}$ is a dummy variable equal to one if the Recommender of the Follower i invests in an asset type j and zero otherwise. We consider the following assets: fund, lottery stocks, high volatility stocks, high skewness stocks, high attention stocks. We include a vector of demographic and financial control variables in $\mathbf{X'}$, and time-region fixed effect $\delta_{i,k}$ in all the regressions, and use robust standard errors.

Table 9 presents the results. The table shows that both the effect of investment strategy of the Recommender and the Follower herself. As expected fund participation by Follower decreases the Return Loss, the log Relative Sharpe ratio, portfolio beta, and diversification losses. Fund participation overall improves the quality of the portfolio. The same is true for the Recommender fund participation. If the Recommender invests in funds the quality of the Follower's portfolio improves. For the lottery stock investment we observe the negative effect of both follower herself and Recommenders' investment. However, the Recommenders' influence is barely significant.

Han *et al.* (2022) show that in the theoretical model high volatility and high skewness assets would spread in the social network. Indeed, we observe high correlation between those investments between recommenders and Followers. However, we do not observe the negative effects of such investments coming from Recommender. In addition, Table

?? shows that Followers that invest in high volatility and high skewness stocks have better portfolio quality compared to the matched sample. Recall we do not price options and structured retail products, and we therefore refrain from including them in this table.

We conclude that Recommenders provide investment advice to Followers and that advice is improving Followers' portfolio quality. Bad advice such as investment in lottery stocks and high volatility and high skewness stocks also spreads through social networks.

4.5 Comparing Recommenders to the general population

There are several attributes of our setting that warrant discussion. First, it is important to recognize that Recommender treatment is non-random. Investors who recommend the platform to friends do not do so by chance, but by design. Thus it is important to understand how Recommenders may differ from the general population, and what may incentivize them to provide advice to others.

Appendix Table B2 provides descriptive statistics comparing Recommenders to the general population drawn from our full sample. As Recommenders generally have longer tenure at the bank, and are more likely to use this account as their main bank, we note that they are typically wealthier, older, have higher income, have larger portfolios and are more active compared to the general population. These investors are more likely to be male, and at the mean show a similar portfolio allocation to risky assets compared to those in the general sample, but hold a larger mix of securities in general and thus participate more broadly across different types of asset classes.

How does the performance of the portfolios of Recommenders compare to the general population? Panel A) of Figure 7 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, which indicates that their portfolios in general are of better quality. Panel B) plots the distribution of Log Relative Sharpe

Ratio loss, again showing a similar pattern.

Having established that Recommenders differ from the marginal investor, we consider why they may provide advice. In our setting, 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 which likely precedes the observed financial advice. And given that Recommenders are wealthy, it seems unlikely that they would do this for the small monetary or token-prize provided. Thus, Recommenders may be incentivized by reputational costs, social utility (Bursztyn *et al.*, 2014), or 'warm glow,' to recommend sound financial advice.[4]

CONTINUE HERE¿.... TALK ABOUT HOW THIS IS A DIFFERENT TYPE OF PEER EFFECTS BUT A GOOD SETTING -¿ CONCLUSION POLICY. [5]

5 Conclusion

In this paper, we use administrative data from a German online bank to analyse peer effects based on a direct recommender-referral relationship. We provide evidence of con-

[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.

[5] an interesting way to look at this similar to advisors (as in Foerster *et al.* (2017) with a recommender fixed effect, but we do not have enough observations, only 5 recommenders reecommend more than one follower

siderable 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 Follower's portfolio is highly correlated with the quality of his or her Recommender's 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.

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.

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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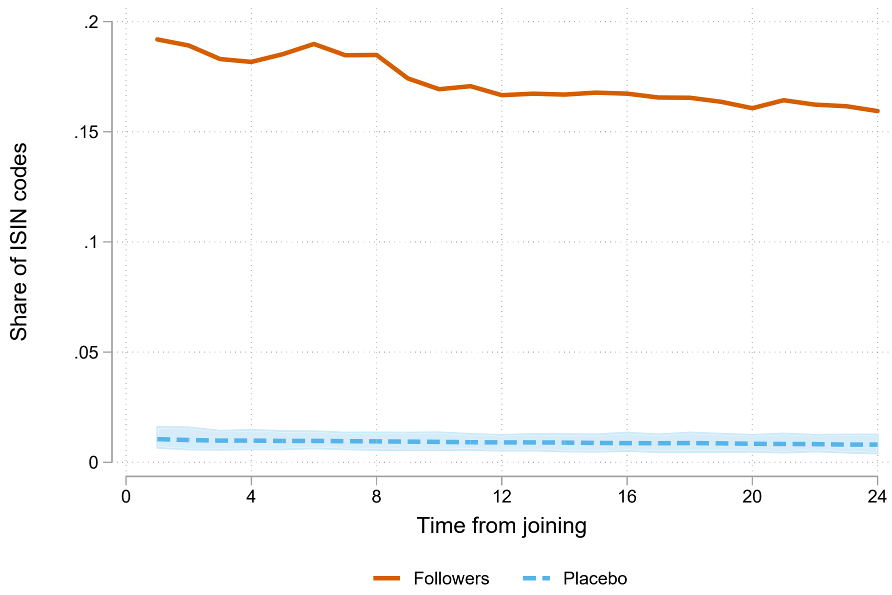
6 Figures

a) Overlap in number of assets



b) Overlap in share of portfolio

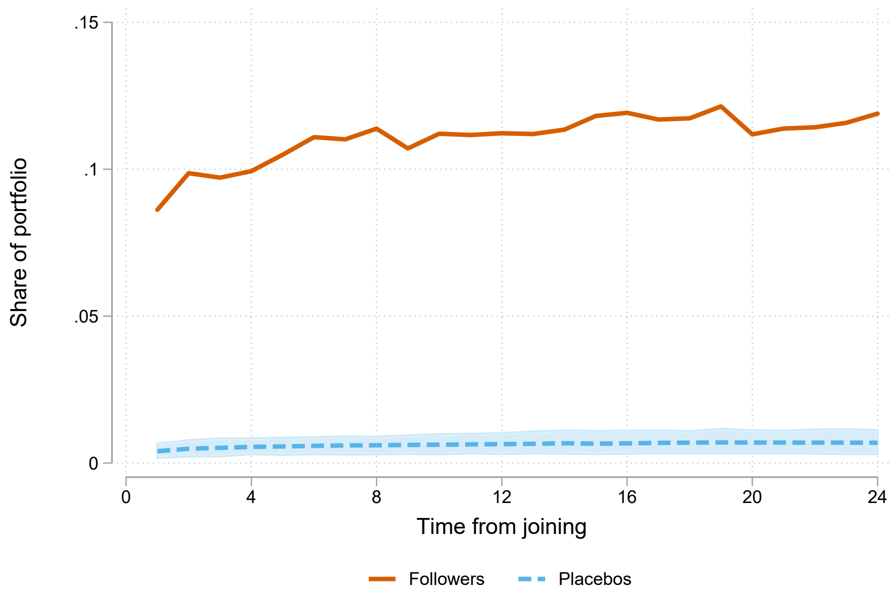


Figure 1: Overlap in number of assets and share of portfolio

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.

