Financial Advisors: A Case of Babysitters?

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Abstract

We use two data sets, one from a large brokerage and another from a major bank, to ask: (i) whether financial advisors are more likely to be matched with poorer, uninformed investors or with richer and experienced investors; (ii) how advised accounts actually perform relative to self-managed accounts; (iii) whether the contribution of independent and bank advisors is similar. We find that advised accounts offer on average lower net returns and inferior risk-return tradeoffs (Sharpe ratios). Trading costs contribute to outcomes, as advised accounts feature higher turnover, consistent with commissions being the main source of advisor income. Results are robust to controlling for investor and local area characteristics. The results apply with stronger force to bank advisors than to independent financial advisors, consistent with greater limitations on bank advisory services.

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1. Introduction

In recent years households have increased their exposure to financial risk taking, partly in response to the demographic transition and increased responsibility for retirement financing. Recent research points to differential financial literacy and sophistication across households, creating the potential for important distributional consequences of these developments (Campbell, 2006; Lusardi and Mitchell, 2007).

In principle, financial advisors could ameliorate consequences of differential ability to handle finances by improving returns and ensuring greater risk diversification among less sophisticated households. Indeed, delegation of portfolio decisions to advisors opens up economies of scale in portfolio management and information acquisition, because advisors can spread information acquisition costs among many investors. Such economies of scale, as well as possibly superior financial practices of advisors, create the potential for individual investors to improve portfolio performance by delegating financial decisions.

But delegation entails costs in terms of commissions and fees, and might give rise to agency problems between advisors and firms and between advisors and poorly informed customers, as shown by Inderst and Ottaviani (2009): on the one hand they need to sell financial products and on the other they need to advise customers on what is best for them to do.[1] The notion that financial advisors tend to be used by less informed or unsophisticated investors who could be easily misled by them, underlies much of the existing literature on financial literacy, the possible role of financial advice and the case for regulation of financial advisors.

In this paper, we examine three questions. First, we ask whether financial advisors tend to be matched with poorer, uninformed investors or rather with richer, experienced investors with higher opportunity cost of time. Second, how brokerage accounts run by individuals without financial advisors actually perform compared to accounts run by (or in consultation with) financial advisors. Third, whether the estimated contribution of financial advisors is persistent across different advisory models such as independent financial advisors (IFA) and bank financial

[1] Stulz and Mehran (2007) review the existing empirical literature on the nature and implications of various conflicts mainly focusing on analysts.

advisors (BFA). Direct performance comparisons are made possible by two unique administrative data sets: one from a large German brokerage firm that allows its clients choice of whether to run their accounts themselves or with the guidance of an independent financial advisor; and another from a large German commercial bank that offers (optional) advice to its customers with investment accounts The answers we obtain provide a novel perspective on the role of financial advice in individual portfolio performance.

Our first dataset, from the online brokerage, tracks accounts of 32,751 randomly selected individual customers. Our second data set contains full data of 4,447 clients of a German branch-based commercial bank. Both datasets cover 34 months, from January 2003 to October 2005. In many respects, discussed in this paper, descriptive statistics for both samples paint a very similar picture of the role of financial advisors as econometric analysis that controls for investor and region characteristics.

Involvement of financial advisors is found to lower portfolio returns net of direct cost, to worsen risk-return profiles, as measured by the Sharpe ratio; and to increase account turnover and investment in mutual funds, consistent with incentives built into the commission structure of both types of financial advisors. If anything, negative advisory effects on portfolio performance are even stronger for BFAs than for IFAs. This is consistent with greater limitations faced by BFAs in the range of products they offer and in the way they can confer financial advice to clients.

Regression analysis of who delegates portfolio decisions presents a further twist. It suggests that advisors are matched with richer, older, more experienced, self-employed, female investors rather than with poorer, younger, inexperienced and male ones. In this respect, advisors are similar to babysitters: babysitters are matched with well-to-do parents, they perform a service that parents themselves could do better, they charge for it, but observed child achievement is not boosted by babysitters but by positive characteristics of the family. No issues of regulating babysitters emerge, however, because the nature of the activity and the contribution is known to all parties involved.

The paper is organized as follows. In Section 2 we discuss the role of financial advice in overcoming investors' informational constraints and their incentives in handling financial portfolios in view of relevant existing literature. Section 3 describes the brokerage and the commercial bank data sets, the measures that we use to characterize portfolio performance, and the estimation procedure. Section 4 compares records of account performance with and without involvement of financial advisors. Section 5 studies econometrically the role of investors' characteristics in determining which investors are matched with financial advisors. Section 6 reports regression estimates of the effects of financial advisors on account performance, return variance, Sharpe ratios, trading frequency, turnover, and diversification. Section 7 presents similar results from the second sample on bank financial advisors. Section 8 concludes.

2. The Role of Financial Advice

There is a limited but budding theoretical literature on the possible role of financial advisors. Current theoretical work but also policy debate on financial regulation seem to be based on the idea that financial advisors know what is good for individual customers but have an incentive to misrepresent this and to take advantage of their customers, who are typically uninformed and cannot figure out the poor quality of advice. Regulation is then needed to make sure that this conflict of interests is dealt with.

In a recent pioneering paper, Inderst and Ottaviani (2009) analyze 'misselling', i.e. the practice of misdirecting clients into buying a financial product that is not suitable for them. Their model emphasizes the internal agency problem between the firm and its sales agents. The agency problem is complicated by the fact that sales agents perform the dual task of prospecting for customers and of providing adequate advice to them on whether to buy a particular product. As a consequence, higher sales incentives will increase the likelihood that sales agents sell unsuitable products to customers. If this occurs, there is a probability with which the firm receives a complaint and has to pay a fine. To avoid misselling the firm can set internal suitability standards for advising customers and exert costly monitoring to verify compliance with these standards. The standards implemented by the firm in equilibrium are increasing in the fine (or equivalently in the reputation damage), the transparency of the incentive scheme, and in the effectiveness of monitoring, but they are decreasing in the sales incentives and the private cost for the agent to investigate the match between product and customer.

There are two relevant implications for our study. First, sales incentives can lead financial advisors to systematically recommend unsuitable products to their clients that entail suboptimal outcomes on the client side. Second, due to agency costs from multitasking and monitoring, a firm employing sales agents (such as BFAs) would be expected to choose lower standards than an entrepreneur (IFA). Our findings below are quite consistent with these predictions and provide two further insights: (i) advisors may affect portfolio outcomes not only by recommending unsuitable products but also by encouraging excessive trading; and (ii) the notion that advisors have an edge over their clients need not refer solely to unsophisticated clients, but also to experienced but inattentive ones who fail to monitor advisors and the outcome of their activities effectively.

The empirical literature on financial advice has so far mostly focused on whether professional analysts and advisors have an informational advantage to contribute to individual investors when it comes to predicting stock price movements. Ever since Cowles (1933), there have been questions regarding the ability of stock market forecasters and analysts to predict and reveal movements in the stock market.[2]

For example, Womack (1996) examines stock price movements following 'buy' or 'sell' recommendations by fourteen major U.S. brokerage firms. He documents significant price and volume reactions in the direction of the recommendation, especially for new 'sell' recommendations. He concludes that there is value to these recommendations viewed as returns to information search costs. However, new 'buy' recommendations occur seven times more often than 'sell' recommendations, suggesting that brokers are reluctant to issue sell recommendations, both in order to avoid harming potential investment banking relationships and to maintain future information flows from managers.

Metrick (1999) analyzes a database of recommendations of 153 investment newsletters and finds no evidence that newsletters have superior stock-selection skill. Average abnormal returns are close to zero; and even the performance of the best newsletters seems to be driven more by

[2] Early studies include Barber and Loeffler (1993) on The Wall Street Journal's Dartboard column and Desai and Jain (1995) on "Superstar" money managers in *Barron's*.

luck then by skill. In related work, Anderson and Martinez (2008) examine abnormal returns around stock recommendations by Swedish brokers. A sizeable share of abnormal profits results from transactions before the recorded recommendation date, suggesting that tipping of customers may be taking place. However, given the small size of these abnormal profits (only 0.04% in yearly performance of total Swedish equity fund assets under management), the authors wonder whether clients are fully compensated for the costs of commissions charged by brokers.

Barber et al. (2001) explicitly take into account trading costs from following analyst recommendations. They analyze abnormal gross and net returns that would result from purchasing (selling short) stocks with the most (least) favorable consensus recommendations, in conjunction with daily portfolio rebalancing and a timely response to recommendation changes. Although they find that such strategies would yield annual abnormal gross returns greater than four percent, they also show that abnormal net returns are not statistically significant. Bergstresser, Chalmers, and Tufano (2009) compare performance of mutual fund 'classes' distinguished by their distribution channel: directly sold to investors versus sold through brokers, with correspondingly different fee structures. They find that funds sold through brokers offer inferior returns, even before the distribution fee, no superior aggregate market timing ability, and exhibit the same return-chasing behavior as observed among direct-channel funds. Finally, more sales are directed to funds with larger distribution fees.

Our reading of the literature on informational contributions of analysts or brokers to direct stockholding is that these may be present but unlikely to be exploitable by individuals given the trading costs they entail. Therefore, in a world in which financial advisors solely provided security selection advice we would expect the effect of financial advice on abnormal portfolio returns to be around zero on average after transaction costs.

However, some researchers take a different angle and point out that, even if professional advisors do not have superior information that is exploitable for the normal trading within an individual account, they may be less likely to exhibit behavioral biases that hurt account performance. They could thus help either by running the account themselves or by encouraging investors to behave appropriately.

