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Abstract

We use two administrative data sets, from a large internet broker and from a major commercial bank, together with regional data to ask three questions: (i) whether financial advisors tend to be matched with poorer, uninformed investors or with richer, experienced but presumably busy investors; (ii) how accounts run without financial advice actually perform relative to those run with advice; (iii) whether the contribution of advisors is similar across advisory models - independent (IFA) versus bank financial advisors (BFA). Controlling for investors' characteristics and for the possibility that unobserved factors contribute both to the use of IFAs and to account performance, advised accounts offer on average lower raw and abnormal returns and higher diversifiable risk. Higher trading costs contribute to return outcomes, as advised accounts feature more frequent trading and higher portfolio turnover. Robustness analysis suggests that the negative role of advisors is not sensitive to the choice of asset pricing model, and applies with similar or stronger force to BFAs, consistent with greater limitations faced by them on recommended products and nature of advice.

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JEL codes: G1, E2, D8.

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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 customers, as shown by Inderst and Ottaviani (2009). These arise mainly because of conflicting incentives for financial advisors: 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. Stulz and Mehran (2007) reviews the existing empirical literature on the nature and implications of various conflicts mainly focusing on analysts. Underlying much of the existing literature on financial literacy, the possible role of financial advice and the case for regulation of financial advisors is the notion that financial advisors tend to be used by less informed or sophisticated investors who could be easily misled by them. Regulation and/or incentives are then needed to make sure that advisors contribute their expertise to these inexperienced investors.

In this paper, we examine three questions. First, we ask whether financial advisors tend to be matched with poorer, uninformed investors or with richer, experienced but presumably busy investors. 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 advisors (BFA). Direct performance comparisons are made possible by new administrative data sets: 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 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 account performance.

Our main data, from the internet broker, track accounts of 32,751 randomly selected individual customers over 66 months. Performance records, likely to shape perceptions of the public, paint a positive picture in most respects: financial advisors accounts offer on average greater raw and abnormal returns; lower risk, systematic and unsystematic; lower probabilities of losses and of substantial losses; and greater diversification through investments in mutual funds as opposed to directly held stocks. On the other hand, the turnover rate (based on purchases) among advised accounts is higher than among non-advised accounts. In econometric analysis that controls for client demographics and experience and for possible endogeneity of the use of an IFA, the latter are seen to lower total and abnormal returns (regardless of whether abnormal returns are computed using a single- or a four-factor model), have no statistically significant effect on portfolio risk (total or systematic, though they do raise diversifiable risk), and no effect on the probabilities of losses and of substantial losses. Consistent with the incentives provided by a commission-based structure, they tend to increase trading frequency and portfolio turnover through purchases, and to reduce the share of directly held stocks relative to what account owners of given characteristics tend to achieve on their own. 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 ones. In this respect, advisors are similar to babysitters: babysitters are matched with well-to-do households, they perform a service that parents themselves could do better, they charge for it, but observed child achievement is often better than what people without babysitters obtain, because other contributing factors are favorable.

Our second data set contains full data of 4,447 clients of a German branch-based bank and covers 34 months. We subject the role of bank financial advisors (BFAs) to the same scrutiny and find that the pattern of results is robust, but 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 nature of financial advice.

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 broker data and the measures that we use to characterize portfolio performance. Section 4 compares records of account performance with and without involvement of financial advisors which might help shape public perceptions about the usefulness of IFAs. Section 5 studies econometrically the role of investor characteristics and regional factors 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 the results from the second sample, of 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 incentives is dealt with. In early work, Ottaviani (2000) built a model of financial advice, where an informed agent (financial advisor) provides information to investors who are otherwise uninformed and have an uncertain degree of strategic sophistication. The emphasis was on deriving incentives for truthful information disclosure and information acquisition.

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 policy-determined 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) and in the effectiveness of monitoring, but they are decreasing in the sales incentives, the intransparency of the incentive scheme and the private cost for the agent to investigate the match between product and customer.

Two implications that are highly relevant for our study are the following. First, financial advisors can lower portfolio performance by recommending suboptimal products. 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) the advisor may affect portfolio outcomes not only through selecting unsuitable products but also by encouraging ill-advised trades; and (ii) the notion of advisor advantage need not refer solely to unsophisticated investors, but also to experienced but inattentive ones who fail to monitor advisors effectively.

An issue that has received considerable attention in existing empirical literature is 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.[1]

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

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[1] 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*.

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 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, such as trading on the basis of past returns, reference prices, or the size of holding period gain or loss (Grinblatt and Keloharju, 2001).

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.

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 through 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 the abnormal returns (net of transactions costs) and the level of diversifiable portfolio risk 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 (not to theoretical portfolios), which may include directly held stocks, bonds, and mutual funds; and it accounts for a number of investor 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. Our first dataset covers independent financial advisors (IFA) whereas the second dataset pertains to employed bank advisors (BFA). The two datasets allow us to perform a robustness test on the general effects from professional financial advice and to compare portfolio performance under two different advisory regimes. We focus more extensively on the IFA data set, both because it is likely to be more favorable to financial advisors and because it covers a longer time period.

3. The Brokerage Firm Dataset

The primary data set we use in this study is administrative information from a large German brokerage firm. It covers the investments of 32,751 randomly selected customers who opened an account with the brokerage firm prior to January 2001 and kept the account active through June 2006. 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.[2] 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 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 assets.

3.1. Independent Financial Advisors

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 house by IFAs. About 90% of IFAs registered with the internet broker 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

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[2] 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 between account opening date and January 2001 to measure trading experience at the beginning of our observation period.

investment accounts to the brokerage firm. The remaining 10% of IFAs in our sample are not former bank employees but directly joined a larger team of IFAs and built up their own customer base, again drawing mostly from former bank customers.

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, 12.7 percent consult IFAs registered with the brokerage firm. More than half of these customer 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 (presumably other) customers 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 our total sample and of the two subsamples distinguished by whether the customer was advised by an independent financial advisor or not, after dropping accounts that report age of account owner below 18.[3] As shown in the Table, 77.8 percent of account owners were male, and 47.8 percent married. Overall, 86.1 percent were employed, 13.2 percent self-employed, and 0.7 percent public servants, retirees, housewives or

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[3] 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 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.

students. Average trading experience as of January 2001 was 7.56 years. Among IFA-assisted customers, men are underrepresented relative to their share in the overall account owner pool, and so are married owners. Older owners (above 50) are overrepresented, and advised customers have on average more years of experience and larger initial size of accounts.

Importantly, transaction amounts are *net* of any transactions costs and provisions charged by the brokerage house or the IFA and processed through the brokerage house.[4] 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 a flat fee as a percentage of account volume. As this flat 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 observation period, average annual account volume was 10,015 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.

A crucial issue in estimating the effect of IFAs on account performance is the endogeneity of the choice of consulting a financial advisor. This choice is likely to be correlated with account performance and to bias the econometric results. For instance, clients who are more risk averse might be more inclined to consult an IFA as well as to invest in a safer portfolio; richer clients

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[4] Although we do not observe costs separately in our data, we know from the data provider that the bank 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 and kick-backs from mutual funds.

might also be more likely to consult IFAs and to have different investment strategies resulting in different return levels than the rest. Experience may also influence the choice of whether to be advised or not and is also likely to influence investment outcomes. Estimated effects from OLS regressions could reflect the influence of these underlying factors rather than a direct influence of IFA use on account performance.