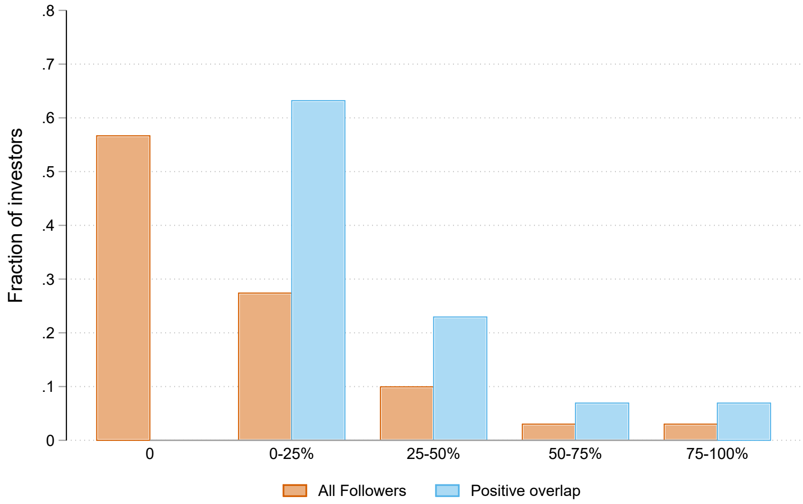


Figure 2: Distribution of overlap share

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.

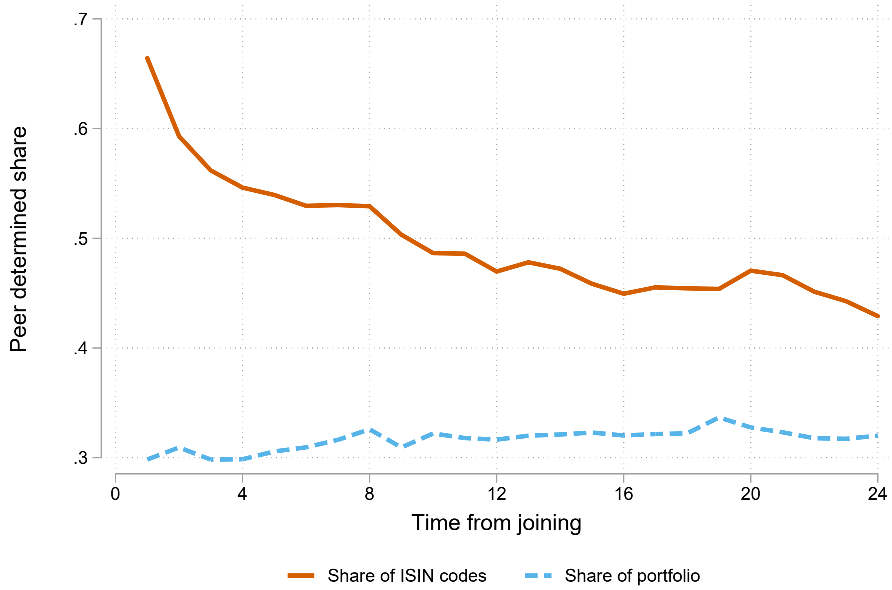


Figure 3: Overlap and unweighted overlap for Followers with positive overlap

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 .

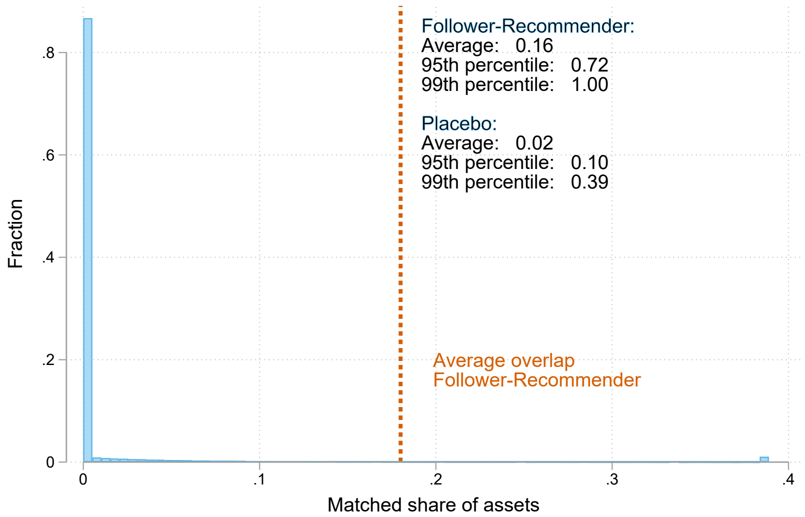
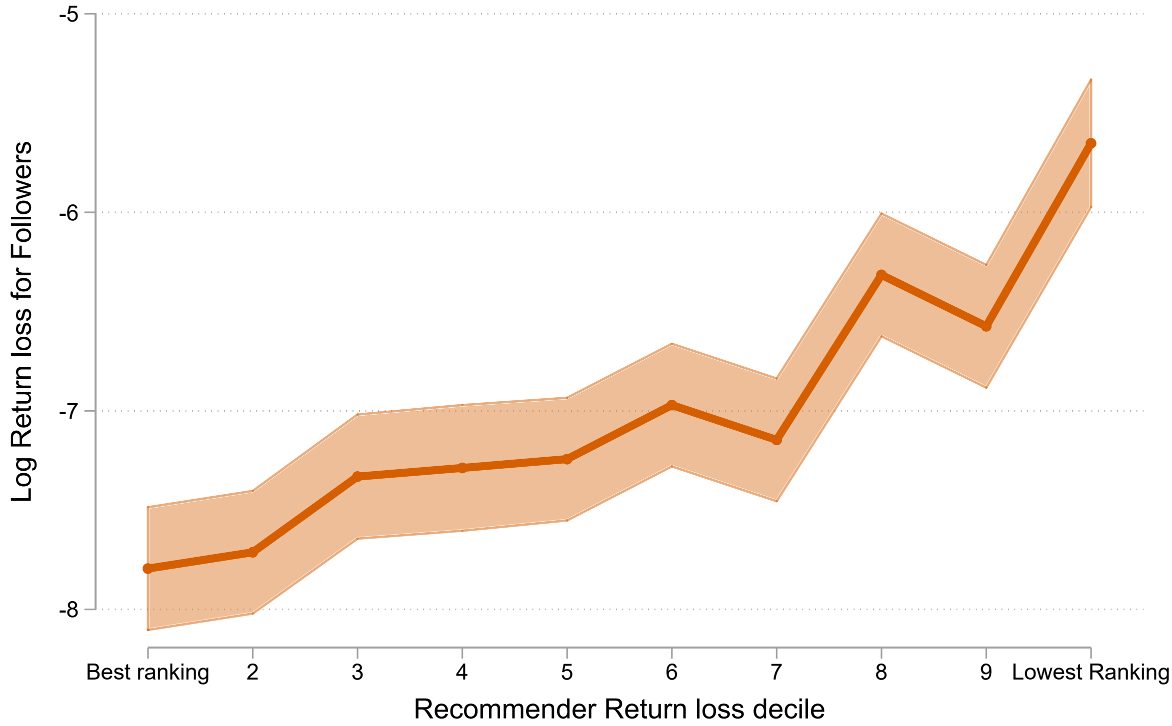
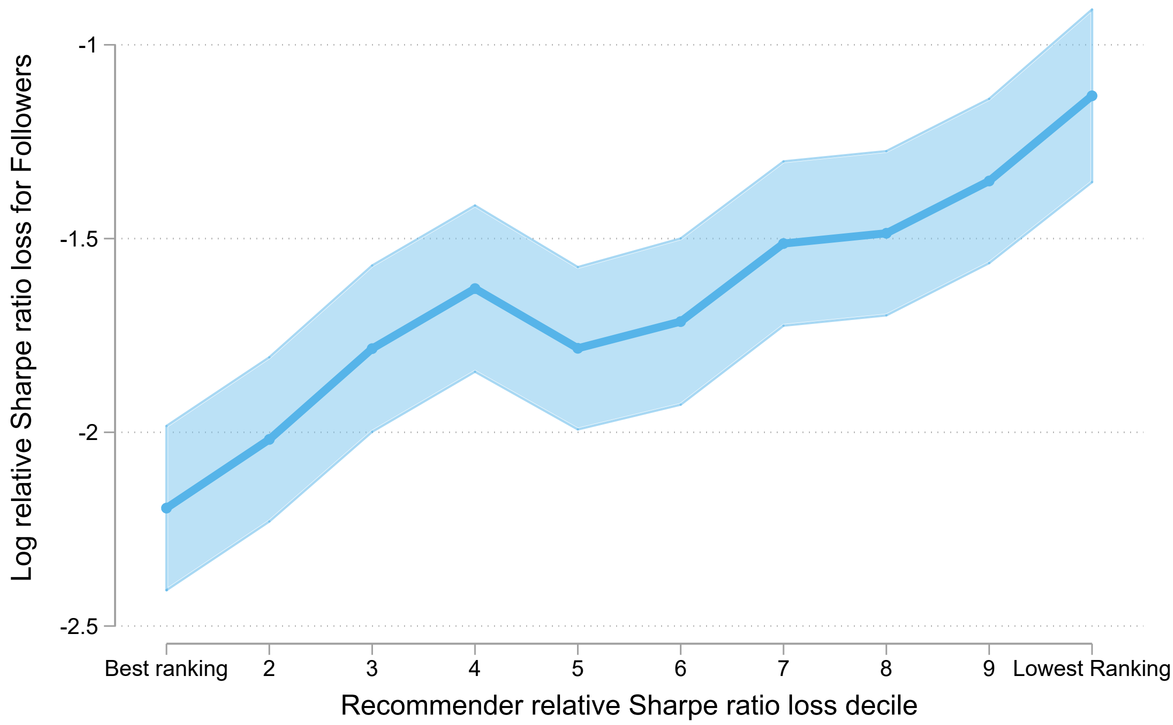


