The Impact of Financial Advice on Trade Performance and Behavioral Biases*

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Abstract

We use a dataset from a large retail bank to examine the impact of financial advice on investors' stock trading performance and behavioral biases. Our data allow us to classify each individual trade as either advised or independent and to compare them in a trade-by-trade within-person analysis. Thus, our study is not plagued by the endogeneity problems typically faced by studies on financial advice. We document that advisors hurt trading performance. However, they help to reduce some of the behavioral biases retail investors are subject to, but this does not overcompensate the negative performance effects of the bad stock recommendations.

JEL Classification: D14, G11, G21

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1. Introduction

A large fraction of households relies on financial advice when making investment decisions.[1] However, there is still no consensus in the literature about the influence of financial advisors on their clients' performance. While some papers find a positive effect of advisors on individual investors' portfolio performance (Shapira and Venezia, 2001; von Gaudecker, 2014), others find a negative effect (Hackethal et al., 2012), and again others find no impact (Kramer, 2012).[2]

In this paper, we argue that one reason for the mixed findings is data limitations existing studies suffer from and that we are able to overcome. We use unique data from a large and representative Swiss retail bank containing information on contacts between clients and their financial advisors to provide new evidence on the value of financial advice. More specifically, we first analyze how financial advice impacts individual investors' stock trading performance to shed light on the question of whether financial advice has informational value. Second, we investigate whether financial advice helps individual investors to overcome behavioral biases and improve overall portfolio performance.[3]

Our dataset provides information on almost 10,000 clients, their approximately 400 advisors, and more than 75,000 stock trades executed by these clients between January 2002 and June 2005. Optional advice free of charge is available to all customers through bank employees. The unique feature of our data is that we know when clients and advisors interact with each other and whether the contact was initiated by the client or by the advisor. This allows us to classify each trade as either carried out by the client independently or as being advised. Thus, we can compare the performance and the extent to which clients are subject to behavioral biases across advised and independent trades in a within-person setting using

[1] For instance, in the U.S., about 19% of individuals talk to their bank advisor and about 29% to other professional financial advisors when planning or reviewing their finances (BlackRock, 2013). Similar numbers pertain to Switzerland, which is covered by our study. In Switzerland, 38% of individuals are reported to talk to their bank advisor and about 20% to other professional financial advisors.

[2] Focusing on mutual funds, Bergstresser et al. (2009) and Del Guercio and Reuter (2014) find that broker-sold funds underperform direct-sold funds.

[3] We use the term 'behavioral biases' to refer to psychological traits individual investors are often subject to when making stock-picking decisions and the investment mistakes these psychological traits eventually can lead to.

client fixed effects. Thereby, we control for all unobserved client characteristics which are constant over time.[4]

Existing studies on the impact of financial advice do not investigate the value of financial advice on the trade level but focus on overall portfolio performance. Thereby, they do not differentiate between clients who exclusively trade on advice and clients who only consult their advisors for guidance occasionally but also place orders independently. Portfolios of both types of clients are typically defined as advised. This is problematic because many clients who are classified as advised clients according to this procedure might regularly conduct trades on their own as well as trades that follow advice. For instance, in our sample, even clients who do sometimes trade based on advice (and thus would be classified as advised clients in most existing studies) still conduct over 70% of their trades independently! Classification at the investor level can lead to a severe endogeneity problem: Investors with poor investment skills might be more likely to rely on financial advice. However, even if these investors sometimes rely on advice, they will typically not completely delegate trading. Hence, focusing on the overall portfolio performance of these clients could be misleading as inferior portfolio performance could be driven by the poor performance of the trades conducted by these clients independently, even if the advice they received was good. In our study, we address these endogeneity concerns by comparing performance and behavioral biases between advised and independent trades of the same client.

In addition, as previous studies concentrate on overall portfolio performance they are also not able to separate the informational value of advisor stock trading recommendations from advisors' effect on behavioral biases and eventually performance. Previous research suggests that the impact of advice on behavioral biases and eventually performance is also mixed.[5] Thus, the focus on performance on the client level rather than the trade level can lead to

[4]In robustness tests, we run our analysis with combined client-advisor fixed effects rather than client fixed effects to not only account for time-invariant client characteristics but also for advisor characteristics that do not change over time as well as for a potential endogenous matching between clients and advisors. Our findings remain virtually unchanged.

[5]Financial advisors seem to induce excessive trading (Shapira and Venezia, 2001; Hackethal et al., 2012; Mullainathan et al., 2012). However, financial advisors also help clients to improve overall portfolio diversification (Shapira and Venezia, 2001; Kramer, 2012; von Gaudecker, 2014) and to reduce the home bias (Kramer, 2012) as well as the disposition effect (Shapira and Venezia, 2001).

ambiguous results. For instance, if advisors have a positive impact on performance by reducing behavioral biases but suffer from poor stock-picking abilities, the overall effect on portfolio performance could be zero. Since we focus on trades rather than on overall portfolios, we are able to separately investigate advisors' stock-picking skills and their impact on behavioral biases.

In the first part of our analysis, we examine the informational value of financial advice. We document that advised trades perform significantly worse than common benchmarks. We then compare the performance of advised and independently executed transactions in multivariate analyses with client fixed effects and find consistent evidence that advised trades underperform independent trades of the same client. The effect is statistically highly significant as well as economically meaningful. It is mainly driven by purchases, while the performance difference for sales transactions is much less pronounced.

Our empirical setup including client fixed effects alleviates the endogeneity problems discussed above to a large extent. However, there is one more endogeneity concern in our setting: Clients could approach their advisor with their own trading ideas in mind, for instance, to seek reassurance, and might do so particularly for their worst trading ideas, while the same clients may execute their good trading ideas independently. We address this concern by separately investigating trades following advisor-initiated contacts and trades after client-initiated contacts. We find the underperformance of advised transactions to be particularly severe if the client-advisor contact was initiated by the advisor, suggesting that advisors actively approach clients with rather poor trading ideas.

We then investigate potential drivers of advisor recommendations to better understand the sources of the underperformance of advised trades. We show that advised trades are more likely to be trades in stocks recommended by sell-side analysts and that these recommended stocks perform particularly poorly during our investigation period. This is consistent with the findings of Malmendier and Shanthikumar (2007) who document that the upward biased buy recommendations of sell-side analysts underperform common benchmarks. Moreover, we document that advised trades tend to be trades in stocks with extreme positive returns in the recent past. Consistent with Bali et al. (2011), we show that these trades also subsequently perform worse than other trades. These findings suggest that advisors follow at least to a certain extent a common investment strategy that performs particularly poorly over our investigation period.[6] Interestingly, investors even ex-post do not seem to be aware of the bad performance of the suggested trading ideas, as we find no evidence that they are less likely to rely on advice after having experienced poor performance of advised trades in the past.

In the second part of the paper, we take a closer look at advisors' effect on behavioral biases. Using our approach of a within-person comparison of advised and independent trades of the same client, we investigate whether advised trades help clients to overcome under-diversification (e.g., Goetzmann and Kumar, 2008), the home and local bias (e.g., French and Poterba, 1991; Grinblatt and Keloharju, 2001), and the disposition effect (e.g, Odean, 1998). We find evidence that advisors help to better diversify clients' portfolios and to reduce the local bias (but not the home bias) and the disposition effect. However, overall, the negative stock-picking abilities of advisors are not offset by them reducing the negative impact of behavioral biases on performance. We find that even without taking into account trading costs (which are typically higher for advised clients due to higher trading activity) the overall portfolios of advised clients underperform the portfolios of clients that always trade independently.

Related empirical papers focusing on the influence of advice on portfolio performance try to address endogeneity concerns in various ways. Hackethal et al. (2012) use an instrumental variable approach and Kramer (2012) compares the portfolio performance of clients before and after their first interaction with the advisor. However, both approaches do not entirely resolve the problem discussed above that clients who are classified as advised still execute trades on their own as well as trades on advice. In a contemporaneous paper, Chalmers and Reuter (2015) analyze the investment choice and portfolio performance of participants in Orgeon University System's Optional Retirement Plan. They argue that in the absence of broker advice plan participants would most likely invest in target-date funds. They then compare the performance of portfolios influenced by broker recommendations with the performance of target-date funds and find that the former perform worse than the latter, which is consistent

[6]Our results are also consistent with Fecht et al. (2013) who show that banks deliberately push poorly performing stocks from their proprietary portfolios into their retail clients' portfolios. However, as we have no information on the bank's proprietary portfolio, we cannot explicitly test for this channel.

with our results.

Our findings also provide empirical support for theoretical research on financial advice. Inderst and Ottaviani (2012) show that if financial advisors are remunerated indirectly through fees and commissions they generate and if customers naively believe that they receive unbiased advice, this can result in the exploitation of clients. Bolton et al. (2007) document that in a setting with conflicted financial advisors, uninformed clients, and profit margins which differ across products, advice can be biased, even if there is competition among financial institutions. Piccolo et al. (2015) develop a model with multiple investors and show that if advisors face sales incentives they might induce clients to take excessive risks. In another recent study, Gennaioli et al. (2015) show that if advisors are compensated through the fees and commissions they generate and clients hold biased expectations, clients' trust causes managers to pander to investor beliefs, resulting in investment advisors underperforming passive strategies even before fees. At our bank, advisors' remuneration is also linked to the commissions and fees they generated with customers.[7] Thus, our findings in the first part of the study that advised trades perform poorly relative to benchmarks and independently executed transactions are consistent with the theoretical prediction that indirectly compensated advisors may encourage trades even when their recommendations lack merit. Specifically, our finding that advised trades are more likely to be trades in stocks with recent extreme positive returns supports the prediction of Gennaioli et al. (2015) that advisors particularly encourage trusting clients who want to invest in hot stocks. Reputational costs might have a mitigating effect on misselling by advisors (e.g., Gennaioli et al., 2015; Piccolo et al., 2015). However, reputational concerns of advisors seem to be less of an issue in our setting as we do not find much evidence that clients react to the past performance of advised trades. Our results in the second part of the paper are also consistent with advisors being incentivized to maximize profits as mitigating behavioral biases leads to portfolio turnover, which in turn generates revenues for the bank.

[7] While we have no information on the details of the individual compensation contracts of our advisors, we know that the bank pays them a fixed salary as well as a bonus that depends on the overall performance of the bank, the performance of the branch, and the individual performance of the advisor. The performance is measured by means of different key figures such as new money acquired and the commissions and fees generated with clients.

The structure of the paper is as follows. In the next section, we introduce the proprietary dataset from the Swiss retail bank and describe our variables. In Section 3, we compare the performance of advised and independently executed transactions to shed light on the question of whether financial advice has informational value. Section 4 analyzes whether advised trades help clients to overcome behavioral biases. Section 5 concludes.

2. Data and Variables

2.1 DATA AND SAMPLE SELECTION

Our data come from a large Swiss retail bank, which we will simply call *the bank* henceforth. This bank offers a broad range of financial services to its customers such as checking accounts, savings accounts, securities accounts, loans, and mortgages. Thus, the range of services offered by our bank includes typical services offered by brokerage firms in the U.S. It operates a network of bank branches throughout Switzerland as well as a small number of branches abroad. In those areas where the bank operates branches, its market share is between 20% and 30%. The dataset covers the time period from January 2002 to June 2005. This investigation period includes bullish and bearish market conditions. Both the blue chip index SMI (Swiss Market Index) and the broader SPI (Swiss Performance Index) decrease during the first part of the sample period and reach their lowest level on March 12, 2003. Subsequently, both indices increase steadily. At the end of the sample period, both indices are close to their starting level.