In order to handle this endogeneity issue, we employ regional instruments from a second data set we retrieved from the *destatis* files of the German Federal Statistical Office, which provides a broad set of structural data on some 500 German regions. We obtained size of region in square kilometers, population per region, total disposable income per region, disposable income per capita per region, fraction of college graduates and average voter participation in communal, state and federal elections per region. The system of German zip codes is more granular than the regional grid of *destatis*. We mapped customer accounts to regions by assuming that all zip-codes in the same *destatis* region share the same structural characteristics. Finally, we augmented our second data set with the number of bank branches per *destatis* region, which we acquired from a commercial data provider.

3.2.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 and diversifiable risk. In order to compute monthly portfolio returns, we assume as in Dietz (1968) and that all transactions occur in the middle of a given month:

$$R_{p,t} = \frac{(V_{p,t} - V_{p,t-1}) - (P_{t-1\to t} - S_{t-1\to t}) + E_{t-1\to t}}{V_{p,t-1} + \left(\frac{P_{t-1\to t} - S_{t-1\to t} + E_{t-1\to t}}{2}\right)} \tag{1}$$

where:

$V_{p,t}$ = market value of portfolio p at end of month t;

$P_{t-1\to t}$ = market value of all purchases (including fees) between t and t-1;

$S_{t-1\to t}$ = market value of all sales (including fees) between t and t-1;

$E_{t-1 \to t}$ = cash proceeds from dividends, coupons etc. received between t and t-1.

Monthly returns from (1) are winsorized by treating returns that fall into the first or the 100th percentile as missing values.[5] 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*;

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 = log return on the one-month Euribor;

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

We also decompose total portfolio risk into systematic risk and unsystematic risk:

$$\sigma_p^2 = \beta_p^2 \sigma_B^2 + \sigma_{\varepsilon,p}^2 \tag{3}$$

where

σ_p^2 = total variance of log returns of portfolio p;

β_p^2 = square of estimated benchmark beta for portfolio p;

σ_B^2 = variance of log returns on benchmark portfolio B (MSCI-World index);

$\sigma_{\varepsilon,p}^2$ = variance of error term from the regression in (2).

[5] 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 63 or 64 instead of 65 monthly return observations.

The first term on the right hand side of (3) measures systematic risk and the second term measures diversifiable portfolio risk. In our regressions, we use the portion of diversifiable risk in total risk:

$$\frac{\sigma^2_{\varepsilon,p}}{\sigma^2_p} = \frac{\sigma^2_{\varepsilon,p}}{\beta^2_p \sigma^2_B + \sigma^2_{\varepsilon,p}} \tag{4}$$

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 for the period Jan 1990 to Nov 2009. The model is specified as follows:

$$r_{i,t} = \alpha_i + \beta_{1i} R_{m,t} + \beta_{2i} SMB_t + \beta_{3i} HML_t + \beta_{4i} MOM_t + \varepsilon_{it} \tag{5}$$

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.

Beyond alternative concepts of returns and risk, investors may be interested in the probability of bad outcomes. We also consider the probability that returns fall short of some target return. This is a special case (for n=0) of lower partial moments (LPM_n) of returns as measures for (downside) risk:

$$LPM_n = \sum_{x=-\infty}^{\tau} P(X = x)(\tau - x)^n \tag{6}$$

where τ = monthly target return (we use 0 or -5 percent p.a.) and n is the order of the moment.

4. Performance Record of Independent Financial Advisors

For many 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. Even in the absence of official records (indeed our internet broker does not compute or print performance records of the two types of accounts), prospective clients may still be influenced by the experiences of existing clients through word of mouth or summary descriptions by the IFA. In this Section, we make use of our extensive sample and ask how IFA accounts (defined as those that benefit from the input of IFAs collaborating with the brokerage firm, which ranges from mere consultation to full responsibility for trades) have performed over the observation period compared to those run without input from IFAs.

Figure 1 plots histograms of average monthly log returns over our observation period for accounts that were self-managed and for those run with IFA input. We see clearly that the IFA accounts exhibit more mass towards the center and higher end of the distribution, indicating better performance. Table 1 shows monthly logarithmic returns. The sample mean log (gross) return on IFA accounts is considerably higher than that of self-managed accounts: -0.44% versus -0.80%. Interestingly, IFA customers were getting on average a return net of all transactions costs that was comparable to what they would have gotten if they had invested in the DAX for the duration of our sample period. Table 1 confirms that IFA accounts can claim a higher average excess return on accounts run with their input, as well as a higher average return. It also shows that the favorable comparison of IFA run accounts to the rest is robust to considering abnormal returns; and that this is so regardless of whether we use a traditional CAPM or a four-factor model to compute abnormal returns.

These higher returns offered by IFAs are not associated with more risk in the portfolio. Table 1 shows that the overall portfolio risk of IFA accounts is about two thirds of that of non-IFA accounts; unsystematic risk is twenty percent lower for IFA accounts; and the beta coefficient capturing covariance with the market portfolio (proxied by the MSCI World Index) is two thirds of its value without IFA involvement, implying that systematic risk is also two thirds. 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.

Some prospective clients may pay particular attention to the probability of making losses or substantial losses. This would be particularly evident with loss aversion utility or rank-dependent utility, but even under expected utility clients could be influenced by very bad states because of high marginal utility of consumption in those states. IFA accounts have exhibited, on average, lower probabilities of losses or substantial losses. Table 1 shows that the fraction of investors that exhibited a loss (the return is negative) over a month is 48 percent for investors with IFA and 45 percent without (45 and 40 percent, respectively, for substantial losses).

Comparison of IFA and non-IFA accounts also shows that frequency of trades is smaller among IFA accounts, but average portfolio turnover (which is sensitive to the size of purchases) is much greater. The average monthly number of trades per 1000 euro of account volume is .32 for IFA and .44 for non-IFA accounts, but the turnover rate is more than double for IFA accounts. Looking at Figures 3 and 4, IFA accounts tend to be clustered closer to zero trades per year standardized by account volume, but to be distributed away from zero in terms of turnover. In other words, IFAs get commission based on the volume of purchases and tend to exhibit greater purchases than individual clients on average, but they do not do so by pushing the trading button more often. 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.

All in all, performance records paint a positive view of IFA account performance: IFA accounts have offered greater returns, both in total and relative to the security market line; lower risk, systematic and unsystematic; lower probabilities of losses and of substantial losses; and greater diversification. The deeper question is, of course, whether these differences are due to IFAs themselves or to the customers they tend to attract. It is to this that we now turn.

5. Who Has a Financial Advisor?

We first consider which characteristics of the brokerage firm client contribute to the client’s account being run with input from an IFA. A priori, two very different cases seem plausible. One is that IFAs tend to be matched with smaller, younger, less experienced investors, to whom they promise to offer knowledge and guidance that will help avoid mistakes and improve account performance. Another is that IFAs tend to be matched with wealthier, older, more experienced investors who can benefit from IFA services by saving valuable time and/or by improving returns on sizeable investments.