Figure 4: Overlap with all investors

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.



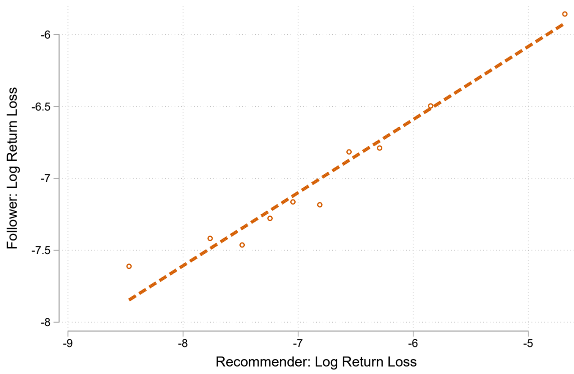
A) Return Loss



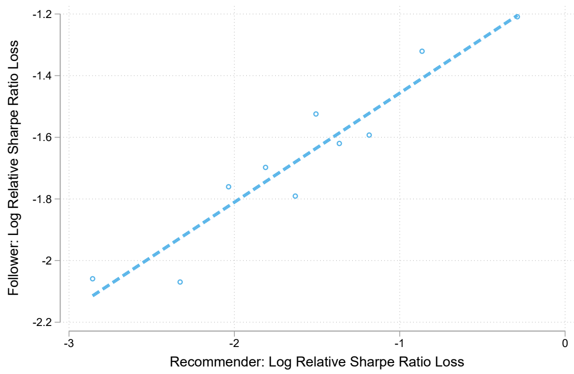
B) Relative Sharpe Ratio loss

Figure 5: Follower portfolio quality conditional on Recommender portfolio quality

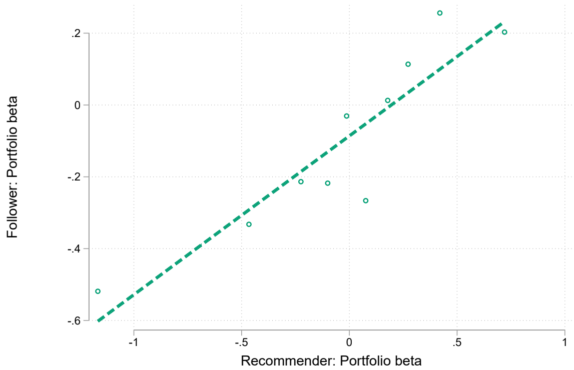
Notes: The figure plots the log Return Loss (Panel A) and the Log Relative Sharpe Ratio Loss (Panel B) for the Follower against Recommender rank. Recommenders are sorted into deciles by log Return loss and the Log Relative Sharpe Ratio Loss, and the average value for Followers is shown on the y-axis.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