Customers at our bank tend to be traditional bank branch customers relying on a strong and long-lasting bank relationship. The clients in our dataset constitute a random sample comprising 90% of the bank's private clients whose main account is denominated in Swiss Francs (CHF) and whose wealth at the bank exceeds CHF 75,000 (equivalent to roughly USD 56,000 during our sample period) at least once prior to December 2003.[8] As of December 2003, 42.0% of Swiss residents subject to taxation have a net wealth (including non-financial wealth) of more than CHF 50,000 (Swiss Federal Statistical Office, 2012). Hence, clients in

[8] The bank did not provide information on all its clients for confidentiality reasons.

our sample represent the wealthier part of the population. We think that this is an advantage if one wants to study the impact of financial advice on investment performance since wealthier individuals provide a larger revenue potential for the bank, giving advisors incentives to pay more attention to these clients as compared to low net-wealth accounts. Thus, the quality of financial advice found in our study probably marks an upper bound of the quality of financial advice offered to the average retail client.

We apply several filters to our raw data. First, a small number of accounts are directly managed by advisors without any client interactions. We eliminate these completely-delegated accounts since managed accounts only contain trades executed by the bank. However, our identification strategy relies on the comparison of transactions influenced by bank employees and trades carried out independently.[9] For the same reason, we exclude clients that do not trade at all during our investigation period. We then follow previous research and focus on *stock* trades rather than all trades of financial assets (e.g., Odean, 1998, 1999; Barber and Odean, 2000, 2001; Shapira and Venezia, 2001; Goetzmann and Kumar, 2008). Lack of data makes it difficult to calculate the performance of trades in other asset classes. Our final sample consists of 9,976 clients that execute at least one stock trade during our investigation period. They are assigned to 400 advisors and perform 75,446 stock trades in 2,474 different stocks.

In addition to the information provided by the bank, we use daily return data on individual stocks as well as indices from Thomson Reuters Datastream to measure performance. We also obtain information on market capitalizations, book-to-market ratios, and dividends from Thomson Reuters Datastream and data on sell-side analyst recommendations from IBES (Institutional Brokers' Estimate System).

[9] In our stability tests (not reported), we investigate the performance of stock trades in managed accounts and compare it to the performance of optional-advice-driven trades. We find that purchases in managed accounts do even worse than purchases influenced by optional financial advice. Moreover, for a small subset of 234 clients that either switch from a self-managed to a managed account or vice versa during our sample period, we measure the performance of their independently executed buys before or after the switch and find it to be significantly better than the performance of buys in managed accounts. Thus, consistent with the results of our analysis of optional financial advice, we do not find evidence that transactions in managed accounts contain informational value.

2.2 ADVISED AND INDEPENDENT TRADES AND CLIENTS

A client who opens an account at our bank is assigned to an advisor. This advisor is the main contact person for the client. Clients can either conduct their financial transactions independently or they can make use of optional financial advice provided by bank employees for free. Our sample contains information on 38,851 contacts between the clients and their advisors during the sample period from January 2002 to June 2005. Contacts as defined in this dataset include everything from a client receiving a rather impersonal mailing to an in-person meeting between the client and the advisor. We focus on 7,958 contacts that are explicitly classified as advisory contacts. For each contact, we know the day on which it occurred, the means of communication, and whether it was initiated by the advisor or the client. 35.4% of all advisory contacts are meetings, 57.9% are phone calls, and 0.9% letters or emails. For the remaining 5.8% of advisory contacts, the means of communication is unknown. Moreover, 46.6% of all advisory contacts are advisor-initiated.

Overall, the clients in our final sample execute 75,446 stock transactions. Figure 1 shows how stock trades are distributed around advisory contacts. Advisory contacts are clearly associated with an increased number of trades. In the figure, the contact between the client and the advisor takes place on day t = 0 and trades peak on this day. However, an exceptionally high number of trades also takes place on the days following the advisory contact. Thus, we define an *advised trade* as a trade executed within five days of an advisory contact, that is, between t = 0 and t = 4.[10] 31.6% of all advisory contacts are associated with at least one subsequent stock trade during this period. If a client decides to trade after interacting with the advisor, the client executes 1.7 stock transactions on average. This leads to 4,297 advised stock transactions in our dataset, that is, 5.7% of all stock trades are advised trades. 76.7% of all advised trades take place on day t = 0, 11.5% on day t = 1, 5.1% on day t = 2, 4.0% on day t = 3, and 2.8% on day t = 4. 40.4% of the advised stock trades take place after a contact between the client and the advisor that was initiated by the advisor. 43.3% of the advised stock trades follow a personal meeting, 54.2% follow a phone call, and only approximately

[10] In our robustness tests in Table A2 in Appendix B, we rerun our analysis with alternative definitions of advised trades. Results are relatively similar across different definitions.

0.5% follow a letter or an email. The means of communication is unknown for the remaining 2.0% of advised transactions.[11]

Our trade classification could be problematic if clients meet with advisors but then do not follow the advice they get but instead trade in other stocks. While it is not clear why they should do so, to still investigate this possibility we analyze a small subset of 558 client-advisor contacts in our dataset for which the securities discussed between the client and the advisor are reported in the bank's internal system. Unfortunately, this is not the case for all other contacts. If these 558 contacts result in a trade within the following five days, in more than 90% of cases these trades involve a security mentioned by the advisor.[12] Thus, our definition of advised trades does capture recommendations of advisors that the overwhelming majority of clients follow.

There are 1,095 clients that can be defined as *advised clients*, meaning that they execute at least one stock trade on advice during our investigation period, while 8,881 clients are completely *independent clients* who only trade stocks independently. Independent clients execute a total of 58,016 *independent transactions*, while advised clients execute 13,133 stock trades independently in addition to the 4,297 advised transactions. This shows that even among clients classified as advised clients most trades are executed independently, highlighting the importance of analyzing the impact of optional financial advice on the trade level and not on the level of the overall portfolio.

2.3 DESCRIPTIVE STATISTICS

The bank's database includes various investor characteristics such as gender, age, education, employment, and place of residence. In addition, the dataset provides information on whether

[11] In unreported tests, we separately run our analysis for trades following meetings and trades following phone calls. Results are economically and statistically slightly stronger for transactions that follow phone calls.

[12] Obviously, these percentages could still be driven by clients approaching their advisors with a very specific trading idea in mind. However, this does not seem to be the case for the following reasons: First, 330 of these contacts are advisor-initiated and if clients trade after an advisor-initiated contact, in more than 90% of all cases they trade in a security mentioned in the advisory talk, indicating that advisors actively approach clients with trading ideas and clients seem to follow these recommendations. Second, there are typically several identical entries across different clients by the same advisor in the database, indicating that advisors contact different clients with the same trading recommendations.

investors receive product information, whether they have e-banking access, and on the length of the bank relationship. Moreover, the dataset contains clients' total bank wealth, individual security positions, and transactions data. All client characteristics are collected by the bank on the date of the account opening and updated according to new information provided by clients. Appendix A provides detailed descriptions of these and all other variables used throughout the study.

Table I reports descriptive statistics on the clients and their portfolios. Panel A presents various socio-demographic variables on the clients and information on their accounts. 60.8% of the clients in our sample are male and their average age is 58.9 years as of January 2002. The education variable is assigned a value between 1 and 7 based on the highest education a client received. Out of all clients, 76.0% completed a vocational education, 16.2% hold a university degree, and the remaining 7.8% are assigned to categories such as 'unskilled', 'semi-skilled', 'high-school degree', 'higher vocational education', or 'technical college'. 65.1% of the clients in our sample are employed, 29.2% are retired, and 5.7% belong to other categories like 'self-employed', 'housewives', or 'students'. We only have information on the clients' education and their employment status for 2,408 and 8,072 clients, respectively. 84.8% of our sample clients live in Switzerland. 81.0% of them receive some kind of product information, which is typically distributed via mass mailings. It provides information about new and existing bank products and is only partially personalized to clients' characteristics. 19.8% of all clients have an e-banking account. On average, clients have been with the bank for 6.6 years as of January 2002.

Panel B reports portfolio characteristics. The average individual holds stock worth CHF 109,695 (equivalent to about USD 82,000). Hence, a large part of clients' financial wealth appears to be represented in our dataset and we can reasonably assume that the accounts at our bank typically are the clients' main accounts rather than 'play money' accounts.[13]

[13] Stock holdings of clients at our bank tend to be substantially larger than their private pension provisions and eventually are an important source of retirement income. The Swiss pension system is based on three pillars: the state pension system, occupational pension provisions, and private pension provisions. Private pension provisions typically take the form of retirement saving accounts that offer higher interest rates than normal savings accounts as well as tax benefits. 21.9% of the clients in our sample have a retirement savings account at our bank during the investigation period. On average, they hold CHF 31,165 in these accounts.

Portfolios of clients at our bank are substantially larger than client portfolios in the typical discount brokerage datasets used in the literature like the one of Barber and Odean (2000), in which the mean stock portfolio amounts to approximately USD 47,000. On average, clients hold four stocks in their portfolios. This is in line with Barber and Odean (2000) who find that the average investor in their sample also holds a portfolio with four stocks. Moreover, investors in our sample invest 88.3% (51.7%) of their equity portfolios in Swiss (local) stocks. A local company is headquartered within a 50-kilometer radius of where an investor lives. The fraction of Swiss (local) stocks in the portfolio is only computed for clients living in Switzerland. Investors execute 2.3 stock trades p.a. The average trade size is about CHF 24,000, resulting in an annual stock trading volume of approximately CHF 56,000.

2.4 WHO TRADES ON ADVICE?

To investigate which of these clients make use of optional financial advice provided by bank employees, we next estimate a cross-sectional OLS regression with the average annual percentage of advised trades over the entire investigation period as dependent variable. We include client and portfolio characteristics as independent variables. To capture a possible non-linear impact of age, we include three age category dummies for 45 to 59 years, 60 to 74 years, and above 75 years, respectively.[14] Thus, the base case are all clients with an age below 45. Moreover, we use beginning-of-period values for the portfolio size to minimize endogeneity concerns.

The coefficient estimates are reported in Table II. The results in the first column show that male clients are less likely to trade on advice than female clients. This finding is consistent with Guiso and Jappelli (2006) who document that male investors tend to be more overconfident and overconfidence reduces the propensity to seek advice.[15] Moreover, the coefficients on all age dummies are positive and two out of three are statistically significant, indicating that clients who are older than the base category are more likely to trade on advice. The coefficient

[14] van Rooij et al. (2011) document that the relation between age and financial literacy is hump-shaped. Moreover, Korniotis and Kumar (2011) find that the relation between age and investment skills is non-linear.

[15] In unreported tests, we also find that male investors in our sample overall trade more than female investors, confirming the results of Barber and Odean (2001).

estimates suggest that the probability of an advised trade is between 0.5 percentage points and 3.1 percentage points higher for clients aged 45 or above compared to the base case of those below 45. Given that the overall percentage of advised stock trades amounts to 5.7%, this effect is economically meaningful. Furthermore, we document that Swiss clients and clients with an e-banking account are less likely to rely on advice. The coefficients on the product information dummy and the length of the bank relationship are both statistically not significant. Finally, the coefficient on the size of the client's portfolio is positive and statistically highly significant, suggesting that wealthier clients are more likely to trade on advice.

In Column 2, we add education as additional explanatory variable. As information about the level of education is available for only approximately 24.1% of clients in our sample, the sample size is substantially reduced if we add this variable. Nevertheless, most of the results from Column 1 hold, but statistical significance is in some cases reduced due to the much smaller number of observations. In this specification, clients who receive product information, that is, mass mailings, are significantly less likely to trade on advice. This result is probably driven by the bank sending more product information to clients who have not traded on advice so far. Finally, the coefficient on the education variable itself is positive and significant (at the 10% level). Thus, there is weak evidence that better educated clients are more likely to trade on advice. Overall, we find that there are significant differences between clients making use of financial advice and clients acting independently, suggesting selection effects if one focuses on the overall portfolio performance of advised and independent clients rather than on individual trades.