Table 2 reports probit regressions of whether the client makes use of an IFA on a number of factors; rather than the original coefficients, we report marginal effects. The first column uses as regressors only characteristics of the client. We see that an extra year of self-reported experience with the relevant financial products actually increases the probability of using an IFA. Being self-employed increases the probability of IFA use by a sizeable amount of about 6.5 percentage points, while there is no significant effect for employees relative to remaining occupational categories in the population. Given other characteristics, males are less likely to use an IFA, suggesting an analogy to the role of gender in trading behavior and reinforcing the view that males tend to have more (over)confidence in their ability to run financial investments. Married clients are also less likely to use an IFA, controlling for other factors, probably because spouses can be used as sounding boards both for investment decisions and for whether an IFA should be hired. We also find that clients between 50 and 60, and even more so those over 60 years of age, have a significantly greater probability of using an IFA, the latter by about 15 percentage points. The comparison group (i.e. the excluded age category) is investors younger than 30 years (but above 18).

Column 2 uses the same regressors but controls also for account volume at the very start of the observation period. This serves as a scale or ‘wealth’ variable, and we focus on the beginning-of-period value to minimize endogeneity problems running from the use of IFA to account volume. Introduction of this control has small influence on estimated marginal effects, except for lowering the contribution of old age and eliminating statistical significance of experience on the choice to use an IFA, suggesting that these were partly proxying for wealth.

In column 3 we introduce our regional instruments and control for features of the region where the client is located, constructed from primary information on zip codes. Being located in a region with a larger fraction of high-school graduates or of college graduates substantially reduces the probability of using an IFA (for instance, moving from the first to the third quartile of the fraction of high-school and college graduates reduces the probability by 3.2 and 4 percentage points, respectively). Voter’s participation is also found to have a negative effect on the probability of being matched with a financial advisor (moving from the first to third quartile of participation reduces the probability by 0.8 percentage points).

These findings on regional variables could be due to two, not mutually exclusive, factors. First, IFAs are less needed because these regions have greater concentrations of educated neighbors from whom investors can learn. To the extent that voter participation proxies for social interactions among the region’s inhabitants, higher participation and higher average education make it more likely that a given potential or actual investor in the region will meet a neighbor with whom relevant information can be exchanged. IFAs should also be more likely to locate themselves in areas where they can hope to be in greater demand, and locating in areas with low average education and less sociable households widens the hunting ground.

Given the characteristics of the region where they locate, regression (3) shows that IFAs are most likely to make successful matches with older, more experienced, single, female investors. These investors have better reasons to want to delegate to IFAs than others in their area, such as high opportunity cost or low inclination to spend a lot of time managing investments, as well as sizeable wealth holdings. IFAs are also more likely to earn higher commissions on busy, wealthy clients. Indeed, the fact that most IFAs and about half of IFA customers in the sample had a former banking relationship puts IFAs in an eminent position to target such clients. In a nutshell, IFAs seem to have chosen to go for the big players who have a lot to invest and little time to spend, rather than for the younger, smaller, inexperienced investors who have a lot to learn.

6. Independent Financial Advice and Portfolio Performance

We now turn to how IFA use affects various aspects of account performance once we control for client characteristics. Table 3 presents estimates regarding the influence of IFA use on raw log returns, and on abnormal returns constructed on the basis of a plain single-factor and of a four-factor model in the spirit of Carhart (1997), respectively, to examine robustness with respect to the underlying asset pricing model.

6.2.Portfolio Returns

Column 1 in Table 3 reports OLS estimates of the IFA effect on the average portfolio returns over the 66 months observation period after all transaction cost have been paid to the brokerage. Controlling for investor characteristics, we see that the estimated effect of IFA use is positive and statistically significant.

Male gender detracts from account returns, consistent with the literature on overconfidence. Years of experience contribute to higher total return, albeit by a small estimated amount. This is consistent with some recent studies indicating that the magnitude of investment mistakes decreases with sophistication and experience. 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.[6] They conclude that sophistication and

[6] 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 d ate *t*, a time-varying covariate.

experience eliminate the reluctance to realize losses, but only reduce the propensity to realize gains by 37%.[7]

However, OLS regressions are problematic, since both use of an IFA and account performance could be due to some unobserved factor that creates the appearance of a relationship between performance and IFA use. We therefore carry out instrumental variable estimation, using as instruments the following variables (recorded at the broader region level and assigned to each customer based on the customer's zip code): bank branches relative to area GDP, the share of financial services in area GDP, voter participation, and population shares with secondary and tertiary education. The assumption is that these regional variables can influence the choice of whether to use an IFA or not, but they affect individual account performance only through that choice and not directly. The standard errors of the estimates are corrected for clustering at the zip code level.

To assess the quality of our instruments, we perform the test of over-identifying restrictions and the rank test. In each of the regressions, the Hansen-Sargan test does not reject the over-identifying restrictions: the p-values associated with the test always exceed 5 percent, except in the case of the regressions for log returns (p-value of 0.045) and Jensen's alpha (p-value of 0.029), where they exceed 1 percent. We also check the rank condition testing the null hypothesis that the coefficients of the four instruments are jointly equal to zero in the first-stage regression. The F-test (37.44) rejects this null at 1 percent level and implies that the rank condition is satisfied.

Column 2 of Table 3 presents IV estimates for the role of IFA on returns net of all transaction fees. We see that the sign of the IFA effect turns negative through the use of instrumental variables, implying that advised customers actually get lower returns from the IFA involvement than they could have achieved alone. Controlling for IFA use, factors such as being male, inexperienced, in the 40-50 age category, and a smaller account holder still contribute to poorer returns, regardless of the estimation method employed and with similar sizes of effects.

Is it the case that IFAs create value for their customers by increasing risk adjusted returns? Column 3 in Table 3 reports a regression for alphas from a model with the return on the MSCI

[7] See also Grinblatt and Keloharju (2001), Zhu (2002, Feng and Seasholes (2005), and Lusardi and Mitchell (2007).

world index as the single factor (denoted Jensen's alpha). The IFA contribution is again negative, once the characteristics of the account owner are taken into account. The coefficient estimates and the patterns of sign and significance are very similar to those for total returns.

Finally, in column 4, we examine whether our findings are robust with respect to the underlying estimation model for abnormal returns. We estimate excess returns on the basis of the four-factor model outlined above. Table 1 shows that the average excess returns among advised and non-advised accounts are hardly sensitive to the choice of underlying asset pricing model. Table 3 (column 6) shows that the strongly statistically significant negative effect of IFA use is observed regardless of whether we use a single- or a four-factor model for estimating excess returns. Moreover, use of the four-factor model yields remarkably similar coefficient estimates and patterns of statistical significance for the whole range of investor characteristics we consider.

The implication of our findings in this section is that involvement of IFAs with these brokerage accounts tends on average to reduce both the total portfolio return and the excess return, once the characteristics of the owner are taken into account. While our OLS regression results on raw returns above were consistent with the higher average returns shown for advised customers in descriptive statistics, the instrumental variable estimates reverse the impression from performance records that IFAs improve returns. Higher observed returns among advised customers appear to be due to tendency of IFAs to be matched with the older, wealthier, more experienced account owners and not to what they contribute to owners of given characteristics. Our results are consistent with a situation in which the cost of financial advice exceeds the benefits from informational contributions, if there are any. Importantly, this does not necessarily imply that (some) IFAs engage in misselling.

