

# Personal Financial Advice and Portfolio Quality

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## 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.

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# 1 Introduction

Family and friends are important sources of advice for many decisions. Whether it is related to education, consumption (Bailey, Johnston, Kuchler, Stroebel, and Wong, 2022), housing (Bailey, Ruiqing Cao, Kuchler, and Stroebel, 2018), or finance, it is natural to ask close connections for advice on important topics, as a personal relationship creates incentives for providing sound advice. Recent survey data from FINRA’s National Financial Capability Study indicate that 25 percent of surveyed investors rely on information ‘somewhat’ or ‘a great deal’ from friends, family, and colleagues when forming investment decisions, comparable to the reliance on financial advisors (27 percent) and significantly higher than information from social media (12 percent).<sup>1</sup> But despite the prevalence of advice from family and friends, we have limited evidence on the nature and quality of financial advice in close personal relationships, what we call *personal financial advice*. Notably, several studies suggest that advice shared within pseudonymous online relationships is driven by realized returns (Heimer, and Simon, 2015; Escobar Pradilla, and Pedraza, 2019; Lim, Lane, and Uzzi, 2020; Ammann, and Schaub, 2021) and is associated with under-diversification and worse portfolio performance, a phenomenon we term *return-biased transmission*.<sup>2</sup> Yet, the incentives for providing advice to anonymous versus personal connections may differ, and we may consequently expect different outcomes. Ex-ante, it is unclear whether higher levels of trust and socializing with friends enhance the quality of advice, or whether personal financial advice would enable the spread of behavioral biases and risky investment strategies.

This paper offers several novel facts regarding personal financial advice that contrast with previous literature focusing on anonymous relationships. We use unique brokerage-level data on social ties and portfolio composition, which we complement with a survey of (unrelated) retail investors. Both sources consistently portray personal financial advice in a more positive light than studies focusing on online relationships. We find that personal financial advice is widespread among retail investors and rests on trust and expertise. We find little evidence that past returns influence the decision to follow advice or guide

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<sup>1</sup>The European Central Bank’s Survey of Consumer Expectations asks respondents to list their most important source of financial advice. Across 11 countries in the survey, 17 percent of respondents list “Relatives, friends or acquaintances” as the most important source. The share in Germany is somewhat lower at 15 percent.

<sup>2</sup>Other studies show that social interactions propagate active trading, return-chasing, and financial mistakes (Ammann, and Schaub, 2021; Heimer, and Simon, 2015; Hvide, and Östberg, 2015; Heimer, 2016; Lim, Lane, and Uzzi, 2020; Han, Hirshleifer, and Walden, 2022; Kakhbod, Kazempour, Livdan, and Schuerhoff, 2023).

portfolio choices, in contrast to the previous literature. Finally, we demonstrate that personal financial advice has a positive impact on portfolio diversification, risk-taking, and risk-adjusted returns. Overall, our results indicate that personal financial advice is both widespread and generally of high quality, findings that contrast with results from pseudonymous relationships.

We begin by discussing a survey of individual investors to understand their use of informal or personal advice from anonymous peers and trusted contacts. First, survey respondents are much more willing to engage in advice discussions with family and friends than they are with people on social media. When asked who they turn to for financial advice, 51 percent of respondents, who declared that they receive financial advice (whom we term *Followers*), frequently consult family and friends, compared to 13 percent who turn to social media and 20 percent who turn to financial advisors.<sup>3</sup> Second, Followers seek trust and expertise from their personal advisors, with few mentioning financial returns. The role of expertise also becomes apparent when examining who provides advice: respondents who typically advise family and friends possess more experience, larger portfolios, and higher self-assessed financial aptitude. These results align closely with our findings among brokerage clients. The importance of trust echoes characteristics observed in relationships with professional financial advisors. For example, 60 percent of respondents in a recent YouGov survey of US households report that trustworthiness is the most important aspect when choosing a financial advisor.

Next, we turn to a referral campaign at a large German online bank and brokerage to examine how personal advice affects portfolio composition. The referral program involves customers of the bank (*Recommenders*) inviting acquaintances (*Followers*) to join the bank and brokerage. Consistent with the marketing literature (e.g., Baker, Donthu, and Kumar, 2016), we argue and provide evidence that these recommendation campaigns attract customers with strong social ties. We compare the assets that Followers purchase upon joining the bank to the assets that Recommenders hold in their portfolios. Followers and Recommenders share, on average, 18 percent of securities, a proportion that remains persistently high over a two-year period. The portfolio overlap is consistently higher than any placebo-pair estimate and is our primary evidence that our bank setting captures

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<sup>3</sup>Our two potential mechanisms are similar to those that investors may employ when dealing with professional financial advisors, as in Schoar, and Sun (2024). We primarily focus on personal financial advice in this study, but note that financial advisors also play a crucial role (see, e.g., Reuter, and Schoar, 2024). For example, several survey respondents state that they recommend their financial advisor to their friends.

personal financial advice.

A key concern in identifying peer effects stems from common shocks or preferences for similar stocks driving portfolio overlap. Notably, the overlap share for assets that the Followers *transfer* to the bank when opening an account, which can be attributed to similar preferences between the Follower and Recommender, is around 5 percent. We exclude these assets from the overlap calculations and fix Recommenders' portfolios one month prior to Follower's enrollment to mitigate endogeneity concerns. However, the threat to identification due to a *change* in Follower preferences for certain stocks correlated with their bank enrollment remains. We argue that if investor preferences for specific securities are time-varying, it would likely affect other investors as well. To address this concern, we conduct a wide range of placebo and other empirical tests to support a causal interpretation of the portfolio overlap between Follower and Recommender. For instance, the overlap does not stem from the most commonly held stocks, and we can construct placebo overlap estimates based on geographical location, wealth levels, and demographics to account for similar stock preferences and local bias in stock picking. Additionally, we match each Follower to all other new investors, and find that the average overlap share among Followers is consistently above the 95th percentile of the distribution of all possible overlaps, even if we condition on demographics, location, risky share, and assets under management. We also demonstrate that the overlap is similarly high for Recommender-Follower pairs that are unlikely to be in a close relationship (e.g., they are not likely to be spouses). Finally, the bank does not promote its own funds, and we can accurately track bank advice in our data. We can therefore rule out common institutional recommendations to both Recommenders and Followers as a source of the overlap.

We find a strong correlation between Recommenders' and Followers' participation in funds. If a Recommender invests in funds, her Follower is 53 percent more likely to invest in funds, with larger effects for passive funds than for active funds. In contrast to the prediction from return-biased transmission (Han, Hirshleifer, and Walden, 2022), we also find that the correlation between Recommender and Follower's participation in assets likely to experience abnormally high returns (e.g. *lottery stocks* or *attention stocks*) is approximately half the magnitude of the correlation for funds. Notably, Recommender's influence exceeds that of bank advice. Overall, we find little evidence that realized returns influence the decision to follow advice or guide the choice over asset classes. We also find that Followers have a similar level of turnover in their portfolios and pay similar fees to other new investors. Ultimately, Followers choose the same assets as their Recommender

and end up with a higher-risk portfolio share, earn higher realized and expected returns, and have better diversified portfolios than other new investors.

The survey further provides important new context for key mechanisms in models of social transmission (Han, Hirshleifer, and Walden, 2022). Seventy-nine percent of Recommenders report that family and friends directly *seek their advice*, contradicting the notion that advice is initiated by Recommenders experiencing high returns. Seventy-five percent of Recommenders report that they always share performance information, while only eight percent do so only when results are good. Recommenders typically provide advice to friends, neighbors, or co-workers (77 percent) and family members (87 percent) rather than to individuals on the internet (5 percent). They use personal meetings to provide advice, with only four percent of Recommenders reporting that they provide advice by posting broadly on social media. These findings highlight the differences between our setting and pseudonymous contexts, underscoring that focusing solely on information sharing in anonymous or online relationships can overlook a significant component of personal financial advice.

We acknowledge the limitations regarding external validity and sample selection when studying a recommendation campaign from a single bank in a single country. We take several steps to alleviate these concerns. First, investors in our sample resemble those in other studies using German data (e.g., Meyer, and Uhr, 2024; Laudenbach, Loos, Pirsched, and Wohlfart, 2021). Second, Germany’s level of stock market participation is comparable to that of other countries. Third, the survey sample is not limited to the bank clients to ensure that our results are not driven by selection into the bank. Fourth, we also utilize data from FINRA and the European Central Bank’s Consumer Expectations Survey to show that the share of households listing family and friends as an important source of advice is comparable in Germany and other countries.

We argue that the differences between our results and previous studies stem from 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, and Hull, 2024), necessitating a more active trading strategy. Additionally, connections 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 succeed or simply avoid the potential repercussions of a bad stock tip. As one survey respondent, who stated that they neither provided nor received advice, remarked, “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 alters the nature of advice and compels the Recommender to internalize the Follower’s outcomes. While our findings do not invalidate the role of returns in other settings, they suggest that personal financial advice has different incentives and outcomes.

Finally, financial advice is likely shaped by a wide range of factors, including personal experiences, social pressures, and overconfidence. We acknowledge that these factors are important. Even if Recommenders are positively selected on expertise or trustworthiness, they may still be subject to biases or misinformation, as evidenced by the literature on the portfolios of financial advisors (e.g., Linnainmaa, Melzer, and Previtero, 2021). Ex ante, it is unclear what financial advice retail investors would provide, given the lack of compensation for advice, potential behavioral biases, and short interaction periods. This makes our finding of generally positive results for advice quality even more relevant. We would also point the interested reader toward the more nuanced view of social financial interactions in the open-ended survey questions.

In conclusion, our results speak to a broader problem: financial advice on social media is easily accessible to everyone regardless of their background, but the quality of such advice is a reasonable concern. Several recent media articles note that young households increasingly use social media for investment advice.<sup>4</sup> Not all advice provided on social media is detrimental, but many social media accounts promote risky strategies such as get-rich-quick schemes, crypto investments, or day trading. The kind of personal advice we document is less easily accessible since it requires connections to experts, but it is of high quality instead. With homophily and sorting in social networks (Balakina, Bäckman, and Parakhonyak, 2024), not everyone will have access to high-quality advice and may instead be channeled towards advice provided on social media. To fully understand the landscape of financial advice provided by social networks, a better understanding is needed of who has access to sound advice, how advice affects portfolio composition, and who is left to the vagaries of social media. Illuminating this problem constitutes an important contribution of our study and highlights a new agenda for future research into peer effects in finance.

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<sup>4</sup>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.

*Related literature* – Why does the personal financial advice that we study yield better portfolio outcomes than the settings examined in related literature? On the one hand, online investment communities have been characterized by investment biases, herding, and sentiment (Heimer, 2016; Cookson, Engelberg, and Mullins, 2023), qualities likely to erode returns. On the other hand, evidence suggests that nonprofessional analysts or social media analysts may increase informativeness in markets (Farrell, Green, Jame, and Markov, 2022; Dim, 2023). In these settings, Recommenders may face reputational or pecuniary costs (J. L. Campbell, DeAngelis, and Moon, 2019). A personal connection, as in our setting, introduces an additional, unique dimension. Recommenders with personal relationships may feel obliged to help Followers and guide them away from excessive risk-taking. While nonprofessional analysts may benefit from accurately predicting the next winner or loser, the reputational costs faced by excessive risk-taking or providing an incorrect recommendation may outweigh these benefits in a personal setting, resulting 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, Rachel Cao, Kuchler, Stroebel, and Wong, 2018; Cookson, and Niessner, 2020; Hung, 2021; Huang, Hwang, and Lou, 2021; Knüpfer, Rantapuska, and Sarvimäki, 2021; Cookson, Engelberg, and Mullins, 2023; Hirshleifer, Peng, and Q. Wang, 2023), as well as on peer effects in investment decisions and saving behavior (e.g., Bursztyn, Ederer, Ferman, and Yuchtman, 2014; Beshears, Choi, Laibson, Madrian, and Milkman, 2015; Heimer, 2016; Kaustia, and Knüpfer, 2012; Ouimet, and Tate, 2019).<sup>5,6</sup> In contrast to recent work, we highlight that personal financial advice can improve portfolio outcomes.

We also contribute to an extensive literature on retail investors' performance and investment behavior. This literature documents that retail investors trade too much (Barber, and Odean, 2000) or are too passive or inert (Biliás, Georgarakos, and Haliassos, 2010; Calvet, J. Y. Campbell, and Sodini, 2009), are under-diversified and expose themselves to idiosyncratic risk (Calvet, J. Y. Campbell, and Sodini, 2007), chase trends or high at-

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<sup>5</sup>See also the survey in Hwang (2022) and Hong, Kubik, and Stein (2004), J. R. Brown, Ivković, Smith, and Weisbenner (2008), Haliassos, Jansson, and Karabulut (2020), Maturana, and Nickerson (2019), and Georgarakos, Haliassos, and Pasini (2014). Similarly, several studies examine social ties among professionals such as financial agents (Ammann, Cochardt, Cohen, and Heller, 2022), analysts (Cohen, Frazzini, and Malloy, 2010), and advisors (Dimmock, Gerken, and Graham, 2018).