A behavioral bias that has received considerable attention is the 'disposition effect', i.e. the tendency of some individuals to sell winners and keep losers when it comes to direct stockholding (Odean, 1998). Shapira and Venezia (2001) found that the disposition effect is significantly less pronounced among professional than among self-directed investors. Well trained advisors could therefore aid their clients in reducing the disposition effect, potentially enhancing risk adjusted portfolio returns.

Advisors might also be simply able to moderate trading activity (Campbell and Viceira, 2003). Barber and Odean (2000) show that some investors trade excessively in brokerage accounts, suffering transactions costs that result in significantly lower returns. Such behavior is often attributed to overconfidence, especially pronounced among male investors (Odean, 1998; 1999; Barber and Odean, 2001; Niessen and Ruenzi, 2008). Shu et al. (2004) analyze the returns on common stock investments by 52,649 accounts at a brokerage house in Taiwan for 45 months ending in September 2001. They find a U-shaped turnover and performance relation rather than the monotonic one predicted by overconfidence: the most frequent traders in the top turnover quintile perform better than investors in the middle three quintiles. Other behavioral biases have been found to influence some individual investors. For instance, Venezia et al. (2011) focus on herding, and also document that professional investors herd less than amateurs, while (Grinblatt and Keloharju (2001) suggest that investors trade on the basis of past returns, reference prices, or the size of holding period gain or loss

While the list of potential behavioral biases can grow longer, an important question - consistent with our approach in this paper - remains as to whether individuals who exhibit such biases are likely to make use of professional investors. For example, Guiso and Jappelli (2006) argued that overconfidence (i.e. the disposition of investors to overstate the value of their private information) reduces their propensity to seek advice. Indeed, the Barber and Odean data come from a discount broker that does not offer advice. Even if overconfident traders approach financial advisors, one might wonder whether financial advisors who earn sales commissions would actually discourage them from executing too many trades without some incentive scheme.

On the other hand, financial advisors may help correct behavioral biases or investment mistakes when such correction is aligned with their interests. A case in point is diversification. A number of empirical studies find that many individual investors hold undiversified portfolios (see e.g. Blume and Friend, 1975; Campbell, 2006; Goetzmann and Kumar, 2008). Financial advisors who earn commissions for selling mutual funds have an incentive to promote such sales and through them diversification of their client's accounts. Shapira and Venezia (2001) find that the number of different stocks and the number of transactions per year is about three times as high for accounts managed by professionals than for self-managed accounts. This finding indicates that financial advisors might promote diversification through single stocks if they participate in brokerage commissions.[3]

Taken together, literature suggests an ambiguous effect of financial advice on net returns and risk profiles of client portfolios. Although it seems to be rather unlikely that advisors enhance portfolio performance through informational contributions they might in fact improve the risk-return profile by ironing out behavioral biases of their clients. Of course, such positive effects must exceed the cost of advice in order to yield an overall positive effect.

Our paper takes a direct approach to the issue of the role and contribution of financial advisors. Recognizing both the potential informational advantage and the potential contribution of professional investors to controlling behavioral biases and correcting investment mistakes, it compares directly portfolio returns (net of transactions costs) and portfolio risk levels that investors actually accomplish on their own versus what they accomplish with the guidance of a financial advisor. It does so with reference to portfolios actually chosen and adjusted by investors, which include directly held stocks, bonds, and mutual funds; and it accounts for a number of investors' and region characteristics observable in our data and for how they influence the tendency to use a financial advisor. Moreover, we are able to measure the effects of advice across two distinct advisory models (IFAs and BFAs).

[3] Moreover, Shapira and Venezia (2001) find that the round trip performance of professionally managed accounts is slightly (and for some specifications also statistically) higher than that of independently run accounts. The discrepancy to our own results is likely due to the fact that they focus on round trip returns for stock investments in one particular year, whereas we measure total portfolio returns for a longer time period, and in addition control for individual investor characteristics.

3. Data, Measurement, and Estimation

3.1. Data on Independent Financial Advisors

The first data set we use is administrative information from a large German brokerage firm. It covers the investments of 32,751 randomly selected customers. They all had an active account with the brokerage firm over the sample period from January 2003 to October 2005. If customers opened multiple accounts we consolidated them into one single account.

For each sampled customer we have information on date of birth, gender, marital status, profession (including status as employed or self-employed), zip-code of place of residence, nationality, and self-reported security-trading experience in years.[4] All information was collected by the brokerage firm on the date of account opening and updated according to new information that the firm has obtained from the customer in the interim.

On average (not excluding account owners aged under 18), sample customers held 38.6 percent of their account volume in the form of equity mutual funds, 47.4 percent in the form of single stocks (28 percent thereof in German stocks), 2.4 percent in the form of bond mutual funds, 3.8 percent in the form of single bonds and the remainder in the form of structured investment certificates, warrants, and other securities.

Our administrative data set includes a variable that indicates whether a given brokerage customer is also a client of an IFA who registered with the brokerage firm. We know from the brokerage firm that, typically, advised customers were brought to the brokerage by IFAs. About 90% of IFAs registered with the brokerage are former employees of commercial banks advising customers on investment accounts. They decided to leave the bank and become independent, thereby offering lower costs than banks and greater choice of financial products. Thus, they were able to persuade many of their former customers at the bank to transfer investment accounts to the brokerage firm. The remaining 10% of IFAs in our sample are not former bank employees but they instead joined a larger team of IFAs directly and built up their own customer base, again drawing mostly from former bank customers.

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[4]Self-reported trading experience is reported on a scale with intervals equal to five years. We construct a variable that has the interval midpoints as values and then add the number of years that elapsed since account opening to approximate total trading experience at the beginning of our observation period.

At the time of account opening, IFAs had typically obtained a client mandate to place orders on behalf of the client. We do not have information on which clients fully delegate trading decisions to their IFAs and which only consult their IFAs for guidance and then place trades themselves. The brokerage firm offers several compensation schemes to IFAs. Only for a negligible fraction of IFAs are revenues dependent solely on assets under management. More than 90% of IFAs generate at least a portion of revenues from trades, such as sales commissions. In the case of mutual funds the commission is a function of the upfront load the brokerage firm earns from the fund producer.

Of the customers in our sample, 12.8 percent consult IFAs registered with the brokerage firm. More than half of these customers are IFAs' former banking clients, with the remaining half (typically also former bank customers) having been acquired over the years, most importantly through existing customers' referrals. We cannot rule out that customers coded as not using an IFA obtain professional advice from outside advisors. This is, however, rather unlikely because such outside advisors do not participate in the fees and commissions paid by the client to the brokerage firm and must therefore charge their services on top of the full brokerage fees and commissions.

Table 1 shows descriptive statistics of the total brokerage sample and of the two sub-samples distinguished by whether sample customers were advised by IFAs or not, after dropping accounts that report age of account owner below 18.[5] As shown in the Table, 77.8 percent of account owners were male, and 47.9 percent married. Overall, 86.1 percent were employed (excluding public servants) and 13.2 percent were self-employed, with the remaining 0.7 percent being public servants, retirees, housewives or students. Average trading experience as of January 2003 was 9.34 years. Among IFA-assisted customers, men are underrepresented relative to their share in the overall account owner pool, and so are married owners (as indicated by the corresponding t-statistics and p-values in the last two columns of Table 1). Older owners (above

[5] These are typically accounts run by parents on behalf of their children. Specifically, 796 investors in our original sample were younger than 18 on September 5, 2006, and the youngest investor in that sample was just under 6 years old. Tax advantages for parents arise because during the observation period there was a per person threshold level of interest or dividend income above which capital income tax needed to be paid. We have also run the regressions including investors under 18, but our results were hardly affected in terms of sign, significance, and even size of estimates, except for small changes in the estimates for age categories.

50) are overrepresented, and advised customers have on average more years of experience and larger initial size of accounts.

Table 1 also reports performance figures for the brokerage accounts. As indicated by the t-statistics, raw returns, abnormal returns (see section 3.3. for definitions), raw return variance and Sharpe ratios are on average significantly lower for IFA-assisted than for self-directed customers.

All reported return figures are monthly and *net* of any transactions costs and provisions charged by the brokerage on its own account or on behalf of the IFA.[6] Transaction costs and provisions are divided between the brokerage and IFA, with the bank typically earning roughly 30 basis points for transaction fees, account maintenance, and front loads, leaving about 170 basis points for the IFA. There is a minority of advisors who follow a different business model: instead of earning front loads, they forward those to their clients and earn an extra fee as a percentage of account volume. As this extra fee is not run through the bank, it is not observed by us and it is not taken into account in computing returns and other measures of performance net of costs. Since we obtain negative effects of IFAs on account performance in econometric estimations below, the resulting understatement of costs in these cases, if anything, strengthens our findings on the role of IFAs.

The monthly position statements list for each item the type of security (e.g. stocks, bonds, mutual funds etc.), the number of securities, and the market value per security at month end. At the start of the sample period (January 2003), average annual account volume was 10,963 Euro. We computed monthly turnover by dividing the combined transaction value of all purchase transactions for a given month by the average of beginning-of-month and end-of-month account volume. Average monthly turnover was 4.7 percent in our sample, but about double of this for advised customers.

[6] Although we only observe net returns in our data and therefore cannot directly measure transaction cost, we know from the data provider that the brokerage and the IFA combined earn typically 100-200 basis points on clients with account volume greater than 50,000 Euros. For smaller accounts, this number is typically in the neighborhood of 200 basis points, although it can be as high as 300-500 basis points, due to front loads (principally observable in the dataset) and kick-backs (not observable) from mutual funds.