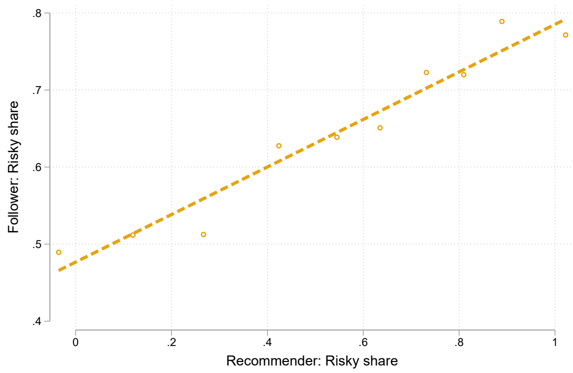
Return Loss



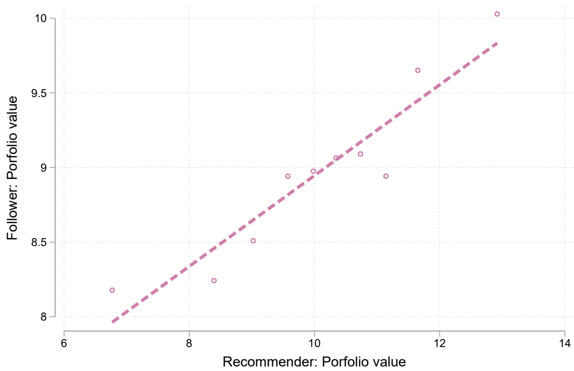
Relative Sharpe Ratio loss



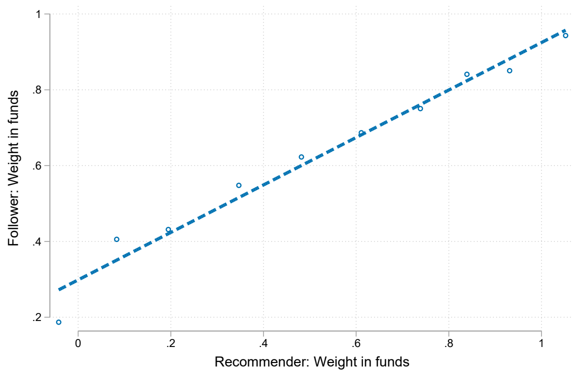
Portfolio Beta



Risky Share



Portfolio value

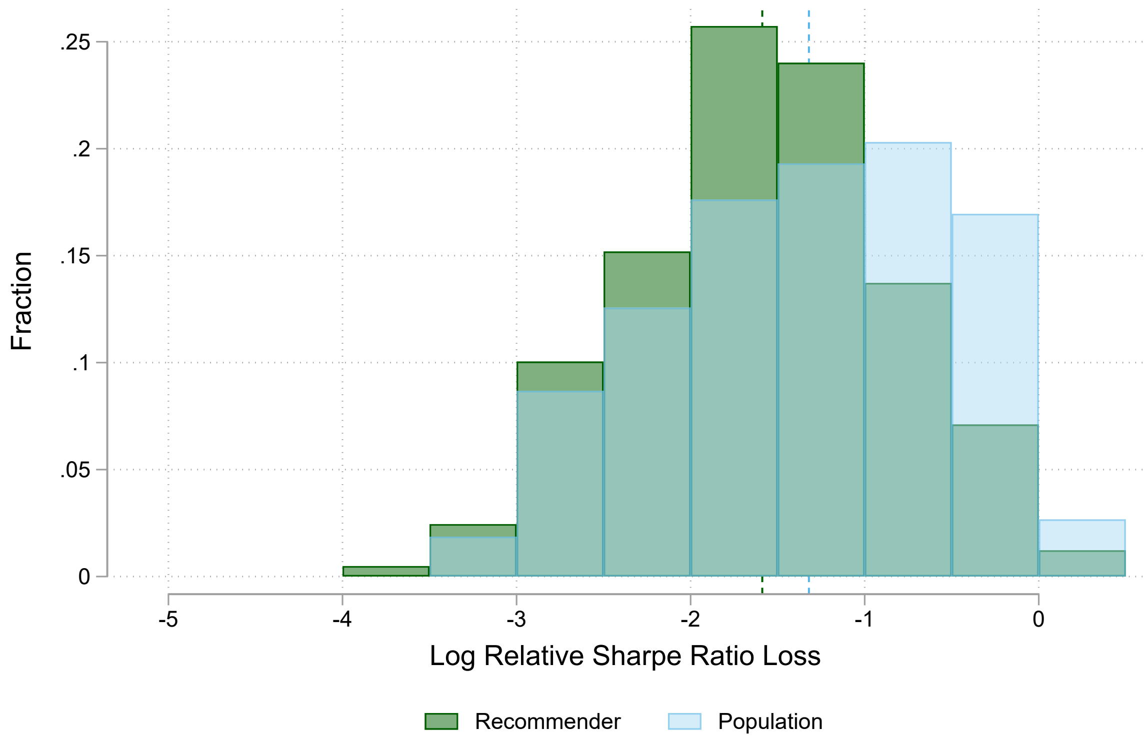


Weight in funds

Figure 6: 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 a wide range of Follower characteristics (See table B5), and plots the Follower variable on the y-axis and the corresponding variable for the Recommender over the same time period on the x-axis.

A) Log Return Loss



B) Log Relative Sharpe Ratio loss

Figure 7: 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.

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) Follower	(2) General sample	(3) Recommender	(4) T-test (2) - (1)
A. Demographic characteristics				
Male	0.51	0.72	0.77	0.21***
	(0.50)	(0.45)	(0.42)	[10.79]
Age	41.55	41.78	43.55	0.23
	(15.60)	(13.81)	(14.37)	[0.39]
Academic title	0.06	0.06	0.06	-0.00
	(0.24)	(0.23)	(0.23)	[-0.41]
Joint account	0.10	0.15	0.16	0.05***
	(0.30)	(0.35)	(0.37)	[3.09]
Main bank	0.31	0.28	0.49	-0.02
	(0.46)	(0.45)	(0.50)	[-1.10]
B. Wealth and income				
Total AUM (EUR)	35,516.74	29,058.17	62,725.98	-6,458.58***
	(49,882.76)	(46,104.21)	(76,460.28)	[-3.31]
Income proxy	2,619.06	2,962.36	4,611.66	343.31
	(5,888.92)	(9,917.57)	(11,301.12)	[0.83]
Portfolio value (EUR)	28,252.10	23,340.75	102,029.77	-4,911.35
	(81,913.33)	(107,797.80)	(221,540.01)	[-1.08]
C. Portfolio Quality				
Log Return Loss	-6.94	-6.71	-6.83	0.23***
	(1.23)	(1.50)	(1.19)	[3.54]
Log Relative Sharpe Ratio Loss	-1.63	-1.33	-1.59	0.30***
	(0.79)	(0.87)	(0.77)	[8.23]
Log Risky Share	-0.66	-0.86	-0.57	-0.20***
	(0.83)	(1.03)	(0.92)	[-4.67]
Log Portfolio Beta	-0.09	-0.28	-0.06	-0.19***
	(0.74)	(1.19)	(0.63)	[-3.72]
B. Wealth and income				
Total AUM (EUR)	35,517	29,058	62,726	-6,459***
	(49,883)	(46,104)	(76,460)	[-3]
Income proxy	2,619	2,962	4,612	343
	(5,889)	(9,918)	(11,301)	[1]
Portfolio value (EUR)	28,252	23,341	102,030	-4,911
	(81,913)	(107,798)	(221,540)	[-1]
Observations	573	26,590	567	27,163

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 *** denote significance at the 10%, 5% and 1% levels, respectively.

	(1) Follower	(2) Placebo	(3) Placebo with weights	(4) Recommender
Total logins	25.131	31.453	49.284	6.322*
	(94.943)	(88.056)	(110.632)	[1.70]
Number of trades	1.764	2.038	3.330	0.274
	(2.149)	(4.958)	(7.616)	[1.32]
Stock market participant	0.499	0.560	0.759	0.061***
	(0.500)	(0.496)	(0.428)	[2.89]
B. Portfolio composition				
Risky share	0.642	0.576	0.546	-0.066***
	(0.298)	(0.316)	(0.368)	[-4.95]
Number of securities	4.987	4.543	13.488	-0.445*
	(5.001)	(5.723)	(14.937)	[-1.84]
Weight stocks	0.317	0.397	0.381	0.080***
	(0.416)	(0.442)	(0.376)	[4.29]
Weight bonds	0.034	0.030	0.031	-0.005
	(0.153)	(0.145)	(0.122)	[-0.74]
Weight funds	0.608	0.521	0.520	-0.087***
	(0.432)	(0.452)	(0.391)	[-4.57]
C. Portfolio characteristics				
Portfolio beta	1.256	1.014	1.068	-0.242**
	(4.832)	(2.579)	(0.593)	[-2.15]
Portfolio expected return	0.005	0.004	0.004	-0.001**
	(0.018)	(0.009)	(0.002)	[-2.15]
Standard deviation of returns	0.084	0.065	0.067	-0.019
	(0.645)	(0.939)	(0.296)	[-0.47]
Sharpe ratio	0.089	0.076	0.088	-0.013***
	(0.028)	(0.035)	(0.027)	[-8.36]
Return loss	0.006	0.004	0.004	-0.001
	(0.072)	(0.113)	(0.035)	[-0.29]
Relative Sharpe Ratio loss	0.268	0.371	0.274	0.103***
	(0.232)	(0.291)	(0.225)	[8.36]
Trade risk	1.799	1.872	1.891	0.074
	(1.426)	(1.465)	(1.626)	[1.19]
Herfindahl-Hirschman-Index	0.216	0.288	0.156	0.072***
	(0.313)	(0.356)	(0.249)	[4.82]
D. Investment Styles				
I: Active Fund Investment	0.384	0.331	0.553	-0.053***
	(0.487)	(0.470)	(0.498)	[-2.68]
Passive Investment	0.546	0.417	0.659	-0.129***
	(0.498)	(0.493)	(0.474)	[-6.19]
Warrants and Options	0.171	0.154	0.369	-0.017
	(0.377)	(0.361)	(0.483)	[-1.12]
I: Lottery Investment, Kumar	0.105	0.152	0.243	0.048***
	(0.306)	(0.359)	(0.430)	[3.14]
I: High Volatility Investment	0.122	0.154	0.246	0.032**
	(0.328)	(0.361)	(0.431)	[2.09]
I: High Skewness Investment	0.204	0.248	0.374	0.043**
	(0.403)	(0.432)	(0.484)	[2.39]
I: Attention Investment, CSS	0.188	0.223	0.347	0.034*
	(0.391)	(0.416)	(0.477)	[1.95]
I: Attention Investment, Coverage	0.185	0.204	0.301	0.019
	(0.389)	(0.403)	(0.459)	[1.14]
I: Attention Investment, Recency	0.290	0.335	0.434	0.045**
	(0.454)	(0.472)	(0.496)	[2.25]
I: Lottery Investment, MAX	0.312	0.367	0.469	0.055***
	(0.464)	(0.482)	(0.500)	[2.69]
I: Attention Investment, SUE	0.108	0.127	0.177	0.019
	(0.311)	(0.334)	(0.382)	[1.37]
Observations	573	26,590	567	27,163