<sup>6</sup>Outside of the finance literature, we also contribute to the work on word-of-mouth in marketing (e.g., Vita Kumar, Petersen, and Leone, 2010; Schmitt, Skiera, and Van den Bulte, 2011; Lovett, Peres, and Shachar, 2013; Baker, Donthu, and Kumar, 2016).

tention stocks (Barber, and Odean, 2008), and tilt their portfolios towards specific assets or asset classes, e.g., local stocks (Seasholes, and Zhu, 2010), dividend-paying securities (Hartzmark, and Solomon, 2019; Bräuer, Hackethal, and Hanspal, 2022), and cryptocurrencies or meme-stocks (Hackethal, Hanspal, Lammer, and Rink, 2022; Hasso, Müller, Pelster, and Warkulat, 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, and Stockler, 2025). We contribute to this literature by quantifying the role of personal social interactions in the portfolio performance of retail investors.

## 2 The Bank and the Marketing Campaign

We use administrative 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 due to its online-only structure, clients are not assigned a fixed or physical advisor. We can accurately observe customers receiving robo- or telephone advice in our data. We later discuss how bank advice affects the estimation of peer effects. Finally, the bank does not market its own funds and instead acts as an online broker.

The online bank continuously runs a referral campaign, incentivizing referrals with a cash bonus of 50 EUR or non-cash bonuses such as mixers, suitcases, headphones, or coffee machines. Customers can recommend a person via their online banking portal by sending a Facebook message or a link via email. While the bonus surely matters for the decision to recommend the bank, it is important to note that the referral campaign is generic and does not market specific assets or asset classes to customers.<sup>7</sup> This type of marketing message would pose a problem for our identification strategy if it encouraged correlated investment behavior. This does not apply in our setting.

Banks set up referral programs because recommended customers have higher contribution margins at the beginning of the relationship, higher retention, and are more valuable (Schmitt, Skiera, and Van den Bulte, 2011). Referral programs also serve an important function for banks, as banking goods and services function more as experience goods than as search goods (e.g. Bolton, Freixas, and Shapiro, 2007; McKechnie, 1992), and recommenders help reduce the uncertainty of choosing a new bank or product. The

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<sup>7</sup>Messages about specific asset classes appear more frequently among *neo-brokers*.

referral program setup requires Recommenders to know referred customers at least by an email address or through Facebook friendship. Therefore, referral programs target customers with strong ties, e.g., personal friends or family members (Baker, Donthu, and Kumar, 2016). Connections with strong ties are closer due to more frequent contact, which consequently enhances knowledge of needs and preferences (Ryu, and Feick, 2007). This knowledge increases the personalization and persuasion of communication (Baker, Donthu, and Kumar, 2016). The literature calls the effect the “strength of strong ties” (J. J. Brown, and Reingen, 1987). The higher trust placed in Recommenders within strong ties and the increased homophily boost the likelihood of a purchase (Baker, Donthu, and Kumar, 2016).

## 2.1 Brokerage Data

Our data sample includes 258,000 randomly selected clients with socio-demographic and transaction data from January 2003 until September 2017.<sup>8</sup> The customer referral data enables us to identify direct peers by linking referred customers with their Recommenders. We have a list of 4,011 customers who served as Recommenders and 4,011 customers who were referred. We rarely observe multiple recommendations. After matching the referral data to demographic data and restricting our sample to Recommenders with securities accounts, we obtain 673 Followers. We further restrict the sample by age, exclude Followers who act as Recommenders, and those who do not open a brokerage account or open one before the recommendation date. Finally, we exclude Followers who had an account at the bank before the campaign started in 2012, and those with missing data. Our final sample comprises 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 performance measures at a monthly frequency. In addition to Sharpe ratio, we use a Capital Asset Pricing Model to calculate two measures of portfolio quality, the Relative Sharpe Ratio Loss and Return Loss, following Calvet, J. Y. Campbell, and Sodini (2007). Since German households mostly invest in German stocks, we assume that CAPM 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 quantifies the loss from imperfect diversification, and the Return Loss quantifies the loss incurred by an individual choosing their portfolio

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<sup>8</sup>See Hackethal, Hanspal, Lammer, and Rink, 2022 for additional discussion of this dataset.

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 to indicate whether an investor holds specific asset types. We also classify investments into funds (ETFs, passive, and active funds), lottery stocks, and attention stocks. We describe asset classification 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 aggregate the data to one observation per individual. Although we have a longer time series, we chose the first twelve months of trading to prevent learning and luck from influencing portfolio choice (Anagol, Balasubramaniam, and Ramadorai, 2021). Overall, however, this has little impact on our results, which remain 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 test some of the mechanisms implied by different theories of personal financial advice. We selected individuals aged between 25 and 85 years who currently hold investments in stocks, funds, ETFs, or certificates, or who had such investments in the last three years. We recruited participants using a large panel provider in Europe. The survey participants are not connected to the bank sample.

**Survey Structure.** Respondents began by answering two screening questions (investment portfolio and age) and one attention check. The attention check screens out inattentive respondents.<sup>9</sup> We then briefly describe to respondents the survey’s focus on personal financial advice in stocks and funds, defining personal advice as “advice from your friends, acquaintances, colleagues, or family members about investments in stocks and funds.” We asked respondents whether they typically provide advice, receive advice, or neither. Depending on their answers, respondents are sorted into tracks for either providing or

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<sup>9</sup>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.

receiving advice. Respondents who answer “Neither” received random assignment to one track. At the survey’s conclusion, we asked all respondents about portfolio characteristics, demographics, and return expectations. For consistency with the bank setting, we adopt the terminology of Recommenders and Followers for survey respondents. Our main analysis focuses on respondents who state they typically provide or receive advice.

**Open-ended questions.** For both receiving and providing tracks, we begin with open-ended questions, allowing respondents to describe the financial advice they provide or receive from family and friends. Open-ended questions offer a key advantage: they do not prime respondents’ reasoning in a particular manner, and their answers remain unrestricted. Open-ended questions thus capture what comes to respondents’ minds when we mention financial advice for family and friends. Researchers have recently used this approach to elicit reasoning about taxes (Stantcheva, 2021) or to understand mental models of the stock market (Andre, Schirmer, and Wohlfart, 2023). Ferrario, and Stantcheva (2022) and Haaland, Roth, Stantcheva, and Wohlfart (2024) discuss the advantages and disadvantages of this approach. We ask respondents, who typically provide advice, to describe the 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 what kind of advice they have received about investments in stocks and funds from family and friends. We then ask what qualities they seek in a personal financial advisor. In the questions, we emphasize the value of their answers to our research project and ask them to respond carefully.

We classify open-ended text responses into broad categories, assigning finer categories to each answer when possible. We use an inductive approach to coding the answers, starting with the data to create codes based on our own categorization. This approach aids discovery and hypothesis generation (Haaland, Roth, Stantcheva, and Wohlfart, 2024). Two independent persons always categorize the answers, then work to align the categories. After deciding on categories, two persons again categorize the answers. Finally, a third person reviews any discrepancies and completes the categorization.

## 4 Who are the Followers and Recommenders?

Our context of personal financial advice differs from that in the previous literature, which tends to focus on social interactions in anonymous or pseudonymous online relationships. While we do not observe the exact nature of the interaction in the bank setting that

leads to the recommendation of the brokerage, we posit that it could occur in several ways. First, acquaintances may seek financial advice, which can include recommendations on how to invest (e.g., how to open a brokerage account). In this setting, the bank itself may be recommended as part of financial advice. Several pieces of evidence in the survey support this type of interaction: 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 on how to start investing, with 36 percent stating that they frequently provide advice on how to find a brokerage. Alternatively, experienced Recommenders may offer financial advice and encourage equity participation to less experienced friends and family during informal gatherings, work events, or family parties after conversations turn to financial matters. In this alternative scenario, the Recommender initiates the advice. Indeed, 75 percent of Followers state that family and friends typically approach them with advice. Note that the responses of Recommenders and Followers are inconsistent. While interesting, this inconsistency does not pose a challenge, as a close personal relationship exists between Recommender and Follower in either case.

At the opposite extreme, Recommenders might blindly send marketing material to (e.g., Facebook) acquaintances, hoping for a reaction and a small cash bonus or prize. We consider this interaction highly unlikely for several reasons. For example, blindly posting to social contacts and friends would generate a distribution of successful recommendations, with some Recommenders achieving several successful recommendations by chance. This is not what we observe in our data: very few Recommenders have more than one successful recommendation. Instead, the success rate is consistent with targeted communications with close friends. We also verified with another large German bank partner that their recommendation campaign attracts primarily individuals with close relationships.

## 4.1 Summary Statistics for Followers and Recommenders

We provide demographic and portfolio summary statistics from the brokerage data in Table 1. The first two columns include averages across monthly data for the first 12 months after brokerage account opening for Followers and other new investors, respectively. Column 3 provides a t-test for mean differences between Followers and new investors. Columns 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 available observations for Recommenders and all investors. Column 6 provides a

t-test for mean differences between Recommenders and all investors. Summary statistics from the survey appear in Table 2, with further results in Appendix Table B4. Columns 2 and 3 provide results for Recommenders and Followers, respectively, and Column 4 presents results from a t-test of differences in means. The brokerage-level statistics in Table 1 are from 2011-2017 and the survey statistics in Table 2 are from 2024, which creates a natural difference in portfolio values.

A striking finding in the brokerage data is that Recommenders' average portfolio value (Total AUM) of 58,174 EUR is considerably higher than the one for Followers (27,864 EUR) and other investors (30,585 EUR). Recommenders also have larger incomes than other investors. They achieve higher risk-adjusted returns, as measured by the Sharpe ratio, and are more likely to invest in both active and passive funds than other investors. Recommenders' portfolios are also better diversified, indicated by a lower Relative Sharpe ratio loss. In terms of portfolio composition, Recommenders hold 13 securities on average, and their risky share is higher than other investors but not the Followers. Finally, Recommenders are less likely to invest in lottery or attention stocks compared to other investors. These results align with the survey findings in Table 2: Recommenders report considerably larger portfolio values than Followers, possess more experience, rate themselves as having greater 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? According to the brokerage data, Followers hold more securities, have a higher risky share, and exhibit a higher Sharpe ratio and lower Relative Sharpe Ratio Loss compared to other new investors joining the bank. Followers are also more likely to invest in both active and passive funds and less likely to hold lottery or attention stocks. In these dimensions, Followers resemble Recommenders, which could reflect either shared preferences and information sets or financial advice from Recommenders. In the survey, Followers are less experienced, have lower portfolio values, financial aptitude, and risk aversion, and hold a higher share of their portfolio in funds. About a third of Followers holds only funds, compared with 14 percent of Recommenders.

Overall, Recommenders in the brokerage data and the survey are individuals with large portfolios and considerable experience. They hold a substantial share of both stocks and funds, but with relatively high exposure to the market portfolio. Recommenders do not appear to invest a large share in lottery or attention stocks, the types of assets the return-biased transmission view predicts. This profile matches what Followers state they

look for in a personal advisor. In the open question regarding qualities Followers seek in a financial advisor, 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. Appendix Table B2 provides a more detailed breakdown of the answers to open-ended questions, and we discuss these results further in Section 6.2.

## 5 Identifying Personal Financial Advice in the Brokerage Data

This section discusses how we identify personal financial advice by examining the overlap in portfolio composition in the brokerage data. The section begins by describing the methodology and then presents results demonstrating that the overlap between Followers and Recommenders' portfolios is considerably higher than for any placebo match. We conclude the section by showing correlates of the overlap share.

### 5.1 Methodology

Our analysis faces three main challenges. First, we must ensure the *direction of causality* flows from Recommender to Follower. Second, we may observe similar behavior in Recommenders and Followers due to inherent unobserved characteristics, such as similar levels of risk aversion. We therefore must account for *contextual effects* that may simultaneously inform the portfolio decisions of both Followers and Recommenders. Third, similar behavior may arise if both Recommender and Follower are exposed to the same external factors, such as local shocks. Our analysis therefore must account for *correlated effects*.

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

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

where  $\mathbb{1}_{k=m}$  is an indicator equal to one if asset  $k$  is in both the Follower and the Rec-

ommender's portfolio in pair  $i$ . This measure is simply the number of individual assets  $k$  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 accounts for asset-holding values,  $WeightedOverlap_i^F = \frac{\sum_{k=1}^K V_k \mathbf{1}_{k=m}}{\sum_{k=1}^K V_k}$ , where  $V_k$  is the value of asset  $k$  in Follower's portfolio in pair  $i$ . When constructing overlap shares, we also remove securities Followers transfer to our bank from their previous brokerage account. Of the 515 Followers in our estimation sample, 161 transfer securities.

To address concerns regarding the direction of causality, we fix the Recommender's portfolio one month before the Follower's portfolio is set up. For the first month of trading, the Recommender's portfolio appears before the Follower even has a brokerage account with our bank. It is implausible that the Follower would *advise their Recommender* on asset investments and then wait a month before opening an account (Hvide, and Östberg, 2015). Nonetheless, we examined how using a longer lag affects the overlap share and found that our results are robust to even a 24-month lag. As noted, we also remove assets that Followers transfer to the bank, meaning the Follower's assets are new assets purchased upon joining the bank.

To understand how portfolio overlap addresses peer-effect identification challenges described above, it is worth comparing our setting on portfolio composition to related studies on peer effects in stock market participation, the standard outcome variable in most of the literature (see J. R. Brown, Ivković, Smith, and Weisbenner, 2008; Kaustia, and Knüpfer, 2012; Ouimet, and Tate, 2019; Haliassos, Jansson, and Karabulut, 2020; Maturana, and Nickerson, 2019; Georgarakos, Haliassos, and Pasini, 2014). Contextual effects and correlated shocks likely predict participation in financial markets, but their predictive power for portfolio composition is less clear. Given the large number of choices available to investors, even highly correlated risk aversion among peers is unlikely to result in investments in identical assets.<sup>10</sup> 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, a wide range of specific funds remains available to the individual investor. Observing an overlap in specific assets within a portfolio is considerably more likely to stem from peer effects than observing two neighbors participating in the stock market. Knüpfer, Rantapuska, and Sarvimäki (2021) makes a similar point for overlaps in portfolios across generations.