6.3.Volatility of Returns

The finding that IFAs tend to lower both raw and abnormal account returns, given investor characteristics, need not be negative by itself. It is a priori conceivable that IFA involvement lowers returns in exchange for ensuring that clients are exposed to smaller portfolio risk. We therefore turn next to the effect of IFA involvement on different measures of risk taken on the account. Table 4 reports our findings.

Column 1 reports the results of an OLS regression implying that IFAs reduce portfolio risk in line with descriptive results. Being male, inexperienced, young, single, self-employed, and with a smaller account all contribute significantly to higher total portfolio risk. The results on the control variables are quite intuitive. For example, larger account volume should allow more diversification, and we indeed find below that larger accounts tend to have smaller portfolio shares in directly held stocks.

Column 2 regresses total variance of portfolio returns from equation (3) above on the instrumented IFA dummy and the remaining client characteristics. In contrast to OLS results, we now find no evidence of a systematic moderation of total account risk when an IFA is used.

As equation (3) indicates, overall portfolio variance can be decomposed into systematic risk, resulting from the extent to which the account covaries with the market portfolio (‘beta”), and unsystematic or diversifiable risk. We investigate the impact on each type of risk separately (columns 3 to 4 in Table 4). While involvement of IFAs does not appear to contribute to systematic risk, we do find that it raises the portion of unsystematic risk in total risk, once we control for investor characteristics.

Being male increases both types of risk. Experience has a statistically significant moderating effect on both types of risk, though the effect is quantitatively negligible for unsystematic risk. Self employed customers tend to experience more of both types of risk in their accounts, controlling for other characteristics, consistent with their willingness to assume more occupational risk. On the other hand, being married moderates both risk dimensions. This could be due to a greater tendency of married households to have committed expenditures (e.g., for mortgage payments, children’s education, etc.) that reduce their willingness to assume financial risk, but possibly also to a moderating effect of the spouse on the amount of risk undertaken by the account holder. Bigger accounts tend to exhibit less of both types of risk.

Econometric analysis of portfolio risk so far shows that IFA do not seem to actively manage portfolio risk in the interest of their clients. Our estimation does not find statistically significant effects on total portfolio risk or on the systematic component. Yet, there is evidence that IFAs slightly increase diversifiable risk in their client portfolios.

6.4.Probabilities of Losses

Behavioral finance, and especially literature concerned with departures from expected utility maximization, highlights the importance of losses and of the probabilities of catastrophic events in determining household choices of risky assets. If use of IFAs does not increase returns, excess returns, or returns adjusted for risk, it is also relevant to examine if it limits the probabilities that the accounts will experience losses or substantial losses. Columns 5 and 6 in Table 4 report findings regarding determinants of the relative frequencies of negative portfolio returns; and then of negative returns of more than 5 percent per month (in absolute value).

While descriptive statistics show less frequent occurrences of both adverse events for accounts that are advised, once we control for client characteristics we fail to find statistically significant effects of the use of an IFA on either of these frequencies. This makes it difficult to argue that IFAs help prevent disasters.

Controlling for other factors, being male contributes to greater probabilities of losses and of substantial losses, by more than 1 percentage point. This extends previous results of being male on portfolio returns to risk and to the likelihood of substantial losses. An additional year of financial experience has a strongly significant moderating effect on probabilities of any loss and of sizeable losses, but estimated effects are small, implying that large differences in experience are necessary for sizeable reductions in the probability of losses. Having a spouse is estimated to limit the frequency of both types of losses, probably by influencing portfolio composition in a way that reduces the probability of large return shocks. Indeed, we find below that being married tends to lead to smaller fractions of directly held stocks in the account.

Age effects are of some interest, as they imply that account owners between 30 and 60 years of age are subject to more frequent losses and substantial losses, controlling for other characteristics. Given the cross-sectional nature of our data on account performance, disentangling age from cohort and time effects is problematic, so these results should be interpreted with caution. Controlling for other factors, account volume tends to reduce the probability of both types of losses, presumably because it makes it more likely that the account is diversified. All in all, we fail to find evidence of a positive effect of IFAs on reducing the probability of losses or of substantial losses on the account, once we control for characteristics of the account owner.

6.5. Sharpe Ratios

We next measure the effect of financial advice on a risk adjusted performance measure. In our dataset we are not able to use the Sharpe Ratio as a performance measure because average returns were negative for 87.9% of all investors over the 66 months period.[8] We therefore compute Sharpe Ratios for a truncated IFA sample, considering the return series over the 34 months from January 2003 to October 2005. In this sample, Sharpe Ratios turn out to be positive for over 90% of investors.[9] All other variables are time-invariant.

For comparison with the sample of 66 months we first report in Table 5 OLS and IV regressions for raw returns and portfolio variance computed over the shorter period. The pattern of results is quite similar in the two samples, with the exception that in the shorter sample IFA is negatively related to returns even in OLS estimates. IFA use reduces Sharpe Ratios and the absolute value of the financial advice coefficient is greater in the IV than in the OLS regression.

6.6. Trading, Turnover, and Diversification

Given our results on returns and risk, it is natural to ask what type of behavior underlies them, as already illustrated above. IFAs get commissions mainly when the account owner purchases mutual funds. This creates an incentive to the IFA to encourage the account owner to make fund purchases. The first column of Table 6 examines the effect of IFA on the number of purchases per month. These purchases exclude corporate actions, periodic saving plan investments and portfolio transfers, so as to be more directly linked to the IFA incentives to sell

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[8] Sharpe Ratios can be misleading for negative returns. Imagine two portfolios that produced identical negative average returns. The portfolio with the greater variance will have the greater Sharpe Ratio although it is dominated by the less risky portfolio.

[9] We also ran the regressions dropping all investors with negative Sharpe Ratios over the 34 month period (9.6% of the observations). Results remain qualitatively unchanged.

specific financial instruments. We standardize the number of purchases by account volume as a scale variable.

Our results imply a positive effect of IFAs on the standardized number of purchases, consistent with their incentives. As purchases result in transactions costs, they contribute to lower realized returns on the account net of these costs. The regression also confirms the positive role of male gender found in other studies (see above). Financial experience is found to have a strongly statistically significant effect in moderating the frequency of purchases. This finding is consistent with the finding of Dorn and Huberman (2005) that survey respondents with longer investment experience trade substantially less. Account holders between 40 and 60 seem to be significantly more likely to engage in purchases than other age groups. Subject to the proviso on interpreting age effects, this finding would be consistent with them being in the asset accumulation phase, prior to entering retirement.

Commissions are linked to the size of purchases and not merely to their frequency. The second column of Table 6 examines the effect of IFAs on average account turnover over the observation period, defined in terms of purchases so that it relates to IFA incentives. They show a strongly statistically significant effect of IFAs on increasing account turnover. This could be part of the explanation for why IFAs contribute negatively to portfolio returns.[10] Again, males are more likely to have larger account turnover.[11] Small positive effects are found, somewhat surprisingly, for married account owners, although we did not find statistically significant effects on our measure of the number of trades per se. 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 possible role of IFAs refers to their role in encouraging diversification of the account. Given the incentives of financial advisors to sell mutual funds, we examine the average share of directly held stocks in the account over the 66-month observation period. We find a significant negative effect of IFA use on this share, even after characteristics of

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[10] 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).

