Financial Advisors and Investors' Bias*

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October 31, 2024

Abstract

Can financial advisors mitigate their clients' investment biases? We answer this question by exploiting a natural experiment at a large brokerage firm that provides advisory services to high-net-worth investors. In 2018, the firm changed the information displayed on its internal platform so that financial advisors could no longer observe which of their clients' holdings were in paper gain or loss. Using data on portfolio stock transactions between 2016 and 2021, we show that, while all investors exhibit a significant disposition effect before 2018, i.e., a greater propensity to realize paper gains than losses, highly-advised investors see their bias significantly reduced after 2018. This decrease in disposition effect bias leads to higher portfolio returns, increased client inflow, and a lower likelihood of leaving the firm. Our study highlights how manipulating advisors' information can help mitigate investors' biases.

Keywords: financial advisors, behavioral finance, disposition effect, investor behavior, salience, attention, household finance

JEL codes: G4, G5, D14, G11, G24

*We thank Francesco D'Acunto, Mark Egan, Cary Frydman, Valentin Haddad, Xing Huang, Augustin Landier, Terrance Odean, Alessandro Previtero as well as conference and seminar participants at the Adam Smith Junior Workshop 2023, LBS, USC, UCLA, GT-FRBA Household Finance Conference 2024, New York Fed / NYU Stern Conference on Financial Intermediation (2024), UIC First Finance Conference (2024), FIRS 2024, NBER Summer Institute Household Finance (2024) for helpful comments. The authors acknowledge financial support from the Geneva Institute for Wealth Management.

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1 Introduction

An extensive literature documents the role of behavioral biases in retail traders' investment decisions, e.g., overconfidence (e.g. Daniel et al., 1998; Odean, 1998b; Ben-David et al., 2013), extrapolation (Da et al., 2021), neglect of trading costs (e.g. Barber and Odean, 2000; Bordalo et al., 2012), gambling preferences (e.g. Shefrin and Statman, 2000; Barberis and Huang, 2008) or the disposition effect, i.e., the tendency of retail investors to cash-in gains and avoid realizing losses (e.g. Odean, 1998a; Grinblatt and Han, 2005). A standard view heralded by investment professionals is that financial advisors can help retail investors overcome these biases. For instance, a survey of more than 300 financial advisors by Charles Schwab reports that 49% believe incorporating behavioral finance insights can help improve clients' financial decisions (Cheses, 2019). On its webpage, Charles Schwab argues that "advisors can play a valuable role in educating clients about these biases". At the same time, research has shown that even investment professionals suffer from behavioral biases: for instance, Frazzini (2006) finds a disposition effect in the trading of U.S. mutual fund managers; traders from the CBOT exhibit myopic loss aversion (Haigh and List 2005; see also Larson et al. 2016); overconfidence is observed among professional traders and investment bankers (Glaser et al., 2013). The "money doctor" view of financial advising also suggests that managers may pander to investor beliefs when investors hold biased expectations, casting doubt on the debiasing role of financial advisors (Gennaioli et al., 2015). Whether financial advisors mitigate their clients' investment biases remains an empirical question, which we address in this paper.

To establish the role of advisors on their clients' investment bias, specifically their disposition effect, we leverage a quasi-natural experiment conducted at a large French brokerage and financial advice service firm in January 2018: prior to this date, financial advisors used an online platform that displayed the average acquisition prices for all the assets in their clients' portfolios, and saliently highlighted which positions were experiencing paper gains or losses; in January 2018, the average purchase prices and gain/loss information were removed from the advisors' platform.[1] In contrast, the platform used by clients remained the same throughout the sample period, so the information directly available to them, including average purchase prices, was unchanged. This experiment, which provides variations in the information set of financial advisors while keeping that of their clients constant, is helpful to test advisors' role in mitigating their clients' investment biases. If advisors actively help to reduce the disposition effect, we would expect that removing access to the information they need to identify their

[1] At the same time, the firm also introduced on advisors' platform a proprietary stock-level momentum indicator. We show in Section 5.1 that this did not affect clients' trading behavior.

clients' bias, i.e., information about paper gains and losses, would make them less effective, leading to a surge in their clients' disposition effect after January 2018. If, instead, financial advisors amplify their clients' bias, preventing them from observing the price at which clients acquired their positions should reduce the observed disposition effect.

Our empirical analysis exploits data on all stock transactions operated at the firm by 7,494 investors between February 2016 and May 2021. While prior work on financial advice has mainly studied retail investors' allocations to delegated managed portfolios, the transactions in our data are direct individual stock purchases and sales.[2] The firm's clientele primarily consists of affluent investors: the average equity portfolio in our data is worth 100,000 euros, and 225 portfolios have a value above 1 million euros. While these figures may seem modest compared to studies involving wealthy US pension fund investors (e.g. Giglio et al., 2021), the portfolios in our sample represent only a small portion of investors' financial wealth since they do not include pension savings, which are mostly invested through the French pay-as-you-go pension system.[3]

Despite investors' sizable net worth, trades in our sample exhibit a significant disposition effect: prior to 2018, conditional on selling at least one stock in a given month, investors are nearly twice as likely to sell assets in paper gains than in paper losses; for more than 95% of investor-months in our sample, the share of paper gains realized is greater than the share of paper losses realized. This disposition effect is similar in magnitude to the one measured by Odean (1998a) on U.S. retail investors, even though our sample contains wealthier investors on average.

A unique feature of our setting is that we observe whether investors receive advice from a personal financial advisor, and, if so, who their advisors are, the recommendations they receive, and whether they have frequent or infrequent interactions. In our sample, 60% of investors have a financial advisor, and the remainder trades independently.[4] In the cross-section of investors, advised investors tend to exhibit a smaller disposition effect.[5] However, this cross-sectional comparison may not capture the causal effect of advisors on reducing their clients' biases. Instead, it may reflect the different characteristics of advised vs. independent clients, as non-advised clients tend to hold smaller, less diversified portfolios, to trade more frequently,

[2]Specifically, 80% of clients' assets in our sample are invested in individual stocks, only 10% are held in mutual funds, and the remaining 10% is in cash.

[3]Less than 10% of the French population holds stock portfolios, source AMF (Autorité des Marchés Financiers), November 2023.

[4]Notably, all investors in our sample retain the final decision on which assets to trade: even when receiving advice from the firm, they do not delegate portfolio management to their financial advisors.

[5]The rank effect (Hartzmark, 2015), another well documented trading bias, i.e., the tendency to sell positions with "extreme" paper returns (ranked best or worst return asset since purchase), is not significantly different across investors in our database, advised or not.

and to have lower portfolio returns. Clients in our database are either advised throughout the sample period or not-advised throughout, so we cannot measure how the disposition effect of an individual investor may change after she starts receiving advise from the firm.

To evaluate the effect of advisors on their clients' disposition effect, we turn to our experimental setting. We observe a significant reduction in the average disposition effect of advised customers following the experiment: pre-2018, advised investors are 50% more likely to realize gains than losses and only 20% more likely to do so after the experiment. However, this finding must be interpreted cautiously as other shocks may have coincidentally affected advised investors' trading behavior. To tighten identification, we exploit investors' heterogeneity *within advised clients* in terms of exposure to financial advisors: some investors (*highly-advised*) have frequent contacts with their advisors (every week or every other week) while other investors have more infrequent communications (*lightly-advised*). This allocation of clients into different profiles of advising "intensity" is determined by the firm management during clients' intake process, according to their willingness to have regular discussions with their advisor, and is not communicated to clients. Our main empirical strategy thus compares the trading behavior of highly- and lightly-advised investors around the experiment.

We first check the relevance of this strategy by confirming that financial advisors have more influence on highly-advised clients' trading decisions. To do so, we rely on a particular feature of our institutional setting: every week, the brokerage firm's investment committee issues recommendations – a list of stocks it recommends buying or selling. We show that, compared to lightly-advised investors, highly-advised clients are significantly more likely to buy (sell) stocks once they enter the buy (sell) recommendation list: while a stock on the buy (sell) list has a 24 bps (23 bps) higher probability of being purchased (sold) than a random stock on any given day, this probability is 8.2 bps (10.1 bps) higher for highly-advised clients, a significant increase in the baseline probability. This effect is observed right after the stock is added to the buy list and persists 5-7 weeks after the recommendation is issued.

We then use a standard difference-in-difference strategy to evaluate the effect of the experiment on investors' disposition effect biases. Our identification relies on a standard parallel trend assumption: had the experiment not occurred, the disposition effect displayed by highly- and lightly-advised investors would have evolved similarly after 2018. Visual inspections of pre-trends are consistent with this assumption.

We first implement our difference-in-difference analysis using data aggregated at the profile-month level: for each investor profile (i.e., lightly- or highly-advised) and each month, we calculate the total number of stocks sold when in paper gain; we also calculate the total number of stocks that were in paper gain on any day a sale was realized; the ratio of these two numbers – the proportion of gains realized (PGR) – measures the propensity to sell winner stocks in a given month for both investor profiles. We construct the proportion of losses realized (PLR) similarly. The ratio PGR/PLR measures the disposition effect for a given investor profile in a given month, with PGR/PLR -1 quantifying the strength of the bias. Consistent with prior literature (see e.g. Odean, 1998a), we find that investors exhibit significant disposition effect biases in their trading behavior: on average, prior to the experiment, both highly- and lightly-advised investors are about 1.5 times more likely to realize their paper gains than their paper losses when they sell an asset (i.e., PGR/PLR = 1.5). We find no significant difference in the PGR/PLR ratio of highly-advised versus lightly-advised investors in pre-January 2018. However, the PGR/PLR for highly-advised investors decreases significantly after the experiment (from PGR/PLR = 1.5 to PGR/PLR = 1.1 on average) and becomes significantly lower than that of the lightly-advised. These findings reject the null hypothesis that advisors use information about their clients' gain vs. loss positions to mitigate their clients' disposition effect bias.

We present several important robustness checks that confirm this interpretation. First, we show that our results are qualitatively similar when we aggregate the data at the investor-month level instead. Using investor-month level data allows us to include investor fixed effects, which control for unobservable constant characteristics that may systematically differ between lightly- and heavily-advised clients. It also allows us to include advisor-month fixed effects, i.e., to compare clients with different profiles (highly- and lightly-advised) but advised by the same advisor. Second, our main result also holds when we use investor-stock-day level regressions, where we control for time-varying stock characteristics and include advisor-day, stock-day, and investor-day fixed effects. Third, our conclusions remain unchanged if we use a matching estimator where we match highly-advised clients to lightly-advised ones based on pre-2018 portfolio characteristics, including total assets, number of stocks, and propensity to sell stocks. Fourth, we show that other changes made to the advisors' platform – the introduction of a proprietary stock-level momentum indicator – did not affect investors' selling behavior.

Finally, we investigate whether the experiment affected investors' portfolio performance. We find that, relative to lightly-advised clients, highly-advised investors experience a significant increase in raw portfolio returns after 2018 of about 20 basis points per month. This increase in performance is consistent in magnitude with Odean (1998a) who finds that retail investors' returns would be 3.4 percentage points higher over a year if they had sold paper losses instead of paper gains.[6] We show that the increase in portfolio returns is driven by greater exposures to

[6]See also Choe and Eom (2009) who find a significant decline in performance due to the disposition effect. Odean (1998a) estimates an additional one percentage point (p.p.) per year tax advantage in selling paper

the momentum strategy and lower exposures to value stocks. The risk-adjusted returns against the four-factor model – Fama-French 3 factors (Fama and French, 1992) and momentum – do not increase significantly for highly-advised versus lightly-advised clients in the post-period. We also find evidence consistent with increased satisfaction by highly-advised clients in the form of a significant increase in inflows into their portfolios and a reduced likelihood of liquidating their accounts.

Related literature. Our paper contributes to the literature on behavioral biases in investment decisions (see Liu et al. 2022 for a recent review), and in particular on the disposition effect (Shefrin and Statman, 1985, 2000). There is ample evidence of a disposition effect for retail investors (e.g. Odean 1998a for U.S. retail investors, Feng and Seasholes 2005a in China, Shapira and Venezia 2001 in Israel, Grinblatt and Keloharju 2001 and Seru et al. 2009 in Finland). Professional traders' investment decisions also display a significant disposition effect (Heisler, 1994; Locke and Mann, 2005). Studies of the disposition effect among mutual fund managers report mixed results (see Frazzini 2006 for evidence supporting the disposition effect for mutual fund managers; in contrast, O'Connell and Teo 2009 show that institutional investors are not prone to the disposition effect but instead to dynamic loss aversion). Li et al. (2021) show that the disposition effect of mutual fund investors in China is amplified in periods of higher air pollution. An et al. (2023) show that the disposition effect is concentrated in portfolios that are in net paper loss; it does not occur for portfolios in net paper gain. Closest to us, Frydman and Rangel (2014) and Frydman and Wang (2020) show, in a lab experiment and in a quasi-natural experiment at a Chinese bank respectively, that the salience of the display of investors' paper gains and losses reinforces the disposition effect. Our paper contributes to this literature in two unique ways. First, we show clear evidence of a disposition effect among *high net-worth retail investors*.[7] While the literature has typically used samples from retail brokerage accounts or the universe of retail trades, our paper is the first to rely on a large sample of wealthy investors' trades. Second, our paper provides *causal evidence* on the role of financial advisors in mitigating investors' disposition effect.[8]

Our paper also relates to the literature on financial advisors and their influence on retail in-

losses rather than gains. Similar tax considerations in our sample would also increase the wealth benefits to the highly-advised in the post-period.

[7] Relatedly, Bender et al. (2022) use a survey of U.S. individuals with at least $1 million of investable assets to show what drives wealthy investors' decisions and how these factors differ from the average U.S. investor. Giglio et al. (2021) and Gabaix et al. (2023) analyze portfolio rebalancing decisions in databases of investors that include very high net worth individuals. However, since they do not have transaction-level data, these papers do not discuss trading biases like the disposition effect.

[8] In a lab experiment, Rotaru et al. (2021) show that being asked to build an optimal portfolio for another (e.g., a client) reduces one's own disposition effect. This indicates advising clients may reduce financial advisors' disposition effect bias in their personal portfolios, which is orthogonal to our study.

vestors' trading behaviors (see Beshears et al. 2018 for an extensive discussion). While financial advisors may facilitate stock market participation (Linnainmaa et al., 2020), a growing body of evidence suggests that they offer poor advice. Several papers have found significantly lower performances for retail traders investing with an advisor (Hoechle et al., 2018; Bergstresser et al., 2009; Chalmers and Reuter, 2020; Hackethal et al., 2012; Guercio and Reuter, 2014; Reuter, 2015; Battiston et al., 2021).[9] Mullainathan et al. (2012) use an audit study to show that advisers fail to de-bias their clients, encouraging returns-chasing behavior and pushing for actively managed funds with higher fees. Célérier and Vallée (2017) show that banks profit from advisors recommending risky and complex structured products which yield comparatively low returns to their clients. Bhattacharya et al. (2023) show that women receive worse advise from financial planning firms than men. Foerster et al. (2017) use Canadian data to measure advisors' influence on their clients' allocations to different mutual funds. They find that clients and advisors take similar amounts of portfolio risk and that clients underperform passive benchmarks. Linnainmaa et al. (2021) show that this similarity is due to beliefs and not incentives as advisors typically invest on their own account just as they advise their clients: they trade frequently, chase returns, prefer expensive and actively managed funds, and under-diversify. In the context of our analysis on the disposition effect, it is important to note that the financial advisors in Foerster et al. (2017), Linnainmaa et al. (2020), and Linnainmaa et al. (2021) only provide advice on mutual funds and not on single stocks, which may affect trading biases: Chang et al. (2016) argue that U.S. retail investors exhibit a significant disposition effect only for non-delegated assets (i.e., single stocks they purchase themselves). D'Acunto et al. (2019) show that robo-advising can help mitigate investors' biases such as the disposition or the rank effect.[10] Our paper contributes to this literature by studying how financial advisors affect direct stock trading and by leveraging a quasi-natural experiment to estimate the causal effect of human financial advisors on their clients' investment biases, particularly their disposition effect.