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<sup>10</sup>We observe over 900,000 different assets available to the investors in our sample including various structured retail products, options, and derivatives.

Three separate conditions must be met to observe an overlap: i) the Recommenders must provide advice on specific securities to invest in, ii) they must own these securities themselves, and iii) Followers need to accept this advice. Starting with Recommenders in survey data, Table 4 shows that 34 percent frequently provide advice on which specific securities to buy or sell with 82 percent providing advice on what asset to invest sometimes or frequently. Among Followers, 60 percent state that friends and family's opinions were important or very important for the choice of specific securities to buy. Thus, it seems likely that we could observe an overlap in portfolios because of peer effects.

## 5.2 Placebo Pairs

However, marketing campaigns, formal advice, or preferences for popular and local stocks could still drive the portfolio composition for Followers and Recommenders. We take several steps to address these concerns. We begin our analysis by comparing the portfolio overlap between Followers and Recommenders to the overlap for matched pairs, which we term Placebo pairs. We construct Placebo pairs by first limiting the sample to new investors to match our sample of Followers. We select all new investors who join the bank after 2012. We then create the matched pairs of actual Recommenders and i) a random new individual investor and ii) a new investor matched to each Follower based on demographic characteristics, location, wealth, risky share, and the year they joined the bank. Finally, we calculate the portfolio overlap for the Placebo pairs. This approach further controls for contextual effects and common shocks. By using existing portfolios of other new investors, we naturally account for more popular assets by implicitly assigning them higher weight in the placebo overlap. Conditioning on observable characteristics also helps rule out correlated bank advice, as such advice is generally targeted to specific characteristics. We address the issue of common bank advice in more detail later. If contextual effects or common shocks drive the decision to invest in certain stocks, we would expect to observe a similar portfolio overlap between our pairs and Placebo pairs. We rerun the placebo exercise 100 times to obtain a measure of uncertainty in the Placebo overlap share. Intuitively, this provides an estimate of the rarity of each Recommender-Follower pair's portfolio overlap.

## 5.3 Overlap Results

Figure 1 presents the initial set of results. The figure plots the average overlap in the number of stocks (panel a) and the average value-weighted overlap (panel b) of the Fol-

lower portfolio with the Recommender portfolio over time. The orange solid line in panel a) plots the overlap for Recommender-Follower pairs from the referral campaign. At the time of recommendation, the overlap is close to 20 percent, decreasing to approximately 16 percent two years later. The portfolio overlap share in panel b) in purple is approximately 10 percent at the time of recommendation, increasing over time.

In marked contrast, the average overlap share for the placebo pairs (blue lines in both panels) is close to zero. The blue lines mark the average overlap share for Placebo pairs, and the blue error bars represent the 99th and 1st percentiles of the draws from the population. The average overlap is close to zero percent, indicating that the considerably higher overlap observed for actual Followers is unlikely to occur by chance. Panel a) of Table 3 summarizes several different placebo groups, demonstrating that the placebo average overlap is always below 5 percent. Including more precise matching does not overly affect these estimates, underscoring the rarity of the overlap.

How important is this advice for individual Followers? 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 exhibiting positive overlap. Around 30 percent of Followers with positive overlap share between 75 and 100 percent of their portfolio with their Recommender. For Followers with non-zero overlap over time, the unweighted overlap share is around 50 percent after two years, decreasing from 70 percent at the time of recommendation. The weighted overlap is more stable over time, fluctuating around 35 percent. A substantial fraction of all Followers use significant information provided by their peers to form their portfolios. For completeness, figure 2 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), demonstrating that the distribution is very similar to that 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 offers an alternative illustration of the overlap's rarity. In the figure, we match each Follower portfolio to the portfolios 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 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 (19 percent) is larger than the 95th percentile

of the Placebo portfolios. Thus, it is highly unlikely to observe such a large overlap share among Followers with non-zero overlap by chance. Panel b) of Table 3 provides estimates when we restrict the sample of investors such that 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 we move from 41 million observations for all investors (first row) to 38,829 observations (last row). The last row then only includes investors similar to the Follower in terms of age, gender, education level, location of residence, assets under management, and risky share. This provides a direct matching between each Follower and all individuals who closely resembles them on observable characteristics.

In the most restricted placebo sample, the mean overlap is 2.5 percent, far below the 18 percent observed for Followers and Recommenders. Indeed, the average overlap share in the brokerage data is above the 95th percentile for the placebo overlap in the most restricted sample. Since the probability of one Follower having a positive overlap with other investors is small, the probability of many Followers having a positive overlap by chance is negligible. In total, 202 out of 515 Followers have an overlap with their Recommender that 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.

## 5.4 Robustness and Alternative Explanations

This section discusses several robustness tests, including preferences 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 overlap in portfolios stems not from financial advice but from shared preferences for specific investment types. To assess similar investment preferences, we analyze securities which investors transfer from their brokerage accounts at other banks to our sample bank. Figure 1 plots this share with a green solid line (Transfer overlap). Recall that we remove these securities from the overlap analysis above. However, they still indicate investors' preferences for specific assets: if Followers and Recommenders prefer certain securities and invested previously, Followers should already own those securities before joining the bank. However, we find that the *transfer-overlap*—the share of the Follower's transferred portfolio also present in

the Recommender’s—is approximately five percent, again substantially below the overlap share in Figure 1. In that case, we argue that the threat to identifying peer effects stems not from common preferences for certain securities, but from a *change* in Follower’s preferences correlated with her joining the bank (the Recommender already owns the securities at least one month beforehand). But if Follower’s preferences for certain securities are changing, it would likely affect other investors as well and thus be absorbed by the placebo analysis.

**Financial advice from other sources.** The placebo overlap analysis also helps rule out the formal financial advice channel, which poses a clear threat to identifying peer effects in our setting. For instance, imagine that a Follower and Recommender’s portfolios overlap because the bank advised them both to invest in a specific security. If the bank is conducting such a (successful) promotion campaign, the offer would clearly attract other investors who join the bank concurrently. Since the overlap is an order of magnitude larger than the placebo overlap, this scenario appears unlikely. Moreover, the placebo overlap remains small even when we control for observable characteristics like location, assets under management, age, gender, and risky share, considering that bank advice is likely tailored to such observable characteristics (Bucher-Koenen, Hackethal, Koenen, and Laudenbach, [forthcoming](#); Bhattacharya, A. Kumar, Visaria, and Zhao, [2020](#)).

However, it is still possible that both the Recommender and Follower are more likely to accept bank advice. To rule out this channel, Appendix Figure C1 shows the overlap share is almost identical for all Followers (solid orange line) and for Followers who do not receive bank advice (green dashed line), highlighting that institutional financial advice explains little of the overlap share. We also corroborate this finding in Figure 4, which shows that the overlap share is unrelated to bank advice, robo-trading, and using the bank as their main bank. If it was the case that the overlap was driven by advice from other sources, variables related to advice ought to predict overlap. We do not find that this is the case.

**Shared accounts.** It is also plausible that the overlap is caused by shared accounts, i.e. one person running both accounts. We examine this idea in Figure 4, which shows that the overlap share is unrelated to shared gender, similar age, having a joint account, or a proxy for spouse. If the account was run by only one person, we would expect the overlap to be higher for e.g. spouses or other proxies for close relationships. Instead, only living in the same zip-code as the Recommender significantly affects the overlap share. This positive coefficient is also plausibly related to the closeness of the relationship, suggesting

it may not necessarily reflect an omitted variable. Indeed, the placebo matches on ZIP-codes indicate that geographic proximity alone does not generate overlap.

## 6 What Determines Providing and Receiving Advice?

This section studies the determinants of providing and receiving advice. *Ex ante*, it is not clear what we ought to expect. On the one hand, Recommenders appear to be positively selected based on expertise, and they may have an incentive to provide sound advice to avoid reputational costs. Returns may not be the driving factor behind their decision to provide advice. On the other hand, in return-biased transmission modeled in Han, Hirshleifer, and Walden (2022), the Followers' and Recommenders' decisions to accept and provide financial advice increase with returns. Recommenders may still be subject to biases, as evidenced by the literature on the portfolios of financial advisors (e.g., Linnainmaa, Melzer, and Previtero, 2021), and may therefore be more likely to make recommendations after achieving high returns.

### 6.1 Providing Advice by Recommenders

We begin by examining Recommenders and the determinants of their likelihood of sending financial advice. As noted in Section 4.1, Recommenders exhibit positive selection on several expertise proxies in both bank and survey data, including financial aptitude, portfolio values, and experience. We include two additional pieces of evidence from the survey to test assumptions underlying return-biased transmission. First, 75 percent of Recommenders report always being willing to share their financial results with family and friends. Only 8 percent report sharing only when results are good. Second, 79 percent of Recommenders report that family and friends come to them directly, rather than the Recommender reaching out. These responses are inconsistent with the self-enhancing transmission bias in Han, Hirshleifer, and Walden (2022), in which the probability of *sending* advice positively relates to returns.

We also ask respondents how Recommenders typically provide advice and on what topics. The results are available in Table 4. The predominant form of advice provision is in-person discussion: 98 percent of Recommenders sometimes or frequently meet in person or talk on the phone. 29 percent of respondents write personal messages on social media

platforms, and 14 percent post broadly on social media. Regarding advice topics, 94 percent of Recommenders have sometimes or frequently advised on how to start investing and 92 have advised how to find a brokerage. In the context of our bank analysis, a plausible scenario for how individuals appear in our data is that a Follower reaches out to a knowledgeable investor-friend and asks for financial advice. The Recommender then advises on how to open a brokerage account and suggests asset types to buy. While not conclusive evidence for such a channel, this scenario aligns with the survey and brokerage evidence.

Turning to the bank administrative data, we investigate whether returns relate to recommendation provision. We use the brokerage data to test the determinants of Recommendation *timing*, providing a test of return-biased transmission. Under this hypothesis, Recommenders provide referrals during periods of high returns. Studying the timing allows for the possibility that the two hypotheses described above are not mutually exclusive: an expert Recommender could provide advice only when experiencing high returns. By focusing on the timing of the decision, we can hold Recommender's quality fixed. We also examine the cross-section in Appendix Table B3, to determine whether individuals with high portfolio quality or high returns are more likely to recommend the bank. The results consistently show little evidence that recommendation of the bank is related to returns. This does not invalidate the importance of returns in other settings, but highlights that other types of advice may emerge in the social setting we examine.

We empirically model the decision to provide advice by examining the probability that all Recommenders recommend the bank:

$$Recommendation_{i,k,t} = \alpha + \beta_1 R_{i,t}^R + \gamma_1 Q_i^R + \mathbf{X}'_{i,t} \mu_1 + \delta_{k,t} + \epsilon_{i,t}, \quad (2)$$

where  $R_{i,t}^R$  and  $Q_i^R$  is the Recommender  $i$ 's portfolio return and quality, respectively,  $\mathbf{X}'_{i,t}$  is a vector of demographic characteristics, and  $\delta_{k,t}$  are region-year fixed effects. We use Return Loss and Relative Sharpe Ratio Loss as measures of portfolio quality (Calvet, J. Y. Campbell, and Sodini, 2007). We include several demographic characteristics (gender, age, age squared, income proxy, academic title) and region-year fixed effects to account for varying recommendation propensities across demographics and regions. Region-year fixed effects also help rule out recommendation differences stemming from bank marketing campaigns. We first examine the portfolio evolution over time for the full sample of Recommenders with brokerage accounts, but later limit the sample to Recommenders for

whom we observe a Follower setting up an investment portfolio. The first three columns pertain to all Recommenders (approximately 4,000 individuals in total), and the last three columns pertain to Recommenders in our main overlap sample (approximately 500 individuals).

Overall, the results presented in Table 5 do not suggest returns drive recommendation decisions. In the first column, we include only portfolio returns. The coefficient is statistically significant at the 10 percent level, but is negative and of little economic significance. We find similar results after adding controls in column 2. Column three splits the return variable into active and passive investment returns. It is plausible that the probability of sending advice relates only to active strategies, as these are more likely to experience return spikes. However, we find little evidence supporting this channel. Finally, the regressions in Table 5 include portfolio quality controls. Both Return Loss and Relative Sharpe Ratio Loss are insignificant, indicating that *over-time* variation in portfolio quality did not correlate with the recommendation decision. In Appendix Table B3 we show that, in the cross-section, portfolio quality strongly predicts being a Recommender.<sup>11</sup> These results are also robust to using past returns, specifically the portfolio return in period  $t = \{-6, \dots, -1\}$  and to using other measures of returns instead of the average returns, such as the 95th percentile or maximum return.