3.2. Data on Bank Financial Advisors

In order to compare our findings across different advisory models, we also consider a second data set of investment accounts, this time from a large German commercial bank that offers optional advice to its customers through its bank employees assigned to this task. Unlike the online brokerage that likely attracts a selected sample of the German population interested in trading, the bank has a wide network of branches that reach a broad cross section of the German population. This data set consists of 10,434 randomly selected customers observed over a 34-month period, from January 2003 to October 2005. For 4,447 of those, we have detailed information on whether particular trades were executed following consultation with a bank financial advisor (a bank employee) or without such consultation. Accordingly, we construct a dummy variable for bank financial advisor use (BFA) that takes the value of 1 if the customer has consulted with a BFA at least once during the observation period and 0 if the customer never consulted a BFA during the period. For comparability's sake, we match these accounts to the same regions as in the brokerage data set and use the same regional variables and (virtually) the same set of account owner characteristics as for the brokerage sample.

Table 2 presents descriptive statistics for the bank sample. Again we distinguish between self-managed accounts and accounts that are at least partly managed by an advisor. Male account owners are in a minority in this sample (46.3%) and they are underrepresented (again as indicated by the corresponding t-statistics in the table) among those customers who consulted a bank financial advisor before executing some trade(s). As expected, retirees and housewives are much more strongly represented in the bank sample than in the brokerage sample. They comprise just fewer than 30% of the observations and they are overrepresented among advised customers. The majority of account owners are at least 50 years old, and those above 60 are overrepresented among advised customers. The average account volume at the start of 2003 was slightly higher in this sample, namely 12,694 Euro. The average monthly turnover rate was 5.8%, somewhat higher than in the brokerage sample, and smaller for advised customers than for those who never consulted a BFA.

Finally, Table 2 reports performance figures for the bank accounts, showing that raw returns and Sharpe ratios are on average significantly lower for BFA-assisted customers than for self-directed customers. Given the different composition and advisory models of the two samples, it will be interesting to see if findings on the contribution of financial advice to account performance persist (or differ) across samples.

3.3. Measuring Account Performance

In this paper we are interested in the effect of financial advice on portfolio performance and portfolio risk and in particular on abnormal returns. In order to compute monthly portfolio returns, we assume as in Dietz (1968) that all transactions occur in the middle of a given month:

$$R = \frac{VE - VB - CF}{VB + 0.5 \times CF} \tag{1}$$

where:

VE = market value of the portfolio at end of month including earned dividends and coupons;

VB = market value of the portfolio at beginning of month;

CF = net cash flow for month t from purchases (enter positively) and sales of securities(enter negatively) at transaction prices

Monthly returns from (1) are winsorized by treating returns that fall into the first or the 100th percentile as missing values.[7] We construct log returns and use them and the standard regression model in (2) to estimate abnormal (log) returns for each portfolio based on CAPM.

$$r_{p,t} - r_{f,t} = \alpha_p + \beta_p (r_{M,t} - r_{f,t}) + \varepsilon_{p,t} \tag{2}$$

where:

α_p = estimated abnormal return (Jensen's Alpha) for portfolio p;

[7] Extreme monthly return observations were treated as missing (and not set to the upper/lower boundary that would be customary for winsorization) because (a) they most likely represent erroneous data, and (b) we do not lose customers but just single months. As a consequence, some customers have only 33 instead of 34 monthly return observations.

β_p = estimated market beta for portfolio p;

$r_{M,t}$ = log return of the euro-denominated MSCI-World Index in month t;

$r_{f,t}$ = log return on the one-month Euribor;

$\varepsilon_{p,t}$ = error term of regression for portfolio p.

In order to test robustness of our results to the way abnormal returns are computed, we also present results for an alternative estimate of excess returns based on a four-factor model proposed by Carhart (1997) to measure portfolio performance. The model is specified as follows:

$$r_{i,t} = \alpha_i + \beta_{1ii} R_{m,t} + \beta_{2i} SMB_t + \beta_{3i} HML_t + \beta_{4i} MOM_t + \varepsilon_{it} \qquad (3)$$

where the intercept α_i measures risk-adjusted monthly abnormal portfolio returns, $r_{i,t}$ denotes monthly excess returns on portfolio i relative to the risk-free rate which is captured by monthly returns on the JP Morgan 3 Month Euro Cash Index, $R_{m,t}$ denotes the excess return on the market portfolio which we approximate by the comprehensive German CDAX Performance Index, SMB_t, HML_t, and MOM_t correspond to monthly returns on size, value premium and momentum portfolios. The size portfolio return (*SMB*) is approximated by the difference in monthly returns on the small cap SDAX index and the large cap DAX 30 index. The book-to-market portfolio return (*HML*) is approximated by the return difference between the MSCI Germany Value Index and the MSCI Germany Growth Index. Finally, the momentum portfolio return (*MOM*) is the difference in monthly returns between a group of stocks with recent above-average returns and another group of stocks with recent below average returns. The group with above-average returns is defined as the top 30% of stocks from the CDAX index over the past 11 months and the below-average group contains the lowest 30% of stocks from the same index over the same time period.

4. Performance Record of Financial Advisors

For many brokerage clients, a natural first step towards deciding whether to use an IFA or not would be to compare the historical performance of accounts run with IFA involvement and those run without it. Similarly, bank customers would like to know if those who have contacted bank financial advisors have done better on average than those who did not. Even in the absence of official records (indeed neither the broker or the bank compute or print portfolio performance records for their clients), prospective clients may still be influenced by the experiences of existing clients through word of mouth.

Figure 1 plots histograms of average monthly log returns over our observation period for brokerage accounts that were self-managed and for those run with IFA input. Self-managed accounts exhibit a more symmetric distribution, while advised accounts show higher mass at the lower end of returns. Table 1 shows monthly logarithmic returns. The sample mean log monthly return on IFA accounts over this period is actually lower than that of self-managed accounts: 0.63% versus 1.01%. This corresponds to a difference in annual rates of return of 5 percentage points (7.9% for advised customers versus 12.9% for those who invested alone). Even though the brokerage house itself neither collected nor published such statistics, the difference seems rather hard to miss. Table 1 confirms that IFA accounts are also characterized by lower abnormal returns than self-managed accounts, regardless of whether we use a single-factor model based on the MSCI-World Index or whether we use a four-factor model based on German stock data.

These lower returns offered by IFAs are combined with lower average variance of portfolio returns raising the possibility that they simply reflect an efficient risk-return trade-off. Strikingly, however, the sample average of the Sharpe ratio on advised accounts is also lower than that on self-run brokerage accounts, suggesting that advisees ‘paid’ on average a higher cost (in terms of returns) to attain lower risk than what was available to self-managed accounts. Figure 2 shows that the distribution of total portfolio variance under IFAs is ‘squeezed’ towards values closer to zero compared to what is produced by individuals managing their accounts, but Figure 3 shows a much greater heterogeneity in Sharpe ratios among advised customers than among the rest.

Comparison of IFA and non-IFA accounts also shows a rather small difference in frequency of trades across the two types of accounts, but a much more pronounced one when average portfolio turnover (which is sensitive to the size of purchases) is considered: The average turnover rate is more than double for IFA accounts. Looking at Figures 4 and 5, both measures tend to be clustered closer to zero for self-managed accounts. In other words, IFAs get commission based on the volume of purchases and tend to exhibit greater purchases than individual clients on average. IFA accounts tend also to be larger, and are therefore associated with larger positions and trades.

Finally, IFA accounts tend to exhibit far greater diversification than those run by individuals alone. The average share of directly held stocks among self-managed accounts is just under 60 percent, while that for IFA accounts is about 20 percent. This seems consistent with incentives to sell mutual funds that IFAs have.

Table 2 presents a similar comparison for bank customers who have used the advice of bank employees prior to making trades versus those who have not. Accounts of customers who have resorted to bank advisors exhibit on average lower returns, comparable variance, much lower Sharpe ratios, and smaller shares of directly held stocks than those who did not approach the bench. Unlike what we found for brokerage clients, turnover rates of those who made use of bank advice were on average lower than of those who did not.

All in all, performance records of IFAs and BFAs during this sample period do not appear favorable towards advised accounts, especially in terms of the risk-return tradeoff offered. The deeper question is, of course, whether these differences are due to financial advisors themselves or to the customers they tend to attract. It is to this household finance question that we now turn, focusing first on IFAs and then on BFAs.

5. Who Has a Financial Advisor?

We first consider which client characteristics of the brokerage firm or bank contribute to the client's account being run with advisor input. A priori, it may be that advisors tend to be matched with younger, less experienced and less wealthy investors, who need them most; or that they are matched with older, more experienced and wealthier investors who can pay them most.

Table 3 reports linear probability regressions of whether the client makes use of an IFA or a BFA, respectively.[8] We control for time-invariant characteristics (such as availability and cost of financial advice and characteristics of investor pools) in the region (cols 1, 3) and zip code (cols. 2, 4).[9] We see that, given other characteristics, males are less likely to use an advisor, consistent with the view that males tend to have more (over)confidence. Older clients (over 50) have a significantly greater probability than investors between 18 and 30 of using an advisor, by about ten percentage points in both samples. Wealthier brokerage clients, as proxied by the beginning-of-period account size to minimize endogeneity problems, are significantly more likely to use IFA or BFA.

Married clients are less likely to use an IFA, controlling for other factors, probably because spouses can be used as sounding boards. An extra year of self-reported experience with the relevant financial products increases the probability of using an IFA. We do not have information on the marital status and trading experience of bank customers, but their professional status is statistically insignificant.

Overall our regressions show that advisors are more likely to be matched with wealthier (as measured by account volume), older, more experienced, single, and female investors. Such investors have better reasons to want to delegate to advisors, such as high opportunity cost or low inclination to spend time managing investments, as well as sizeable wealth. The results are remarkably consistent across the two samples, and robust to inclusion of zip code dummies that control for unobserved factors at the local level. Since IFAs and BFAs earn more on wealthy clients with high opportunity costs of time, they seem to go for the big players who have a lot to invest, rather than for the younger, smaller, inexperienced investors who have a lot to learn.