2 Institutional Setting

2.1 Institution

Our dataset comes from Portzamparc, a large French brokerage firm, hereafter referred to as "the firm". This firm is a division of a leading banking group and provides brokerage services to affluent individual investors with high-net-worth in France. The firm also has a dedicated

[9] Relatedly, Egan et al. (2019) examine the market for financial misconduct and provide evidence that some firms cater to unsophisticated consumers so that they can get away with higher levels of misconduct.

[10] Kumar (2023) studies the impact of robo-advisors on the corresponding financial advisors labor market.

discretionary asset management subsidiary, which directly manages a \$600 million portfolio on behalf of clients. Our analysis, however, solely focuses on the trading decisions of clients who use its brokerage services and does not use any information related to the asset management subsidiary.

Investors in our study are, on average, wealthy: even though we observe only their financial wealth invested in direct stock trading at the firm, i.e., a plausibly small fraction of their total wealth, the average equity portfolio in our data is worth $100,000$ euros, and 225 portfolios have a value above 1 million euros. Clients hold relatively undiversified positions and trade rarely. Most assets traded by clients within our dataset are individual stocks (80% of total portfolio holdings). 10% of their portfolio holdings are mutual funds, and the remaining 10% is in cash.

The firm offers two types of brokerage products: (i) non-advised services, providing autonomous access to brokerage facilities, and (ii) advised services, granting autonomous access to brokerage facilities and professional advisory support. When clients join the firm, they decide to be either *advised* or *not advised.* Irrespective of their choice, clients have online access to their accounts, enabling them to buy and sell assets. The firm generates revenue through commissions from transactions and advisory fees.

Most (60%) of the clients opt to be advised, in which case they are matched with one of 45 financial advisors. These advisors provide personalized advice, usually through phone conversations, which can be initiated either by the clients or their advisors. The client-advisor "matching" is random, depending on the availability of financial advisors when new clients join the firm. Given information obtained during the intake process, advisors allocate their clients into different profiles defined by the firm management, e.g., conservative versus risk-taker. The firm does not communicate this internal profile system to its clients. Importantly, one dimension used for this profiling is the client's willingness to discuss with her advisor frequently. We group advised-customers' profiles into two categories based on the firm's internal classification: (1) *lightly-advised* who prefer to trade more independently and to have rare contacts with their advisors, and (2) *highly-advised* who want strong guidance and discuss with their advisors frequently, typically every week or every other week. Importantly, investors are either advised throughout our study or not advised throughout; when advised, they are either highly-advised throughout or lightly-advised throughout: we do not observe clients switching across categories.

Beyond personalized advice, financial advisors relay to their clients the recommendations of the firm's investment committee. The investment committee, comprising advisors, fund managers, and other executives, monitors around 2,000 stocks at any time. Large-capitalization stocks from both the United States and Europe constitute the majority of monitored stocks and clients' portfolios. Every week, approximately one hundred of the monitored stocks are selected to form a list of buy/sell recommendations for advisors to use and convey to their clients in phone conversations. More specifically, the weekly recommendation list contains four categories: (1) "buy", (2) "buy more of", (3) "sell some of", and (4) "sell". Clients can only access these recommendations via conversations with their advisors.

There are 45 distinct advisors in our sample. On average, each advisor is assigned about 150 clients. Advisors' compensation includes a fixed wage and a bonus based on their clients' portfolio returns, the number of transactions their clients make, and qualitative criteria (e.g., the number of clients' complaints). Advisors must provide recommendations based on the firm's weekly investment list. However, they can also provide information and advice on any stock for which the clients express interest.[11]

Whether they choose to be advised or not, the final choice to buy or sell an asset remains solely the clients' decision.

2.2 Quasi-Experimental Setting

Clients' information All of the firm's customers who use its brokerage services have an online access to their accounts, enabling them to buy and sell assets. Irrespective of whether they opt to be advised, this online platform provides clients with the same information. As shown in the platform screenshot in Figure 1, the clients can observe their portfolio's current total value ("Valeur totale"), as well as the total value of their stock and cash portfolios ("Valorisation titres" and "Valorisation espèce"), and the weight of each asset class ("Poids" (weight) column in "Espèce" (cash) and "Actions" (stocks)). It also shows, for each asset in the portfolio its current value ("Valorisation"), the weight in the portfolio ("Poids (%)"), the average purchase price ("PAM") and the average gain/loss on each position in Euros ("PMVL").[12] Paper gains and losses are saliently reported with color coding (losses in red and gains in green). Importantly, the information on the online platform and its display remained unchanged throughout the sample period we analyze.

Advisors' information Financial advisors have access to an online platform that provides information about each of their clients' portfolios. Prior to January 2018, the advisors' platform and the clients' platform were the same, as described above and in the screenshot of Figure 1.

[11] Advisors have access to standard financial information for all stocks. In addition, for the 2,000 stocks that the firm monitors, the firm provides a proprietary momentum rating ("BCAP"), which we discuss below and in Section 5.

[12] The platform also provides the ISIN code for each asset ("Regroupement"), the stock name ("Libellé valeur"), the number of stocks in the portfolio ("Quantité"), the current stock price ("Cours") and the stock industry ("Secteur économique")

In January 2018, the firm rolled out a change in the advisors' platform design, which was completed by May 2018.[13] The firm did not communicate about the new advisors' platform so that clients were likely unaware of this change.

Figure 2 provides a screenshot of the new advisors' platform. There is common information across the old and new displays (e.g., the list of assets in clients' portfolios and their weights). Some information is added to the new platform: for each asset, the realized returns over the past three months ("Rendement"), the stock total market capitalization ("Capitalisation"), the asset ESG rating ("Note ESG"), as well as three proprietary ratings constructed by the firm to capture stocks' momentum relative to different benchmarks ("BCAP Abs.", "BCAP ReL Marché", "BCAP ReL Secteur"; and "Note BCAP", which summarizes the three ratings). While these ratings became more prominently displayed in the new advisors' platform, the investment committee was already providing this information to advisors prior to 2018. We show in Section 5 that the display of these ratings did not impact on clients' disposition effect biases.

Finally, some information present on the investors' platform is no longer shown on the advisors' platform: the market value of each position, the number of stocks held, and, most importantly, the average acquisition price and the corresponding paper gain or loss. We thus interpret the change in information display as a quasi-natural experiment that made it harder for advisors to observe their clients current paper gains and losses.

Motivation behind the new platform The primary rationale for introducing the new advisors' platform was to limit the disposition effect observed on clients' selling decisions. The firm was worried that advisors were either catering to their clients' bias or even amplifying it, either because of their own bias or because of agency issues.[14] In the firm's view, the disposition effect is costly for their clients for two reasons: (1) portfolio performance – the disposition effect leads to higher taxes and might reduce portfolio returns due to momentum (2) extreme negative returns – by keeping losers in the portfolio, clients with a strong disposition effect might end up having positions with significant negative returns; the firm believes that such large negative returns on individual positions might lead clients to close their entire portfolio. Section 5 discusses how the experiment affected clients' realized performance and their likelihood of liquidating their accounts.

[13]The rollout was done progressively across advisors. However, we do not have the precise date at which each advisor was provided with the new platform.

[14]For instance, advisors might be reluctant to advise clients to sell losses, fearing that clients might draw negative inference about the advisor's quality from the realized loss.

Client heterogeneity About 40% of investors in our sample only use the brokerage service of the firm and do not receive any advice. These (*not-advised*) clients can serve as a first control group in our quasi-natural experiment. However, as we show in Section 3, they differ substantially from advised clients on observable characteristics. Thus, we rely on heterogeneity within advised investors for identification purposes. As described above, based on an intake questionnaire, advised clients are sorted into three groups when they join the firm: "follower", "defensive", or "independent". The firm estimates that "follower" and "defensive" investors talk to their advisors two to four times per month and that "independent" investors have less than one call per month. Accordingly, we group advised investors into two categories: *highly-advised* ("follower" and "defensive") and *lightly-advised* ("independent") clients.[15]

Disposition effect bias After the introduction of the new platform in January 2018, financial advisors can no longer directly observe paper gains and losses in their clients' portfolios. This setting provides us with a quasi-natural experiment ideally suited to identify the causal effect of financial advisors on their clients' disposition effect bias. In particular, an essential advantage of our empirical setting is that other factors that may affect investors' disposition effect (e.g., the display on the clients' online platform or the capital gain tax rate) remain unchanged with the introduction of the new advisors' platform.[16] We acknowledge, however, that while the quasi-natural experiment setup allows us to identify *how* financial advisors influence their clients' disposition effect, it does not help us precisely explain *why* they do so. As mentioned before, advisors may be catering to their clients' biases because of their own bias, because of agency issues, or to pander to their clients' beliefs as "money doctors" (Gennaioli et al., 2015).[17] These "rationales" for why advisors may amplify their clients' disposition effect are unchanged by the introduction of the new platform, so we cannot identify which channel operates.

[15] Unfortunately, we do not have data on the frequency of investor phone calls over our sample period. We obtained data on the total number of phone calls made by 34 advisors in September 2023. In the cross-section of advisors, there is a significant positive relationship between the number of calls made by an advisor and the number of her clients who are highly advised: a 1% increase in the number of highly-advised clients increases the number of calls by .4%, while a 1% increase in the number of lightly-advised investors increases the number of calls by .2% (see Appendix Table A.1).

[16] In Section 4 and Section 5, we analyze and rule out the influence of possible changes in market conditions and the type of advice provided.

[17] It would be interesting to analyze whether new advisors who "inherit" clients' portfolios are more inclined to have them realize losses they, as advisors, cannot be held responsible for, similar to Jin and Scherbina (2011). However, we do not have information on advisor switchings. In Appendix Table A.2, we analyze whether there is a greater disposition effect for assets purchased following a "Buy" recommendation from the firm, for which the advisors may feel more direct responsibility than for other positions in their clients' portfolios. We find no significant difference in the disposition effect.

3 Data and Summary Statistics

Sample Description Our dataset covers all the firm's clients using their brokerage service. Our sample contains $7,494$ clients. The sample period starts in February 2016 and ends in May 2021. The data set consists of three files: a trade file, a position file, and an investment committee recommendation file.

The trade file contains account-date-asset level information. It reports every transactions made by each client over the sample period. We focus on individual stock transactions, representing more than 90% of all transactions and totaling approximately 1.6 million transactions. Each transaction comes with a trade execution date, a stock identifier (ISIN code), a number of shares purchased/sold and the transaction amount. We obtain stock daily market prices from the CRSP-COMPUSTAT database.

The position file provides end-of-month snapshots of clients' portfolios. For each client, the file provides reporting dates, identifiers for all stocks owned, the numbers of shares held, positions' market values, and the average purchase price for each position.

The recommendation file archives the weekly investment recommendations made by the investment committee. Each weekly recommendation record includes approximately 100 stocks and comprises recommendation dates, stock identifiers, and the nature of the recommendation. Recommendations fall into one of four categories: "buy" and "buy more of", consolidated as "Buy Recommendation" in our analysis, or "sell" and "sell some of", which we consolidate as "Sell Recommendation".

For advised clients, our dataset also contains the client's "type" (lightly- and highly-advised), as well as the unique identifier of the advisor assigned to each client as of May 2021.[18] Our sample features 45 distinct financial advisors. Because of confidentiality issues, we do not have access to clients' and advisors' demographic information, such as gender, age, or education and could not obtain qualitative information collected by the firm through clients' surveys.

Finally, our dataset includes the firm's proprietary momentum rating system – the "BCAP" index. The "BCAP" index serves as a momentum indicator, calculated using moving averages of stock prices at various horizons, both in absolute terms and relative to benchmark indices and sectors. This index ranges from 0 to 100, and is mapped into rating letters (B, C, A, or P). Further details on the BCAP ratings are provided in Section 5.

From the trade and position files, we compute portfolio returns as follows. For each client i and day t, we determine portfolio weights for each stock at the end of the previous day

[18] While, in principle, clients can change advisors, the firm told us that, in practice, such changes are extremely rare. We thus assume in our empirical analysis that the advisor assigned in May 2021 to a client remains the same throughout the sample period.

$(t-1)$ and then compute the portfolio daily return on day t as the weighted average of stock returns on day t. Monthly returns are then derived by compounding the daily portfolio returns over the month. For each individual stock in our sample, we calculate their beta against the Fama-French 3 factors (market, size and value) and momentum. Factor returns are obtained from Ken French's website. Betas are computed through a regression of daily stock returns on the corresponding factor returns, using a three year rolling window.[19] Each stock's daily risk-adjusted return is obtained by subtracting from the stock's return the product of the stock's betas and the corresponding factors' return. Finally, we compute the daily betas for each portfolio as the weighted average of the betas of constituent stocks. We derive the daily risk-adjusted returns for each portfolio as the weighted average of risk-adjusted returns of stocks in the portfolio. Monthly risk-adjusted returns are computed by compounding the daily risk-adjusted returns over the month.

Descriptive Statistics Table 1 provides summary statistics for clients' portfolios over our sample period. Panel A reports statistics for highly-advised clients (3,756 investors), Panel B for lightly-advised clients (748 investors) and Panel C for the set of clients who do not receive financial advice (2,990 investors). There are 44 distinct advisors providing services to highly-advised investors, and 42 to lightly-advised investors. In total, out of the 45 financial advisors in our sample, 41 advise both types of clients.

Advised investors hold more assets than independent clients (about 144,000 euros vs. 58,000 euros on average). Within advised investors, the lightly-advised have larger average holdings (about 180,000 euros vs. 137,000 euros). The distribution of portfolio size is naturally right-skewed: the median is 71,000 euros for highly-advised investors, 55,000 euros for the lightly-advised and 18,000 euros for clients who are not advised; 225 distinct accounts are above 1,000,000 euros. Appendix Figure A.1 provides an histogram of the distribution of total portfolio size across the three categories of investors.

Clients' portfolios exhibit limited diversification. On average, highly-advised clients hold 11 stocks, lightly-advised clients hold 10 stocks, and non-advised clients 8 stocks. In each case, the median number of stocks held is lower (9, 7 and 4 respectively). Stock positions sold during our sample period were held an average 195 days for highly-advised clients, 226 days for the lightly-advised, and 323 days for the not advised. These average holding periods conceal substantial heterogeneity. For instance, 25% of stock positions sold by highly-advised clients are held for less than 82 days.[20] This number is similar to the median holding period of retail

[19]We use either the US or European factors, depending on the stock's geographical location.

[20]Appendix Figure A.2 shows a histogram of the distribution of holding periods for each investor type.

investors reported in Odean (1998a) in a different context (US retail brokerage data). Given these extended holding periods and the small number of stocks in their portfolio, investors in our sample trade infrequently. On average, highly-advised clients trade 11 times per year, the lightly-advised 18 times, and the not advised 19 times.[21]

Average portfolio returns are larger for highly-advised investors (1.05% per month) than for the lightly-advised (0.57% per month) and the not advised (0.25% per month). Risk-adjusted returns (against the Fama-French 3-factors and Momentum) follow a similar pattern: they are higher for highly-advised investors (-0.35% per month) than for the lightly-advised (-0.60% per month) and not advised clients (-0.78% per month).