We have provided evidence from both stated and revealed preferences that returns do not drive financial advice provision in personal relationships. Instead, the evidence aligns more with Recommenders' positive selection on expertise. The evidence for the self-enhancing transmission bias often stems from anonymous or distant relationships between individuals (e.g., online social networks in Heimer, and Simon (2015) and Ammann, and Schaub (2021)). Compared to these settings, individuals may not be susceptible to the same biases when providing personal financial advice to family and friends. Differences between the previous literature and our setting may arise from examining different relationship types with varying incentives. The responses to the open questions for the group that stated that they neither receive nor provide advice in the survey is revealing in this respect. One respondent, when asked what advice they would provide to family

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<sup>11</sup>In Table B3 , we regress a dummy equal to one if the individual is a Recommender at any point in time 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 becoming a Recommender. The table uses observations from all individuals and years, but we get similar results if we collapse the data to the individual level.

and friends, responded: “I do not give advice regarding securities investments, as this is a very sensitive topic. After all, losses can occur and then you will be held partly responsible for them.” Another respondent wrote “I don’t give advice to friends and relatives. I don’t feel safe enough to do so.” In comments regarding specific advice over investing in a single stock that experienced high returns in the past six months (described in Section 7), one Recommender wrote “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 investing in a single stock that has done well] because I don’t want to be responsible if things go wrong.” These examples illustrate that some Recommenders perceive distinct incentives for providing financial advice to family and friends. Our study emphasizes that personal financial advice to family and friends involves different considerations and incentives than advice in anonymous and pseudonymous settings.

## 6.2 Receiving Advice by Followers

We now examine the determinants of Followers’ likelihood of accepting personal financial advice. In an open question presented to Followers early in the survey (detailed in Appendix Table B2), Followers report seeking experience (36 percent) in a personal advisor; 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, to evaluate on a scale of 1-5 how important that the advice provider is knowledgeable and has high portfolio returns. 72 percent of Followers report it is very important or extremely important that the provider is knowledgeable, whereas 41 percent report it is very important or extremely important that the provider has high returns. A t-test of differences in means shows that the difference of 0.77 is highly statistically significant (t-value of 11.13). Summary statistics on this and other questions appear in Table B5.

Who do Followers seek financial advice from? Friends and family (51 percent) are more common sources than internet and social media (13 percent) and professional advisors (20 percent). A natural age effect exists in the use of social media and professional advisors, as shown in Figure 5, but friends and family remain the most important sources of financial advice across all age groups. Regarding the specific advice respondents receive, most respondents have received advice on how to start investing (94 percent) or how to open

a brokerage account (91 percent). In contrast to the results for Recommenders reporting being approached for financial advice, 73 percent of Followers report that people usually come to them with advice.

In the brokerage data, we empirically model Follower  $f$ 's decision to follow advice within  $x$  months of joining the bank at time  $t$  as

$$PosOverlap_{f,t+x} = \alpha + \beta_1 R_{f,t}^R + \gamma_1 Q_{f,t}^R + \mathbf{X}'_f \mu_1 + \delta_{k,t} + \epsilon_{i,t}, \quad (3)$$

where the outcome variable  $PosOverlap_{f,t+x}$  is an indicator equal to one when the overlap share from equation (1) exceeds zero. Studying the overlap share allows us to focus on Followers who open a brokerage account and, more specifically, to understand recommendations regarding asset choices. The variables of interest are the Recommender portfolio return,  $R_{f,t}^R$ , and the two measures of portfolio quality: Return Loss and Relative Sharpe Ratio Loss. We control for demographic characteristics of the Follower,  $\mathbf{X}'_f$ . Since the propensity to take up advice has been linked to similarity between individuals (Stolper, and 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, and our results are unchanged if we include them.

Table 6 shows that the likelihood of positive overlap share is strongly related to portfolio quality but not to portfolio returns. In the first three columns, we study how Recommender's 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 the results are also robust to using past returns. Decomposing returns into active and passive allows us to examine the prediction that recommendations relate to returns on more narrowly defined portfolios. For example, one might imagine that the Recommender gives advice based only on her active portfolio, as these are more likely to experience high returns. We find little evidence for such behavior, however. The coefficient on portfolio returns is insignificant in columns 1 and 2. In column 3, the coefficient on passive returns is significant at the 10 percent level. Panel a) of Figure C2 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 more extreme positive returns to drive the

likelihood of the positive overlap. These results also remain for active returns (panel b) and total portfolio returns (panel c).

We now test whether the overlap share relates to the Recommender's portfolio quality,  $Q_{f,t}^R$ . We include each portfolio quality measure separately, given their high correlation.<sup>12</sup> Columns 4 and 5 in Table 6 report that higher Return Loss and Relative Sharpe Ratio Loss, indicators of worse portfolio quality, predict a lower likelihood of positive overlap. The coefficient of -0.061 for the Relative Sharpe Ratio Loss represents 12 percent of the dependent variable's standard deviation, indicating economically significant effects. The effects persist even when we control for portfolio returns in columns 6 and 7. It is also reassuring that the control variables show little predictive power for explaining positive overlap, with only marginally significant effects found for academic title in certain regressions. Gender, income, age, main bank dummies, having a joint account, and advice usage are not significant in any regression.

The picture we draw from the survey responses is one of a clear and deliberative process for evaluating financial advice. Respondents appear aware of potential conflicts of interest and the importance of expertise, but appear less focused on finding Recommenders with high past returns. Some respondents explicitly mention the importance of personal relationships and the absence of conflicts of interest. The brokerage-level data shows that following advice in this setting is unrelated to returns but relates instead to measures of portfolio quality.

## 7 Personal Financial Advice and Portfolio Choice

We now examine personal financial advice regarding specific securities. Return-biased transmission predicts that assets with extreme past 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 propagate through social networks. Empirical evidence in several papers supports this mechanism. For instance, Sui, and B. Wang (2022) show that investors tend to post more on social media about their better-performing stocks, leading to the spread of high-variance, high-skewness stocks. These recommendations would manifest as a higher share of lottery and attention stocks in overlaps. On the other hand, investors may recommend assets with desirable or sound

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<sup>12</sup>Calvet, J. Y. Campbell, and Sodini (2007) show that we can write Return Loss as a function of the Relative Sharpe Ratio Loss.

characteristics, for example less risk than single stocks, to their friends. In that case, experienced investors would recommend investments with lower volatility and fees, and higher expected returns (e.g., diversified active or passive funds).

We begin by presenting survey evidence, then moving to the brokerage data. In the survey, we use a combination of open-ended and quantitative questions, and hypothetical scenarios.

## 7.1 Survey Evidence on What Recommenders Advise

We ask respondents who typically provide advice several questions about the advice's content. The first (open) question asks Recommenders to describe, in their own words, the financial advice they provide to family and friends. We note that this question is central to our research, and therefore avoid priming subjects with information about either returns or expertise.

The results show that financial advice to family and friends encompasses various topics. 33 percent of Recommenders have advised on funds or ETFs, and 30 percent have advised on single stocks. 44 percent have provided more general advice on concepts and strategies; 17 percent have recommended a trading platform or a provider. We also ask questions on the likelihood of respondents recommending a) a fund or b) a single stock on a scale of 1-5. Respondents more often recommend funds than single stocks. The difference in the mean response is 0.46 and is significant at the 1 percent level ( $t = 4.49$ ). Cross-tabulating the responses, 16.34 percent of respondents would recommend both funds and stocks (defined as a rating of 4 or 5), 36.34 percent recommend only funds, 21.69 would recommend only stocks, and 25.63 would recommend neither. Among respondents who recommend funds, 69 percent suggest only funds.

To understand how Recommenders perceive different types of advice, we randomly present personalized vignettes to respondents. For one group, we provide 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.” To examine potential gender differences in advice adherence, we randomly vary the name of the person (Emily or Jonas). Respondents then evaluate the advice on a 1-5 scale across several dimensions: its

similarity to their own advice, their comfort in providing it, advice's potential to generate lower or higher returns than the stock market, its perceived risk, their confidence in it as the best advice, and the likelihood of friends following the proposed advice. For each question, we evaluate differences between the stock and fund examples using the following regression:

$$y_i = \alpha + \beta FundExample_i + \epsilon_i, \quad (4)$$

where  $FundExample_i$  is equal to one if respondent  $i$  sees a fund-advice vignette, and zero if she sees stock-advice, and  $y_i$  - respondent  $i$ 's advice evaluation across dimensions described above on a scale from 1-5. We present the results in Figure 6. Each line in the figure is a coefficient from a separate regression and represents the difference between evaluations of the fund and stock hypothetical advice. Recommenders who see the index fund vignette rate the advice as more similar to their own and express greater comfort with the advice compared to the stock advice. While no significant differences in expected returns emerge between the two examples, the fund example is perceived as less risky. Finally, Recommenders are more confident that the fund advice is the best advice and believe their friends would be more likely to follow it.

Respondents also provide comments on the vignettes. Responses to the single-stock vignette, which featured advice on a stock with high past returns, are particularly informative. Six of the 26 responses to the single-stock vignette highlight the riskiness of such advice, and another six indicate a need for more information about the company or the friend receiving the recommendation. 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 Advice given to Followers

We now evaluate the financial advice Followers report receiving. First, we asked Followers to describe, in their own words, the financial advice they received from family and friends. Panel B of Table B2 presents these results. In the survey, 28 percent of Followers reported receiving advice to invest in ETFs/funds, and 19 percent reported advice to invest in stocks. Instead, the most common response (33 percent) related to general investment advice. Only 7 percent of respondents mentioned returns in the advice they received.

We also ask respondents whether they have ever received advice to invest in stocks and funds, and whether they have followed such advice. Responses were coded on a 1-3 scale (Never, Sometimes, Frequently). Respondents received advice to invest in funds more often than in stocks (difference= .26, t-test = 4.6), and were also on average more likely to have followed such advice (difference= .2, t-test = 3.4).

We present the results from the vignette experiment in Figure 7. 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 index fund that covers multiple regions and that has low management fees.” We again randomly vary the name, Emily or Jonas, 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 market 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. We estimate the same model as in equation (4), but for the sample of Followers.

An estimated coefficient indicates how differently respondents perceive the fund advice compared to the stock advice. For instance, the first coefficient shows that respondents receiving the fund example are 0.87 points more likely to report having received similar advice than those 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 hypothetical advice is also rated as having higher expected returns and lower risk. Finally, respondents are more likely to seriously consider the fund advice, perceive it as more competent, and implement it. Overall, these results indicate that Followers are more positively predisposed toward fund-related advice.

Respondents were also asked for comments on 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 survey evidence and comments suggest a deliberative process for evaluating information received from others, with particular attention to the trustworthiness and competence of the advice provider.

### 7.3 Personal Financial Advice in the Brokerage Data

We now turn to the brokerage-level data. We begin by examining the correlation between Recommender and Follower investment strategies. Specifically, we estimate the following equation to examine Follower participation in different asset classes based on whether the Recommender invests in the same asset class:

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

where  $Participation_{i,k,t}^j$  is a dummy equal to one if Follower  $i$  living in region  $k$  in year  $t$  invests in asset class  $j$ . The variable of interest,  $RecommenderParticipation_{i,k,t}^j$ , is a dummy equal to one if the Recommender of the Follower  $i$  invests in asset class  $j$ . We measure participation during the first twelve months after the Follower opens a brokerage account. We include a vector of demographic and financial control variables of the Follower ( $\mathbf{X}'_{i,k,t}$ ), including age, age squared, income, education level, and gender. Account-specific controls include: i) a dummy equal to one if the bank is the individual's main bank; ii) a dummy equal to one for a joint account; and iii) a dummy equal to one if the individual is recorded as having taken advice at least once in the first 12 months. We also include a year  $\times$  region fixed effect to account for regional and temporal differences,  $\delta_{i,k}$ . Finally, we use robust standard errors.

We examine the Follower's full portfolio rather than only the overlapping portfolio with the Recommender. If the peer recommends only certain assets, and the Follower constructs the rest of the portfolio independently, then examining only the overlap portfolio is appropriate. A lack of portfolio overlap would then be consistent with an absence 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. For instance, the Recommender might advise the Follower to invest in a certain asset or asset class, leading the Follower to construct their portfolio with this recommendation in mind. For example, the Recommender could encourage investments in mutual funds, implying a peer effect even with zero overlap. Second, portfolio composition is not independent of the individual assets within it. If the Follower purchases an asset based on a recommendation, they should adjust the rest of their portfolio accordingly. The non-overlap is likely a function of the overlap portfolio share, making it appropriate to examine the full portfolio rather than just the overlapping assets. Our results are generally stronger when examining the sample of Followers with positive overlap.

It is also worthwhile to examine the control variables in the regression. Notably, the coefficient on bank advice, a control variable measuring the bank's influence on asset choice, is only one-third the size of the Recommender's participation effect. Additionally, the advice user variable is not correlated with investments in funds, but is negatively correlated with participation in lottery stocks. No variable in the table exhibits the same magnitude across asset classes as Recommender's participation.

The preceding results focused on how Recommenders affect Followers' portfolio decisions. Appendix Table B7 shows that Followers are 3.8 percentage points more likely to invest in funds than other investors. Within the fund category, Followers are 6.2 pp. more likely to invest in passive funds and 5.9 pp. more likely to invest in active funds. 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.<sup>13</sup>

Overall, Followers invest more in funds, aligning with their Recommender's investment strategy, compared to other new investors. We do not find evidence that Followers invest more in lottery or attention-type stocks than other investors, although a positive correlation in participation still exists between Followers and Recommenders for such asset classes. These results are in contrast to the theoretical predictions in Han, Hirshleifer, and Walden (2022) and the empirical results in Sui, and B. Wang (2022), Heimer (2016) and Cookson, Engelberg, and Mullins (2023). Our work complements these recent studies by demonstrating that investors can largely benefit from the influence of a closely-connected, non-random peer. In general, both the survey and brokerage data are consistent with Recommenders tending to recommend assets with desirable characteristics to their friends.