Table 3: 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	-0.022				-0.031
	(0.019)				(0.026)
Academic title	-0.065***				-0.076***
	(0.019)				(0.022)
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		0.108***			0.139***
		(0.034)			(0.041)
Number of securities		0.001			-0.001
		(0.002)			(0.003)
Portfolio value (EUR)		0.000			-0.000
		(0.000)			(0.000)
Main bank			-0.027		-0.029
			(0.020)		(0.021)
Total logins			0.000**		0.000**
			(0.000)		(0.000)
Joint account			-0.045		-0.026
			(0.029)		(0.031)
Number of trades			0.002		0.000
			(0.004)		(0.004)
Robo-trade			0.011		0.016
			(0.025)		(0.026)
Age difference				0.000	0.001
				(0.000)	(0.001)
Different gender				0.016	0.002
				(0.019)	(0.027)
Income difference				-0.000	-0.000
				(0.000)	(0.000)
Constant	0.148***	0.037*	0.119***	0.094***	0.140***
	(0.031)	(0.020)	(0.016)	(0.014)	(0.049)
Observations	533	533	483	533	483
Adjusted R^2	0.006	0.019	-0.002	-0.004	0.025

Table 4: 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	-0.23***	-0.07	-0.03	0.04	-0.30***	-0.12***	-0.12***	-0.07
	(0.05)	(0.05)	(0.05)	(0.07)	(0.03)	(0.03)	(0.03)	(0.04)
Follower × Positive Overlap				-0.19*				-0.13*
				(0.11)				(0.07)
Male			0.24***	0.24***			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			-0.25***	-0.25***			-0.10***	-0.10***
			(0.05)	(0.05)			(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			0.13***	0.13***			0.03***	0.03***
			(0.02)	(0.02)			(0.01)	(0.01)
Joint account			-0.08***	-0.08***			-0.06***	-0.06***
			(0.02)	(0.02)			(0.01)	(0.01)
Region#Year fixed effect	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Dep. var. mean	-6.72	-6.72	-6.72	-6.72	-1.33	-1.33	-1.33	-1.33
Observations	26699	26699	26699	26699	26696	26696	26696	26696
Adjusted R^2	0.000	0.041	0.056	0.056	0.002	0.190	0.194	0.194

Table 5: Decomposition of return loss

Notes: This table presents results for the decomposition of return loss into its components from equation 9. We regress return loss (the same results as Column 3 of Table 4) 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	-0.03	0.18***	0.08**	-0.16***
	(0.05)	(0.04)	(0.03)	(0.05)
Male	0.24***	0.10***	0.12***	0.10***
	(0.02)	(0.01)	(0.02)	(0.02)
Income proxy (std)	0.03***	-0.06***	-0.01	0.03***
	(0.01)	(0.02)	(0.01)	(0.01)
Academic title	-0.25***	0.08***	-0.10**	-0.14***
	(0.05)	(0.02)	(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	0.13***	0.06***	0.05***	0.06***
	(0.02)	(0.01)	(0.01)	(0.02)
Joint account	-0.08***	-0.18***	-0.03*	-0.06***
	(0.02)	(0.02)	(0.02)	(0.02)
Region#Year fixed effect	Yes	Yes	Yes	Yes
Dep. var. mean	-6.72	-0.86	-0.27	-0.85
Observations	26699	26680	25722	25742
Adjusted R^2	0.056	0.041	0.125	0.231

Table 6: 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	-1.515***	-0.693***	-0.954***	1.389***	1.380***	1.428***	1.212***	1.003***	0.829***	1.281***	0.743***
	(0.019)	(0.016)	(0.016)	(0.019)	(0.015)	(0.019)	(0.016)	(0.017)	(0.016)	(0.015)	(0.018)
Constant	-5.699***	-6.484***	-6.311***	-6.932***	-7.231***	-6.941***	-7.022***	-6.945***	-6.890***	-7.153***	-6.814***
	(0.017)	(0.012)	(0.014)	(0.010)	(0.012)	(0.010)	(0.011)	(0.011)	(0.011)	(0.012)	(0.010)
Observations	26701	26701	26701	26701	26701	26701	26701	26701	26701	26701	26701
Adjusted R^2	0.225	0.048	0.099	0.112	0.198	0.120	0.123	0.078	0.050	0.164	0.028
Panel B: Log Relative Sharpe ratio Loss	Funds			Lottery				Attention			
	Fund	Active	Passive	Kumar	MAX	High Volatility	High Skewness	CSS	CVRG	Recency	—SUE—
Participation	-0.879***	-0.250***	-0.811***	0.612***	0.623***	0.609***	0.522***	0.461***	0.365***	0.604***	0.373***
	(0.009)	(0.011)	(0.010)	(0.011)	(0.009)	(0.011)	(0.010)	(0.010)	(0.010)	(0.009)	(0.012)
Constant	-0.741***	-1.248***	-0.986***	-1.426***	-1.564***	-1.427***	-1.463***	-1.436***	-1.408***	-1.537***	-1.380***
	(0.006)	(0.007)	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.006)
Observations	26698	26698	26698	26698	26698	26698	26698	26698	26698	26698	26698
Adjusted R^2	0.226	0.018	0.214	0.065	0.120	0.065	0.068	0.049	0.029	0.109	0.021

Table 7: 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)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Fund	Active	Passive	Kumar	MAX	High Volatility	High Skewness	CSS	CVRG	Recency	—SUE—	Derivatives
Follower	0.064***	0.064***	0.075***	-0.010	0.002	-0.002	-0.007	-0.001	0.012	0.014	0.011	0.037**
	(0.018)	(0.020)	(0.021)	(0.013)	(0.017)	(0.013)	(0.016)	(0.016)	(0.016)	(0.017)	(0.012)	(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	27161	27161	27161	27161	27161	27161	27161	27161	27161	27161	27161	27161
Adjusted R^2	0.039	0.024	0.121	0.083	0.221	0.074	0.125	0.117	0.102	0.204	0.107	0.020
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	CVRG	Recency	—SUE—	Derivatives
Follower	-0.005	-0.045**	-0.057***	-0.026	-0.030*	-0.041*	-0.031**	-0.012	-0.004	-0.016**	-0.001	-0.085***
	(0.014)	(0.020)	(0.021)	(0.028)	(0.017)	(0.022)	(0.013)	(0.013)	(0.003)	(0.007)	(0.004)	(0.029)
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	17978	9006	11403	4094	9930	4155	6693	6023	5534	9054	3437	4184
Adjusted R^2	0.040	0.047	0.092	0.084	0.175	0.063	0.042	0.027	0.022	0.051	0.033	0.019

