Personal Financial Advice and Portfolio Quality

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September 27, 2024

Abstract

We document widespread use of personal financial advice among retail investors. Individuals seek competent and trusted sources for financial advice among their family and friends. Investors who provide advice to family and friends are positively selected and emphasize the reputational costs of giving risky financial advice. While previous studies have shown that advice shared on social media promotes active trading, we show that personal financial advice encourages investing in funds over single stocks. Our evidence complements the existing literature on financial advice in online social networks by highlighting differences in incentives and outcomes of advice to close personal connections.

JEL Classification: D14, G11, G40, G50
Keywords: Social finance, portfolio choice, investment behavior, peer effects

*We thank Peter Andre, David Hirshleifer, Zhi Da, Anna Piil Damm, Petri Jylhä, Yigitcan Karabulut, Markku Kaustia, Samuli Knüpfer, Elena Mattana, Steffen Meyer, Bianca Putz, Michael Reher, Stefan Ruenzi, Theresa Spickers, and Nate Vellekoop, as well as conference and seminar participants at Aalto University, Aarhus University, the CEPR Advanced Forum in Financial Economics, CEPR European Conference on Household Finance 2023, Goethe University Frankfurt, the Junior European Finance (JEF) Seminar, the Young Scholars Nordic Finance Workshop 2021, the SGF Conference 2022, and the 2022 Econometric Society Winter Meeting for helpful comments and discussions. We are very thankful to a bank for providing us with the data necessary to conduct this research. We gratefully acknowledge research support from the Leibniz Institute for Financial Research SAFE.

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Conflict-of-interest disclosure statement

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I have nothing to disclose

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I have nothing to disclose

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I did not receive financial support for this research, and I have no financial interest in its outcomes. A bank provided data for this research to Goethe University but no financial support. Data provision was subject to non-disclosure agreements to protect the confidentiality of the data. The bank has no right to intervene in the research or authorize any output from it. Full disclosure on my board memberships and advisory roles (all unrelated to this research) can be found here: https://www.old.wiwi.uni-frankfurt.de/fileadmin/user_upload/dateien_abteilungen/abt_fin/2023-11_Hackethal_Disclosure_of_potential_conflict_of_interests.pdf

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I have nothing to disclose

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I have nothing to disclose

1 Introduction

The first question that new acquaintances typically ask, once we reveal that we work in finance, is what to invest in. This question is surely familiar to most readers. Like most, we usually provide advice consistent with popular personal finance advice (Choi, 2022) and 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. We call this view of social interactions in finance 'expertise-based transmission.'

An equally plausible view of social interactions is that communication is based on financial returns. There is considerable empirical evidence for 'return-biased transmission,' formally modeled in Han *et al.* (2022). Several studies provide evidence consistent with the view that investors share investment ideas with their peers if they experience high returns (Heimer & Simon, 2015; Escobar Pradilla & Pedraza, 2019; Lim *et al.* , 2020; Ammann & Schaub, 2021). As a consequence, social interactions 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). But while there is considerable evidence on return-biased transmission using anonymous or pseudonymous relationships, there is little evidence on financial advice on portfolio composition in close personal relationships (*personal financial advice*). A key question is whether the results on portfolio composition extend to other settings: does personal financial advice reflect return chasing and speculation (e.g., return-biased transmission) or passive, diversified investments (e.g., expertise-based transmission)?

In this paper, we document several novel facts consistent with expertise-based transmission using real-world investment decisions and survey data from German retail investors. We focus on financial advice to close personal connections and study both individuals who make recommendations (*Recommenders*) and individuals who look for financial advice to follow (*Followers*). Our results can be summarized as follows. First, personal financial advice is widespread among retail investors. 72 percent of Followers list family members as the most important source of financial advice, and 57 percent list friends, neighbors, or coworkers. In comparison, only four percent of Followers list anonymous online advice as the most important source of financial advice.[1] Second, Followers seek trust and expertise in the person providing advice, with few mentioning financial returns. Followers are more likely to follow advice on funds than over single stocks with high past returns. In a brokerage dataset on real investment decisions, we find that financial returns are not correlated with accepting financial advice. Third, Recommenders (individuals who provide advice) are positively selected based on experience, income, and portfolio quality. Moreover, 79 percent of Recommenders state that family and friends *come to them* directly for advice, which is inconsistent with the idea that Recommenders give advice when they experience high returns. Fourth, in both survey and bank data, funds are more likely to be recommended than single stocks. Overall, the results are consistent with expertise-based transmission and paint a relatively positive picture of personal financial advice.

Why do we find different results from the previous literature? We attribute differences in the advice to the personal nature of the relationships in our setting. Incentives for posting on social trading platforms may include the desire to generate interaction and attract followers (Qi & Hull, 2024), which may necessitate a more active trading strategy. In addition, relationships on social trading platforms are typically weaker because they involve anonymous or pseudonymous followers. Personal financial advice to family and friends is likely motivated by a desire to see friends do well or simply avoid the potential repercussions of a bad stock tip. One survey respondent, who stated that they neither provided nor received advice, stated "I do not give any advice regarding investments in securities as this is a very sensitive topic. After all, losses can occur and then you will be held partly responsible for them." The personal relationship changes the nature of advice and forces the Recommender to internalize the outcomes of the Follower. While our findings do not invalidate the role of returns in other settings, the results suggest that at least a part of the population employs a more deliberative process for accepting financial advice in personal settings.

We use a generic recommendation campaign by a large German online bank and survey data from a sample of German retail investors. The bank campaign, which is not about financial investments, allows us to observe peer relationships and portfolio composition. The peer relationship consists of individuals who recommend (*Recommender*) their bank

[1] We mostly focus on personal financial advice in this study, but note that financial advisors also play an important role (see e.g., Reuter & Schoar, 2024). For example, several survey respondents state that they recommend their financial advisor to their friends.

and brokerage to an acquaintance (*Follower*). For reasons we discuss at length later, we believe these individuals have close personal relationships. In the survey, we analyze open- and closed-ended questions about financial advice from family and friends for respondents who provide (43 percent of the sample) or receive personal financial advice (29 percent). We also allow respondents to answer that they neither provide nor receive advice (28 percent).

We use the bank data to examine the likelihood of accepting different types of personal financial advice. Our proxy for accepting advice in the bank setting is the presence of shared securities between the Recommender and Follower, which we term the portfolio *overlap*. We define the overlap at the security level (ISIN) for each Recommender-Follower pair for new securities that the Follower buyes when joining the bank. Followers and Recommenders share an average of 17 percent of securities between them, which remains persistently high over two years. Several different placebo overlap exercises support a causal interpretation of the overlap between Follower and Recommender: regardless of how strict we match placebo pairs, the placebo overlap is never higher than three percent. For Followers with a positive overlap share, 30 percent share between 75 and 100 percent of their portfolio with their Recommender, indicating that the peer is the primary source of information about which assets to invest in within this group. We discuss several tests at length later, and here simply note that our bank-level results are robust to concerns over contextual effects, correlated effects, and reflection (Manski, 1993), as well as concerns over different popularity of assets, bank advice, marketing campaigns, home bias, popular stocks, and robo-trading.

Both expertise-based transmission and return-biased transmission predict the type of assets recommended in social interactions. The expertise-based view suggests that Recommenders would support investments with lower volatility, fees, and higher expected returns (e.g., diversified active or passive funds). Recommenders would avoid recommending single stocks or securities which carry additional risk, as the reputation penalty if the recommendation turns out badly may be significant. 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 percent 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. 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 such assets between Recommender and Follower is approximately half the magnitude of the correlation in funds. This result is a departure from the previous literature and provides a more positive view of peer effects in financial markets.

Our survey also provides new context on key mechanisms in theoretical models of social transmission. When asked when they are willing to share information about their portfolios' performance, 75 percent of Recommenders say they always share. Only eight percent of Recommenders say they only share when results are good, again a key mechanism in return-biased transmission. Recommenders use personal meetings to provide advice instead of writing on social media, highlighting that our sample differs from other contexts. Recommenders typically provide advice to friends, neighbors or co-workers (77 percent) or family members (87 percent) instead of advice to people on the internet (5 percent). Consistent with the later point, only four percent of Recommenders state that they provide advice by posting broadly on social media. There are obvious concerns with using survey data to analyze this kind of question, but with this caveat in mind, the evidence points towards a more nuanced picture than previous studies that used anonymous or pseudonymous relationships.

In conclusion, we find evidence consistent with expertise-based transmission on both determinants of social interactions and portfolio choice. Given the proliferation of financial advice on social media, these results provide a timely and more positive perspective on peer effects in finance. Our results highlight the importance of studying social interactions in finance in different social contexts. Our goal is not to invalidate other high-quality studies but simply to highlight how a different context can lead to different conclusions. Understanding which explanation applies in different contexts is an important next step for the literature.

Our results speak towards a broader problem: Financial advice on social media is easily accessible to everyone regardless of their background, but one might reasonably be concerned about the quality of the advice. Several recent media articles have noted that young households use social media for investment advice.[2] Far from all the advice provided on social media is bad, but many social media accounts promote risky strategies such as 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 homophily and sorting in social networks (Balakina *et al.* , 2024), not everyone will have access to high-quality advice and may instead be pushed towards the advice provided on TikTok or Instagram. 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 portfolio composition, and who is left to the vagaries of social media. In our view, illuminating this problem 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 financial advice 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 hand, 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). A personal connection, as in our setting, presents an additional and unique dimension. 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;

[2]For example, Evans (2021) report that 41 percent of US investors below the age of 40 used YouTube for financial advice, while 29 percent have talked to family and friends. The most comparable number in our survey is that 19 percent of investors between 25 and 34 years of age turn to social media for advice. Note that our survey also asked about the most *important* source of advice, and that friends and family are more common sources in this question.

Beshears *et al.* , 2015; Heimer, 2016; Kaustia & Knüpfer, 2012; Ouimet & Tate, 2019).[3,4] In contrast to recent work, our study highlights how personal financial advice can improve portfolio outcomes.

We also contribute to an extensive literature on retail investors' performance and investment behavior. This literature has documented that retail investors trade too much (Barber & Odean, 2000) or are too passive or inert (Bilias *et al.* , 2010; Calvet *et al.* , 2009), are under-diversified and expose themselves to idiosyncratic risk (Calvet *et al.* , 2007), chase trends or high attention stocks (Barber & Odean, 2008), and tilt their portfolios towards specific assets or asset classes, e.g., local stocks (Seasholes & Zhu, 2010), dividend-paying securities (Hartzmark & Solomon, 2019; Bräuer *et al.* , 2022), and cryptocurrencies or meme-stocks (Hackethal *et al.* , 2022; Hasso *et al.* , 2021). Several recent papers 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, no fixed advisor or physical advisor is assigned 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 affects 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

[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).

the decision to recommend the bank, it is important to note that the referral campaign is generic and 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*, such as Trade Republic, encouraging investors to recommend others where both parties can earn fractional shares or cryptocurrency tokens. This is not the case in our setting.