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<sup>13</sup>Specifically, we estimate the following equation to examine Follower participation in different asset classes compared to other investors:  $Participation_{i,k,t}^j = \alpha + \gamma Follower_{i,k,t} + \mathbf{X}'_{i,k,t} \beta + \delta_{i,k} + \epsilon_{i,k,t}$ , where  $Participation_{i,k,t}^j$  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 reports the conditional investment in each specific asset type.

## 7.4 Effect on Portfolio Quality

The preceding results indicate that Followers are more likely to invest in funds than other investors. We now consider the effect of personal recommendations on portfolio quality, employing several summary measures from the brokerage data. We begin by examining actual portfolio performance to compare realized returns, then turn to measures of expected returns, and finally compare measures of trading costs associated with investors' strategies.

The first set of results on portfolio quality concerns realized portfolio returns. In particular, we examine realized Sharpe ratios for Followers relative to other investors. The realized Sharpe ratio is equal to the difference between Follower's portfolio Sharpe ratio and that of German DAX-index (the market benchmark). Table 8 shows that Followers achieve higher Sharpe ratios than other investors. In Column 1, Followers exhibit 1.49 point higher realized Sharpe ratios compared to other new investors. Moreover, Columns 4-6 show that the effect is primarily driven by Followers with a positive overlap share.

We now focus on Return Loss, a summary measure of portfolio quality, and then decompose it into its constituent parts. Further detail on this and subsequent measures are provided in Online Appendix A.1. (Calvet, J. Y. Campbell, and Sodini, 2007) show that we can write Return Loss as:

$$RL_i = (Er_m^e) w_i \beta_i \left( \frac{RSRL_i}{1 - RSRL_i} \right). \quad (6)$$

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 the household portfolio, and a transformation of the household's Relative Sharpe Ratio Loss. Taking the logarithm of equation (6):

$$\ln RL_i = \ln(Er_m^e) + \ln w_i + \ln \beta_i + \ln \left( \frac{RSRL_i}{1 - RSRL_i} \right). \quad (7)$$

The decomposition relates Return Loss to the log equity premium (constant across individuals), two measures of individual portfolio aggressiveness (the share invested in risky assets and the portfolio beta), and a measure of portfolio inefficiency (the transformation

of the Sharpe ratio loss). We estimate the following equation:

$$y_{i,k,t} = \alpha + \gamma Follower_{i,k,t} + \mathbf{X}'_{i,k,t} \beta + \delta_{i,k} + \epsilon_{i,k,t} \quad (8)$$

where  $y_{i,k,t}$  is the dependent variable related to portfolio quality, measured for individual  $i$  living in region  $k$  in year  $t$  during the first twelve months after opening their brokerage account.  $\alpha$  is a constant, and  $Follower_{i,k,t}$  is a dummy variable equal to one for Followers and zero for placebo Followers. We include the same vector of demographic and financial control variables as in Table 7.

Table 9 presents the results. Followers exhibit more aggressive risk-taking, as measured by a higher risky share and portfolio beta, and greater efficiency in their portfolio choices, as measured by lower diversification loss. The coefficient on Follower is 0.18 for the log risky share and 0.10 for the log portfolio beta, respectively. Both coefficients are statistically significant at conventional levels. The coefficient on Follower is -0.14 for diversification loss, again significant at the 1 percent level. Since each term is additive in Equation (7), the higher risky share and portfolio beta offset the lower diversification loss, resulting in an insignificant coefficient for Return Loss in the first column.

Recall that 16 percent of new investors use bank financial advice. It is interesting to compare the coefficients on 'Advice user' and 'Follower' to understand how professional financial advice compares to personal financial advice. The coefficients are generally comparable in magnitude for these two variables, with slightly smaller coefficients on Risky share and Diversification loss. Taken together with the important role of trust observed in the survey results, these findings echo the ideas in Gennaioli, Shleifer, and Vishny (2015), where investors delegate investment decisions to fund managers they trust. Personal financial advice may perform a similar role, potentially reducing conflicts of interest with better-aligned incentives.

Not everyone has access to good and trusted personal financial advice, of course, whereas professional financial advice is readily available on the market. Our contention is not that personal financial advice invariably promotes beneficial behavior. Since Recommenders tend to promote their own portfolios, personal financial advice can spread both good and bad advice. In Figure 8 we plot the log Return Loss and the Log Relative Sharpe Ratio Loss for Followers by Recommender rank. We sort Recommenders into deciles of log Return Loss and log Relative Sharpe Ratio Loss and then compare the portfolio quality for Followers across deciles. There is a strong linear relationship between Recommender

rank and Follower portfolio quality for both measures. Panel A highlights that Followers log Return Loss increases from -7.8 to -5.8 between the top and bottom decile. Panel B focuses on the log Relative Sharpe Ratio Loss, again showing an almost linear relationship between Recommender rank and the value for the Follower. Table B8 in Appendix B provides estimates where we regress Follower portfolio measures on Recommender measures with controls, with additional results for the risky share, log beta and the share invested in funds. Overall, the results indicate a strong correlation between the portfolio characteristics of Followers and Recommenders.

The correlation in portfolio characteristics and the earlier overlap analysis suggest that the transmission of portfolio characteristics through social networks depends on the nature of individual portfolios. Portfolios are shaped by a wide range of factors from personal experiences to social pressures to overconfidence to investment biases, and even investors with financial expertise may be subject to biases or be misinformed, as evidenced by the literature on the portfolios of financial advisors (e.g., Linnainmaa, Melzer, and Previtero, 2021). Ex ante, it is unclear what financial advice retail investors would provide, given the lack of compensation for advice, potential behavioral biases, and short interaction periods. This makes it even more relevant that we find generally positive results for the quality of advice. Our evidence suggests that a positive screening process is in place before investors provide advice, leading to better advice being more likely to proliferate.

Finally, a potential concern is that personal financial advice may increase trading costs and turnover, offsetting diversification benefits. We examine trading costs using data aggregated to the monthly level for each investor. Comparing Followers and other new investors over the first two years after account opening in Online Appendix Figure C3, we find that average monthly fees are very similar between the two groups.<sup>14</sup> This suggests that the higher diversification and better risk-adjusted returns among Followers are not driven by increased trading activity or higher transaction costs, and that the benefits of a better portfolio are not diluted by excessive trading.

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<sup>14</sup>Our fee measure is at the transaction level and is comprised of the sum of all commission fees on the transaction, front-loads and kickbacks on mutual funds, CPD fees, exchange related fees, and foreign fees. These various fees vary by instrument, order size, the country of the security's origin, and over time.

## 8 Selection and External Validity

This section addresses key concerns regarding selection and external validity in our setting: selection into the recommendation program at a specific bank, survey response bias, and our focus on Germany.

Observing both individuals' portfolios and their personal relationship is uncommon, particularly when combined with an event such as joining the bank. Clearly, there is a trade-off between unique data from a single bank and the ability to broadly generalize the results. However, the bank in question is a large German bank that offers clients a broad range of financial products and services. The recommendation campaign is ongoing and does not primarily seek clients interested in specific financial products. Table 1 shows that the average total assets under management (excluding retirement accounts) in the brokerage data for all investors is 30,585 Euros, compared to 54,200 Euros including retirement accounts for German households in 2014 (Bundesbank, 2019, page 26). The sample of investors in our bank setting is therefore likely representative of other German investors and comparable to those in other studies using similar German data (e.g., Meyer, and Uhr, 2024; Laudenbach, Loos, Pirsched, and Wohlfart, 2021).

Still, selection into the recommendation campaign remains a reasonable concern. For instance, participants in a referral campaign may be more likely to seek financial advice from friends, biasing results towards finding peer effects. It is reassuring, therefore, that we find highly similar results in the bank and survey data. Note that the survey respondents are a different population of investors, which provides independent corroboration of the brokerage results. This would not have been possible had we surveyed the Followers and Recommenders from the bank directly, given the selection bias inherent in the recommendation campaign. In the survey, we allowed respondents to indicate that they neither provide nor receive financial advice from family and friends, and we did not prime them regarding the paper's main hypothesis. Instead, we began by asking open-ended questions about the advice they would provide or had received, and only subsequently inquired about single stocks and funds. This limits concerns related to survey-demand effects. The survey results provide strong corroboration for the brokerage results, and vice versa. Such consistent results across two distinct investor samples strengthen our conclusions.

A further concern arises from our focus on investors in a single country, Germany. This stems from the unique nature of the bank-brokerage data, which is challenging to repli-

cate in another country. Naturally, the investment culture in Germany is shaped by specific financial and regulatory institutions. Internationally, however, Germany is not an outlier in stock market participation: 18 percent of households participate in the stock market in Germany in 2021 (Bucher-Koenen, Janssen, Knebel, and Tzamourani, 2023), compared to 21 percent in the Survey of Consumer Finances for US households. Kaustia, Conlin, and Luotonen (2023) report data on direct stock market participation from the Survey of Health, Aging and Retirement for 19 countries in Europe, for individuals age 50 or above. For this sample of older households, German stock market participation is around 15 percent, which is consistent with the average participation rate in other European countries. Regarding stock market participation and financial markets, Germany is largely comparable.

Additionally, the importance of family and friends is similar in Germany and other countries. In the National Financial Capability Study for the United States, 25 percent of investors state that they rely on information from Friends, Family, and Colleagues ‘somewhat’ or ‘a great deal,’ compared to 27 percent for Financial Advisors, and 12 percent for Social Media. The share relying on Family and Friends is slightly lower than in our survey, but the relative importance of family and friends is comparable. Moreover, the ECB’s Consumer Expectations Survey asks respondents to identify their most important source of financial advice. In Germany, 15 percent of respondents list “Relatives, friends or acquaintances” as the most important source. The share in Germany is slightly lower than the average share across the 11 countries in the survey (17 percent), but not substantially so.

Finally, while social networks may function differently across cultures or countries, the features German investors seek in an advice provider are not specific to German social networks or even to personal financial advice (trust, experience). For instance, Followers are not seeking advice on German taxes or German stocks, but instead focus on advice regarding funds, diversification, and other general topics. Furthermore, YouGov survey data for US households report that trustworthiness is the most important aspect when choosing a financial advisor (60 percent of respondents), followed by cost of Services (48 percent) and qualification and expertise (46 percent). These results strongly align with what Followers in our survey report seeking.

While we cannot confidently generalize all conclusions regarding the influence of family and friends without studying other countries or settings, the preceding discussion suggests that many external validity concerns are limited. In particular, the similarity of results

between the brokerage data and the survey already alleviates many concerns related to external validity and reinforces the point that personal financial advice is widespread and generally of good quality.

## 9 Conclusion

It is easy to find financial advice on social media these days. The Economist reports that a quarter of American investors aged 18 to 40 have used TikTok for personal finance advice, indicating that many Americans are engaged with finance and investing (Economist, 2022). This type of advice is readily accessible to everyone regardless of background and is often short and readily digestible, as videos are typically under a minute long. Conversely, concerns about the quality of advice provided on social media are reasonable. While not all advice provided on social media is unsound, many social media accounts promote get-rich-quick or pump-and-dump schemes, crypto investments, or day trading.

The advice documented in this paper is less readily accessible but is of high quality. We show that in settings with strong personal connections, advice typically focuses on fund participation, which improves performance. However, gaining access to this advice requires knowing someone with a good portfolio who is willing to share it. Given existing knowledge of homophily and sorting in social networks, not everyone will have access to high-quality advice and may instead be directed toward advice provided on social media. A comprehensive understanding of the landscape of financial advice provided by social networks requires understanding who has access to good advice through their personal connections and who relies on other forms of advice.

Three main questions emerge from this paper. First, research on peer effects in finance should carefully examine the effect of peers on portfolio composition. The literature on the effect of peers on financial mistakes and echo chambers has begun to address this question, but a more explicit portfolio focus would enhance understanding of the quality of advice provided in social networks. Second, it is crucial to consider the social setting and how results from, for example, online social networks generalize to other settings, such as family, friends, or workplace relationships. The incentives for providing advice on social networks differ significantly from those for providing advice to close family members and friends. Third, little is known about who has access to good advice within personal social networks. All these questions present important and intriguing avenues for future research.

## **Data availability**

A bank provided data for this research to Goethe University without 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. As the nature of the data is administrative, it is against the terms of our agreement to make the data publicly available.

Code to recreate the figures and tables, along with the survey data and a pseudo-dataset with brokerage data, is available at [doi:10.7910/DVN/N8C6MQ](https://doi.org/10.7910/DVN/N8C6MQ).

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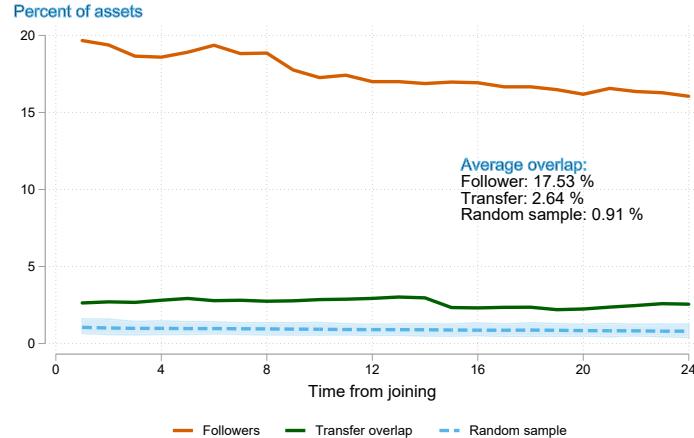
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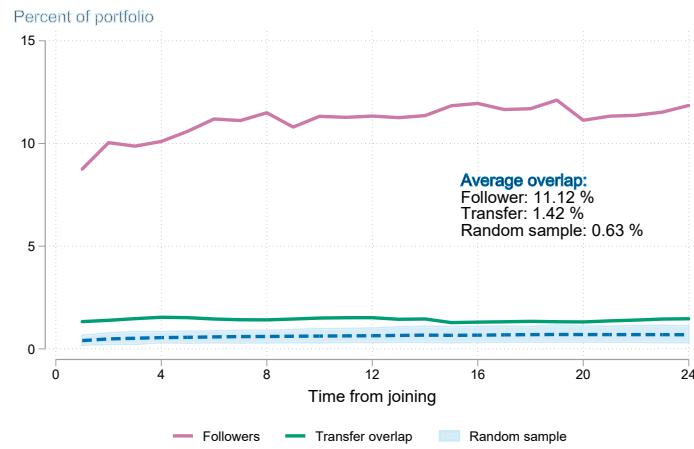
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# 10 Figures



(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.

