Personal Recommendations and Portfolio Quality

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Abstract

Social interactions in finance can lead to better financial outcomes or help propagate financial mistakes. We develop a framework that incorporates two views of social interaction and provide empirical evidence of their relevance in a setting where individuals are personally connected with stronger ties than in an online community. Providing and accepting advice is positively related to portfolio quality but is not driven by high returns. Funds are more likely to be recommended than lottery or attention stocks, leading to increases in portfolio quality. Our evidence suggests that social networks can provide good advice in settings where individuals are personally connected.

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1 Introduction

The first question that new acquaintances typically ask, once we reveal that we work in finance, is what stocks to invest in. This question is surely familiar to most readers who work in finance or economics. Like most, we often recommend the textbook passive investment: buy a low-fee, diversified mutual fund and try to forget you have it. This is, after all, the easiest advice for a new investor without specific knowledge of the stock market, and also one that tends to generate the highest net return in the long run. It is not difficult to imagine that this scenario applies broadly: individuals seek investment advice from their social connections with specific knowledge of finance, and those individuals give the same advice we do. This view of social interactions in finance, which we call 'expertise-based transmission,' is consistent with academic finance theory and popular personal finance advice on investing in funds, as noted in Choi (2022).

An equally plausible view of social interactions is that acquaintances communicate based on financial returns. In what we call 'return-biased transmission,' formally modeled in Han *et al.* (2022), social transmission between individuals is increasing in returns for the sender of information. As a result, assets likely to experience high returns, such as active strategies, lottery, or attention stocks, are more likely to be recommended in social interactions. Several studies have used anonymous or pseudonymous relationships to provide evidence consistent with the view that investors share investment ideas if they experience high returns (Heimer & Simon, 2015; Escobar Pradilla & Pedraza, 2019; Lim *et al.* , 2020; Ammann & Schaub, 2021). As a consequence, social interactions seem to propagate active trading, return-chasing, and financial mistakes (Ammann & Schaub, 2021; Heimer & Simon, 2015; Hvide & Östberg, 2015; Heimer, 2016; Lim *et al.* , 2020; Han *et al.* , 2022).

In this paper, we develop a framework that incorporates these two views of social interactions in finance and provide empirical evidence of their relevance in a setting where individuals are personally connected. Each view makes predictions over whether returns or perceived expertise determine social interactions in finance. Each view also makes predictions on the contents of social transmission of information: active strategies likely to experience high returns or passive strategies that generate high returns in the long run. We test predictions on i) what determines social interactions and ii) what assets are passed on in social networks. To do so, we use data from a generic referral campaign from a large online German retail bank, allowing us to observe peer relationships and portfolio composition. The peer relationship consists of individuals who recommend (*Recommender*) their bank and brokerage to an acquaintance (*Follower*). Followers must be known to the Recommender at least by an e-mail address or Facebook friendship. Referral programs aim at customers with strong ties, e.g., personal friends or acquaintances (Baker *et al.* , 2016).

Our context of personal recommendations differs from the context in the previous literature, which tends to focus on social interactions in anonymous or pseudonymous relationships online (a notable exception is Ammann *et al.* , 2022). While we do not observe the exact nature of the interaction that leads to the recommendation of the bank, we posit that it could occur in several ways. The first is that acquaintances may reach out for financial advice, which also involves recommending how to invest (e.g., how to open a brokerage account). In this setting, the bank itself may be recommended as part of providing financial advice. This type of personal interaction would lead to both an observed link and a positive overlap, consistent with our results. Alternatively, friendly conversations may turn to financial matters and experienced Recommenders may choose to offer financial advice and encourage equity participation to less experienced friends and family in times when these types of conversations arise, e.g., informal get-togethers, work events, family parties, etc. At the opposite extreme, Recommenders may blindly send marketing material to their acquaintances on Facebook, hoping that someone will react and the Recommender can collect a small cash bonus or prize. We believe this interaction is highly unlikely for several reasons. Blindly posting to all Facebook friends, for example, would generate a distribution of successful recommendations: some Recommenders would be lucky with several successful recommendations. In our data, we have very few multiple recommendations, inconsistent with Recommenders blindly posting to all their Facebook friends. We have also verified with another large German bank that their recommendation campaign similarly attracts individuals with close relationships.

Beginning with the question of what determines social interactions in our setting, we find that the data are consistent with the Recommender being positively selected based on expertise. Compared to other investors, Recommenders have higher income, and have almost twice the amount of asset-under-management. Importantly, Recommenders also have higher quality portfolios, measured as the deviation from the benchmark portfolio (i.e., Relative Sharpe Ratio Loss from Campbell *et al.* (2007)). However, we find little evidence that Recommender's returns drive the decision to recommend the bank, even for Followers who open a trading account. Overall, our results support expertise-based transmission.

We next examine the likelihood of accepting financial advice. Our proxy for accepting advice is the presence of shared securities between the Recommender and Follower, which we term the portfolio *overlap*. We define the overlap on the ISIN level for each Recommender-Follower pair. Followers and Recommenders share an average of 17% percent of securities between them, a share that remains persistently high over two years. 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 discuss the interpretation of this measure in considerable detail later. Importantly, spamming Facebook friends would not generate a positive overlap since it is simply a matter of recommending the bank. We find little evidence that Recommender returns determine the overlap: neither active returns, passive returns, nor portfolio returns are significantly related to a positive overlap share, even if we examine overlap as a non-parametric function of returns without any controls. Instead, we find evidence consistent with expertise-based transmission: Recommender Return loss and Relative Sharpe ratio loss are negatively related to positive overlap, showing that higher portfolio quality correlates with a higher likelihood of accepting financial advice. The effect is economically relevant: a one standard deviation increase in the log Relative Sharpe ratio loss is associated with a 0.10 standard deviation increase in the likelihood of a positive overlap.

Both expertise-based transmission and return-biased transmission also predict the type of assets recommended in social interactions. The expertise-based view predicts that investors want to recommend investments with lower volatility, fees, and higher expected returns (e.g., diversified active or passive funds), especially as they do not have monetary incentives to provide biased advice. In support of expertise-based transmission, we show a high correlation between Recommender and Follower participation in funds. Recommender participation in funds is associated with a 49% increase in the likelihood of the Follower investing in funds, with larger coefficients for passive funds than for active funds. Notably, Recommender participation is a considerably stronger predictor of Follower participation than bank advice, a control variable that measures bank influence on asset choice. The return-biased view on the other hand, predicts that assets that experienced higher returns will be recommended. Since stocks with high volatility and skewness are more likely to experience such high-return events, return-biased transmission predicts that these assets will be propagated in social networks (Han *et al.* , 2022). We follow Kumar (2009), Bali *et al.* (2011), Bali *et al.* (2021), and Hackethal *et al.* (2022) to define lottery and attention stocks with these characteristics. The correlation in participation in lottery stocks and attention stocks between Recommender and Follower is approximately half the magnitude of the correlation in funds. Finally, we show that the above results lead to higher portfolio quality for Followers than other new investors. This result primarily derives from a higher propensity of Followers to invest in funds, which leads to better diversification. Overall, the portfolio composition of Followers supports expertise-based transmission.

We run several tests to ensure we capture the effect of personal recommendations instead of other omitted factors. While most factors that would explain the correlation between personally connected investors operate at the portfolio level, not at the level of individual securities (Knüpfer *et al.* , 2021), there are obvious concerns over contextual effects, correlated effects, and reflection (Manski, 1993). To address concerns over reflection, we fix the Recommender portfolio one month before the Follower joins the bank to ensure we capture the advice from Recommender to Follower. We also remove assets that the Follower transferred to the bank from their previous brokerage account. The overlap is thus coming from new assets that the Follower purchased when joining the bank, which we compare to the assets that the Recommender already holds. Using contemporaneous portfolios does not change our results.

To address concerns over correlated effects, such as news or marketing campaigns, we construct placebo pairs based on other investors who joined the bank in the same year and calculate the overlap in portfolios. The placebo overlap is consistently less than 2 percent, an order of magnitude lower share than the overlap between Recommender and Follower. 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. Matching on observable characteristics also helps rule out correlated bank advice since such advice is generally targeted based on characteristics.[1] The placebo estimates also naturally account for popular stocks, concurrent marketing campaigns, and other financial advice provided by the bank.[2] We also show that the overlap results are similar if we exclude Followers who

[1]Note that the bank in question is an online bank, meaning that locally-biased advice from the bank is not relevant. Conditioning on geographical location instead helps alleviate concerns over home bias in portfolio choice.

[2]Investors in our sample have access to over 900,000 different assets, including derivatives. We naturally account

take advice from the bank through robo-trading or personal advice. Finally, the overlap share is unrelated to taking bank advice, being the same gender, a proxy for spouse, having a joint account, or the Recommender using advice.

To rule out contextual effects, the idea that individuals invest in similar assets because they have similar investment styles, we examine a sample of Followers who transfer assets from their previous bank and calculate the overlap in *transferred assets* between the Recommender and Follower. The transfer overlap is approximately 3 percent, considerably lower than the average Follower overlap of 17 percent. This test is akin to the test in Hvide & Östberg (2015), who examine how future co-workers affect stock purchase behavior. If unobserved contextual effects between Followers and Recommenders drove the results, we would expect these similarities would show up in the assets that the Followers transferred to the bank. In our main overlap analysis, we remove all transferred assets, implying that the overlap is based on new assets that the Follower buys when they join the bank.

In conclusion, we find evidence consistent with expertise-based transmission on both determinants of social interactions and portfolio choice. Our results provide a more positive view of social interactions than the literature has previously shown and highlight the importance of studying social interactions in finance in different social contexts. These results provide a timely new perspective on peer effects in finance, given the proliferation of financial advice on social media. Evans (2021) provide survey evidence that 41% of investors below the age of 40 used Youtube for financial advice, while 29% have talked to family and friends. Financial advice on social media is easily accessible to everyone regardless of their background and is often short and easily consumed. On a less positive note, one might reasonably be concerned about the quality of the advice provided on social media. Far from all the advice provided on social media is bad, but there are many social media accounts that promote get-rich-quick schemes, crypto investments, or day trading. The kind of advice we document is less easily accessible, since it requires access to experts, but is instead of high quality. With what we know about homophily and sorting in social networks, not everyone will have access to high-quality advice and may instead be pushed towards the advice provided on TikTok or Instagram.

At the heart of the matter is this dichotomy: social media is accessible to everyone with a smartphone, but the advice is perhaps not as good. Not everyone has friends with good portfo-

for more popular assets by using existing portfolios of other new investors, as we implicitly give them higher weight in the placebo overlap.

lios, but the advice that those friends can provide is good. To fully understand the landscape of financial advice provided by social networks, we need a better understanding of who has access to good advice, how advice affects the portfolio composition, and who is left to the vagaries of social media. In our view, illuminating this dichotomy is an important contribution of our study, and highlights a new agenda for future research into peer effects in finance.

Related literature – Why do the personal recommendations that we study yield better portfolio outcomes than the settings cited in related literature? On one hand, online investment communities have been characterized by investment biases, herding, and sentiment (Heimer, 2016; Cookson *et al.* , 2023), qualities which are likely to erode returns. On the other, there is evidence that nonprofessional analysts or social media analysts may increase informativeness in markets (Farrell *et al.* , 2022; Dim, 2023). In these settings, Recommenders may face reputational or pecuniary costs (Campbell *et al.* , 2019) but a personal connection to followers, as in our setting, presents an additional attribute which is unique to the literature. Recommenders with personal relationships may feel obliged to help Followers and steer them away from excessive risk taking. While nonprofessional analysts may enjoy high returns to accurately predicting the next winner or loser, the reputational costs faced by excessive risk taking or getting a recommendation wrong may far outweigh in a personal setting. As in our expert-based transmission view, this would result in modest recommendations of ETFs rather than highly-skewed assets.