4 Empirical Analysis

4.1 Advisors' Influence on Clients

Our empirical strategy relies on the assumption that investors classified as highly-advised are more likely to be influenced by their advisors than lightly-advised clients. We test this assumption by leveraging data on weekly recommendations issued by the firm's investment committee. These recommendations are provided to all advisors who subsequently present them to their clients (see Section 2). In the data, the recommendations appear to influence investors' portfolio decisions: on average, 57% of the stock purchases we observe correspond to stocks recommended as "Buy" on the week they are purchased; 34% of stock sales correspond to stocks recommended as "Sell" that week. Below, we test whether these recommendations have greater influence on highly-advised clients.

We estimate the following regression model on the set of advised customers:[22]

$$\begin{aligned} 100 \times Sell_{i,j,t} = {} & \beta_s SellReco_{j,t} + \beta_{sh} \left\{ SellReco_{j,t} \times HighlyAdvised_i \right\} \\ & + \beta_b BuyReco_{j,t} + \beta_{bh} \left\{ BuyReco_{j,t} \times HighlyAdvised_i \right\} \\ & + FE_i + FE_j + FE_t + \epsilon_{i,j,t}, \end{aligned} \tag{1}$$

[21] The difference between highly- and lightly-advised investors is quantitatively limited, but nevertheless statistically significant at the 5% confidence level for the average number of stocks in the client's portfolio, and the client's average daily likelihood of selling one or several stocks. As a result, beyond our difference-in-difference design, we also provide matching analyses that specifically match both types of investors based on these two variables and total assets.

[22] The computing resources provided by the firm do not allow us to run regressions that include all investor-stock-day observations, including those for not advised investors. As a result, we run regressions (1) and (2) on advised clients only. Since our analysis aims to test the differential response of highly-advised and lightly-advised clients to recommendations, excluding non-advised investors is justified.

$$
\begin{aligned}
100 \times Buy_{i,j,t} = {} & \gamma_s SellReco_{j,t} + \gamma_{sh} \{SellReco_{j,t} \times HighlyAdvised_i\} \\
& + \gamma_b BuyReco_{j,t} + \gamma_{bh} \{BuyReco_{j,t} \times HighlyAdvised_i\} \\
& + FE_i + FE_j + FE_t + \epsilon_{i,j,t}
\end{aligned} \tag{2}
$$

where i, j, and t denote investor, stock, and day. $Sell_{i,j,t}$ ($Buy_{i,j,t}$) equals one if investor i sells (buys) stock j on day t and zero otherwise. $SellReco_{j,t}$ ($BuyReco_{j,t}$) is a dummy equal to one if the investment committee recommends selling (buying) stock j on the week of day t. $HighlyAdvised_i$ is a dummy equal to one if investor i belongs to the highly-advised category. FE_i, FE_j and FE_t are respectively investor, stock and day fixed effects. Standard errors are double clustered at the investor and day level. A positive β_s (γ_b) implies that, on average, investors are more likely to sell (buy) stocks on the sell (buy) recommendation list. A positive β_{sh} (γ_{bh}) indicates a stronger effect for highly-advised investors. Our hypothesis is that β_s, γ_b, β_{sh}, and γ_{bh} (β_b, γ_s, β_{bh}, and γ_{sh}) are positive (negative).

Columns (1) and (3) of Table 2 present estimates of Equation (1) and (2) respectively. Columns (2) and (4) estimate regressions that further add investor-day fixed effects. From column (1), the probability that a lightly-advised investor sells a stock is .23 percentage points (p.p.) higher for stocks on the sell recommendation list and .05 p.p. lower for stocks on the buy list, both significant at the 1% confidence level. However, these coefficients could reflect stock-level omitted variables that explain why particular stocks are attractive to both retail investors and to the firm's investment committee. Instead, the interaction terms β_{bh}, β_{sh}, γ_{bh} and γ_{sh} capture how receiving more frequent advice influences the clients' portfolio decisions, under the assumption that lightly and highly-advised investors respond to information in a similar way. We find that relative to lightly-advised investors, the highly-advised are .1 p.p. more likely to sell stocks on the sell list and .06 p.p. less likely to sell stocks on the buy list. Similarly, column (3) shows that they are .08 p.p. more likely to buy stocks on the buy list and .1 p.p. less likely to buy stocks on the sell list. All coefficients are significant at the 1% confidence level. These findings are robust to including investor-day fixed effects (columns (2) and (4)). We also find similar results on the *intensive* margin of trading: rather than using a buy and sell dummy as dependent variables, Appendix Table A.3 (A.4) use the number of shares (amount) of stock j sold or purchased. These findings confirm that separating investors into highly and lightly-advised captures variations in financial advisors' influence on portfolio choices.

We tighten our interpretation of these findings by considering the dynamics of selling and purchasing behaviors around changes in the committee's recommendations. Using an event-study specification, we show a sharp increase in the probability of trading a stock right after it is included in the recommendation list, especially for highly-advised investors. The timing of this response reinforces our interpretation that financial advisors affect their clients' portfolio choices.

Specifically, we estimate the following regressions at the investor-stock-day level:

$$\begin{aligned} 100 \times Sell_{i,j,t} = & \sum_{k=-4}^{+8} \left(\beta_{s,k} SellReco(k)_{j,t} + \beta_{sh,k} \left\{ SellReco(k)_{j,t} \times HighlyAdvised_i \right\} \right) \\ & + FE_i + FE_j + FE_t + \epsilon_{i,j,t}, \end{aligned} \tag{3}$$

$$\begin{aligned} 100 \times Buy_{i,j,t} = & \sum_{k=-4}^{+8} \left(\gamma_{b,k} BuyReco(k)_{j,t} + \gamma_{bh,k} \left\{ BuyReco(k)_{j,t} \times HighlyAdvised_i \right\} \right) \\ & + FE_i + FE_j + FE_t + \epsilon_{i,j,t} \end{aligned} \tag{4}$$

where i, j, and t denote investor, stock, and day. k measures the weeks between day t and the recommendation event: $SellReco(k)_{j,t}$ ($BuyReco(k)_{j,t}$) is an indicator variable equal to one if the recommendation on stock j switches to "Sell" ("Buy") k weeks before day t when $k \geq 0$, such that the recommendation remains unchanged until day t, or k weeks after day t when $k < 0$. Standard errors are double clustered at the investor and day level.

Figure 3 plots the coefficients $\beta_{s,k}$ and $\beta_{sh,k}$ in regression (3). Figure 4 plots $\gamma_{b,k}$ and $\gamma_{bh,k}$ in regression (4). Panels A in Figure 3 and in Figure 4 show a sharp rise in the probability that lightly-advised clients buy (resp. sell) stock on the buy list (resp. sell list) right after the stock is added to the investment committee recommendation list. Panels B confirm that this sharp rise is significantly more pronounced for highly-advised investors, which again comforts our interpretation that advisors significantly influence clients portfolio decision. This effect is stronger for "buy" recommendations: the probability of buying a recommended stock is a statistically significant .25 p.p. higher for highly-advised investors than for lightly-advised in the first week following the introduction of the asset to the recommendation list and slowly reverts to zero after eight weeks. For "sell" recommendations, the probability of selling by highly-advised clients is .03 p.p. higher than for lightly-advised investors in the first week post-recommendation, and the difference remains statistically significant in the eight weeks following the recommendation change. One plausible explanation for the asymmetry between buy and sell responses could be that clients can always add a stock to their portfolios following a buy recommendation, whereas selling requires holding the stock before the recommendation. In both cases, the effect of the investment committee recommendations on buy/sell decisions is almost twice as large for highly-advised clients than for the lightly-advised.

Overall, this analysis indicates that (1) the advice provided by financial advisors significantly influences the trading behavior of advised clients, and (2) this is especially true for highly-advised clients; which supports the primary assumption underpinning the identification strategy described in Section 2.

4.2 Trading Biases in the Pre-Treatment Period

We start our empirical analysis of the disposition effect bias by studying clients' transactions in the sample period preceding the new platform's introduction (February 2016 to December 2017). We investigate whether investors are significantly more likely to realize gains than losses, following, first, the methodology of Odean (1998a). Every day in our sample, we keep portfolios that have at least two stocks and feature at least one stock sale. We then compute the number of paper gains and losses, as well as the number of realized gains and realized losses. Paper gains and losses are determined by comparing the closing price on the previous day to the asset's average purchase price. Realized gains and losses compare the actual sale price to the average purchase price. We then obtain the proportions of realized gains (PGR) and realized losses (PLR) for each client type as:

$$\text{PGR}_t^k = \frac{\#\text{Realized Gains}_t^k}{\#\text{Realized Gains}_t^k + \#\text{Paper Gains}_t^k} \tag{5}$$

$$\text{PLR}_t^k = \frac{\#\text{Realized Losses}_t^k}{\#\text{Realized Losses}_t^k + \#\text{Paper Losses}_t^k}, \tag{6}$$

where $\#\text{Realized Gains}_t^k$ corresponds to the total number of realized gains observed on the portfolios of investors of type $k \in \{\text{highly-advised, lightly-advised, not advised}\}$ in period t, $\#\text{Realized Losses}_t^k$ is the total number of realized losses, $\#\text{Paper Gains}_t^k$ is the total number of paper gains in their portfolio and $\#\text{Paper Losses}_t^k$ the total number of paper losses. The ratio $\text{PGR}_t^k/\text{PLR}_t^k$ measures the disposition effect in period t for investors of type k. A ratio greater than one implies that, holding fixed the share of paper gains and losses, investors are more likely to realize gains than losses.[23]

Table 3 reports the distribution of the PGR/PLR ratios calculated at the investor-month level for each client type in the pre-treatment period. Non-advised clients exhibit a significant disposition effect: any given month month, they are on average twice as likely to realize a gain than a loss ($PGR/PLR = 2$). 95% of the time, their monthly PGR/PLR ratio is above 1.7. Advised clients exhibit a smaller disposition effect, comparable to that found by Odean (1998a)

[23] Simply comparing how many stocks sold are paper gains vs. losses would fail to account for potential composition effects: e.g., in undiversified portfolios, a significant share of stocks is likely either in gains or losses. Further, if assets with strictly positive expected returns are held sufficiently long, a majority will be in paper gains.

using data from a large US retail broker. The average PGR/PLR ratio of highly (lightly) advised clients is 1.6 (1.5), and the median is 1.5 (1.5). The disposition effect bias is more dispersed for highly-advised clients (PGR/PLR standard deviation of .5 vs. .36 for the lightly-advised). For both types of investors, the monthly PGR/PLR ratio is strictly greater than one more than 75% of the time. Table 3 shows that high net-worth investors in our sample exhibit a significant disposition effect bias whether or not they receive financial advice.

Because of its aggregation at the investor-month level, the results of Table 3 can conceal significant heterogeneity in the stocks held by the different types of investors. To further assess the existence of a disposition effect in the pre-treatment period, we follow the methodology of Ben-David and Hirshleifer (2012) and estimate the regression at the investor-stock-day level:

$$\begin{aligned} 100 \times Sell_{i,j,t} = {} & \beta Gain_{i,j,t-1} \\ & + \beta_h \left\{Gain_{i,j,t-1} \times HighlyAdvised_i\right\} + \beta_n \left\{Gain_{i,j,t-1} \times NotAdvised_i\right\} \\ & + \gamma X_{i,j,t} + FE_{i\times t} + FE_{j\times t} + \epsilon_{i,j,t}, \end{aligned} \tag{7}$$

where i, j, and t denote investor, stock, and day, respectively.[24] We only include days when a sale occurs within a portfolio comprising two or more stocks. $Sell_{i,j,t}$ is a dummy variable equal to one if investor i sells stock j (partially or fully) on day t and $Gain_{i,j,t-1}$ is a dummy variable equal to one if stock j is in paper gain in investor i's portfolio, using closing market price at $t-1$. $HighlyAdvised_i$ and $NotAdvised_i$ are dummies indicating which group investor i belongs to, where the omitted category is the lightly-advised. $X_{i,j,t}$ is a vector of stock-level control variables that can influence selling decisions. We follow Ben-David and Hirshleifer (2012) and include the natural logarithm of the weighted-average purchase price (Log(Buy Price)), the stock volatility calculated using daily returns over the prior 252 days if the asset is in paper loss (gain) and zero otherwise (Volatility(-) (Volatility(+))), the number of days since purchase (Time Owned), the return since purchase if the asset is in paper loss (gain) and zero otherwise (Return(-) (Return(+))). We also include a dummy variable equal to one if the investment committee's recommendation is to buy (sell) the stock (Buy Reco (Sell Reco)). $FE_{i\times t}$ and $FE_{j\times t}$ denote respectively investor-day fixed effects and stock-day fixed effects. Standard errors are double clustered at the investor and day level.

Table 4 reports the estimation results. Columns (1-2) do not include fixed effects. Columns (3-4) include investor-day fixed effects. Columns (5-6) add stock-day fixed effects. Finally,

[24] Feng and Seasholes (2005b) and Seru et al. (2010) use a hazard model to estimate the disposition effect. However, this approach is limited in its ability to incorporate numerous high-dimensional fixed effects due to the incidental parameters problem that affects maximum likelihood estimators. Additionally, this specification precludes the clustering of standard errors across multiple dimensions.

columns (7-8) compare highly- and lightly-advised investors, excluding non-advised clients. Note that investor fixed effects subsume advisor fixed effects, as the client-advisor pairs remain constant in our analysis. In all specifications, the coefficient β on the Gain dummy is positive and statistically significant at the 1% confidence level and provides a baseline quantification for the disposition effect bias in our sample. Given that, conditional on investors selling a stock, any position in their portfolios has an average 9.5% probability of being sold, the estimates of β between 3 and 5 in Table 4 imply that investors are between 32% and 53% more likely to sell a stock when it is in a paper gain.[25] The estimates for β_h on the $Gain \times HighlyAdvised$ dummy (second line in Table 2) are quantitatively small and statistically insignificant: highly and lightly-advised clients share the same level of disposition effect in the pre-treatment period. The estimates for β_n on the $Gain \times NotAdvised$ dummy confirm that non-advised clients exhibit a more substantial disposition effect than advised investors (with almost twice as high a total loading on the Gain dummy). However, this comparison does not necessarily capture a causal impact of financial advice on the disposition effect.[26] It could reflect instead the endogenous sorting of investors into advised and non-advised clients. To identify the causal impact of financial advisors on their clients' disposition effect, we exploit the quasi-natural experiment described in Section 2.

Finally, we verify whether investors in our pre-treatment period sample display two previously documented biases: the portfolio disposition effect of An et al. (2023) and the rank effect of Hartzmark (2015). Appendix Table A.5 presents the estimation results of regression (7) when adding a dummy variable $PortfolioGain_{i,t-1}$ equal to one if the sum of all paper gains in investor i's portfolio is greater than the sum of all paper losses, using closing market prices at $t-1$, and zero otherwise. As in An et al. (2023), we find that investors display a greater disposition effect bias when their portfolios are in paper loss: the loading on $PortfolioGain \times Gain$ is negative (and significant) and offsets almost entirely the positive (and significant) coefficient on the $Gain$ dummy variable. The coefficient on $PortfolioGain \times Gain$ is not significantly different across investor types, highly-advised, lightly-advised or not-advised.

Appendix Table A.6 provides the estimation results of regression (7) when replacing the $Gain$ dummy variable with $Extreme_{i,j,t-1}$, a dummy variable equal to one if asset j in investor i's portfolio has the highest or lowest paper return since purchase, i.e., the best rank or the worst

[25] Note that the sample mean of the variable $Sell_{i,j,t}$ is larger in Table 4 than in Table 2 because Table 4 only includes days when a sale occurs within a portfolio comprising two or more stocks, while Table 2 also includes investor-days on which no trade occurs.

