The Impact of Financial Advisors on the Stock Portfolios of Retail Investors

Marc Kramer and Robert Lensink[1]

Abstract

This study investigates the impact of financial advisors on portfolio returns, risk, trading, and diversification using a large data set of individual Dutch equity investors, with random assignment to specific advisors. The results suggest that advisory interventions benefit retail investors, because advice improves risk-adjusted equity returns and reduces risk. In addition, advisors reduce trading activity, as proxied by the frequency of trades. This study is unique in terms of the data set, the focus on individual stocks, and the use of the Hausman-Taylor panel estimation technique to control for selection biases.

JEL classifications:

G11, D14, G24

Keywords: Individual investor portfolio performance, Financial advice

[1] Department of Economics, Econometrics and Finance, Faculty of Economics & Business, University of Groningen (NL). Robert Lensink is also affiliated with the Development Economics Group, Wageningen University. E-Mails: m.m.kramer@rug.nl and b.w.lensink@rug.nl. We thank Laura Spierdijk and participants of a PhD conference in Groningen (2009) for their helpful comments.

Most retail investors rely on financial advisors to improve their portfolio investment decisions,[2] such that financial planning and advice represent big business, worth $44 billion in U.S. revenues alone and employing more than 240,000 people (Ibisworld (2011)[3]). Understanding the role and impact of financial advisors thus is of utmost importance, yet little empirical research addresses this topic. Moreover, existing research offers rather negative assessments of the relevance of financial advisors. Some authors find *potential* positive effects (e.g., List (2003); Feng and Seasholes (2005); Bhattacharya et al. (2011); Kramer (2012)), but a long list of research indicates that financial advisors do more harm than good (e.g., Hackethal, Haliassos, and Jappelli (2011); Bergstresser, Chalmers, and Tufano (2009); Zhao (2003)). In theoretical work, Stoughton, Wu, and Zechner (2010) and Inderst and Ottavianni (2009) show that opaque commission structures, in combination with naïve customers, produce biased, bad advice. Yet in a (nonrandom) financial advice choice experiment, Bhattacharya et al. (2011) offered 8,200 execution-only investors the option to receive free and unbiased advice and showed that it had the potential to benefit investors. Thus the negative impacts of advisors may arise due to biased advice, caused by fee structures that lead to moral hazard.

Bad advice as a result of fee structures thus could help explain why financial advisors fail to add value. We argue that the overly negative picture of advisors also reflects the failure of most existing studies to control for the endogeneity of the decision to use financial advisors. In this case, self-selection bias is likely, because investors choose to take advice or not. These selection concerns can seriously bias estimates of the impact of an advisor, and

[2] In the Netherlands—our research domain—approximately 51% of households with an investment portfolio rely on financial advice (Millward Brown (2010)); in the United States, ICI (2010) reports that 81% of mutual fund–owning households rely on a financial advisor. Bluethgen et al. (2008) also find that roughly 80% of individual investors in Germany rely on financial advice for investment decisions, and Hung et al. (2008) discover that 75% of investors participating in a U.S. survey consulted a financial advisor before conducting stock market or mutual fund transactions.

[3] http://www.ibisworld.com/industry/default.aspx?indid=1316

ignoring selection problems probably leads to underestimates of the true impact of advisors, because their advice tends to be solicited primarily by less sophisticated investors.

Unobserved heterogeneity in individual investment behavior is well-established in finance literature. Barnea, Cronqvist, and Siegel (2010) even document the impact of a genetic factor. Therefore, ignoring differences among individual investors creates inference problems. The sample selection bias associated with the endogenous choice to use an advisor could go either way: Hackethal, Haliassos, and Jappelli (2011) argue that more sophisticated investors exhibit greater advice-seeking propensity, but most models instead imply that advisors mainly provide services to less sophisticated investors. Stoughton, Wu, and Zechner (2010) assert that financial advisors sell underperforming active funds to unsophisticated investors, and Inderst and Ottaviani (2010) assume that naïve customers do not rationally anticipate conflicts of interest for their advisors. In a choice experiment, Hung and Yoong (2010) find that some participants can self-select advised or self-directed options. Less sophisticated participants were more likely to take advice, which improved their investment performance. Similarly, with a survey, Van Rooij, Kool, and Prast (2007) reveal that respondents who were more inclined to take risk or considered themselves more financially literate prefered more autonomy in their pension decisions.

As this short review indicates, advice taking is a choice variable, so advice is not random. Yet no existing studies into the impact of financial advisors rigorously control for selection biases. To provide new evidence on the potential added value of financial advisors, we examine whether they provide tangible benefits to customers in terms of risk, returns, costs, or diversification while controlling for selection bias and focusing on common stocks.

In addition, we base our analysis on a unique, rich data set from a Dutch retail bank that allows all investors, even very small ones, to use advisors. The activities of this retail bank concentrate in the northern Netherlands and focus on small traders. Therefore, the pool of clients, whether they use advisors or not, remains similar. However, selection bias is still possible. The data set features more than 190,000 monthly equity returns for approximately 5,500 Dutch common stock investors. Because the bank pays advisors a fixed wage, there is no direct financial incentive related to commissions, and the fee structure does not incentivize advisors to work only with the most profitable investors. Moreover, the bank uses random assignments to specific advisors. Both new and existing investment clients work with whichever advisor is available at the moment the client asks for advice or makes an appointment. Thus, most investors in our sample likely have dealt with various financial advisors over time, and this setting eliminates the possibility that more skilled or experienced investors select the best advisors and/or that advisors select the best investors. To reduce possible selection problems even further, we deliberately focus on common equity holdings, such that the universe of available investment options is equal for both advised and self-directed investors. We also can abstract away from possible incentive conflicts inherent to mutual funds. We are not interested in determining whether financial advisors are capable of beating the market; rather, we aim to compare equity returns for individual investors when they do or do not hire advisors. The remaining selection bias therefore is a result of an investor’s binary choice to use an advisor. Finally, to control for this endogenous choice, we use a Hausman-Taylor panel estimator, which can identify time-invariant variables (e.g., binary choice to use an advisor), even if some variables correlate with a time-invariant individual effect.

In our empirical analyses, we first examine the impact of advisors, with the assumption that selection problems do not exist. For these analyses, we rely on ordinary least squares (OLS) regressions and find advisors do not add value or have only a minor effect. Next, we attempt to control for possible endogeneity problems by estimating the same models with the Hausman-Taylor estimator. In contrast with the OLS estimates, we find that using an advisor benefits individual investors. The impact of advisors on equity returns also is significantly positive for the average private investor. Advisors reduce risk but cannot be attributed to the diversification proxies we use but may relate to a lower degree of volatility specialization (Dorn and Huberman (2010)), in that lower specialization appears to arise in more sophisticated portfolios. Although advisers do not increase the number of equity positions, they increase the share of domestic stock. These findings, as well as higher returns, receive support from evidence in other studies that indicate the informational benefits of holding concentrated (Ivkovic, Sialm, and Weisbenner (2008)) and local (Coval and Moskowitz (2011); Ivkovic and Weisbenner (2005)) portfolios. Moreover, our study reveals that advisors increase costs, though in an amount less than the increase in gross gains, so investors increase their net equity returns. Overall, our study provides a rather positive picture of the potential impact of advisors.

In the next section, we provide a more detailed overview of related studies. Section II contains the data and summary statistics; it also explains in detail how the advisory process functions for the clients in our sample. In Section III we present our results and decribe our methodology for assessing the impact of advisors on portfolio returns. Finally, we conclude in Section IV.

I. Overview of Related Research

A. Possible Links Between Financial Advice and Individual Portfolio Performance

Despite the debate about whether advisors provide clients with tangible benefits, a well-established finding is that advisors have an incentive to missell. Zhao (2003) reports that when there is a conflict of interest, financial advisors—who ultimately serve as the decision makers for investments in load funds—guide customers to funds with higher loads. Vast theoretical literature cites conflicting interests as the main deterrent to unbiased advice. Inderst and Ottaviani (2009) find that they arise because financial advisors perform two tasks:

prospecting for customers and advising on the suitability of products. Loonen (2006) also highlights different financial concerns of financial advisors, including (1) generating commissions for their financial institutions, (2) generating performance-based bonuses, and (3) enhancing the performance of investors' portfolios. Stoughton, Wu, and Zechner (2010) model intermediaries as distinct agents between investors and money managers; in their model, financial advisors facilitate the entry of small investors into the market by economizing on information costs. However, when investors are unsophisticated, kickbacks to financial advisors support aggressive marketing and negatively affect the portfolio performance of mutual funds. Their model further predicts that underperforming funds get sold only to unsophisticated investors through indirect channels—a result confirmed empirically by Bergstresser, Chalmers, and Tufano (2009). A similar conclusion emerges from Inderst and Ottaviani's (2010) model: When customers are naïve about the true conflict of interest, firms exploit their incorrect perceptions. In Krausz and Paroush's (2002) model, conflicts of interest and information asymmetry induce advisors to exploit clients, so some exploitation occurs when investors pay for both financial advice and investment execution as a joint product and the cost of switching is nonnegligible. When different assets earn different commissions, advisors also might be tempted to choose higher commission products, regardless of their suitability for the client. Ottaviani (2000) derives similar conclusions from a model in which the advisor faces a trade-off between providing good advice, which leads to returning clients and good publicity, versus maximizing commissions and offering preferential treatment to product providers.