Our study complements the growing literature on peer effects and social networks (Siming, 2014; Bailey *et al.* , 2018; Cookson & Niessner, 2020; Hung, 2021; Huang *et al.* , 2021; Knüpfer *et al.* , 2021; Cookson *et al.* , 2023; Hirshleifer *et al.* , 2023) and the literature on peer effects in investment decisions and saving behavior (e.g., Bursztyn *et al.* , 2014; Beshears *et al.* , 2015; Heimer, 2016; Kaustia & Knüpfer, 2012; Ouimet & Tate, 2019).[3,4] In contrast to recent work, our study highlights how personal recommendations can improve portfolio outcomes by examining a framework with competing views of social interaction.

We also contribute to a large literature on retail investors' performance and investment behavior. This literature has documented that retail investors trade too much (Barber & Odean, 2000) or are too passive or inert (Bilias *et al.* , 2010; Calvet *et al.* , 2009), are under-diversified and

[3]See also the survey in Hwang (2022) and Hong *et al.* (2004); Brown *et al.* (2008); Haliassos *et al.* (2020); Maturana & Nickerson (2019); Georgarakos *et al.* (2014). Relatedly, several studies examine social ties among professionals such as financial agents (Ammann *et al.* , 2022), analysts (Cohen *et al.* , 2010), and advisors (Dimmock *et al.* , 2018).

[4]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).

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.* , 2022), and cryptocurrencies or meme-stocks (Hackethal *et al.* , 2022; 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 trading behavior (Balakina, 2022). We contribute to this literature by quantifying the role of social interactions on the portfolio performance of retail investors.

2 The bank and the marketing campaign

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, and brokerage services. The bank provides robo- and telephone advice to customers, but since it is an online bank, there is no fixed advisor or physical advisor attached to the clients. Importantly, we can accurately observe the customers who receive robo- or telephone advice in our data. We later discuss how bank advice affect the estimation of peer effects.

The online bank is constantly running a referral campaign, which incentivizes referrals with a cash bonus of 50 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. While the bonus surely matters for the decision to recommend the bank, it is important to note that the referral campaign is generic in that it does not market specific assets or asset classes to customers. This would be problematic for our identification strategy if marketing messages encouraged correlated investment behavior. Such messages are used more frequently among *neo-brokers*, encouraging investors to recommend others where both parties can earn fractional shares or cryptocurrency tokens.

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 setup of the referral program is such that referred customers must be known to the Recommender at least by an e-mail address or Facebook friendship. Therefore, referral programs aim at customers with strong ties, e.g., personal friends or family members (Baker *et al.* , 2016). Connections with strong ties are closer due to more frequent contact, and therefore, the knowledge of needs and preferences is also greater (Ryu & Feick, 2007). This knowledge increases the personalization and persuasion of communication (Baker *et al.* , 2016). The effect is described in the literature as "strength of strong ties" (Brown & Reingen, 1987). The higher level of trust for the Recommender in strong ties and the higher level of homophily increases the likelihood of a purchase (Baker *et al.* , 2016).

2.1 The relationship between Followers and Recommenders

Our data is consistent with strong ties between Followers and Recommenders. To see this, note that the average number of Facebook friends in 2013 was 338 (Smith, 2014), and posting a message to all of them would likely generate some successful recommendations. if Recommenders simply sent a generic post to all of their hundreds of Facebook friends, we expect some Recommenders to have a high number of succesful recommendations by chance. This is not what we see in our data: very few Recommenders have more than 1 successful recommendation, which is instead consistent with targeted communications with close friends. We also spoke to another large bank in Germany to confirm this supposition, and they stated that personal recommendations indeed are done in a very targeted manner. This makes us more confident that we are identifying a close personal connection between Recommender and Follower.

What scenario can we envisage for the interaction between Recommender and Follower that fits with the recommendation campaign? There are two plausible scenarios. In the first scenario, the Follower initiates the discussion with their friend, who they know is an investor, to ask for financial advice. The Recommender provides portfolio advice and also helps the Follower sign up for the bank, in the process collecting a small campaign bonus. This is plausible, because new investors would typically also need help setting up a trading account. The second scenario is that the Recommender reaches out to the Follower to provide investment advice and recommend their bank. The Follower then joins the bank and follows the investment advice provided by their friend.

3 Data, variables and summary statistics

Our data sample includes 258,000 randomly selected clients with socio-demographic and transaction data from January 2003 until September 2017.[5] The data on customer referrals allow us to identify direct peers by linking referred customers with their Recommenders. We have a list of 4,011 customers who recommended someone and 4,011 customers who were referred. We observe multiple recommendations only on rare occasions. After matching the data on referrals to demographic data and restricting our sample to Recommenders who are securities account holders, we are left with 673 Followers. We further restrict the sample by age, remove Followers who act as Recommenders, and remove Followers who do not open a brokerage account or open a brokerage account before the recommendation date. Finally, we remove Followers who had an account at the bank before the campaign started in 2012, and remove Followers with missing data. Our final Follower sample consists of 515 directly matched peer pairs. A full sample selection table is available in Table C1 in Online Appendix B.

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

Our main dataset contains demographic, account, and investment portfolio characteristics of Followers, Recommenders, and a large number of other investors. For most results, we include only the first 12 months of trading activity and collapse the data to one observation per in-

[5]See Hackethal *et al.* (2022) for additional discussion of this dataset.

dividual. Although we have a longer time series, we chose the first twelve months of trading to avoid learning and luck from influencing portfolio choice (Anagol *et al.* , 2021). Overall, however, this has little impact on our results, which are robust to using both shorter or longer time-periods.

3.1 Summary statistics

Table 1 provides demographic and portfolio summary statistics. Panel a) provides information on demographic characteristics, panel b) provides information on wealth and income, and panel c) provides information on portfolio composition. The first two column includes observations for Followers and new investors, defined as the periods in the first 12 months after opening a brokerage account. We compute the average across monthly data for the first 12 months after opening a brokerage account for both Followers and new investors. Column 3 provides a t-test for differences in means across Follower and new investors. Followers are less likely to be male, are older, are less likely to have a joint account, are more likely to use the bank as the main bank, and are more likely to use advice. Advice is measured by either personal advice or robo-advice. Note that the bank does not have physical offices, and so that there is no bank-advisor attached to the individual. Followers also have more assets under management compared to other new investors, but have similar incomes. Examining the portfolio composition, we see that compared to other new investors, Followers hold more securities, have a higher risky share, have higher Sharpe ratio and lower Relative Sharpe ratio losses. Followers are also more likely to invest in both active and passive funds, and are less likely to hold lottery or attention stocks.

Column 4 and 5 provide summary statistics for Recommenders and all investors. We exclude Followers from both samples. We compute the average across monthly data using all observations for Recommenders and all investors. Examining Recommenders, we see that a higher proportion of them are male, that they are more likely to use the bank as their main bank, and that they are more likely to take advice from the bank. Recommenders also have substantially larger portfolios than other investors: Total assets under management for Recommenders is 58,173 Euros, approximately 28,000 Euros more than the average holdings for other investors. In terms of portfolio composition, we find that they hold more 5 securities on average, and that their risky share is higher. More importantly, we find that Recommenders achieve higher risk-adjusted returns as measured by the Sharpe ratio, and that they are more likely to invest in both active and passive funds. Finally, we find that they are less likely to invest in lottery or attention stocks.

4 Identifying peer effects

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

4.1 Methodology

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

To address concerns over contextual effects and correlated effects, we examine the portfolio overlap between the portfolios of the Recommender and the Follower. We calculate portfolio overlap $Overlap_i^F$ as the number of securities that are present in both the Recommender portfolio and the Follower portfolio divided by the number of securities in the Follower portfolio:

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

where $\mathbb{1}_{k=m}$ is an indicator equal to one if asset k is in both the Follower and the Recommender portfolio. 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. We also calculate a weighted overlap that takes asset-holdings values into account, $WeightedOverlap_i^F = \frac{\sum_{k=1}^{K} V_k \mathbb{1}_{k=m}}{\sum_{k=1}^{K} V_k}$, where V_k is the value of asset k in the portfolio of Follower i. When constructing the overlap shares, we also remove securities that the Follower transfers to our bank from their previous brokerage account. 161 Followers out of 515 in our estimation sample transfer securities.

To address concerns over the direction of causality, we fix the Recommender portfolio one month before the Follower portfolio. For the first month of trading, the portfolio of the Recommender appears before the Follower even has a brokerage account. It is implausible that the Follower would *advise their Recommender* on what assets to invest in, and then wait a month before opening an account (Hvide & Östberg, 2015). As noted we also remove assets that the Followers transfers to the bank, meaning that the assets of the Follower consists of new assets that they purchase upon joining the bank.

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 (see Brown *et al.* , 2008; Kaustia & Knüpfer, 2012; Ouimet & Tate, 2019; Haliassos *et al.* , 2020; Maturana & Nickerson, 2019; Georgarakos *et al.* , 2014). Contextual effects and correlated shocks likely predict participation in financial markets, but it is less clear that they would predict portfolio composition. Given the large number of choices available to investors, even highly correlated risk aversion among peers is unlikely to lead to investments in identical assets.[6] A similar logic applies to common shocks: even if a local newspaper or financial literacy program promotes a specific asset class such as mutual funds or ETFs, there is still a wide range of specific funds available to the individual investor. Observing an overlap in the specific assets within a portfolio is considerably more likely to be because of peer effects than observing that two neighbors participate in the stock market. Knüpfer *et al.* (2021) makes this point when they examine inter-generational linkages in portfolio composition.

However, it is still possible that marketing campaigns, advice, or preferences for popular and local stocks drive the portfolio composition for the Follower and Recommender. We take a number of steps to address these concerns. We start our analysis by comparing the overlap in portfolios between Followers and Recommenders to the overlap for matched pairs, which we call Placebo pairs. We construct Placebo pairs by first limiting the sample to new investors to match our sample construction of Followers. Specifically, we select all new investors who join the bank after 2012. We then create the matched pairs by i) randomly matching individual investors ii) matching each investor to other similar investors based on demographic characteristics, location,

[6]We observe over 900,000 different assets available to the investors in our sample including various structured retail products, options, and deriviatves.

wealth, and risky share. This approach allows us to further control for contextual effects and common shocks. By using existing portfolios of other new investors, we naturally account for more popular assets by implicitly giving them higher weight in the placebo overlap. Conditioning on observables also helps rule out correlated bank advice, since such advice is generally targeted based on characteristics. We later address bank advice in more detail. If contextual effects or common shocks drive the decision to invest in certain stocks, we should observe a similar portfolio overlap between Followers and Placebo Followers. We re-run the placebo exercise 100 times to attain a measure of uncertainty in the Placebo overlap share. In an additional exercise, we also calculate the overlap share for Followers who do not receive advice from the bank, in the form of robo-advice or personal advice, and we calculate the overlap share for Followers who do not transfer assets to the bank. 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.

4.2 Overlap results

Figure 1 presents the first set of results. The figure plots the average number of stocks in panel a) and the average portfolio share in panel b) of the Follower portfolio that overlaps with the Recommender portfolio over time. We fix the Recommender portfolio one month before the Follower joins the bank and normalize time to zero in the month of recommendation. We also ensure that the Follower does not have a brokerage account at the bank at the time of recommendation and remove assets that the Followers bring from other banks in the overlap analysis. Therefore, it is highly likely that the direction of causality runs from the Recommender to the Follower. The orange solid line in panel a) plots the number of assets that overlap between the Follower and the Recommender. At the time of recommendation, the overlap is close to 20 percent, decreasing to approximately 16 percent two years after the recommendation date. The portfolio overlap share in panel b) is approximately 10 percent at the time of recommendation, and the share increases over time.