[11] 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.

account holders are controlled for. This finding is consistent both with the descriptive statistics at the start of the paper and the incentive of IFAs to sell mutual funds. However, the reduction in directly held shares does not seem to be very effective when it comes to diversification. Recall that IFAs tend to increase the amount of diversifiable risk in client portfolios (Table 4).

Controlling for other factors, male account owners tend to have a tendency 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 reported in columns 1 and 2. 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 and the greater likelihood of receiving relevant information in the course of their everyday business. Interestingly, experience tends to lower the share of directly held stocks, indicating that experience works more as a factor dampening overconfidence than as one that encourages account owners to handle the usually more difficult task of managing direct investments in stocks. The conclusion from the regression analysis is that IFAs seem to encourage frequent trading and a large volume of purchases, while they reduce the fraction of the account invested in directly held stocks.

7. Results for Bank Financial Advisors

Given the rather striking nature of these results on the contribution of IFAs to portfolio performance, the question arises as to whether our results are specific to the data set of internet brokerage accounts we considered, 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 with a wide network of bank branches that reach a broad cross section of the German population.

The 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 original data set and use the same set of regional instruments and (virtually) the same set of account owner characteristics as used in the main body of this paper.

There are important similarities and differences between IFA and BFA. Our discussions with IFAs and the commercial bank suggest that the differences in advisors' incentives are not very pronounced. For example, upfront loads for mutual funds, which are 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 advisors, it gives powerful non-monetary incentives to its sales force through its sales control system.[12] On the other hand, IFAs are not subject to the constraints imposed by banks on their own employees acting as advisors, e.g. with respect to the range of products they can offer to clients and the specific targets to be achieved. 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 their clients to purchase funds or structured products produced by the bank itself or one of its subsidiaries.[13] In summary, we expect that the negative association between BFA use and portfolio returns might be even stronger than in the IFA sample.

Table 7 reports our results with the new data set. Column 1 presents the matching regression for who has used a BFA in making any of the trades. Quite consistent with the results on IFAs, we find that, controlling for other characteristics, male customers are less likely to use a BFA, while older account holders (above 60) and those with larger initial account volumes are more

[12] Another example 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.
[13] See Yoong and Hung (2009) who extend Ottaviani and Inderst (2009) to address this kind of self-dealing.

likely to use the services of a BFA. Bank customers in areas with a larger fraction of high-school graduates and with greater voter participation are less likely to use the bank advisor, as they are also less likely to use an independent financial advisor. Although we do not see a significant effect of the share of college graduates in the area on BFA matches, the results for matches between BFAs and customers are very much in line with those for IFAs. This suggests that they have less to do with whether financial advisors are employees of the host financial institution or not, and probably more to do with the informational gap that advisors fill.

Column 2 presents OLS results on raw returns, where use of a BFA is seen to have a statistically significant negative effect, This is confirmed in the IV estimates (column 3). Looking at columns 4 and 5, BFAs seem to increase total portfolio risk in the OLS estimates but not in the IV regressions, the same pattern we observe in the IFA sample.

In order to measure the effect of financial advice on a risk adjusted performance measure we examine the Sharpe Ratio.[14] This is possible because average returns have been positive for over 90% of investors over the 34-month period from January 2003 to October 2005. Columns 6 and 7 in Table 7 report the corresponding OLS and IV results. The coefficients for BFA are negative and statistically different from zero for both estimations, mirroring the performance effects of IFA use in Table 5. Comparing the advice coefficients from Tables 5 and 7 indicates that BFA use has a stronger estimated negative impact on Sharpe Ratios than IFA use. This is consistent with Inderst and Ottaviani (2009) who posit that advisory standards should be lower for bank advisors than for IFAs because the latter face no internal agency conflicts with costly monitoring.

When interpreting the coefficients of controls, the BFA results point to two relevant account characteristics: the gender of the account holder, with males exhibiting lower returns and more risky portfolios; and the initial size of the account, that is seen to contribute to higher returns, in levels or normalized by risk, and to lower portfolio variance. These results are entirely consistent with our findings for IFAs above. The difference, if any, is that performance features of investment accounts in banks tend not to be systematically linked to as wide a range of account

[14] Since the BFA dataset only comprises 34 months, we are not able to estimate reliable abnormal returns. As a matter of fact, more than 80% of the estimated alphas turned out to be insignificant.

owner characteristics as those in the internet brokerage. All in all, our robustness exercises produce remarkably consistent results and seem to be pointing to systematic negative effects of financial advisors and not to statistical flukes, modeling nuances, or sample peculiarities.

8. Conclusions

We have investigated who tends to use a financial advisor, whether individual investors tend to produce better account performance on their own rather than with the help of financial advisors, and whether results depend on the advisory model (IFA versus BFA). Our main data set tracks accounts of a major internet brokerage for a large number of randomly selected individual customers over a period of 5.5 years, who may or may not invest their portfolio with the help of an independent financial advisor (IFA). As suggested by sample statistics and confirmed by regression analysis, advisors tend to be matched with richer, older, more experienced investors rather than with poorer, younger ones.

Descriptive statistics paint a generally positive picture of such accounts relative to those run by the customers themselves. Once we control for investors' characteristics and for the possibility that unobserved factors contribute both to the use of IFAs and to account performance, we find that accounts run by or with input from financial advisors offer on average lower raw and abnormal returns and higher diversifiable risk. We do not find systematic effects on total portfolio variance, systematic risk or on probabilities of losses and of substantial losses. Higher trading costs and the associated commissions earned by IFAs certainly contribute to these outcomes, since we find that IFA-accounts feature more frequent trading and higher portfolio turnover relative to non-IFA accounts. Consistent with their remuneration incentives, IFAs seem to discourage account owners from investing bigger shares in directly held stocks. Robustness analysis suggests that our results on the negative role of IFAs are not due to the choice of factor model and of a sample from an internet brokerage, but apply with even stronger force to bank financial advisors of a commercial bank with very wide customer base.

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 internet broker data we consider and for the data on investment accounts of a large commercial bank with a broad customer base.

A further important policy issue is whether financial advice is a substitute for financial literacy and sophistication. Given the rapidly growing literature on investment mistakes, providing financial advice to inexperienced, naïve investors could have been an alternative to trying to educate them in financial matters. Our findings caution against relying on this alternative when financial advisor incentives and tendencies of inexperienced clients result in relatively few matches. Other alternatives, such as simpler products and carefully designed default options, may be more promising than financial advice in averting negative distributional consequences.