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[8] Results from probit models (omitting zip-code dummies) deliver very similar results to the linear probability models, and are available on request.

[9] The German Zip Code (*Postleitzahlen*) is a five digit number consisting of the wider area that is placed on the thousandth position and the postal district (the unit, tenth and hundredth positions). Regressions in columns 1, 3, 4 and 6 include dummies for broader regions (Dresden, Berlin, Hamburg, Hannover, Dusseldorf, Bonn, Frankfurt, Stuttgart, Munich and Nuremberg), while regressions in columns 2 and 5 include dummies at the zip code level. There are 5,652 zip code dummies for the brokerage sample and 646 for the bank sample.

6. Independent Financial Advisors and Portfolio Performance

We now turn to how IFA use affects account performance once we control for client characteristics. An important estimation issue is omitted variable bias: unobserved factors may simultaneously affect the probability of using an advisor as well as account performance. For instance, our data do not report willingness to undertake financial risk: more risk adverse clients may be inclined to consult an advisor and to invest in a safer portfolio, thus influencing account returns and variance. Other factors could also influence both advisor use and account performance: financial literacy and sophistication; attitudes developed in formative years, e.g. through parental influence or observation of others in the parental social circle; social attitudes, such as trust in others, that have been shown to influence portfolio composition (e.g., participation in stockholding) and delegation to a financial advisor. In order to attenuate this problem, we control for as many possible factors that are observed in our dataset as well as for regional dummies and a finer classification of zip code dummies.

A second issue is the potential endogeneity of the choice of consulting a financial advisor. Investors with low performing portfolios may be induced to use a financial advisor by the media or specific campaigns that advisor-assisted portfolios perform better. A negative correlation between advisor consultation and, say, returns, might therefore be driven by the effectiveness of these campaigns, rather than by a negative role of financial advisors per se. In order to handle this possibility, we present (in Appendix 1) instrumental variable estimates using as instrument the local GDP share of financial services. Results are consistent with our OLS findings below.

6.1. IFA Effect on Portfolio Returns

Table 4 presents OLS estimates regarding the influence of IFA use on raw net returns, and on abnormal net returns, constructed on the basis of a single-factor and of a four-factor model in the spirit of Carhart (1997). Columns 1 and 2 report estimated effects on average portfolio returns, controlling for investor characteristics and regional dummies. Model (2) adds zip code dummies as controls for time-invariant local characteristics. IFA effects are almost identical in both models: negative and statistically significant at the 1% level, implying that IFA use reduces monthly log returns by roughly 0.4 percentage points. Thus, the lower returns for advised accounts in descriptive statistics survive controls for personal and regional characteristics.

Even if IFAs reduce raw returns, they might still be found to create value by increasing risk adjusted returns. Columns 3 and 4 in Table 4 report OLS regressions for alphas from a model with the return on the MSCI world index as the single factor (denoted Jensen's alpha). The IFA contribution is again negative and of similar magnitude as for raw returns, once characteristics of the account owner and region are taken into account. In columns 5 and 6, we examine robustness with respect to using the four-factor model for German stock markets outlined above. The strongly statistically significant negative effect of IFA use is observed regardless of whether we use a single or a four-factor model, and its size is remarkably similar with the other models and with the descriptive statistics from Table 1.

Across all models, male gender is found to detract from account returns, consistent with the literature on overconfidence. Years of experience tend to contribute to higher total return, albeit by a small estimated amount. This is consistent with recent studies indicating that the magnitude of investment mistakes decreases with sophistication and experience.[10]

Findings in this section imply that involvement of IFAs with brokerage accounts tends to reduce both raw and abnormal returns, even after investor and area characteristics are taken into account. Our results are consistent with the cost of financial advice exceeding, on average, any benefits from informational contributions. Importantly, this does not necessarily imply that (some) IFAs engage in misselling or that all IFAs give uniformly bad advice.

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[10] For example, Feng and Seasholes (2005) ask whether investor sophistication and trading experience eliminate behavioral biases, such as the disposition effect, using data from the PR of China. They proxy sophistication mainly by the *number of trading rights* (indicating the number of methods to trade)and an indicator of *initial portfolio diversification*, both at the start of the observation period. Experience is proxied by the number of positions taken by investor *i* up until date *t*, a time-varying covariate. They conclude that sophistication and experience eliminate the reluctance to realize losses, but only reduce the propensity to realize gains by 37%. See also Grinblatt and Keloharju (2001), Zhu (2002, Feng and Seasholes (2005), and Lusardi and Mitchell (2007).

6.2. IFA Effect on Variance of Returns and Sharpe Ratio

The finding that IFAs tend to lower both raw and abnormal account returns, given investor characteristics, need not be negative, if IFAs ensure that clients are exposed to smaller portfolio risk. Descriptive statistics above seem to be pointing in this direction. We therefore turn next to the effect of IFA involvement on variance of monthly portfolio returns and on the risk-return tradeoff as captured by the Sharpe ratio. Table 5 reports our findings.

Column 1 reports OLS results for a model with regional dummies, whereas column 2 reports results when zip-code dummies are included. In both models, IFAs reduce portfolio risk in line with descriptive results. Being male, inexperienced, single, self-employed, and with a smaller account all contribute significantly to higher total portfolio risk. Results on control variables are intuitive. For example, larger accounts should allow more diversification, and we indeed find below that they tend to have smaller portfolio shares in directly held stocks.

Set against the negative effects of IFAs on account returns, their moderating effect on variance raises the question of whether IFAs help achieve an efficient risk-return tradeoff. We present two regressions (columns 3 and 4), one with regional and the other with zip code dummies. Both show a statistically significant negative effect of IFAs on Sharpe ratios. Male gender contributes to inferior risk-return tradeoffs, consistent with overconfidence; while more experienced or married investors tend to achieve better tradeoffs. Interestingly, self-employed and older clients are seen to have a tendency to expose themselves to more risk than what is efficient for a given increase in expected return. Finally, wealthier investors tend to achieve better risk-return tradeoffs, presumably by exploiting economies of scale in asset management. We conclude from Table 5 that IFAs tend to reduce portfolio risk but do not compensate sufficiently for lower returns: IFA use decreases ex post portfolio efficiency.

6.3. IFA Effect on Trading, Turnover, and Diversification

What type of behavior underlies our results on returns and risk? The fact that IFAs earn commissions mainly when the account owner purchases mutual funds creates an incentive for them to encourage fund purchases. The first two columns of Table 6 examine the effect of IFA on the number of purchases per month scaled by account volume. These exclude account transactions from corporate actions, periodic saving plan investments and portfolio transfers, so as to be more directly linked to the IFA incentives to sell specific financial instruments.

Our results imply a negative effect of IFAs on the standardized number of purchases. Purchases result in transactions costs and could contribute to lower net returns, but it appears that the negative effect of IFAs on net returns reported above does not result simply from an increased frequency of purchases. The regression does confirm the positive role of male gender found in other studies (see above). Financial experience is estimated to reduce the number of purchases, consistent with Dorn and Huberman's (2005) finding that respondents with longer investment experience trade less, but the effect is not statistically significant. Account holders between 40 and 60 are significantly more likely to engage in purchases than other age groups. Subject to the proviso on interpreting age effects, this finding is consistent with them being in the asset accumulation phase, prior to entering retirement.

Although we did not find a simple channel through frequency of trading, this does not mean that IFAs do not respond to incentives offered by commissions. It is useful to recall that commissions are linked to the size, and not merely to the frequency of purchases. The third and fourth columns of Table 6 show a positive and strongly statistically significant effect of IFAs on average account turnover. This could be part of the explanation for why IFAs contribute negatively to portfolio returns.[11] Again, males are more likely to have larger account turnover[12] and more experienced investors are less likely to turn over their portfolio frequently. Younger investors, between 30 and 60 years of age, are estimated to have higher purchase turnovers, as they actively expand their portfolios.

A different perspective on the role of IFAs applies to encouraging diversification. Columns 5 and 6 of Table 6 report a negative IFA effect on the average share of directly held stocks in the account, even after characteristics of account holders and areas are controlled for.[13] This finding

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[11] Higher turnover might be motivated simply by commissions but also by an incentive of IFAs to justify their fees by rebalancing client portfolios (see e.g. Lakonishok et al., 1992).
[12] Indeed, Niessen and Ruenzi (2006) show gender effects even for fund managers. According to their estimates, portfolio turnover is lower for female than for male fund managers.
[13]Since the share of single stocks is bound between zero and one, we also run Obit regressions. Results deliver very similar results to the OLS estimates, and are available on request.

is consistent both with the descriptive statistics at the start of the paper and the incentive of IFAs to sell mutual funds. It is also one channel through which the reduction in portfolio variance that we found in Table 5 is likely to be accomplished by IFAs.

Controlling for other factors, males tend to put larger shares of their account in directly held stocks, suggesting overconfidence in portfolio behavior, in addition to the gender effects on frequency of trading and on the volume of purchases.[14] Interestingly, experience tends to lower the share of directly held stocks, dampening overconfidence rather than encouraging account owners to manage direct investments in stocks. The conclusion from the regression analysis is that IFAs seem to boost the volume of purchases, while reducing the fraction of the account invested in directly held stocks.

7. Bank Financial Advisors and Portfolio Performance

Given the rather striking nature of the estimated contribution of IFAs to portfolio performance, the question arises as to whether our results are specific to brokerage accounts, e.g. because of selectivity into these types of accounts, or because financial advisors are independent and not accountable to the financial institution. For this reason, we consider a second data set of investment accounts, this time from a large German commercial bank.