3. The Impact of Financial Advice on Trade Performance

In our main analysis, we investigate how financial advice impacts stock trading performance to shed light on the question of whether financial advice has informational value. We first compare the performance of advised and independently executed trades in a univariate setting (Section 3.1). We then examine the impact of advisors on performance in a trade-by-trade within-person analysis using regressions with client fixed effects (3.2). In Section 3.3, we form calendar-time portfolios on advised and independent trades to corroborate our findings from the trade-by-trade analysis. We then investigate potential drivers of advisor recommendations to better understand the performance differences between advised and independent trades (Section 3.4). Finally, we examine whether clients react to the past performance of advised transactions by relying more or less on advisors (Section 3.5).

3.1 UNIVARIATE COMPARISONS

We first examine the performance of advised and independent stock trades in a univariate setting. To determine whether the exposure of advised and independent trades to the equity market risk factor and the investment style factors of Fama and French (1993) and Carhart (1997) differs, we compare the stock beta with respect to the SPI (Swiss Performance Index), the market capitalization, the book-to-market ratio, and the past 1-year raw return decile across advised and independently executed transactions.

Results are reported in Panel A of Table III. We find that advised stock purchases have a significantly smaller market risk exposure than independently executed purchases, while the beta does not differ for stocks sold. Moreover, advised stock trades involve significantly larger stocks in terms of market capitalization and stocks with significantly lower book-to-market ratios, suggesting that advisors lean more towards a large-cap and growth strategy than client acting independently. Finally, results show that advised buys are more likely to involve stocks that performed relatively well in the past compared to independent buys. The reverse pattern holds for sells, indicating that advisors tilt more towards a momentum strategy as compared to independent trades. These differences suggest that we should not only control for the market risk exposure when determining abnormal returns but also for the size, value, and momentum factors.

Thus, we analyze three performance metrics over three horizons: (1) raw returns, (2) cumulative abnormal returns (CARs) based on a simple market model with the SPI return as a proxy for the equity market risk factor[16], and (3) the CARs based on a 5-factor model where we include the SPI as well as the MSCI World Index as proxies for the equity market risk factor and Swiss size, value, and momentum factors.[17] In the 5-factor model, we include the world equity market factor because 34.9% of stock trades in our sample are in non-Swiss stocks. To compute the CARs of a trade, we first estimate the market model and the 5-factor model over 1-year rolling windows using daily data from day t = -252 to day t = -1. Estimated factor loadings are then used to calculate daily abnormal returns starting on the day after the transaction day. We only start on the following day to avoid incorporating the bid-ask spread into returns (Odean, 1999). We then compute raw returns and CARs over the following 1-month, 6-month, and 1-year period. To mitigate the effect of extreme stock returns, we winsorize raw returns and CARs at the 1% level and at the 99% level.[18]

The results of the univariate performance comparison of advised and independent trades are reported in Panel B of Table III. We find that advised purchases deliver 2.5% lower raw returns than independent purchases over the 1-year horizon. This difference is statistically significant at the 5% level. However, the differences are insignificant for the shorter 1-month and 6-month horizons. When we look at the more meaningful results based on the market model and the 5-factor model, the difference between advised and independent trades amounts to 2.9% and 2.0%, respectively and is statistically significant at the 1% level. In case of the 5-factor model, advised buys deliver a 1-year CAR of -1.6% and the 1-year CAR of independent buys is 0.4% (both significant at the 1% level). These findings show that advised purchases not only underperform benchmarks but also independently executed transactions and provide first suggestive evidence that advisors do not help investors to make superior stock purchases.

The performance analysis for sales provides some weak evidence that advised sells are more beneficial, that is, they do worse subsequently, than independent sells based on 1-year

[16]In unreported tests, we also run our analysis with market-adjusted returns and use the SPI as a proxy for the market. Results are similar to the findings obtained from the simple market model.

[17]The size factor SMB (small minus big companies) is approximated by the difference in daily returns between the Vontobel Small Cap Index and the SMI (Swiss Market Index), the blue chip index. The value factor HML (high minus low book-to-market ratio) is approximated by the return difference between the MSCI Switzerland Value Index and the MSCI Switzerland Growth Index. Finally, the momentum factor is computed using overlapping portfolios of the 30% top performing stocks in the SPI and the 30% worst performing stocks in the SPI, a formation period of six months, a skipped month, and a holding period of six months.

[18]Results are similar if we do not winsorize CARs as shown in Table A2 in Appendix B.

raw returns. However, the more meaningful results based on the 5-factor model suggest that advisors also do not help clients to make better stock sells as stocks sold after advice outperform stocks sold independently by 1.1% p.a. (significant at the 5% level).

3.2 MULTIVARIATE ANALYSIS

The univariate performance comparison of advised and independent trades partially resolves the selection and endogeneity problems described above. However, it could still be the case that those clients who trade based on advice have worse investment skills and thus decide to rely more heavily on advice and possibly, such clients might perform even worse if they were not advised. We address this concern by looking at the within-person variation of the impact of advice on stock trading performance. We run OLS regressions of individual trade performance on a dummy variable that equals one if the trade is advised, and zero otherwise, and include client fixed effects. The latter are a key component of our identification strategy as they control for all unobserved client characteristics that are constant over time. The advised trade dummy then captures the difference in trade performance between advised and independent trades after controlling for the average trade performance of the client. For easier comparison of results between purchases and sales, we multiply the raw return (CAR) after a sale by -1, that is, we can in both cases interpret a negative coefficient on the advised trade dummy as evidence that advised trades underperform.

Results are reported in Table IV. Coefficient estimates for purchases (sales) are reported in Columns 1 to 3 (5 to 7). As a starting point, we use the 1-year raw return as the dependent variable. The results in Column 1 show that advised purchases perform worse than independent purchases. However, the difference is not statistically significant. In Columns 2 and 3, we replace the 1-year raw return by the 1-year CARs based on the market model and the 5-factor model, respectively. In both specifications, the within-person difference is negative and statistically significant (at least at the 5% level). The coefficient estimates suggest that the difference in abnormal returns between advised and independent trades is 3.0% and 1.7%

p.a., respectively.[19]

An additional advantage of our dataset is that for each advisory contact our data contain information on whether this contact was advisor-initiated or client-initiated. While client fixed effects should alleviate most endogeneity concerns, there is still a concern in this setting: Clients could approach their advisors with their own trading ideas in mind and might be more likely to do so when their trade ideas are of inferior quality, while they might execute their good investment ideas independently. Our data allow us to address this concern by separately investigating trades after client-initiated contacts and trades following advisor-initiated contacts. To do so, we add a dummy variable to our regression specification that takes on the value one if the advisory contact was initiated by the advisor, and zero otherwise. It measures the incremental effect of an advisor-initiated contact on the trade performance of advised trades. Consequently, in this regression, the advised trade dummy itself then measures the effect of advice on trade performance following a client-initiated contact.

The results in Column 4 of Table IV show that the complete underperformance of advised purchases can be attributed to advised purchases following advisor-initiated contacts. The coefficient on the advised trade dummy is no longer statistically different from zero, while advisor-initiated advice is associated with a reduction in the 1-year CAR of 3.3%. This result is troublesome as it suggests that advisors are not caught flat-footed by clients approaching them with a bad specific trading idea in mind for which they only seek reassurance. In contrast, our findings indicate that advisors do particularly poorly when they actively approach their clients.

The results on sales in Columns 5 to 8 of Table IV are much weaker and show only weak evidence that advised stock sales perform worse than independent stock sales. However, we can clearly reject the hypothesis that advised sales are better than independent sales. A likely reason for the weak and insignificant results on stock sales may be that they are often

[19] In further analyses, we compare the performance of independent trades by independent clients to that of independent trades by advised clients in a univariate setup (not reported). The 1-year CAR of independent purchases by non-advised clients is 0.5% and that of independent purchases by advised clients is 0.1%, with the difference being statistically insignificant (t-statistic of 1.04). Hence, the performance of independent trades is very similar across the two groups of investors and only the advised trades are associated with a significantly worse performance. These findings underscore the importance of comparing trades rather than clients to assess the impact of advice.

liquidity-driven. Furthermore, sales decisions are more restricted because the clients in our sample do not hold short positions and thus only the typically few stocks in their portfolios are candidates for sale.

Another advantage of our dataset is that it includes information on the identity of the advisor. Hence, in Table A1 in Appendix B, we re-estimate the regressions from Table IV and add combined client-advisor fixed effects to all specifications. Thus, we essentially compare the performance of advised and independent trades within each client-advisor pair, thereby we control for all advisor characteristics that remain constant over time as well as for a potential endogenous matching between clients and advisors. We find our results to remain virtually unchanged.

An explanation for the superior performance of independently executed purchases of a client versus this client's advised purchases could be that the client not only follows the advice of the bank advisor, but additionally seeks advice from an external financial advisor who may provide more valuable recommendations than the bank advisor. The trades following such external advice would then show up as independent trades in our sample. However, conversations with representatives of our bank and other industry representatives suggest that the same client only rarely relies on both bank advice and external financial advice. Independent financial advisors in Switzerland typically cooperate with a bank as they do not dispose of a banking license and thus cannot offer financial services such as securities accounts to their clients. In order to participate in the fees and commissions the client pays directly to the bank for these services, independent advisors enter into a revenue sharing agreement with the bank. Our bank offers such cooperation to independent financial advisors. However, clients with these independent financial advisors do not directly interact with our bank but only indirectly through the independent advisor. Thus, this type of clients is not included in our sample. If external advisors do not cooperate with our bank, they would have to charge for their services on top of the fees and commissions charged by our bank, which makes it rather unattractive (and unlikely) for bank clients to consult outside advisors.[20]

[20]Moreover, fee-based advice is still not very widespread in Europe. In a survey among purchasers of retail financial services in Europe, only 7% of respondents say they have made a direct payment in return for financial advice (Chater et al., 2010).

Nevertheless, to shed light on potential effects of independent financial advisors on the trade performance of clients in our sample, we collect information on the number of independent financial advisors in each village and town in Switzerland from the Swiss Federal Statistical Office and scale it by the number of residents. This information is available as of the beginning of our sample period in December 2001 and as of the end in December 2005. As of December 2001, there were about 7,700 independent financial advisors in Switzerland (equivalent to 950 inhabitants per advisor). In December 2005, this figure had increased to 8,200 (equivalent to 910 inhabitants per advisor). We then regress the performance of independently executed trades of clients on the fraction of independent financial advisors in the place of residence of a client. We hypothesize that the probability that a trade is executed with the support of an independent financial advisor is higher, the higher the fraction of independent financial advisors in the population. Thus, if independent financial advisors positively affect the performance of independently executed trades, we expect the coefficient on the percentage of independent advisors in a village or town to be positive. We control for the full set of client and portfolio characteristics included in Table II.

Results are reported in Table A2 in Appendix B. In Columns 1 and 2 (3 and 4), the dependent variable is the 1-year CAR based on the market model (5-factor model). Moreover, in Columns 1 and 3, we use data from December 2001 to determine the density of independent financial advisors in each village and town and in Columns 2 and 4, the figure is calculated using data from December 2005. When relying on data from 2001, the coefficient on the fraction of independent financial advisors is not statistically significant. When using data from 2005, the coefficient is negative and statistically significant at least at the 5% level, suggesting that independent trades (which potentially could be misclassified externally advised trades) perform worse if there are more external advisors available. Thus, if anything, a higher penetration with independent financial advisors further worsens the performance of trades not executed with the help of a bank advisor.

Another explanation for the underperformance of advised purchases could be that clients decide not to follow good trading ideas of advisors, but only follow the bad recommendations. This could be the case if, for some reason, advisors present good ideas in a less appealing way than their bad ones. Even though this appears rather implausible, our results could potentially be driven by such a selection effect at the trade level rather than by poor investment skills of advisors. To address this concern, we make use of our small subset of 558 client-advisor contacts for which the securities discussed between clients and advisors are known. In a univariate test (not reported), we compare the performance of recommendations that clients follow with the performance of recommendations that clients do not follow. We do not find a significant performance difference between these two groups of recommendations, suggesting that the above concern is not justified. However, we caution that these results are based on a relatively small sample size.