In marked contrast, the overlap share for the placebo estimates in blue in both panels are close to zero. The blue lines mark the average overlap share for the Placebo Followers, and the blue error bars represent the 99th and 1st percentile of the draws from the population. The average overlap is close to zero percent, indicating that the considerably higher overlap that we observe for Followers is unlikely to occur by chance. Panel a) of Table 2 summarizes several different placebo groups, showing that the placebo average overlap is always below 5 percent. Including more precise matching does not overly affect these estimates, showing the rarity of the overlap.

To examine similar preferences for certain stocks, we examine securities that investors transfer from their brokerage account at another bank. This share is plotted in Figure 1 with a green solid line (Transfer overlap). Recall that we remove these securities from the overlap analysis above. However, they are still potentially informative about investor preferences for specific assets: if Followers and Recommenders have a preference for certain securities and were investing before, it is reasonable that they should already both own those securities before the Follower joins the bank. We find, however, that the *transfer-overlap*, the share of the Followers transferred portfolio that is also present in the Recommender, is approximately five percent, again substantially below the overlap share in Figure 1. The threat to identifying peer effects is then not common preferences for certain securities, but instead a *change* in preferences for the Follower that is correlated with the Follower joining the bank (recall that the Recommender already owns the securities at least one month beforehand). But if investor preferences for certain securities are changing, it seems likely that it would affect other investors as well, and therefore would be aborbed by the placebo overlap analysis.

The placebo overlap analysis is also useful for ruling out a potential financial advice channel, a clear threat to the identification of peer effects in our setting. Imagine, for instance, that a Follower and Recommender have an overlap because both have been advised by the bank to invest in a certain security. If the bank is running such a (successful) recommendation campaign, the offer should clearly be attractive to other investors who join the bank at the same time. Since the overlap is an order of magnitude larger than the placebo overlap, this seems unlikely. Moreover, the placebo overlap is small even if we condition on observable characteristics such as location, assets under management, age, gender, and risky share. Financial advise would likely be tailored on such observable characteristics (Bucher-Koenen *et al.* , 2021; Bhattacharya *et al.* , 2020). It is still possible, however, that both the Recommender and Follower are more likely to accept bank advice. To rule out this channel, Figure 2 plots the overlap in the number of assets for three separate samples: i) all Followers, marked with a solid orange line (this is the same line as in panel a) of Figure 1); ii) Followers who do not receive bank advice, marked with a green dashed line; and iii) Followers with no asset transfer, marked with a blue dotted line. The overlap share is almost identical across Followers who do not receive advice and all Followers, highlighting that financial advice explains very little of the overlap share. For completeness, we also plot the overlap share for Followers who do not transfer assets. The overlap share is somewhat higher for this group, with an average overlap of 21%, compared to 18% for all Followers.

Figure 3 provides an alternative illustration of the rarity of the overlap. In the figure, we match each Follower portfolio to the portfolio of *all* investors active over the same 12-month window. For each Follower, we have approximately 90,000 portfolios. The figure shows little overlap between investor portfolios, reflecting the dizzying number of assets that investors could potentially choose. For more than 80 percent of the sample, the overlap is zero. Moreover, the average overlap for the Placebo sample is again close to zero. The average overlap in Follower-Recommender portfolios of 19 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. Panel b) of Table 2 provides estimates when we restrict the sample of investors so that the each potential investor is similar based on demographics, location, AUM, and risky share. In each row, we further restrict the sample of other investors, meaning that we move from 41 million observations for all investors (first row) to 38,829 observations (last row). The last row then only includes investors who are similar to the Follower in terms of age, gender, education level, location of residence, assets under management, and risky share. In the most restricted sample, we have that the mean overlap is 2.5%, far below the 18% we have for Followers and Recommenders. Indeed, the *average* overlap share is above the 95th percentile for the most restricted sample.

Finally, Figure 4 plots coefficients from regressing the overlap share on Follower characteristics. The sample consists of all Followers. The figures shows that the overlap share is not explained by shared gender, similar age, robo-trade, using the bank as the main bank, having a joint account and a proxy for spouse. Instead, the only variable that has a significant effect on the overlap share is living in the same zip-code as the Recommender.

How should we think about these statistics? The probability of one Follower having a positive overlap with other investors is small, making the probability that many Followers have a positive overlap by chance negligible. In total, 202 out of 515 Followers have an overlap with their Recommender which is higher than the mean overlap of 2.3 percent for the direct matches, and

163 Followers have an overlap greater than the 95th percentile value of 0.14 for the placebo sample. We interpret these results as evidence that Recommenders provide advice about portfolio composition that Followers use to form their portfolios.

How important is this advice for the individual Follower? Figure 5 plots the overlap distribution for All Followers (orange bars) and Followers with positive overlap (gray bars). While most Followers have no overlap, the share is considerable among the 30 percent of Followers with positive overlap. Around 30 percent of Followers with positive overlap share between 75 and 100 percent of their portfolio with their Recommender. Examining the overlap for Followers with a non-zero overlap over time, the unweighted overlap share is around 50 percent after two years, decreasing from 70 percent at the time of the recommendation. The weighted overlap is more stable across time, fluctuating around 35 percent. For a substantial fraction of all Followers, their peer provides a substantial part of the information Followers use to form their portfolios. For completeness, the figure also plots the overlap share for Followers who do not transfer assets (blue bars) and for Followers who do not use bank advice (green bars), showing that the distribution is very similar to the distribution for all Followers.

5 Sending and receiving advice

In this section we study what determines the likelihood of sending and receiving advice. We use a augmented version of the Han *et al.* (2022) framework that incorporates both return-biased transmission and expertise-based transmission. Specifically, we let the probability of sending and receiving advice depend on both Recommender returns and quality. Our empirical results suggest that Recommender advice (the sending function) is not related to returns, but that Recommenders are positively selected on a number of indicators of quality.

5.1 The sending function

What determines probability of providing financial recommendations? In return-biased transmission modeled in Han *et al.* (2022), the Recommender's decision to give financial advice is an increasing function of returns. In the expertise-based transmission view, the decision to give advice is related to experience or expertise in finance. To incorporate both views, we augment the Han *et al.* (2022) framework and describe the probability that the Recommender provides financial advice as:

$$s(R, Q) = \beta R + \gamma Q + \delta$$

where the probability of sending advice S(R) is a function of investment return R, Recommender quality and a constant parameter δ that represents the conversability of investment choice. The fixed parameter δ reflects a fixed propensity of the Recommender to provide financial advice, perhaps because investments is an attractive topic for conversation. The return-biased transmission view is that higher return for the Recommender increases the likelihood that they provide advice. Moreover, the more important returns are for Recommenders, the higher β will be. The equation differs from Han *et al.* (2022) because of the inclusion of γQ, where we let the probability of providing advice depend on Recommender quality Q. The idea is that a higher quality Recommender will be more likely to send advice. The parameter γ reflect a propensity for investors with high quality to give financial advice.

Focusing on Recommenders, we empirically model the decision to provide advice by examining the probability of recommending the bank:

$$Recommendation_{i,k,t} = \alpha + \beta_1 R^R_{i,t} + \gamma_1 Q^R_i + \mathbf{X_i'}\mu_1 + \delta_{k,t} + \epsilon_{i,t}, \tag{2}$$

where $R^R_{i,t}$ and $Q^R_{i,t}$ is the portfolio return and portfolio quality of Recommenders, $X'_{i,t}$ is a vector of demographic characteristics, and $\delta_{i,k}$ are region-year fixed effects. We use Return loss and relative Sharpe Ratio loss to describe portfolio quality (Calvet *et al.* , 2007). We include a number of demographic characteristics (gender, age, age squared, income proxy, academic title) and region-year fixed effects to account for differences in the propensity to recommend across different demographics and regions. Region-year fixed effects also helps rule out differences in recommendation due to bank marketing campaigns. We first examine the portfolio developments over time for the full sample of Recommenders with brokerage account but later limit the sample to Recommenders where we observe a successful recommendation.

It is useful to explain the idea behind focusing on the sample of Recommenders and their portfolio returns over time. At this stage, we are not comparing Recommenders to other investors. Instead, the above regression will examine whether if individuals who recommended the bank are more likely to do so following periods of high returns for their securities. Overall, the results presented in Table 3 do not suggest that returns drive the decision to recommend. The first three columns selects all Recommenders (approximately 4,000 individuals in total) and provides three sets of results. In the first column, we only include the portfolio returns. The coefficient is statistically significant at a 10% level, but is negative and with little economic significance. We find similar results when adding controls in column 2. Column three splits the return variable into the return on active and passive investments. It is feasible that the probability of sending advice is related to active strategies only, since they are more likely to experience spikes in returns. However, we find little evidence for this channel. The last three columns selects Recommenders who are in our main overlap sample (approximately 500 individuals). These results are also robust to using past returns, i.e. the portfolio return in period $t = \{-6, ..., -1\}$. Overall, the results consistently show little evidence that recommendation of the bank is related to returns

Instead, we find evidence consistent with expertise-based transmission. In general, the summary statistics presented in Table 1 is consistent with the Recommender being positively selected: compared to investors, Recommenders are have higher income and have almost three times as large asset under management and two times as large portfolios. Recommenders also have a higher risky share, a lower Relative Sharpe Ratio loss and are more likely to hold passive investments, which the expertise-based transmission view would consider an indication of quality. They are also less likely to hold Lottery and Attention stocks. Table 4 provides a more formal analysis, regressing a dummy equal to one if the individual is a Recommender on portfolio returns and portfolio quality. The table compares Recommenders to all other investors. The findings suggest that a higher portfolio quality, measured as a *lower* log return loss or log relative Sharpe ratio loss, predicts a higher likelihood of being a Recommender. The table uses observations for all individuals and years, but we get similar results if we collapse the data down to the individual level instead.

5.2 The receiving function

We model accepting financial advice with a receiving function, again following Han *et al.* (2022). Letting $r(R, Q)$ be the probability that the Follower receives (accepts) the advice, we can write:

$$r(R, Q) = aR + bR^2 + cQ + d$$

where the parameter a captures the persuasiveness of higher Recommender returns for Followers. The parameter b captures the extent to which more extreme returns receive more attention from Followers, and c captures the importance of Recommender portfolio quality for Followers. Finally, d is a constant parameter that captures a fixed propensity of following financial advice. Han *et al.* (2022) provide considerable empirical evidence that accepting financial advice depends on Recommender returns (sender returns, in their terminology), and show that the functional forms for receiving and sending advice arise under reasonable assumptions. We augment their model by allowing the susceptibility of advice to depend on Recommender quality.

We empirically model the decision of Follower f to follow advice within a period x months from the time of joining the bank at time t as

$$PosOverlap_{f,t+x} = \alpha + \beta_1 R^R_{f,t} + \mu_1 Q^R_{f,t} + \mathbf{X_i}'\mu_1 + \delta_{k,t} + \epsilon_{i,t}, \tag{3}$$

where the outcome variable $PosOverlap_{f,t+x}$ is an indicator equal to one if the overlap share from equation (1) is greater than zero. Studying the overlap share allows us to focus on the sample of Followers who actually open a brokerage account, and more specifically allows us to understand recommendations around asset choices. The variables of interest are the return on the Recommender portfolio, $R^R_{f,t}$, and the two measures of portfolio quality, Return loss and Relative Sharpe ratio loss. We do not include a square return above, but instead later study how the overlap share depends on a non-parametric functions of returns. We control for the same variables as in Table 3. Since the propensity to take up advice has been linked to similarity between individuals, (Stolper & Walter, 2019), we can also control for differences in age or income between Recommenders and Followers. However, we find no statistically or economically significant evidence that the overlap share in portfolios is larger if the Follower and the Recommender are more similar in either income, or gender. We therefore omit these controls from this specification. Our results are unchanged if we include them.