Our discussions with the brokerage and the commercial bank suggest that there are important similarities and differences between incentives facing IFAs and BFAs. For example, upfront loads for mutual funds, a key component of any incentive scheme, are typically fixed by the mutual fund producer and therefore identical for all sales organizations. Although the bank does not funnel all commissions through to its BFAs, it gives powerful non-monetary incentives to its sales force through its sales control system.[15] On the other hand, IFAs are not subject to the

[14] Being married tends to have the opposite effect, presumably because more people are at risk and maybe vocal in encouraging diversification. Employees and self-employed account owners tend to invest more in directly held stocks, probably because of their increased social interactions.
[15] Another similarity refers to legal fines for any detected misselling. Since they are a function of the loss to the client they should be identical across IFAs and banks.

constraints imposed by banks on BFAs. In fact, many banks not only narrow down the menu of financial products offered to investors, but also provide extra incentives for their agents to advise clients to purchase funds or structured products produced by the bank itself or by one of its subsidiaries.[16] We expect the negative association between BFA use and portfolio returns to be even stronger than in the brokerage sample.

As with the brokerage sample, we introduce regional and zip code dummies to capture unobserved heterogeneity. Columns 1 and 2 in Table 7 present OLS results on raw returns, where use of a BFA is seen to have a statistically significant negative effect. According to this model, BFAs reduce monthly log returns by 0.3 percentage points, slightly less than IFAs in Table 4 (-0.4). However, unlike IFAs, who were found to reduce overall portfolio risk, BFAs are found in columns 3 and 4 of Table 7 to increase total portfolio risk.

Given the negative BFA effect on returns and their positive effect on total risk, we expect a strong negative effect on Sharpe ratios, and this is confirmed by the last two columns in Table 7.[17] This pronounced negative effect of BFAs is consistent with our conjecture form above and with Inderst and Ottaviani (2009) who posit that advisory standards should be lower for BFAs than for IFAs because the latter face no internal agency conflicts with costly monitoring.

Consistent with results on IFAs, males exhibit lower returns and riskier portfolios. The initial size of the account contributes to higher returns, in levels or normalized by risk, and to lower portfolio variance. Columns 1 and 2 of Table 8 point to higher turnover rates (based on purchases). for BFA accounts. The estimated BFA coefficients are larger than the corresponding IFA ones (Table 6), suggesting lower advisory standards for BFAs than for IFAs.

Finally, regressions reported in columns 5 and 6 of Table 8 confirm that BFAs, as indeed IFAs, tend to push towards investing in mutual funds, consistent with their compensation incentives. All in all, our analysis of the bank sample produces remarkably consistent results with the brokerage sample and points to systematic negative effects of financial advisors rather than to statistical flukes or sample peculiarities.

[16] Yoong and Hung (2009) extend Ottaviani and Inderst (2009) to address this kind of self-dealing.

[17] The coefficients of the BFA dummy are negative (-0.18), with values considerably larger than the corresponding IFA coefficients in Table 5 (-0.05 in columns 3 and 4).

8. Conclusions

We have investigated who tends to use a financial advisor, whether investors tend to produce better account performance on their own rather than with the help of financial advisors, whether results depend on the advisory model (IFA versus BFA), and whether they can be traced to trading behavior and security choice. We have also examined robustness of our findings with respect to asset pricing model, dummies for wider regions or zip codes, control variables, and estimation procedure (OLS versus IV).

Our first data set tracks accounts of a major brokerage firm, some of which are run with the help of an independent financial advisor (IFA). Sample statistics and regression analysis show that advisors tend to be matched with wealthier, older, more experienced, and female investors rather than with poorer, younger and inexperienced ones. Our second data set comes from a major commercial bank with branches throughout the country. We find that also bank clients who tend to consult a bank employee prior to executing a trade are older, wealthier and more likely to be female.

Descriptive statistics as well as regression analysis that controls for investors' characteristics and characteristics of the region of the account paint a very similar picture of the role of IFA and BFAs in account performance. In both samples, advised accounts offer lower returns than those run by similar investors without advisor input. Although IFA use reduces total portfolio risk, it still reduces ex post Sharpe ratios significantly. BFAs increase portfolio variance, lowering Sharpe ratios even more.

Trading costs and associated commissions earned by both IFAs and banks certainly contribute to these outcomes, since we find that advised accounts feature higher portfolio turnover (though not necessarily more frequent trading) relative to self-managed accounts. Consistent with their remuneration incentives, financial advisors tend to encourage lower account shares in directly held stocks. Robustness analysis suggests that our results on the negative role of IFAs are not an artifact of endogeneity between account performance and advisor use, nor of the way we adjust portfolio net returns for systematic risk.

Our results provide a new perspective on the role of financial advisors that might be useful for theoretical and policy analysis of their conflicting incentives, their likely effects, and the need to regulate them. Based on our findings, it should not be taken for granted that financial advisors provide their services to small, young investors typically identified as in need of investment guidance. Indeed, the opposite is true both for the broker and for the bank data we consider. The finding stands to reason: financial advisors with commission-based incomes naturally prefer to devote time to customers likely to trade on a bigger scale. However, it also creates doubts as to how viable financial advice is as a solution to the problem of limited financial literacy in the population. In view of the rapidly growing literature on investment mistakes, providing financial advice to inexperienced, naïve investors could be an alternative to trying to educate them in financial matters, but financial advisor incentives and tendencies of inexperienced clients might result in relatively few matches. Other alternatives, such as simpler products and carefully designed default options, may be more promising than currently existing forms of financial advice in averting negative distributional consequences.

Our findings imply that many financial advisors end up collecting more in fees and commissions than any monetary value they add to the account. This raises the further question of whether advisors overcharge and should be regulated. While the case for regulation seems much clearer when advisors are matched with inexperienced investors, negative effects appear even when the tendency is for experienced investors to be using an advisor. In such cases, it may be that investors are inattentive and fail to monitor the advisors effectively; or that they face high opportunity costs of running accounts by themselves and are willing to pay a luxury premium to have their advisors run their accounts. What distinguishes these two cases is customer awareness of the financial advisor incentives and effects. Even if regulation is not warranted in both cases, transparency and information on the role and outcome of financial advice seem crucial.

Moreover, this need is not limited to naïve, inexperienced customers but extends also to older, experienced ones. Questionnaires on investor experience, such as those dictated by MIFID (the EU directive aimed at increasing financial markets transparency and competition), should not waive the need for information regarding incentives, ensuing conflicts of interest, and the outcomes of professional financial advice in terms of portfolio returns and risks, even for experienced investors. Our study found, in two different samples, robust negative effects of financial advice and more likely use of it by experienced investors.

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Figure 1

The Distributions of Log Monthly Returns

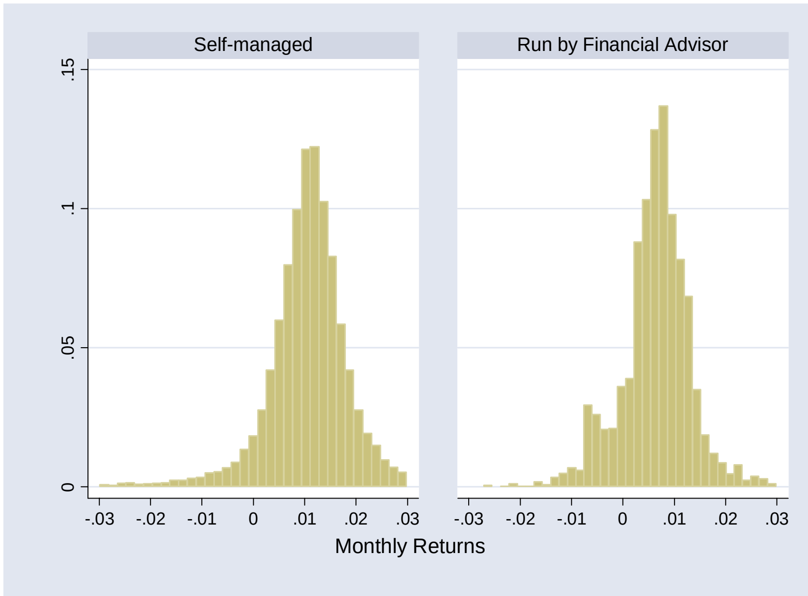

Figure 2

The Distributions of the Variance of Monthly Returns

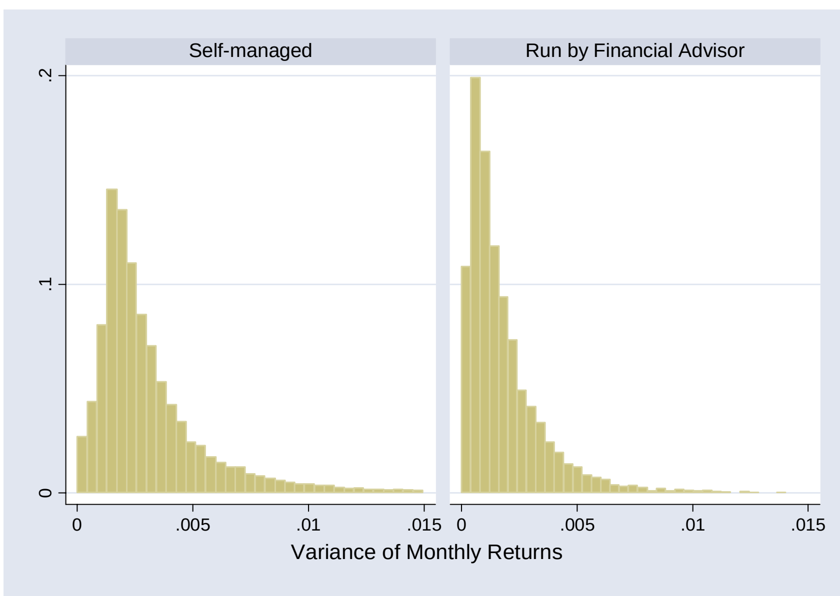

Figure 3

The Distribution of the Sharpe Ratio

Figure 4

The Distribution of Number of Trades (per ‘000 account volume)