We run a number of additional stability tests. Results are reported in Table A3 in Appendix B. First, in Column 1 (Column 7), we rerun the analysis from Column 2 (Column 3) of Table IV and replace the advised trade dummy variable by a set of dummy variables for whether the advisory contact took place on the day of the trade or one, two, three, or four days before the trade. As we classify advised trades as trades executed within five days of an advisory contact, we test whether our results depend on the exact time period used in our definition of advised trades. For the first four days following an advisory contact, the coefficient estimates are always negative, suggesting that results are relatively similar across variations of our specific definition of advised trades. In Column 2 (Column 8), we exclude all trades in non-Swiss stocks, as our factor model might be more precise in capturing trade performance of Swiss stocks. Results remain similar in this specification. Thus, our findings should not be driven by the choice of the factor model. In Column 3 (Column 9), we run the analysis without winsorizing CARs at the 1% level and the 99% level. Results again remain similar. In Columns 4 and 5 (Columns 10 and 11), we re-estimate Column 2 (Column 3) of Table IV for the bearish (January 2002 to February 2003) and the bullish (March 2003 to June 2005) market environments separately. In both specifications, the coefficient on the advised trade dummy is negative. However, while the coefficient is statistically different from zero for trades executed in the bearish period, the coefficient estimate lacks significance for transactions executed in the bullish period. Finally, in Column 6 (12), we replicate the analysis measuring performance over a 6-month period rather than a 1-year period.[21] Our results also hold over a 6-month horizon. Overall, even though some of these tests deliver only statistically weak or insignificant results, there is no evidence that advised stock purchases would even perform better than independently executed purchases.

Finally, one reason why results for sales are not statistically significant could be that advised sales are merely a byproduct of advised purchases. In our small subset of 558 client-advisor contacts for which we observe the securities discussed between the client and the advisor, we find that 23.9% of advised purchases are accompanied by a sales transaction that is not explicitly mentioned in the advisory talk. To investigate whether the informativeness of advised sales differs if they do not come along with a buy transaction, in Table A4 in Appendix B, we rerun the analysis from Columns 6 and 7 of Table IV, focusing on advisory contacts that are only followed by sell transactions. However, this does not materially change our findings. The coefficient on the advised sale dummy remains statistically insignificant, suggesting that even if a financial advisor explicitly recommends to sell a stock, this recommendation does not perform differently from an independently executed sale.

3.3 CALENDAR-TIME PORTFOLIOS

One potential shortfall of our multivariate regression approach is that it weights each trade equally, irrespective of its size. Furthermore, our analysis so far does not take into account the problem of cross-sectional dependence of stock returns. Our dataset spans 3.5 years and contains roughly 75,000 trades in about 2,500 different stocks. Performance is evaluated over 12-month windows. Hence, the performance of individual trades is not independent across trade observations. To account for both, the cross-sectional correlation of stock returns and the relative size of trades when investigating the relative performance of advised and independent stock trades, we follow previous work on individual investors and construct value-weighted calendar-time portfolios (e.g., Barber et al., 1999; Odean, 1999; Seasholes and

[21] To develop an understanding of the investment horizon of clients, we examine the duration of roundtrips, that is, trades where there was a buy and a subsequent sale so that at the end of the roundtrip the client does not hold the stock anymore. The average length of roundtrips in our sample is 243 calendar days, which is equivalent to about eight months.

Zhu, 2010).[22] The main disadvantage of the calendar-time portfolio approach is that we can no longer investigate the impact of advice on trade performance in a within-person setting. Rather, we form one portfolio consisting of advised stock trades and one portfolio consisting of independent stock trades, and then compare their performance. Specifically, a stock enters the advised (independent) portfolio with its weight in Swiss Francs if there is any advised (independent) purchase or sale of that stock by any of our clients. The weight of this stock is adjusted upwards or downwards when the same or another investor conducts an advised (independent) subsequent buy or sell transaction in this stock. Although individual investors typically do not hold short positions, our portfolio tracking the trades of the investor groups might lead to effective short positions as we assume a holding of zero for all stocks at the beginning of our investigation period.[23] We compute the daily excess returns over the risk-free interest rate of the advised trade portfolio and of the independent trade portfolio as well as the daily return of the difference portfolio that goes long the advised trade portfolio and short the independent trade portfolio. To determine alphas we then estimate risk factor models with the same set of factors as above based on daily portfolio returns. To be able to form portfolios from a sufficiently large number of trades, the first month of the sample period is defined as a phase-in period. Hence, we investigate the period from February 2002 to June 2005.

The results are reported in Table V. In Column 1, we present results for the portfolio formed from advised trades. The daily raw return of the portfolio of advised trades is -0.012% and the CAPM (5-factor model) alpha is -0.009% (-0.008%) per day. Even though not statistically significant, this again provides suggestive evidence that advised trades underperform benchmarks. Column 2 reports average daily raw returns and alphas for the portfolio of independent trades. They range from 0.009% to 0.012% per day and are again not statisti-

[22]In Table A5 in Appendix B, we replicate the analysis from Columns 2 and 3 of Table IV clustering standard errors at different levels to control for different types of within correlation which may confound the results from our standard fixed effects regression setup. This analysis complements our calendar-time portfolio analysis. We use standard errors which are clustered at the client-month, advisor-month, and stock-month level, respectively. While the statistical significance is slightly reduced as compared to Table IV, all coefficients on the advised trade dummy remain significant at least at the 10% level.

[23]In unreported tests, we rerun the calendar-time portfolio analysis assuming a holding period of one year for every transaction (Seasholes and Zhu, 2010). Hence, potential short positions are closed after one year at the latest. Results become even stronger using this specification.

cally different from zero. In Column 3, results for the difference portfolio are presented. The CAPM alpha and the 5-factor model alpha of the difference portfolio are both significantly negative at the 10% level and amount to -0.020% per day, that is, the advised trade portfolio significantly underperforms the independent trade portfolio by approximately 5% p.a.

Overall, our findings from the calendar-time portfolio analysis and from the within-person analysis of individual trades clearly show that advisors are not helpful in generating superior stock trading performance for investors as compared to both passive benchmarks and the trades they conduct independently.

3.4 SOURCES OF UNDERPERFORMANCE

Next, we take a closer look at the specific investment strategies suggested by advisors to better understand the sources of the underperformance of advised trades. In our univariate analysis in Table III, we documented an underperformance of advised transactions vis-à-vis benchmarks and in our multivariate analysis in Table IV, we showed that advised trades perform worse than independent transactions of the same client. To analyze potential sources of both types of underperformance, we compare the stock characteristics of advised and independent stock purchases by running logit regressions with the advised trade dummy as dependent variable. As explanatory variables we include the loading on the market factor, the natural logarithm of the market capitalization, the book-to-market ratio, and the past 1-year return decile of the stocks traded. We include these variables because the univariate comparison in Table III revealed that advised and independent transactions differ with respect to these factors. In addition, to analyze whether financial advisors follow sell-side analysts, we include a dummy variable that equals one for stocks with more than 50% buy recommendations on IBES, and zero otherwise. We create the variable MAX that measures the maximum daily return over the past 1-year period to analyze whether advisors have a preference for stocks with extreme positive returns (Bali et al., 2011). To do so, on each trading day, we sort stocks in our stock universe into MAX deciles. In addition, we include a dummy variable that equals one for stocks paying a dividend in a given fiscal year. In Switzerland, dividend income is taxable for private investors, while capital gains are not. Advisors might help clients to avoid taxes by avoiding stocks paying dividends.[24]

Results are presented in Panel A of Table VI. The regression specification in Column 1 does not yet include client fixed effects and may thus help us to understand why advised trades underperform benchmarks and independent trades in our univariate setting in Table III. Consistent with our univariate analysis, we find that advised stock purchases have a significantly smaller market risk exposure and involve significantly larger stocks in terms of market capitalization. However, in contrast to our univariate comparison, the coefficient on the book-to-market ratio is now positive, suggesting that advisors lean more towards a value strategy. Moreover, advised and independent trades do no longer differ significantly with respect to their past 1-year raw returns. The coefficient on the dummy variable for strongly recommended stocks is positive and significant, indicating that advisors follow the recommendations of sell-side analysts more than clients' independent trades. The coefficient estimate suggests that the probability of a trade being advised is 0.6 percentage points higher for strongly recommended stocks. This is economically meaningful, given that the overall percentage of advised stock trades amounts to 5.7%. Trades are also more likely to be advised if the respective stock experienced a positive extreme return in the past 1-year period, suggesting that advisors have a stronger preference for stocks with lottery-like payoffs than clients. The coefficient on the dividend-paying stock dummy is not statistically different from zero, indicating that advisors do not help clients to trade in a tax-efficient way. In Column 2, we rerun our logit regression from Column 1 adding client fixed effects. This specification may help to explain why advised trades perform significantly worse than independent trades in our within-person analyses in Table IV. In Column 2, all coefficients turn statistically insignificant except for the coefficients on the market capitalization and the MAX decile. As our 5-factor model already includes a size factor, differences in size are unlikely to explain differences in the performance of advised and independent transactions (except if our size factor does not properly capture this effect). However, advisors' stronger preference for lottery-type stocks might provide an explanation for return differences between advised and independently

[24]Cici et al. (2016) show that investors who purchase mutual funds through brokers exhibit a stronger tendency to avoid taxable distributions than investors who buy mutual funds directly.

executed transactions in our within-person setting.

To investigate whether the differences in stock characteristics documented above are likely to explain differences in performance between advised and independent trades, we next sort trades on characteristics found to be significant in Panel A and analyze their performance. Thus, in Panels B and C of Table VI, we split trades into two groups based on whether they have more or less than 50% buy recommendations and based on whether their MAX decile is above or below the median across all trades. We then investigate the average 1-year trade performance in each group using our three performance metrics. In Panel B, we show that trades in strongly recommended stocks with more than 50% buy recommendations significantly underperform trades with a lower fraction of buy recommendations. Moreover, trades in strongly recommended stocks significantly underperform benchmarks (t-statistic of -5.07 in case of the market model and -11.84 in case of the 5-factor model). This is consistent with Barber et al. (2003) who also document highly recommended stocks to underperform the market as well as stocks least favored by analysts in the early 2000s. Moreover, our findings are in line with Malmendier and Shanthikumar (2007) who find that recommendations of sell-side analysts are upward biased and subsequently underperform. Moreover, in Panel C, we find the group of trades with relatively high past extreme returns to significantly underperform the group of trades with less extreme returns. This is consistent with Bali et al. (2011) who document a negative relation between past extreme positive returns and expected returns. Moreover, this is also in line with Kumar (2009) who finds that stocks with lottery-type features underperform. Overall, our findings suggest that the investment strategies suggested by financial advisors perform particularly poorly during our investigation period.

Finally, our finding of bad performance of advised purchases could also be driven by advisors that deliberately push unattractive stocks from their bank's proprietary portfolios into their retail clients' portfolios and that these stocks subsequently underperform (Fecht et al., 2013). However, as we have no information on the bank's proprietary portfolio, we cannot explicitly test for this channel.

3.5 DO INVESTORS REACT TO THE PAST PERFORMANCE OF ADVISED TRADES?

The last question we address in this section is why clients do not internalize the poor performance of advised transactions. To this end, we analyze whether investors react to the performance of advised trades by relying more (less) on financial advice if this advice was particularly good (bad) in the past. For every client, we form a portfolio consisting of advised stock trades and a portfolio containing independently executed stock transactions. We estimate logit models with a dummy variable that equals one for advised purchases and zero for independently executed purchases as our dependent variable. The past performance of the portfolio of advised trades, the past performance of the portfolio of independent trades, the past market return, and the past market volatility prior to the date of the transaction are used as independent variables. Moreover, we include client fixed effects to control for all client characteristics that remain constant over time.