In addition, financial advisors may be more biased than clients or, in facing agency conflicts, have an incentive to exacerbate clients' biases. Shapira and Venezia (2001) find more trading activity in professionally managed accounts, which they propose is an outcome of greater overconfidence among the managed group. Glaser, Weber, and Langer (2010) document that though all participants are overconfident to some extent, financial professionals tend to be more overconfident than laypeople, and Kaustia and Perttula (2011) confirm overconfidence among financial advisors. Kaustia, Laukkanen, and Puttonen (2009) find strong framing effects among financial advisors too, whereas Mullainathan et al. (2010) analyze whether advisors debias clients. Although advisors tend to match portfolios to client characteristics, they fail to debias customers and in some cases even exacerbate client biases.

Such agency problems often give rise to biased advice that hurts the investor, but potentially, advisors can add value by providing greater financial sophistication, based on their investment experience, financial education, and investment knowledge. Kaustia, Alho, and Puttonen (2008) find that financial expertise significantly attenuates anchoring in financial decision making, and List (2003) shows that the degree of market experience correlates positively with the degree of rationality in decision making. Feng and Seasholes (2005) support this finding with evidence that increased sophistication and trading experience relate strongly to the elimination of biased decision making. Shapira and Venezia (2001) further report that professionally managed accounts exhibit less biased decision making than do independent individual investors. Dhar and Zhu (2006) also document a negative relationship among financial literacy, trading experience, and the disposition effect. Therefore, education and experience—characteristics that should be associated with a financial advisor—should reduce behavioral biases that hurt performance, even if they do not completely eliminate them.

B. Portfolio Performance of Individual and Professional Investors

Most prior studies of individual investor portfolio performance exclude investors who use financial advice or investigate only the behavior of online investors. The average individual investor in these studies performs poorly (e.g., Odean (1999); Barber and Odean (2000); Barber et al. (2008); Bauer, Cosemans, and Eichholtz (2009)). Yet we still find great heterogeneity in the results; some groups of investors perform well. Ivkovic, Sialm, and Weisbenner (2008) show that skilled individual investors earn abnormal returns by concentrating their portfolios in stocks about which they have favorable information. Ivkovic and Weisbenner (2005) also indicate that individual investors can exploit informational advantages about local holdings, though Seasholes and Zhu (2010) challenge their claim. Coval, Hirschleifer, and Shumway (2005) instead document that some individual investors are persistently better than others.

These empirical studies ignore the large proportion of investors who use financial advice. Some recent empirical studies explicity investigate the role and impact of financial advisors on retail portfolios. Bergstresser, Chalmers, and Tufano (2009) investigate the value of brokers for helping clients select mutual funds: They compare the performance of directly and indirectly (i.e., funds sold through an advisor) sold funds, and they find lower risk-adjusted gross returns for broker-sold mutual funds than for directly sold funds. Thus they conclude that advisors deliver benefits that customers do not observe or that conflicts of interest prevent advisors from giving optimal advice. Yet they do not investigate the portfolios of the investors directly.[4] Hackethal, Haliassos, and Jappelli (2011) study German retail investors who receive advice from independent or bank financial advisors. The advised clients tend to be older, women, wealthier, and more experienced; furthermore, independent advisors are associated with lower returns but also lower portfolio variance, whereas bank advisors are associated with both lower returns and higher risk. Both advisors produce high turnover and a lower share of single stocks, indicating better diversification. Their main results thus rely on associations, though they attempt to solve the endogeneity issue. As we

[4] There may be an alternative explanation for their results: Broker-sold funds reveal a different universe than directly sold funds, so it is not clear whether the advisor performs poorly or if the problem lies with the supplier. A fund supplier might offer only underperforming funds to advisors' distribution channel, as predicted by Stoughton, Wu, and Zechner (2010). Bergstresser, Chalmers, and Tufano (2009) show that the asset-weighted performance of funds sold by brokers is not as poor as equally weighted performance. That is, the asset-weighted returns indicate the quality of decisions, whereas the equally weighted returns represent available choice options. This finding implies that brokers provide customers with a valuable service, given choice options they have.

noted in the introduction, Bhattacharya et al.'s (2011) (nonrandom) financial advice choice experiment included 8,200 execution-only investors, who had the option to receive free and unbiased advice. Clients who choose to participate received portfolio recommendations derived from a portfolio optimizer (Markowitz (1952)), and those who rejected the offer acted as a control group. Only 385 (5%) investors accepted the offer, and 157 (2%) at least partly followed the recommendations. In line with Hackethal, Haliassos, and Jappelli (2011), clients that accepted the advice were older, wealthier, and more sophisticated, and those who followed the recommedations improved their portfolio risk–return trade-off. That is, if the advice is unbiased, it has the potential to benefit investors. Kramer (2012) investigates a sample of 16,000 Dutch advised and self-directed investors and finds that the characteristics and portfolios of the two groups differ remarkebly. Although he finds no portfolio perfomance differences, advisors seem to add value through better diversifcation and lower ideosycnratic risk. A sample of investors that switch from execution-only to advice confirms these findings.

Other studies compare the performance of professionals and retail investors more generally. Professionals (who have difficulty outperforming the market[5]) perform better than individual investors. Grinblatt and Keloharju (2000) find that professional institutions significantly outperform less sophisiticated investors, such as domestic households; Shapira and Venezia (2001) confirm this claim by comparing independent and professionally managed investors in Israel and finding better performance among the latter. Barber et al. (2009) also document underperformance by the aggregate portfolio of Taiwanese individual investors, even when institutional investors gain in their trading. Thus, though retail and

[5] Jensen (1967) was one of the first to show that mutual funds cannot outperform buy-and-hold strategies on average. More recent studies indicate that money managers have difficulty outperforming passive indexes (e.g., Busse, Goyal, and Wahal (2010); Fama and French (2010)). Bergstresser, Chalmers, and Tufano (2009) indicate that equity funds in general, whether directly or broker sold, exhibit negative alphas.

professional investors both tend to exhibit mediocre investment performance, in principle, advisors could improve the performance of individual investors.

As this literature survey shows, research on financial advisors is expansive and growing. Not all existing papers mention the potential for self-selection bias, but it seems surprising that no study explicitly and rigorously controls for possible endogeneity problems, even though advisor choice clearly is endogenous. Failing to account for possible selection problems can bias results considerably. The three studies most closely related to our study do not control for selection explicitly but attempt to estimate the likely impact of selection on their results. That is, Bergstresser, Chalmers, and Tufano (2009) indicate that advised investors are less educated and more risk averse; Bhattacharya et al. (2011) acknowledge that their study is not based on a random assignment, though they argue that their basic empirical methodology (difference-in-difference) can ameliorate that shortcoming; and Hackethal, Haliassos, and Jappelli (2011, p.14) suspect “that portfolio performance actually induced the choice of the advisor” and attempt to estimate an instrumental variables model as a robustness check. They note that “finding suitable instruments in our context is not easy” (Hackethal, Haliassos, and Jappelli (2011, p.14)) and admit they cannot test the quality of their instrument.

II. Data, the Advisory Process, and Descriptive Statistics

For our analysis, we draw on the complete history of common stock portfolio holdings and transaction data for a sample of customers from a medium-sized, full-service retail and business bank that offers an array of financial products. The bank, which advertises itself as a relationship bank, offers services throughout the Netherlands through a network of bank branches, though it has a particularly strong presence in the northern part of the country. The bank offers both advisory and execution-only investment services. Customers typically have an account manager who communicates all the financial services the bank offers. Although the bank is accessible to all people, the typical investment client (both advised and execution only) is a man or couple, older than 50 years of age, with middle-class income and wealth.

The data span a 52-month period, from April 2003 to August 2007. We only use accounts of private investors with unrestricted accounts and exclude those owned by a business, portfolios linked to mortgage loans, or portfolios that represent part of a company savings plan. Our final sample therefore consists of 5,661 equity investors and 193,418 monthly equity return observations. For most investors in our sample, equity is the most important asset class (on average, 82% of portfolio value, with almost 60% in individual equity positions), and because we want to abstract from incentive conflicts that are inherent to mutual fund advice, we deliberately consider only advisory impacts on common stock recommendations. We also gather information about the type of client (execution-only or advised), gender, zip code, and age. On a six-digit zip code level,[6] we gain information about income and residential value. A comparison of some key characteristics in our data set with retail investor data sets in the Netherlands (Bauer, Cosemans, and Eichholtz (2009)), Germany (Bhattacharya et al. (2011); Dorn and Huberman (2010)), and the United States (Ivkovic and Weisbenner (2005)) reveal that our data offer a high degree of external validity.