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 referral program setup requires that referred customers 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 literature describes the effect 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 Bank data

Our data sample includes 258,000 randomly selected clients with socio-demographic and transaction data from January 2003 until September 2017.[5] The customer referral data allows 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

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

started in 2012, and remove Followers with missing data. Our final Follower sample consists of 515 directly matched peer pairs. A full sample selection table is available in Table B1 in Online Appendix B.

Finally, we merge asset prices, characteristics, and returns 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 stocks, 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 an individual loses by choosing their portfolio instead of a combination of the benchmark portfolio and bonds to achieve the same risk level. The estimation procedure is detailed 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, passive, and active funds), lottery stocks, and attention stocks. We describe how we classify these assets in 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 individual. Although we have a longer time series, we chose the first twelve months of trading to avoid learning and luck from influencing portfolio choice (Anagol *et al.* , 2021). Overall, however, this has little impact on our results, which are robust to using both shorter or longer time-periods.

3 The survey

We conducted an online-survey in May 2024 with 854 German investors to ask about personal financial advice from family and friends. Our goal is to provide evidence on the external validity of our main findings and to provide evidence on some of the mechanisms implied by different theories of personal financial advice. We selected individuals who were between 25 and 85 years old, who have investments in stocks, funds, ETFs or certificates currently or who had such investments in the last three years. We recruit participants using a large panel provider in Europe.

Survey structure. Each respondent starts by answering two screening questions (whether they have an investment portfolio and age) and one attention check. The attention check is designed to screen out inattentive respondents.[6] We then briefly describe that the survey is about personal financial advice in stocks and funds, where we state that we define personal advice as "advice from your friends, acquaintances, colleagues, or family members about investments in stocks and funds." We then ask respondents whether they usually provide advice, receive advice or neither. Depending on what they answers, respondents are sorted into tracks for either providing advice or receiving advice. Respondents who answer "Neither" are randomly assigned to one track. At the end of the survey, we ask all respondents about portfolio characteristics, demographics and return expectations. We adopt the terminology of Recommenders and Followers for the survey respondents for consistency with the bank setting below. In our main analysis, we focus on respondents who state that they usually provide advice or receive advice,

Open-ended questions. For both the receiving and providing tracks, we start with open-ended questions where we allow respondents to describe the financial advice that they provide or receive from family and friends. The key advantage of using open-ended questions is that we do not prime the respondents' reasoning in a particular manner and that the answers are not restricted. The open-ended questions thus allows us to capture what comes to mind when we mention financial advice for family and friends. This approach has recently been used to elicit peoples' reasoning about taxes (Stantcheva, 2021) or to understand peoples' mental model of the stock market (Andre *et al.* , 2023). Ferrario & Stantcheva (2022) and Haaland *et al.* (2024) discuss the advantages and disadvantages of this approach. For respondents who state that they typically provide advice, we ask them to describe what kind of advice they would give about investments in stocks and funds to family and friends. For respondents who typically receive advice, we first ask which kind of advice they have received about investments in stocks and funds from family and friends. We then ask what they look for in the person who gives financial advice. We note in the questions that their answers are very valuable to our research project, and ask them to take the time to respond carefully.

[6] In total, 1,855 respondents went to the survey link. Of those, 242 did not own stocks and 53 were below 25 years of age. 518 respondents failed the attention check. We further drop 31 respondents who did not complete the entire survey, and 150 respondents who completed the survey in less than three minutes. Finally, we drop 7 respondents who state that their portfolio value is 0.

We classify the open-ended text responses into broad categories, and when possible, assign finer categories to each answer. We use a inductive approach to coding the answers, where we start with the data and create codes based on our own categorization. This approach is useful for discovery and hypothesis generation (Haaland *et al.* , 2024). We always have two independent persons categorize the answers, and then work to align the categories together. After deciding on categories, we again have two persons categorize the answers. In the end, we have a third person go over any discrepancies and finish the categorization.

4 Who are the Followers and Recommenders?

Our context of personal financial advice differ from the context in the previous literature, which tends to focus on social interactions in anonymous or pseudonymous relationships online. While we do not observe the exact nature of the interaction in the bank setting 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. Several pieces of evidence in the survey supports this type of interactions: 79 percent of Recommenders in the survey state that people usually reach out to them for advice. 40 percent of Recommenders state that they have frequently provided advice over how to start investing, with 36 percent stating that they frequently provide advice on how to find a brokerage. Alternatively, 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. In this alternative story, the Recommender reaches out to offer advice. 75 percent of Followers state that family and friends usually come to them with advice. Note that the responses of Recommenders and Followers are inconsistent. We find this interesting, but not necessarily a challenge since in either case, there is a close personal relationship between Recommender and Follower.

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. 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 successful recommendations by chance. This is not what we see in our data: very few Recommenders have more than 1 successful recommendation. This is instead consistent with targeted communications with close friends. We have also verified with another large German bank that their recommendation campaign attracts individuals with close relationships. And in the survey, we ask how Recommenders usually provide advice, and only 4 percent state that they frequently post broadly on social media to provide advice. In contrast, 63 percent state that they frequently meet in person or talk on the phone.

4.1 Summary statistics on Followers and Recommenders

We proceed to describe the portfolio and demographic characteristics of Recommenders and Followers. Our goal is to provide a brief overview of the characteristics of investors. In particular, we are interested in proxies for expertise among Followers and Recommenders, in line with the expertise-based transmission view. We will examine the importance of returns in Section 6.

We provide demographic and portfolio summary statistics from the bank-level data in Table 1. The first two columns include 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. 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. Column 6 provides a t-test for differences in means across Recommenders and all investors. We provide summary statistics from the survey in Table 2 and further results in Appendix Table B3. Column 2 and 3 provide results for Recommenders and Followers, respectively, and Column 4 presents results from a T-test of differences in means. Note that the survey results in Table 2 are from 2024, whereas the bank-level data in Table 1 is from 2011-2017. There is naturally a discrepancy in the portfolio values between the data samples.

A striking finding in the bank data is that the average portfolio values (Total AUM) of 58,174 EUR for Recommenders is considerably higher than the average portfolios for Followers (27,864 EUR) and other investors (30,585 EUR). Recommenders also have larger incomes than other investors. Recommenders achieve high risk-adjusted returns as measured by the Sharpe ratio, and are more likely to invest in both active and passive funds than other investors. Their portfolios are also better diversified, as indicated by a lower Relative Sharpe ratio loss. In terms of portfolio composition, we find that they hold 13 securities on average, and that their risky share is higher than other investors but not Followers. Finally, we find that they are less likely to invest in lottery or attention stocks compared to other investors. These results are consistent with the survey results in Table 2: Recommenders in the survey have considerably larger portfolio values compared to Followers, have more experience, rate themselves as having more financial aptitude, and are less risk averse. Recommenders in the survey on average invest 50 percent of their assets into funds, a lower share than Followers.

What about Followers? Examining the portfolio composition in the bank data, Followers hold more securities, have a higher risky share, have higher Sharpe ratio and lower Relative Sharpe ratio losses compared to other new investors. Followers are also more likely to invest in both active and passive funds, and are less likely to hold lottery or attention stocks. In these dimensions, Followers are similar to Recommenders, which could reflect either shared preferences and information sets, or financial advice from the Recommenders. In the survey, Followers are less experienced, with lower portfolio values, financial aptitude, risk aversion, and hold a higher share of their portfolio in funds. About a third of Followers hold only funds, compared to 14 percent of Recommenders.

Overall, the picture that emerges of Recommenders in both settings is of an individual with a large portfolio and considerable experience. They hold a considerable number of assets and invest a large share of their assets into stocks and funds, with relatively high exposure towards the market portfolio. They do not seem to invest a large share into lottery or attention stocks, the types of assets the return-biased view predicts. This profile match what Followers state that they are looking for in the survey. In the open question presented to Followers on what they look for in the person giving financial advice, 36 percent of the 240 respondents mention experience (in some form), 39 percent mention expertise, skill or competence, and 30 percent mention trust. Only 7 percent mention past performance of any kind. A more detailed breakdown of the open-ended questions is available in Table 3, and we discuss these results in more detail in Section 6.2.

5 Identifying personal financial advice in the bank data

This section discusses how we identify personal financial advice by examining the overlap in portfolio composition in the bank data. 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.

5.1 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 k 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 with our bank. 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). Nonetheless, we have examined how using a longer lag affects the overlap share, and find that our results are robust to even a 24-month lag. 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 our setting on portfolio composition to related studies which examine 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.[7] 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.

5.2 Placebo pairs

However, it is still possible that marketing campaigns, formal 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. We select

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

all new investors who join the bank after 2012. We then create the matched pairs by i) randomly matching individual investors and ii) matching each investor to other similar investors based on demographic characteristics, location, wealth, and risky share. This approach allows us to further control for contextual effects and common shocks. 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. Intuitively, this provides an estimate of the rarity of the specific portfolio composition of each Follower.

5.3 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. 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 4 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.

How important is this advice for the individual Follower? Figure 2 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. We further discuss results for Followers who transfer assets and for Followers who use bank advice in the robustness section below.

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 4 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 in the bank data is above the 95th percentile for the placebo overlap in the the most restricted sample.

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 14 percent for the placebo sample.

We interpret these results as evidence that Recommenders provide advice about specific assets that Followers use to form their portfolios. Three separate conditions need to be met for us to observe an overlap: i) the Recommender needs to provide advice on specific securities to invest in, ii) they need to own these securities themselves, and iii) the Follower needs to accepts this advice. Starting with Recommenders in survey data, Table 5 shows that 34 percent frequently provide advice over which specific securities to buy or sell. The share that sometimes or frequently provides advice on what assets to invest is 82 percent. Among Followers, 60 percent state that friends and family were important or very important for which specific securities to buy.

5.4 Robustness and alternative explanations

In this section we discuss several robustness tests, among them a preference for similar stocks, financial advice from the bank or other sources, marketing campaigns, and local stocks.

Preferences for similar stocks. A potential concern is that the overlap results is not derived from financial advice, but rather from a shared preference for a certain type of investment. To examine similar preferences for certain investments, we examine securities that investors transfer from their brokerage account at another bank to our sample 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 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 absorbed by the placebo overlap analysis.