Results are reported in Table VII. In Column 1, we focus on the past 1-month period, in Column 2 on the past six months, and in Column 3 on the past 1-year period. Across all specifications, the coefficients on both the past performance of advised trades and the past performance of independently executed transactions are insignificant (except for Column 3 where the coefficient on the past performance of independent trades is weakly statistically significant (t-statistic of 1.79)). Hence, the past performance of advised and independent trades does not seem to materially impact the decision of clients to rely on advice. This might be because investors are simply not aware of the bad performance of advised trades or they have an overly optimistic perception of the past performance of advised trades. Consistent with this view, Goetzmann and Peles (1997) find that mutual fund investors' recollections of past performance are consistently biased above actual past performance, providing an explanation why many investors stay with funds that consistently perform poorly. They argue that this is due to investors trying to avoid cognitive dissonance. Furthermore, advisors might be good at convincing investors that their advice is valuable, although it is not. In fact, Kaustia et al. (2015) document that lower skilled advisors are genuinely more optimistic. They hypothesize that these optimistic beliefs help them to convince clients and thereby generate enough sales to stay in business. We also find that advised trades are more likely to take place when the market recently performed well. This might be because advisors have an easier time convincing clients to trade when the market environment is friendly. In addition, advised trades are significantly positively correlated with past market volatility, suggesting that investors feel more insecure and eventually rely more heavily on financial advice in turbulent times. Thus, the overall market environment seems to be much more important for clients' reliance on financial advice than the past performance of advised trades.

4. The Impact of Financial Advice on Behavioral Biases

Although advisors do not help investors to conduct superior performing stock trades, they might offer other benefits to them. By having access to the overall equity portfolio composition of the investors, advisors might analyze the stock holdings of investors in context and help them to overcome behavioral biases. Thus, in the following, using a similar trade-by-trade within-person setting as in our performance analysis, we investigate whether advisors mitigate under-diversification (e.g., Goetzmann and Kumar, 2008), the home and local bias (e.g., French and Poterba, 1991; Grinblatt and Keloharju, 2001), and the disposition effect (e.g., Odean, 1998).

We first investigate the effect of advice on portfolio diversification. In our descriptive statistics in Table I, we report that clients only hold four stocks in their accounts on average, suggesting that they do not hold a well-diversified portfolio. To assess the diversification effect of a trade on the portfolio, we estimate the beta of a newly purchased stock relative to the existing equity portfolio of a client over a 1-year period prior to the transaction. The idea is that if a new stock has a high beta with respect to the already existing portfolio its diversification potential is low. As a second measure to capture the diversification effect of a trade, we create a dummy variable that equals one if a client already holds a newly purchased stock in the existing portfolio, and zero otherwise. We use these two proxies for the diversification effect of a trade as dependent variables in an OLS regression and a logit regression, respectively. The advised trade dummy serves as explanatory variable. Both regressions contain client fixed effects. Results are reported in Columns 1 and 2 of Panel A in Table VIII. In Column 1, there is weak evidence that advised purchases are less correlated with clients' existing portfolios than independent transactions and eventually might help to diversify the portfolio better. In Column 2, the coefficient on the advised trade dummy is negative and statistically significant at the 5% level, again suggesting that advisors help clients to hold better diversified portfolios.

Next, we analyze the impact of advice on the home and the local bias. In our descriptive statistics, we find that 88.3% of equity portfolios of clients living in Switzerland are invested in Swiss stocks. However, the Swiss stock market only accounts for 2.2% of the global market capitalization as of the end of 2005 (World Bank, 2015). Thus, clients in our sample suffer from a substantial home bias. Similarly, we find that Swiss clients hold 51.7% of their portfolios in stocks located within a 50-kilometer radius of their home, while for the average client only 10.0% of Swiss market capitalization is headquartered within the same radius. This indicates that clients are also subject to a substantial local bias. To analyze the effect of a newly purchased stock on the home bias and the local bias, we create dummy variables equal to one for Swiss and for local stocks, respectively. We estimate logit regressions with client fixed effects and use the two dummies as dependent variables and the advised trade dummy as main explanatory variable. When analyzing the effect of advice on the home bias and the local bias, we only consider trades of Swiss clients. Results are presented in Columns 3 and 4 of Panel A in Table VIII. In Column 3, we do not find evidence for a statistically significant difference between advised and independent trades, suggesting that advisors do not help to reduce the home bias in clients' portfolios. However, in Column 4, we find strong evidence that advised trades are less likely to involve local stocks, suggesting that advisors help clients to overcome the local bias.

Finally, to investigate whether clients in our dataset are subject to the disposition effect and whether financial advisors help clients to overcome the disposition effect, we follow the approach of Grinblatt et al. (2012) and create a dummy variable that equals one if an investor sells a stock for which the purchase price is known, and zero for all stocks in the client's portfolio that are not sold the same day and for which the purchase price is also known. We use this dummy as the dependent variable in a logit regression. As explanatory variables we include dummies for various ranges of gains and losses. The omitted dummy represents capital losses between zero and 20%. In this setting, we classify all portfolio positions as advised if the sale takes place within five days of an advisory contact. All gain/loss dummies are then interacted with the advised dummy variable.

Results of this analysis are reported in Panel B of Table VIII. We first document that loss dummies have significantly negative benchmark coefficients, while the gain dummies are significantly positive, indicating that individuals in our sample are more likely to sell winners than losers and thus are subject to the disposition effect. Moreover, consistent with Grinblatt et al. (2012), we find that the coefficients on loss dummies decrease in the magnitude of the loss. Thus, investors tend to hold on to bigger losers longer than to smaller losers. The coefficients on the interaction terms between the loss dummies and the advised dummy variable are all positive and two out of three are highly statistically significant while the third one is not significant at conventional levels (t-statistic of 1.57). This suggests that advisors help clients to realize capital losses, probably by resolving investors' cognitive dissonance.[25] In summary, there is evidence that bank advisors mitigate under-diversification, the local bias (but not the home bias), and the disposition effect of individual investors.

Finally, we examine whether the reduction in the behavioral biases under investigation or in another behavioral bias that we do not analyze here leads to superior overall performance of advised clients despite the negative informational value of advice we document at the stock trade level. To this end, we compare the overall portfolio performance (based on all trades) of advised clients (that is, clients that trade on advice at least once during our sample period) and independent clients (that never trade on advice). We still find the overall portfolio of advised clients to significantly underperform that of completely independent clients by 6.3% p.a. in terms of raw returns and by 4.4% (4.2%) in terms of CAPM (5-factor model) alphas. When taking into account trading costs, the performance of advised clients would become even

[25]Chang et al. (2016) argue that the disposition effect is the result of investors feeling a cognitive dissonance discomfort when faced with (realized) losses. However, the disutility of (realized) losses can be resolved if the investor can delegate the investment decision and blame someone else.

worse due to their higher trading activity.[26] This finding suggests that the underperformance of advised trades documented in Section 3 is not offset by other positive effects like the reduction of behavioral biases.

5. Conclusion

We examine the impact of financial advice on individual trade performance of bank clients as well as on various behavioral biases individual investors are often subject to. Using a unique dataset from a Swiss retail bank, we can run a within-person comparison of advised and independent trades of a client and we are thus able to overcome methodological problems that earlier studies on the impact of financial advice face. We can show that advice does not improve stock trading performance. In contrast, we provide evidence that stock trades that follow the advice of a bank advisor on average perform significantly worse than benchmarks and than the trades the same investor carries out independently. Furthermore, our results indicate that those advised trades that follow a contact between the client and the advisor that was initiated by the advisor perform particularly poorly, suggesting that advisors actively contact clients with rather poor trading ideas.

Advisors' recommendations seem to follow sell-side analysts and advisors induce clients to trade stocks with lottery-like payoffs. Consistent with the literature, we document that trades with these characteristics perform particularly poorly (e.g., Malmendier and Shanthikumar, 2007; Bali et al., 2011), providing an explanation for why advised trades underperform both benchmarks and independent transactions. Interestingly, we find no evidence that investors react to the bad past performance of financial advice by relying less on advice subsequently.

While advisors do not seem to help in achieving a better trade performance, they seem to assist clients in reducing some behavioral biases. We document that they help clients to better diversify their portfolios, reduce the local bias (but not the home bias), and encourage clients to realize their losses thereby alleviating the disposition effect. However, overall, the negative stock-picking abilities of advisors are not offset by a reduction of the negative

[26]On average, advised clients execute 5.0 trades p.a., of which 1.2 trades are advised. In contrast, independent clients only execute 2.0 trades p.a. on average.

impact of behavioral biases on performance. Overall, portfolios of advised clients still perform significantly worse than portfolios of independent clients.

While our setting and the structure of our dataset has many advantages, the main limitation of our study is that all information we use comes from one Swiss bank. Thus, it is a valid question whether the customers of this bank and particularly the skills and performance of its advisors are representative. We see no obvious reasons that would make us believe that the clients and advisors of our bank are different from the clients and advisors of other financial institutions in any fundamental way. According to a recent survey by BlackRock (2013), individuals' reliance on advice fluctuates roughly between 20% and 40% across a broad range of industrialized countries (Belgium, Canada, France, Germany, Italy, Netherlands, Switzerland, U.K., U.S.). Hence, financial advice is of similar importance across different developed countries. Moreover, to investigate whether our clients and their trading behavior differs substantially between our sample and other samples, in unreported tests, we replicate a number of studies on individual investors' behavior that use a dataset from a large U.S. brokerage house, including Barber and Odean (2000, 2001, 2002), Ivkovic et al. (2008), and Seasholes and Zhu (2010), and find their results to hold in our dataset. Hence, there is no reason to expect investors in our sample to behave differently from investors in other datasets. We can of course not completely rule out differences between our customers and advisors and the customers and advisors of other banks. However, this is a problem we share with most other studies on individual investors.

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Tables

Table I: Descriptive statistics

This table presents descriptive statistics on client and portfolio characteristics. For time-varying variables, beginning-of-period values (*age*, *length of relationship*) or averages over the sample period from January 2002 to June 2005 (all portfolio characteristics) are reported. Appendix A provides detailed descriptions of all variables used throughout the study.

	Mean	10%	Median	90%	Std. dev.	N
Panel A: Client characteristics						
Male (d)	0.608	0.000	1.000	1.000	0.488	9,976
Age (years)	58.95	37.00	60.00	79.00	15.79	9,976
Age $<$ 45 (d)	0.208	0.000	0.000	1.000	0.406	9,976
45 $\leq$ age $<$ 60 (d)	0.272	0.000	0.000	1.000	0.445	9,976
60 $\leq$ age $<$ 75 (d)	0.344	0.000	0.000	1.000	0.475	9,976
Age $\geq$ 75 (d)	0.176	0.000	0.000	1.000	0.381	9,976
Education (1-7)	3.76	3.00	3.00	7.00	1.54	2,408
Employment, employed (d)	0.651	0.000	1.000	1.000	0.477	8,072
Employment, retired (d)	0.292	0.000	0.000	1.000	0.455	8,072
Swiss (d)	0.848	0.000	1.000	1.000	0.359	9,976
Product information (d)	0.810	0.000	1.000	1.000	0.392	9,976
E-banking account (d)	0.198	0.000	0.000	1.000	0.399	9,976
Length of relationship (years)	6.61	2.08	7.08	8.25	2.37	9,976
Panel B: Portfolio characteristics						
Avg. portfolio size (CHF)	109,695	1,371	30,668	215,411	383,146	9,966
Avg. # stocks	3.96	0.69	2.12	9.38	4.94	9,966
Avg. % Swiss stocks	88.30	57.79	100.00	100.00	22.88	8,431
Avg. % local stocks	51.71	0.00	48.35	100.00	42.32	8,431
Avg. # stock trades p.a.	2.31	0.29	0.57	4.86	6.81	9,976
Avg. trading volume p.a. (CHF)	55,702	509	7,571	98,202	418,697	9,976

Table II: Determinants of trading on advice

The table presents the results from OLS regressions. The dependent variable is the clients' average percentage of advised trades p.a. over the entire investigation period from January 2002 to June 2005. For *portfolio size* beginning-of-period values are used. Appendix A provides detailed descriptions of all variables used throughout the study. The t-values (in parentheses) are based on heteroskedasticity-robust White (1980) standard errors. ***, **, * denote statistical significance at the 1%, 5%, 10% level.