Table 8: Conditional 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) 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
Leader Participation	0.566***	0.410***	0.490***	0.132***	0.360***	0.211***	0.157***	0.263***	0.262***	0.282***	0.219***	0.241***
	(0.057)	(0.045)	(0.050)	(0.050)	(0.056)	(0.055)	(0.058)	(0.052)	(0.051)	(0.058)	(0.065)	(0.043)
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	436	436	436	436	436	436	436	436	436	436	436	436
Adjusted R^2	0.268	0.240	0.235	0.102	0.302	0.099	0.087	0.193	0.178	0.248	0.190	0.146

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) Coverage	(10) Recency	(11) SUE	(12) Derivatives
Recommender Portfolio weight	0.638***	0.390***	0.648***	0.729***	0.559***	0.486***	0.327**	0.652***	0.395***	0.605***	0.649***	0.316***
	(0.043)	(0.077)	(0.055)	(0.246)	(0.083)	(0.143)	(0.130)	(0.155)	(0.118)	(0.094)	(0.136)	(0.101)
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	436	436	436	436	436	436	436	436	436	436	436	436
Adjusted R^2	0.367	0.176	0.296	0.380	0.500	0.301	0.197	0.248	0.157	0.374	0.249	0.105

Table 9: Portfolio Quality vs 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		Relative Sharpe ratio loss		Risky Share		Beta		Diversification Loss	
	(1) Follower	(2) Recommender	(3) Follower	(4) Recommender	(5) Follower	(6) Recommender	(7) Follower	(8) Recommender	(9) Follower	(10) Recommender
Funds										
Fund	-1.43***	-1.03***	-0.75***	-0.51***	0.15	-0.01	-0.38***	-0.29***	-1.01***	-0.65***
	(0.15)	(0.17)	(0.09)	(0.10)	(0.11)	(0.11)	(0.09)	(0.09)	(0.16)	(0.14)
Lottery										
MAX	0.74***	0.28	0.37**	0.13	0.38**	0.20	0.05	0.12	0.51**	0.07
	(0.20)	(0.24)	(0.14)	(0.15)	(0.15)	(0.16)	(0.13)	(0.17)	(0.25)	(0.23)
High Volatility	0.64***	0.27	0.32**	-0.03	-0.22*	0.10	0.11	0.12	0.46**	0.03
	(0.18)	(0.23)	(0.13)	(0.14)	(0.12)	(0.13)	(0.11)	(0.13)	(0.21)	(0.20)
High Skewness	-0.03	0.08	-0.07	0.12	-0.04	-0.11	0.16	-0.05	-0.14	0.18
	(0.20)	(0.23)	(0.14)	(0.15)	(0.14)	(0.20)	(0.14)	(0.18)	(0.24)	(0.23)
Attention										
CSS	-0.20	-0.02	-0.04	-0.00	0.08	0.08	-0.01	-0.00	-0.17	0.05
	(0.19)	(0.21)	(0.13)	(0.13)	(0.14)	(0.17)	(0.13)	(0.14)	(0.22)	(0.18)
Region fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region#Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	399	399	399	399	399	399	394	394	394	394
Adjusted R^2	0.503	0.236	0.361	0.166	0.107	0.091	0.109	0.065	0.285	0.114

Table 10: 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.

	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	0.725***	-0.102	0.378	0.297**	0.310	0.093	0.283	0.342*	0.220	0.259	-0.091	-0.295
	(4.46)	(-0.47)	(1.63)	(2.04)	(1.46)	(0.59)	(1.42)	(1.75)	(1.29)	(1.24)	(-0.68)	(-1.54)
Recommender: Active Funds	0.655***	0.112	0.009	0.236	0.364	0.094	0.302	0.461*	0.201	0.311	-0.075	-0.223
	(3.18)	(0.41)	(0.03)	(1.13)	(1.30)	(0.48)	(1.16)	(1.81)	(0.96)	(1.15)	(-0.42)	(-0.91)
Recommender: Passive Investments	1.013***	-0.028	0.876***	0.397**	0.260	0.178	0.301	0.330	0.071	0.239	-0.031	-0.330
	(7.50)	(-0.11)	(3.89)	(2.34)	(1.08)	(0.94)	(1.30)	(1.52)	(0.39)	(1.01)	(-0.24)	(-1.43)
Recommender: Lottery, Kumar	1.076***	0.781*	-0.099	0.725*	0.808	0.592	0.660	0.810	0.701*	0.608	0.176	0.314
	(3.03)	(1.94)	(-0.21)	(1.71)	(1.56)	(1.42)	(1.20)	(1.52)	(1.82)	(1.13)	(0.53)	(0.84)
Recommender: Lottery, MAX	0.701**	0.343	-0.013	0.895***	0.737**	0.544*	0.733**	0.967***	0.647**	0.687**	0.146	0.134
	(2.46)	(1.08)	(-0.04)	(3.13)	(2.19)	(1.75)	(2.08)	(2.87)	(2.27)	(2.00)	(0.53)	(0.59)
Recommender: High Volatility	1.168***	0.778**	0.071	0.763*	0.796	0.535	0.598	0.878*	0.672	0.545	0.132	0.435
	(3.08)	(2.08)	(0.14)	(1.87)	(1.50)	(1.19)	(1.05)	(1.69)	(1.66)	(0.99)	(0.42)	(1.12)
Recommender: High Skewness	1.102***	0.860**	0.196	0.434	0.402	0.156	0.220	0.691*	0.473	0.351	-0.187	0.125
	(3.47)	(2.40)	(0.53)	(1.24)	(0.97)	(0.42)	(0.50)	(1.72)	(1.47)	(0.83)	(-0.61)	(0.46)
Recommender: High Attention, CSS	0.763**	0.491	0.051	0.643*	0.624	0.526	0.673	1.116***	0.399	0.700*	0.223	0.314
	(2.39)	(1.28)	(0.13)	(1.82)	(1.49)	(1.51)	(1.62)	(2.91)	(1.27)	(1.78)	(0.70)	(1.03)
Recommender: High Attention, CVRG	0.911**	0.838*	0.156	0.752**	0.793*	0.512	0.517	0.828*	0.294	0.508	-0.205	0.311
	(2.37)	(1.96)	(0.34)	(2.08)	(1.83)	(1.30)	(1.13)	(1.81)	(0.76)	(1.09)	(-0.59)	(1.09)
Recommender: Highattention, Recency	0.924***	0.674**	0.097	0.839***	0.785**	0.503	0.496	1.023***	0.413	0.794**	0.099	0.041
	(2.89)	(2.04)	(0.27)	(2.74)	(2.07)	(1.52)	(1.27)	(2.79)	(1.42)	(2.09)	(0.37)	(0.17)
Recommender: HighAttention, SUE	-0.118	0.785	-0.884	0.607	1.221**	0.167	0.434	1.296**	0.766	0.806	0.438	-0.109
	(-0.18)	(1.25)	(-1.25)	(1.34)	(2.11)	(0.33)	(0.64)	(2.04)	(1.63)	(1.28)	(0.74)	(-0.29)
Recommender: Derivatives	0.997***	0.474	0.556	0.360	0.090	0.023	-0.037	0.392	-0.008	0.054	-0.020	-0.314
	(4.08)	(1.37)	(1.57)	(1.64)	(0.27)	(0.10)	(-0.11)	(1.31)	(-0.03)	(0.16)	(-0.08)	(-0.91)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 11: 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	-0.073***	-0.070***	-0.054**	-0.057**				
	(0.021)	(0.021)	(0.024)	(0.024)				
Rec: log RSRL					-0.116***	-0.111***	-0.077**	-0.078**
					(0.030)	(0.031)	(0.034)	(0.034)
Follower controls								
Male		-0.001	-0.054	-0.031		0.003	-0.051	-0.031
		(0.050)	(0.056)	(0.057)		(0.050)	(0.056)	(0.057)
Income proxy (std)		-0.000	-0.018	-0.012		-0.000	-0.019	-0.014
		(0.037)	(0.047)	(0.049)		(0.037)	(0.046)	(0.048)
Academic title		-0.147	-0.209**	-0.164*		-0.155	-0.218**	-0.176*
		(0.096)	(0.095)	(0.093)		(0.098)	(0.096)	(0.094)
Age		0.006	0.010	0.009		0.008	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		-0.013	0.019	0.019		-0.015	0.017	0.016
		(0.053)	(0.062)	(0.062)		(0.053)	(0.062)	(0.062)
Joint account		-0.121	-0.093	-0.084		-0.101	-0.079	-0.067
		(0.080)	(0.087)	(0.086)		(0.083)	(0.089)	(0.089)
Recommender controls								
Rec: age				0.004**				0.004**
				(0.002)				(0.002)
Rec: Academic title				-0.164*				-0.164*
				(0.086)				(0.087)
Rec: Male				0.110				0.094
				(0.070)				(0.070)
Rec: Income proxy				-0.000				-0.000
				(0.000)				(0.000)
Region#Year fixed effect	No	No	Yes	Yes	No	No	Yes	Yes
Observations	419	419	406	406	419	419	406	406
Adjusted R^2	0.028	0.023	0.062	0.077	0.030	0.024	0.060	0.074