Table 5 provides the results. Overall, the results support expertise-based transmission. The overlap share is strongly related to measures of portfolio quality, but not to portfolio returns. In the first three columns, we study how Recommender returns affect overlap. We split returns into portfolio returns (column 1), active returns (column 2), and passive returns (column 3). Returns are measured in the month the Follower joins the bank, but are also robust to using past returns. Disaggregating returns into active and passive allows us to examine the prediction that recommendation is related to returns on more narrow portfolio definitions. We can imagine, for example, that the Recommender gives advice based on their active portfolio only, since those are more likely to experience high returns. We find little evidence of such behavior, however. The coefficient on portfolio returns is not significant in either Column 1 or 2. In column 3, the coefficient on passive returns is significant at the 10 percent level. In unreported results where we control for portfolio quality, the coefficient on passive returns is not significant. More importantly, panel a) of Figure 6 shows that the positive association between passive returns and overlap is driven by lower overlap for *negative* returns. Under the return-biased transmission hypothesis, we would instead expect that more extreme positive returns would drive overlap. This is not what we find. These results also extend to active returns (panel b) and total portfolio returns (panel c). Overall, the results in Table 5 do not support the return-biased transmission view.

We now report results where we test for the expertise-based transmission view. Specifically, we test whether the overlap share is related to the portfolio quality of the Recommender. We include each portfolio quality measure separately, as they are highly correlated. When we examine the effect of personal recommendations on the portfolio quality measures in Section 6.3, we show that we can write Return loss as a function of the relative Sharpe ratio loss. Column 4 and 5 in Table 5 report that higher return loss and relative Sharpe ratio losses, indicators of worse portfolio quality, predict a lower likelihood of a positive overlap. These results are consistent with expertise-based transmission. The coefficient of -0.061 for the Relative Sharpe ratio loss represents 12% of the dependent variable mean and standard deviation, both economically significant effects. These effects are still present even if we control for portfolio returns in columns 6 and 7. It is also reassuring that the control variables show little predictive power for explaining a positive overlap share – we find only marginally significant effects for academic title in certain regressions. Gender, income, age, dummies for main bank, having a joint account, and using advice is not significant in any regression. Overall, we conclude that the results support expertise-based transmission.

6 Recommended assets and portfolio quality

Expertise-based transmission and return-biased transmission have different predictions for what assets will get recommended through social interactions. Return-biased transmission predicts that assets that experienced higher returns will be recommended. Since stocks with high volatility and skewness are more likely to experience such high-return events, the return-biased view predicts that these assets will be propagated in social networks (Han *et al.* , 2022). 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. In our empirical setup, these recommendations would be captured by a higher share invested in lottery and attention stocks. On the other hand, expertise-based transmission predicts that investors may want to recommend assets with desirable characteristics to their friends, especially as they do not have monetary incentives to provide biased advice. In that case, experienced investors may recommend investments with lower volatility, fees, and higher expected returns (e.g., diversified active or passive funds). We now show that Followers generally invest more into funds, and that their investments in lottery and attention stocks are not generally higher than for other new investors.

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

6.1 Followers compared to Recommenders

We begin by examining the correlation in investment strategies of Recommenders and Followers. We interpret these results as Recommenders providing advice to Followers. Under the hypothesis of return-biased transmission, assets that are more likely to experience high returns should be more likely to show up in the Follower portfolios. Under the expertise-based transmission view, Recommenders will be more likely to recommend funds.

Specifically, we estimate the following equation to examine participation in different assets classes for Followers depending on whether the Recommender invests in the same asset class:

$$Participation^{j}_{i,k,t} = \alpha + \gamma RecommenderParticipation^{j}_{i,k,t} + \mathbf{X'_{i,k,t}}\beta + \delta_{i,k} + \epsilon_{i,k,t} \qquad (4)$$

where $Participation^{j}_{i,k,t}$ is a dummy equal to one if individual i living in region k in year t invests in asset class j. The variable of interest is $RecommenderParticipation^{j}_{i,k,t}$, a dummy equal to one if the Recommender invests in asset class j. We measure participation in the first twelve months after the Followers opens a brokerage account. We include a vector of demographic and financial control variables in $\mathbf{X'_{i,k,t}}$, including age, age squared, income, education level, and gender. We also include several account-specific controls: i) a dummy equal to one if the bank is the main bank of the individual ii) a dummy equal to one for having a joint account, iii) a dummy equal to one if the individual is recorded as having taken advice at least once in the first 12 months. We also include a year $\times$ region fixed effect to account for differences across regions and time. Note that these fixed effects also absorb variation related to year and geography. Finally, we use robust standard errors.

Table 6 shows a high and significant correlation between most investment strategies of Recommender and Follower. However, the correlation is higher for funds than for lottery or attention stocks. For example, Followers are 49.3 percentage points more likely to invest in funds if the Recommender him or herself invests in funds. Followers are from 14.8 to 33.5 percentage points percent more likely to invest in lottery stocks if the Recommender invests. If returns were driving the decision to both send and accept financial advice, we expect lottery and attention stocks to be more likely to be shared between Followers and Recommenders since these assets are more likely to experience high returns. This is not what we find. Instead, we find that assets that tend to experience more steady returns are more likely to be shared, consistent with expertise-based transmission.

It is also worth exploring the control variables in the regression. Notably, Recommender participation is a stronger predictor of Follower participation than both advice, a control variable that measure the bank influence on asset choice. However, the magnitude of the coefficient is only a third of the size of Recommender participation, showing the importance of personal recommendation for portfolio choice. Additionally, the advice user variable is not correlated with investments into funds, but is negatively correlated with lottery stocks in particular. No variable in the table has the same magnitude across asset classes as Recommender participation.

Table 7 shows that Recommender participation in a specific asset class generally imply that participation in *other* asset classes for the Follower is lower. Each cell in the table represents a separate regression, where the dependent variables are listed in columns and the independent variables are listed in rows. For instance, in the first row the independent variable of interest is a dummy variable equal to one if the Recommender invests in funds (Recommender: Funds), and the first column is a dummy variable equal to one if the Follower invests in funds. The coefficient indicates that Follower are 49.3 percent more likely to invest in funds if the Recommender invests in funds. This is the same coefficient as in Table 6, column (1). In column 2, we see that the Follower is 22.9 percent *less* likely to invest in lottery stocks if the Recommender invests in funds. Overall, investments into funds crowds out participation both lottery and attention stocks. Notably, if the Recommender invests in lottery stocks, the Follower is more likely to invest in attention stocks. Overall, the table indicates that there is crowding out between asset classes. If the Recommender invests in funds, the Followers more invests in funds and less in lottery stocks. This is again consistent with expertise-based transmission, where individuals receive advice from high-quality investors.

6.2 Followers compared to other new investors

The above tables focuses on how Recommenders affect the portfolio decisions of the Followers. In what follows, we focus on comparing Followers to *other new* investors, i.e. a sample of other investors who are in their first year of trading. Specifically, we estimate the following equation to examine participation in different assets classes of Followers compared to other investors:

$$Participation^{j}_{i,k,t} = \alpha + \gamma Follower_{i,k,t} + \mathbf{X'_{i,k,t}}\beta + \delta_{i,k} + \epsilon_{i,k,t} \quad (5)$$

where $Participation^{j}_{i,k,t}$ is a dummy equal to one if individual i living in region k in year t invests in asset class j. $Follower_{i,k,t}$ is a dummy variable equal to one for Followers and zero for other new investors. We measure participation during the first twelve months after opening a brokerage account for both Followers and other investors. The control variables are the same as in equation (4).

Table 8 shows the difference in participation rates between Followers and other new investors. Panel A examines the participation rate (extensive margin), while Panel B states the conditional investment in each specific asset type. Panel A shows that Followers are 3.8 percentage points more likely to invest in funds compared to other investors. Within the fund category, Followers are 6.2 pp. more likely to invest in passive funds and 5.9 pp. more likely to invest in active funds. These results are also economically significant. For example, being a Follower is associated with a $0.062/0.5 = 0.124$ standard deviation increase in passive participation. These results are consistent with expertise-based transmission. Followers are not more likely to invest in lottery or attention stocks compared to other new investors – the coefficients in columns 4-11 are all close to zero and statistically insignificant. These results are inconsistent with return-biased transmission, where these types of assets should be more likely to be promoted through social interactions.

Panel B focuses on the portfolio weight allocated to asset classes, conditional on participation in the asset class. Followers invest a somewhat lower share of their portfolio in passive funds. However, there is no statistical difference for the fund portfolio share or the active fund portfolio share. Moving on to lottery and attention stock investments, we find that Followers invest a smaller amount in certain classifications of lottery and attention stocks. For instance, Column 7 in Panel B shows that Followers invest 2.8 pp. lower share in high skewness stocks compared to other investors who invest in high skewness stocks.

Overall, the evidence is supportive of expertise-based transmission. Followers invest more into funds, following the investment strategy of their Recommender compared to other new investors. We do not find evidence that Followers invest more in lottery or attention type stocks than other investors, although there is still a positive correlation in participation between Followers and Recommenders for such asset classes. These results are in contrast to the theoretical predictions in Han *et al.* (2022) and the empirical results in Sui & Wang (2022), Heimer (2016) and Cookson *et al.* (2023). Our study complements these recent studies by showing that investors can largely benefit from the influence of a closely connected, non-random peer. The results are consistent with Recommenders being inclined to recommend assets with desirable characteristics to their friends, especially as they do not have monetary incentives to provide biased advice.

6.3 Effect on portfolio quality

The above results indicate that Followers are more likely to invest in funds compared to other other investors. We now consider the effect of personal recommendations on total portfolio quality, using several summary measures of portfolio quality.

We again compare Followers to a sample of other investors who are in their first year of trading. Specifically, we estimate the following equation to examine the portfolio quality of Followers:

$$y_{i,k,t} = \alpha + \gamma Follower_{i,k,t} + \mathbf{X'_{i,k,t}}\beta + \delta_{i,k} + \epsilon_{i,k,t} \tag{6}$$

where $y_{i,k,t}$ is dependent variable related to portfolio quality, measured for individual i living in region k in year t during the first twelve months after opening their brokerage account. α is a constant, $Follower_{i,k,t}$ is a dummy variable equal to one for Followers and zero for placebo Followers. We include the same vector of demographic and financial control variables as in Table 6.

Table 9 provides the results. The dependent variable in the first three columns is log Return Loss, and the dependent variable in the last three columns is the log relative Sharpe ratio loss. The results in the first three columns show that Followers have lower Return Loss but the coefficients are not statistically or economically significant after adding controls. In 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 for Return loss, the results for the RSRL are economically and statistically significant, showing that Followers have more diversified portfolios. The coefficient in column 4 is -0.28, approximately 33 percent of the dependent variable standard deviation. When we add controls the coefficient is reduced but remains significant. The coefficient on Follower is -0.10 when we add region $\times$ year fixed effect in Column 5 and is -0.89 in column 6 when we add individual-level controls. The coefficient of -0.08 in column 6 corresponds to 9.6 percent of the dependent variable standard deviation.