[26] In Appendix Table A.2, we analyze whether the clients' disposition effect bias is different for assets purchased following a "Buy" recommendation. This comparison allows us to tease whether a form of "delegated" decision reduces the disposition effect bias, as suggested by Chang et al. (2016). We find no significant difference in the disposition effect for stocks purchased following a "Buy" recommendation.

rank in the portfolio, using closing market prices at $t-1$, and zero otherwise. As in Hartzmark (2015), we find that investors in our sample have a greater probability of selling the "extreme" positions than other assets in their portfolios: the coefficient on the *Extreme* dummy is positive and significant in all specifications. However, the coefficient on the *Extreme* dummy is not significantly different across investor types, highly-advised, lightly-advised or not-advised.[27]

4.3 Quasi-Natural Experiment

Aggregate analysis We first examine the effect of the experiment in a simple difference-in-differences analysis with data aggregated at the investor type-month level. Figure 5 reports the monthly PGR/PLR ratio for portfolios held by highly-advised (green) and lightly-advised (red) clients. The shaded areas correspond to 95% confidence intervals computed through a bootstrap procedure.[28] The vertical shaded line corresponds to the start of the treatment period.

Consistent with Section 4.2, Figure 5 shows that both categories of clients exhibit a significant and similar disposition effect bias in the pre-treatment period. In the post-treatment period, Figure 5 shows a statistically significant reduction in the relative disposition effect of highly-advised investors: for the highly-advised, the PGR/PLR ratio becomes statistically indistinguishable from one, corresponding to unbiased trading, in most months post January 2018, while it hovers around 1.5 for the lightly-advised.

We quantify these effects by estimating the following regression:

$$PGR/PLR_{i,t} = \beta \left\{HighlyAdvised_i \times Post_t\right\} + \alpha HighlyAdvised_i + \gamma Post_t + \epsilon_{i,t}, \qquad (8)$$

where i and t denote investor profile and month, $HighlyAdvised_i$ is a dummy equal to one if profile i corresponds to the highly-advised and $Post_t$ is a dummy equal to one after January 2018.[29] Table 5 presents the coefficient estimates. The change in financial advisors' information display in January 2018 significantly reduced the disposition effect of highly-advised clients: relative to lightly-advised clients, their PGR/PLR ratio drops by a highly significant .6 to

[27] In the Internet Appendix, we test whether the portfolio disposition bias and the rank bias were affected by the quasi-natural experiment treatment. We find the experiment did not significantly change clients' portfolio disposition effect. We do find a negative effect on the rank bias, although this effect is only marginally significant in our baseline specifications and becomes insignificant once we control for Investor × Day fixed effects (see Appendix Tables A.7 and A.8). We also test and reject that the disposition effect of highly-advised investors was mechanically lowered, due to the portfolio disposition effect, via changes in the composition of portfolios in paper gains versus losses: we find that highly-advised investors are not more likely to sell assets from portfolios in paper gain in the post-period compared to the lightly advised.

[28] We compute confidence intervals as follows: for each client category and month, we randomly draw 10,000 samples of clients with replacement and calculate the resulting 95% confidence interval over these bootstrapped samples.

[29] Because we aggregate the data at the profile-month level, we correct standard errors for heteroskedasticity without clustering.

.7 after the new platform's introduction. This effect is robust to controlling for date fixed effects (column (2)), and is not driven by treatment-specific pre-trends: column (3) controls for Year -1 (a dummy equal to 1 for all months in 2017) interacted with a highly-advised dummy. Appendix Table A.9 replicates these findings and shows they are robust to excluding the pilot phase (January 2018 to May 2018).

Investor-level analysis For robustness purposes, we also conduct a more granular analysis where the PGR and PLR ratios are constructed at the investor-month level. This approach enables us to include investor fixed effects and advisor-month fixed effects. These fixed effects allow us to identify the treatment effect by comparing investors who are in different categories (highly- and lightly-advised) but share the same financial advisor. Specifically, we estimate the following difference-in-differences regression:

$$PGR/PLR_{i,t} = \beta \left\{ HighlyAdvised_i \times Post_t \right\} + \alpha_i + \delta_{a\times t} + \gamma_{cohort\times t} + \epsilon_{i,t}, \tag{9}$$

where i, a, and t denote investor, advisor, and month, respectively. α_i and $\delta_{a\times t}$ denote investor and advisor-month fixed effects. $\gamma_{cohort\times t}$ denotes cohort-month fixed effects, and controls for possible differences in investor cohorts over time, where the definition of a cohort corresponds to the initial semester a client is recorded in the database. Standard errors are clustered at the investor level.

Column (1) of Table 6 estimates regression (8) with year-month and investor fixed effects, columns (2) and (4) have investor and advisor-month fixed effects, columns (3) and (4) add cohort-month fixed effects. All specifications show a reduction of .3 in the PGR/PLR ratio for highly-advised investors relative to lightly-advised ones, statistically significant at the 1% confidence level. This finding is robust to excluding the pilot phase (see Appendix Table A.10).

For robustness, we replicate our analysis using the difference PGR - PLR as the dependent variable instead of the ratio PGR/PLR.[30] Our findings, presented in Appendix Table A.11, remain consistent. We also analyze PGR and PLR separately, and show that a decrease in the propensity to realize gains in the post-treatment period is the main driver of our results (see Appendix Table A.12). Furthermore, we replicate our analysis by aggregating realized gains and losses and paper gains and losses for each investor and quarter (as opposed to each month). The estimation results in Appendix Table A.13 confirm our earlier findings. Finally, Appendix Table A.14 shows that our main findings are robust when we include non-advised investors as an additional control group.

[30]Nearly half of the observations in our sample involve investors who do not sell any stocks at a paper loss (i.e., $PLR = 0$), leading us to exclude these observations from our analysis of the ratio PGR/PLR.

We investigate the timing of the treatment effect through the event-study specification:

$$PGR/PLR_{i,t} = \sum_{k=-2,k\neq-1}^{3} \beta_k \left\{HighlyAdvised_i \times TreatmentYear(k)_t\right\} + \alpha_i + \gamma_t + \epsilon_{i,t}, \quad (10)$$

where i and t denote the investor and month, and $TreatmentYear(k)_t$ is a dummy equal to one if month t is part of year k before/after the new platform introduction in 2018. We use year -1 as the baseline year. α_i and γ_t denote investor and year-month fixed effects respectively. Standard errors are clustered at the investor level.

Figure 6 reports the estimated β_k coefficients. The PGR/PLR ratios of both investor types follow a similar dynamic before the new platform introduction: relative to the baseline year -1, the coefficients β_k for years -2 and 0 are small quantitatively and not significantly different from 0. Starting in year 1, the estimated coefficients become negative and statistically significant at the 1% confidence level. The effect in all three years following the experiment represents a significant decline of .5 in highly-advised investors' average PGR/PLR ratio.

Investor-stock level analysis We also implement an investor-stock-day level analysis similar to regression (7), which allows us to control for stock-level time-varying characteristics:

$$\begin{aligned} 100 \times Sell_{i,j,t} = {} & \beta Gain_{i,j,t-1} + \beta_h \left\{Gain_{i,j,t-1} \times HighlyAdvised_i\right\} \\ & + \beta_p \left\{Gain_{i,j,t-1} \times Post_t\right\} + \beta_{ph} \left\{Gain_{i,j,t-1} \times Post_t \times HighlyAdvised_i\right\} \quad (11) \\ & + \gamma X_{i,j,t} + FE_{i\times t} + FE_{j\times t} + \epsilon_{i,j,t}, \end{aligned}$$

where i, j, and t denote investor, stock, and day, respectively. Table 7 presents the estimation results. Columns (1-2) omit fixed effects. Columns (3-4) include advisor-day fixed effects, i.e., the identification relies on comparing the behaviors of highly- and lightly-advised investors who share the same financial advisors. Columns (5-6) include stock-day fixed effects, and columns (7-8) add investor-day fixed effects. Across all specifications, the interaction coefficient β_{ph} is negative and statistically significant at the 1% confidence level: relative to the lightly-advised, highly-advised investors become significantly less likely to sell paper gains in the post period, i.e., after the new platform's introduction. Quantitatively, the estimated effect ranges between 2.3 and 3.9 p.p., corresponding to a decline in the probability of selling gains between 25% and 44% relative to the sample mean.

Matching To help reduce concerns that our results may be affected by systematic differences between highly and lightly-advised clients, we perform two matching exercises using portfolio characteristics in the pre-treatment period.

First, we rely on a propensity score procedure to match each highly-advised client with her closest lightly-advised counterpart. Specifically, we estimate a logit specification at the individual level, in which the dependent variable is a dummy indicating whether the client is highly-advised, and the independent variables are the logarithm of the client's average total assets, the average number of stocks in the client's portfolio, and the client's average daily likelihood of selling one or several stocks, all measured in the pre-treatment period only. For each highly-advised client, we identify the lightly-advised client with the closest propensity score and allow the same lightly-advised investor to serve as a match for multiple highly-advised clients.[31] The 1,302 highly-advised clients in the pre-treatment period are matched with 305 distinct lightly-advised clients. Using this matched sample of treated and controls, we estimate regression (11). The results are reported in Table 8, Panel A. They are similar to Table 7 and leave our conclusion unchanged.

Second, we perform a coarse matching exercise. Specifically, for each highly-advised client, we identify the set of lightly-advised clients that are (i) in the same quartile of the distribution of the logarithm of average total assets in the pre-treatment period, (ii) in the same quartile of the distribution of the average number of stocks in the pre-treatment period, and (iii) in the same quartile of the distribution of average daily likelihood of selling one of several stocks in the pre-treatment period. Using this matched sample of treated and controls, we estimate regression (11). The results are reported in Table 8, Panel B. Once again, they are similar to Table 7 and leave our conclusion unchanged.

Returns and selling probability We extend our analysis beyond the strict asymmetry between paper gains and losses. We follow the methodology of Ben-David and Hirshleifer (2012) and analyze how the returns realized on each asset affect the probability of a sale pre- and post-January 2018. We focus on the year following investors' stock purchases and estimate the probability that a stock is sold as a function of the return realized on this stock since its purchase. For every asset in the investors' portfolios, we calculate the daily compound return between the time of purchase and the time of sale if the sale occurs within a year. If no sale occurs during the year, we calculate the daily compound return since purchase. Figure 7 shows a binscatter plot where we group securities based on these daily compound returns and calculate the probability of being sold within a year for the stocks in each bin. The top left (right) panel shows the binscatter plot for lightly-advised investors in the period preceding (following) the

[31] We do not perform a matching without replacement as our sample has more highly-advised than lightly-advised clients.

experiment. The bottom panels provide the corresponding results for highly-advised investors.

Similar to the results in Ben-David and Hirshleifer (2012), for all advised clients prior to January 2018, the probability of selling a security as a function of realized returns follows a V-shaped pattern centered around 0 (top and bottom left panels of Figure 7): the decisions to sell assets are, on average, driven by large gains and losses. The scatterplots also show that the V shape is asymmetric, with a higher average probability of sales for positive returns, consistent with the disposition effect we document in Tables 3 and 4.[32] For lightly-advised investors (top right panel of Figure 7), the disposition effect remains noticeable in the post-treatment period: though the V-shape is less pronounced, the probability of selling remains significantly higher for positive than for negative returns. For highly-advised investors, on the other hand, there is no remaining asymmetry between gains and losses in the post-period (bottom right panel of Figure 7), consistent with the results of Tables 5, 6, and 7. Further, we no longer observe a clear relation between the probability of selling a stock and its realized returns.[33]

5 Discussion

5.1 Alternative Interpretation

As described in Section 2, the new platform design of January 2018 introduced two main changes for financial advisors: for each stock held by their clients, (1) it removed the average acquisition price, and (2) it added a "BCAP" rating – a proprietary grading system quantifying a stock's momentum. This BCAP index is computed using moving averages of stock prices across several time frames, both in absolute terms and relative to benchmark indices and sectors. The index ranges from 0 to 100 and is binned into rating letters (B, C, A, or P). Note that this index was already communicated to advisors prior to 2018.

Our interpretation so far has emphasized the role of the removal of acquisition prices from the advisors' platform: when advisors cannot easily observe whether their clients' positions are paper gains or losses, the selling decisions of investors they influence most (highly-advised clients) exhibit a reduced disposition effect. An alternative interpretation could be instead centered around the increased prominence in the display of BCAP ratings: if paper gains are more likely to be high BCAP stocks (i.e., high momentum stocks), and if the display's change made advisors less likely to recommend selling high BCAP stocks, it could mechanically limit

[32] As in Ben-David and Hirshleifer (2012), there is only a small if any, discontinuous increase in the probability of selling assets at small positive returns versus small negative returns.

[33] Note that, controlling for fixed effects (investors-day, stocks-day or advisors-day), the rank effect bias is still observed for both highly-advised and lightly-advised investors in the post-period: both the best paper return position and the worst paper return position are more likely to be sold than other assets in the portfolio (Appendix Table A.8).

the disposition effect.

Using data on stock-level BCAP ratings, we investigate the correlation between BCAP and paper gains/losses. In our sample, stocks with a higher BCAP rating (A or P) have a 58% probability of being in paper gains compared to 50% for stocks with lower BCAP (B or C).[34] We confirm this positive correlation using a regression analysis at the investor-stock-day level. We regress the BCAP index on a Gain dummy, controlling for investor, stock, and advisor-day fixed effects. The results reveal an economically small but statistically significant regression coefficient: a stock in paper gain has a BCAP index about 9 points higher on average than a stock in paper loss (Appendix Table A.15).

To further investigate the potential role of BCAP ratings, we evaluate whether investors become less likely to sell high BCAP stocks after the new platform's introduction. We use the empirical strategy developed in Section 4. We consider only portfolio days with at least two stocks and one sale. We then calculate the proportions of high BCAP realized (PHBR) and low BCAP realized (PLBR) in the same way we compute PGR and PLR in Section 4:

$$\mathrm{PHBR}_t^k = \frac{\#\text{Realized High BCAP}_t^k}{\#\text{Realized High BCAP}_t^k + \#\text{Paper High BCAP}_t^k} \tag{12}$$

$$\mathrm{PLBR}_t^k = \frac{\#\text{Realized Low BCAP}_t^k}{\#\text{Realized Low BCAP}_t^k + \#\text{Paper Low BCAP}_t^k} \tag{13}$$

where $\#\text{Realized High BCAP}_t^k$ is the number of high BCAP stocks (rating letter A and P) sold in period t by investor type k, and $\#\text{Paper High BCAP}_t^k$ is the number of high BCAP stocks in the portfolios of investors of type k that were not sold. We estimate the difference-in-differences specification of regression (9), using the ratio PHBR/PLBR as the dependent variable instead of PGR/PLR. Appendix Table A.16 presents the estimation results. Across all specifications, we find a quantitatively negligible and statistically insignificant effect of the display change on the PHBR/PLBR ratio of highly-advised clients relative to the lightly-advised.