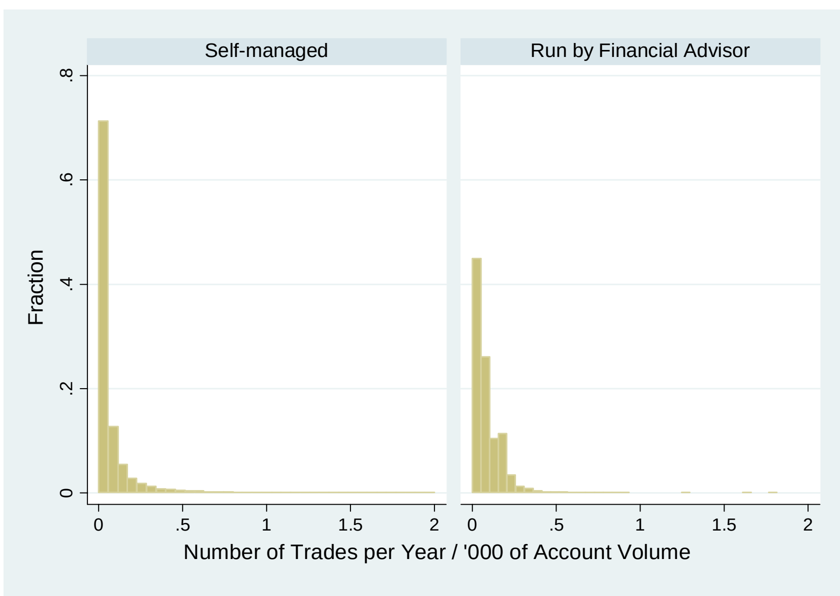

Figure 5

The Distribution of the Monthly Turnover Rate

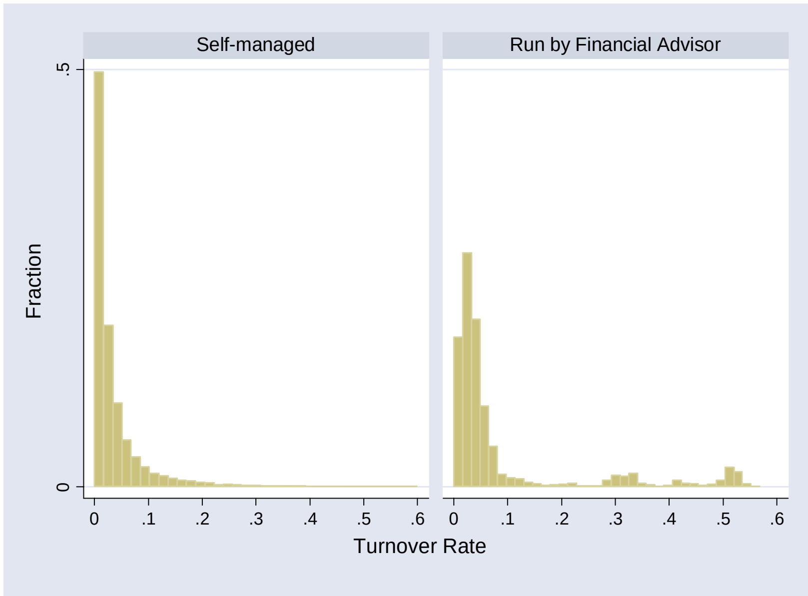

Table 1

Descriptive statistics for the brokerage sample (IFAs)

	Self-managed accounts Sample mean	Accounts run by IFA Sample mean	T-test for difference in means	All Accounts Sample mean	All Accounts Standard deviation
Dependent variables					
Log monthly returns	0.0101	0.0063	24.70	0.0097	0.0089
Jensen's alpha	0.0098	0.0061	23.72	0.0093	0.0091
Alpha – four factor model	0.0093	0.0055	22.31	0.0088	0.0100
Variance of monthly returns	0.0032	0.0019	28.39	0.0031	0.0027
Sharpe ratio	0.2229	0.1916	11.73	0.2189	0.1585
N. of trades / account volume in '000	0.0861	0.0884	0.87	0.0864	0.2609
Monthly turnover rate	0.0405	0.0895	33.38	0.0468	0.0865
Share of directly held stocks	0.5777	0.2000	58.70	0.5295	0.3838
Control variables					
Male	0.7925	0.6739	15.37	0.7774	0.4160
Married	0.4812	0.4636	0.92	0.4790	0.4996
Employed (excluding public servants)	0.8655	0.8334	4.93	0.8614	0.3455
Self-employed	0.1280	0.1577	5.10	0.1318	0.3383
Experience	9.3415	11.1535	16.27	9.5684	6.2182
18≤Age≤30	0.0101	0.0415	3.43	0.0462	0.2100
30< Age≤40	0.0098	0.1180	18.35	0.2409	0.4276
40< Age ≤50	0.0093	0.2680	8.66	0.3346	0.4719
50< Age ≤60	0.0530	0.2287	5.00	0.1995	0.3997
Age > 60	0.0708	0.3437	28.11	0.1787	0.3831
Log Account volume in 2003	9.1588	10.2823	42.98	9.3023	1.4917
Observations	25,173	3,686		28,321	28,321

Note. The t-test refers to a test of the null hypothesis that the mean of the sample with self-managed accounts equals the mean of the sample with accounts run by an Independent Financial Advisor (IFA).

Table 2

Descriptive statistics for the bank sample (BFAs)

	Self-managed accounts Sample mean	Accounts run by BFAs Sample mean	T-test for difference in means	All Accounts Sample mean	All Accounts Standard deviation
Dependent variables					
Log monthly returns	0.0076	0.0040	11.59	0.0054	0.0101
Variance of monthly returns	0.0045	0.0046	0.43	0.0046	0.0130
Sharpe ratio	0.4252	0.2662	12.23	0.3253	0.4020
Monthly turnover rate	0.0680	0.0520	8.34	0.0579	0.1103
Share of directly held stocks	0.2975	0.1188	20.07	0.1853	0.3009
Control variables					
Male	0.5102	0.4350	4.86	0.4630	0.4986
Employed (excluding public servants)	0.4413	0.3501	6.06	0.3840	0.4864
Executive employee	0.0284	0.0257	0.54	0.0267	0.1613
Housewife	0.0665	0.1034	4.22	0.0897	0.2858
Retired	0.1577	0.2205	5.05	0.1972	0.3979
$18 \leq Age \leq 30$	0.1203	0.0920	2.92	0.1020	0.3033
$30 < Age \leq 40$	0.1644	0.0941	6.88	0.1203	0.3253
$40 < Age \leq 50$	0.1922	0.1385	4.80	0.1585	0.3652
$50 < Age \leq 60$	0.1753	0.1736	0.22	0.1742	0.3793
$Age > 60$	0.3476	0.5016	10.05	0.4443	0.4969
Log account volume in 2003	9.0002	9.7146	10.63	9.4489	2.1695
Observations	1,648	2,792		4,440	4,440

Note. The t-test refers to a test of the null hypothesis that the mean of the sample with self-managed accounts equals the mean of the sample with accounts run by a Bank Financial Advisor (BFA).

Table 3

The determinants of having the account run by an IFA or a BFA

	Brokerage Sample (IFAs)		*Bank sample (BFAs)*	
	(1)	(2)	(3)	(4)
Male	-0.062***	-0.061***	-0.049***	-0.038**
	(12.06)	(10.92)	(3.14)	(2.15)
Employee	0.057**	0.061**	-0.054***	-0.039*
	(2.44)	(2.52)	(2.93)	(1.91)
30< Age <=40	-0.031***	-0.025**	-0.050	-0.060
	(3.32)	(2.40)	(1.44)	(1.49)
40< Age <=50	-0.004	0.004	-0.013	-0.021
	(0.36)	(0.35)	(0.38)	(0.57)
50< Age <=60	0.023**	0.021*	0.053*	0.042
	(2.20)	(1.81)	(1.67)	(1.16)
Age > 60	0.088***	0.088***	0.112***	0.089***
	(7.53)	(6.71)	(3.87)	(2.73)
Log Account Volume	0.045***	0.044***	0.027***	0.034***
	(22.07)	(20.19)	(7.51)	(7.92)
Self-employed	0.060**	0.064**		
	(2.48)	(2.55)		
Experience / 100	0.159***	0.148***		
	(3.45)	(3.03)		
Married	-0.023***	-0.025***		
	(5.61)	(5.10)		
Executive			-0.003	0.032
			(0.06)	(0.59)
Housewife			0.002	0.016
			(0.06)	(0.49)
Retired			-0.025	-0.009
			(1.11)	(0.34)
Constant	-0.358***	-0.316***	0.366***	0.303***
	(12.58)	(10.34)	(7.68)	(6.58)
Observations	28,321	28,321	4,440	4,440
R-squared	0.09	0.37	0.05	0.23
Zip code dummies	NO	YES	NO	YES

Note. The table reports estimates from a linear probability model of having an Independent Financial Advisor or a Bank Financial Advisor. Log account volume is measured in January 2003. All regressions include regional dummies (absorbed by zip code dummies where present).Asymptotic standard errors corrected for clustering at the zip code level are reported in parentheses. One star denotes statistical significance at the 10 percent level; two stars at the 5 percent level; three stars at the 1 percent level