Financial advice from other sources. The placebo overlap analysis is also useful for ruling out a potential formal 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, Appendix Figure C1 shows that the overlap share is almost identical across all Followers (marked with a solid orange line) and for Followers who do not receive advice (green dashed line), highlighting that financial advice explains very little of the overlap share. We corroborate this finding in Figure 4, where we show that the overlap share is not explained by bank advice, 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. This positive coefficient is also plausible related to the closeness of the relationship, meaning that it may not necessarily reflect an omitted variable. Indeed, the placebo matches on ZIP-codes is indicative that geographic proximity by itself is not sufficient to generate an overlap.

6 What determines providing and receiving advice?

In this section we study what determines the likelihood of providing and receiving advice. There are two competing hypothesis. The first hypothesis is that providing and receicing advice is related to returns: In return-biased transmission modeled in Han *et al.* (2022), the Recommender's decision to give financial advice is an increasing function of returns.

The Follower's propensity to follow the advice is also related to returns. The second hypothesis in the expertise-based transmission view is that Recommenders with more expertise are more likely to provide personal financial advice, and that Followers look for individuals with expertise to share.

6.1 Providing advice by Recommenders

We begin by studying Recommenders, and what determines their likelihood of sending financial advice. As noted in Section 4.1, Recommenders are positively selected on several proxies for expertise in both bank and survey data, including financial aptitude, portfolio values, and experience. We include two other pieces of evidence from the survey to test the assumptions of the return-biased transmission. First, 75 percent of Recommenders state that they are always willing to share their financial results with family and friends. Only 8 percent state that they share when results are good. Second, 79 percent of Recommenders state that family and friends come to them directly, as opposed to the Recommender reaching out to them. These responses are inconsistent with the self-enhancing transmission bias in Han *et al.* (2022), where the probability of *sending* advice is positively related to returns.

We now turn to the bank-level data to investigate whether returns are related to providing recommendations. We use the bank data to test what determines the *timing* of Recommendations, which provides a test of return-biased transmission. Under this hypothesis, Recommenders would provide recommendations in periods where they earn high returns. The idea behind studying the timing is that the two hypotheses described above are not mutually exclusive: an expert Recommender could be providing advice only when they experience high returns. By focusing on the timing of the decision, we can hold the quality of the Recommmender constant. We also examine the cross-section in Appendix Table B2, i.e. whether individuals with high portfolio quality are more likely to recommend the bank. The results consistently show little evidence that recommendation of the bank is related to returns. Of course, this does not invalidate the importance of returns in other settings, but instead highlights that other types of advice may appear in the type of social setting that we are operating in.

We empirically model the decision to provide advice by examining the probability of recommending the bank for all Recommenders:

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

where $R_{i,t}^R$ and $Q_{i,t}^R$ 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. The first three columns select all Recommenders (approximately 4,000 individuals in total), and the last three columns select Recommenders who are in our main overlap sample (approximately 500 individuals).

Overall, the results presented in Table 6 do not suggest that returns drive the decision to recommend. 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. Finally, the regressions in Table 6 include controls for portfolio quality. Both Return loss and relative Sharpe Ratio loss are insignificant, showing that variation *over time* in portfolio quality did not correlate with the decision to recommend. In Appendix Table B2 we show that in the cross-section, portfolio quality is a strong predictor of being a Recommender.[8] These results are also robust to using past returns, i.e. the portfolio return in period $t = \{-6, ..., -1\}$. The results are also robust to using other measures of returns instead of the average returns, such as the the 95th percentile.

We have provided evidence from both stated and revealed preferences that returns do not drive the decision to provide financial advice in personal relationships. Instead, the evidence is more in line with Recommenders being positively selected on expertise. We note that the evidence for the self-enhancing transmission bias is often based on

[8]In Table B2 , we regress 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.

anonymous or distant relationships between individuals (e.g. online social networks in Heimer & Simon (2015) and Ammann & Schaub (2021)). Compared to these settings, individuals may not be susceptible to the same kind of biases when providing personal financial advice to family and friends. A possible explanation for differences between the previous literature and our setting is that we are examining different types of relationships with different incentives. The responses to the open questions for the group that stated that they neither receive or provide advice in the survey is revealing in this respect. One respondent, who was asked what advice they would provide to family and friends, stated that "I do not give any advice regarding investments in securities as this is a very sensitive topic. After all, losses can occur and then you will be held partly responsible for them." Another respondent writes "I don't give advice to friends and relatives. I don't feel safe enough to do so." In comments to specific advice about investing in a single stock that has experienced a high return in the past six months, described in Section 7, one Recommender writes "I don't recommend any specific stocks. Why? If the recommendation goes well, everything is fine. If price losses occur, the friendship often suffers,' and another Recommender writes " I wouldn't give such tips [over an investing in a single stock that has done well] because I don't want to be responsible if things go wrong." This example illustrates that at least some Recommenders perceive different incentives for financial advice for family and friends. A contribution of our study is to emphasize that personal financial advice to family and friends are subject to different considerations and incentives compared to advice on social media.

6.2 Receiving advice by Followers

We now move on to studying what determines the likelihood of accepting financial advice by Followers. In an open question presented to Followers early in the survey and detailed in Table 3, Followers state that they look for experience (36 percent), 39 percent mention expertise, skill, or competence, and 30 percent mention trust. One person writes "I make sure that the person is giving advice selflessly and that I trust the person based on a long-term personal relationship." Little mention is made of returns in the open question. In a follow up question, we first ask, on a scale of 1-5, how important it is that the provider of the advice is knowledgeable and how important it is that the provider has high returns. 72 percent state that it is very important or extremely important that the provider is knowledgeable, whereas 41 percent state that it is very important or extremely that the provider has high returns. A t-test of differences in means shows that this difference of

0.77 is highly statistically different (t-value of 11.13). Summary statistics on this and other questions are available in Table 7.

In the bank data, we empirically model the decision of Follower f to follow advice within a period of 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 6. 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 8 shows that 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 again 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 5 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. These results also extend to active returns (panel b) and total portfolio returns (panel c).

We now 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.[9] Column 4 and 5 in Table 8 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.

The picture we draw from the survey responses are of a clear and deliberative process of evaluating financial advice. Respondents seem aware of potential conflicts of interest and the importance of expertise, but seem less focused on finding Recommenders who have made high returns in the past. Some respondents explicitly mention the importance of personal relationships and no conflicts of interest. The bank-level data shows that following advice in this setting is not related to returns, but is instead related to measures of portfolio quality.

7 Personal financial advice and portfolio choice

We now examine personal financial advice over specific securities. 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

[9] Calvet *et al.* (2007) show that we can write Return loss as a function of the relative Sharpe ratio loss.

their better-performing stocks and that this leads to the spread of high-variance, high-skewness stocks. 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 begin by presenting evidence from the survey, and then move on to the bank level data. In the survey, we use a combination of open-ended questions, quantitative questions and hypothetical scenarios.

7.1 Survey evidence on what Recommenders recommend

We ask respondents who state that they usually provide advice a number of questions related to what advice they provide. The first (open) question we ask Recommenders is to describe the financial advice that they provide to family and friends in their own words. We note that this is an important question for our research project and do not prime subjects on returns or expertise.

The results show that financial advice to family and friends encompasses a number of different topics. 33 percent of Recommenders have provided advice on funds or ETFs, and 30 percent have provided advice on single stocks. 44 percent have provided more generic advice on general concepts and strategies, 17 percent have recommended a trading platform or provider.

We also ask closed questions on how likely the respondent would be to recommend a) a fund or b) a single stock on a scale of 1-5. Respondents are more likely to recommend an investment in a fund rather than a single stock. The difference in the mean response is 0.46 and is significant at the 1 percent level ($t = 4.49$). If we cross-tabulate the responses, 16.34 percent of respondents would recommend both funds and stocks (defined as a value of 4 or 5 on the scale), 36.34 percent recommend only funds, 21.69 would recommend only stocks, and 25.63 would recommend neither. Out of the respondents who state that they would recommend funds, 69 percent would only recommend funds. We find limited heterogeneity depending on portfolio values or returns in in Figure 6. Respondents are more likely to recommend funds, regardless of portfolio values. We note that the 33 respondents who report either very low or very high returns are more likely to recommend stocks than funds. These respondents hold a higher share of single stocks in their portfolios.

To see how Recommenders view and think about different types of advice, we conduct an exercise where we randomly present personalized vignettes to respondents. To examine potential differences in advice adherence by gender, we vary the name of the person randomly between Emily and Jonas. For one group, we provide them with the following example: "For example, Emily tells a story of how one of her investments had done really well lately, and how she told her friends to invest in the same stock." The other example is "For example, Emily told us that when her friends ask her where to invest their spare money, she always recommends them to invest their money into an index fund that covers multiple regions and that has low management fees." On a scale of 1-5, we then ask respondents to evaluate the advice based on how similar it is to the advice that they would give, how comfortable they would be to provide the same advice, whether the advice would generate lower or higher returns than the stock market, how risky the advice is, how confident they are that this is the best advice, and whether they think their friends would follow the advice. For each question, we evaluate differences across the stock example and the fund example using a regression:

$$y_i = \alpha + \beta FundExample_i + \epsilon_i \tag{4}$$

We present the results in Figure 7. Each line in the figure is a coefficient from a separate regression. The results show that Recommenders who see a vignette related to index funds rate the advice as more similar to what they would provide and that they would be more comfortable with the fund advice relative to the stock advice. There are no significant differences in expected returns between the two examples, but the fund example is perceived as less risky. Finally, Recommenders are more confident that the fund advice is the best advice, and believe that their friends would be more likely to follow this advice.

We also allow respondents to comment on the vignettes. The answers to the vignette with advice to invest in a single stock with high returns in the past are especially informative. Six of the 26 responses for the single stock vignette mention that such advice is risky, and six responses state that they need more information about the company or about the friend that they are making the recommendation to. One person writes "I don't recommend any specific stocks. Why? If the recommendation goes well, everything is fine. If price losses occur, the friendship often suffers', and another writes "I wouldn't give such tips because I don't want to be responsible if things go wrong."

7.2 Survey evidence on the advice given to Followers

We now move on to evaluating the advice that Followers state that they have received. We first ask Followers to write in their own words what financial advice they have received from family and friends. Panel B of Table 3 provides the results. 28 percent of Followers in the survey report, in their own words, that they have received advice to invest in ETFs/funds, and 19 percent report that they have been adviced to invest in stocks. The most common reponse is instead related to general investment advice (33 percent). Only 7 percent of respondents mention any version of returns in the advice that they have received.

We also ask Followers if they have received advice on investing in funds or stocks, and whether they would be likely to follow such advice. We ask respondents whether they have ever received advice to invest in stocks and funds, and whether they have followed such advice. The possible answers are Never, Sometimes and Frequently, coded on a scale of 1-3. Respondents are more likely to have receive advice to invest in funds than in stocks (difference= .26, t-test = 4.6), and are also more likely on average to have followed such as advice (difference= .2, t-test = 3.4).