Execution-only and advised investors represent different departments, so investors with advisory relationships cannot trade through the execution-only department, and investors who use execution-only services cannot rely on the help of an advisor. The investors choose between an advisory relationship or execution-only services. For our sample period, all customers were eligible for advice, which is unusual, in that most banks require a minimum investment to be eligible for advisory services. Thus our data set is unique. After the sample period, the bank stopped offering advisory services to clients whose portfolios were worth less than €100,000; therefore, we restrict our sample to the period before 2008.

[6] In the Netherlands, 6,940,000 households represent 436,000 six-digit zip codes; these variables offer average values for an average of 16 households each.

Advisors receive a fixed wage only, so there is no direct personal financial incentive to generate commissions. Furthermore, clients' assignments to advisors is random. Both new and existing investment clients work with advisors based on availability. The advisory relationship always starts with an initial intake meeting, in which an advisor assesses the investor's investment goals, preferences, knowledge, and experience. From this first meeting, they develop a risk profile, which constitutes the main input for the recommended strategic asset allocation. This asset allocation advice is predetermined by the bank, and the individual advisor has no real impact. After the initial meeting, some advice is given in face-to-face meetings, but most recommendations occur over the telephone. We cannot discern whether granted advice is followed by the investors; Bhattacharya et al. (2011) report that less than 50% of investors that choose to receive advice actually follow it. However, the investors in their sample initially opted for an execution-only investment service, then considered whether to receive advice from an automatic portfolio optimizer. Their sample appears likely to behave quite differently than the investors in our sample, who deliberately opted to receive advice. In discussions with the bank management, we also learned that most calls initiated by the advisor contain explicit advice, as the very reason for the call, whereas calls initiated by investors rarely prompt any portfolio changes.

Advisors offer concrete stock recommendations and have great latitude about which stocks to recommend. In our sample period, advisors received research on financial markets and individual firms from an external research agency. They could use this research in their recommendations as they pleased. Advisors also could recommend stocks based simply on their own preferences.

Because we include accounts that were opened or closed during the sample period for only the months in which they were active, our data set is free of survivorship bias. We calculate individual investor performance using a modified Dietz (1968) measure, which accounts for both the size and the timing of deposits and withdrawals. We report gross and net (market adjusted) returns, but we focus on the latter in our regression specifications; to calculate net returns, we deduct transaction and custodian fees. Net returns are calculated as:

$$R_{it}^{net} = \frac{MV_{it} - MV_{it-1} - \sum NC_{it}^{net} - \text{COSTS}_{it}}{MV_{it-1} + \sum w_{itc} NC_{it}^{net}}, \qquad (1)$$

where R_{it}^{net} is the net monthly return of investor *i* in month *t*, MV_{it} is the end-of-month market value of the portfolio, NC_{it}^{net} is the net contribution (deposits minus withdrawals) in month *t*, and w_{itc} is the weight attributed to each contribution, determined by the timing of contributions. When a contribution takes place earlier in the month, its weight is higher. Finally, $COSTS_{it}$ are transaction costs and custodial fees, recalculated monthly.

Table 1 contains the summary statistics for the portfolio returns and investor and portfolio characteristics. Individual investors in our sample underperform the market by a small margin in gross terms, but they underperform in net terms by 20 basis points per month. Advised investors perform better than self-directed investors in both raw and market-adjusted gross and net terms, but the differences are modest. The average volatility of net returns is 5.45%, considerably higher than the volatility of the Dutch stock market (3.51%), which may reflect the average portfolio holding of only 4.4 stocks. Advised portfolios exhibit significantly less volatility and idiosyncratic risk, likely due to the higher number of stocks in their portfolios (5.2 versus 3.3 for self-directed portfolios). Advised portfolios also are associated with a lower market beta, though this difference is statistically insignificant. Most portfolios are joint accounts (44%), and 21% are held by women. Advised accounts are more common among joint account holders and women. The average age of the primary account holder is 57 years, but advised investors are marginally older. Advised investors also seem more wealthy in their gross monthly income, residential value, and portfolio value. The average size of advised stock portfolios is €57,000, almost four times greater than the size of self-directed portfolios. Common stock, the focus of our study, constitutes the largest asset class; almost 60% of the average portfolio consists of common stock, and the rest represents a combination of common bonds, equity and bond mutual funds, and structured products. Trading activity, with an average monthly turnover of almost 5%, appears broadly in line with activity documented in other studies.[7] Advised portfolios reveal significantly higher turnover than self-directed portfolios and execute more trades. Among our observations, 60% come from advised investors who are active for an average of 45 months during the sample period, whereas 40% represent the benchmark group of execution-only investors.

III. Empirical Results

To estimate the impact of an advisor on the returns of individual investor portfolios, we applied a general model: $Y_{it} = \alpha + A_i\beta_1 + X_{it}\beta_2 + \varepsilon_{it}$, where Y_{it} is the net return on the portfolio of investor *i* in month *t*, α is a constant term, and A_i is a dummy variable that takes the value of 1 if the investors receive investment advice and 0 otherwise.

In addition, X_{it} represents a set of control variables known to influence returns. Bauer, Cosemans, and Eichholtz (2009) indicate that turnover, gender, age, income, and account size are significant determinants, and Barber and Odean (2000, 2001), suggest that portfolio turnover hurts net returns and that men trade 45% more than women. Because of the trading costs they incur, men underperform women by almost 1% per year. Bauer, Cosemans, and Eichholtz (2009) also report that the most active traders outperform in gross terms but underperform in net terms. Wealth often serves as a proxy for investor sophistication: Anderson (2008) finds a positive relation between portfolio value and trading performance, and Bauer, Cosemans, and Eichholtz (2009) indicate that large portfolios outperform small portfolios. Yet Barber and Odean (2000) find no significant risk-adjusted return differentials

[7] Barber and Odean (2000) report an average of 6%, and Hackethal, Haliassos, and Jappelli (2011) report an average of almost 5%.

between the largest and smallest portfolios. We use three variables related to wealth: portfolio value, residential value, and income (the latter two measured at the six-digit zip code level). Age also should relate to investor experience. Bauer, Cosemans, and Eichholtz (2009) report a negative impact of age on performance, and Korniotis and Kumar (2011) show that older, more experienced investors exhibit greater investment knowledge, though they appear to have poor investment skills, perhaps due to cognitive aging, and suffer 3–5% lower annual returns.

Our sample might suffer from cross-sectional dependence too. Investors may make similar decisions at the same time and hold the same securities in their portfolios. Petersen (2009) shows that ignoring cross-sectional dependence leads to biased standard errors and overly small confidence errors. When time effects are fixed, such that they have the same impact on all investors, time dummies can completely remove correlations between observations in the same period. We therefore include time dummies in all our estimations.

In Table 2, we present the results based on ordinary least squares (OLS); the first two columns show that the difference in raw and risk-adjusted performance between advised and self-directed investors is indistinguishable from 0. Many of the other relationships between advice and portfolio behavior are also insignificant or small. Based on these estimates, without controlling for selection effects that arise because investors make the choice of whether to hire an advisor, the advisory impact seems rather limited.

A. Controlling for Self-Selection

We investigate the effect of an advisor on the outcome of investment decisions. If we assume no unobserved individual heterogeneity, we could estimate our model with OLS, as in Table 2. However, returns likely are affected by unmeasurable attributes, such as investment skills, financial literacy, or risk aversion, so an OLS model, which suffers from an omitted variable bias, is inappropriate. To allow for unobserved individual heterogeneity, we can use fixed and random estimators. The random effects model assumes that all unobserved factors that affect returns are distributed randomly across cross-sectional units. It also predicts that unobserved, time-invariant individual effects are uncorrelated with all other regressors in the model. In our specification, this effect implies that unobservable variables such as skill, literacy, and risk aversion do not relate to the choice of advice, which seems highly unlikely. For every specification, we thus formally test differences in the coefficients from fixed effects and random effects regressions, using a Hausman-like test. The random effects estimator is rejected in all our specifications, whereas the fixed effects estimator allows for correlation between unobserved individual effects and regressors. Because it also eliminates time-invariant elements, it cannot identify time-invariant variables. However, our main variable of interest, the advice dummy, is time invariant, so identifying the impact of the advisor with a fixed effects model is impossible.