Table 4

The determinants of portfolio returns in the brokerage sample

	Log Returns		*Jensen's Alpha*		*Alpha 4 Factor Model*	
	(1)	(2)	(3)	(4)	(5)	(6)
Financial Advisor (IFA)	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***
	(26.45)	(18.33)	(26.88)	(18.22)	(27.03)	(17.11)
Male	-0.001***	-0.000***	-0.000***	-0.000***	-0.001***	-0.001***
	(4.34)	(3.14)	(3.95)	(2.99)	(5.37)	(4.17)
Married	0.000	0.000	0.000	0.000	0.000**	0.000
	(0.79)	(0.22)	(1.16)	(0.43)	(2.12)	(1.49)
Employee	-0.001	-0.001	-0.001	-0.001	-0.001*	-0.001*
	(1.57)	(1.43)	(1.47)	(1.39)	(1.95)	(1.72)
Self-employed	-0.001*	-0.001*	-0.001*	-0.001*	-0.001**	-0.002**
	(1.91)	(1.77)	(1.86)	(1.74)	(2.35)	(2.11)
Experience / 100	0.002**	0.001	0.001	0.000	0.001	0.001
	(2.28)	(0.98)	(1.58)	(0.43)	(1.31)	(0.53)
30< Age <=40	0.000*	0.001*	0.000*	0.001*	0.000	0.000
	(1.84)	(1.70)	(1.86)	(1.71)	(0.89)	(1.07)
40< Age <=50	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.32)	(0.37)	(0.46)	(0.43)	(1.36)	(0.97)
50< Age <=60	0.000	0.000	0.000	0.000	-0.000	-0.000
	(0.15)	(0.43)	(0.18)	(0.48)	(1.11)	(0.33)
Age > 60	-0.001*	-0.000	-0.000	-0.000	-0.001***	-0.001
	(1.80)	(0.95)	(1.64)	(0.79)	(2.63)	(1.58)
Log Account Volume	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(6.92)	(4.81)	(6.68)	(4.62)	(7.51)	(5.24)
Constant	0.008***	0.008***	0.008***	0.008***	0.007***	0.008***
	(11.92)	(9.78)	(11.24)	(9.36)	(9.48)	(7.90)
Observations	28,321	28,321	28,321	28,321	28,321	28,321
R-squared	0.03	0.23	0.02	0.22	0.02	0.22
Zip code dummies	NO	YES	NO	YES	NO	YES

Note. Log account volume is measured in January 2003. All regressions include regional dummies (absorbed by zip code dummies where present). Asymptotic t-statistics corrected for clustering at the zip code level are reported in parentheses. One star denotes statistical significance at the 10 percent level; two stars at the 5 percent level; three stars at the 1 percent level.

Table 5

The determinants of portfolio return variance and Sharpe ratios in the brokerage sample

	Variance of Monthly Returns		*Sharpe Ratio*	
	(1)	(2)	(3)	(4)
Financial Advisor (IFAs)	-0.001***	-0.001***	-0.056***	-0.052***
	(14.74)	(9.95)	(13.87)	(10.92)
Male	0.001***	0.001***	-0.022***	-0.021***
	(15.82)	(13.11)	(10.31)	(7.85)
Married	-0.000***	-0.000***	0.006***	0.006***
	(8.01)	(6.27)	(3.26)	(2.62)
Employee	0.000*	0.000	-0.021**	-0.017
	(1.77)	(0.24)	(2.10)	(1.39)
Self-employed	0.001***	0.001***	-0.033***	-0.029**
	(5.18)	(2.93)	(3.22)	(2.21)
Experience / 100	-0.000	-0.000	0.056***	0.043**
	(0.50)	(0.47)	(3.74)	(2.31)
30< Age <=40	0.000*	0.000	0.001	0.002
	(1.77)	(1.19)	(0.17)	(0.42)
40< Age <=50	0.000***	0.000***	-0.012***	-0.013**
	(5.46)	(3.99)	(2.59)	(2.33)
50< Age <=60	0.000***	0.000***	-0.014***	-0.013**
	(5.84)	(4.21)	(2.77)	(2.19)
Age > 60	0.001***	0.000***	-0.018***	-0.015**
	(6.22)	(3.99)	(3.58)	(2.45)
Log Account Volume	-0.001***	-0.001***	0.023***	0.021***
	(39.58)	(31.94)	(26.96)	(20.47)
Constant	0.007***	0.008***	0.066***	0.064***
	(38.35)	(32.36)	(5.22)	(4.12)
Observations	28,321	28,321	28,321	28,321
R-squared	0.12	0.31	0.05	0.25
Zip code dummies	NO	YES	NO	YES

Note. Log account volume is measured in January 2003. All regressions include regional dummies (absorbed by zip code dummies where present). Asymptotic t-statistics corrected for clustering at the zip code level are reported in parentheses. One star denotes statistical significance at the 10 percent level; two stars at the 5 percent level; three stars at the 1 percent level.

Table 6

The determinants of trading, turnover and diversification in the brokerage sample

	Number of Trades		*Turnover Rate*		*Share of Single Stocks*	
	(1)	(2)	(3)	(4)	(5)	(6)
Financial Advisor (IFA)	-0.008***	-0.009**	0.062***	0.053***	-0.353***	-0.341***
	(2.59)	(2.14)	(16.77)	(15.21)	(47.19)	(37.72)
Male	0.035***	0.036***	0.018***	0.017***	0.077***	0.079***
	(16.04)	(12.32)	(16.10)	(13.15)	(14.71)	(12.37)
Married	0.001	-0.001	0.001	-0.000	-0.027***	-0.029***
	(0.32)	(0.19)	(1.37)	(0.14)	(6.03)	(5.03)
Employee	-0.010	-0.015	-0.001	-0.001	0.082***	0.068**
	(0.80)	(0.89)	(0.19)	(0.26)	(2.94)	(1.99)
Self-employed	-0.006	-0.012	-0.004	-0.005	0.128***	0.108***
	(0.46)	(0.71)	(0.99)	(0.91)	(4.47)	(3.10)
Experience / 100	-0.020	-0.003	-0.073***	-0.054***	-0.571***	-0.556***
	(1.07)	(0.12)	(8.58)	(5.42)	(15.22)	(11.91)
30< Age <=40	0.005	0.004	0.004**	0.003	0.000	0.001
	(1.39)	(0.80)	(2.05)	(1.17)	(0.03)	(0.04)
40< Age <=50	0.015***	0.016***	0.010***	0.009***	0.028**	0.026*
	(4.02)	(2.95)	(4.29)	(3.44)	(2.50)	(1.88)
50< Age <=60	0.024***	0.026***	0.016***	0.014***	0.061***	0.064***
	(5.35)	(4.28)	(6.53)	(4.78)	(5.06)	(4.33)
Age > 60	0.020***	0.021***	0.011***	0.011***	0.077***	0.072***
	(4.11)	(3.17)	(4.28)	(3.50)	(6.27)	(4.74)
Log Account Volume	0.015***	0.016***	-0.009***	-0.007***	-0.027***	-0.030***
	(13.23)	(10.75)	(15.95)	(12.03)	(17.05)	(14.69)
Constant	-0.097***	-0.093***	0.101***	0.089***	0.689***	0.735***
	(6.21)	(4.57)	(16.08)	(12.43)	(21.07)	(18.62)
Observations	28,303	28,303	28,321	28,321	28,321	28,321
R-squared	0.02	0.21	0.07	0.32	0.14	0.32
Zip code dummies	NO	YES	NO	YES	NO	YES

Note. Number of trades is expressed as a fraction of account volume in '000. Log account volume is measured in January 2003. All regressions include regional dummies (absorbed by zip code dummies where present). Asymptotic t-statistics corrected for clustering at the zip code level are reported in parentheses. One star denotes statistical significance at the 10 percent level; two stars at the 5 percent level; three stars at the 1 percent level.

Table 7

The determinants of portfolio returns, variance and Sharpe ratio in the bank sample

	Log Monthly Returns		*Variance of Monthly Returns*		*Sharpe Ratio*	
	(1)	(2)	(3)	(4)	(5)	(6)
Financial Advisor (BFA)	-0.003***	-0.003***	0.001***	0.001*	-0.180***	-0.178***
	(9.20)	(8.07)	(2.80)	(1.92)	(12.20)	(10.20)
Male	0.001**	0.001*	0.001***	0.001***	-0.031**	-0.033**
	(2.18)	(1.75)	(3.05)	(2.63)	(2.37)	(2.13)
Employee	0.001***	0.001*	0.001	0.001	-0.008	-0.005
	(2.59)	(1.88)	(1.49)	(0.92)	(0.47)	(0.25)
Executive	0.001	0.002	0.002	0.002	-0.013	-0.030
	(1.37)	(1.57)	(1.46)	(1.33)	(0.31)	(0.65)
Housewife	0.001	0.001*	0.000	0.000	0.008	0.020
	(1.58)	(1.70)	(0.19)	(0.14)	(0.34)	(0.72)
Retired	-0.000	0.000	-0.000	-0.000	-0.010	0.001
	(0.27)	(0.48)	(0.22)	(0.58)	(0.53)	(0.04)
30< Age <=40	0.001*	0.001	0.000	0.000	0.034	0.029
	(1.86)	(1.49)	(0.09)	(0.14)	(1.21)	(0.86)
40< Age <=50	0.000	0.000	0.002*	0.001	0.023	0.010
	(0.41)	(0.32)	(1.87)	(1.46)	(0.91)	(0.33)
50< Age <=60	-0.000	-0.001	0.000	0.001	0.023	0.015
	(0.64)	(1.08)	(0.52)	(0.65)	(0.81)	(0.46)
Age > 60	-0.002**	-0.002**	0.001	0.001	0.028	0.012
	(2.58)	(2.33)	(0.88)	(1.21)	(1.10)	(0.40)
Log Account Volume	0.001***	0.000***	-0.001***	-0.001***	0.023***	0.024***
	(5.44)	(3.81)	(8.04)	(7.15)	(5.08)	(4.85)
Constant	0.001	0.003**	0.013***	0.013***	0.197***	0.210***
	(1.01)	(2.18)	(8.47)	(8.58)	(4.33)	(4.48)
Observations	4,440	4,440	4,440	4,440	4,440	4,440
R-squared	0.06	0.20	0.04	0.19	0.05	0.19
Zip code dummies	NO	YES	NO	YES	NO	YES

Note. Log account volume is measured in January 2003. All regressions include regional dummies (absorbed by zip code dummies where present). Asymptotic t-statistics corrected for clustering at the zip code level are reported in parentheses. One star denotes statistical significance at the 10 percent level; two stars at the 5 percent level; three stars at the 1 percent level.