We present the results from the vignette experiment in Figure 8. For one group, we provide the following example: "Emily told us that a good friend of hers had earned a high return on a company stock in the past 6 months. Emily's friend suggested that she should buy the same stock". The other example is "Emily told us that a good friend of hers recommended that Emily should invest in a low-cost an index fund that covers multiple regions and that has low management fees". We again randomly vary the name in the example. We then ask respondents if they received similar advice, whether they think this advice would generate lower or higher returns than the index, how risky the advice is, how seriously they would consider similar advice themselves, whether they would implement such advice, and how competent they view the provided advice to be.

Recall that a positive coefficient means that the respondents who receive the fund example has a more positive response. For example, the first coefficient shows that respondents who receive the fund example are 0.87 points more likely to state that they have received similar advice compared to the respondents who received the single stock example. The average score for receiving similar advice is 3.4 for the fund example and 2.5 for the single stock example. The fund example is also rated as having a higher expected return and less risk. Finally, respondents are more likely to seriously consider the fund advice, perceive it as more competent and are more likely to implement such advice. Overall, the results indicate that Followers are more positively predisposed towards advice related to funds, evidence consistent with the expertise view of advice.

We also ask respondents if they have any comments about the different examples. We received 11 comments for the fund example and 26 comments for the stock example, out of 237 total responses. Several respondents add that one should do their own research and that trust in the person providing advice is important. Many comments for the single stock example ask for more detail about the investment, the friendship, or about Emily/Jonas. Overall, the comments imply that Followers in the survey critically evaluate the individuals providing advice. The evidence and comments in the survey appear to point toward a deliberative process of evaluating information received from others, and a particular attention on the trustworthiness and competency of the person providing advice.

7.3 Personal financial advice in the bank data

We now turn towards the bank level data. We begin by examining the correlation in investment strategies of Recommenders and Followers. 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:

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

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. 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 × region fixed effect to account for differences across regions and time. Finally, we use robust standard errors.

We examine the full portfolio of the Follower instead of 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.

Table 9 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. In Appendix Table B4, we further show that shows that Recommender participation in a specific asset class generally implies a crowding-out effect on participation in *other* asset classes.[10]

[10]Each cell in the table represents a separate regression, where the dependent variables are listed in

It is also worth exploring the control variables in the regression. Noteably, the coefficient on bank advice, a control variable that measure the bank influence on asset choice, is only a third of the size of Recommender participation. 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.

The above results focused on how Recommenders affect the portfolio decisions of Followers. In Appendix Table B5 we show that compared to other investors, Followers are 3.8 percentage points more likely to invest in funds compared. 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. Followers are not more likely to invest in lottery or attention stocks compared to other new investors 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.[11]

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. In general, both the survey and the

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 9, 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.

[11]Specifically, we estimate the following equation to examine participation in different assets classes of Followers compared to other investors: $Participation^j_{i,k,t} = \alpha + \gamma Follower_{i,k,t} + \mathbf{X'_{i,k,t}}\beta + \delta_{i,k} + \epsilon_{i,k,t}$, 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 (5). Panel A examines the participation rate (extensive margin), while Panel B states the conditional investment in each specific asset type.

bank-level data are consistent with Recommenders being inclined to recommend assets with desirable characteristics to their friends.

8 Further survey evidence

In this section we provide additional survey evidence. We start by examining *who* Followers ask for financial advice. Friends and family (51 percent) are more common sources to turn to than internet and social media (13 percent) and professional advisers (20 percent). There is a natural age effect in the use of social media and professional advisors, shown in Figure 9, but friends and family are the most important sources for financial advice across all age groups. Family and friends are naturally more inclined to provide self-less advice, and involve more complex relationship with a greater basis in trust than e.g. financial advisors, who are trying to sell something.

We also ask respondents how they usually provide advice. The predominant form of providing advice is to talk in person: 98 percent sometimes or frequently meet in person or talk on the phone to provide advice. 30 percent of respondents write personal messages on social media platforms, and 15 percent post broadly on social media. Interestingly, respondents who state that they post broadly on social media are *more* likely to say that they would recommend investing in funds to their family and friends (67 percent of social media Recommenders say that they would recommend funds, versus 50 percent of non-social media Recommenders). Finally, 79 percent of Recommenders state that people to come them for advice, as opposed to them reaching out to others.

We also ask respondents whether they have provided advice on a number of different topics. The statistics for all questions are available in Table 5, and here we simply note that 94 percent of Recommenders have sometimes or frequently provided advice on how to start investing and how to find a brokerage. Related to our bank analysis, a plausible scenario for how individuals come to appear in our data is that a Follower reaches out a knowledgeable investor and asks for their financial advice. The Recommender then advises on how to open a brokerage account and makes a recommendation over what type of assets to buy. Although this is not conclusive evidence for such a channel, this scenario is consistent with the survey evidence and the bank-level evidence.

Looking at the specific advice that respondents receive, most respondents have received advice on how to start investing (94 percent) or open a brokerage account (91 percent). In contrast to the results for the Recommenders, 73 percent state that people usually come to the respondents with advice. Recall that Recommenders stated mostly that people come to them for advice.

9 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 40 have used TikTok for personal finance advice, a clear sign that many Americans are enthusiastic about finance and investing. This type of advice 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. While not all advice provided on social media is bad, there are many social media accounts that promote get-rich-quick or pump-and-dump 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 social media.

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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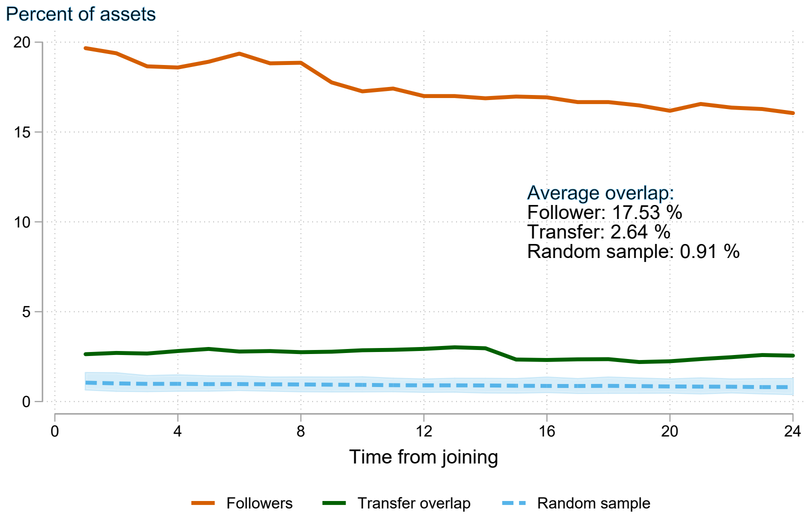
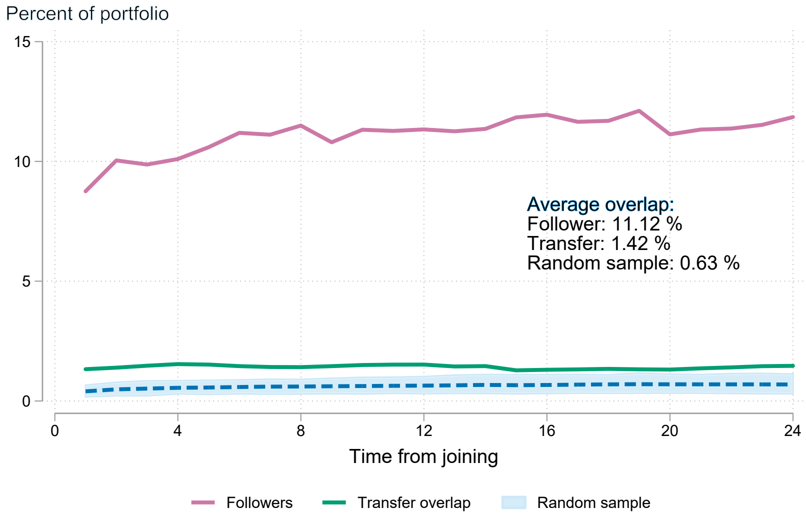
10 Figures



(a) Number of assets



(b) Number of assets

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.

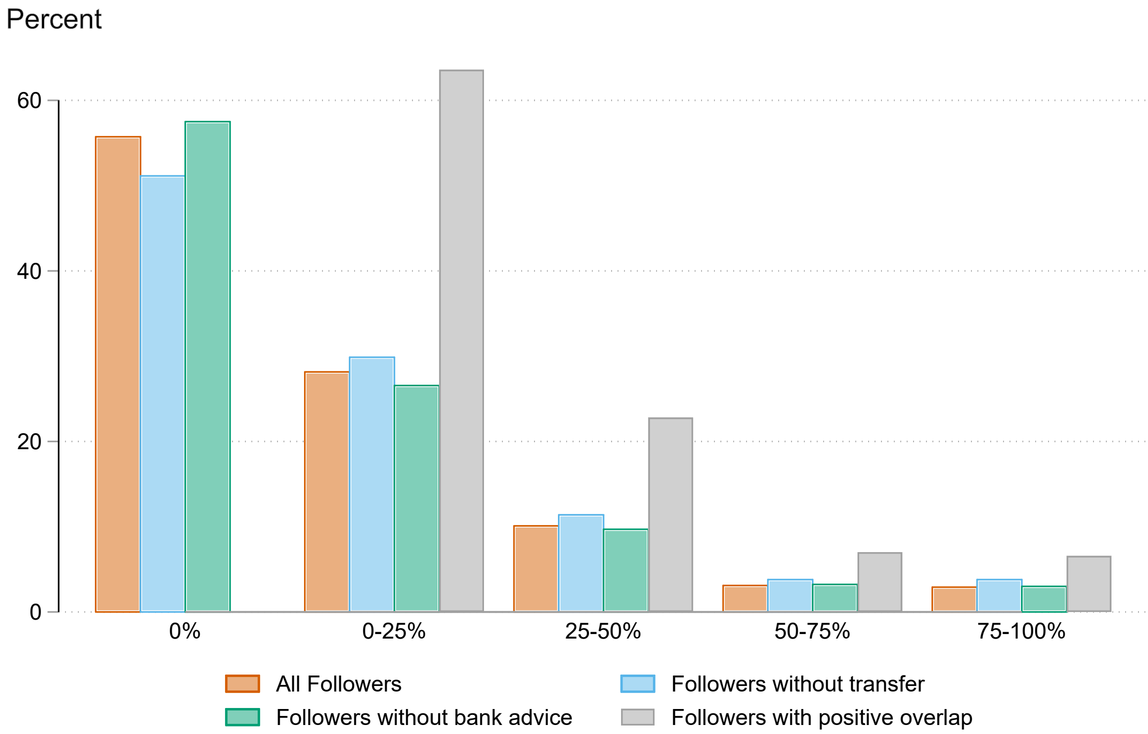


Figure 2: Overlap for selected samples

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.