Finally, the Hausman-Taylor approach (Hausman and Taylor (1981)) preserves the advantages of both a fixed effect estimator (i.e., correlation between individual effects and regressors) and the random effects estimator (i.e., identifying the effect of time-invariant regressors). This hybrid model (Cameron and Trivedi (2005)) also requires no external instruments, which solves the problem of finding suitable instruments. Because all the variables are instrumented in the fixed effects approach, including those that are exogenous, the Hausman-Taylor approach may be more efficient than a fixed effects model. However, it requires us to distinguish between exogenous and endogenous variables, which in practice is not obvious, though Hausman and Taylor (1981) suggest economic intuition can indicate which variables to treat as endogenous. The technique has been advocated by Angrist and Krueger (2001) and McPherson and Trumbull (2008), as well as used in various economic settings, usually to assess the impact of some time-invariant variable or policy intervention assigned in a non-random fashion. Hausman and Taylor (1981) apply it to a classical example of estimating the effect of education on wages. Greenwood, McDowell, and Zahniser (1999) assess the influence of social programs on immigration; Garcia, Molinaab, and Navarroc (2010) consider the effects of education on spouse satisfaction; Egger and Pfaffermayr (2004) investigate the effects of distance between countries on investment trades; Dixit and Pal (2010) study the impact of group incentives on firm performance; Serlenga and Shin (2007) use the method for gravity models in international trade; and Contoyannis and Rice (2001) employ it to determine the impact of health on wages in the United Kingdom.

B. Hausman-Taylor Estimation

The Hausman-Taylor specification assumes that any set of explanatory variables contains time-varying and time-invariant variables. A subset of both types of variables would be exogenous and assumed to be uncorrelated with the unobserved time-invariant individual effect, though some of both types of variables may correlate with the time-invariant individual effect. In line with the OLS, random effects, and fixed effects approaches, the Hausman-Taylor model assumes that no regressors correlate with ε_{it}, the individual time-varying disturbance term. The model can be specified as follows:

$$Y_{i\tau} = \nu + X_{1i\tau}\beta_1 + X_{2i\tau}\beta_2 + M_{1i}\gamma_1 + M_{2i}\gamma_2 + \mu_i + \varepsilon_{i\tau},$$

where Y_{it} denotes the net returns of private investor *i* in period *t;* ν is a constant term; the vectors *X* and *M* capture sets of observed time-varying and time-invariant control variables, respectively, that affect the outcome variable; μ_i represents the individual fixed effect; and ε_{it} refers to the time-varying individual error. The subscript 1 denotes variables that are assumed to be uncorrelated with μ_i (and ε_{it}), whereas the subscript 2 refers to those that are assumed to be correlated with μ_i (but still uncorrelated with ε_{it}). Our main variable of interest is advice, which equals 1 if private investor *i* uses an advisor in period *t,* and 0 otherwise. Because advice is entirely time invariant and likely endogenous, we include it in M_{2i}. We provide an overview of all included variables and their main specifications in Table

3. We assume all wealth-related variables are endogenous. Therefore, in addition to advice, portfolio value, residential value, and household income appear in our list of endogenous variables that must be instrumented. Unobservable variables such as ability, financial literacy, investment skill, and motivation likely drive the wealth variables, in that they influence the portfolio performance measures that serve as our dependent variables. In other finance settings, wealth is considered endogenous; for example, Becker (2006) argues that wealth may be endogenous for assessing CEO compensation, because highly skilled CEOs should have accumulated more wealth. Similarly, Hurst and Lusardi (2004) state that the traits that render some households more likely to accumulate wealth make them more likely to behave particularly in other settings too.

In the Hausman-Taylor approach, a generalized least square (GLS) transformation applies to all dependent and independent variables, as in a random effects estimation, and all the variables are instrumented. In line with the fixed effects model, both time-varying exogenous and endogenous variables are instrumented by a within-variable transformation, whereas the time-invariant endogenous variables use the individual averages of the exogenous time-variant variables. The time-invariant exogenous variables are instruments themselves.[8]

For our estimations, we first report a robust version of a Hausman test (Schaffer and Stillman (2010))[9] to determine if a fixed or random effects estimation is preferable. In all cases, the fixed effects estimator is better. As is true of many multistage estimation techniques, the asymptotic sampling distribution is hard to derive, so we calculate standard errors using a bootstrap with 250 replications. To confirm the quality of our instruments, we

[8] The Hausman-Taylor approach assumes that no regressors correlate with the time-varying individual effects (ε_{it}), but some unobservable variables might change over time, such as investment experience. Insofar as this time-varying effect changes at a constant rate, the inclusion of *age* and a proxy for *experience* variables solves this issue.

[9] We use the xtoverid command in Stata that reports a Sargan-Hansen statistic as an alternative to the Hausman fixed versus random effects test; it is robust to arbitrary heteroskedasticity and within-group correlation. Using the standard Hausman test yields similar results.

report the F-statistic for the first-stage regression with advice taking, the *p*-values of the Sargan test, and the Hansen-J statistic of overidentifying restrictions.

C. Impact of Advisers on Portfolio Returns: Empirical Results

In Table 4, we present the performance results of our Hausman-Taylor specification, including the small, significant, positive impact of advice on portfolio performance. Advised portfolios are associated with lower market risk (see Table 1), so this advisory impact is slightly stronger when we consider risk-adjusted performance (column 2). This result contradicts findings by Hackethal, Haliassos, and Jappelli (2011) and Bergstresser, Chalmers, and Tufano (2009), but it aligns with Battacharya et al.'s (2011) findings. We focus on common equity, for which unbiased advice is more likely, as was true for Battacharya et al. (2011), whereas the inclusion of mutual fund advice increases the likelihood of bias in the other studies. Mutual fund inflows relate positively to front-end loads, so advisors may put their own interests before those of clients. For common equity though, advisors have much less incentive to direct clients to securities that benefit only advisors, though conflicts of interest remain possible. Because income from stock advice depends on the trade commission, advisors might encourage churn in portfolios, as we address subsequently. Fecht, Hackethal and Karabulut (2010) also find that banks relocate underperforming stocks from proprietary portfolios into retail clients' portfolios.

The negative coefficient for *Turnover* indicates that trading activity has a negative effect on returns; Barber and Odean (2000) similarly report that active traders underperform passive traders in net terms, because of their large trading costs. The small but negative coefficients for *Woman* and *Joint* contrast with Barber and Odean's (2001) findings though. It appears that their finding that women's performance is superior mainly reflects the lower turnover in portfolios held by women, for which we explicitly control.

Portfolio size (*Value*) relates negatively to returns, but other wealth proxies have a positive (residential value) or insignificant (income) effect. The negative relation between portfolio size and returns contrasts with findings by Bauer, Cosemans, and Eichholtz (2009) but might be explained by Ivkovic, Sialm, and Weisbenner (2008), who report lower returns for better diversified portfolios. In our sample, larger portfolios tend to better diversified.

Our methodology controls for selection bias due to unobserved characteristics that do not change over time. Moreover, assignments to specific advisors are random. Yet we cannot entirely rule out the possibility that our results are partly biased by selection on time-varying unobservable variables, such as investment experience. It has a positive impact on portfolio returns and increases over time. By including the number of months the investor is active in our sample period, we try to proxy for experience; the effect is insignificantly positive and quite small.

All (cluster-robust) F-statistics of the first-stage regressions for *Advice* are greater than 10, so the instruments appears relevant and reasonably explanatory for the advice dummy. In addition, the high *p*-values on both the Sargan and Hansen-J statistics indicate the instruments are valid for all our specifications.

D. Impact of Advisers on Risk

The impact of advisors on portfolio returns is small but positive for the average investor. To assess the value of financial advisors, we consider their impact on the risk exhibited by clients' portfolios. Contrary to lessons from portfolio theory, individual investors generally diversify poorly; as Barber and Odean (2000) document, a typical investor holds only four stocks (similar to the 4.4 stocks we report in Table 1). Finance textbooks routinely illustrate the positive effect of adding more stocks to a portfolio: It reduces nonsystematic risk (e.g., Berk and DeMarzo (2010)). Sophisticated investors follow these lessons, as Goetzman and Kumar (2008) show, but most investors still suffer significant idiosyncratic risk because they choose imperfectly correlated stocks. These findings reflect recent evidence noted by Dorn and Huberman (2010) that individual investors expose themselves to idiosyncratic risk due to volatility specialization. Because diversification is a basic lesson, we expect financial advisors, in principle, to increase portfolio diversification. Bluethgen et al. (2008) and Kramer (2011) also confirm better portfolio diversification among advised investors, though mainly as a result of adding mutual funds to retail portfolios.