*Alt text:* Line charts showing portfolio overlap between Followers and Recommenders over 24 months. Panel A displays unweighted overlap in number of assets, while Panel B shows value-weighted portfolio overlap. Both panels demonstrate that Followers maintain persistently higher overlap with their Recommenders compared to placebo matches, evidence for personal financial advice effects.

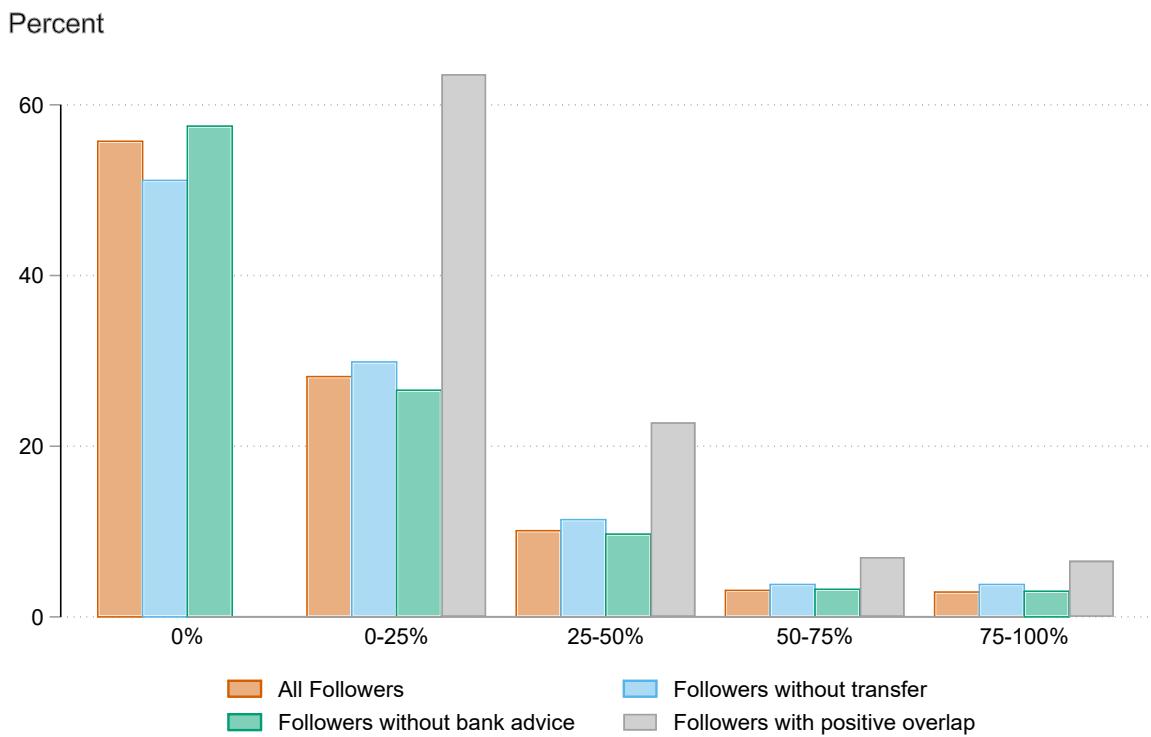


Figure 2: Overlap for selected samples.

*Notes:* The figure plots the distribution of the unweighted overlap for different samples of Followers. We divide sample into different bins on the x-axis, and plot the share of Followers who fall in each bin on the y-axis. For each sample, the portfolio for the Recommender is lagged one month relative to the Follower.

*Alt text:* Histogram displaying the distribution of portfolio overlap across different samples of Followers. The figure shows that Followers consistently exhibit higher overlap with their Recommenders compared to various control groups, supporting the identification of personal financial advice effects.

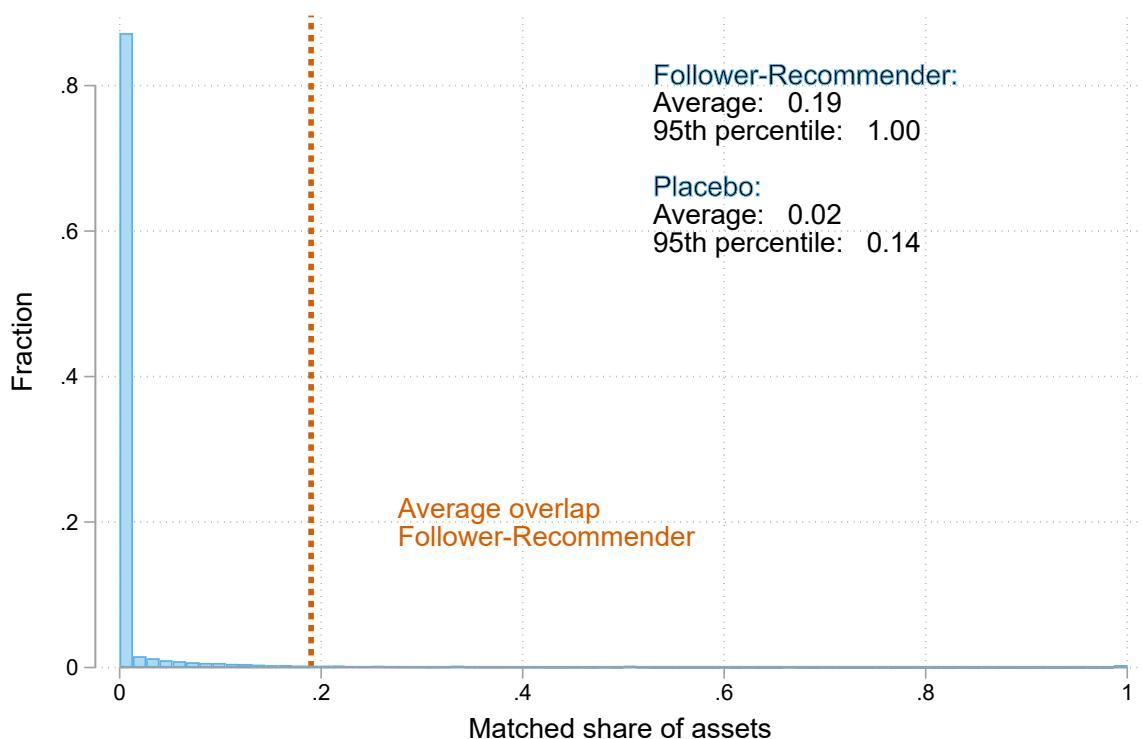


Figure 3: Overlap with all investors.

*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.

*Alt text:* Histogram comparing portfolio overlap between Followers and Recommenders versus all other investors. The red line shows average Follower-Recommender overlap is substantially higher than the distribution for random investor pairs, confirming that personal connections drive portfolio similarity.

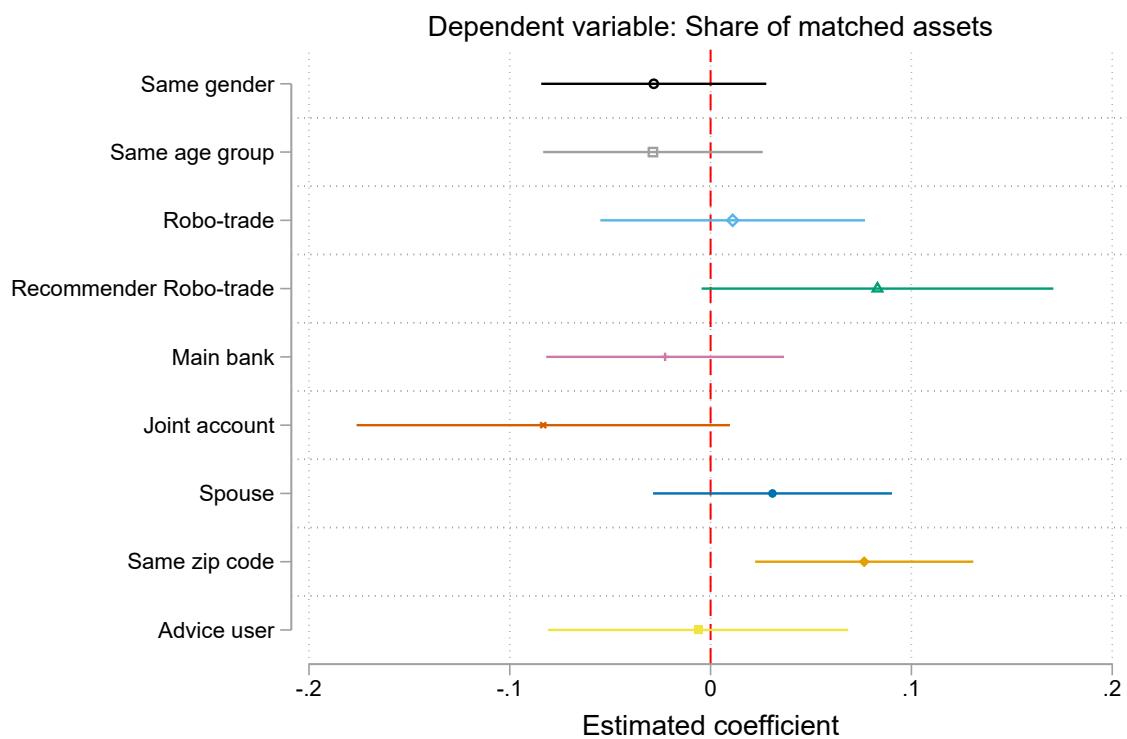


Figure 4: Determinants of overlap.

*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).

*Alt text:* Coefficient plot identifying characteristics that predict portfolio overlap between Followers and Recommenders. The figure shows which Follower and Recommender attributes are associated with higher overlap, helping understand what drives personal financial advice transmission.

When you look for advice, who do you turn to?  
 Share that answer Frequently

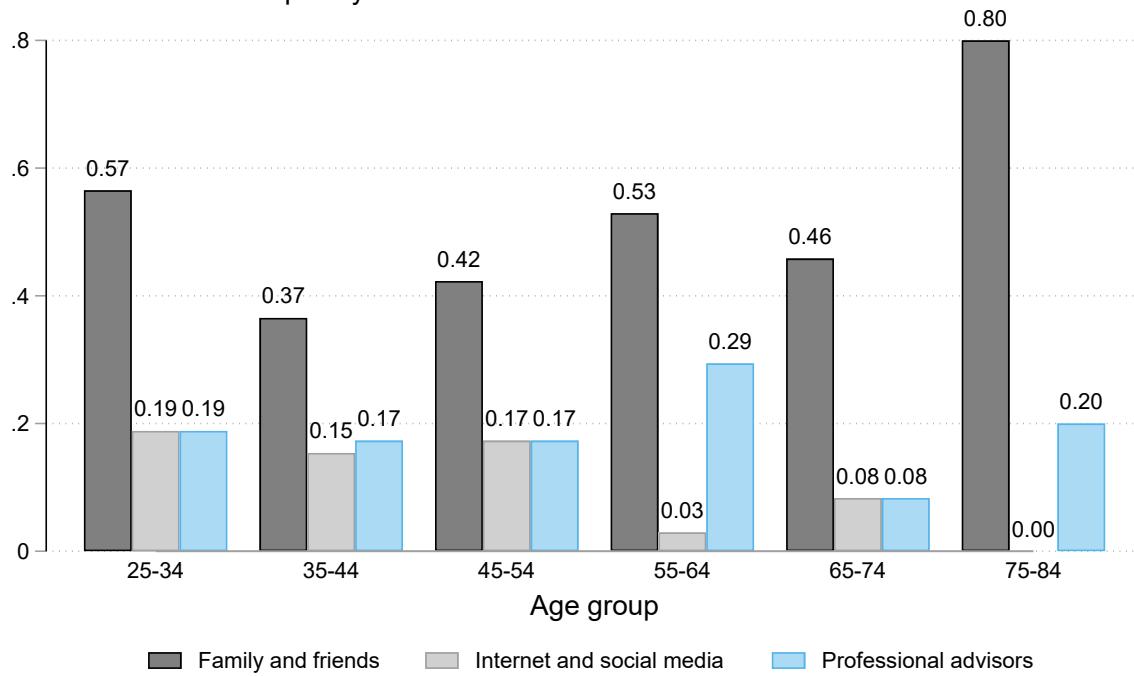


Figure 5: Who do you turn to for financial advice?

*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”.

*Alt text:* Bar chart showing the share of survey respondents who frequently turn to Family and Friends, Social Media, or Professional Advisors for financial advice, by age group. The figure reveals that personal connections remain important advice sources across all ages, with family and friends being the most common source.