	Avg. % advised trades p.a.	
	(1)	(2)
Client characteristics		
Male (d)	-0.026***	-0.026**
	(-5.27)	(-2.24)
$45 \leq$ age < 60 (d)	0.005	0.017**
	(1.05)	(2.13)
$60 \leq$ age < 75 (d)	0.029***	0.035***
	(5.42)	(3.91)
Age ≥ 75 (d)	0.031***	0.050**
	(4.31)	(2.43)
Swiss (d)	-0.090***	-0.046**
	(-10.04)	(-2.54)
Product information (d)	-0.007	-0.048***
	(-1.04)	(-2.67)
E-banking account (d)	-0.016***	-0.011
	(-3.69)	(-1.64)
Length of relationship (years)	0.000	0.002
	(0.07)	(1.10)
Education (1-7)		0.005*
		(1.69)
Portfolio characteristics		
Log(portfolio size)	0.013***	0.010***
	(13.21)	(5.36)
Constant	0.008	-0.003
	(0.56)	(-0.08)
Adj. R^2	0.066	0.073
N	8,228	2,034

Table III: Univariate comparisons of the performance of advised and independent trades

The table presents univariate comparisons of trade and performance characteristics of advised and independent trades. Results for purchases and sales are reported separately. Performance is measured in terms of the 1-month (6-month, 1-year) raw return of a trade, the 1-month (6-month, 1-year) cumulative abnormal return (CAR) of a trade based on the market model, or the 1-month (6-month, 1-year) CAR of a trade based on the 5-factor model. Abnormal returns are calculated as the difference between the daily returns and the returns predicted by the market model and the 5-factor model, respectively. Both the market model and the 5-factor model are estimated over the time period from t = -252 to t = -1. The market model uses the SPI (Swiss Performance Index) as proxy for the equity market risk factor. The 5-factor model includes the SPI as well as the MSCI World Index as proxies for the market and Swiss SMB, HML, and momentum factors. Appendix A provides detailed descriptions of all variables used throughout the study. Means of the subgroups are tested for equality using a standard t-test. ***, **, * denote statistical significance at the 1%, 5%, 10% level.

	Advised	Independent	Difference	t-value	N
Panel A: Trade characteristics					
Buys					
Past 1-year beta (SPI)	0.893	0.920	-0.027*	-1.84	37,117
Market capitalization (CHFbn)	42.003	26.462	15.540***	13.85	37,800
Book-to-market ratio	0.624	0.668	-0.044***	-3.94	35,525
Past 1-year raw return decile	5.456	5.285	0.170***	2.78	37,109
Sells					
Past 1-year beta (SPI)	0.929	0.922	0.007	0.57	35,904
Market capitalization (CHFbn)	56.034	35.825	20.209***	17.54	36,563
Book-to-market ratio	0.536	0.603	-0.066***	-6.87	34,773
Past 1-year raw return decile	5.566	5.627	-0.061	-1.18	35,895
Panel B: Performance					
Buys					
Raw returns					
1-month raw return (%)	1.426	1.385	0.041	0.13	37,788
6-month raw return (%)	6.172	5.567	0.605	0.80	37,581
1-year raw return (%)	16.717	19.253	-2.536**	-2.25	37,329
Market model					
1-month CAR (%)	0.120	0.377	-0.257	-0.96	37,091
6-month CAR (%)	-0.539	0.817	-1.357**	-2.14	36,896
1-year CAR (%)	-0.997	1.896	-2.893***	-3.65	36,655
5-factor model					
1-month CAR (%)	-0.065	0.307	-0.372	-1.46	37,091
6-month CAR (%)	-0.811	0.127	-0.939*	-1.68	36,896
1-year CAR (%)	-1.598	0.423	-2.021***	-2.99	36,655
Sells					
Raw returns					
1-month raw return (%)	0.852	1.151	-0.299	-1.21	36,413
6-month raw return (%)	5.357	6.177	-0.820	-1.34	36,150
1-year raw return (%)	14.711	18.206	-3.495***	-3.78	35,676
Market model					
1-month CAR (%)	-0.690	-0.516	-0.174	-0.84	35,770
6-month CAR (%)	-3.174	-3.640	0.466	0.98	35,522
1-year CAR (%)	-5.006	-5.785	0.778	1.35	35,059
5-factor model					
1-month CAR (%)	-0.785	-0.531	-0.254	-1.27	35,770
6-month CAR (%)	-2.711	-3.386	0.675	1.56	35,522
1-year CAR (%)	-4.320	-5.457	1.137**	2.20	35,059

Table IV: Determinants of trade performance

The table presents the results from OLS regressions with client fixed effects. Results for purchases (Columns 1 to 4) and sales (Columns 5 to 8) are reported separately. The dependent variable is either the 1-year raw return of a trade (Columns 1 and 5), the 1-year cumulative abnormal return (CAR) of a trade based on the market model (Columns 2 and 6), or the 1-year CAR of a trade based on the 5-factor model (Columns 3, 4, 7, and 8). 1-year raw returns and 1-year CARs for sales are multiplied by -1 to facilitate the comparison of results across purchases and sales. Abnormal returns are calculated as the difference between the daily returns and the returns predicted by the market model and the 5-factor model, respectively. Both the market model and the 5-factor model are estimated over the time period from t = -252 to t = -1. The market model uses the SPI (Swiss Performance Index) as proxy for the equity market risk factor. The 5-factor model includes the SPI as well as the MSCI World Index as proxies for the market and Swiss SMB, HML, and momentum factors. Appendix A provides detailed descriptions of all variables used throughout the study. The t-values (in parentheses) are based on heteroskedasticity-robust White (1980) standard errors. ***, **, * denote statistical significance at the 1%, 5%, 10% level.

	Buys				Sells			
		1-year CAR (%)				1-year CAR (%)		
	1-year raw return (%)	Market model	5-factor model		1-year raw return (%)	Market model	5-factor model	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Advised (d)	-1.139	-2.958***	-1.725**	-0.450	-0.044	-0.339	-0.876	-1.453
	(-0.80)	(-3.18)	(-2.08)	(-0.45)	(-0.03)	(-0.45)	(-1.25)	(-1.55)
Advisor-initiated (d)				-3.310**				1.194
				(-2.15)				(0.99)
Constant	19.183***	1.899***	0.408***	0.404***	-17.976***	5.756***	5.440***	5.444***
	(76.22)	(10.85)	(2.70)	(2.67)	(-75.60)	(39.03)	(40.72)	(40.71)
Client fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.046	0.076	0.047	0.047	0.060	0.040	0.021	0.021
N	37,329	36,655	36,655	36,655	35,676	35,059	35,059	35,059

Table V: Performance of calendar-time portfolios formed on advised and independent trades

The table presents the performance of a value-weighted calendar-time portfolio formed on advised trades (Column 1), the performance of a value-weighted calendar-time portfolio formed on independent trades (Column 2), and the performance difference between the two portfolios (Column 3). Performance is measured in terms of daily raw returns, daily alphas from the CAPM model, and daily alphas from the 5-factor model. The CAPM uses the SPI (Swiss Performance Index) as proxy for the equity market risk factor. The 5-factor model includes the SPI as well as the MSCI World Index as proxies for the market and Swiss SMB, HML, and momentum factors. The first month of the sample period is defined as a phase-in period. Hence, we investigate the period from February 2002 to June 2005. The t-values (in parentheses) are based on heteroskedasticity-robust White (1980) standard errors. ***, **, * denote statistical significance at the 1%, 5%, 10% level.

	Portfolio of advised trades	Portfolio of independent trades	Difference portfolio (Advised - Independent)
	(1)	(2)	(3)
Daily raw return (%)	-0.012	0.009	-0.021
	(-0.51)	(0.53)	(-0.73)
Daily CAPM alpha (%)	-0.009	0.011	-0.020*
	(-0.79)	(1.18)	(-1.75)
Daily 5-factor model alpha (%)	-0.008	0.012	-0.020*
	(-0.71)	(1.50)	(-1.91)

Table VI: Advisor recommendations

The table presents results from logit regressions (Panel A), univariate comparisons of the performance of trades in strongly and weakly recommended stocks (Panel B), and univariate comparisons of the performance of trades in stocks with high and low past extreme positive returns (Panel C). Only purchases are considered. In Panel A, the dependent variable is a dummy variable that equals one for advised trades and zero for independent trades. In Panel B, we classify trades as *strongly recommended* and *weakly recommended* based on whether more or less than 50% of sell-side analysts currently recommend to buy the stock. In Panel C, we classify trades as *high MAX* and *low MAX* based on whether their MAX decile is above or below the median across all trades. MAX is the maximum daily return of a stock within a year. The sorting of stocks into MAX deciles is performed on each trading day. In Panels B and C, performance is measured in terms of the 1-year raw return of a trade, the 1-year cumulative abnormal return (CAR) of a trade based on the market model, or the 1-year CAR of a trade based on the 5-factor model. Abnormal returns are calculated as the difference between the daily returns and the returns predicted by the market model and the 5-factor model, respectively. Both the market model and the 5-factor model are estimated over the time period from t = -252 to t = -1. The market model uses the SPI (Swiss Performance Index) as proxy for the equity market risk factor. The 5-factor model includes the SPI as well as the MSCI World Index as proxies for the market and Swiss SMB, HML, and momentum factors. Appendix A provides detailed descriptions of all variables used throughout the study. In Panel A, the t-values are reported in parentheses. In Column 1 of Panel A, we report marginal effects. In Panels B and C, means of the subgroups are tested for equality using a standard t-test. ***, **, * denote statistical significance at the 1%, 5%, 10% level.

Panel A: Determinants of advisor recommendations

	Advised (d)	
	(1)	(2)
Past 1-year beta (SPI)	-0.013***	-0.181
	(-4.47)	(-1.54)
Log(market capitalization)	0.011***	0.063*
	(13.97)	(1.85)
Book-to-market ratio	0.017***	0.006
	(5.10)	(0.05)
Past 1-year raw return decile	-0.001	0.029
	(-0.99)	(1.39)
Strongly recommended (d)	0.006**	-0.139
	(2.35)	(-1.51)
Past 1-year MAX decile	0.002***	0.064**
	(2.96)	(2.10)
Dividend-paying (d)	0.002	0.110
	(0.70)	(0.96)
Constant		0.078
		(0.08)
Client fixed effects	No	Yes
Pseudo R^2	0.029	0.236
N	29,164	4,793

Panel B: Univariate comparisons of the performance of trades in strongly/weakly recommended stocks

	Strongly recommended	Weakly recommended	Difference	t-value	N
1-year raw return (%)	15.207	23.577	-8.370***	-15.28	32,887
1-year CAR, market model (%)	-1.012	6.553	-7.565***	-20.34	32,765
1-year CAR, 5-factor model (%)	-2.085	5.161	-7.247***	-22.83	32,765

Panel C: Univariate comparisons of the performance of trades in high/low MAX stocks

	High MAX	Low MAX	Difference	t-value	N
1-year raw return (%)	21.991	17.457	4.534***	8.63	36,657
1-year CAR, market model (%)	0.983	2.583	-1.601***	-4.46	36,655
1-year CAR, 5-factor model (%)	0.251	0.843	-0.592*	-1.90	36,655

Table VII: Do investors react to the past performance of advised trades?