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

$$RL_i = (Er_m^e) w_i \beta_i (\frac{RSRL_i}{1 - RSRL_i}). \tag{7}$$

The return loss is a function of the expected excess return on the mean-variance efficient market portfolio (Er_m^e), the household's weight in risky assets w_i, the beta of household portfolio, and a transformation of the household's relative Sharpe ratio loss. Taking logs of equation (7):

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

The decomposition relates the return loss to the log equity premium, which is constant across individuals, to two measures of how aggressive the individual portfolio is (the share invested in risky assets and the beta of the individual portfolio), and to a measure of portfolio inefficiency (the transformation of the Sharpe ratio loss). We can use this decomposition to examine why we have an insignificant effect on Return loss. Table 10 presents the results. We present results for return loss (the same results as Column 3 of Table 9) and each component of return loss. The empirical setup corresponds to (6). The decomposition reveals that Followers are more aggressive in their risk-taking, as measured by a higher risky share and a higher portfolio beta, and more efficient in their portfolio choices, as measured by the lower diversification loss. The coefficient on Follower is 0.18 and 0.10 for the log risky share and log portfolio beta, respectively. Both coefficients are statistically significant at conventional levels. The coefficient on Follower is -0.14 for diversification loss, again significant at the 1 percent level. Since each term is additive in Equation (8), the higher risky share and portfolio beta cancel out the lower diversification loss.

6.4 Welfare implications

Are Followers better off because of the peer effect in portfolio composition that we uncover? The higher risky share and portfolio betas imply that Followers are taking more risk, moving to the right in an expected return-volatility framework. At the same time, the lower diversification loss implies that Followers have a higher ex-ante expected return for the same level of volatility, moving them upwards in an expected return-volatility framework. Whether more risk is appropriate for Followers is less clear and depends on whether the Followers are learning from their peers or simply imitating them. We can distinguish between mindful learning, where the investor learns from an informed peer, and mindless imitation, where the investor derives utility from similarity in choices (see Ambuehl *et al.* , 2022, for experimental evidence). For mindful imitation, the welfare implications are clearer, and more likely to be positive. With mindful learning, Recommenders improve financial outcomes by helping Followers make more informed decisions about their financial investments. For mindless imitation, Followers simply copy the portfolio without regard to their preferences. The welfare implications of mindless imitation would also be unclear, as the preferences of Recommenders and Followers may differ (for a formal model, see Gagnon-Bartsch, 2017). What is right for the Recommenders may not be right for the Follower.

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

7 Conclusion

It is easy to find financial advice on social media these days. The Economist reports that a quarter of American investors between 18 and 4 have used TikTok for personal finance advice, a clear sign that many Americans are enthusiastic about finance and investing. Financial advice on TikTok is easily accessible to everyone regardless of their background and is often short and easily consumed, given that the videos are usually less than a minute long. On a less positive note, one might reasonably be concerned about the quality of the advice provided on social media. Far from all the advice provided on social media is bad, but there are many social media accounts that promote get-rich-quick schemes, crypto investments, or day trading.

The kind of advice we document in this paper is less easily accessible, but is instead of high quality. We show that in a setting where it's highly likely that there is a personal connection, the advice generally tends to be good. Recommenders spread good investment advice to their friends, leading to better portfolios among the Followers. However, gaining access to this advice requires that you know someone with a good portfolio who is willing to share advice. With what we know about homophily and sorting in social networks, not everyone will have access to high-quality advice and may instead be pushed towards the advice provided on TikTok or Instagram.

At the heart of the matter is this dichotomy: social media is accessible to everyone with a smartphone, but the advice is perhaps not as good. Not everyone has friends with good portfolios, but the advice that those friends can provide is good. To fully understand the landscape of financial advice provided by social networks, we need a better understanding of who has access to good advice through their social networks and who is left to the vagaries of social media. In our view, illuminating this dichotomy is an important contribution of our study.

Our framework and results provide a new agenda for future research into peer effects in finance. In our view, three main questions naturally follow: First, research into peer effects in finance should carefully consider the effect of peers on portfolio composition. The literature on the effect of peers on financial mistakes and echo chambers has started to address this question, but a more explicit portfolio focus would be useful for understanding the quality of advice provided in social networks. Second, we need to think carefully about the social setting and how results from, e.g., online social networks generalize to other settings, like family, friends or work-place relationships. The incentives for providing advice on social networks is clearly different from the incentives to provide advice to your close family. Third, we know little about who has access to good advice in their social networks. We believe that all these questions offer important and intriguing possibilities for future research.

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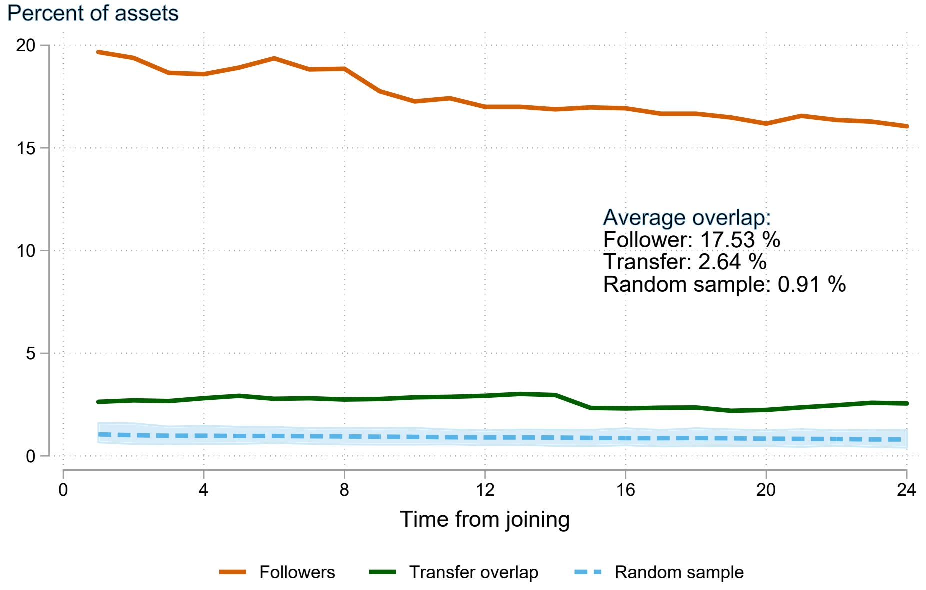
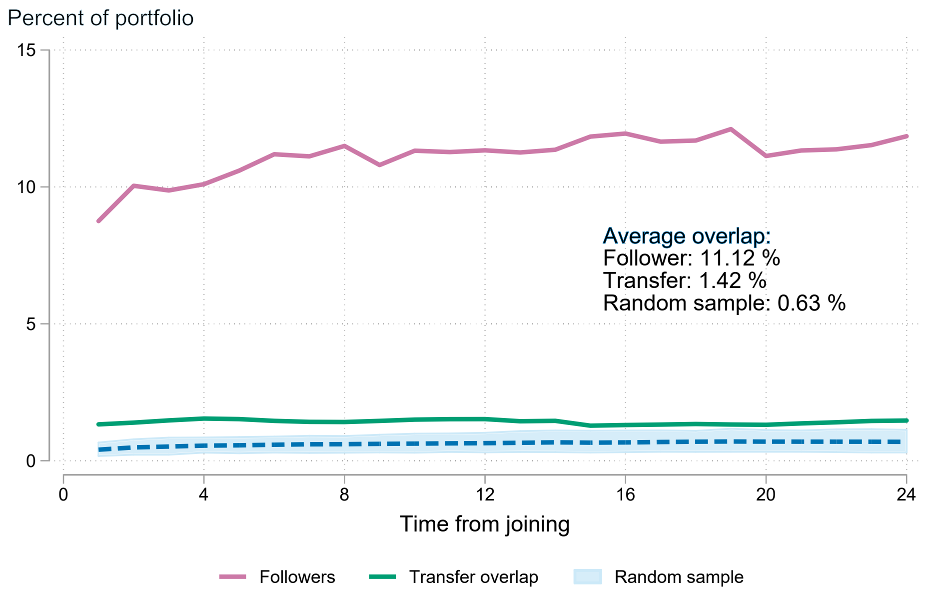
8 Figures



(a) Number of assets



(b) 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 lines for shows the development of peer-determined number of shares from 0 to 24 months after the referral date. The portfolio for the Recommender is lagged one month relative to the Follower. The green line plots the overlap share based on transferred assets. We lag the portfolio of the Recommender one month relative to the time the Follower transferred the assets. The blue dashed lines shows the peer-determined share for Placebo Followers. who are randomly matched to each other. Placebo Followers are defined as individuals who begin trading during one of the years where we observe Followers. The blue confidence intervals mark the 1 and 99th percentile of the distribution of placebo overlap shares.

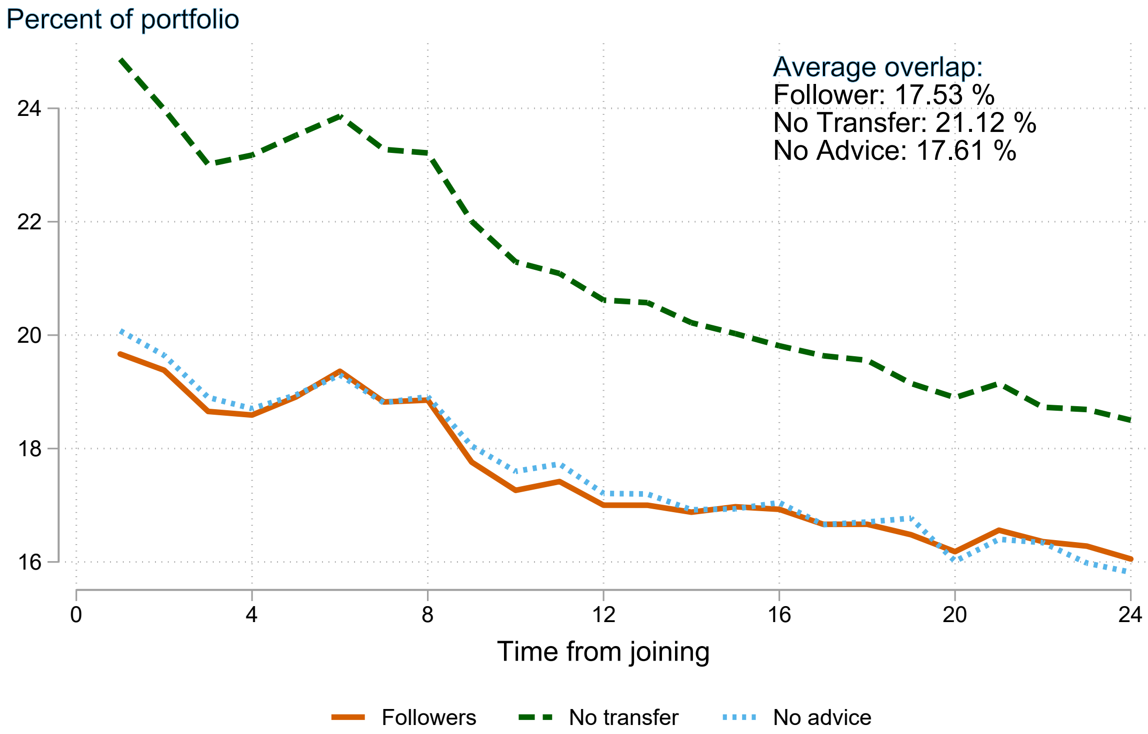


Figure 2: Overlap over time for select samples

Notes: The figure plots the unweighted overlap share, the overlap in number of assets, for different samples. Follower overlap, marked with an orange solid line, is the same line as in panel a) of Figure 1. The portfolio for the Recommender is lagged one month relative to the Follower. The green dashed line is the unweighted overlap share for Followers who do not transfer assets from another bank. The blue dotted line is the overlap share for Followers who do not receive bank advice.