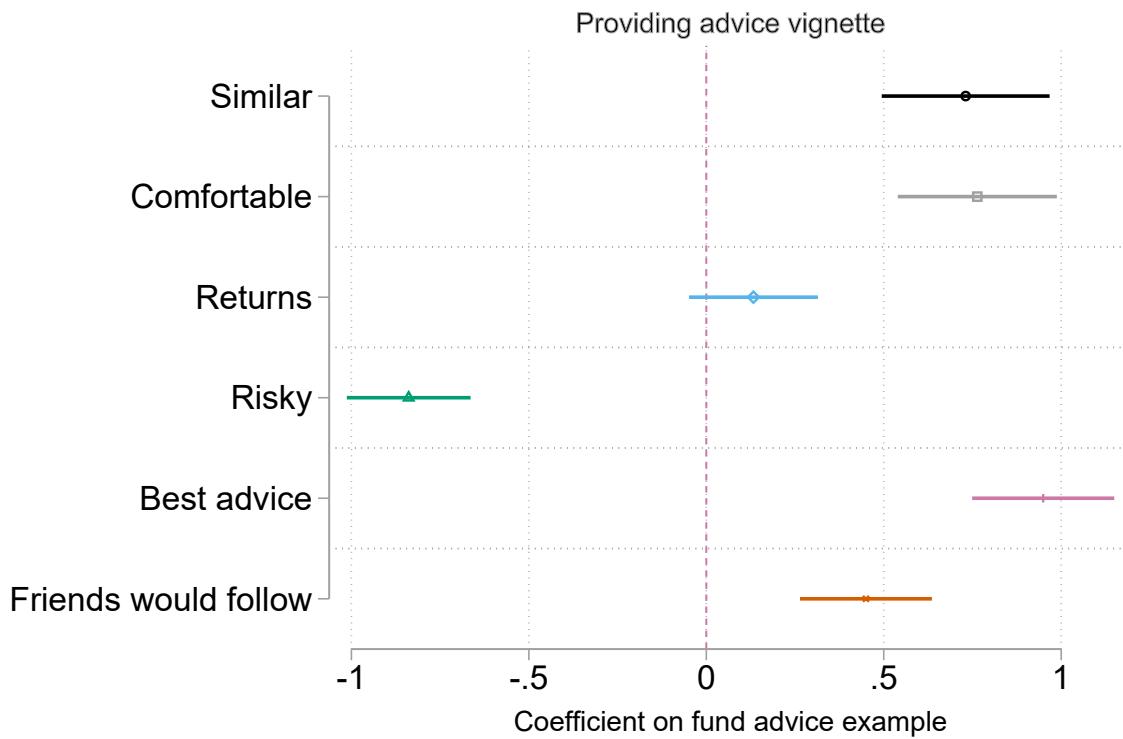


Figure 6: Recommender vignettes.

*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?

*Alt text:* Coefficient plot comparing how Recommenders evaluate single stock versus index fund advice across six criteria. Recommenders prefer fund advice, rating it as more similar to their own advice, less risky, and more likely to be followed by friends.

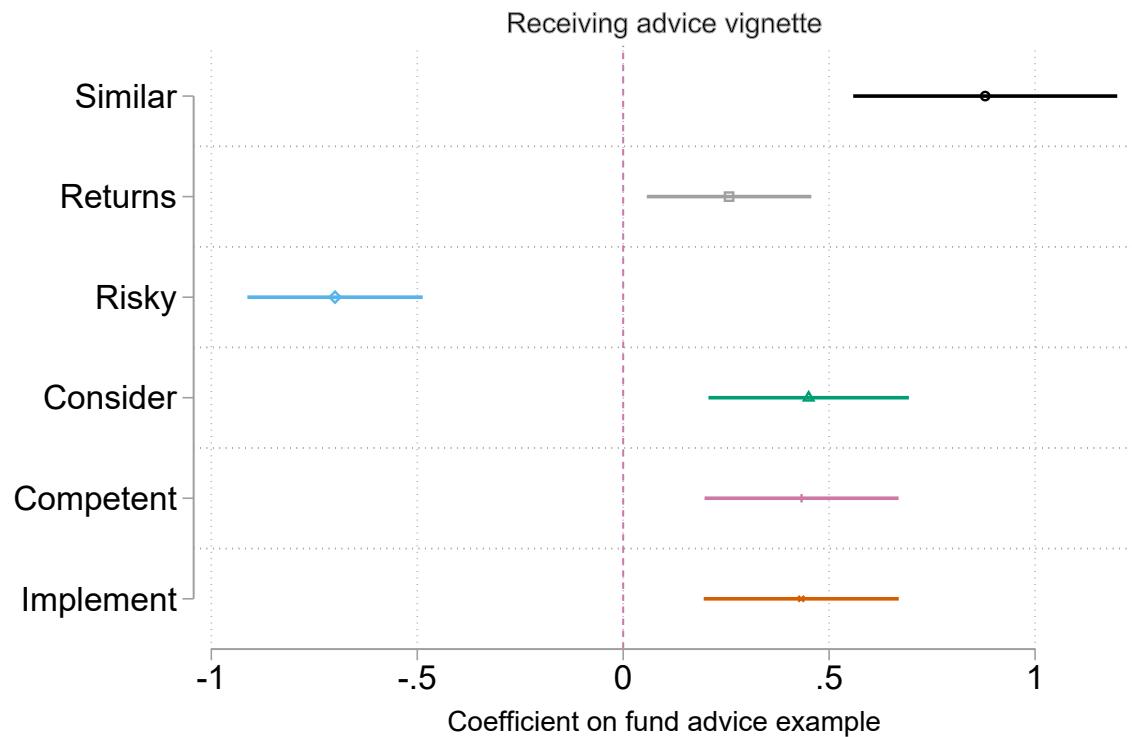
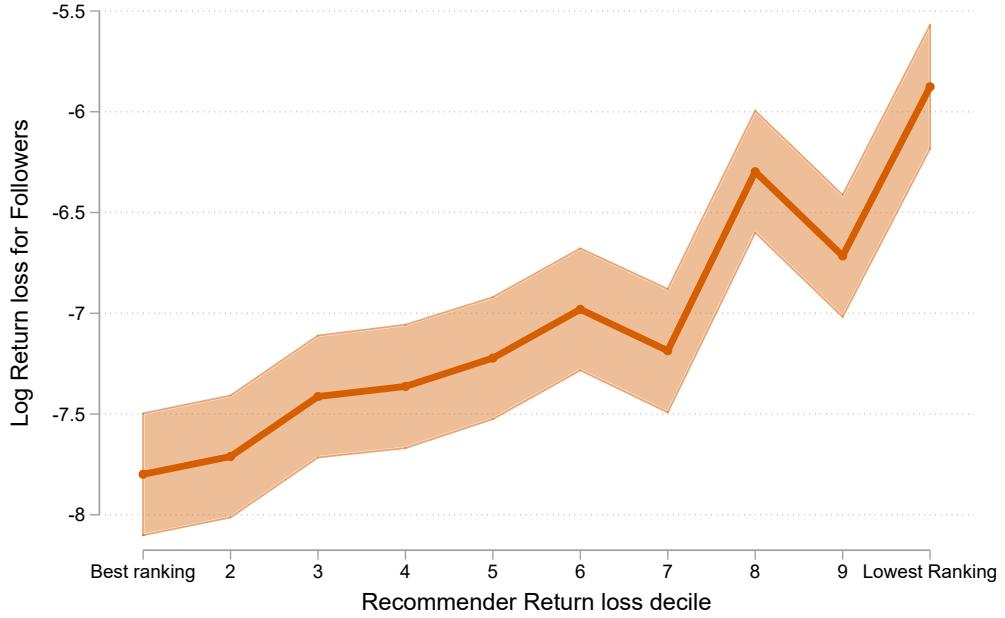


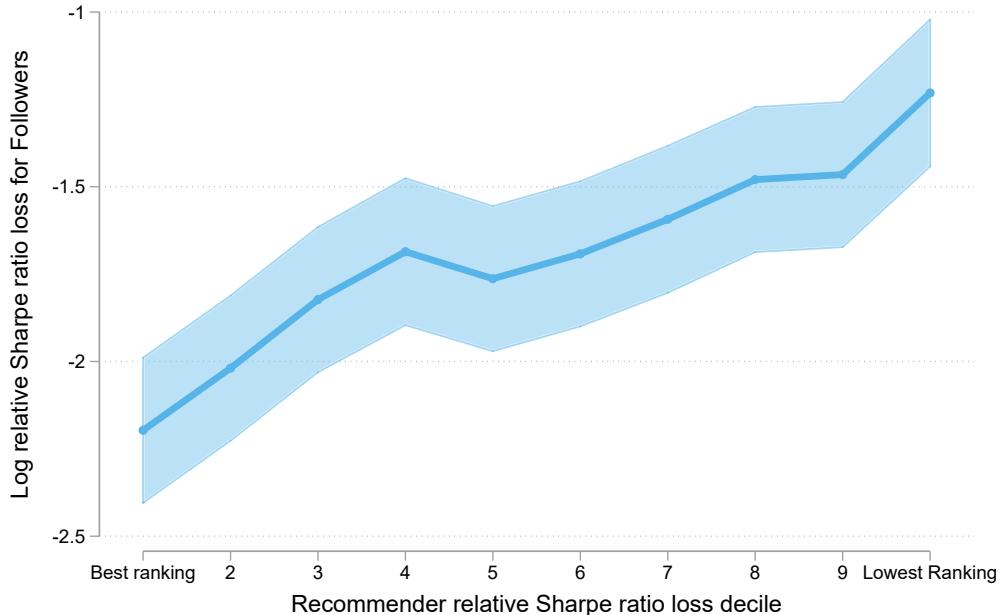
Figure 7: Follower vignettes.

*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?

*Alt text:* Coefficient plot comparing how Followers evaluate single stock versus index fund advice from friends across six criteria. Followers view fund advice as more competent, less risky, and are more likely to implement it, showing they prefer diversified advice from personal connections.



(a) Return Loss



(b) Relative Sharpe Ratio loss

Figure 8: Follower portfolio quality conditional on Recommender portfolio quality.

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

*Alt text:* Scatter plots showing the relationship between Recommender and Follower portfolio quality across two measures. Panel A displays Return Loss while Panel B shows Relative Sharpe Ratio Loss. Both panels demonstrate a strong positive linear relationship, indicating that Followers with better-advising Recommenders achieve better portfolio outcomes.

# 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
<b>A. Demographic characteristics</b>						
Male	0.52 (0.50)	0.66 (0.47)	-0.14*** [-23.33]	0.81 (0.39)	0.73 (0.44)	0.08*** [30.97]
Age	40.34 (15.57)	38.61 (16.01)	1.73*** [8.26]	42.99 (14.58)	45.57 (15.47)	-2.57*** [-29.37]
Academic title	0.06 (0.23)	0.04 (0.20)	0.01*** [4.87]	0.05 (0.22)	0.05 (0.22)	-0.00 [-0.22]
Joint account	0.10 (0.30)	0.14 (0.35)	-0.05*** [-10.23]	0.15 (0.36)	0.14 (0.34)	0.01*** [6.55]
Main bank	0.32 (0.47)	0.21 (0.41)	0.10*** [19.32]	0.52 (0.50)	0.32 (0.47)	0.20*** [76.72]
Advice user	0.16 (0.36)	0.07 (0.25)	0.09*** [26.70]	0.17 (0.37)	0.06 (0.23)	0.11*** [82.75]
<b>B. Wealth and income</b>						
Total AUM (EUR)	27,863.42 (46,192.44)	18,328.06 (39,664.85)	9,535.36*** [18.31]	58,173.92 (77,369.78)	30,585.03 (56,007.06)	27,588.89*** [86.91]
Income proxy	2,371.28 (11,542.78)	2,284.93 (16,443.55)	86.35 [0.40]	4,121.89 (14,593.32)	2,230.58 (19,381.02)	1,891.32*** [17.26]
<b>C. Portfolio Composition</b>						
Number of securities	5.35 (5.06)	4.92 (6.81)	0.43*** [4.02]	13.19 (14.30)	8.33 (12.45)	4.85*** [58.29]
Stock market participant	0.45 (0.50)	0.47 (0.50)	-0.03*** [-3.31]	0.75 (0.44)	0.74 (0.44)	0.01*** [3.07]
Risky share	0.48 (0.41)	0.31 (0.39)	0.17*** [34.00]	0.49 (0.39)	0.34 (0.40)	0.15*** [67.00]
Sharpe ratio	0.09 (0.03)	0.08 (0.04)	0.01*** [12.62]	0.09 (0.03)	0.08 (0.04)	0.01*** [34.57]
Return Loss	0.00 (0.02)	0.00 (0.22)	-0.00 [-0.48]	0.00 (0.08)	0.01 (1.14)	-0.01 [-1.21]
Relative Sharpe Ratio Loss	0.24 (0.22)	0.30 (0.30)	-0.06*** [-12.62]	0.28 (0.26)	0.36 (0.31)	-0.07*** [-34.57]
I: Active Fund Investment	0.37 (0.48)	0.31 (0.46)	0.06*** [7.88]	0.53 (0.50)	0.41 (0.49)	0.11*** [34.42]
I: Passive Investment	0.51 (0.50)	0.41 (0.49)	0.10*** [13.00]	0.52 (0.50)	0.24 (0.43)	0.28*** [96.52]
I: Warrants and Options	0.11 (0.32)	0.10 (0.30)	0.02*** [3.75]	0.30 (0.46)	0.16 (0.37)	0.14*** [59.01]
I: Lottery Stocks	0.45 (0.50)	0.62 (0.48)	-0.17*** [-26.91]	0.57 (0.50)	0.67 (0.47)	-0.10*** [-38.33]
I: Attention Stocks	0.40 (0.49)	0.59 (0.49)	-0.18*** [-28.66]	0.51 (0.50)	0.63 (0.48)	-0.11*** [-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
<b>Investor characteristics</b>				
Portfolio value (EUR)	69,118.94 (108,642.04)	104,886.69 (126,595.73)	40,700.43 (73,577.19)	64,211.68*** [7.08]
Experience in years	6.93 (3.20)	7.34 (3.05)	5.25 (3.28)	2.09*** [7.85]
Portfolio return	6.88 (10.08)	10.13 (12.17)	4.41 (12.46)	5.70*** [5.53]
Financial aptitude (1-5)	3.27 (0.71)	3.90 (0.67)	3.16 (0.75)	0.75*** [12.72]
Risk attitude (1-5)	2.67 (1.00)	3.36 (0.94)	2.64 (0.97)	0.73*** [9.13]
Probability stock prices higher	38.93 (31.86)	50.62 (29.00)	39.79 (29.40)	11.05*** [4.53]
Expected return	6.77 (5.92)	8.70 (8.43)	7.90 (7.90)	0.81 [1.17]
Would invest in new popular investment (1-5)	2.71 (0.75)	3.20 (0.77)	3.19 (0.69)	0.01 [0.19]
<b>Portfolio composition</b>				
Share stocks	27.09 (34.17)	34.21 (32.11)	23.45 (31.77)	11.24*** [4.20]
Share funds	63.79 (37.20)	50.14 (33.82)	63.33 (35.82)	-13.61*** [-4.69]
Share bonds	3.57 (12.34)	4.10 (9.39)	3.85 (12.51)	0.22 [0.25]
Share currencies	0.04 (0.66)	2.07 (6.63)	0.85 (3.39)	1.20** [2.58]
Share derivatives	4.52 (15.13)	5.22 (12.48)	3.89 (11.85)	1.47 [1.43]
Share crypto	0.98 (5.17)	4.26 (11.07)	4.62 (12.49)	-0.52 [-0.53]
<b>When are you willing to share your financial results?</b>				
Share when results are good	0.03 (0.17)	0.08 (0.27)	0.10 (0.30)	-0.02 [-0.90]
Share when results are bad	0.01 (0.09)	0.02 (0.14)	0.02 (0.15)	-0.00 [-0.12]
Always share	0.33 (0.47)	0.75 (0.43)	0.56 (0.50)	0.19*** [4.90]
Never share	0.63 (0.49)	0.16 (0.36)	0.32 (0.47)	-0.17*** [-4.86]
Observations	227	353	232	592