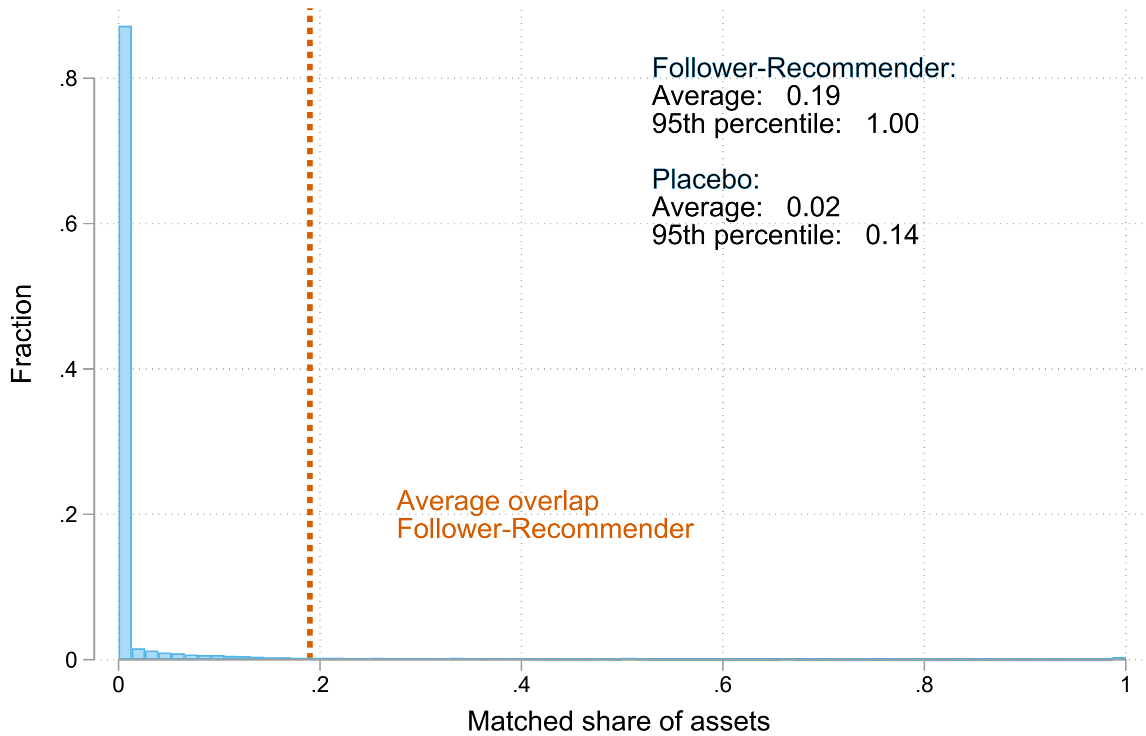


Figure 3: Overlap with all investors

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.

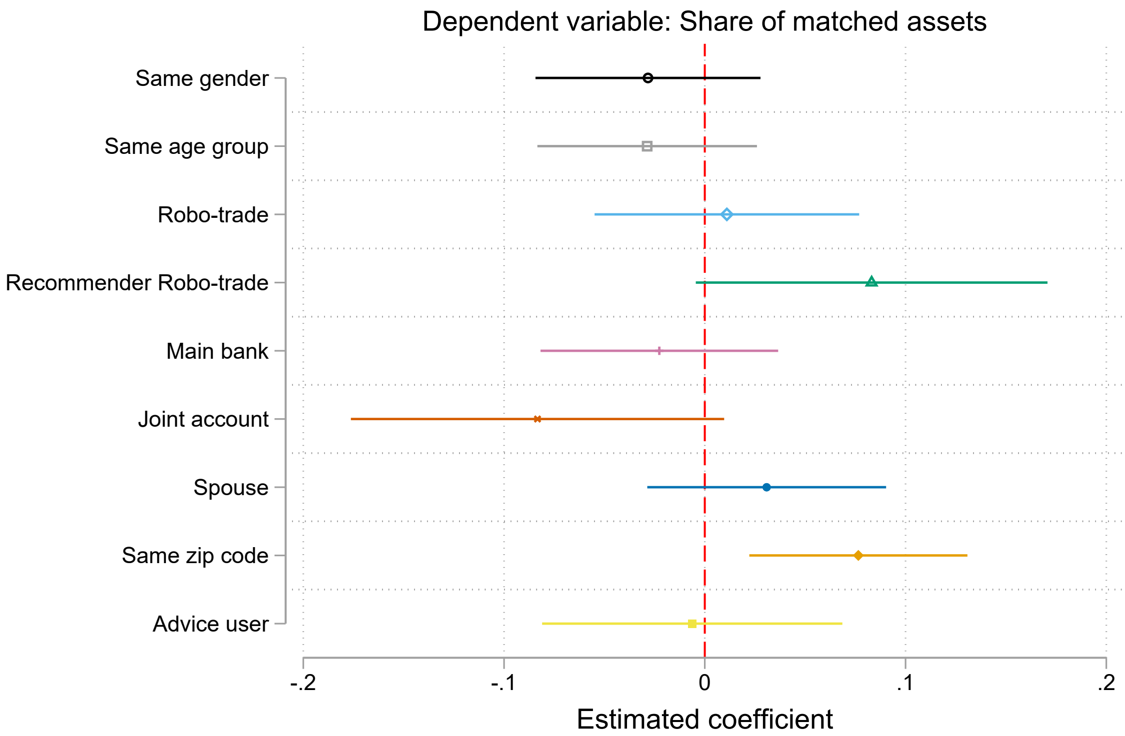
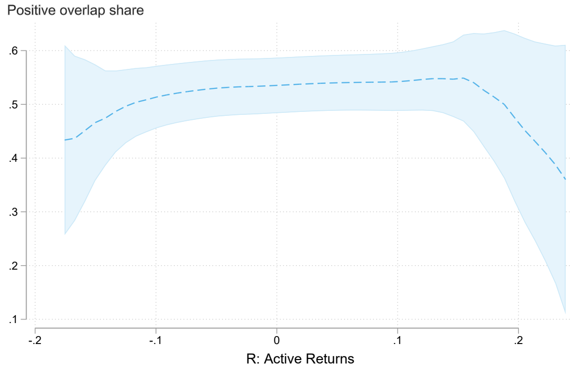


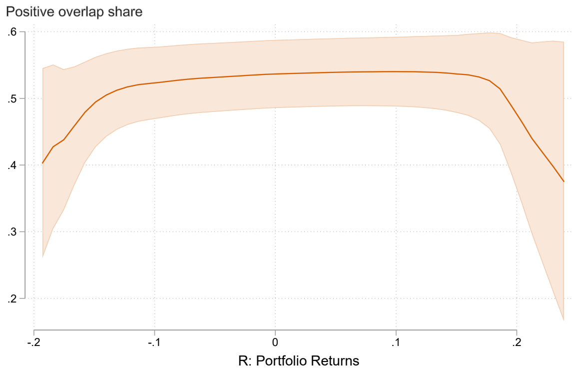
Figure 4: Determinants of overlap

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).