Our findings imply that 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, we found that negative effects appear even when the tendency is for experienced investors to be using an advisor. In such 'babysitter' cases, it may be that investors are inattentive and fail to monitor their advisors effectively; or that they are too busy to run 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 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, payment schemes, conflicts of interest, and overall role of financial advisors, 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 Monthly Returns

Figure 2

The Distributions of the Variance of Portfolio Returns

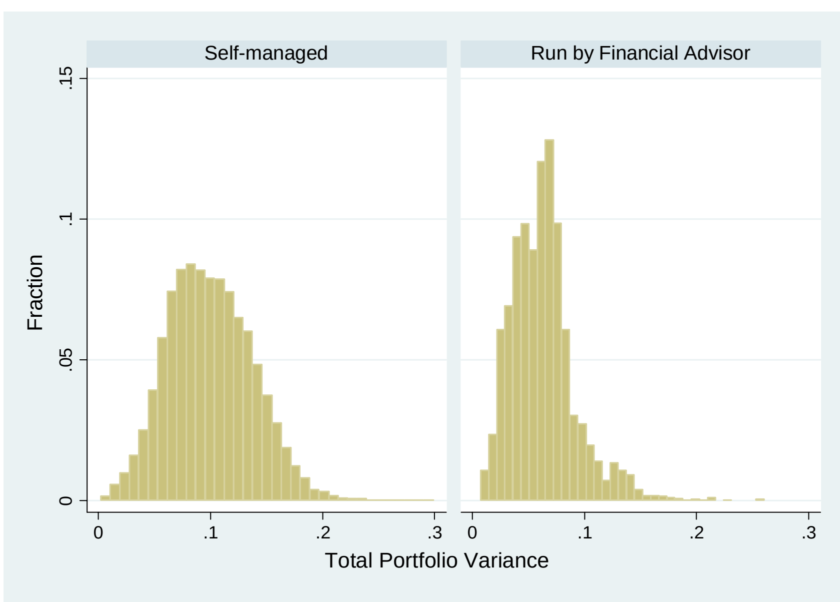

Figure 3

The Distribution of Number of Trades

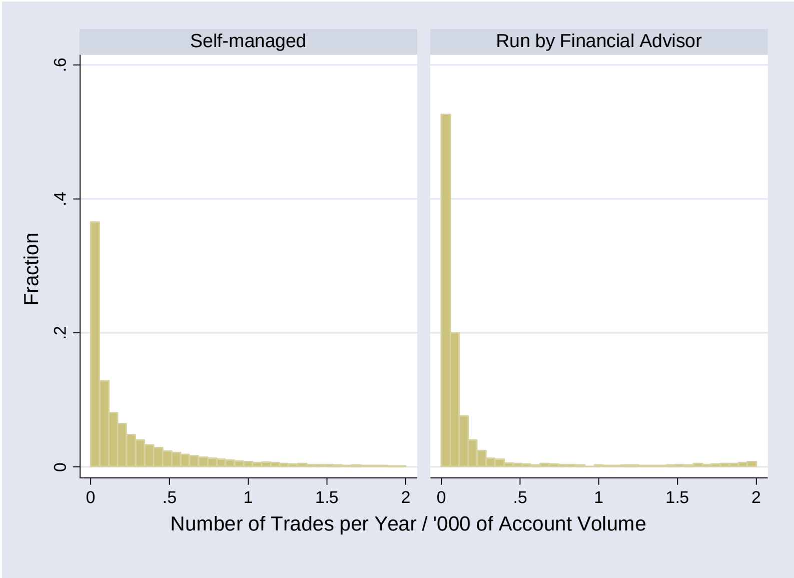

Figure 4

The Distribution of the Turnover Rate

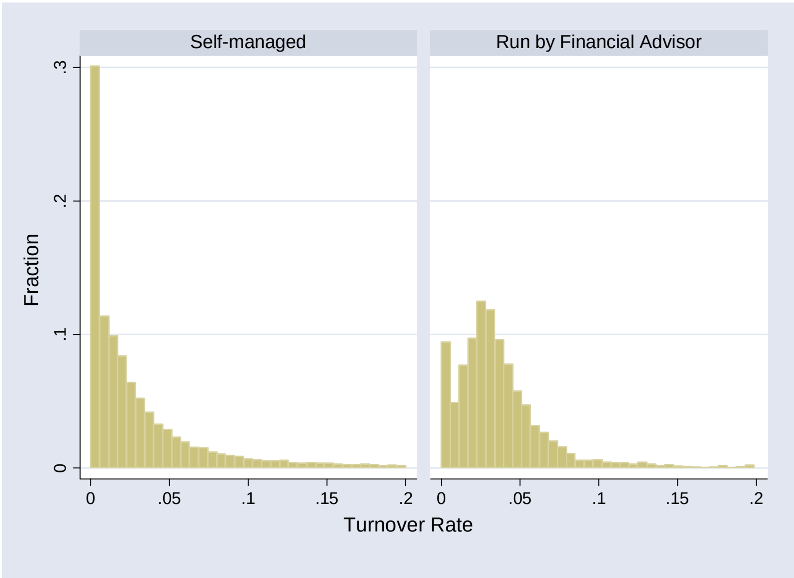

Table 1

Descriptive statistics

	Sample mean			*Median*	*Standard deviation*
	Self-managed account	***Run by financial advisor***	***All accounts***	***All accounts***	***All accounts***
Dependent variables					
Log monthy returns	-0.008	-0.004	-0.008	-0.006	0.009
Jensen's Alpha	-0.005	-0.003	-0.005	-0.003	0.009
Alpha – factor model	-0.006	-0.003	-0.006	-0.004	0.009
Portfolio variance	0.100	0.063	0.095	0.092	0.039
Beta	1.289	0.843	1.233	1.272	0.387
Unsystematic risk	0.050	0.040	0.049	0.046	0.021
Probability return <-5%	0.451	0.401	0.445	0.446	0.065
Probability return < 0	0.479	0.447	0.475	0.469	0.058
N. of trades / '000 account volume	0.444	0.319	0.428	0.113	1.265
Turnover rate	0.041	0.089	0.047	0.020	0.086
Share of directly held stocks	0.588	0.211	0.540	0.575	0.373
Control variables					
Male	0.793	0.674	0.778	1.000	0.416
Married	0.480	0.464	0.478	0.000	0.500
Employed	0.865	0.834	0.861	1.000	0.346
Self-employed	0.129	0.158	0.132	0.000	0.339
Experience	7.336	9.161	7.563	3.900	6.211
18≤Age≤30	0.047	0.042	0.046	0.000	0.210
30< Age≤40	0.260	0.119	0.242	0.000	0.428
40< Age ≤50	0.344	0.269	0.335	0.000	0.472
50< Age ≤60	0.195	0.229	0.199	0.000	0.399
Age > 60	0.154	0.341	0.178	0.000	0.382
Log account volume in 2001	9.854	11.119	10.015	9.897	1.344
Bank branches / GDP	0.094	0.088	0.094	0.036	0.102
Financial services / GDP	0.303	0.301	0.303	0.287	0.079
Voters' Participation	0.600	0.593	0.599	0.600	0.060
Pop. share with secondary education	0.403	0.391	0.402	0.392	0.070
Pop. share with tertiary education	0.403	0.226	0.238	0.239	0.080
Observations	25,475	3,701	29,176	29,176	29,176

Table 2

The determinants of having the account run by an independent financial advisor. Probit estimates

	(1)	(2)	(3)
Male	-0.060***	-0.066***	-0.059***
	(12.80)	(14.99)	(13.03)
Married	-0.018***	-0.015***	-0.020***
	(4.47)	(3.99)	(4.95)
Employee	0.035	0.038**	0.037*
	(1.58)	(1.96)	(1.68)
Self-employed	0.064**	0.046*	0.066**
	(2.26)	(1.85)	(2.33)
Experience	0.003***	0.000	0.003***
	(7.79)	(0.86)	(8.55)
30< Age <=40	-0.035***	-0.035***	-0.033***
	(3.18)	(3.73)	(3.12)
40< Age <=50	0.014	-0.012	0.015
	(1.19)	(1.22)	(1.32)
50< Age <=60	0.057***	0.003	0.057***
	(4.51)	(0.32)	(4.59)
Age > 60	0.143***	0.037***	0.143***
	(9.77)	(3.21)	(9.93)
Log Account Volume in 2001		0.059***	
		(38.84)	
Bank branches / GDP			-0.047
			(1.25)
GDP Share of financial services			-0.004
			(0.09)
Voters' Participation			-0.093*
			(1.88)
Secondary education			-0.468***
			(10.02)
Tertiary education			-0.372***
			(7.08)
Observations	28628	28628	28628

Note. The table reports probit estimates for the probability of having a financial advisor. We report marginal effects rather the original probit coefficients. Asymptotic standard errors corrected for clustering at the zip code level are reported in parenthesis.