To assess the impact of advisors on risk, we apply Glesjer's (1969) heteroskedasticity test (see Cheng (2008)). First, we obtain residuals from a Fama-French three-factor model, which we apply to all time series of net monthly portfolio returns for each individual investor with at least 24 monthly return observations in our sample. Second, we use the absolute value of the residuals of the regressions in the first step and regress it on the same predictors as in our previous models. We proceed as we did for estimating the impact on returns. Specifically, we estimate:

$$R_{it} = \alpha_i + \beta_{1i}\left(R_{mt} - R_{ft}\right) + \beta_{2i} SMB_t + \beta_{3i} HML_t + \varepsilon_{it}$$

where R_{it} is the return on the portfolio of investor i in month *t*; $R_{mt} - R_{ft}$ is the excess return on the MSCI Netherlands index in month *t*; R_{ft} is a proxy for the risk-free rate, for which we use the three-month Euribor; SMB_t is the return on a zero-investment factor that mimics portfolio size; and HML_t is the return on a zero-investment factor that mimics portfolio value. We take the residuals from this model and use the absolute value as a proxy for the variability of the investor's portfolio return.

The OLS results for the second step of Glejser's (1969) test in Table 2 indicate, similar to our previous return regressions, a small relationship with advisory intervention. Advised portfolios appear associated with less risk, but a selection bias may drive these results. We cannot infer the *impact* of advice from these regressions, so we turn again to the Hausman-Taylor methodology (see Column 3, Table 4). For portfolio volatility, we find a much larger negative impact of advisory intervention. Apparently advisors improve diversification, as we discuss subsequently. This finding may be intuitive, in that survey results from various countries indicate low levels of financial literacy (Van Rooij, Lusardi, and Alessie (2011); Lusardi and Mitchell (2007)). Therefore, we assert that financial advisors provide the necessary investment knowledge and experience to increase diversification. The average value of the monthly return residuals of 2.9% in Table 1 suggests the impact of advice is considerable.

The controls we use exhibit the expected signs. Portfolio value has a large negative impact on idiosyncratic risk, in line with Dorn and Huberman's (2010) reports of a negative relation between the Herfindahl-Hirschmann index[10] and wealth. Diversification in portfolios of individual securities is less expensive when portfolios grow larger, considering the fixed costs associated with adding each new security. Turnover relates positively to diversifiable risk. Turnover is often considered a proxy for overconfidence, which drives excessive risk-taking. Barber and Odean (2000) report lower risk aversion for active traders. Finally, in line with previous findings, we note that joint accounts are associated with lower avoidable risk, but the coefficient for women is insignificant.

E. Impact of Advisers on Trading Activity and Costs

In Table 5 we report the Hausman-Taylor estimates of activity and cost measures. *Trades* is the number of common equity transactions in each month; *Cost* is the difference between the gross and net return of each individual investor in each month, such that it captures the effect of transaction costs and custodial fees. The coefficient for *Advice* reveals some interesting patterns. In contrast with the results in Table 2, we find that advisors lower the number of trades (Table 5, columns 1 and 2). Apparently, they reduce the number of trades investors execute, which conflicts with the commonly held belief that advisors induce

[10] This index is calculated as the sum of the squared weights of the assets in a portfolio and therefore serves as a proxy for the amount of diversification.

churn to generate more commissions. Women and joint accounts engage in less trading activity, consistent with Barber and Odean's (2001) findings that single men trade most. Increased portfolio value is associated more trades, though these relationships appear nonmonotonic, according to the sign changes when we add a squared variable for value. By adding squared terms for both value and age, we overidentify the model and can test for the quality of our instruments. When we include them, the impact of advice on trading diminishes, though the effect is still considerable. The Sargan and Hansen-J statistics indicate no correlation between our instruments and the error term. In line with Dorn and Huberman (2005), our estimates show that respondents with more experience trade significantly less.

Although trading declines in advised portfolios, advisors have a positive impact on costs (Table 5, column 3). When advisors execute trades, investors pay more in commissions compared with execution-only services. Consistent with our expectations, increased portfolio value lowers costs, and higher turnover increases costs. Experience lowers cost, though the effect is small.

F. Impact of Advisers on Diversification

Better diversification lowers unnecessary risk in portfolios. As Table 4 already revealed, advisors lower idiosyncratic risk, whether by increasing the number of securities in a portfolio or selecting securities with low correlations. Dorn and Huberman (2010) show that retail investors typically specialize in volatility, in that they select securities with similar volatilities rather than low correlations. To assess the diversification skill of advisors, we use two measures: the advisory impact on the number of individual shares in each portfolio and the effect on home bias. Although home bias is widespread (French and Poterba (1991)), debate continues about whether it actually harms investors. Normative finance theory indicates diversification benefits from investing abroad, but others argue that home bias (or local bias within a country) may offer information advantages (Ivkovic and Weisbenner

(2005); Coval and Moskowitz (2001)). We calculate home bias by dividing the initial monthly common stock portfolio value invested in Dutch stocks by the total initial monthly value in common equity. Our findings in Table 6 (column 1) reveal that though the coefficient of *Advice* on the number of equity position is positive, it is far from significant. With our assumption that sophistication drives advisor choice, we could predict a positive sign of advisory intervention on the number of equity positions. However, recent evidence also suggests that holding concentrated portfolios can be beneficial (Ivkovic, Sialm, and Weisbenner (2008)).

We also note from Table 6 (column 2) that advisors increase exposure to domestic equity, which seems intuitively to conflict with our previous finding that advisors lower idiosyncratic risk. It might be explained by findings from Kramer (2012) and Hackethal, Haliassos, and Jappelli (2011), who indicate a positive effect of advisors on mutual fund holdings. Most mutual funds distributed in the Netherlands have a strong international focus, so advisors could focus on domestic stocks for their domestic portfolio and diversify internationally through mutual funds. This finding also supports prior results (Ivkovic and Weisbenner (2005); Coval and Moskowitz (2001)) that indicate investors benefit from local holdings due to the informational advantages they provide. Our finding that advisors focus more on domestic equity and achieve higher returns is consistent with this view.

IV. Conclusion

We estimate the causal impact of an advisor on the portfolio returns of an individual investor. We use a unique database of approximately 195,000 monthly equity returns for more than 5,500 Dutch investors, who are either advised or self-directed. Because our variable of interest is likely endogenous, due to self-selection, and does not change over time, we employ the instrumental variable approach developed by Hausman and Taylor (1981).

We find, irrespective of the exact model specification, a small positive effect of advisors on portfolio returns for average individual investors. In addition, a Glesjer (1969) test shows that advice lowers idiosyncratic risk. There is a significant positive impact of advisory intervention on the home bias, but apparently it does no harm in terms of risk and return, consistent with the view that retail and professional investors have an informational advantage when selecting domestic stocks.

These results contrast with recent findings that incorporate mutual fund advice. Inherent to mutual fund advice is the moral hazard problem in an advisor–advisee relationship. Mutual funds typically have opaque fee structures that benefit advisors, not their customers. However, our findings are supported by evidence based on unbiased advice. Thus, when considering common stock advice only, incentive conflicts may be less pronounced, and advisors add value. Although we lack an empirical test, our findings glean support from research that indicates a positive effect of experience and financial knowledge on less biased decision making.

We also show that advisors affect trading activity. The number of trades declines as a result of advisory intervention. Advisers do not engage in churning behavior driven by conflicts of interest, perhaps because financial market regulations explicitly forbid churning.

In summary, our results show that advisors improve the portfolio decision making of retail investors when conflicts of interest are minimal. Current attempts by policy makers in many countries to replace the current incentive structure, based on product fees, with a more transparent fee model, in which investors pay for advice directly, thus appears likely to benefit retail investors.

V. References

Anderson, A., 2008, Is online trading gambling with peanuts? Working Paper, SSRN: http://ssrn.com/abstract=871435.

Angrist, J. and A.B. Krueger, 2001, Instrumental variables and the search for identification: From supply and demand to natural experiments, NBER Working Paper 8456, National Bureau of Economic Research.

Barber B.E., Y.T. Lee, Y.J. Liu, and T. Odean, 2009, Just how much do individual investors lose by trading? *Review of Financial Studies* 22, 609-632.

Barber, B.E. and T. Odean, 2000, Trading is hazardous to your wealth: The common stock investment performance of individual investors, *Journal of Finance* 55, 773-806.

Barber, B.E. and T. Odean, 2001, Boys will be boys: Gender, overconfidence, and common stock investment, *Quarterly Journal of Economics* 116, 261-292.

Barnea, A., H. Cronqvist, and S. Siegel, 2010, Nature or nuture: What determines investor behavior? *Journal of Financial Economics* 98, 583-604.

Bauer, R., M. Cosemans, and P. Eichholtz, 2009, Option trading and individual investor performance, *Journal of Banking and Finance* 33, 731-746.

Becker, B, 2006, Wealth and executive compensation, *Journal of Finance* 61 (1), 379–397.