We also directly test if the decreased propensity to sell paper gains observed for highly-advised clients in Table 7 is driven by high BCAP stocks. We re-estimate regression (11), adding a quadruple interaction term $\{HighBCAP_{j,t} \times Gain_{i,j,t-1} \times Post_t \times HighlyAdvised_i\}$, and all corresponding interaction terms, where $HighBCAP_{j,t}$ is a dummy equal to one if stock j has a high BCAP rating (A or P) on day t, and equal to zero if stock j has a low BCAP rating (B or C). Appendix Table A.17 presents the estimation results. We find that highly-advised clients are, on average, significantly less likely to sell high BCAP stocks (negative and

[34]The probability of paper gains is 48%, 53%, 58%, and 59% when the BCAP rating is B, C, A, and P, respectively.

significant coefficients on $HighBCAP \times HighlyAdvised$), further proof that the highly-advised are more likely to follow advisors' recommendations. However, the new information display does not affect the propensity of highly-advised investors to sell high BCAP stocks: the coefficient on $HighBCAP \times Post \times HighlyAdvised$ is not statistically significant. As in Table 7, the coefficient on $Gain \times Post \times HighlyAdvised$ is negative and statistically significant throughout. Importantly, this effect is not significantly more pronounced for high BCAP stocks: in all specifications, the coefficient on $HighBCAP \times Gain \times Post \times HighlyAdvised$ is economically small and statistically insignificant.

These results show that introducing the BCAP ratings to the platform display did not significantly affect the trading decisions of highly-advised versus lightly-advised investors. They confirm our interpretation that the observed reduction in the disposition effect is caused by removing stocks' average acquisition prices from the advisors' platform. We note that our results do not contradict Frydman and Camerer (2016) who find, in a lab experiment, that telling subjects that returns are persistent, i.e., have momentum, lowers their disposition effect biases. Appendix Table A.17 simply shows that adding the BCAP ratings to the advisors' platform does not affect their clients' disposition effect. One plausible interpretation is that financial advisors were already using the BCAP ratings when providing recommendations to investors in the pre-January 2018 period.

5.2 Portfolio Returns

Odean (1998a) finds that the average one-year excess return on stocks sold while in paper gains is 3.4 p.p higher than on paper losses that could have been sold instead. In other words, the disposition effect lowers portfolio performance for retail investors. We evaluate how the disposition effect bias affects portfolio performances in our sample by leveraging the same natural experiment and identification strategy as in Section 4.

Table 9 presents our estimation results. In Panel A, we estimate regression (8) at the profile-month level, using the ex-post return difference between winning stocks sold and paper loss positions that could have been sold as the dependent variable instead of PGR/PLR. We consider four investment horizons: three months, six months, one year, and two years.[35] We find that in the post-January 2018 period, compared to lightly-advised clients, highly-advised investors experience a significant decrease in the return difference over the following year between

[35]We compute the ex-post return difference between winning stocks sold and paper loss positions that could have been sold as follows: For each stock in the sample, we calculate its return over the subsequent 3-month, 6-month, 12-month, and 24-month periods on any given day. Then, for each profile (highly- or lightly-advised) and month, we determine the average of these ex-post returns for the stocks that were sold at a gain and for the losing stocks that were not sold. Finally, we subtract the average returns of the losing stocks from those of the winning stocks to obtain the difference.

winner stocks sold and loser stocks kept in portfolios, of 2 p.p. at the 3-month and 6-month horizon, and 3 p.p. at the 1-year horizon.

To assess how this affects investors' portfolio performance, we estimate regression (9) at the investor-month level, using portfolio returns (risk-adjusted returns using Fama-French 3 factors and Momentum) as the dependent variable instead of PGR/PLR. Panel B (Panel C) of Table 9 presents the estimation results. After the new platform's introduction, highly-advised clients experience a relative increase in portfolio returns of around 20 basis points per month (Panel B). This increase is statistically significant at the 5% level when we control for year-month, investors, advisor × year-month, and cohort × year-month fixed effects. Highly-advised investors' risk-adjusted returns, on the other hand, are unchanged in the post-period (Panel C), indicating that improvements in raw portfolio returns are due to changes in portfolio exposures to common risk factors. We document this result in Appendix Table A.18, where we estimate regression (9) at the investor-month level, using portfolio beta loadings on the Fama-French 3 factors and on the momentum factor as dependent variables. Following the experiment, we find that relative to the lightly-advised, highly-advised portfolios tend to load less on the market and the value factors, and to load more on the size and momentum factors. This result is consistent with a reduction in the disposition effect leading to a tilt toward momentum stocks (recent winners) and away from value stocks.

5.3 Client Inflows and Loyalty

Does the firm benefit from its clients' reduced disposition effect? The results in Section 5.2 suggest that clients experience increased performance, which should lead to increased satisfaction. Given the firm's fee structure (custody and advisory fee), this increased satisfaction should lead to increased profits if it leads to increased capital inflows into accounts or reduced account terminations.

Using transaction-level data, we define monthly inflows as the total amount of incoming bank transfers into an account in a given month normalized by the previous month's total portfolio value. Outflows correspond to total flows out of the account in a given month, normalized by the previous month's total portfolio value. We estimate regression (9) at the investor-month level, using inflows and outflows as dependent variables. Panels A and B of Table 10 present the coefficient estimates. Panel A (Inflows) shows that, following the platform's introduction, inflows from highly-advised clients increase significantly by .011 to .014 p.p. relative to lightly-advised clients. This effect corresponds to between 107% and 136% of the average inflows in our sample (0.01 p.p.). Panel B shows that the experiment does not significantly affect outflows.[36]

We also investigate the extensive margin, i.e., the probability that clients close their accounts at the firm. We estimate regression (9) at the investor-month level, using $100 \times Exit_{i,t}$ as the dependent variable, where $Exit_{i,t}$ is a dummy equal to one if investor i exits our sample in month t before the end of the sample period.[37] Panel C of Table 10 shows that highly-advised clients become between .08 and .1 p.p. less likely to terminate their relationship with the firm following the platform's introduction, relative to the lightly-advised. This effect corresponds to between 150% and 178% of the average probability of exiting the firm in our sample (0.05 p.p.).

Overall, Table 10 shows that the firm gains from reducing their clients' disposition effect through increased inflows into existing accounts and a decreased probability of clients exiting the firm.

6 Conclusion

This paper investigates the role of financial advisors in mitigating their clients' biases. We exploit a quasi-natural experiment run by a prominent French brokerage firm that removed stocks' average acquisition prices from the online platform used by financial advisors. We present three main findings. First, even in our sample of high-net-worth investors receiving regular financial advice, the disposition effect – investors' tendency to hold on to their losing positions and sell their winning stocks – is a pervasive investment bias. Second, financial advisors do exert a significant influence on their clients' investment decisions. Third, financial advisors do not actively mitigate their clients' biases: when advisors have access to information relevant to their clients' disposition effect – whether stocks in their portfolio are in paper gains or losses – clients exhibit more, not less, disposition effect.

While our empirical analysis allows us to reject several plausible alternative interpretations, some critical questions remain open, that the data and quasi-natural experiment in our study cannot address. First, do advisors fail to reduce their clients' biases because they are themselves biased or because of some form of agency issues? Second, how does the advisors' influence affect other investment biases, such as under-diversification? Third, can brokerage firms design more efficient interventions to curtail their clients' disposition effect? We leave these questions for future research.

[36] We also verify whether the lower propensity to realize gains, documented in Appendix Table A.12, results in a decrease in overall transactions, which could be costly to the firm. We found no significant reduction in the number of trades executed by highly advised clients in the post period (see Appendix Table A.19).

[37] We do not include investor fixed effects in those specifications as a client can only exit the firm once in our sample.

Tables

Variable	Obs	Mean	Sd	5%	25%	50%	75%	95%
Panel A: Highly Advised								
Number of Investors	3,756	.	.	.	.	.	.	.
Number of Advisors	44	.	.	.	.	.	.	.
Total Assets (EUR)	.	136,977	370,871	1,948	20,034.7	71,418	151,753	443,253
Number of Stocks	.	10.72	8.99	1	3	9	16	27
Number of Trades per Year	.	11.46	17.76	0	1	5	15	43
Holding Period (Days)	.	195.72	151.9	15	82	159	273	504
Monthly Return (%)	.	1.05	1.7	-1.06	.44	.9	1.59	3.78
Monthly Risk-Adjusted Return (%)	.	-.35	2	-3.45	1.17	-.23	.63	2.36
Panel B: Lightly Advised								
Number of Investors	748	.	.	.	.	.	.	.
Number of Advisors	42	.	.	.	.	.	.	.
Total Assets (EUR)	.	180,113	684,021	1,592.1	17,128.9	54,937.3	148,157	570,627
Number of Stocks	.	9.55	10.05	1	3	7	13	27
Number of Trades per Year	.	18.38	43.96	0	1	6	18	74
Holding Period (Days)	.	226.04	148.63	22	106	201.25	332	502
Monthly Return (%)	.	.57	1.8	-2.11	.04	.68	1.17	2.8
Monthly Risk-Adjusted Return (%)	.	-.6	2.18	-4.54	1.34	-.34	.49	2.12
Panel C: Not Advised								
Number of Investors	2,990	.	.	.	.	.	.	.
Number of Advisors	0	.	.	.	.	.	.	.
Total Assets (EUR)	.	58,371.6	185,581	480.75	4,757.94	17,985.4	54,827	213,314
Number of Stocks	.	7.56	9.84	1	2	4	10	24
Number of Trades per Year	.	19.49	65.47	0	0	2.25	13.5	93
Holding Period (Days)	.	323.37	195.85	37	153.5	307	485	658
Monthly Return (%)	.	.25	1.94	-2.86	-.28	.62	1.1	2.42
Monthly Risk-Adjusted Return (%)	.	-.78	2.11	-4.29	-1.59	-.42	.4	1.62

TABLE 1: **Clients' Portfolios Summary Statistics.** Summary statistics of equity holdings at the investor level. Total Assets, Number of Stocks, Number of Trades per Year and Holding Period corresponds to the variable median value for each investor over our sample period spanning from February 2016 to May 2021. Holding Period corresponds to the number of days between the purchasing and selling dates. Monthly Return is the average monthly return of the investor. Monthly Risk-Adjusted Return is the average monthly return adjusted for exposures to the Fama-French 3 factors and Momentum.

	Sell × 100		Buy × 100	
	(1)	(2)	(3)	(4)
Sell Reco × Highly Advised	0.101***	0.112***	-0.035**	-0.028*
	(0.017)	(0.016)	(0.017)	(0.015)
Buy Reco × Highly Advised	-0.064***	-0.057***	0.082***	0.094***
	(0.018)	(0.019)	(0.020)	(0.021)
Sell Reco	0.233***	0.238***	-0.097***	-0.083***
	(0.016)	(0.016)	(0.017)	(0.015)
Buy Reco	-0.053***	-0.075***	0.238***	0.211***
	(0.018)	(0.019)	(0.022)	(0.023)
Investor × Day FE	No	Yes	No	Yes
Investor FE	Yes	No	Yes	No
Stock FE	Yes	Yes	Yes	Yes
Day FE	Yes	No	Yes	No
Observations	4.42e+07	4.42e+07	4.42e+07	4.42e+07
R^2	0.01	0.16	0.01	0.20

TABLE 2: **Advised Clients' Investments and Advisors' Recommendations.** Regressions are estimated at the investor-stock-day level. The dependent variable is a variable equal to 100 if the investor sells some shares of the stock on that day, 0 otherwise, in columns 1 and 2. In column 3 and 4, the dependent variable is a variable equal to 100 if the investor buy some shares of the stock on that day, 0 otherwise. Sell (Buy) Reco is a dummy equal to 1 if the stock belongs to the list of the investment committee and its recommendation is to sell (buy) the stock on that day. Highly Advised is a dummy equal to 1 if the investor is in the *Highly Advised* group. The omitted category is the *Lightly Advised* group of investors. Standard errors are double clustered at the investor and day level. ***, ** and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

		PGR/PLR						
Investor Group	Number of Investors	Mean	Sd	5%	25%	50%	75%	95%
All	3,278	1.809	0.247	1.524	1.599	1.811	1.981	2.137
Highly Advised	1,384	1.558	0.525	0.864	1.090	1.481	1.950	2.544
Lightly Advised	539	1.526	0.369	1.046	1.260	1.490	1.713	2.149
Not Advised	1,355	2.029	0.185	1.741	1.891	2.038	2.173	2.278

Table 3: **Summary statistics of the ratio of proportion of gains realized (PGR) and proportion of losses realized (PLR) in the pre-treatment period.** For each investor-month in the pre-treatment period (from February 2016 to December 2017) we compute the ratio PGR/PLR. We present the distribution of these ratios in each client category.

	Sell × 100							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gain	3.004*** (0.711)	3.901*** (1.055)	4.067*** (0.749)	5.004*** (1.007)	3.634*** (0.546)	4.521*** (0.704)	4.132*** (0.533)	4.156*** (0.717)
Gain × Highly Advised	0.113 (0.813)	0.448 (0.812)	-0.407 (0.846)	-0.098 (0.816)	0.185 (0.626)	-0.043 (0.599)	0.172 (0.609)	0.078 (0.573)
Gain × Not Advised	2.983*** (1.020)	2.629** (1.040)	3.383*** (1.076)	2.831*** (1.037)	2.932*** (0.767)	2.531*** (0.735)		
Highly Advised	1.008 (0.718)	0.850 (0.588)						
Not Advised	-1.208 (0.825)	-0.752 (0.701)						
Log(Buy Price)		-0.408*** (0.100)		-0.129 (0.099)		1.133*** (0.378)		-0.625 (0.564)
Volatility(+)		3.760** (1.592)		2.797** (1.303)		-162.159* (83.331)		-101.910 (308.078)
Volatility(-)		0.036* (0.020)		-0.018 (0.024)		-163.760* (83.391)		-112.115 (308.069)
$\sqrt{\text{Time Owned}}$		-0.288*** (0.026)		-0.257*** (0.027)		-0.211*** (0.019)		-0.337*** (0.023)
Gain × $\sqrt{\text{Time Owned}}$		-0.104*** (0.036)		-0.122*** (0.032)		-0.115*** (0.022)		-0.047* (0.026)
Return(+)		1.473 (1.046)		0.726 (0.786)		-0.016 (0.686)		1.416 (0.880)
Return(-)		5.596*** (1.324)		8.617*** (1.217)		14.133*** (1.581)		-1.803 (2.741)
Return(+) × $\sqrt{\text{Time Owned}}$		-0.085** (0.038)		-0.040 (0.031)		0.010 (0.025)		-0.014 (0.033)
Return(-) × $\sqrt{\text{Time Owned}}$		0.016 (0.054)		-0.032 (0.053)		-0.052 (0.044)		0.312*** (0.101)
Buy Reco		-1.559*** (0.357)		-3.043*** (0.240)				
Sell Reco		3.811*** (0.399)		3.030*** (0.297)				
Investor × Day FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Stock × Day FE	No	No	No	No	Yes	Yes	Yes	Yes
Observations	865,562	865,562	865,562	865,562	865,562	865,562	304,470	304,470
R^2	0.01	0.03	0.11	0.12	0.35	0.36	0.46	0.46

TABLE 4: **Propensity to Sell Gains in the Pre-Treatment Period.** Regressions are estimated at the investor-stock-day level in the pre-treatment phase (from February 2016 to December 2017). The dependent variable is equal to 100 if a stock is sold (fully or partially) on a given day and zero otherwise. Gain is a dummy variable equal to one if the return since purchase is positive and zero otherwise. Highly Advised and Not Advised are dummy variables indicating the client category. The omitted category is the *Lightly Advised* group of investors. In columns (7) and (8), not advised clients are not included. Log(Buy Price) is the natural logarithm of the weighted-average purchase price. Volatility(-) (Volatility(+)) is the stock volatility calculated using daily returns over the prior 252 days if the return since purchase is negative (positive) and zero otherwise. Time Owned is the number of days since purchase. Return(-) (Return(+)) is the return since purchase if the return since purchase is negative (positive) and zero otherwise. Buy Reco (Sell Reco) is a dummy variable equal to one if the investment committee's recommendation is to buy (sell) the stock. We include only days where investors have more than 2 assets in their portfolios and sell at least one stock. Standard errors are double-clustered at the investor and day level. Standard errors are double clustered at the investor and day level. ***, ** and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	PGR / PLR		
	(1)	(2)	(3)
Highly Advised × Year -1			-0.166
			(0.136)
Highly Advised × Post	-0.629***	-0.629***	-0.712***
	(0.124)	(0.087)	(0.110)
Highly Advised	0.030	0.030	0.113
	(0.098)	(0.068)	(0.096)
Post	0.147*		
	(0.088)		
Constant	1.517***	1.609***	1.609***
	(0.069)	(0.030)	(0.030)
Year-Month FE	No	Yes	Yes
Observations	128	128	128
R^2	0.36	0.84	0.85