Table 3

The determinants of log returns. OLS and Instrumental Variable estimates

	Log returns *OLS*	*Log returns* *IV*	*Jensen's Alpha* *IV*	*Alpha factor mode* *IV*
	(1)	(2)	(3)	(4)
Ind. Financial Advisor	0.002***	-0.007***	-0.008***	-0.006***
	(16.43)	(3.91)	(4.49)	(3.69)
Male	-0.001***	-0.002***	-0.002***	-0.002***
	(11.50)	(11.12)	(10.30)	(9.53)
Married	0.000***	0.000	0.000	0.000
	(3.39)	(1.37)	(1.34)	(0.76)
Employee	-0.002***	-0.001**	-0.001**	-0.001*
	(3.13)	(1.97)	(1.97)	(1.81)
Self-employed	-0.002***	-0.002***	-0.001***	-0.001**
	(4.09)	(2.94)	(2.94)	(2.53)
Experience	0.000***	0.000***	0.000***	0.000***
	(13.18)	(12.14)	(11.26)	(12.04)
30< Age <=40	-0.000	-0.001**	-0.000	-0.000
	(1.16)	(2.22)	(1.52)	(1.54)
40< Age <=50	-0.001***	-0.001***	-0.001***	-0.001***
	(3.16)	(3.67)	(2.96)	(3.06)
50< Age <=60	-0.001**	-0.001**	-0.000	-0.001**
	(2.15)	(2.13)	(1.64)	(2.12)
Age > 60	0.000	0.001**	0.001*	0.000
	(0.90)	(2.33)	(1.85)	(1.01)
Log Account Volume	0.001***	0.001***	0.001***	0.001***
	(13.71)	(9.82)	(9.20)	(6.95)
Constant	-0.012***	-0.017***	-0.013***	-0.012***
	(18.87)	(14.57)	(11.69)	(9.87)
Observations	28628	28628	28628	28628

Note. The table reports OLS estimates for log returns and instrumental variables estimates using the following instruments for financial advice at the zip code level: bank branches to GDP ratio, GDP share of financial services, voters' participation, and fraction of the population with secondary and tertiary education. Asymptotic t-statistics corrected for clustering at the zip code level are reported in parenthesis.

Table 4

The determinants of portfolio variance, Beta, unsystematic risk, probability of low returns. Instrumental variable estimates

	Portfolio Variance OLS (1)	Portfolio Variance IV (2)	Beta IV (3)	Unsystematic Risk IV (4)	Less than -5% IV (5)	Less than zero IV (6)
Ind. Financial Advisor	-0.029***	0.008	-0.045	0.009**	0.001	0.008
	(39.42)	(1.12)	(0.67)	(2.19)	(0.08)	(0.83)
Male	0.008***	0.011***	0.079***	0.006***	0.015***	0.011***
	(16.66)	(15.25)	(11.03)	(15.46)	(12.80)	(10.23)
Married	-0.004***	-0.003***	-0.009*	-0.002***	-0.003***	-0.003***
	(7.79)	(5.41)	(1.82)	(6.72)	(3.90)	(3.38)
Employee	0.006**	0.004	0.038	0.002	0.018***	0.016***
	(2.38)	(1.55)	(1.22)	(1.26)	(3.80)	(3.93)
Self-employed	0.010***	0.008***	0.059*	0.005***	0.026***	0.023***
	(3.91)	(3.05)	(1.89)	(3.26)	(5.18)	(5.56)
Experience	-0.001***	-0.001***	-0.005***	-0.000***	-0.001***	-0.001***
	(15.05)	(14.11)	(12.55)	(9.90)	(13.39)	(13.61)
30< Age <=40	0.004***	0.006***	0.060***	0.002***	0.005***	0.002
	(3.92)	(4.86)	(5.19)	(2.78)	(2.61)	(1.18)
40< Age <=50	0.006***	0.007***	0.064***	0.003***	0.010***	0.005***
	(5.66)	(6.01)	(5.58)	(4.17)	(4.75)	(2.91)
50< Age <=60	0.005***	0.005***	0.048***	0.002***	0.008***	0.004**
	(4.28)	(4.16)	(3.96)	(3.12)	(3.60)	(2.13)
Age > 60	-0.001	-0.003**	-0.038***	-0.000	-0.002	-0.002
	(0.54)	(2.04)	(2.95)	(0.51)	(1.03)	(1.14)
Log Account Volume	-0.004***	-0.006***	-0.047***	-0.004***	-0.008***	-0.006***
	(20.24)	(12.10)	(9.18)	(12.87)	(8.95)	(7.74)
Constant	0.126***	0.147***	1.616***	0.079***	0.493***	0.511***
	(40.62)	(28.61)	(30.87)	(28.27)	(57.35)	(68.46)
Observations	28628	28628	28628	28628	28628	28628

Note. The table reports instrumental variables estimates using the following instruments for financial advice at the zip code level: bank branches to GDP ratio, GDP share of financial services, voters' participation, and fraction of the population with secondary and tertiary education. Asymptotic t-statistics corrected for clustering at the zip code level are reported in parenthesis. One star denotes statistical significance at the 10 percent level; two stars at the 5 percent level; three starts at the 1 percent level.