Bergstresser, D., J.M.R. Chalmers, and P. Tufano, 2009, Assessing the costs and benefits of brokers in the mutual fund industry, *Review of Financial Studies* 22, 4129-4156.

Berk, J. and P. DeMarzo, 2007. *Corporate Finance* (New York: Pearson/Addison Wesley).

Bhattacharya, U., A. Hackethal, S. Kaesler, B. Loos, and S. Meyer, 2011, Is unbiased financial advice to retail investors sufficient? Answers from a large field study. *Review of Financial Studies*, forthcoming.

Bluethgen, R., A. Gintschel, A. Hackethal and A. Müller, 2008. Financial advice and individual investors' portfolios. Working Paper, SSRN: http://ssrn.com/abstract=968197.

Busse, J.A., A. Goyal, and S. Wahal, 2010, Performance and persistence in institutional investment management, *Journal of Finance* 65, 765-790.

Cheng, S., 2008, Board size and the variability of corporate performance, *Journal of Financial Economics* 87, 157-176.

Cameron A.C., and P.K. Trivedi, 2005, *Microeconometrics, Methods and Applications* (Cambridge University Press, New York, NY.)

Contoyannis, P. and N. Rice, 2011, The impact of health on wages: Evidence from the British Household Panel Survey, *Empirical Economics* 26, 599-622

Coval, J.D., D.A. Hirshleifer, and T. Shumway, 2005, Can individual investors beat the market? Working Paper, SSRN: http://ssrn.com/abstract=364000.

Coval, J.D., and T.J. Moskowitz, 2001, The geography of investment, *Journal of Political Economy* 109, 811-841

Dhar R. and N. Zhu, 2006, "Up Close and Personal: Investor Sophistication and the Disposition Effect," Management Science 52, 726-740.

Dietz, P.O., 1968, Components of a measurement model: Rate of return, risk and timing, *Journal of Finance* 23, 267-275.

Dixit, K. and R. Pal 2010, The impact of group incentives on performance of small firms: Hausman–Taylor estimates, *Managerial and Decision Economics* 31, 403–414

Dorn, D. and G. Huberman, 2010, Preferred risk habitat of individual investors, *Journal of Financial Economics* 97, 155-173.

Egger, P. and M. Pfaffermayr, 2004, Distance, trade and FDI: a Hausman–Taylor SUR approach. *Journal of Applied Econometrics* 19, 227–246. doi: 10.1002/jae.721.

Fama, E.F. and K. French, 2010, Luck vs. skill in the cross-section of mutual fund returns, *Journal of Finance* 65, 1915-1947.

Fecht, F., A. Hackethal and Y. Karabulut, 2010, Is Proprietary Trading Detrimental to Retail Investors?, Working Paper, SSRN: http://ssrn.com/abstract=1783679.

Feng, L. and M.S. Seasholes, 2005, Do investor sophistication and trading experience eliminate behavioral biases in financial markets? *Review of Finance* 9, 305–351.

French, K. and J. Poterba, 1991, Investor diversification and international equity markets, *American Economic Review* 81, 222–226

García, I., J.A. Molinaab, and M. Navarroc, 2010, The effects of education on spouses' satisfaction in Europe, *Applied Economics* 42, 3607-3618

Glaser, M., M. Weber, and T. Langer, 2010, "Overconfidence of Professionals and Lay People: Individual Differences Within and Between Tasks," University of Mannheim Working Paper. Available at SSRN: http://ssrn.com/abstract=712583.

Glesjer, H., 1969, A new test for heteroscedasticity, *Journal of the American Statistical Association* 64, 316-323.

Goetzmann, W.N. and A. Kumar, 2008, Equity portfolio diversification, *Review of Finance* 12, 433-463.

Greenwood, M.J., J.M. McDowell, and S.S. Zahniser, 1999, The influence of social programs in source countries on various classes of U.S. immigration, *Journal of the American Statistical Association* 94, 64-74

Grinblatt, M. and M. Keloharju, 2000, The investment behavior and performance of various investor types: A study of Finland's unique data set, *Journal of Financial Economics* 55, 43-67.

Hackethal, A., M. Haliassos, and T. Jappelli, 2011, Financial advisors: A case of babysitters, *Journal of Banking and Finance*, forthcoming.

Hausman, J.A, and W.E. Taylor, 1981, Panel data and unobservable individual effects *Econometrica* 49 (1), 377-1, 398.

Hung, A.A., N. Clancy, J. Dominitz, E. Talley, C. Berrebi, and F. Suvankulov, 2008, Investor and industry perspectives on investment advisers and broker-dealers, RAND Technical Report, ISBN 978-0-8330-4403-7.

Hung, A.A. and J.K. Yoong, 2010. Asking for Help: Survey and experimental evidence on financial advice and behavior change. Working Paper, SSRN: http://ssrn.com/abstract=1532993.

Hurst, Erik and Annamaria Lusardi, 2004, Liquidity constraints, household wealth, and entrepreneurship, *Journal of Political Economy* 112 (April), 319-347.

Investment Company Institute (ICI), 2010, Characteristics of mutual fund investors, retrieved 10 January 2011, from http://www.ici.org/pdf/fm-v19n7.pdf.

Inderst, R. and M. Ottaviani, 2009, Misselling through agents, *American Economic Review* 99, 883-908.

Inderst, R and M. Ottaviani, 2010, How (not) to pay for advice: A framework for consumer financial protection. Available at http://www.kellogg.northwestern.edu/Faculty/ottaviani/homepage/.

Ivković, Z., S. Sialm, and S.J. Weisbenner, 2008, Portfolio concentration and the performance of individual investors, *Journal of Financial and Quantitative Analysis* 43, 613-656.

Ivkovic, Z. and S.J. Weisbenner, 2005, Local does as local is: Information content of the geography of individual investors' common stock investments, *Journal of Finance* 60, 267-306.

Jensen, M. C., 1967, The performance of mutual funds in the period 1945-1964, *Journal of Finance* 23, 389-416.

Kaustia, M., E. Alho, and V. Puttonen, 2008, How much does expertise reduce behavioral biases? The case of anchoring effects in stock return estimates, *Financial Management* 37, 391-412.

Kaustia, M., H. Laukkanen, and V. Puttonen, 2009, "Should Good Stocks Have High Prices or High Returns?" *Financial Analysts Journal* 65, 55-62.

Kaustia, M. and M. Perttula, 2011, "Overconfidence and Debiasing in the Financial Industry," Aalto University, School of Economics Working Paper. Available at: http://finance.aalto.fi/en/people/kaustia.

Korniotis, G.M., and A. Kumar, 2011, Do older investors make better investment decisions? *Review of Economics and Statistics*, forthcoming.

Kramer, M.M., 2012. Financial advice and individual investor portfolio performance, *Financial Management*, forthcoming.

Krausz, M. and J. Paroush, 2002, Financial advising in the presence of conflict of interests, *Journal of Economics and Business* 54, 55-71.

List, J.A., 2003, Does market experience eliminate market anomalies? *Quarterly Journal of Economics* 118, 41-71.

Lo, A.W. and D.V. Repin, 2002, The psychophysiology of real-time financial risk processing, *Journal of Cognitive Neuroscience* 14, 323-339.

Loewenstein, G., 2003, Emotions in economic theory and economic behavior, *American Economic Review* 90, 426-432.

Loonen, A.J.C.C.M., 2006, Een Kwestie van Vertrouwen, Phd dissertation, University of Amsterdam.

Lusardi, A. and O.S. Mitchell, 2007, Baby Boomer retirement security: The roles of planning, financial literacy, and housing wealth, *Journal of Monetary Economics* 54, 205-224.

Markowitz, H.M., 1952, Portfolio Selection, *Journal of Finance* 7, 77-91

McPherson, M. and W. Trumbull, 2008, Rescuing observed fixed effects: Using the Hausman-Taylor method for out-of-sample trade projections, *International Trade Journal* 22, 315-340.

Millward Brown, 2010, Yearly survey of Dutch private investors, retrieved 15 April 2010 from: http://www.millwardbrown.nl/?pm=branches_d&type=publicatie&id=106.

Mullainathan, S., M. Nöth, and A. Schoar, 2010, "The Market for Financial Advice: An Audit Study," The National Bureau of Economic Research Working Paper. Available at: http://www.cfr-cologne.de.

Odean, T., 1999, Do investors trade too much? *American Economic Review* 89, 1279-1298.

Ottaviani, M., 2000, The economics of advice. Working paper, http://www.kellogg.northwestern.edu.

Petersen, M.A., 2009, Estimating standard errors in finance panel data sets: Comparing approaches, *Review of Financial Studies* 22, 435-480.

Seasholes, M.S. and N. Zhu, 2010, Individual investors and local bias, *Journal of Finance* 65, 1987-2010.