Table 8

The determinants of turnover and diversification in the bank sample

	Turnover Rate		*Share of Single Stocks*	
	(1)	(2)	(3)	(4)
Financial Advisor (BFA)	0.099***	0.121***	-0.158***	-0.148***
	(6.11)	(5.91)	(16.31)	(13.22)
Male	0.072***	0.075***	0.056***	0.055***
	(4.72)	(4.37)	(5.88)	(4.85)
Employee	0.041**	0.019	0.045***	0.037***
	(1.98)	(0.82)	(3.66)	(2.59)
Executive	0.147**	0.137**	0.046	0.054*
	(2.43)	(2.02)	(1.63)	(1.72)
Housewife	0.035	0.029	0.010	0.004
	(1.07)	(0.76)	(0.62)	(0.19)
Retired	0.038	0.023	-0.016	-0.019
	(1.54)	(0.84)	(1.16)	(1.16)
30< Age <=40	0.011	0.046	0.072***	0.079***
	(0.38)	(1.32)	(3.69)	(3.52)
40< Age <=50	0.016	0.038	0.088***	0.099***
	(0.56)	(1.19)	(4.69)	(4.45)
50< Age <=60	0.051*	0.069**	0.053***	0.061***
	(1.87)	(2.14)	(3.04)	(3.02)
Age > 60	-0.012	0.016	0.014	0.029
	(0.47)	(0.55)	(0.85)	(1.58)
Log Account Volume	0.065***	0.062***	-0.006***	-0.008***
	(14.85)	(12.42)	(2.70)	(2.90)
Constant	-0.339***	-0.368***	0.275***	0.267***
	(6.53)	(7.07)	(10.04)	(9.73)
Observations	4,440	4,440	4,440	4,440
R-squared	0.10	0.26	0.13	0.26
Zip code dummies	NO	YES	NO	YES

Note. Log account volume is measured in January 2003. All regressions include regional dummies (absorbed by zip code dummies where present). Asymptotic t-statistics corrected for clustering at the zip code level are reported in parentheses. One star denotes statistical significance at the 10 percent level; two stars at the 5 percent level; three stars at the 1 percent level.

Appendix 1: Endogeneity of Financial Advice

Although we define as advised portfolios those portfolios that are continuously assisted from 2003 to 2006, if performance is persistent over time one may suspect that portfolio performance actually induced the choice of the advisor. As mentioned in Section 6, in such a case, OLS regressions are problematic. In this Appendix we carry out IV estimation to examine the robustness of our main findings to possible endogeneity of financial advice. Finding suitable instruments in our context is not easy, and the robustness exercise described below, based on regional variation, is indicative and unavoidably rests on the validity of the identification assumption.

We choose to exploit regional variability in the share of financial services over GDP, and merge our two datasets with administrative data available from the German Federal Statistical Office, which provides a broad set of structural data on some 500 local areas. The system of German zip codes is more granular than the regional grid used by the Federal Statistical Office. Accordingly, we map the zip codes for customer accounts into the regional grid of the Statistical Office by assuming that zip-codes from the same region share the same structural characteristics.

We motivate the use of the GDP share of financial services by reference to the potential role that the density of financial services plays in reducing the cost of gathering financial information: the greater such density, the more likely it is that investors are able to gather information from local sources more cheaply, substituting for financial advice. Our identification assumption is that regional proximity with financial intermediaries affects account performance by facilitating the matching of account holders to financial advisors, but not directly. The instrument is collinear with the zip code dummies, which cannot be used in the estimation. Note however that in the IV estimates we still use wider regional dummies.

Table A1 reports the first-stage estimates for IFA and for BFA, and shows that being located in an area with a larger density of intermediaries reduces the probability of having an account run by an IFA or a BFA. In both cases, the coefficients are statistically different from zero (at the 1 and 5% level, respectively).

The IV estimates for portfolio performance are reported in Table A2. They are based on a standard IV estimator (with a linear probability model in the first stage) and standard errors adjusted for clustering at the local area level. With only one instrument, the model is exactly identified and we cannot provide a test of over-identification restrictions. However, we do find that the instrument has statistically significant impact on use of IFA (the F-statistic is reported in the last row of Table A2). The signs of the instrumented advisor effects on returns, variance and Sharpe ratios remain qualitatively unchanged as compared to the OLS results, for both the brokerage and bank sample. In particular, we find that advised accounts yield lower returns and Sharpe ratios, and that the negative effects are larger in the bank sample. Moreover, factors such as being female, experienced, and wealthier still contribute to higher returns, lower variance and higher Sharpe ratios.

Table A1

First-stage results: The determinants of having the account run by an IFA or a BFA

	Brokerage Sample (IFAs)	*Bank sample (BFAs)*
Male	-0.063***	-0.049***
	(12.32)	(3.16)
Employee	0.058**	-0.048***
	(2.49)	(2.61)
30< Age <=40	-0.030***	-0.049
	(3.11)	(1.41)
40< Age <=50	-0.002	-0.011
	(0.25)	(0.33)
50< Age <=60	0.023**	0.055*
	(2.21)	(1.74)
Age > 60	0.089***	0.113***
	(7.62)	(3.89)
Log Account Volume	0.046***	0.028***
	(22.60)	(7.73)
Self-employed	0.062**	
	(2.56)	
Experience / 100	0.165***	
	(3.58)	
Married	-0.025***	
	(6.06)	
Executive		0.001
		(0.01)
Housewife		0.005
		(0.18)
Retired		-0.022
		(0.95)
Financial services / regional GDP	-0.238***	-0.324**
	(6.58)	(2.53)
Constant	-0.301***	0.446***
	(9.85)	(7.54)
Observations	28,321	4,440
R-squared	0.10	0.05

Note. The table reports estimates from a linear probability model of having an Independent Financial Advisor or a Bank Financial Advisor. Log account volume is measured in January 2003. The regressions include regional dummies. Asymptotic standard errors corrected for clustering at the zip code level are reported in parentheses. One star denotes statistical significance at the 10 percent level; two stars at the 5 percent level; three stars at the 1 percent level

Table A2

Instrumental variable regressions for the brokerage and bank sample

	Brokerage sample with IFAs			Bank sample with BFAs		
	Log Monthly Returns (1)	*Variance of Monthly Returns* (2)	*Sharpe Ratio* (3)	*Log Monthly Returns* (4)	*Variance of Monthly Returns* (5)	*Sharpe Ratio* (6)
Financial Advisor	-0.012***	-0.002**	-0.166***	-0.023***	0.003	-0.529*
	(3.68)	(2.54)	(3.27)	(2.60)	(0.34)	(1.73)
Male	-0.001***	0.000***	-0.029***	-0.000	0.001**	-0.048**
	(4.20)	(6.99)	(7.64)	(0.38)	(2.27)	(2.30)
Employee	-0.000	0.000**	-0.015	0.000	0.001	-0.026
	(0.54)	(2.14)	(1.31)	(0.12)	(1.17)	(1.12)
30< Age <=40	0.000	0.000	-0.003	0.000	0.000	0.017
	(0.80)	(1.08)	(0.53)	(0.43)	(0.18)	(0.49)
40< Age <=50	-0.000	0.000***	-0.013***	0.000	0.002*	0.019
	(0.44)	(5.31)	(2.59)	(0.06)	(1.89)	(0.64)
50< Age <=60	0.000	0.000***	-0.011**	0.001	0.000	0.041
	(0.69)	(5.97)	(2.10)	(0.59)	(0.32)	(1.16)
Age > 60	0.000	0.001***	-0.009	0.000	0.001	0.067
	(0.44)	(5.57)	(1.21)	(0.34)	(0.37)	(1.45)
Log Account Volume	0.001***	-0.000***	0.028***	0.001***	-0.001***	0.032***
	(4.66)	(11.75)	(11.60)	(4.37)	(4.09)	(3.42)
Self-employed	-0.001	0.001***	-0.027**			
	(0.86)	(5.23)	(2.31)			
Experience / 100	0.003***	0.000	0.073***			
	(2.97)	(0.39)	(4.24)			
Married	-0.000	-0.000***	0.004			
	(0.58)	(7.58)	(1.53)			
Executive				0.001	0.002	-0.014
				(0.95)	(1.47)	(0.32)
Housewife				0.001	0.000	0.009
				(1.13)	(0.18)	(0.34)
Retired				-0.001	-0.000	-0.019
				(0.90)	(0.13)	(0.83)
Constant	0.005***	0.007***	0.027	0.009**	0.012***	0.325***
	(4.02)	(18.28)	(1.20)	(2.31)	(3.28)	(2.72)
Observations	28321	28321	28321	4440	4440	4440
Cragg-Donald F-stat.	43.30	43.30	43.30	11.23	11.23	11.23

Note. The instrument is the GDP ratio of the financial asset share at the zip code level. The first stage regressions are reported in column 1 (brokerage sample) and column 2 (bank sample) of Table A1. Log account volume is measured in January 2003. All regressions include regional dummies. Asymptotic t-statistics corrected for clustering at the zip code level are reported in parentheses. One star denotes statistical significance at the 10 percent level; two stars at the 5 percent level; three stars at the 1 percent level.