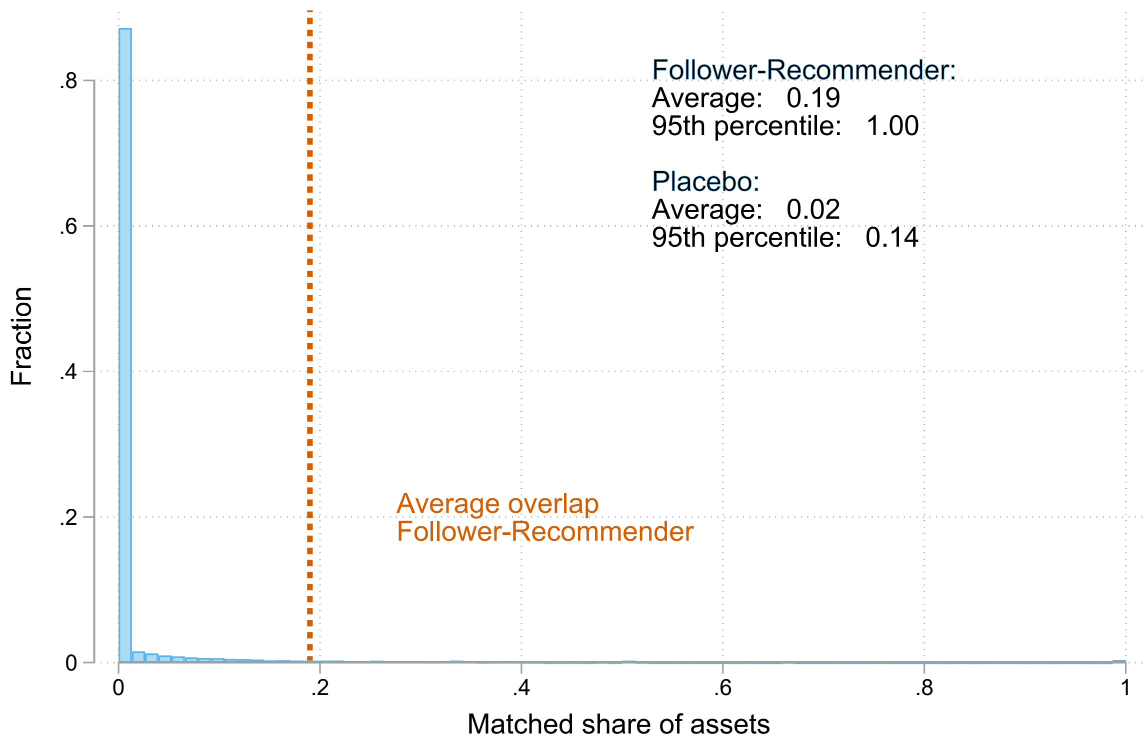


Figure 3: Overlap with all investors

Notes: The figure plots a histogram of the overlap between each Follower and all other investors. 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 new investors in the sample.

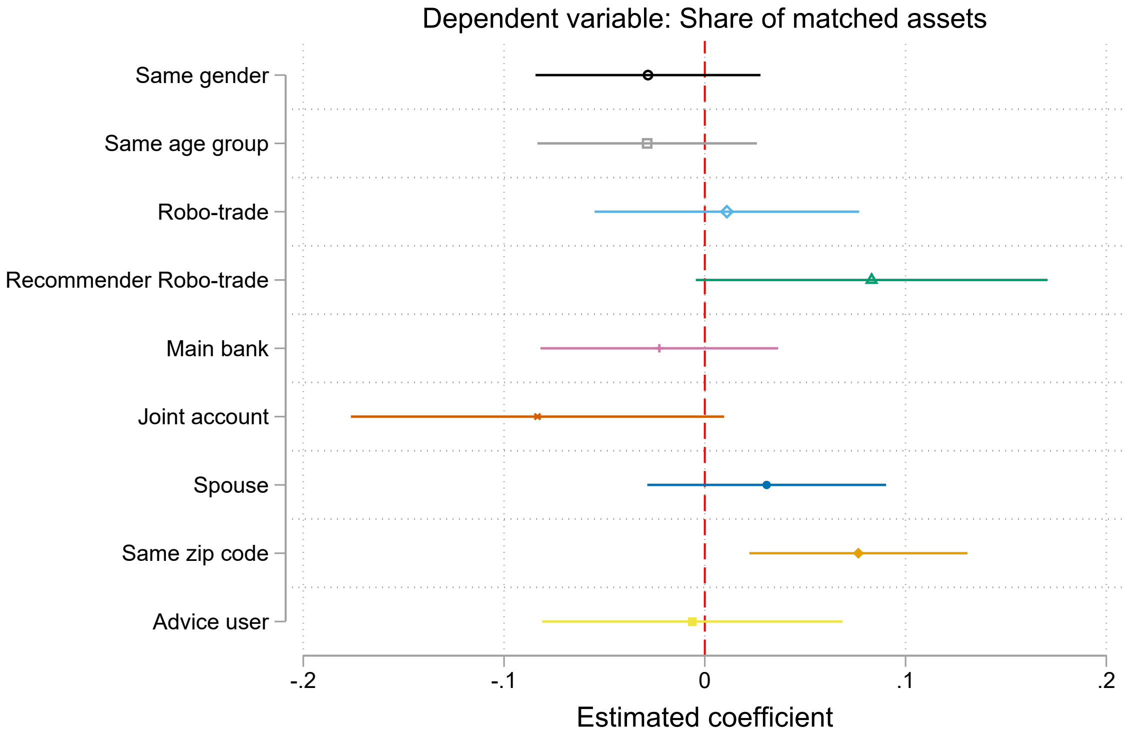


Figure 4: Determinants of overlap

Notes: The figure plots coefficients from a regression of the form $Overlap = \beta x_i + \epsilon$, where x_i is a variable listed in the figure. The sample consists of all Followers (515 observations).

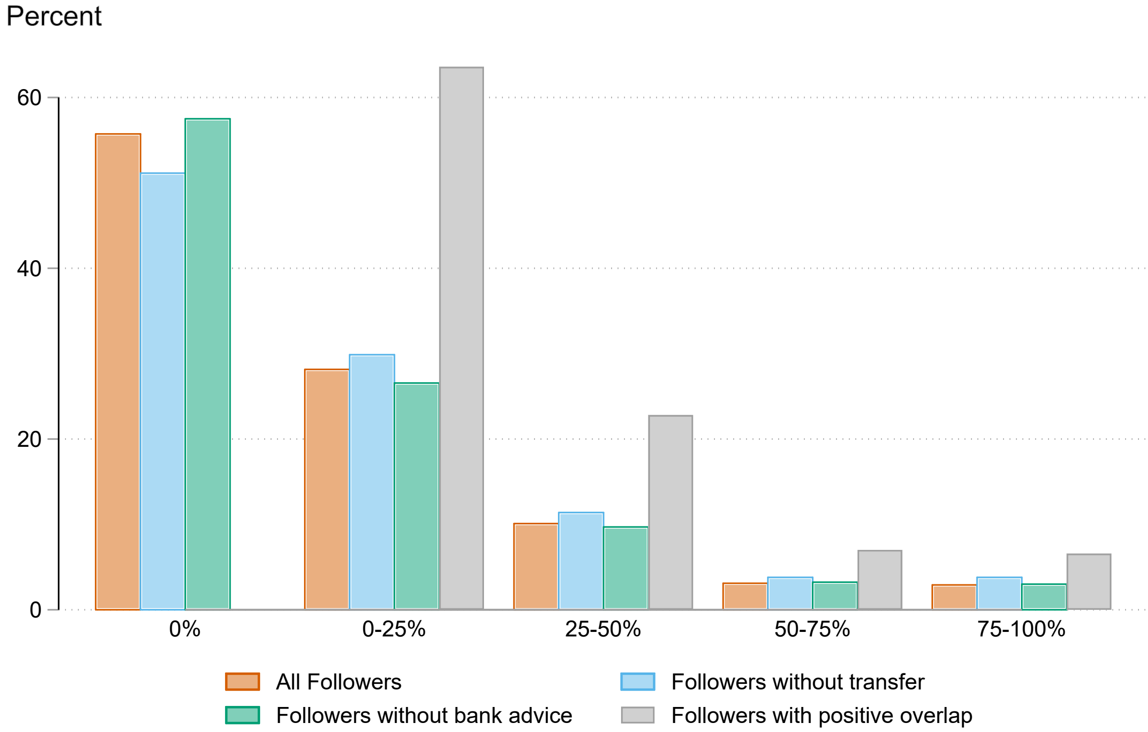
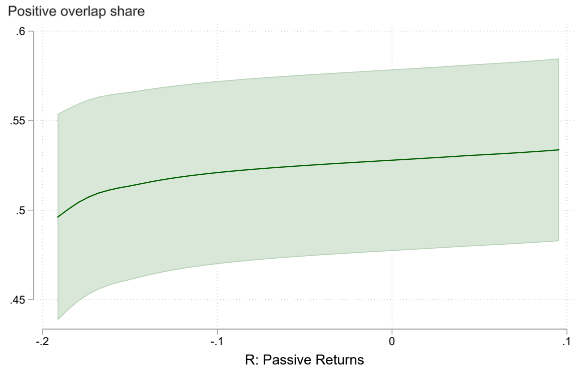
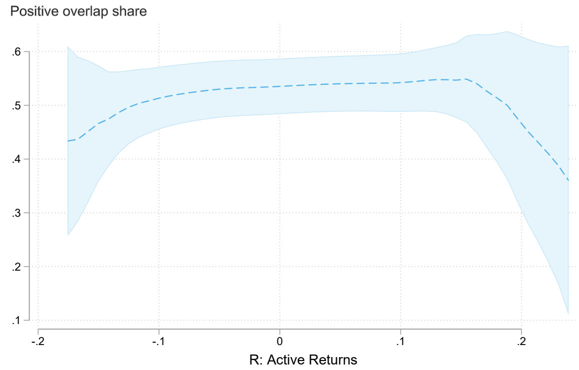


Figure 5: Overlap for selected samples

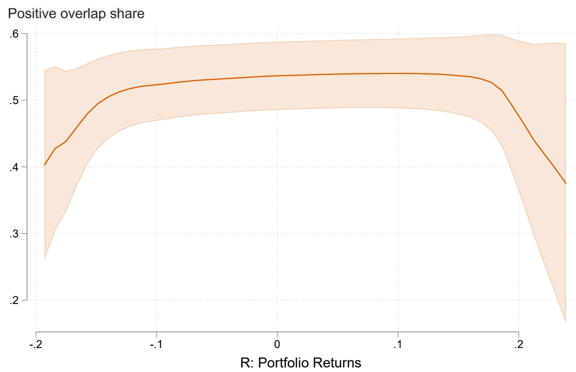
Notes: The figure plots the distribution of the unweighted overlap for different samples of Followers. For each sample, the portfolio for the Recommender is lagged one month relative to the Follower.



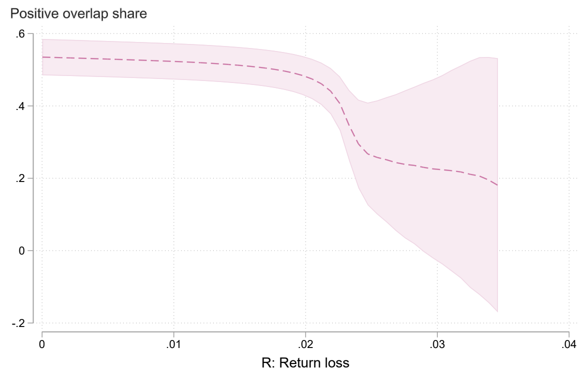
(a) Passive



(b) Active



(c) Portfolio



(d) Return Loss

(e) Relative Sharpe Ratio loss Loss

Figure 6: Positive overlap and returns

Notes: The figure plots the results from local polynomial regressions, where the dependent variabel is a dummy variable equal to one if the overlap share is positive. The independent variable is passive returns in panel a), active returns in panel b), and portfolio returns in panel c). All returns are measured as one-month returns in the month of Recommendation. The independent variable in panel d) and e) is the Recommender Return loss and Relative Sharpe ratio loss, respectively.