TABLE 5: **Disposition Effect at the Profile-Month Level.** The dependent variable is the Ratio of the Proportion of Gain Realized (PGR) to the Proportion of Loss Realized (PLR) for a given profile-month. We compute the PGR/PLR ratio by aggregating realized gains and losses as well as paper gains and losses, within each investor category and month. Highly Advised is a dummy equal to 1 if the investor is in the *Highly Advised* group. The omitted category is the *Lightly Advised* group of investors. Post is a dummy equal to 1 for months following January 2018. Year -1 is a dummy equal to 1 for all months from January 2017 to December 2017. ***, ** and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	PGR / PLR			
	(1)	(2)	(3)	(4)
Highly Advised × Post	-0.330*** (0.090)	-0.311*** (0.092)	-0.340*** (0.091)	-0.314*** (0.093)
Constant	1.127*** (0.053)	1.114*** (0.055)	1.133*** (0.054)	1.116*** (0.055)
Year-Month FE	Yes	No	No	No
Investor FE	Yes	Yes	Yes	Yes
Advisor × Year-Month FE	No	Yes	No	Yes
Cohort × Year-Month FE	No	No	Yes	Yes
Observations	30,274	30,274	30,274	30,274
R^2	0.32	0.38	0.33	0.40

TABLE 6: **Disposition Effect at the Investor-Month Level.** The dependent variable is the Ratio of the Proportion of Gain Realized (PGR) to the Proportion of Loss Realized (PLR) for a given investor-month. We compute the PGR/PLR ratio by aggregating realized gains and losses as well as paper gains and losses, within each investor and month. Highly Advised is a dummy equal to 1 if the investor is in the *Highly Advised* group. The omitted category is the *Lightly Advised* group of investors. Cohort is defined as the initial semester in which the client is first recorded in our database. Post is a dummy equal to 1 for months following January 2018. All months where $PLR = 0$ are excluded from the sample. Standard errors are clustered at the investor level. ***, ** and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Sell × 100							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gain × Post × Highly Advised	-3.977***	-3.554***	-3.743***	-3.294***	-2.824***	-2.430***	-2.539***	-2.268***
	(0.907)	(0.897)	(0.822)	(0.824)	(0.803)	(0.754)	(0.890)	(0.858)
Gain × Post	0.972	1.436*	0.667	1.153	1.404*	1.069	1.287*	1.060
	(0.834)	(0.825)	(0.762)	(0.759)	(0.716)	(0.667)	(0.768)	(0.745)
Gain	3.004***	1.664*	3.584***	2.311***	3.754***	2.327***	4.132***	2.848***
	(0.711)	(0.895)	(0.692)	(0.825)	(0.534)	(0.581)	(0.533)	(0.587)
Post	-0.676	-0.882						
	(0.684)	(0.559)						
Highly Advised	1.008	0.786	-0.045	-0.056	-0.843*	-0.721*		
	(0.718)	(0.580)	(0.548)	(0.488)	(0.467)	(0.410)		
Gain × Highly Advised	0.113	0.829	0.053	0.732	0.649	0.508	0.172	0.059
	(0.812)	(0.806)	(0.774)	(0.744)	(0.574)	(0.537)	(0.608)	(0.571)
Post × Highly Advised	1.366*	0.908	2.012***	1.556***	1.626***	1.234**		
	(0.742)	(0.637)	(0.594)	(0.555)	(0.552)	(0.486)		
Log(Buy Price)		-0.066		-0.034		-0.220		-0.497
		(0.065)		(0.049)		(0.310)		(0.323)
Volatility(+)		-0.027		-0.009		-48.004		-60.941
		(0.073)		(0.064)		(41.532)		(39.795)
Volatility(-)		-0.027		-0.047**		-48.036		-60.935
		(0.028)		(0.021)		(41.537)		(39.799)
$\sqrt{\text{Time Owned}}$		-0.475***		-0.499***		-0.386***		-0.361***
		(0.020)		(0.021)		(0.015)		(0.015)
Gain $\times \sqrt{\text{Time Owned}}$		0.091***		0.084***		0.064***		0.052***
		(0.022)		(0.020)		(0.015)		(0.015)
Return(+)		-0.586**		-0.112		-0.357		-0.141
		(0.282)		(0.280)		(0.364)		(0.349)
Return(-)		0.299		2.047*		6.034***		4.894***
		(1.174)		(1.060)		(1.217)		(1.186)
Return(+) $\times \sqrt{\text{Time Owned}}$		0.055***		0.048***		0.037**		0.023
		(0.018)		(0.018)		(0.016)		(0.016)
Return(-) $\times \sqrt{\text{Time Owned}}$		0.037		-0.007		0.039		0.074*
		(0.047)		(0.048)		(0.042)		(0.043)
Buy Reco		-3.401***		-3.977***				
		(0.206)		(0.188)				
Sell Reco		7.163***		7.007***				
		(0.343)		(0.322)				
Advisor × Day FE	No	No	Yes	Yes	Yes	Yes	No	No
Stock × Day FE	No	No	No	No	Yes	Yes	Yes	Yes
Investor × Day FE	No	No	No	No	No	No	Yes	Yes
Observations	1582102	1582102	1582102	1582102	1582102	1582102	1582102	1582102
R^2	0.00	0.03	0.04	0.07	0.32	0.33	0.37	0.38

TABLE 7: **Propensity to Sell Gains.** Regressions are estimated at the investor-stock-day level. The dependent variable is equal to 100 if the stock is sold (fully or partially) on a day and zero otherwise. Gain is a dummy variable equal to one if the return since purchase is positive and zero otherwise. Highly Advised and Not Advised are dummy variables indicating the client category. The omitted category is the *Lightly Advised* group of investors. Post is a dummy equal to 1 for months following January 2018. Log(Buy Price) is the natural logarithm of the weighted-average purchase price. Volatility(-) (Volatility(+)) is the stock volatility calculated using daily returns over the prior 252 days if the return since purchase is negative (positive) and zero otherwise. Time Owned is the number of days since purchase. Return(-) (Return(+)) is the return since purchase if the return since purchase is negative (positive) and zero otherwise. Buy Reco (Sell Reco) is a dummy variable equal to one if the investment committee's recommendation is to buy (sell) the stock. We include only days where investors have more than 2 assets in their portfolios and sell at least one stock. Standard errors are double-clustered at the investor and day level. ***, ** and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Propensity Score Matching

	Sell × 100							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gain × Post × Highly Advised	-5.788***	-5.696***	-5.847***	-5.545***	-4.498***	-4.168***	-4.301**	-4.028**
	(1.732)	(1.696)	(1.590)	(1.597)	(1.534)	(1.455)	(1.699)	(1.614)
Gain × Post	2.307	2.901*	2.378	2.829*	3.012**	2.807**	2.876**	2.756**
	(1.654)	(1.594)	(1.531)	(1.512)	(1.303)	(1.210)	(1.460)	(1.367)
Gain	2.463**	0.605	2.452**	0.918	3.032***	1.159	3.513***	1.710**
	(1.233)	(1.565)	(1.207)	(1.445)	(0.741)	(0.807)	(0.750)	(0.824)
Post	-0.468	-0.534						
	(1.111)	(0.798)						
Highly Advised	1.325	0.789	-0.864	-1.012	-0.977	-1.005		
	(1.175)	(0.837)	(0.955)	(0.858)	(0.746)	(0.683)		
Gain × Highly Advised	1.496	2.654**	1.988	2.741**	1.303	1.246	0.711	0.665
	(1.350)	(1.302)	(1.312)	(1.199)	(0.830)	(0.760)	(0.839)	(0.774)
Post × Highly Advised	2.128*	2.127**	2.861***	2.893***	2.542***	2.427***		
	(1.168)	(0.867)	(0.967)	(0.940)	(0.920)	(0.862)		
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Advisor × Day FE	No	No	Yes	Yes	Yes	Yes	No	No
Stock × Day FE	No	No	No	No	Yes	Yes	Yes	Yes
Investor × Day FE	No	No	No	No	No	No	Yes	Yes
Observations	614,097	614,097	614,097	614,097	614,097	614,097	614,097	614,097
R^2	0.00	0.03	0.05	0.08	0.41	0.41	0.45	0.45

Panel B: Coarse Matching

	Sell × 100							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gain × Post × Highly Advised	-5.297***	-5.092***	-5.121***	-4.835***	-3.920***	-3.573***	-3.833***	-3.558***
	(1.368)	(1.350)	(1.269)	(1.281)	(1.279)	(1.220)	(1.399)	(1.335)
Gain × Post	1.904	2.353*	1.834	2.271*	2.325**	2.149**	2.220*	2.121*
	(1.271)	(1.238)	(1.193)	(1.188)	(1.067)	(0.998)	(1.166)	(1.100)
Gain	2.275**	0.627	2.391***	0.921	2.720***	0.857	3.192***	1.297*
	(0.906)	(1.226)	(0.894)	(1.140)	(0.588)	(0.685)	(0.600)	(0.697)
Post	-0.288	-0.298		0.000	0.000		0.000	0.000
	(0.850)	(0.680)		(0.000)	(0.000)		(0.000)	(0.000)
Highly Advised	1.348	0.852	0.020	-0.139	-0.492	-0.388		0.000
	(0.905)	(0.680)	(0.752)	(0.676)	(0.617)	(0.567)		(0.000)
Gain × Highly Advised	1.597	2.506**	1.891*	2.564***	1.609**	1.430**	1.172	1.008
	(1.056)	(1.020)	(1.023)	(0.948)	(0.710)	(0.655)	(0.740)	(0.683)
Post × Highly Advised	1.912**	1.840**	2.196***	2.106***	1.901**	1.675**		0.000
	(0.924)	(0.757)	(0.779)	(0.763)	(0.799)	(0.754)		(0.000)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Advisor × Day FE	No	No	Yes	Yes	Yes	Yes	No	No
Stock × Day FE	No	No	No	No	Yes	Yes	Yes	Yes
Investor × Day FE	No	No	No	No	No	No	Yes	Yes
Observations	690,563	690,563	690,563	690,563	690,563	690,563	690,563	690,563
R^2	0.00	0.03	0.05	0.08	0.39	0.40	0.43	0.44

TABLE 8: **Matching Exercises** This table presents estimations of regressions similar to those presented in Table 7, but using the sample of Highly Advised clients and a sample of matched Lightly Advised. Regressions are estimated at the investor-stock-day level. The dependent variable is equal to 100 if the stock is sold (fully or partially) on a day and zero otherwise. Gain is a dummy variable equal to one if the return since purchase is positive and zero otherwise. Highly Advised and Not Advised are dummy variables indicating the client category. The omitted category is the *Lightly Advised* group of investors. Post is a dummy equal to 1 for months following January 2018. Control variables are the same as in Table 7. In Panel A, we use a propensity score matching procedure to match each Highly Advised client with her closest Lightly Advised counterpart in the pre-treatment period. The matching variables include the logarithm of the client's average total assets, the average number of stocks in the client's portfolio, and the client's average daily likelihood of selling one or several stocks. In Panel B, we perform a coarse matching exercise, matching each Highly Advised client in the pre-treatment period with the Lightly Advised clients that are (i) in the same quartile of the distribution of logarithm of average total assets, (ii) in the same quartile of the distribution of average number of stocks in the client's portfolio, and (iii) in the same quartile of the distribution of average daily likelihood of selling one or several stocks in the pre-treatment period. As in Table 7, we include only days where investors have more than 2 assets in their portfolios and sell at least one stock. Standard errors are double-clustered at the investor and day level. ***, ** and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Ex-post Return Difference Between Winning Stocks Sold and Unrealized Losses (%)

	3-Month		6-Month		1-Year		2-Year	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Highly Advised × Post	-2.066***	-2.066***	-2.017**	-2.017**	-2.885**	-2.885**	-2.914	-2.914
	(0.729)	(0.689)	(0.874)	(0.821)	(1.441)	(1.239)	(3.478)	(3.754)
Highly Advised	1.049*	1.049*	1.340**	1.340**	1.687	1.687*	2.400	2.400
	(0.571)	(0.540)	(0.673)	(0.632)	(1.066)	(0.917)	(2.240)	(2.417)
Post	1.577***		1.786***		2.929***		4.160*	
	(0.515)		(0.618)		(1.019)		(2.460)	
Constant	-0.863**	0.104	-1.403***	-0.344	-3.004***	-1.402***	-5.690***	-3.965***
	(0.404)	(0.237)	(0.476)	(0.285)	(0.754)	(0.436)	(1.584)	(1.308)
Year-Month FE	No	Yes	No	Yes	No	Yes	No	Yes
_cons	Yes	No	Yes	No	Yes	No	Yes	No
Observations	124	124	118	118	106	106	82	82
R^2	0.08	0.59	0.07	0.59	0.08	0.66	0.04	0.44

Panel B: Portfolio Return

	Monthly Return (%)			
	(1)	(2)	(3)	(4)
Highly Advised × Post	0.270***	0.204**	0.265***	0.202**
	(0.078)	(0.080)	(0.079)	(0.082)
Constant	0.933***	0.971***	0.936***	0.972***
	(0.044)	(0.045)	(0.045)	(0.046)
Year-Month FE	Yes	No	No	No
Investor FE	Yes	Yes	Yes	Yes
Advisor × Year-Month FE	No	Yes	No	Yes
Cohort × Year-Month FE	No	No	Yes	Yes
Observations	56,381	56,381	56,381	56,381
R^2	0.68	0.71	0.68	0.71

Panel C: Risk-adjusted Portfolio Return

	Risk-Adjusted Return (%)			
	(1)	(2)	(3)	(4)
Highly Advised × Post	-0.085	-0.129	-0.094	-0.117
	(0.151)	(0.160)	(0.150)	(0.161)
Constant	-0.053	-0.028	-0.049	-0.035
	(0.084)	(0.090)	(0.084)	(0.090)
Year-Month FE	Yes	No	No	No
Investor FE	Yes	Yes	Yes	Yes
Advisor × Year-Month FE	No	Yes	No	Yes
Cohort × Year-Month FE	No	No	Yes	Yes
Observations	56,381	56,381	56,381	56,381
R^2	0.22	0.30	0.23	0.31

TABLE 9: **Effects on Client Portfolios' Performance.** Regressions are estimated at the profile-month in Panel A, and at the investor-month level in Panels B and C. The dependent variable is the ex-post return difference between winning stocks sold and unrealized paper losses, at various horizons in Panel A, the portfolio monthly return in Panel B, and the portfolio risk-adjusted return (using Fama-French 3 factors and Momentum) in Panel C. Highly Advised is a dummy equal to 1 if the investor is in the *Highly Advised* group. The omitted category is the *Lightly Advised* group of investors. Cohort is defined as the initial semester in which the client is first recorded in our database. Post is a dummy equal to 1 for months following January 2018. Standard errors are clustered at the investor level in Panels B and C. ***, ** and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Asset Inflows