Table 3: Overlap and placebo overlap

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

	Average overlap	5th percentile	95th percentile	
Follower-Recommender	0.18	0.00	1.00	
<b>Panel A: Random matches</b>				
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	
<b>Panel B: Direct matches across all investors</b>				
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 4: 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
<b>How likely (1-5) would you be to recommend an investment in the following?</b>					
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
<b>What kind of financial advice? Share that answer Frequently</b>					
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
<b>How do you usually provide advice? Share that answer Frequently</b>					
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
<b>Do you reach out to give advice or do family and friends come to you?</b>					
Peple come to me directly.	0.79	0.41	1.00	0.00	1.00
<b>Who do you provide advice to? Multiple answers possible</b>					
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 5: 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)	-0.0000* (0.0000)		0.0116 (0.0117)	0.0117 (0.0118)	
Passive returns			0.0130 (0.0107)			0.0067 (0.0115)
Active returns			0.0017 (0.0027)			0.0202 (0.0132)
R: Log Return Loss	-0.0004 (0.0004)	-0.0004 (0.0004)		-0.0004 (0.0010)	-0.0004 (0.0010)	
R: RSRL	-0.0000 (0.0007)	0.0000 (0.0007)		-0.0000 (0.0015)	0.0000 (0.0015)	
Male	0.0004 (0.0009)	0.0004 (0.0009)		0.0007 (0.0021)	0.0007 (0.0021)	
R: Age	-0.0000 (0.0000)	-0.0000 (0.0000)		-0.0000 (0.0001)	-0.0000 (0.0001)	
Academic title	0.0000 (0.0014)	0.0000 (0.0014)		0.0001 (0.0033)	0.0001 (0.0033)	
Income proxy	0.0000 (0.0000)	0.0000 (0.0000)		0.0000 (0.0000)	0.0000 (0.0000)	
Advice	0.0004 (0.0011)	0.0004 (0.0011)		-0.0004 (0.0021)	-0.0004 (0.0021)	
Joint account	0.0002 (0.0008)	0.0002 (0.0008)		-0.0012 (0.0021)	-0.0012 (0.0021)	
Main bank	-0.0002 (0.0007)	-0.0002 (0.0007)		-0.0005 (0.0016)	-0.0005 (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 6: 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  $R: \log \text{Return Loss}$  and  $R: \log \text{RSRL}$ , the log Return Loss and log Relative Sharpe Ratio Loss for the Recommender. We include region  $\times$  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 (0.614)					0.655 (0.597)	0.608 (0.607)
R: Active return		-0.115 (0.232)					
R: Passive return			1.898** (0.830)				
R: Log Return Loss				-0.061** (0.026)		-0.062** (0.027)	
R: RSRL					-0.092** (0.036)	-0.093*** (0.036)	
<b>Follower controls</b>							
Male	-0.060 (0.060)	-0.059 (0.060)	-0.055 (0.059)	-0.058 (0.059)	-0.055 (0.060)	-0.058 (0.059)	-0.055 (0.059)
Income proxy (std)	-0.030 (0.050)	-0.032 (0.049)	-0.032 (0.049)	-0.026 (0.050)	-0.026 (0.049)	-0.024 (0.051)	-0.025 (0.050)
Academic title	-0.187 (0.128)	-0.173 (0.126)	-0.180 (0.123)	-0.165 (0.118)	-0.161 (0.120)	-0.181 (0.120)	-0.175 (0.122)
Age	0.017 (0.011)	0.016 (0.011)	0.018 (0.011)	0.016 (0.011)	0.018 (0.011)	0.017 (0.011)	0.018 (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 (0.067)	0.020 (0.066)	0.024 (0.066)	0.024 (0.065)	0.019 (0.065)	0.027 (0.065)	0.022 (0.065)
Joint account	-0.046 (0.104)	-0.047 (0.104)	-0.051 (0.102)	-0.057 (0.099)	-0.035 (0.102)	-0.058 (0.099)	-0.035 (0.102)
Advice user	0.027 (0.078)	0.025 (0.078)	0.022 (0.078)	0.009 (0.078)	0.012 (0.077)	0.010 (0.078)	0.013 (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 7: 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*** (0.062)	0.389*** (0.050)	0.441*** (0.055)	0.131** (0.053)	0.350*** (0.057)	0.199*** (0.060)	0.198*** (0.058)	0.248*** (0.053)	0.300*** (0.053)	0.290*** (0.061)	0.255*** (0.067)
Male	-0.047 (0.039)	0.075 (0.050)	0.035 (0.051)	0.015 (0.030)	0.063 (0.044)	0.050 (0.034)	0.043 (0.043)	0.069* (0.041)	0.064 (0.039)	0.068 (0.044)	0.013 (0.031)
Income proxy (std)	0.007 (0.017)	0.064*** (0.023)	0.053** (0.026)	-0.005 (0.015)	0.006 (0.027)	-0.017 (0.016)	0.015 (0.026)	0.022 (0.029)	-0.018 (0.024)	0.013 (0.029)	-0.026* (0.014)
Academic title	0.134 (0.093)	0.018 (0.107)	0.184 (0.111)	0.070 (0.077)	0.109 (0.091)	0.051 (0.075)	0.021 (0.090)	-0.029 (0.078)	0.203** (0.102)	0.097 (0.085)	0.040 (0.078)
Age	-0.002 (0.008)	0.012 (0.010)	0.000 (0.010)	-0.009 (0.007)	0.001 (0.009)	-0.003 (0.007)	0.004 (0.009)	-0.009 (0.009)	-0.001 (0.008)	0.001 (0.009)	0.005 (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 (0.044)	0.036 (0.051)	0.024 (0.054)	0.149*** (0.041)	0.128** (0.050)	0.136*** (0.044)	0.122** (0.051)	0.073 (0.046)	0.128*** (0.048)	0.123** (0.051)	0.111*** (0.039)
Joint account	0.064 (0.058)	0.074 (0.088)	0.001 (0.092)	-0.014 (0.045)	0.059 (0.077)	0.035 (0.064)	0.109 (0.086)	0.029 (0.079)	0.010 (0.074)	0.070 (0.084)	-0.030 (0.056)
Advice user	0.132*** (0.046)	0.147** (0.070)	0.115* (0.069)	-0.035 (0.025)	-0.142*** (0.052)	-0.078** (0.034)	-0.151*** (0.045)	-0.085* (0.049)	-0.066 (0.045)	-0.117** (0.052)	-0.034 (0.032)
Constant	0.416*** (0.160)	-0.139 (0.202)	0.245 (0.203)	0.171 (0.153)	0.001 (0.190)	0.065 (0.158)	-0.000 (0.195)	0.229 (0.188)	0.024 (0.178)	0.019 (0.197)	-0.067 (0.142)
Region#Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	398	398	398	398	398	398	398	398	398	398	398
Adjusted $R^2$	0.295	0.241	0.219	0.121	0.315	0.122	0.133	0.181	0.213	0.264	0.211

Table 8: Effect on portfolio performance: Sharpe ratio

*Notes:* This table presents results for the realized Sharpe ratio. We regress realized Sharpe ratio on a dummy for Follower as well as on demographic and financial variables. Control variables include a dummy for male, income proxy, academic title, age and age squared, as well as controls for having our bank as the main bank and a dummy equal to one if the account is a joint account. Robust standard errors are in parentheses. \*, \*\*, and \*\*\* denote significance at the 10%, 5% and 1% levels, respectively.

	All			Positive Overlap		
	(1)	(2)	(3)	(4)	(5)	(6)
Follower	1.49*** (0.29)	1.62*** (0.48)	1.52*** (0.44)			
Follower, Positive Overlap				1.55*** (0.29)	1.41*** (0.41)	1.34*** (0.40)
Male		0.04 (0.56)			0.04 (0.56)	
Income proxy (std)			-0.05 (0.24)			-0.04 (0.24)
Academic title			0.73 (1.77)		0.75 (1.80)	
Age			-0.15 (0.12)			-0.15 (0.12)
Age squared			0.00 (0.00)			0.00 (0.00)
Main bank			-0.17 (0.70)			-0.16 (0.71)
Joint account			0.22 (0.70)			0.24 (0.71)
Advice user			0.64 (0.56)			0.66 (0.57)
Region#Year fixed effect	No	Yes	Yes	No	Yes	Yes
Dep. var. mean	-1.44	-1.44	-1.44	-1.44	-1.44	-1.44
Dep. var. std. dev	44.63	44.63	44.63	44.63	44.63	44.63
Number of Followers	515	515	515	207	207	207
Observations	25468	25468	25468	25160	25160	25160
Adjusted $R^2$	-0.000	0.006	0.006	-0.000	0.006	0.006

Table 9: Effect on portfolio quality and risk taking

*Notes:* This table presents results for the decomposition of Return Loss into its components from equation 7. We regress log Return Loss and each component of Return Loss on a dummy for Follower as well as on demographic and financial variables. Control variables include a dummy for male, income proxy, academic title, age and age squared, as well as controls for having our bank as the main bank and a dummy equal to one if the account is a joint account. Robust standard errors are in parentheses. \*, \*\*, and \*\*\* denote significance at the 10%, 5% and 1% levels, respectively.

	Return Loss $\ln(RL_i)$	Risky share $\ln w_i$	Risky portfolio beta $\ln \beta_i$	Diversification loss $\ln \left( \frac{RSRL_i}{1-RSRL_i} \right)$
Follower	-0.05 (0.05)	0.16*** (0.04)	0.08*** (0.03)	-0.14*** (0.05)
Male	0.23*** (0.02)	0.09*** (0.01)	0.12*** (0.02)	0.11*** (0.02)
Income proxy (std)	0.03*** (0.01)	-0.06*** (0.02)	-0.00 (0.01)	0.04*** (0.01)
Academic title	-0.25*** (0.04)	0.07*** (0.03)	-0.11** (0.04)	-0.13*** (0.03)
Age	-0.01*** (0.00)	-0.02*** (0.00)	-0.00 (0.00)	-0.02*** (0.00)
Age squared	0.00** (0.00)	0.00*** (0.00)	-0.00 (0.00)	0.00*** (0.00)
Main bank	0.13*** (0.02)	0.06*** (0.01)	0.05*** (0.01)	0.06*** (0.02)
Joint account	-0.09*** (0.02)	-0.18*** (0.02)	-0.03* (0.02)	-0.06*** (0.02)
Advice user	-0.54*** (0.02)	0.25*** (0.02)	-0.21*** (0.02)	-0.33*** (0.02)
Region#Year fixed effect	Yes	Yes	Yes	Yes
Dep. var. mean	-6.73	-0.85	-0.26	-0.86
Dep. var. std. dev	1.31	1.02	1.15	1.35
Number of Followers	515	515	515	515
Observations	25605	25587	25605	25605
Adjusted $R^2$	0.086	0.046	0.131	0.241