9 Tables

Table 1: Descriptive Statistics

Notes: This table reports the descriptive statistics for demographics and portfolio characteristics. The first two column includes observations for Followers and new investors, defined as the periods in the first 12 months after opening a brokerage account. Column 4 and 5 provide descriptive statistics for Recommenders and all investors (excluding Followers). We define investors as individuals with a brokerage account. Column 3 and 6 present the differences in means between groups, where t-statistics are reported in brackets. Main bank is an indicator equal to one if a customer allocates at least half of the tax exemption limit to this bank. Joint account 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. Advice is a dummy equal to one if the individual uses either personal advice or robo-advice. Return loss and Relative Sharpe ratio loss are defined in Appendix A.1. Variables marked with "I:" are indicators equal to one or zero. Standard deviations are in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

	Followers and new investors			Recommenders and all investors		
	(1) Follower	(2) New investors	(3) T-test	(4) Recommenders	(5) All investors	(6) T-test
A. Demographic characteristics						
Male	0.52	0.66	-0.14***	0.81	0.73	0.08***
	(0.50)	(0.47)	[-23.33]	(0.39)	(0.44)	[30.97]
Age	40.34	38.61	1.73***	42.99	45.57	-2.57***
	(15.57)	(16.01)	[8.26]	(14.58)	(15.47)	[-29.37]
Academic title	0.06	0.04	0.01***	0.05	0.05	-0.00
	(0.23)	(0.20)	[4.87]	(0.22)	(0.22)	[-0.22]
Joint account	0.10	0.14	-0.05***	0.15	0.14	0.01***
	(0.30)	(0.35)	[-10.23]	(0.36)	(0.34)	[6.55]
Main bank	0.32	0.21	0.10***	0.52	0.32	0.20***
	(0.47)	(0.41)	[19.32]	(0.50)	(0.47)	[76.72]
Advice user	0.16	0.07	0.09***	0.17	0.06	0.11***
	(0.36)	(0.25)	[26.70]	(0.37)	(0.23)	[82.75]
B. Wealth and income						
Total AUM (EUR)	27,863.42	18,328.06	9,535.36***	58,173.92	30,585.03	27,588.89***
	(46,192.44)	(39,664.85)	[18.31]	(77,369.78)	(56,007.06)	[86.91]
Income proxy	2,371.28	2,284.93	86.35	4,121.89	2,230.58	1,891.32***
	(11,542.78)	(16,443.55)	[0.40]	(14,593.32)	(19,381.02)	[17.26]
C. Portfolio Composition						
Number of securities	5.35	4.92	0.43***	13.19	8.33	4.85***
	(5.06)	(6.81)	[4.02]	(14.30)	(12.45)	[58.29]
Stock market participant	0.45	0.47	-0.03***	0.75	0.74	0.01***
	(0.50)	(0.50)	[-3.31]	(0.44)	(0.44)	[3.07]
Risky share	0.48	0.31	0.17***	0.49	0.34	0.15***
	(0.41)	(0.39)	[34.00]	(0.39)	(0.40)	[67.00]
Sharpe ratio	0.09	0.08	0.01***	0.09	0.08	0.01***
	(0.03)	(0.04)	[12.62]	(0.03)	(0.04)	[34.57]
Return loss	0.00	0.00	-0.00	0.00	0.01	-0.01
	(0.02)	(0.22)	[-0.48]	(0.08)	(1.14)	[-1.21]
Relative Sharpe Ratio loss	0.24	0.30	-0.06***	0.28	0.36	-0.07***
	(0.22)	(0.30)	[-12.62]	(0.26)	(0.31)	[-34.57]
I: Active Fund Investment	0.37	0.31	0.06***	0.53	0.41	0.11***
	(0.48)	(0.46)	[7.88]	(0.50)	(0.49)	[34.42]
I: Passive Investment	0.51	0.41	0.10***	0.52	0.24	0.28***
	(0.50)	(0.49)	[13.00]	(0.50)	(0.43)	[96.52]
I: Warrants and Options	0.11	0.10	0.02***	0.30	0.16	0.14***
	(0.32)	(0.30)	[3.75]	(0.46)	(0.37)	[59.01]
I: Lottery Stocks	0.45	0.62	-0.17***	0.57	0.67	-0.10***
	(0.50)	(0.48)	[-26.91]	(0.50)	(0.47)	[-38.33]
I: Attention Stocks	0.40	0.59	-0.18***	0.51	0.63	-0.11***
	(0.49)	(0.49)	[-28.66]	(0.50)	(0.48)	[-41.55]
Number of observations	5,924	384,857		31,326	9,505,854	
Number of individuals	515	37,143		454	137,766	

Table 2: Overlap and placebo overlap

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

	Average overlap	5th percentile	95th percentile
Follower-Recommender	0.18	0.00	1.00
Panel A: Random matches			
Random sample	0.01	0.01	0.01
CEM1	0.01	0.01	0.01
CEM2	0.01	0.01	0.01
CEM3	0.01	0.01	0.01
CEM4	0.01	0.01	0.01
Exact	0.03	0.02	0.04

	Mean	Standard deviation	95th percentile	N
Panel B: Direct matches across all investors				
All investors	0.023	0.098	0.139	41,537,743
Demographics	0.024	0.096	0.148	3,684,067
Location	0.026	0.100	0.159	411,669
AUM	0.023	0.092	0.161	73,041
Risky share	0.025	0.102	0.164	36,829

Table 3: Sending function: Recommendation decision and portfolio returns

Notes: The dependent variable is a dummy which is equal to 1 if an investor recommends successfully the bank in a given month, and zero otherwise. The sample consists of Recommenders only. Explanatory variables include Recommenders' portfolio performance and portfolio quality characteristics, and participation characteristics. Robust standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

	All Recommenders			Successful recommendation		
	(1)	(2)	(3)	(4)	(5)	(6)
Portfolio returns		-0.0000**	-0.0000*	0.0052	0.0116	0.0117
		(0.0000)	(0.0000)	(0.0136)	(0.0117)	(0.0118)
Passive returns	0.0130			0.0039		
	(0.0107)			(0.0140)		
Active returns	0.0017			0.0173		
	(0.0027)			(0.0159)		
R: Log Return loss	-0.0004		-0.0004	-0.0005		-0.0004
	(0.0004)		(0.0004)	(0.0010)		(0.0010)
R: RSRL	0.0000		-0.0000	0.0000		-0.0000
	(0.0007)		(0.0007)	(0.0015)		(0.0015)
Male	0.0004		0.0004	0.0007		0.0007
	(0.0009)		(0.0009)	(0.0021)		(0.0021)
R: Age	-0.0000		-0.0000	-0.0000		-0.0000
	(0.0000)		(0.0000)	(0.0001)		(0.0001)
Academic title	0.0000		0.0000	0.0001		0.0001
	(0.0014)		(0.0014)	(0.0033)		(0.0033)
Income proxy	0.0000		0.0000	0.0000		0.0000
	(0.0000)		(0.0000)	(0.0000)		(0.0000)
Advice	0.0004		0.0004	-0.0004		-0.0004
	(0.0011)		(0.0011)	(0.0021)		(0.0021)
Joint account	0.0002		0.0002	-0.0012		-0.0012
	(0.0008)		(0.0008)	(0.0021)		(0.0021)
Main bank	-0.0002		-0.0002	-0.0005		-0.0005
	(0.0007)		(0.0007)	(0.0016)		(0.0016)
Region#Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.002	0.002	0.002	0.002	0.002	0.002
Observations	111,643	111,643	111,643	23,809	23,809	23,809

Table 4: Sending function: Recommenders compared to other investors

Notes: The dependent variable is a dummy which is equal to 1 if the individual is a Recommender, and zero otherwise. The sample consists of all investors excluding Followers and new investors with a brokerage account active after 2011. Control variables include gender, age, academic title, and an income proxy.
We include region× year fixed effects in all specifications. Robust standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

	All Recommenders			Successful recommendation		
	(1)	(2)	(3)	(4)	(5)	(6)
Portfolio returns × 100	0.0003	0.0003	0.0003	-0.0001**	-0.0000	-0.0001**
	(0.0007)	(0.0007)	(0.0007)	(0.0000)	(0.0000)	(0.0000)
Log return loss		-0.0002***			-0.0004***	
		(0.0000)			(0.0000)	
Log Relative Sharpe ratio loss			-0.0017***			-0.0009***
			(0.0001)			(0.0000)
Demographics	Yes	Yes	Yes	Yes	Yes	Yes
Region#Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.002	0.002	0.003	0.001	0.001	0.001
Observations	4,996,207	4,996,205	4,996,207	4,911,863	4,911,861	4,911,863

Table 5: Recommending function: Overlap and Recommender portfolio quality

Notes: The dependent variable is a dummy equal to one if the overlap is greater than zero. The independent variables of interest is *R: log Return loss* and *R: log RSRL*, the log Return loss and log Relative Sharpe ratio loss for the Recommender. We include region× year fixed effects in all specifications. Robust standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

	Returns			Portfolio quality		Combined	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
R: Portfolio return	0.565					0.655	0.608
	(0.614)					(0.597)	(0.607)
R: Active return		-0.115					
		(0.232)					
R: Passive return			1.898**				
			(0.830)				
R: Log Return loss				-0.061**		-0.062**	
				(0.026)		(0.027)	
R: RSRL					-0.092**		-0.093***
					(0.036)		(0.036)
Follower controls							
Male	-0.060	-0.059	-0.055	-0.058	-0.055	-0.058	-0.055
	(0.060)	(0.060)	(0.059)	(0.059)	(0.060)	(0.059)	(0.059)
Income proxy (std)	-0.030	-0.032	-0.032	-0.026	-0.026	-0.024	-0.025
	(0.050)	(0.049)	(0.049)	(0.050)	(0.049)	(0.051)	(0.050)
Academic title	-0.187	-0.173	-0.180	-0.165	-0.161	-0.181	-0.175
	(0.128)	(0.126)	(0.123)	(0.118)	(0.120)	(0.120)	(0.122)
Age	0.017	0.016	0.018	0.016	0.018	0.017	0.018
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(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)	(0.000)	(0.000)
Main bank	0.022	0.020	0.024	0.024	0.019	0.027	0.022
	(0.067)	(0.066)	(0.066)	(0.065)	(0.065)	(0.065)	(0.065)
Joint account	-0.046	-0.047	-0.051	-0.057	-0.035	-0.058	-0.035
	(0.104)	(0.104)	(0.102)	(0.099)	(0.102)	(0.099)	(0.102)
Advice user	0.027	0.025	0.022	0.009	0.012	0.010	0.013
	(0.078)	(0.078)	(0.078)	(0.078)	(0.077)	(0.078)	(0.078)
Region#Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dep. var. mean	0.527	0.527	0.527	0.527	0.527	0.527	0.527
Dep. var. std dev	0.500	0.500	0.500	0.500	0.500	0.500	0.500
Adjusted R^2	0.060	0.058	0.071	0.077	0.078	0.078	0.078
Observations	374	374	374	374	374	374	374