	Inflow (%)			
	(1)	(2)	(3)	(4)
Highly Advised × Post	0.011**	0.014**	0.012**	0.014**
	(0.006)	(0.006)	(0.006)	(0.006)
Constant	0.002	0.001	0.002	0.001
	(0.003)	(0.003)	(0.003)	(0.003)
Year-Month FE	Yes	No	No	No
Investor FE	Yes	Yes	Yes	Yes
Advisor × Year-Month FE	No	Yes	No	Yes
Cohort × Year-Month FE	No	No	Yes	Yes
Observations	56,381	56,381	56,381	56,381
R^2	0.12	0.23	0.13	0.24

Panel B: Asset Outflows

	Outflow (%)			
	(1)	(2)	(3)	(4)
Highly Advised × Post	-0.044	-0.015	-0.046	-0.019
	(0.033)	(0.016)	(0.035)	(0.017)
Constant	0.049***	0.032***	0.050**	0.034***
	(0.019)	(0.009)	(0.020)	(0.010)
Year-Month FE	Yes	No	No	No
Investor FE	Yes	Yes	Yes	Yes
Advisor × Year-Month FE	No	Yes	No	Yes
Cohort × Year-Month FE	No	No	Yes	Yes
Observations	56,381	56,381	56,381	56,381
R^2	0.21	0.32	0.22	0.33

Panel C: Likelihood of Leaving the Firm

	100 × Exit			
	(1)	(2)	(3)	(4)
Highly Advised × Post	-0.085*	-0.078*	-0.091*	-0.080*
	(0.047)	(0.045)	(0.046)	(0.044)
Highly Advised	0.051	0.025	0.049	0.023
	(0.037)	(0.032)	(0.038)	(0.033)
Constant	0.063***	0.076***	0.068***	0.079***
	(0.021)	(0.022)	(0.020)	(0.023)
Year-Month FE	Yes	Yes	No	No
Advisor FE	No	Yes	No	Yes
Cohort × Year-Month FE	No	No	Yes	Yes
Observations	56,381	56,381	56,381	56,381
R^2	0.00	0.00	0.01	0.01

Table 10: **Effects on Flows and Client Departure.** Regressions are estimated at the investor-month level. In Panels A, B and C, the dependent variables are the percentage inflow, the percentage outflow, and a dummy equal to one if the client leaves the firm respectively. Highly Advised is a dummy equal to 1 if the investor is in the *Highly Advised* group. The omitted category is the *Lightly Advised* group of investors. Cohort is defined as the initial semester in which the client is first recorded in our database. Post is a dummy equal to 1 for months following January 2018. Standard errors are clustered at the investor level. ***, ** and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Figures

Information compts

Position du	23/02/2023	Valorisation titres	274 883,64 EUR
		Valorisation espèces	13 751,31 EUR
		Valeur totale	288 634,95 EUR

Espèce:

Regroupement	Libellé	Solde	Valorisation	Poids (%)
- Total espèces			13 751,31	4,76
- ESPECES				
- Espèces EUR	Espèces EUR		13 751,31	4,76
. Espèces	. Espèces	13 751,31 EUR	13 751,31 EUR	4,76

Titres

Regroupement	Libellé valeur	HG	BL	Quantité	PAM	Cours	Date Cours	PMVL	Valorisation	Poids (%)	Secteur économique
- ACTIONS									255 945,86	88,67	
NL0000235190	AIRBUS SE-(AIR)			90	105,3960 EUR	124,4400 EUR	23/02/2023	1 713,96 EUR	11 199,60 EUR	3,88	Divers
FR0013412285	AM.E.P.SP500 EUR-(IPE50)			357	31,9910 EUR	30,4000 EUR	23/02/2023	-567,99 EUR	10 852,80 EUR	3,76	Divers
FR0013412269	AM.ETF P.NAS.100-(IPANX)			249	38,0750 EUR	33,1250 EUR	23/02/2023	-1 232,55 EUR	8 248,13 EUR	2,86	Divers
NL0010273215	ASML HOLDING-(ASML)			17	289,9460 EUR	594,7000 EUR	23/02/2023	5 180,82 EUR	10 109,90 EUR	3,50	Divers
FR0000120628	AXA-(CS)			349	27,8360 EUR	28,7100 EUR	23/02/2023	305,03 EUR	10 019,79 EUR	3,47	Divers
- IE00BD1RP616	BANK IRELAND GRP								9 192,64	3,18	Divers
. DUBLIN	Divers			953	6,7070 EUR	9,6460 EUR	23/02/2023	2 800,87 EUR	9 192,64 EUR	3,18	Divers
FR0000131104	BNP PARIBAS ACT.A-(BNP)			156	55,2820 EUR	64,7900 EUR	23/02/2023	1 483,25 EUR	10 107,24 EUR	3,50	Divers
- ES0140609019	CAIXABANK								8 255,89	2,86	Divers
. MADRID	Divers			2 097	3,3170 EUR	3,9370 EUR	23/02/2023	1 300,14 EUR	8 255,89 EUR	2,86	Divers
FR0000130403	CHRISTIAN DIOR-(CDI)			16	641,6050 EUR	803,0000 EUR	23/02/2023	2 582,32 EUR	12 848,00 EUR	4,45	Divers
- AT0000818802	DO CO								7 545,60	2,61	Divers
. Vienne	Divers			72	88,8190 EUR	104,8000 EUR	23/02/2023	1 150,63 EUR	7 545,60 EUR	2,61	Divers
FR0000035818	ESKER-(ALESK)			39	163,4800 EUR	152,8000 EUR	23/02/2023	-416,52 EUR	5 959,20 EUR	2,06	Divers
FR0000121667	ESSILOR LUXOTTICA-(EI)			49	168,6560 EUR	167,1500 EUR	23/02/2023	-73,79 EUR	8 190,35 EUR	2,84	Divers
FR0014008VX5	EUROAPI-(EAPI)			3	12,5000 EUR	15,3000 EUR	23/02/2023	8,40 EUR	45,90 EUR	0,02	Divers
FR0000052292	HERMES INTL-(RMS)			10	477,1260 EUR	1 722,5000 EUR	23/02/2023	12 453,74 EUR	17 225,00 EUR	5,97	Divers
- DE0006231004	INFINEON TECHN.								7 032,63	2,44	Divers
. XETRA	Divers			202	36,6090 EUR	34,8150 EUR	23/02/2023	-362,39 EUR	7 032,63 EUR	2,44	Divers
FR0000073298	IPSOS-(IPS)			147	50,9140 EUR	57,1000 EUR	23/02/2023	909,34 EUR	8 393,70 EUR	2,91	Divers
FR0000121014	LVMH MOET VUITTON-(MC)			15	427,9200 EUR	809,0000 EUR	23/02/2023	5 716,20 EUR	12 135,00 EUR	4,20	Divers
LU1834988781	LY.I.L.S.E.600TRAV-(TRV)			216	28,0080 EUR	28,3530 EUR	23/02/2023	74,52 EUR	6 124,25 EUR	2,12	Divers
FR0000039620	MERSEN -EXCARBONL-(MRN)			134	44,0850 EUR	44,3000 EUR	23/02/2023	28,81 EUR	5 936,20 EUR	2,06	Divers
- FI4000297767	NORDEA BANK								7 161,15	2,48	Divers
. Stockholm	Divers			602	10,8280 EUR	131,5404 SEK	23/02/2023	642,70 EUR	7 161,15 EUR	2,48	Divers
- DK0060534915	NOVO NORDISK B								11 600,86	4,02	Divers
. Copenhague	Divers			86	85,9310 EUR	1 004,0003 DKK	23/02/2023	4 210,79 EUR	11 600,86 EUR	4,02	Divers
FR0000120693	PERNOD RICARD-(RI)			35	200,5970 EUR	202,6000 EUR	23/02/2023	70,10 EUR	7 091,00 EUR	2,46	Divers
FR0000130577	PUBLICIS GROUPE-(PUB)			162	61,3230 EUR	75,8200 EUR	23/02/2023	2 348,51 EUR	12 282,84 EUR	4,26	Divers
- DE0007037129	RWE A								5 323,99	1,84	Divers
. XETRA	Divers			133	42,9440 EUR	40,0300 EUR	23/02/2023	-387,56 EUR	5 323,99 EUR	1,84	Divers
FR0000073272	SAFRAN-(SAF)			68	127,8950 EUR	134,8400 EUR	23/02/2023	472,26 EUR	9 169,12 EUR	3,18	Divers
- FI0009003305	SAMPO CL.A								7 126,23	2,47	Divers
. Helsinki	Divers			157	45,7570 EUR	45,3900 EUR	23/02/2023	-57,62 EUR	7 126,23 EUR	2,47	Divers
FR0010282822	SES IMAGOTAG-(SESL)			66	130,2780 EUR	121,8000 EUR	23/02/2023	-559,55 EUR	8 038,80 EUR	2,79	Divers
- DE0007236101	SIEMENS AG-(SIA)								10 218,60	3,54	Divers
. XETRA	Divers			70	142,3990 EUR	145,9800 EUR	23/02/2023	250,67 EUR	10 218,60 EUR	3,54	Divers
FR0000125486	VINCI-(DG)			79	99,0480 EUR	107,7400 EUR	23/02/2023	686,67 EUR	8 511,46 EUR	2,95	Autres services
- OPCVM ACTIONS									18 937,78	6,56	
FR0013292802	POR.EUR.PME IS.P3D			40,258	107,4000 EUR	106,1500 EUR	22/02/2023	-50,32 EUR	4 273,39 EUR	1,48	Divers
FR0013292786	PORTZ.ENTR.ISR P3D			67,830	103,5630 EUR	103,8000 EUR	22/02/2023	16,08 EUR	7 040,75 EUR	2,44	Divers
FR0013292836	PORTZ.PME ISR P 3D			17,864	204,3860 EUR	426,7600 EUR	22/02/2023	3 972,49 EUR	7 623,64 EUR	2,64	Divers

Figure 1: **Clients' Platform**

This figure provides a screenshot of the platform available to clients over our sample period. The figure displays one client's account on 2023-02-23. The French convention is to write 416, 52 for 416.52 and 23/02/2023 for 02/23/2023. We provide the translation for the following terms: "compte" = account; "espèce"= cash; "titres" or "valeurs" = assets, "actions" = equity, "libellé "= ticker, "valorisation" = value, "poids"=weight, "cours"= market value, "PAM"= average buy price, "PMVL" = average gain.

Performance moy. 3 mois relative 1,94 % | Rendements moyens 2,2 %

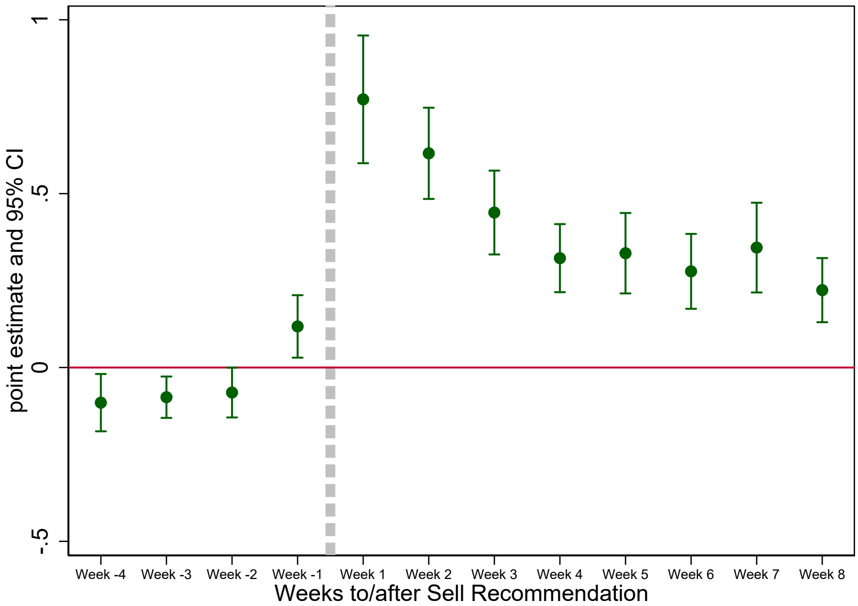
Liste des valeurs

#	Valeur	Poids dans le portefeuille	Note BCAP	BCAP Abs.	BCAP Rel. Marché	BCAP Rel. Secteur	Rendement	Date de détachement	Capitalisation	Dernier cours de clôture	Note ESG	SRRI
1	ESPÈCES EUR	6,19 %	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
2	NOVO NORDISK B	5,86 %	95	A	P	A	1,26 %	16/08/2022	207,11 Md €	118,87 €	7	7
3	HERMES INTL-(RMS)	5,55 %	100	A	A	A	0,52 %	27/04/2022	162,84 Md €	1 542,50 €	8	7
4	EQUINOR-(EQNR)	4,73 %	85	A	P	P	2,10 %	29/11/2022	117,25 Md €	36,93 €	7	7
5	CHRISTIAN DIOR-(CDI)	4,17 %	84	A	A	A	1,66 %	05/12/2022	130,69 Md €	724,00 €	N/A	7
6	LVMH MOET VUITTON-(MC)	3,98 %	84	A	A	A	1,63 %	05/12/2022	371,05 Md €	737,30 €	7	7
7	AM.E.P.SP500 EUR-(IPE50)	3,97 %	69	C	P	N/A	N/A	N/A	N/A	30,90 €	N/A	6
8	AIRBUS SE-(AIR)	3,54 %	61	P	P	P	1,37 %	21/04/2022	86,07 Md €	109,20 €	7	7
9	PORTZ.ENTR.ISR P3D	3,45 %	N/A	N/A	N/A	N/A	N/A	N/A	N/A	100,15 €	N/A	N/A
10	NORDEA BANK	3,29 %	92	A	P	P	6,92 %	04/04/2022	36,66 Md €	10,01 €	6	7
11	ESSILOR LUXOTTICA-(EI)	3,13 %	99	A	A	A	1,42 %	21/06/2022	79,33 Md €	177,30 €	7	7
12	GTT-(GTT)	3,05 %	58	C	P	C	2,77 %	08/06/2022	4,42 Md €	119,30 €	3	7
13	BNP PARIBAS ACT.A-(BNP)	3,00 %	75	A	A	C	6,87 %	25/05/2022	65,95 Md €	53,43 €	6	7
14	DO CO	3,00 %	55	C	A	C	0,00 %	05/08/2019	0,86 Md €	88,60 €	7	7
15	AM.ETF P.NAS.100-(IPANX)	2,92 %	28	B	P	N/A	N/A	N/A	N/A	32,53 €	N/A	7
16	IPSOS-(IPS)	2,89 %	97	A	A	A	2,11 %	05/07/2022	2,43 Md €	54,60 €	2	7
17	VINCI-(DG)	2,75 %	82	A	P	P	3,36 %	17/11/2022	57,78 Md €	96,62 €	4	7
18	DANONE-(BN)	2,74 %	25	C	B	B	3,87 %	12/05/2022	33,85 Md €	50,08 €	8	6
19	SAMPO CL.A	2,74 %	91	A	P	P	4,33 %	31/05/2022	25,87 Md €	48,54 €	6	7
20	PUBLICIS GROUPE-(PUB)	2,70 %	98	A	A	P	3,85 %	06/07/2022	15,84 Md €	62,40 €	7	7

FIGURE 2: **Advisors' Platform Introduced in 2018**

This figure provides a screenshot of the platform available to advisors from January 2018. The figure displays one client's account visualized through the platform on 2023-02-23. The French convention is to write "207, 11 Md €" for 207.11 billion euros. We provide the translation for the following terms: "valeurs" = assets, "Poids dans le portefeuille" = portfolio weight, "Rendement"= return over the past 3 months, "Date de détachement" = last date a dividend was paid, "Capitalisation"= market capitalization; "Dernier cours de clôture"= last closing day market price. In addition, "Notes BCAP" is a proprietary momentum rating system of the firm, "BCAP abs" is the outright rating grade, "BCAP Rel. Marché" is the grade relative to the index, "BCAP Rel. Secteur" is the grade relative to the industry of the asset; "Note ESG" is an ESG rating determined by the firm, and "SRRI" stands for Synthetic Risk and Reward Indicator and indicates the level of risk of the asset based on its past volatility by providing a number from 1 to 7 (with 1 representing low risk and 7 representing high risk). Finally, "Performance moy. 3 mois relative" is the average portfolio return over the past 3 months relative to the index and "Rendements moyens" is the portfolio return over the past 3 months.