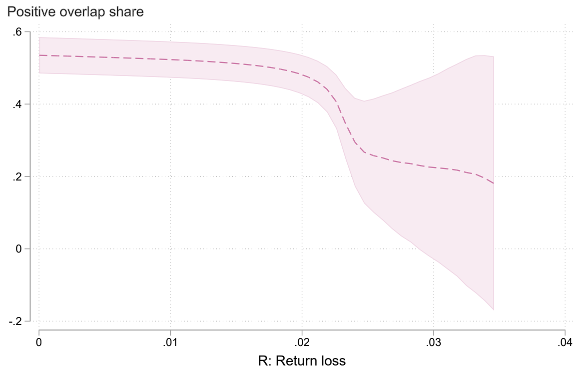
(a) Passive



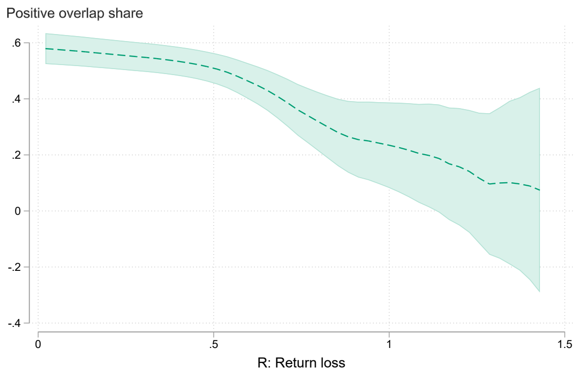
(b) Active



(c) Portfolio



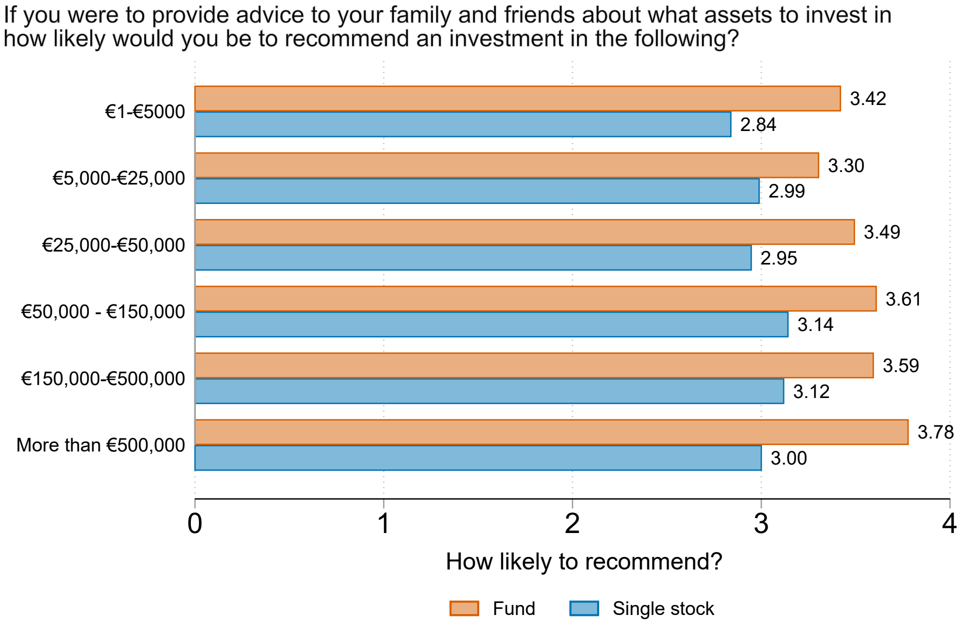
(d) Return Loss



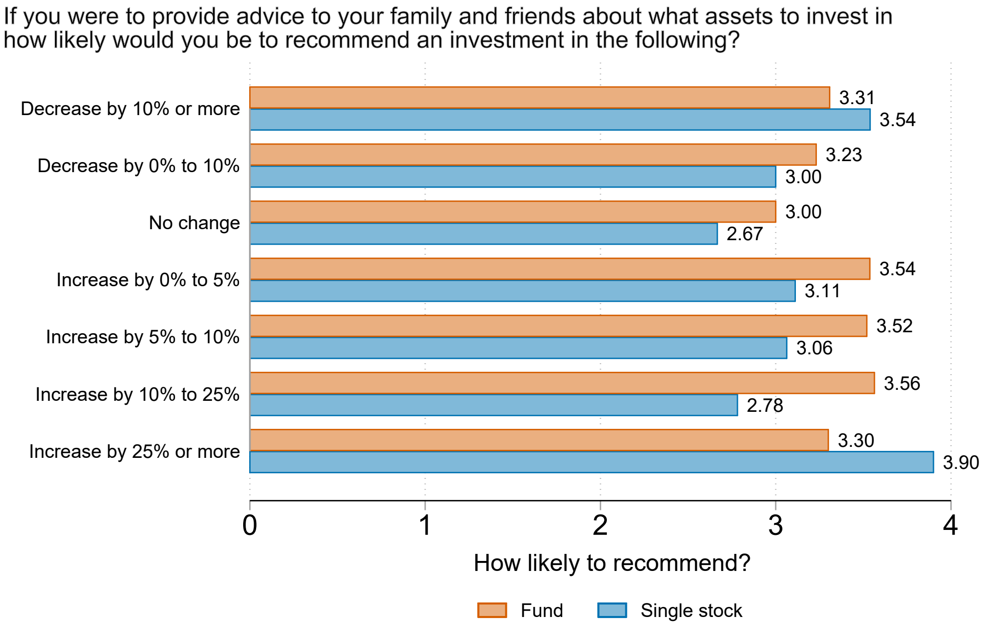
(e) Relative Sharpe Ratio loss Loss

Figure 5: 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.



(a) Portfolio value



(b) Portfolio returns

Figure 6: Survey evidence on what Recommenders would recommend

Notes: We ask respondents how likely they are to recommend an investment into i) a single stock ii) a mutual fund, on a scale of 1 to 5, where 1 is very unlikely to recommend and 5 is highly likely to recommend. The figure plots the average value for each question, split by portfolio value in panel a) and portfolio returns in panel b). We select only individuals who state that they usually provide advice. The full question is "If you were to provide advice to your family and friends about what assets to invest in, how likely would you be to recommend an investment in the following?".

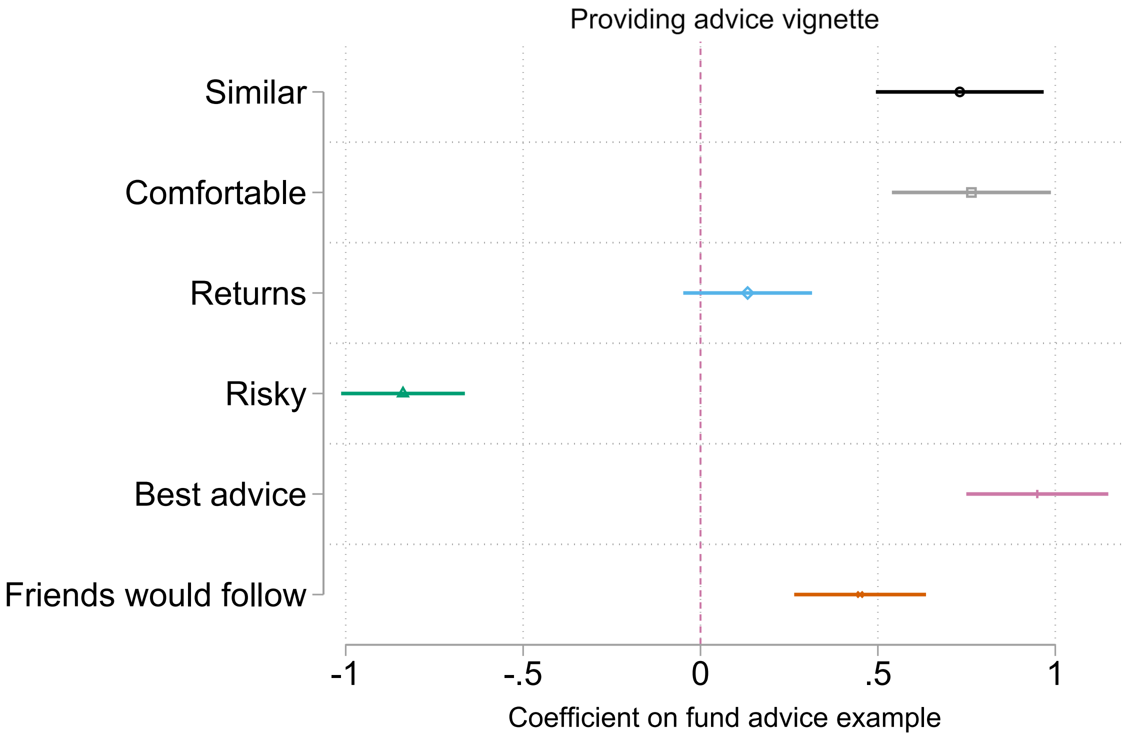


Figure 7: Recommender vignettes

Notes: The figure reports results from a regression: $y_i = \beta FundVignette + \epsilon$, where y_i is a variable listed on the y-axis in the figure. We randomize respondents to one of two vignettes described below, and report the coefficient on the fund example. The estimated coefficient in the figure is therefore the difference in the mean answer between the single stock and fund vignette. We select only respondents who state that they usually provide advice. In the single stock vignette, the example is "Emily tells a story of how one of her investments had done really well lately, and how she told her friends to invest in the same stock". In the fund vignette, the example is "Emily told us that when her friends ask her where to invest their spare money, she always recommends them to invest their money into an index fund that covers multiple regions and that has low management fees". We randomize the names of the individuals in the vignette between Emily and Jonas. We ask respondents to evaluate the advice on a scale of 1-5 on the following criteria: i) How similar is Emily's advice to the advice that you would give to your family and friends? ii) Would you be comfortable giving the same advice as Emily to your friends? iii) Do you think Emily's advice is likely to generate higher or lower returns than the stock market index? iv) How risky do you think Emily's advice is? v) How confident are you that this is the best advice? vi) Do you think your friends would follow Emily's advice?

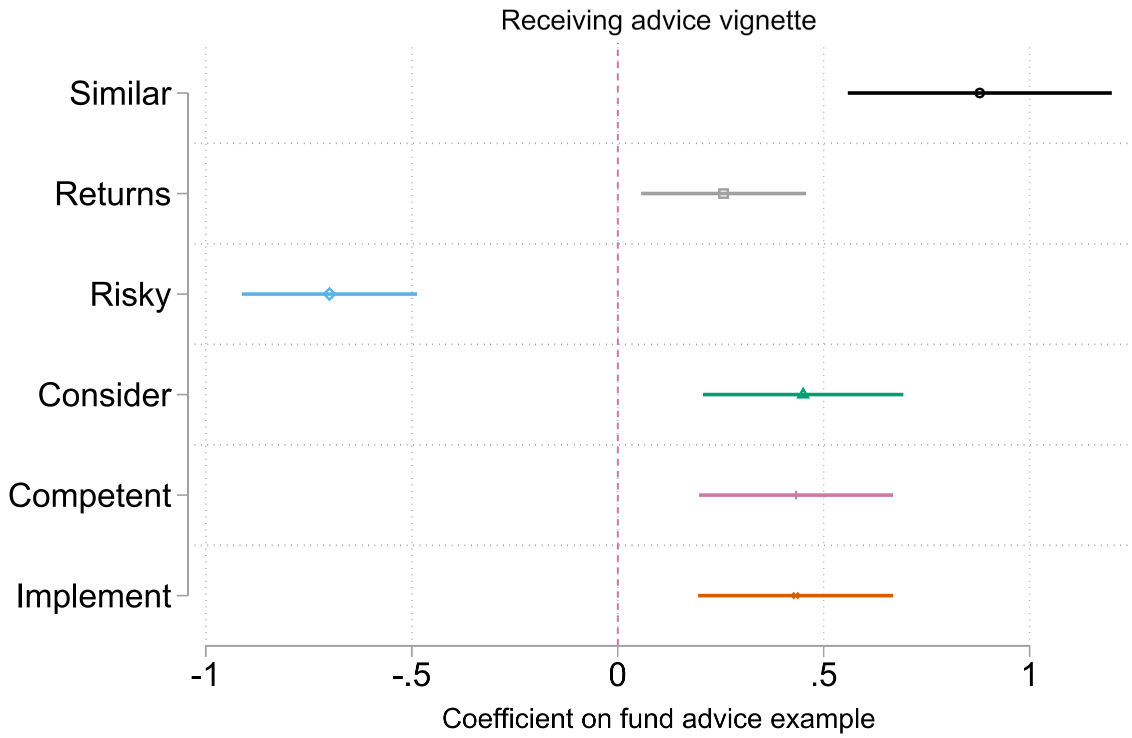


Figure 8: Follower vignettes

Notes: The figure reports results from a regression: $y_i = \beta FundVignette + \epsilon$, where y_i is a variable listed on the y-axis in the figure. We randomize respondents to one of two vignettes described below, and report the coefficient on the fund example. The estimated coefficient in the figure is therefore the difference in the mean answer between the single stock and fund vignette. We select only respondents who state that they usually receive advice. In the single stock vignette, the example is "Emily told us that a good friend of hers had earned a high return on a company stock in the past 6 months. Emily's friend suggested that she should buy the same stock. " In the fund vignette, the example is "Emily told us that a good friend of hers recommended that Emily should invest in a low-cost an index fund that covers multiple regions and that has low management fees. " We randomize the names of the individuals in the vignette between Emily and Jonas. We ask respondents to evaluate the advice on a scale of 1-5 on the following criteria: i) Have you received similar advice to Emily? ii) Do you think the advice from Emily's friend is likely to generate higher or lower returns than the stock market index? iii) How risky do you think the kind of advice that Emily received is? iv) How likely would you seriously consider the advice provided in such a situation? v) In your opinion how competent is the advice provided? vi) How likely would you implement the advice provided in such a situation?