Table 6: Recommender and Follower participation in asset classes

Notes: The table compares how likely Followers are to invest in each asset classes listed in the column header if their Recommender invests in the specific asset class. The dependent variable is Follower participation in each asset class listed in the column headers. *Recommender participation* a dummy equal to one if the associated Recommender invests in a specific asset class. *, **, 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
Recommender Participation	0.526***	0.389***	0.441***	0.131**	0.350***	0.199***	0.198***	0.248***	0.300***	0.290***	0.255***
	(0.062)	(0.050)	(0.055)	(0.053)	(0.057)	(0.060)	(0.058)	(0.053)	(0.053)	(0.061)	(0.067)
Male	-0.047	0.075	0.035	0.015	0.063	0.050	0.043	0.069*	0.064	0.068	0.013
	(0.039)	(0.050)	(0.051)	(0.030)	(0.044)	(0.034)	(0.043)	(0.041)	(0.039)	(0.044)	(0.031)
Income proxy (std)	0.007	0.064***	0.053**	-0.005	0.006	-0.017	0.015	0.022	-0.018	0.013	-0.026*
	(0.017)	(0.023)	(0.026)	(0.015)	(0.027)	(0.016)	(0.026)	(0.029)	(0.024)	(0.029)	(0.014)
Academic title	0.134	0.018	0.184	0.070	0.109	0.051	0.021	-0.029	0.203**	0.097	0.040
	(0.093)	(0.107)	(0.111)	(0.077)	(0.091)	(0.075)	(0.090)	(0.078)	(0.102)	(0.085)	(0.078)
Age	-0.002	0.012	0.000	-0.009	0.001	-0.003	0.004	-0.009	-0.001	0.001	0.005
	(0.008)	(0.010)	(0.010)	(0.007)	(0.009)	(0.007)	(0.009)	(0.009)	(0.008)	(0.009)	(0.007)
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)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Main bank	0.005	0.036	0.024	0.149***	0.128**	0.136***	0.122**	0.073	0.128***	0.123**	0.111***
	(0.044)	(0.051)	(0.054)	(0.041)	(0.050)	(0.044)	(0.051)	(0.046)	(0.048)	(0.051)	(0.039)
Joint account	0.064	0.074	0.001	-0.014	0.059	0.035	0.109	0.029	0.010	0.070	-0.030
	(0.058)	(0.088)	(0.092)	(0.045)	(0.077)	(0.064)	(0.086)	(0.079)	(0.074)	(0.084)	(0.056)
Advice user	0.132***	0.147**	0.115*	-0.035	-0.142***	-0.078**	-0.151***	-0.085*	-0.066	-0.117**	-0.034
	(0.046)	(0.070)	(0.069)	(0.025)	(0.052)	(0.034)	(0.045)	(0.049)	(0.045)	(0.052)	(0.032)
Constant	0.416***	-0.139	0.245	0.171	0.001	0.065	-0.000	0.229	0.024	0.019	-0.067
	(0.160)	(0.202)	(0.203)	(0.153)	(0.190)	(0.158)	(0.195)	(0.188)	(0.178)	(0.197)	(0.142)
Region#Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	398	398	398	398	398	398	398	398	398	398	398
Adjusted R^2	0.295	0.241	0.219	0.121	0.315	0.122	0.133	0.181	0.213	0.264	0.211

Table 7: Recommender participation and Follower participation across asset classes

Notes: The table measures how Recommender participation in Funds, Lottery stocks, and Attention stocks affect Follower participation in Funds, Lottery stocks, and Attention stocks. Each cell in the table represents a separate regression, where the dependent variables are listed in columns and the independent variables are listed in rows. 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, a dummy equal to one if the account is a joint account, and a dummy equal to one if the individual uses bank advice. Robust standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

	(1) Fund	(2) Lottery	(3) Attention
Recommender: Funds	0.526***	-0.207***	-0.203***
	(0.062)	(0.064)	(0.064)
Recommender: Lottery	-0.255***	0.326***	0.349***
	(0.046)	(0.060)	(0.058)
Recommender: Attention	-0.264***	0.325***	0.322***
	(0.046)	(0.060)	(0.059)

Table 8: Participation in asset types compared to general sample

Notes: The table compares how likely Followers are to invest in each asset classes listed in the column header relative to other investors. The dependent variable is listed in the column headers. We estimate the following equation: $y_{i,k,t} = \alpha + \gamma Follower_{i,k,t} + \mathbf{X}'_{\mathbf{i,k,t}}\beta + \delta_{i,k} + \epsilon_{i,k,t}$. Follower is a dummy equal to one if the individual is a Follower. Panel A) presents results for the extensive margin (participation in asset classes) and Panel B presents results for the intensive margin (given participation in each asset class, what is the share of the portfolio allocated to each asset). 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, a dummy equal to one if the account is a joint account, and a dummy equal to one if the individual uses bank advice. Robust standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

Panel A: Extensive margin (participation in asset class)

	Funds			Lottery				Attention			
	(1) Fund	(2) Active	(3) Passive	(4) Kumar	(5) MAX	(6) High Volatility	(7) High Skewness	(8) CSS	(9) CVRG	(10) Recency	(11) —SUE—
Follower	0.045**	0.054**	0.054**	-0.006	-0.008	-0.001	-0.011	-0.011	0.003	0.004	0.004
	(0.018)	(0.021)	(0.021)	(0.013)	(0.018)	(0.014)	(0.017)	(0.016)	(0.016)	(0.018)	(0.013)
Region#Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dep. var. mean	0.687	0.346	0.440	0.150	0.371	0.152	0.249	0.227	0.212	0.340	0.133
Dep. var. std dev	(0.464)	(0.476)	(0.496)	(0.358)	(0.483)	(0.359)	(0.433)	(0.419)	(0.409)	(0.474)	(0.339)
Observations	25605	25605	25605	25605	25605	25605	25605	25605	25605	25605	25605
Adjusted R^2	0.072	0.047	0.155	0.089	0.244	0.080	0.138	0.132	0.118	0.226	0.120

Panel B: Intensive margin (weight in asset class)

	Funds			Lottery				Attention			
	(1) Fund	(2) Active	(3) Passive	(4) Kumar	(5) MAX	(6) High Volatility	(7) High Skewness	(8) CSS	(9) CVRG	(10) Recency	(11) —SUE—
Follower	0.001	-0.022	-0.049**	0.011	-0.029	-0.029	-0.032***	-0.010	-0.003	-0.013*	-0.004
	(0.015)	(0.020)	(0.022)	(0.029)	(0.018)	(0.022)	(0.012)	(0.015)	(0.003)	(0.007)	(0.004)
Region#Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dep. var. mean	0.790	0.421	0.608	0.131	0.288	0.145	0.127	0.114	0.041	0.121	0.030
Dep. var. std dev	(0.311)	(0.319)	(0.380)	(0.192)	(0.241)	(0.204)	(0.157)	(0.146)	(0.037)	(0.097)	(0.031)
Observations	17599	8849	11256	3839	9502	3874	6374	5813	5422	8688	3387
Adjusted R^2	0.056	0.080	0.102	0.081	0.193	0.072	0.043	0.034	0.027	0.065	0.046

Table 9: 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)
Follower	-0.27***	-0.11**	-0.05	-0.28***	-0.10***	-0.08**
	(0.05)	(0.05)	(0.05)	(0.03)	(0.03)	(0.03)
Male			0.23***			0.07***
			(0.02)			(0.01)
Income proxy (std)			0.03***			0.02***
			(0.01)			(0.00)
Academic title			-0.25***			-0.09***
			(0.04)			(0.02)
Age			-0.01***			-0.01***
			(0.00)			(0.00)
Age squared			0.00**			0.00***
			(0.00)			(0.00)
Main bank			0.13***			0.06***
			(0.02)			(0.01)
Joint account			-0.09***			-0.05***
			(0.02)			(0.01)
Advice user			-0.54***			-0.21***
			(0.02)			(0.01)
Region#Year fixed effect	No	Yes	Yes	No	Yes	Yes
Dep. var. mean	-6.73	-6.73	-6.73	-1.39	-1.39	-1.39
Dep. var. std. dev	1.31	1.31	1.31	0.83	0.83	0.83
Number of Followers	515	515	515	515	515	515
Observations	25605	25605	25605	25605	25605	25605
Adjusted R^2	0.001	0.055	0.086	0.002	0.212	0.222

Table 10: Decomposition of return loss

Notes: This table presents results for the decomposition of return loss into its components from equation 8. We regress log Return loss (the same results as Column 3 of Table 9) 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	-0.05	0.16***	0.08***	-0.14***
	(0.05)	(0.04)	(0.03)	(0.05)
Male	0.23***	0.09***	0.12***	0.11***
	(0.02)	(0.01)	(0.02)	(0.02)
Income proxy (std)	0.03***	-0.06***	-0.00	0.04***
	(0.01)	(0.02)	(0.01)	(0.01)
Academic title	-0.25***	0.07***	-0.11**	-0.13***
	(0.04)	(0.03)	(0.04)	(0.03)
Age	-0.01***	-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	-0.09***	-0.18***	-0.03*	-0.06***
	(0.02)	(0.02)	(0.02)	(0.02)
Advice user	-0.54***	0.25***	-0.21***	-0.33***
	(0.02)	(0.02)	(0.02)	(0.02)
Region#Year fixed effect	Yes	Yes	Yes	Yes
Dep. var. mean	-6.73	-0.85	-0.26	-0.86
Dep. var. std. dev	1.31	1.02	1.15	1.35
Number of Followers	515	515	515	515
Observations	25605	25587	25605	25605
Adjusted R^2	0.086	0.046	0.131	0.241

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:

$$r^e_{j,t} = \beta_j r^e_{m,t} + \epsilon_{j,t} \tag{9}$$

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^2_i of the excess return and the Sharpe ratio for the individual portfolio as $S_i = \mu_i/\sigma^2_i$. The Sharpe ratio for the index is then simply $S_B = \mu_B/\sigma^2_B$, and the loss from poor diversification relative to the benchmark can be quantified by the relative Sharpe ratio loss $RSRL_i$:

$$RSRL_i = 1 - \frac{S_i}{S_B}. \tag{10}$$

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:

$$(1 - RSRL_i)^2 = 1 - \frac{\sigma_{k,i}^2}{\sigma_i^2}. \tag{11}$$

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:

$$RL_i = w_i(S_B\sigma_i - \mu_i) \tag{12}$$

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:

$$RL_i = (Er_m^e)w_i\beta_i(\frac{RSRL_i}{1 - RSRL_i}). \tag{13}$$

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 (13):

$$\ln RL_i = \ln(Er_m^e) + \ln w_i + \ln \beta_i + \ln\left(\frac{RSRL_i}{1 - RSRL_i}\right). \tag{14}$$

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 B1 presents the CEM matching methods description.

Table B1: 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 B1. 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.[7] Table C3 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 highest k^{th} idiosyncratic volatility percentile, and the highest k^{th} idiosyncratic skewness percentile.[8] 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 C3 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.* (2022), we define high attention stocks as stocks in the 25^th highest percentile of the monthly average Composite Sentiment Score (CSS) from RavenPack.[9] The second proxy,

[7]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.

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

[9]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.

following Bali *et al.* (2021), is analyst coverage (CVRG), which shows whether a firm has a high profile in public discussion. If the firm is in the public spotlight, more investors learn about its characteristics, including lottery-like characteristics, such as extreme returns. We use the number of different earnings forecasts for a stock in a month from the Institutional Brokers' Estimate System (I/B/E/S) database. A high attention stock has a number of forecasts in the 25^th percentile.

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

B Online Appendix: Tables

Table C1: Sample selection

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

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

Table C2: Overlap share and Follower Characteristics

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

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

Table C3: Asset type participation and portfolio performance

Notes: The table estimates how investments into different asset classes is correlated with log Return loss (panel A) and log Relative Sharpe ratio loss (panel B). The independent variable is a dummy equal to one if the investor has an investment in the specific asset class listed in the column header. Robust standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

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

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