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:

$$r^e_{j,t} = \beta_j r^e_{m,t} + \epsilon_{j,t} \tag{4}$$

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 β_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 μ_i and standard deviation σ_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 $RSRL_i$:

$$RSRL_i = 1 - \frac{S_i}{S_B}. \tag{5}$$

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:

$$(1 - RSRL_i)^2 = 1 - \frac{\sigma_{k,i}^2}{\sigma_i^2}. \tag{6}$$

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:

$$RL_i = w_i(S_B\sigma_i - \mu_i) \tag{7}$$

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:

$$RL_i = (Er_m^e) w_i \beta_i (\frac{RSRL_i}{1 - RSRL_i}). \tag{8}$$

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 (8):

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

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-Württemberg, Bayern, Berlin, Brandenburg, Bremen, Hamburg, Hessen, Mecklenburg-Vorpommern, Niedersachsen, Nordrhein-Westfalen, Rheinland-Pfalz, Saarland, Sachsen, Sachsen-Anhalt, Schleswig-Holstein, Thüringen, 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 1), 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 1 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. [6] Table 6 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 (2009) and defines lottery stocks as stocks in the lowest k^{th} stock price percentile, the

[6] 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.

highest k^{th} idiosyncratic volatility percentile, and the highest k^{th} idiosyncratic skewness percentile.[7] 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 6 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 $25^t h$ highest percentile of the monthly average Composite Sentiment Score (CSS) from RavenPack.[8] 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 $25^t h$ percentile.

The third attention proxy is based on the magnitude of news events, measured by the

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

[8] 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.

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.

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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
Final sample	536		10,217	

Table B2: 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 checks account's high and low balances. Geo wealth proxy is measured on a scale from 1 to 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 across all investors. Standard deviations are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1) Recommender	(2) All Investors	(3) T-test (2) - (1)
A. Demographic characteristics			
Male	0.77	0.72	-0.06***
	(0.42)	(0.45)	[-3.02]
Age	43.57	41.78	-1.79***
	(14.39)	(13.81)	[-3.04]
Academic title	0.06	0.06	-0.00
	(0.23)	(0.23)	[-0.13]
Joint account	0.16	0.15	-0.01
	(0.36)	(0.35)	[-0.67]
Main bank	0.49	0.28	-0.21***
	(0.50)	(0.45)	[-10.80]
B. Wealth and income			
Total AUM (EUR)	62,801.48	29,058.17	-33,743.31***
	(76,561.58)	(46,104.21)	[-16.91]
Income proxy	4,612.00	2,962.36	-1,649.64***
	(11,317.94)	(9,917.57)	[-3.90]
Portfolio value (EUR)	102,333.29	23,340.75	-78,992.54***
	(221,979.72)	(107,797.80)	[-15.02]
C. Portfolio Quality			
Log Return Loss	-6.83	-6.71	0.12
	(1.19)	(1.50)	[1.62]
Log Relative Sharpe Ratio Loss	-1.59	-1.33	0.26***
	(0.77)	(0.87)	[6.34]
Log Risky Share	-0.58	-0.86	-0.29***
	(0.92)	(1.03)	[-5.80]
Log Portfolio Beta	-0.06	-0.28	-0.22***
	(0.63)	(1.19)	[-3.87]
B. Wealth and income			
Total AUM (EUR)	62,801	29,058	-33,743***
	(76,562)	(46,104)	[-17]
Income proxy	4,612	2,962	-1,650***
	(11,318)	(9,918)	[-4]
Portfolio value (EUR)	102,333	23,341	-78,993***
	(221,980)	(107,798)	[-15]
Observations	565	26,590	27,155

Table B3: 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 *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1) Recommender	(2) All Investors	(3) T-test (2) - (1)
Total logins	48.961	31.453	-17.508***
	(110.689)	(88.056)	[-4.65]
Number of trades	3.326	2.038	-1.288***
	(7.629)	(4.958)	[-6.02]
Stock market participant	0.758	0.560	-0.198***
	(0.429)	(0.496)	[-8.41]
B. Portfolio composition			
Risky share	0.545	0.576	0.031**
	(0.368)	(0.316)	[2.30]
Number of securities	13.496	4.543	-8.953***
	(14.969)	(5.723)	[-31.42]
Weight stocks	0.382	0.397	0.015
	(0.376)	(0.442)	[0.72]
Weight bonds	0.032	0.030	-0.002
	(0.122)	(0.145)	[-0.31]
Weight funds	0.518	0.521	0.003
	(0.391)	(0.452)	[0.13]
C. Portfolio characteristics			
Portfolio beta	1.069	1.014	-0.055
	(0.594)	(2.579)	[-0.45]
Portfolio expected return	0.004	0.004	-0.000
	(0.002)	(0.009)	[-0.45]
Standard deviation of returns	0.067	0.065	-0.002
	(0.297)	(0.939)	[-0.04]
Sharpe ratio	0.088	0.076	-0.012***
	(0.027)	(0.035)	[-7.03]
Return loss	0.004	0.004	-0.000
	(0.035)	(0.113)	[-0.00]
Relative Sharpe Ratio loss	0.274	0.371	0.097***
	(0.226)	(0.291)	[7.03]
Trade risk	1.887	1.872	-0.015
	(1.627)	(1.465)	[-0.24]
Herfindahl-Hirschman-Index	0.157	0.288	0.131***
	(0.250)	(0.356)	[7.81]
D. Investment Styles			
I: Active Fund Investment	0.551	0.331	-0.220***
	(0.498)	(0.470)	[-9.85]
i_passive_inv_part	0.658	0.417	-0.240***
	(0.475)	(0.493)	[-10.26]
(max) i_instruments_participation_l	0.371	0.154	-0.217***
	(0.484)	(0.361)	[-12.57]
I: Lottery Investment, Kumar	0.244	0.152	-0.092***
	(0.430)	(0.359)	[-5.38]
I: High Volatility Investment	0.247	0.154	-0.093***
	(0.432)	(0.361)	[-5.38]
I: High Skewness Investment	0.376	0.248	-0.128***
	(0.485)	(0.432)	[-6.22]
I: Attention Investment, CSS	0.349	0.223	-0.126***
	(0.477)	(0.416)	[-6.36]
I: Attention Investment, Coverage	0.302	0.204	-0.098***
	(0.460)	(0.403)	[-5.09]
I: Attention Investment, Recency	0.436	0.335	-0.101***
	(0.496)	(0.472)	[-4.50]
I: Lottery Investment, MAX	0.471	0.367	-0.104***
	(0.500)	(0.482)	[-4.54]
I: Attention Investment, SUE	0.178	0.127	-0.050***
	(0.383)	(0.334)	[-3.16]
Observations	565	26,590	27,155