The table presents results from logit regressions. Only purchases are considered. The dependent variable is a dummy variable that equals one for advised trades and zero for independent trades. Appendix A provides detailed descriptions of all variables used throughout the study. The t-values are reported in parentheses. ***, **, * denote statistical significance at the 1

	Advised (d)		
	(1)	(2)	(3)
Past 1-month raw return of advised trades (%)	-0.001		
	(-0.13)		
Past 1-month raw return of independent trades (%)	0.002		
	(0.19)		
Past 1-month SPI return (%)	0.038**		
	(2.22)		
Past 1-month SPI return volatility (%)	0.428***		
	(2.66)		
Past 6-month raw return of advised trades (%)		-0.002	
		(-0.48)	
Past 6-month raw return of independent trades (%)		-0.004	
		(-0.73)	
Past 6-month SPI return (%)		0.025***	
		(3.79)	
Past 6-month SPI return volatility (%)		1.064***	
		(5.57)	
Past 1-year raw return of advised trades (%)			0.004
			(1.09)
Past 1-year raw return of independent trades (%)			0.007*
			(1.79)
Past 1-year SPI return (%)			-0.003
			(-0.85)
Past 1-year SPI return volatility (%)			0.911***
			(4.71)
Client fixed effects	Yes	Yes	Yes
Pseudo R^2	0.210	0.221	0.219
N	2,194	2,194	2,194

Table VIII: Determinants of behavioral biases

The table presents the results from an OLS regression (Column 1 in Panel A) and logit regressions (Columns 2 to 4 in Panel A and Panel B). In Panel A, only purchases are considered. Moreover, in Columns 3 and 4 of Panel A, only trades of Swiss clients are included. In Panel A, the dependent variable is either the beta of a newly purchased stock relative to the existing stock portfolio of a client estimated over a 1-year period prior to the transaction (Column 1), a dummy variable that equals one if the client already holds the newly purchased stock in the portfolio (Column 2), a dummy variable which equals one for Swiss stocks (Column 3), or a dummy variable which equals one for local stocks (Column 4). In Panel B, we follow the approach of Grinblatt et al. (2012) and create a dummy variable that equals one if an investor sells a stock for which the purchase price is known and zero for all stocks in the client's portfolio that are not sold the same day and for which the purchase price is also known. As explanatory variables we include dummies for various ranges of gains and losses. The omitted dummy represents capital losses between zero and 20%. In this setting, we classify all portfolio positions as advised if the sale takes place within five days of an advisory contact. All gain/loss dummies are then interacted with the advised dummy variable. Appendix A provides detailed descriptions of all variables used throughout the study. In the OLS regression, the t-values (in parentheses) are based on heteroskedasticity-robust White (1980) standard errors. ***, **, * denote statistical significance at the 1%, 5%, 10% level.

Panel A: Diversification, home bias, and local bias

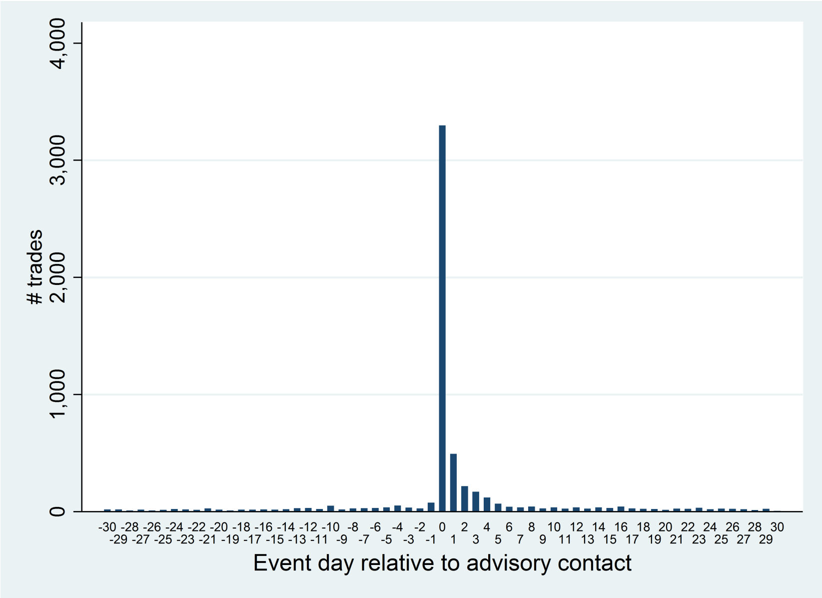
	Beta relative to portfolio	Already in portfolio (d)	Swiss stock (d)	Local stock (d)
	(1)	(2)	(3)	(4)
Advised (d)	-0.024*	-0.219**	-0.164	-0.797***
	(-1.66)	(-2.44)	(-1.29)	(-4.18)
Constant	0.633***	0.219	1.386	-1.253
	(286.44)	(0.15)	(1.24)	(-1.56)
Client fixed effects	Yes	Yes	Yes	Yes
Adj. R^2	0.295			
Pseudo R^2		0.188	0.221	0.223
N	30,545	29,371	18,490	12,421

Panel B: Disposition effect

	Sale (d)	
	Benchmark	× Advised (d)
Advised (d)	-0.245	
	(-1.30)	
[-100%,-60%) (d)	-0.491***	1.397***
	(-5.05)	(3.29)
[-60%,-40%) (d)	-0.419***	0.688
	(-5.15)	(1.57)
[-40%,-20%) (d)	-0.150**	1.113***
	(-2.54)	(3.64)
[0%,20%) (d)	1.398***	0.390*
	(38.60)	(1.90)
[20%,40%) (d)	1.583***	0.361
	(28.65)	(1.33)
[40%,60%) (d)	1.523***	-0.104
	(17.65)	(-0.25)
[60%,∞) (d)	1.482***	0.464
	(13.86)	(1.14)
Client fixed effects	Yes	
Pseudo R^2	0.089	
N	41,164	

Figure 1: Number of stock trades around advisory contacts

This figure shows the number of stock trades around advisory contacts. The contact between the client and the advisor takes place on day t = 0. There are 75,446 stock trades in our sample between January 2002 and June 2005, of which 4,297 stock trades take place within the time period from t = 0 to t = 4 after an advisory contact.



Appendix

Appendix A: Variable descriptions

This table defines the variables used throughout the study. The source of the data and the frequency of occurrence of the variable is provided (in parentheses). Client characteristics are time-invariant as they are collected by the bank on the date of the account opening and overwritten if new information is provided by clients.

Variable	Description	Source (frequency)
Advice characteristics		
Advised	Dummy variable that equals one for trades executed within five days of an advisory contact, that is, between t = 0 and t = 4, and zero otherwise	Bank (daily)
Advisor-initiated	Dummy variable that equals one for advised trades that follow a contact that was initiated by the advisor, and zero otherwise	Bank (daily)
% advised trades p.a.	Number of advised trades p.a. / Total number of trades p.a.	Bank (yearly)
Performance measures		
Raw return	1-month/ 6-month/ 1-year raw return of a trade	Datastream (daily)
CAR	Cumulative abnormal 1-month/ 6-month/ 1-year return of a trade. Abnormal returns are calculated as the difference between the daily returns and the returns predicted by the market model and the 5-factor model, respectively. Both the market model and the 5-factor model are estimated over the time period from t = -252 to t = -1. The market model uses the SPI (Swiss Performance Index) as proxy for the equity market risk factor. The 5-factor model includes the SPI as well as the MSCI World Index as proxies for the market, a Swiss SMB factor (return difference between Vontobel Swiss Small Cap Index and the SMI (Swiss Market Index)), a Swiss HML factor (return difference between the MSCI Switzerland Value Index and the MSCI Switzerland Growth Index), and a Swiss momentum factor (return difference between the portfolio of 30% top performing stocks in the SPI minus the 30% of bottom performing stocks using a formation period of six months, a holding period of six months, and skipping one month in between)	Datastream (daily)
Market variables		
Risk-free rate	Swiss 3-month LIBOR	Datastream (daily)
Client characteristics		
Male	Dummy variable that equals one for male clients and zero for female clients	Bank (time-invariant)
Age	Client's age (in years)	Bank (yearly)
Education	Client's education (1: unskilled; 2: semiskilled; 3: apprenticeship/ vocational education; 4: high school; 5: higher vocational education; 6: technical college; 7: university)	Bank (time-invariant)

Employment, employed	Dummy variable that equals one for employed clients, and zero otherwise	Bank (time-invariant)
Employment, retired	Dummy variable that equals one for retired clients, and zero otherwise	Bank (time-invariant)
Swiss	Dummy variable that equals one for clients living in Switzerland and zero for clients living abroad	Bank (time-invariant)
Product information	Dummy variable that equals one for clients receiving product information, and zero otherwise	Bank (time-invariant)
E-banking account	Dummy variable that equals one for clients with e-banking access, and zero otherwise	Bank (time-invariant)
Length of relationship	Number of years since account was opened (in years). This variable is missing for some clients in our sample that opened their account before December 1995. We assume that these customers created their account in December 1995	Bank (yearly)
Portfolio characteristics		
Portfolio size (CHF)	Value of stock portfolio of a client (in Swiss Francs)	Bank (monthly)
Log(portfolio size)	Natural logarithm of portfolio size	Bank (monthly)
# stocks	Number of stocks in the client's portfolio	Bank (monthly)
% Swiss stocks	Value of Swiss stocks in the client's portfolio / Portfolio size. A Swiss company is headquartered in Switzerland. This variable is only computed for clients in our sample that are Swiss residents	Bank, headquarters information hand-collected (monthly)
% local stocks	Value of local stocks in the client's portfolio / Portfolio size. Household zip codes and headquarters zip codes are translated in latitudes and longitudes. The distance between two points is calculated by means of the haversine approach. A local company is headquartered within a 50-kilometer radius of where an investor lives. This variable is only computed for clients in our sample that are Swiss residents	Bank, headquarters information hand-collected (monthly)
# stock trades p.a.	Number of stock trades p.a.	Bank (yearly)
Trading volume p.a. (CHF)	Value of all transactions executed p.a. (in Swiss Francs)	Bank (yearly)
Trade characteristics		
Beta (SPI)	Beta of a stock from a simple market model. The market model is estimated over the time period from t = -252 to t = -1 and uses the return on the SPI (Swiss Performance Index) as proxy for the market	Datstream (daily)
Market capitalization (CHFbn)	Number of ordinary shares outstanding × Stock price (in billions of Swiss Francs)	Datastream (daily)
Log(market capitalization)	Natural logarithm of market capitalization	Datastream (daily)
Book-to-market ratio	Book value of equity / Market capitalization	Datastream (daily)
Return decile	Daily decile sorting of all stocks in the dataset based on the past 1-year raw return. Decile 1 contains the worst performing stocks and decile 10 the top performing stocks	Datastream (daily)