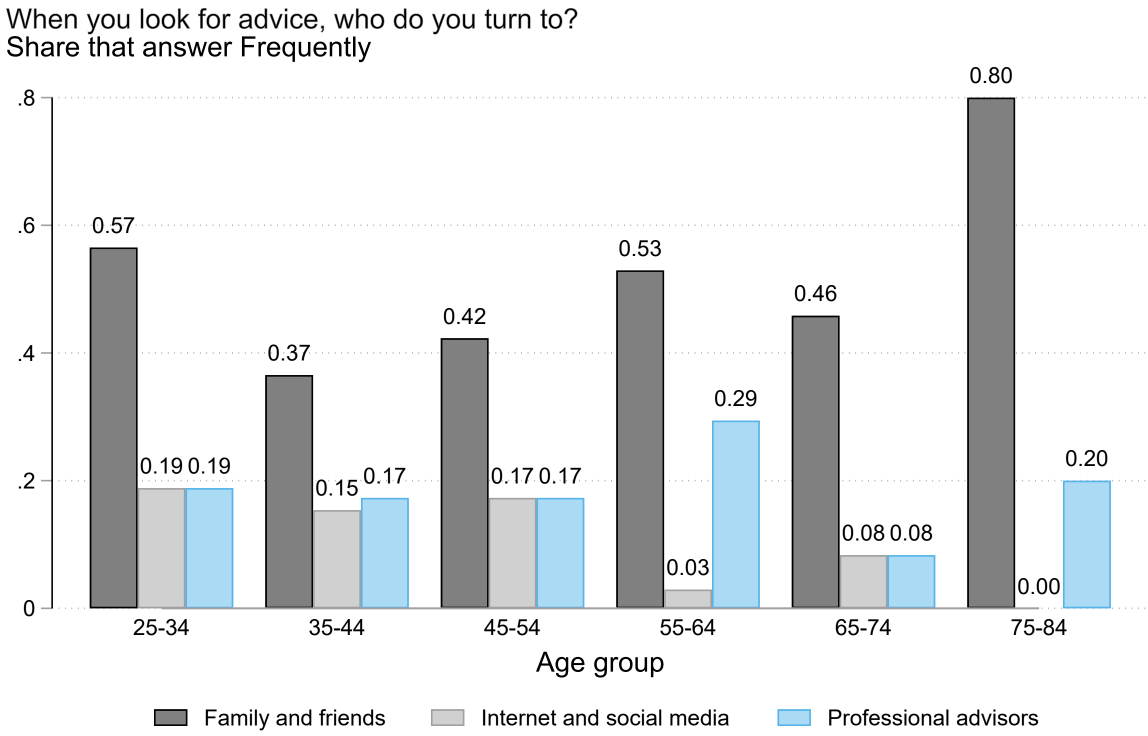


Figure 9: Who do you turn to for financial advice?

Notes: The figure plots the share of respondents who answers that they frequently turn to Family and Friends, Internet and Social media, or Professional advisors. We split the results by age. We select only respondents who say that they usually receive advice. In the survey, we ask respondents “When you look for advice, who do you turn to?” The potential answers are “Never”, “Sometimes” and “Frequently”.

11 Tables

Table 1: Descriptive statistics from bank data

Notes: This table reports the descriptive statistics for using bank data. 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). Column 3 and 6 present the differences in means between groups, where t-statistics are reported in brackets. 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: Descriptive statistics on survey respondents

Notes: This table reports the descriptive statistics for the survey respondents. The first column presents results for respondents who state that they neither provide nor receive advice from family and friends, the second column presents results for respondents who state that they usually provide advice (Recommenders) and the third column provides results for respondents who state that they usually receive advice (Followers). Column 4 provides present the differences in means between Followers and Recommenders (Column 2 minus Column 3), where t-statistics are reported in brackets.*, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

	(1) Neither receive nor provide	(2) Recommender	(3) Follower	(4) Diff 2-3
Investor characteristics				
Portfolio value (EUR)	69,118.94	104,886.69	40,700.43	64,211.68***
	(108,642.04)	(126,595.73)	(73,577.19)	[7.08]
Experience in years	6.93	7.34	5.25	2.09***
	(3.20)	(3.05)	(3.28)	[7.85]
Portfolio return	6.88	10.13	4.41	5.70***
	(10.08)	(12.17)	(12.46)	[5.53]
Financial aptitude (1-5)	3.27	3.90	3.16	0.75***
	(0.71)	(0.67)	(0.75)	[12.72]
Risk attitude (1-5)	2.67	3.36	2.64	0.73***
	(1.00)	(0.94)	(0.97)	[9.13]
Probability stock prices higher	38.93	50.62	39.79	11.05***
	(31.86)	(29.00)	(29.40)	[4.53]
Expected return	6.77	8.70	7.90	0.81
	(5.92)	(8.43)	(7.90)	[1.17]
Would invest in new popular investment (1-5)	2.71	3.20	3.19	0.01
	(0.75)	(0.77)	(0.69)	[0.19]
Portfolio composition				
Share stocks	27.09	34.21	23.45	11.24***
	(34.17)	(32.11)	(31.77)	[4.20]
Share funds	63.79	50.14	63.33	-13.61***
	(37.20)	(33.82)	(35.82)	[-4.69]
Share bonds	3.57	4.10	3.85	0.22
	(12.34)	(9.39)	(12.51)	[0.25]
Share currencies	0.04	2.07	0.85	1.20**
	(0.66)	(6.63)	(3.39)	[2.58]
Share derivatives	4.52	5.22	3.89	1.47
	(15.13)	(12.48)	(11.85)	[1.43]
Share crypto	0.98	4.26	4.62	-0.52
	(5.17)	(11.07)	(12.49)	[-0.53]
When are you willing to share your financial results?				
Share when results are good	0.03	0.08	0.10	-0.02
	(0.17)	(0.27)	(0.30)	[-0.90]
Share when results are bad	0.01	0.02	0.02	-0.00
	(0.09)	(0.14)	(0.15)	[-0.12]
Always share	0.33	0.75	0.56	0.19***
	(0.47)	(0.43)	(0.50)	[4.90]
Never share	0.63	0.16	0.32	-0.17***
	(0.49)	(0.36)	(0.47)	[-4.86]
Observations	227	353	232	592

Table 3: Survey evidence from open-ended questions

Notes: The table presents results from the open-ended questions. Panel A summarizes responses for the question what respondents look for in the person providing financial advice ("In your own words, what do you look for in the person you receive advice from?"), Panel B summarizes responses on what advice Followers have received ("What kind of advice have you received about investments in stocks and funds from your family and friends? "), and Panel C summarizes responses on what advice Recommenders provide (" Please describe what kind of advice you would give about investments in stocks and funds to your family and friends. Please also motivate why you would give this kind of advice. "). We remove all respondents who answer that they neither provide nor receive advice.

Panel A: What do you look for in the person providing advice?

Broad category	Subcategory	N	Percent
Experience	Experience (all forms)	86	0.36
	Has/knows ETFs/stocks	26	0.10
Skills	Expertise/competence/knowledge (all forms)	94	0.39
	Can explain well/plausible	9	0.03
	Works in fin industry	17	0.07
	Watches/researches markets	4	0.01
	Good judgement regarding my own circumstances	8	0.03
Trust	Trust (all forms)	73	0.30
	Personal relationsship	27	0.11
	No conflict of interest	10	0.04
	Family only	4	0.01
	Reliable source	10	0.04
Success	Past performance	17	0.07
	Has built wealth/Successful life	9	0.03
	Promised performance	3	0.01
Other	Other	22	0.09

Panel B: What advice have you received?

Broad category	Subcategory	N	Percent
Which security to buy	Fund/ETF	68	0.28
	Stock	46	0.19
	General	52	0.21
	Other	14	0.05
Recommendation	General investment advice	80	0.33
	Diversification	11	0.04
	Returns	18	0.07
	Practical advice	34	0.14
	Other	13	0.05

Panel C: What advice have you provided?

Broad category	Subcategory	N	Percent
Which security to buy	Single Stocks	107	0,30
	Funds/ ETFs	118	0,33
	Other asset classes	17	0,04
General advice	General concepts and strategies	158	0,44
	Explicitly: diversification	27	0,07
	Explicitly: encouragement to learn	23	0,06
	Which provider to select	63	0,17
	Which opportunities to seize (timing, industry. . .)	30	0,08
	Other	33	0,09

Table 4: 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 5: Summary statistics for Recommenders in the survey

Notes: The table reports descriptive statistics from the survey respondents who state that they usually provide advice.

	Mean	Std. dev	Median	Min	Max
How likely (1-5) would you be to recommend an investment in the following?					
Recommend single stock	3.07	1.34	3.00	1.00	5.00
Recommend fund	3.52	1.20	4.00	1.00	5.00
What kind of financial advice? Share that answer Frequently					
Start investing	0.40	0.49	0.00	0.00	1.00
Find brokerage	0.36	0.48	0.00	0.00	1.00
How much to invest	0.29	0.45	0.00	0.00	1.00
Which share to invest in different asset classes	0.39	0.49	0.00	0.00	1.00
Which specific securities to buy or sell	0.34	0.48	0.00	0.00	1.00
When to buy or sell	0.27	0.44	0.00	0.00	1.00
How to invest in funds	0.28	0.45	0.00	0.00	1.00
Information about a promising company	0.29	0.46	0.00	0.00	1.00
How do you usually provide advice?					
Meeting in person / talk on the phone	0.63	0.48	1.00	0.00	1.00
Write personal messages on social media platforms	0.07	0.25	0.00	0.00	1.00
Post broadly on social media	0.04	0.19	0.00	0.00	1.00
Do you reach out to give advice or do family and friends come to you?					
Peple come to me directly.	0.79	0.41	1.00	0.00	1.00
Who do you provide advice to? Multiple answers possible					
Parents	0.33	0.47	0.00	0.00	1.00
Spouse	0.46	0.50	0.00	0.00	1.00
Sibling	0.38	0.49	0.00	0.00	1.00
Extended family member	0.44	0.50	0.00	0.00	1.00
Co-worker	0.38	0.49	0.00	0.00	1.00
Friend	0.72	0.45	1.00	0.00	1.00
Neighbor	0.07	0.26	0.00	0.00	1.00
Anonymous people on the internet (e.g. on LinkedIn or Facebook)	0.02	0.13	0.00	0.00	1.00
Other	0.05	0.23	0.00	0.00	1.00
None	0.00	0.05	0.00	0.00	1.00
Friends on the internet	0.05	0.21	0.00	0.00	1.00
Observations	333				

Table 6: The importance of returns for providing advice in bank data

Notes: The table uses bank data to estimate the importance of returns for providing advice. 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*		0.0116	0.0117	
	(0.0000)	(0.0000)		(0.0117)	(0.0118)	
Passive returns			0.0130			0.0067
			(0.0107)			(0.0115)
Active returns			0.0017			0.0202
			(0.0027)			(0.0132)
R: Log Return loss		-0.0004	-0.0004		-0.0004	-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 7: Summary statistics for Followers in the survey

Notes: The table reports descriptive statistics from the survey respondents who state that they usually receive advice.