Table B4: Log Return Loss and Relative Sharpe Ratio Loss for different time horizons

Notes: The table replicates Table 4 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	-0.22***	-0.05	-0.01	0.05	-0.33***	-0.11***	-0.11***	-0.07*
	(0.05)	(0.05)	(0.05)	(0.07)	(0.03)	(0.03)	(0.03)	(0.04)
Follower × Positive Overlap				-0.18*				-0.10
				(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	26623	26623	26623	26623	26621	26621	26621	26621
Adjusted R^2	0.000	0.047	0.061	0.061	0.003	0.228	0.231	0.231
12 months								
Follower	-0.23***	-0.07	-0.03	0.04	-0.30***	-0.12***	-0.12***	-0.07
	(0.05)	(0.05)	(0.05)	(0.07)	(0.03)	(0.03)	(0.03)	(0.04)
Follower × Positive Overlap				-0.19*				-0.13*
				(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	26699	26699	26699	26699	26696	26696	26696	26696
Adjusted R^2	0.000	0.041	0.056	0.056	0.002	0.190	0.194	0.194
24 months								
Follower	-0.19***	-0.06	-0.02	0.03	-0.24***	-0.10***	-0.09***	-0.07
	(0.05)	(0.05)	(0.05)	(0.07)	(0.03)	(0.03)	(0.03)	(0.04)
Follower × Positive Overlap				-0.11				-0.06
				(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	26750	26750	26750	26750	26747	26747	26747	26747
Adjusted R^2	0.000	0.032	0.048	0.048	0.002	0.137	0.142	0.142

Table B5: Follower and Recommender portfolio composition

Notes: This table provides the regressions from binscatter figures in Figure 6. 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	0.51***				
	(0.07)				
Recommender: Log relative Sharpe Ratio loss		0.36***			
		(0.05)			
Recommender: Risky share			0.30***		
			(0.03)		
Recommender: Log Beta				0.44***	
				(0.10)	
Recommender: Share of funds					0.64***
					(0.04)
Control variables (Recommender)					
Academic title	-0.32	-0.16	0.07	-0.03	0.04
	(0.19)	(0.14)	(0.05)	(0.15)	(0.07)
Age	-0.01	-0.00	-0.01	-0.01	-0.00
	(0.02)	(0.01)	(0.00)	(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	0.22**	0.09	0.04	0.16**	-0.12***
	(0.11)	(0.08)	(0.03)	(0.06)	(0.04)
Income proxy (std)	-0.02	0.04	-0.07**	-0.00	0.00
	(0.05)	(0.04)	(0.03)	(0.04)	(0.03)
Main bank	0.16	0.03	-0.01	0.11	-0.02
	(0.13)	(0.08)	(0.03)	(0.08)	(0.04)
Joint account	-0.17	-0.02	-0.03	-0.09	0.07
	(0.15)	(0.12)	(0.04)	(0.11)	(0.06)
Constant	-3.54***	-1.22***	0.51***	0.17	0.43***
	(0.64)	(0.31)	(0.11)	(0.22)	(0.16)
Region#Year fixed effect	Yes	Yes	Yes	Yes	Yes
Observations	428	428	550	419	436
Adjusted R^2	0.291	0.181	0.168	0.166	0.366

C Online Appendix: Results for Positive Overlap sample

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

Notes:

	Return loss			Relative Sharpe ratio loss		
	(1)	(2)	(3)	(4)	(5)	(6)
Follower	-0.21**	-0.17*	-0.09	-0.23***	-0.21***	-0.18***
	(0.09)	(0.09)	(0.09)	(0.05)	(0.05)	(0.06)
Male			0.33***			0.11***
			(0.05)			(0.02)
Income proxy (std)			0.04***			0.04**
			(0.01)			(0.02)
Academic title			-0.38**			-0.13***
			(0.16)			(0.04)
Constant	-6.87***	-6.87***	-7.09***	-1.50***	-1.50***	-1.57***
	(0.02)	(0.02)	(0.04)	(0.01)	(0.01)	(0.02)
Region fixed effect	No	Yes	Yes	No	Yes	Yes
Year fixed effect	No	Yes	Yes	No	Yes	Yes
Age fixed effect	No	Yes	Yes	No	Yes	Yes
Region#Year fixed effect	No	Yes	Yes	No	Yes	Yes
Observations	18699	18699	18699	18696	18696	18696
Adjusted R^2	0.000	0.025	0.036	0.001	0.036	0.046

Table C2: **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	-0.09	0.15***	0.06	-0.23***
	(0.09)	(0.06)	(0.05)	(0.08)
Male	0.33***	0.07***	0.14***	0.17***
	(0.05)	(0.02)	(0.04)	(0.03)
Income proxy (std)	0.04***	-0.01	-0.04*	0.08**
	(0.01)	(0.01)	(0.02)	(0.04)
Academic title	-0.38**	0.10***	-0.21	-0.18***
	(0.16)	(0.03)	(0.15)	(0.06)
Region fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Age fixed effect	Yes	Yes	Yes	Yes
Region#Year fixed effect	Yes	Yes	Yes	Yes
Observations	18699	18993	18068	18081
Adjusted R^2	0.036	0.061	0.028	0.050

Table C3: Participation, Extensive and Intensive margin (Positive Overlap)

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. 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) Coverage	(10) Recency	(11) SUE	(12) Derivatives
Recommender Participation	0.804***	0.699***	0.736***	0.269***	0.525***	0.273***	0.383***	0.228**	0.399***	0.463***	0.305***	0.351***
	(0.092)	(0.078)	(0.078)	(0.087)	(0.099)	(0.091)	(0.087)	(0.105)	(0.099)	(0.111)	(0.094)	(0.085)
Region fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
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	189	189	189	189	189	189	189	189	189	189	189	189
Adjusted R^2	0.438	0.451	0.417	0.136	0.411	0.183	0.250	0.198	0.190	0.295	0.351	0.257
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) Coverage	(10) Recency	(11) SUE	(12) Derivatives
Recommender Portfolio weight	0.860***	0.636***	0.845***	1.269***	0.688***	0.617***	0.691***	0.857***	0.719***	0.784***	0.941***	0.420***
	(0.069)	(0.110)	(0.081)	(0.290)	(0.136)	(0.203)	(0.197)	(0.162)	(0.200)	(0.139)	(0.215)	(0.113)
Region fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
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	189	189	189	189	189	189	189	189	189	189	189	189
Adjusted R^2	0.495	0.288	0.450	0.648	0.493	0.347	0.411	0.592	0.194	0.490	0.481	0.137