Strongly recommended	Dummy variable that equals one if at least 50% of sell-side analysts recommend to buy the stock, and zero otherwise	IBES (daily)
MAX decile	MAX is the maximum daily return of a stock within a year. Daily decile sorting of all stocks in the dataset based on MAX. Decile 1 contains low MAX stocks and decile 10 high MAX stocks	Datastream (daily)
Dividend-paying	Dummy variable that equals one if a stock pays a dividend in a certain fiscal year, and zero otherwise	Datastream (daily)
Past raw return of advised trades	Past 1-month/ 6-month/ 1-year raw return of a portfolio formed on all advised stock trades of a client	Bank, Datastream (daily)
Past raw return of independent trades	Past 1-month/ 6-month/ 1-year raw return of a portfolio formed on all independent stock trades of a client	Bank, Datastream (daily)
Past SPI return	Past 1-month/ 6-month/ 1-year raw return of the SPI (Swiss Performance Index)	Datastream (daily)
Past SPI return volatility	Past 1-month/ 6-month/ 1-year volatility of daily raw returns of the SPI (Swiss Performance Index)	Datastream (daily)
Proxies for behavioral biases		
Beta relative to portfolio	Beta of a newly purchased stock relative to the existing stock portfolio determined by means of a simple regression model. The regression model is estimated over the time period from t = -252 to t = -1 prior to a trade and uses the return of the newly purchased stock as dependent variable and the return on the client's existing stock portfolio as explanatory variable	Datastream (daily)
Already in portfolio	Dummy variable that equals one if the client already holds the newly purchased stock in the portfolio, and zero otherwise	Bank (daily)
Swiss stock	Dummy variable that equals one for Swiss stocks and zero for foreign stocks. A Swiss company is headquartered in Switzerland. This variable is only computed for clients in our sample that are Swiss residents	Bank, headquarters information hand-collected (time-invariant)
Local stock	Dummy variable that equals one for local stocks and zero for remote stocks. Household zip codes and headquarters zip codes are translated in latitudes and longitudes. The distance between two points is calculated by means of the haversine approach. A local company is headquartered within a 50-kilometer radius of where an investor lives. This variable is only computed for clients in our sample that are Swiss residents	Bank, headquarters information hand-collected (time-invariant)
Sale	Dummy variable that equals one if an investor sells a stock for which the purchase price is known and zero for all stocks in the client's portfolio that are not sold the same day and for which the purchase price is also known	Bank (daily)

Appendix B: Results from robustness tests

Table A1: Determinants of trade performance – with combined client-advisor fixed effects

The table presents the results from OLS regressions with combined client-advisor fixed effects. Results for purchases (Columns 1 to 4) and sales (Columns 5 to 8) are reported separately. The dependent variable is either the 1-year raw return of a trade (Columns 1 and 5), the 1-year cumulative abnormal return (CAR) of a trade based on the market model (Columns 2 and 6), or the 1-year CAR of a trade based on the 5-factor model (Columns 3, 4, 7, and 8). 1-year raw returns and 1-year CARs for sales are multiplied by -1 to facilitate the comparison of results across purchases and sales. Abnormal returns are calculated as the difference between the daily returns and the returns predicted by the market model and the 5-factor model, respectively. Both the market model and the 5-factor model are estimated over the time period from t = -252 to t = -1. The market model uses the SPI (Swiss Performance Index) as proxy for the equity market risk factor. The 5-factor model includes the SPI as well as the MSCI World Index as proxies for the market and Swiss SMB, HML, and momentum factors. The t-values (in parentheses) are based on heteroskedasticity-robust White (1980) standard errors. ***, **, * denote statistical significance at the 1%, 5%, 10% level.

	Buys				Sells			
		1-year CAR (%)				1-year CAR (%)		
	1-year raw return (%)	Market model	5-factor model		1-year raw return (%)	Market model	5-factor model	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Advised (d)	-1.709	-3.355***	-1.990**	-0.586	0.389	-0.087	-0.718	-1.154
	(-1.16)	(-3.52)	(-2.34)	(-0.57)	(0.29)	(-0.11)	(-1.00)	(-1.20)
Advisor-initiated (d)				-3.593**				0.899
				(-2.30)				(0.72)
Constant	19.233***	1.934***	0.440***	0.434***	-18.008***	5.733***	5.424***	5.426***
	(76.86)	(11.06)	(2.91)	(2.87)	(-76.17)	(38.90)	(40.51)	(40.48)
Client-advisor fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.072	0.090	0.056	0.056	0.079	0.050	0.027	0.027
N	37,169	36,499	36,499	36,499	35,667	35,050	35,050	35,050

Table A2: Determinants of trade performance of independently exectued transactions

The table presents the results from OLS regressions. Only independently executed purchases of clients living in Switzerland are considered. The dependent variable is either the 1-year cumulative abnormal return (CAR) of a trade based on the market model (Columns 1 and 2) or the 1-year CAR of a trade based on the 5-factor model (Columns 3 and 4). Abnormal returns are calculated as the difference between the daily returns and the returns predicted by the market model and the 5-factor model, respectively. Both the market model and the 5-factor model are estimated over the time period from t = -252 to t = -1. The market model uses the SPI (Swiss Performance Index) as proxy for the equity market risk factor. The 5-factor model includes the SPI as well as the MSCI World Index as proxies for the market and Swiss SMB, HML, and momentum factors. The variable *% independent advisors* is defined as the number of independent financial advisors in the village or town a clients lives in divided by the number of inhabitants. In Columns 1 and 3 (Columns 2 and 4), we use data from December 2001 (December 2005) on the penetration with independent financial advisors. All regressions contain the variables *male (d)*, $45 \leq age < 60$ *(d)*, $60 \leq age < 75$ *(d)*, $Age \geq 75$ *(d)*, *product information (d)*, *e-banking (d)*, *length of relationship*, and *log(portfolio size)* as controls. Control variables are not reported for space reasons. Appendix A provides detailed descriptions of all variables used throughout the study. The t-values (in parentheses) are based on heteroskedasticity-robust White (1980) standard errors. ***, **, * denote statistical significance at the 1%, 5%, 10% level.

	1-year CAR (%)			
	Market model		5-factor model	
	December 2001	December 2005	December 2001	December 2005
	(1)	(2)	(3)	(4)
% independent advisors	-0.570	-5.948***	0.671	-3.786**
	(-0.34)	(-2.74)	(0.47)	(-2.05)
Constant	9.876***	10.173***	2.341*	2.607**
	(6.44)	(6.63)	(1.81)	(2.01)
Client and portfolio characteristics	Yes	Yes	Yes	Yes
Adj. R^2	0.005	0.005	0.003	0.003
N	25,667	25,667	25,667	25,667

Table A3: Determinants of trade performance – additional robustness tests (buys)

The table presents the results from OLS regressions with client fixed effects. Only purchases are considered. The dependent variable is either the 1-year cumulative abnormal return (CAR) of a trade based on the market model (Columns 1 to 5), the 6-month CAR of a trade based on the market model (Column 6), the 1-year CAR of a trade based on the 5-factor model (Columns 7 to 11), or the 6-month CAR of a trade based on the 5-factor model (Column 12). We rerun the regressions from Columns 2 and 3 of Table IV replacing the advised trade dummy variable by a set of dummy variables for whether the advisory contact took place on the day of the trade or one, two, three, or four days before the trade (Columns 1 and 7), only considering Swiss stocks (Columns 2 and 8), not winsorizing CARs (Columns 3 and 9), for the bearish market environment (January 2002 to February 2003; Columns 4 and 10), for the bullish market environment (March 2003 to June 2005; Columns 5 and 11), and for a 6-month investment horizon (Columns 6 and 12). Abnormal returns are calculated as the difference between the daily returns and the returns predicted by the market model and the 5-factor model, respectively. Both the market model and the 5-factor model are estimated over the time period from t = -252 to t = -1. The market model uses the SPI (Swiss Performance Index) as proxy for the equity market risk factor. The 5-factor model includes the SPI as well as the MSCI World Index as proxies for the market and Swiss SMB, HML, and momentum factors. The t-values (in parentheses) are based on heteroskedasticity-robust White (1980) standard errors. ***, **, * denote statistical significance at the 1%, 5%, 10% level.

	Market model						5-factor model					
	1-year CAR (%)						1-year CAR (%)					
	Alt. definition	Only Swiss stocks	No winsorizing	Bearish market	Bullish market	6-month CAR (%)	Alt. definition	Only Swiss stocks	No winsorizing	Bearish market	Bullish market	6-month CAR (%)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Advised (d)		-3.733***	-3.391***	-11.583***	-1.162	-1.427*		-2.090*	-2.079**	-5.082*	-0.903	-1.395**
		(-2.69)	(-3.52)	(-3.40)	(-1.28)	(-1.76)		(-1.74)	(-2.38)	(-1.76)	(-1.03)	(-1.96)
Advised (0)	-1.436						-0.492					
	(-1.38)						(-0.53)					
Advised (1)	-7.188***						-4.805**					
	(-3.54)						(-2.47)					
Advised (2)	-6.184**						-4.537*					
	(-2.06)						(-1.82)					
Advised (3)	-8.092***						-5.624*					
	(-2.66)						(-1.95)					
Advised (4)	0.183						-0.675					
	(0.03)						(-0.13)					
Constant	1.889***	4.386***	2.575***	15.424***	-4.718***	0.821***	0.399***	3.131***	1.080***	5.596***	-2.137***	0.150
	(10.79)	(20.54)	(12.80)	(39.68)	(-28.41)	(5.77)	(2.64)	(17.60)	(6.23)	(16.88)	(-13.67)	(1.19)
Client fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.076	0.040	0.055	0.101	0.062	0.047	0.047	-0.003	0.039	0.082	0.040	0.032
N	36,655	24,286	36,655	12,113	24,542	36,896	36,655	24,286	36,655	12,113	24,542	36,896

Table A4: Determinants of trade performance – additional robustness tests (sells)

The table presents the results from OLS regressions with client fixed effects. Only sales are considered. The dependent variable is either the 1-year cumulative abnormal return (CAR) of a trade based on the market model (Column 1) or the 1-year CAR of a trade based on the 5-factor model (Column 2). We rerun the regressions from Columns 6 and 7 of Table IV only considering advised sales that are not accompanied by advised purchases. Abnormal returns are calculated as the difference between the daily returns and the returns predicted by the market model and the 5-factor model, respectively. Both the market model and the 5-factor model are estimated over the time period from t = -252 to t = -1. The market model uses the SPI (Swiss Performance Index) as proxy for the equity market risk factor. The 5-factor model includes the SPI as well as the MSCI World Index as proxies for the market and Swiss SMB, HML, and momentum factors. The t-values (in parentheses) are based on heteroskedasticity-robust White (1980) standard errors. ***, **, * denote statistical significance at the 1%, 5%, 10% level.

	1-year CAR (%)	
	Market model	5-factor model
	(1)	(2)
Advised (d)	-0.526	-0.739
	(-0.57)	(-0.86)
Constant	5.753***	5.426***
	(39.32)	(40.81)
Client fixed effects	Yes	Yes
Adj. R^2	0.051	0.028
N	34,394	34,394

Table A5: Determinants of trade performance – cluster-robust standard errors

The table presents the results from OLS regressions with client fixed effects. Only purchases are considered. The dependent variable is either the 1-year cumulative abnormal return (CAR) of a trade based on the market model (Column 1 to 3) or the 1-year CAR of a trade based on the 5-factor model (Columns 4 to 6). We rerun the regressions from Columns 2 and 3 of Table IV clustering standard errors at different levels as indicated in the respective column header. Abnormal returns are calculated as the difference between the daily returns and the returns predicted by the market model and the 5-factor model, respectively. Both the market model and the 5-factor model are estimated over the time period from t = -252 to t = -1. The market model uses the SPI (Swiss Performance Index) as proxy for the equity market risk factor. The 5-factor model includes the SPI as well as the MSCI World Index as proxies for the market and Swiss SMB, HML, and momentum factors. The t-values (in parentheses) are based on cluster-robust Huber-White (Huber, 1967; White, 1982) standard errors. ***, **, * denote statistical significance at the 1%, 5%, 10% level.

	1-year CAR (%)					
	Market model			5-factor model		
	Client-month level	Advisor-month level	Stock-month level	Client-month level	Advisor-month level	Stock-month level
	(1)	(2)	(3)	(4)	(5)	(6)
Advised (d)	-2.958***	-2.947***	-2.958***	-1.725*	-1.722*	-1.725*
	(-2.78)	(-2.59)	(-2.77)	(-1.92)	(-1.74)	(-1.69)
Constant	1.899***	1.913***	1.899**	0.408**	0.426*	0.408
	(8.72)	(6.01)	(2.05)	(2.36)	(1.90)	(0.52)
Client fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.076	0.079	0.076	0.047	0.050	0.047
N	36,655	36,499	36,655	36,655	36,499	36,655