Table 5. Regression results for independent financial advisors.
January 2003 – October 2005

	Log return OLS	*Log returns IV*	*Portfolio variance OLS*	*Portfolio variance IV*	*Sharpe Ratio OLS*	*Sharpe Ratio IV*
Ind. Financial Advisor	-0.004***	-0.010***	-0.001***	-0.000	-0.047***	-0.157***
	(23.02)	(5.46)	(21.06)	(0.87)	(11.29)	(5.46)
Male	-0.000***	-0.001***	0.001***	0.001***	-0.018***	-0.025***
	(2.70)	(4.08)	(14.30)	(11.27)	(8.49)	(8.79)
Married	0.000	-0.000	-0.000***	-0.000***	0.006***	0.004*
	(0.16)	(0.86)	(8.49)	(7.61)	(3.26)	(1.75)
Employee	-0.001	-0.000	0.000***	0.000***	-0.026***	-0.020*
	(1.58)	(0.92)	(2.88)	(2.60)	(2.65)	(1.92)
Self-employed	-0.001	-0.000	0.001***	0.001***	-0.032***	-0.026**
	(1.43)	(0.85)	(5.47)	(5.17)	(3.14)	(2.42)
Experience	0.000***	0.000***	-0.000***	-0.000***	0.001***	0.001***
	(4.37)	(4.40)	(6.43)	(6.49)	(8.01)	(7.90)
30< Age <=40	0.001**	0.000	0.000	0.000	0.004	0.000
	(2.27)	(1.49)	(1.38)	(1.61)	(0.84)	(0.00)
40< Age <=50	0.000	0.000	0.000***	0.000***	-0.005	-0.007
	(0.55)	(0.12)	(4.00)	(4.12)	(1.01)	(1.45)
50< Age <=60	0.000	0.000	0.000***	0.000***	-0.002	-0.002
	(1.22)	(1.15)	(2.99)	(3.00)	(0.38)	(0.42)
Age > 60	-0.000	0.000	0.000	0.000	0.000	0.006
	(0.14)	(0.80)	(1.43)	(0.99)	(0.05)	(1.10)
Log Account Volume	-0.000**	0.000**	-0.000***	-0.000***	0.006***	0.013***
	(2.00)	(2.24)	(14.69)	(6.66)	(7.05)	(6.29)
Constant	0.012***	0.009***	0.004***	0.005***	0.201***	0.140***
	(17.41)	(7.29)	(22.67)	(14.05)	(15.91)	(6.78)
Observations	28628	28628	28628	28628	28628	28628
R-squared	0.02		0.05		0.02	

Note. Returns, portfolio variance and Sharpe Ratio are computed using the return series over the 34 months from January 2003 to October 2005. The instruments for financial advice at the zip code level are: bank branches to GDP ratio, GDP share of financial services, voters' participation, and fraction of the population with secondary and tertiary education. Asymptotic t-statistics corrected for clustering at the zip code level are reported in parenthesis. One star denotes statistical significance at the 10 percent level; two stars at the 5 percent level; three starts at the 1 percent level.

Table 6

Trading frequency, turnover and diversification.
Instrumental variable estimates

	Number of Trades	*Turnover*	*Share of Directly Held Stocks*
	(1)	(2)	(3)
Ind. Financial Advisor	0.629***	0.148***	-0.212**
	(3.07)	(6.90)	(2.14)
Male	0.223***	0.023***	0.107***
	(11.91)	(12.24)	(11.72)
Married	0.017	0.003**	-0.028***
	(1.05)	(2.47)	(4.73)
Employee	0.014	-0.003	0.090***
	(0.28)	(0.55)	(2.65)
Self-employed	-0.052	-0.008	0.138***
	(0.99)	(1.43)	(4.01)
Experience	-0.006***	-0.001***	-0.008***
	(5.46)	(9.86)	(17.32)
30< Age <=40	0.040	0.007***	0.010
	(1.09)	(2.80)	(0.66)
40< Age <=50	0.075**	0.009***	0.024*
	(2.04)	(3.65)	(1.68)
50< Age <=60	0.078**	0.011***	0.039***
	(2.08)	(4.37)	(2.62)
Age > 60	0.009	-0.001	0.028*
	(0.21)	(0.29)	(1.75)
Log Account Volume	-0.192***	-0.009***	-0.014*
	(12.81)	(5.95)	(1.93)
Constant	2.081***	0.102***	0.575***
	(15.61)	(7.67)	(8.45)
Observations	28628	28628	28628

Note. The table reports instrumental variables estimates for number of trades and turnover, and instrumental variable tobit estimates for the share of directly help stocks using the following instruments for financial advice at the zip code level: bank branches to GDP ratio, GDP share of financial services, voters' participation, and fraction of the population with secondary and tertiary education. Asymptotic t-statistics corrected for clustering at the zip code level are reported in parenthesis. One star denotes statistical significance at the 10 percent level; two stars at the 5 percent level; three starts at the 1 percent level.

Table 7. Regression results for bank financial advisors

	Bank Financial Advisor Probit	*Log returns OLS*	*Log returns IV*	*Portfolio variance OLS*	*Portfolio variance IV*	*Sharpe Ratio OLS*	*Sharpe Ratio IV*
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*
Bank Fin. Advisors		-0.003***	-0.008**	0.001***	0.006	-0.177***	-0.344**
		(9.08)	(2.53)	(2.85)	(1.28)	0.014	0.136
Male	-0.052***	0.001**	0.001	0.001***	0.002***	-0.032**	-0.041***
	(3.26)	(2.23)	(1.33)	(3.06)	(3.26)	0.012	0.014
Employee	-0.050***	0.001**	0.001*	0.001	0.001*	-0.002	-0.011
	(2.70)	(2.43)	(1.84)	(1.51)	(1.71)	0.016	0.018
Executive	-0.000	0.001	0.001	0.002	0.002	-0.007	-0.007
	(0.00)	(1.36)	(1.31)	(1.46)	(1.46)	0.042	0.042
Housewife	0.017	0.001	0.001	0.000	0.000	-0.005	-0.009
	(0.53)	(1.60)	(1.55)	(0.15)	(0.16)	0.019	0.019
Retired	-0.022	-0.000	-0.000	-0.000	-0.000	0.007	0.007
	(0.85)	(0.36)	(0.57)	(0.22)	(0.05)	0.023	0.023
30 < Age <= 40	-0.049	0.001*	0.001	0.000	0.000	0.044	0.037
	(1.42)	(1.76)	(1.44)	(0.10)	(0.36)	0.036	0.037
40 < Age <= 50	-0.012	0.000	0.000	0.002*	0.002*	0.041	0.041
	(0.37)	(0.44)	(0.36)	(1.92)	(1.93)	0.036	0.037
50 < Age <= 60	0.052*	-0.001	-0.000	0.000	0.000	0.037	0.048
	(1.71)	(0.75)	(0.37)	(0.58)	(0.26)	0.037	0.039
60 < Age	0.113***	-0.002**	-0.001	0.001	0.000	0.045	0.066
	(3.93)	(2.58)	(1.62)	(0.89)	(0.22)	0.037	0.042
Log account volume	0.029***	0.001***	0.001***	-0.001***	-0.001***	0.021***	0.025***
	(7.97)	(5.79)	(6.11)	(8.01)	(6.73)	0.004	0.004
Bank branches / GDP	-0.470						
	(0.23)						
GDP Share of fin. services	-0.216						
	(1.27)						
Voters' participation	-0.009**						
	(2.54)						
Secondary education	-0.352**						
	(2.49)						
Tertiary education	-0.193						
	(1.09)						
Constant		0.002	0.003*	0.012***	0.011***	0.211***	0.269***
		(1.39)	(1.81)	(9.33)	(5.01)	0.05	0.074

Note. The table reports probit for financial advice, OLS and IV estimates for log returns, portfolio variance and Sharpe Ratio. The instruments for financial advice at the zip code level are: bank branches to GDP ratio, GDP share of financial services, voters’ participation, and fraction of the population with secondary and tertiary education. The sample includes 4447 observations. Asymptotic t-statistics corrected for clustering at the zip code level are reported in parenthesis. One star denotes statistical significance at the 10 percent level; two stars at the 5 percent level; three starts at the 1 percent level.