Serlenga, L. and Y. Shin, 2007, Gravity models of intra-EU trade: Application of the CCEP-HT estimation in heterogeneous panels with unobserved common time-specific factors, *Journal of Applied Econometrics* 22, 361–381

Schaffer, M.E., and S. Stillman, 2006, Xtoverid: Stata module to calculate tests of overidentifying restrictions after xtreg, xtivreg, xtivreg2, xthtaylor, Statistical Software Components S456779, Boston College Department of Economics, revised 02 Nov 2011.

Shapira, Z. and I. Venezia, 2001, Patterns of behavior of professionally managed and independent investors, *Journal of Banking and Finance* 25, 1573-1587.

Stoughton, N.M., Y. Wu, and J. Zechner, 2011, Intermediated investment management, *Journal of Finance* 66, 947-980.

Van Rooij, M., C. Kool, and H. Prast, 2007, Risk-return preferences in the pension domain: are people able to choose? *Journal of Public Economics* 91, 701-722.

Van Rooij, M., A. Lusardi, and R. Alessie, 2011, Financial literacy and stock market participation. *Journal of Financial Economics* forthcoming.

Zhao, X., 2003, The role of brokers and financial advisors behind investments into load funds, Working Paper, SSRN: http://ssrn.com/abstract=438700.

Table 1: Summary Statistics of Individual Investors and portfolio characteristics

The sample consists of 6,145 individual investors that hold common equity positions at least once during the sample period of 52 months. Gross (Net) excess monthly portfolio return is the return in excess of 3 months Euribor. *Gross (Net) Market adjusted return* is the gross (net) monthly return minus the return on the MCSI-Netherlands Index. *Return Volatility* is the standard deviation of the monthly net returns. *Market beta* is the loading on the market factor obtained from using the Fama and French 3 factor model on each individual investor's time series of portfolio returns. *Return residual* is the ideosyncratic component of the factor model described above. *Woman* is the percentage of account held by a woman only. *Joint Accounts* is the percentage of portfolios held by 2 persons, mostly a man and a woman. *Age* is the age of the primary account holder. *Income* is the average gross monthly income in the 6 digit zip code of the investor. *Residential Value* is the average house price in the 6 digit zip code of the investor. *Active months* is the average amount of months that an investor holds a portfolio in our dataset. *Account value* is the beginning of the month account value of common equity. *Common equity positions* is de average number of stocks in each portfolio. *Turnover* is the sum of buys and sells of common equity devided by the beginning of the month account value of common equity.

	All	Advised	Self Directed	Difference Advice-Self Directed	P-Value
Monthly Returns					
Gross Monthly Return (%)	1,63	1,65	1,59	0,06	0,01
Net Monthly Return (%)	1,48	1,51	1,43	0,08	0,00
Gross Market Adjusted return (%)	-0,04	-0,03	-0,07	0,04	0,05
Net Market Adjusted return (%)	-0,20	-0,18	-0,23	0,06	0,01
Observations (#)	193.418	121.413	72.005		
Risk					
Return Volatility (%)	5,45	5,34	5,74	-0,40	0,00
Market Beta	0,72	0,69	0,78	-0,09	0,61
Return residual (%)	2,88	2,72	3,13	-0,42	0,00
Investor Characteristics					
Investors (#)	5.661	3.648	2.013		
Woman (%)	21%	23%	18%	5%	0,00
Joint accounts (%)	44%	44%	45%	-1%	0,00
Age (years)	56,50	58,68	52,86	5,82	0,00
Income (2006) (€)	2.205	2.251	2.131	119	0,00
Residential Value (2006) (€)	151.104	157.130	141.212	15.918	0,00
Active months	44,97	45,45	44,15	1,29	0,00
Portfolio					
Common equity value (€)	44.866	62.534	15.075	47.459	0,00
Domestic equity (%)	92,7%	93,0%	92,3%	0,63%	0,29
Common equity positions (#)	4,44	5,21	3,29	1,92	0,00
Equity Turnover (%)	4,96	5,27	4,39	0,88	0,01
Equity Trades per month (#)	0,56	0,74	0,23	0,51	

Table 2: Financial Advice and Return, Risk, Trades, Cost and Dsiversification, OLS estimates

This table presents coefficient estimates of financial advice on retail investor portfolio return, risk, Trading, Costs, Number of Equity positions and the share of domestic stock using pooled OLS. *Return* is the net monthly equity portfolio returns of each individual portfolio, *Risk adjusted return* is the individual portfolio market beta's adjusted return, Risk is the monthly absolute net return residual that has been calculated using the 3 factor Fama and French (1993) model for each indivudual portfolio. *Trades* is the number of monhtly equity trades in each individual portfolio. *Cost* is is the difference between the gross and net monthly portfolio return, *Number of equity positions* which is the number of individual common stock positions in each individual investor portfolio at the beginning of each month and *Share domestic stock* which is the percentage of portfolio value allocated to domestics common stock position at the beginning of each month. Independend variables are *Advice* which is a dummy variable equal to 1 is an investor is advised, *Age* which is the age of the primary account holder, *Woman* which is a dummy equal to 1 if the account was held by a woman, *Joint Account* which is a dummy variable equal to 1 if the account was held by 2 persons, mostly a man and a woman, *ln(Value)* which is the logarithm of the beginning of the month account value of common equity positions, *ln(Turnover)* which is the logarithm of the sum of buys and sells of common equity positions devided by the beginning of the month account value of common equity positions, *ln(Income)* which is the logarithm of the average gross monthly income in the 6 digit zip code of the investor, *ln(Residential Value)* which is the logarithm of the average house price in the 6 digit zip code of the investor, *Experience* which is the number of months that each investor holds a portfolio during the sample period. In each regression time dummies for each of the 52 months in the sample are used. Portfolios with equity values of below € 250 are excluded. Bootstrapped standard errors (in parentheses) are presented below the corresponding parameters (250 replications), with ***, **, * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

	Log returns	Log risk adjusted returns	Risk	Trades	Costs	No. Equity positions	Share domestic stock
	(2)	(4)	(6)	(8)	(10)	(12)	(14)
Advice	0.000	-0.000	-0.072***	0.003	0.000***	0.348***	0.001
	(0.393)	(0.604)	(0.000)	(0.340)	(0.000)	(0.000)	(0.518)
Age	0.000**	0.000**	0.006***	-0.002***	0.000***	-0.029***	0.000***
	(0.042)	(0.020)	(0.000)	(0.000)	(0.001)	(0.000)	(0.006)
Woman	-0.000*	-0.000	-0.063***	-0.100***	0.000***	-0.609***	-0.005***
	(0.088)	(0.186)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Joint Account	0.000*	0.000	-0.151***	-0.052***	0.000***	0.261***	0.003**
	(0.084)	(0.237)	(0.000)	(0.000)	(0.003)	(0.000)	(0.011)
ln (Value)	0.001***	0.000***	-0.952***	0.227***	-0.001***	4.308***	-0.001
	(0.000)	(0.009)	(0.000)	(0.000)	(0.000)	(0.000)	(0.209)
ln (Turnover)	-0.004***	-0.004***	0.646***		0.007***	0.545***	-0.014***
	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
ln (Income)	0.000	0.001	-0.017	-0.018	0.000	0.590***	-0.023***
	(0.775)	(0.515)	(0.788)	(0.383)	(0.388)	(0.000)	(0.000)
ln (Residential Value)	0.000	0.000	0.173***	0.030	-0.000***	0.153*	-0.071***
	(0.522)	(0.640)	(0.000)	(0.101)	(0.003)	(0.050)	(0.000)
Experience	0.000***	-0.000	-0.005***	-0.008***	-0.000***	0.025***	0.002***
	(0.000)	(0.484)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-0.038***	-0.019***	7.618***	-0.234***	0.008***	-15.795***	1.084***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	154,397	154,396	154,397	154,397	154,397	154,353	154,353
R-Squared	31.3%	9.5%	12.5%	3.7%	23.3%	43.0%	2.3%

Table 3: List of variables

This tables provides an overview of the variables used in various regressions. For each variable is indicated wheter is is time variant or time invariant and wheter we treat the variable as endogenous or exonenous in the Hausman-Taylor specifications.