	Mean	Std. dev	Median	Min	Max
General advice questions					
I have someone who can provide good financial advice	0.80	0.40	1.00	0.00	1.00
I need advice (1-5)	3.91	0.82	4.00	1.00	5.00
Advice and willingness to follow. Share that answer Frequently					
Receive single stock	0.09	0.29	0.00	0.00	1.00
Receive Fund	0.25	0.44	0.00	0.00	1.00
Would follow single stock	0.15	0.36	0.00	0.00	1.00
Would follow fund	0.23	0.42	0.00	0.00	1.00
How important (1-5) is it that the provider of the advice...?					
is knowledgeable	4.04	0.85	4.00	2.00	5.00
has high returns	3.29	1.03	3.00	1.00	5.00
How important (1-5) was family and friends for the following decisions?					
Start investing	3.43	1.14	3.00	1.00	5.00
Find brokerage	3.38	1.30	3.00	1.00	5.00
How much to invest	3.17	1.32	3.00	1.00	5.00
Which share to invest in different asset classes	3.57	1.14	4.00	1.00	5.00
Which specific securities to buy or sell	3.72	1.14	4.00	1.00	5.00
When to buy or sell	3.46	1.22	4.00	1.00	5.00
How to invest in funds	3.34	1.26	4.00	1.00	5.00
Information about a promising company	3.31	1.21	3.00	1.00	5.00
Do you reach out for advice or do family and friends come to you?					
People usually come to me with advice	0.75	0.44	1.00	0.00	1.00
When you look for advice, who do you turn to? Share that answer Frequently					
Friends and Family	0.51	0.50	1.00	0.00	1.00
Internet and social media	0.13	0.33	0.00	0.00	1.00
Professional advisors	0.20	0.40	0.00	0.00	1.00
How do you usually receive advice? Share that answer Frequently					
Meeting in person / talk on the phone	0.63	0.48	1.00	0.00	1.00
Personal messages on social media platforms	0.08	0.28	0.00	0.00	1.00
Read posts on social media	0.03	0.16	0.00	0.00	1.00
Who are the most important sources for financial advice? Multiple options possible					
Parents	0.20	0.40	0.00	0.00	1.00
Spouse	0.27	0.44	0.00	0.00	1.00
Sibling	0.22	0.41	0.00	0.00	1.00
Extended family member	0.31	0.46	0.00	0.00	1.00
Co-worker	0.21	0.41	0.00	0.00	1.00
Friend	0.46	0.50	0.00	0.00	1.00
Neighbor	0.03	0.18	0.00	0.00	1.00
Anonymous people on the internet (e.g. on LinkedIn or Facebook)	0.04	0.19	0.00	0.00	1.00
Other	0.05	0.22	0.00	0.00	1.00
Observations	181				

Table 8: Receiving advice for Followers – Overlap, returns and 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 9: Personal financial advice and asset class participation

Notes: The table uses bank data to compare 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

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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:

$$r^e_{j,t} = \beta_j r^e_{m,t} + \epsilon_{j,t} \tag{6}$$

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 $RSRL_i$:

$$RSRL_i = 1 - \frac{S_i}{S_B}. \tag{7}$$

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:

$$(1 - RSRL_i)^2 = 1 - \frac{\sigma_{k,i}^2}{\sigma_i^2}. \tag{8}$$

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:

$$RL_i = w_i(S_B\sigma_i - \mu_i) \tag{9}$$

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:

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

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 (10):

$$\ln RL_i = \ln(Er_m^e) + \ln w_i + \ln \beta_i + \ln\left(\frac{RSRL_i}{1 - RSRL_i}\right). \tag{11}$$

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 create a set of dummy variables that signify whether an individual invests in an asset type using ISIN-level assets. We now describe this procedure in more detail.

First, we identify individuals who generally invest in mutual funds, specifically in active, passive, or ETF funds. We use internal bank reporting to define funds that divides assets into categories. The definition of active funds and ETFs comes from Morningstar database.[12]

Second, Second, 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.[13] 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).

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.[14] The second proxy, following Bali *et al.* (2021), is analyst coverage (CVRG), which shows whether a firm has a high profile in public discussion. If the firm is in the public spotlight, more investors learn about its characteristics, includ-

[12]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.

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

[14]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.

ing 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.

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B Online Appendix: Tables

Table B1: Sample selection

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

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

Table B2: Providing advice by Recommenders and returns: 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 B3: Additional descriptive Statistics on survey respondents

Notes: This table reports the descriptive statistics for the survey respondents. The first column presents results for respondents who state that they neither provide nor receive advice from family and friends, the second column presents results for respondents who state that they usually provide advice (Recommenders) and the third column provides results for respondents who state that they usually receive advice (Followers). Column 4 provides present the differences in means between Followers and Recommenders (Column 2 minus Column 3), where t-statistics are reported in brackets.*, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

	(1) Neither receive nor provide	(2) Recommender	(3) Follower	(4) Diff 2-3
Account type				
Account at main bank	0.44	0.34	0.43	-0.09**
	(0.50)	(0.47)	(0.50)	[-2.21]
Account outside main bank	0.20	0.15	0.23	-0.08**
	(0.40)	(0.36)	(0.42)	[-2.56]
Online only account	0.19	0.27	0.10	0.18***
	(0.40)	(0.45)	(0.30)	[5.34]
Neobroker (e.g., Traderepublic)	0.11	0.22	0.19	0.02
	(0.32)	(0.41)	(0.40)	[0.67]
Other/Do not have account currently	0.05	0.02	0.05	-0.03*
	(0.23)	(0.14)	(0.21)	[-1.86]
Demographics				
Age	56.40	48.78	45.73	3.06***
	(14.49)	(13.88)	(14.29)	[2.60]
Male	0.59	0.72	0.35	0.37***
	(0.49)	(0.45)	(0.48)	[9.50]
Employed	0.57	0.79	0.81	-0.01
	(0.50)	(0.41)	(0.40)	[-0.43]
Retired	0.37	0.16	0.13	0.03
	(0.48)	(0.37)	(0.34)	[1.09]
Other profession	0.06	0.05	0.06	-0.02
	(0.24)	(0.21)	(0.24)	[-0.97]
Marital status	2.36	2.42	3.04	-0.62***
	(1.71)	(1.79)	(1.89)	[-4.06]
Manage my own finances	0.76	0.86	0.68	0.18***
	(0.43)	(0.34)	(0.47)	[5.45]
Manage finances evenly	0.21	0.11	0.22	-0.11***
	(0.41)	(0.31)	(0.41)	[-3.64]
Partner or someone else manages finances	0.03	0.03	0.10	-0.07***
	(0.17)	(0.17)	(0.30)	[-3.78]
Checked securities account	2.91	2.08	3.06	-0.98***
	(1.49)	(1.17)	(1.45)	[-9.06]
Observations	242	355	237	592

Table B4: 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 B5: Personal financial advice and asset class participation: Followers compared to general sample of investors

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: $y_{i,k,t} = \alpha + \gamma Follower_{i,k,t} + \mathbf{X'_{i,k,t}}\beta + \delta_{i,k} + \epsilon_{i,k,t}$. 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)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Fund	Active	Passive	Kumar	MAX	High Volatility	High Skewness	CSS	CVRG	Recency	—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)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Fund	Active	Passive	Kumar	MAX	High Volatility	High Skewness	CSS	CVRG	Recency	—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

C Online Appendix: Figures

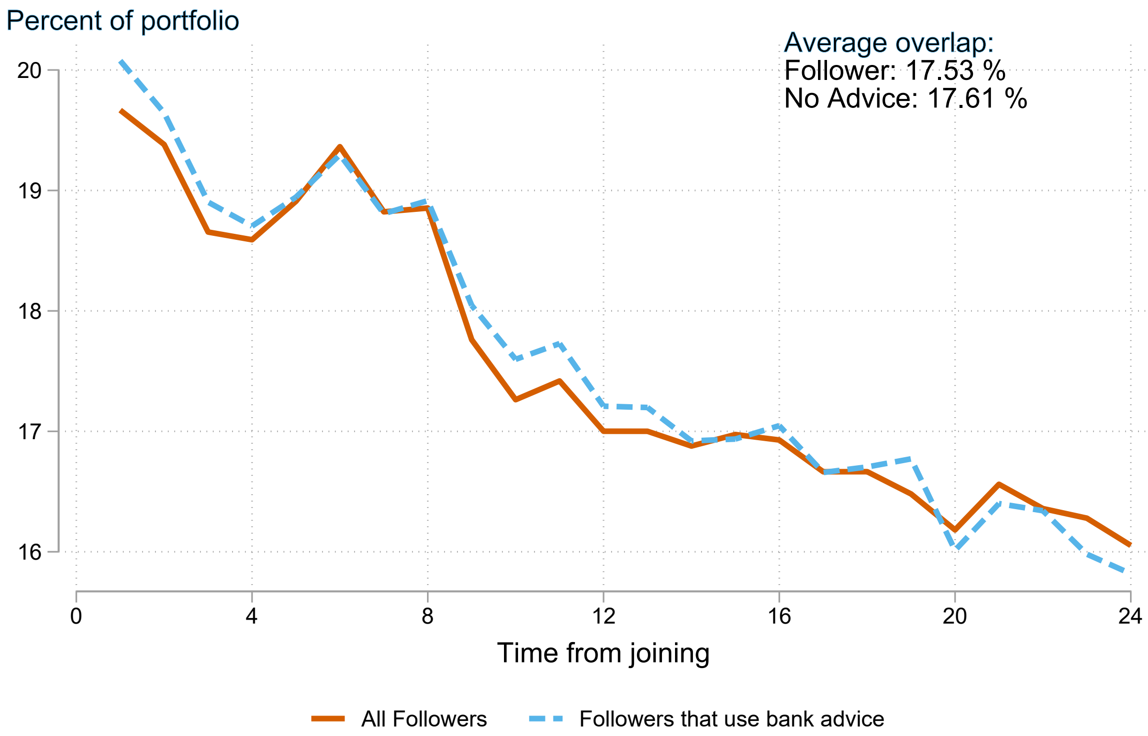

Figure C1: Overlap over time for Followers that use bank advice

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.