Variable	Description	Time Variant (TV) or Time Invariant (TI)	Exogneous (Ex) or Endogenous (End)
Advice	Dummy variable that is 1 if the accountholder is advised by advisor from the bank, zero otherwise	TI	End
Woman	Dummy variable that is 1 if the account is held by a woman only	TI	Ex
Joint	Dummy variable that is 1 if the account is held by 2 person, mostly a man and women together	TI	Ex
Age	Age of primary account holder in years	TV	Ex
ln(Income)	Logaritm of gross monthly income in Euro's at 6 digit zip code level in 2006	TV	End
ln(Residential Value)	Logaritm of residential value inEuro's in 2006 at 6 digit zip code level	TV	End
ln(Account Value)	Logaritm of value of all common equity positions at the beginning of each month	TV	End
Turnover	Logaritm of the absolute summ of all buys and sells devided by the beginning of the month account value	TV	Ex
Experience	Number of months that investor hold a portfolio during our sample period	TI	Ex
M1-M51	Time dummies, 1 in a specific month, zero otherwise	TV	Ex

Table 4 The Influence of Financial Advice on risk and Return, Hausman Taylor Estimates

This table presents coefficient estimates on retail investor portfolio return and risk using the Hausman-Taylor technique. Dependent variables are (1) Return which is the net monthly equity portfolio returns of each individual portfolio, (2) Risk adjusted return which is the individual portfolio beta's adjusted return and (3) Risk which is is the monthly absolute net return residual that has been calculated using the 3 factor Fama and French (1993) model for each indivudual portfolio. Advice is a dummy variable equal to 1 is an investor is advised. Age is the age of the primary account holder. Woman is a dummy equal to 1 if the account was held by a woman. Joint Account is a dummy variable equal to 1 if the account was held by 2 persons, mostly a man and a woman. ln(Value) is the logarithm of the beginning of the month account value of common equity positions. ln(Turnover) is the logarithm of the sum of buys and sells of common equity positions devided by the beginning of the month account value of common equity positions. ln(Income) is the logarithm of the average gross monthly income in the 6 digit zip code of the investor. ln(Residential Value) is the logarithm of the average house price in the 6 digit zip code of the investor. Experience is the number of months that each investor holds a portfolio during the sample period. In each regression time dummies for each of the 52 months in the sample are used. Portfolios with equity values of below € 250 are excluded. The reported endogeniety test is a Wald test based on a comparison of fixed and random effect estimators using the Stata Xtoverid command. Bootstrapped standard errors (in parentheses) are presented below the corresponding parameters (250 replications), with ***, **, * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

Dependent variable:	Log returns	Log risk adjusted returns	Risk
	(1)	(2)	(3)
Advice	0.022***	0.029***	-1.488***
	(0.000)	(0.008)	(0.000)
Age	0.000**	-0.000	0.017***
	(0.028)	(0.879)	(0.000)
Woman	-0.002***	-0.003**	0.026
	(0.000)	(0.036)	(0.643)
Joint	-0.001	-0.000	-0.192***
	(0.147)	(0.717)	(0.000)
ln (Value)	-0.009***	-0.008***	-1.220***
	(0.000)	(0.000)	(0.000)
ln (Turnover)	-0.004***	-0.004***	0.597***
	(0.000)	(0.000)	(0.000)
ln (Income)	-0.007	-0.007	-0.039
	(0.144)	(0.213)	(0.895)
ln (Residential Value)	0.006*	0.005	0.020
	(0.094)	(0.143)	(0.929)
Experience	0.000***	-0.000	0.001
	(0.000)	(0.748)	(0.729)
Constant	-0.002	0.015	9.113***
	(0.855)	(0.340)	(0.000)
Observations	154.397	143.941	143.941
Endogeniety test (FE vs RE)	231,92	136,84	548,15
p-value endogeniety test (FE vs RE)	0,00	0,00	0,00
Cluster Robust F-statistic first stage regression (on *Advice)*	19,58	14,10	14,10
p-value Sargan Statistic (HT)	0,82	0,79	0,61
p-value Hansen J Statistic (HT)	0,50	0,47	0,28

Table 5 The Influence of Advice on Trading Activity and Costs, Hausman-Taylor Estimates

This table presents coefficient estimates on retail investor portfolio return and risk using the Hausman-Taylor technique. Dependent variables are (1) Trades, which is the number of monhtly equity trades in each individual portfolio and (2) Cost which is is the difference between the gross and net monthyl portfolio return. Advice is a dummy variable equal to 1 is an investor is advised. Age is the age of the primary account holder. Woman is a dummy equal to 1 if the account was held by a woman. Joint Account is a dummy variable equal to 1 if the account was held by 2 persons, mostly a man and a woman. ln(Value) is the logarithm of the beginning of the month account value of common equity positions. ln(Turnover) is the logarithm of the sum of buys and sells of common equity positions devided by the beginning of the month account value of common equity positions. ln(Income) is the logarithm of the average gross monthly income in the 6 digit zip code of the investor. ln(Residential Value) is the logarithm of the average house price in the 6 digit zip code of the investor. Experience is the number of months that each investor holds a portfolio during the sample period. In each regression time dummies for each of the 52 months in the sample are used. Portfolios with equity values of below € 250 are excluded. The reported endogeniety test is a Wald test based on a comparison of fixed and random effect estimators using the Stata Xtoverid command. Bootstrapped standard errors (in parentheses) are presented below the corresponding parameters (250 replications), with ***, **, * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

Dependent variable:	Trades	Trades	Cost
	(1)	(2)	(3)
Advice	-0.400***	-0.264*	0.002***
	(0.003)	(0.068)	(0.000)
Age	-0.001	0.002	0.000
	(0.497)	(0.620)	(0.185)
Age Squared		-0.000	
		(0.283)	
Woman	-0.075***	-0.084***	-0.000
	(0.001)	(0.001)	(0.669)
Joint	-0.047**	-0.028	0.000
	(0.031)	(0.196)	(0.519)
ln (Value)	0.325***	-1.617***	-0.003***
	(0.000)	(0.001)	(0.000)
ln (Value Squared)		0.249***	
		(0.000)	
ln(Turnover)			0.008***
			(0.000)
ln (Income)	0.142	0.155	0.000
	(0.150)	(0.113)	(0.750)
ln (Residential Value)	-0.080	-0.120*	-0.000
	(0.248)	(0.089)	(0.725)
Experience	-0.010***	-0.009***	-0.000***
	(0.000)	(0.000)	(0.000)
Constant	-0.678**	2.876***	0.010***
	(0.015)	(0.003)	(0.000)
Observations	154,397	154,397	154,397
Endogeniety test (FE vs RE)	105.55	108.83	270.56
p-value endogeniety test (FE vs RE)	0.00	0.00	0.00
Cluster Robust F-statistic first stage regression (on *Advice)*	22.65	16.97	19.58
p-value Sargan Statistic (HT)		0.998	0.303
p-value Hansen J Statistic (HT)		0.999	0.037

Table 6 The Influence of Advice on Diversification, Hausman-Taylor Estimates

This table presents coefficient estimates on retail investor portfolio return and risk using the Hausman-Taylor technique. Dependent variables are (1) Number of equity positions which is the number of individual common stock positions in each individual investor portfolio at the beginning of each month and (2) Share domestic stock which is the percentage of portfolio value allocated to domestics common stock position at the beginning of each month. Advice is a dummy variable equal to 1 is an investor is advised. Age is the age of the primary account holder. Woman is a dummy equal to 1 if the account was held by a woman. Joint Account is a dummy variable equal to 1 if the account was held by 2 persons, mostly a man and a woman. ln(Value) is the logarithm of the beginning of the month account value of common equity positions. ln(Turnover) is the logarithm of the sum of buys and sells of common equity positions devided by the beginning of the month account value of common equity positions. ln(Income) is the logarithm of the average gross monthly income in the 6 digit zip code of the investor. ln(Residential Value) is the logarithm of the average house price in the 6 digit zip code of the investor. Experience is the number of months that each investor holds a portfolio during the sample period. In each regression time dummies for each of the 52 months in the sample are used. Portfolios with equity values of below € 250 are excluded. The reported endogeniety test is a Wald test based on a comparison of fixed and random effect estimators using the Stata Xtoverid command. Bootstrapped standard errors (in parentheses) are presented below the corresponding parameters (250 replications), with ***, **, * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

Dependent variable:	No. Equity positions	Share domestic stock
	(1)	(2)
Advice	0.082	0.162***
	(0.906)	(0.004)
Age	-0.028***	-0.001***
	(0.000)	(0.002)
Woman	-0.573***	-0.011
	(0.000)	(0.292)
Joint	0.231*	0.010
	(0.087)	(0.145)
ln (Value)	4.428***	0.025**
	(0.000)	(0.013)
ln(Turnover)	-0.065***	0.001
	(0.000)	(0.374)
ln (Income)	-0.030	0.004
	(0.943)	(0.831)
ln (Residential Value)	0.554	-0.016
	(0.114)	(0.243)
Experience	0.025***	0.002***
	(0.000)	(0.000)
Constant	-14.926***	0.732***
	(0.000)	(0.000)
Observations	154.353	154.353
Endogeniety test (FE vs RE)	114,662	164,116
p-value endogeniety test (FE vs RE)	0,000	0,000
Cluster Robust F-statistic first stage regression (on *Advice)*	19,58	19,58
p-value Sargan Statistic (HT)	0,95	0,04
p-value Hansen J Statistic (HT)	0,99	0,32