Panel A: Overall effect of Sell Recommendation



Panel B: Additional effect of Sell Recommendation on the Highly Advised

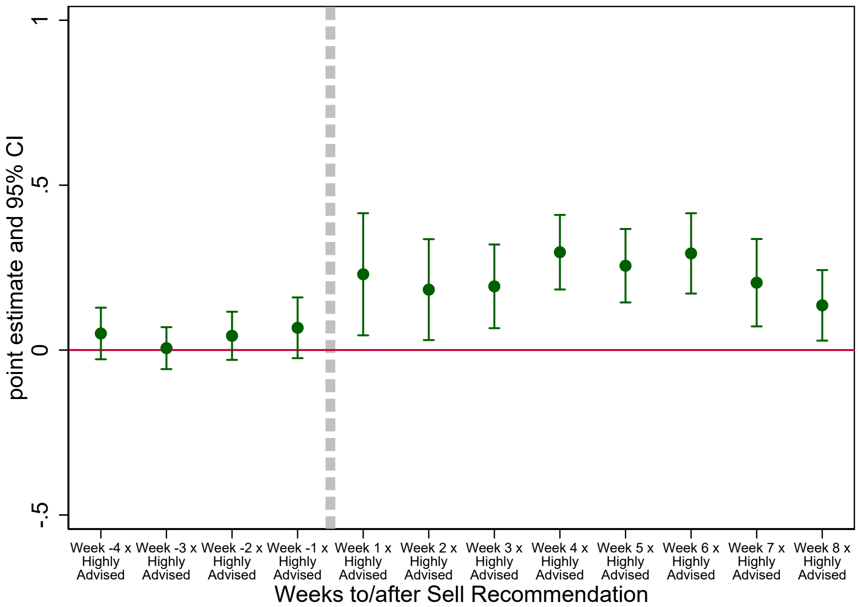
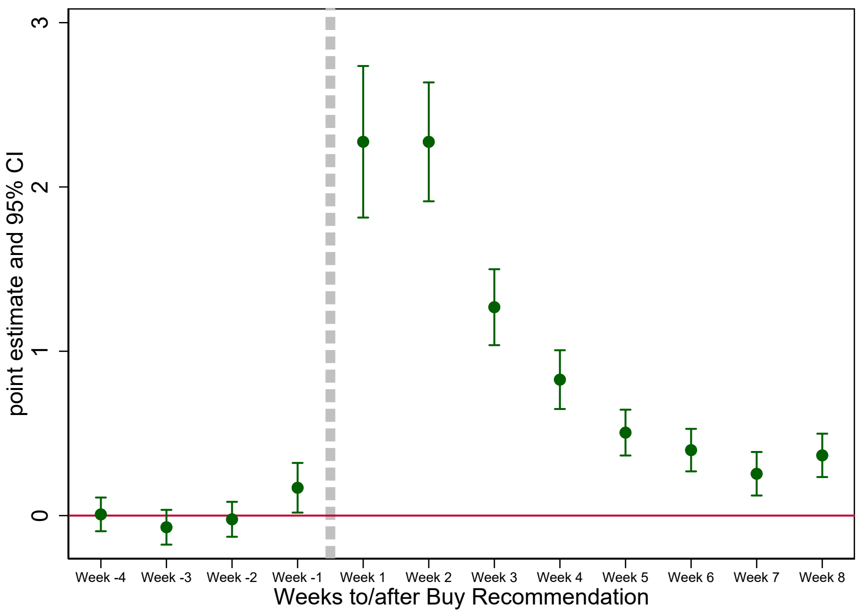


FIGURE 3: **Event Study: Following Sell Recommendations.** These figures plot the coefficient on the 4 weeks before and 8 weeks after the committee recommendation on a stock switches to "Sell". Panel A provides the coefficients $\beta_{s,k}$ and Panel B the coefficients $\beta_{sh,k}$ of regression (3): $100 \times Sell_{i,j,t} = \sum_{k=-4}^{+8} [\beta_{s,k} SellReco(k)_{j,t} + \beta_{sh,k} SellReco(k)_{j,t} \times HighlyAdvised_i] + FE_i + FE_j + FE_t + \epsilon_{i,j,t}$, where, for any advised investor i, stock j and day t, $Sell_{i,j,t}$ is a dummy equal to 1 if some stock j is sold by investor i on day t; $HighlyAdvised_i$ is a dummy equal to 1 if the investor is in the *Highly Advised* group (the omitted category is the *Lightly Advised* group of investors); FE_i, FE_j and FE_t are respectively investor, stock and day fixed effects; and $SellReco(k)_{j,t}$ is a dummy equal to one if the firm's committee recommendation on stock j switches to "Sell" k weeks before t when $k \geq 0$ or k weeks after t when $k \leq 0$. Standard errors are double clustered at the investor and day level.

Panel A: Overall effect of Buy Recommendation



Panel B: Additional effect of Buy Recommendation on the Highly Advised

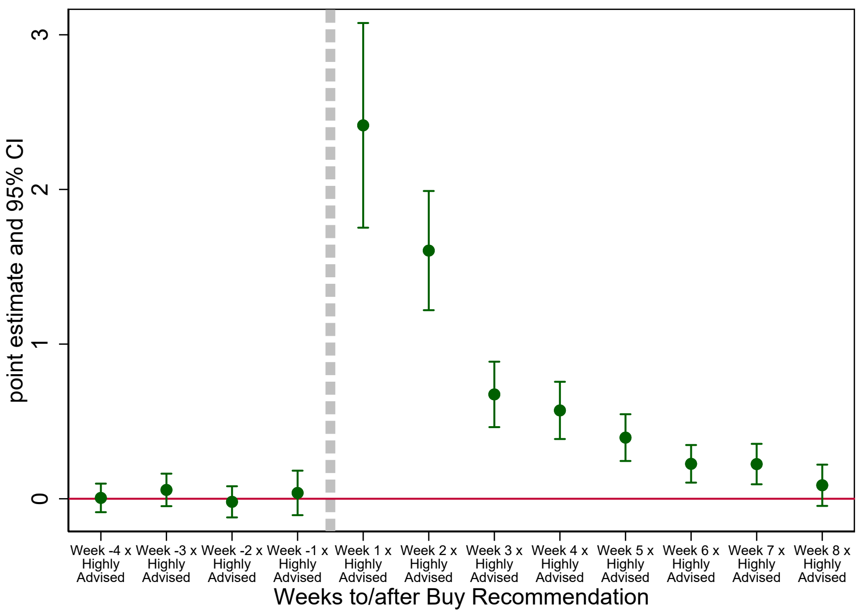


FIGURE 4: **Event Study: Following Buy Recommendations.** These figures plot the coefficient on the 4 weeks before and 8 weeks after the committee recommendation on a stock switches to "Buy". Panel A provides the coefficients $\beta_{b,k}$ and Panel B the coefficients $\beta_{bh,k}$ of regression (4): $100 \times Buy_{i,j,t} = \sum_{k=-4}^{+8} [\beta_{s,k} BuyReco(k)_{j,t} + \beta_{sh,k} BuyReco(k)_{j,t} \times HighlyAdvised_i] + FE_i + FE_j + FE_t + \epsilon_{i,j,t}$, where, for any advised investor i, stock j and day t, $Buy_{i,j,t}$ is a dummy equal to 1 if some stock j is bought by investor i on day t; $HighlyAdvised_i$ is a dummy equal to 1 if the investor is in the *Highly Advised* group (the omitted category is the *Lightly Advised* group of investors); FE_i, FE_j and FE_t are respectively investor, stock and day fixed effects; and $BuyReco(k)_{j,t}$ is a dummy equal to one if the firm's committee recommendation on stock j switches to "Buy" k weeks before t when $k \geq 0$ or k weeks after t when $k \leq 0$. Standard errors are double clustered at the investor and day level.

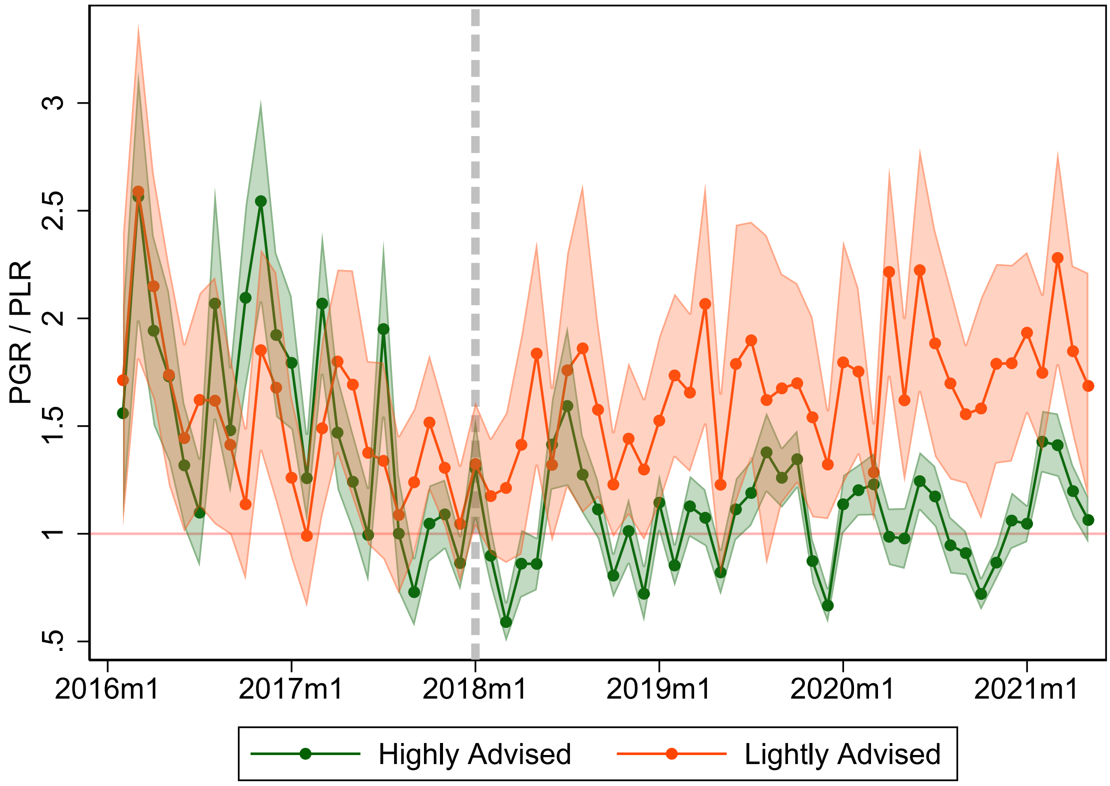


Figure 5: **Disposition Effect by Investors' Profile.** This figure displays the evolution of the ratio of the Proportion of Gain Realized (PGR) to the Proportion of Loss Realized (PLR). PGR is the number of realized gains divided by the number of realized gains plus the number of paper (unrealized) gains, and the PLR is the number of realized losses divided by the number of realized losses plus the number of paper (unrealized) losses. Realized gains, paper gains, losses and paper losses are aggregated each month and across all investors in a given profile (*Highly Advised* or *Lightly Advised*). The shaded areas represent the 95% intervals around the estimated values, computed using a bootstrap procedure.

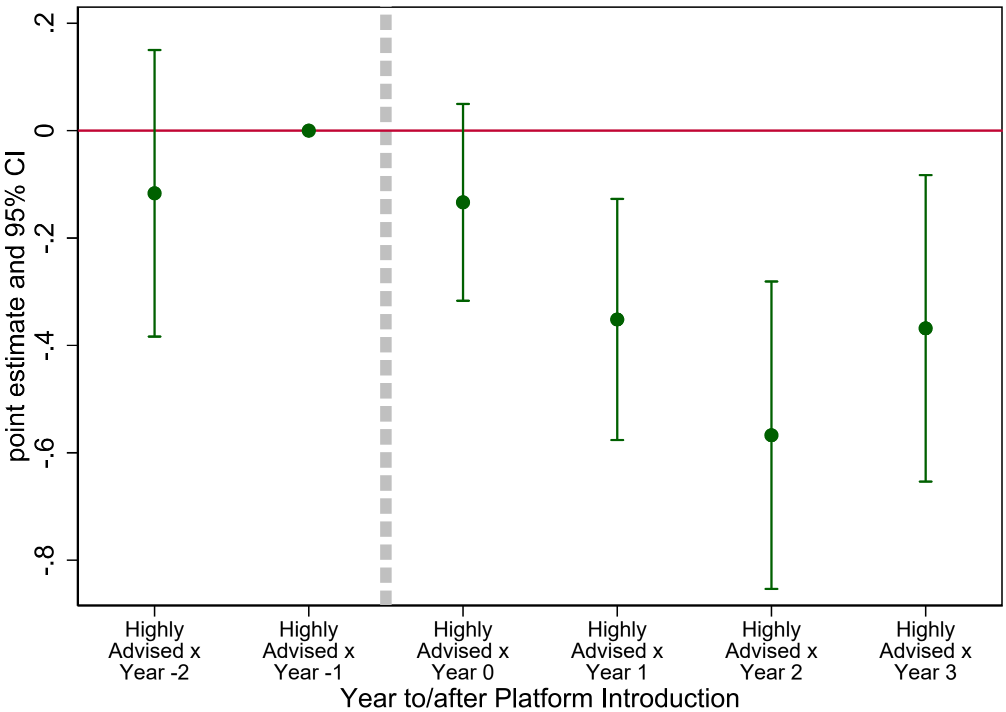


FIGURE 6: **Dynamics of the Reduction in the Disposition Effect of Investors.** This figure plots the coefficients β_k on each year in equation (10): $PGR/PLR_{i,t} = \sum_{k=-2,k\neq-1}^{3} \beta_k \{HighlyAdvised_i \times TreatmentYear(k)_t\} + \alpha_i + \gamma_t + \epsilon_{i,t}$, where i and t denote the investor and month, and $TreatmentYear(k)_t$ is a dummy equal to one if month t is part of year k before/after the new platform introduction in 2018. We use year -1 as the baseline year. α_i and γ_t denote investor and year-month fixed effects respectively. The dependent variable is the ratio of the Proportion of Gain Realized (PGR) to the Proportion of Loss Realized (PLR). PGR is the number of realized gains divided by the number of realized gains plus the number of paper (unrealized) gains, and the PLR is the number of realized losses divided by the number of realized losses plus the number of paper (unrealized) losses. Realized gains, paper gains, losses and paper losses are aggregated over month and investor. Highly Advised is a dummy equal to 1 if the investor is in the *Highly Advised* group. The omitted category is the *Lightly Advised* group of investors. Horizontal bars correspond to 95% confidence intervals. Standard errors are clustered at the investor level.

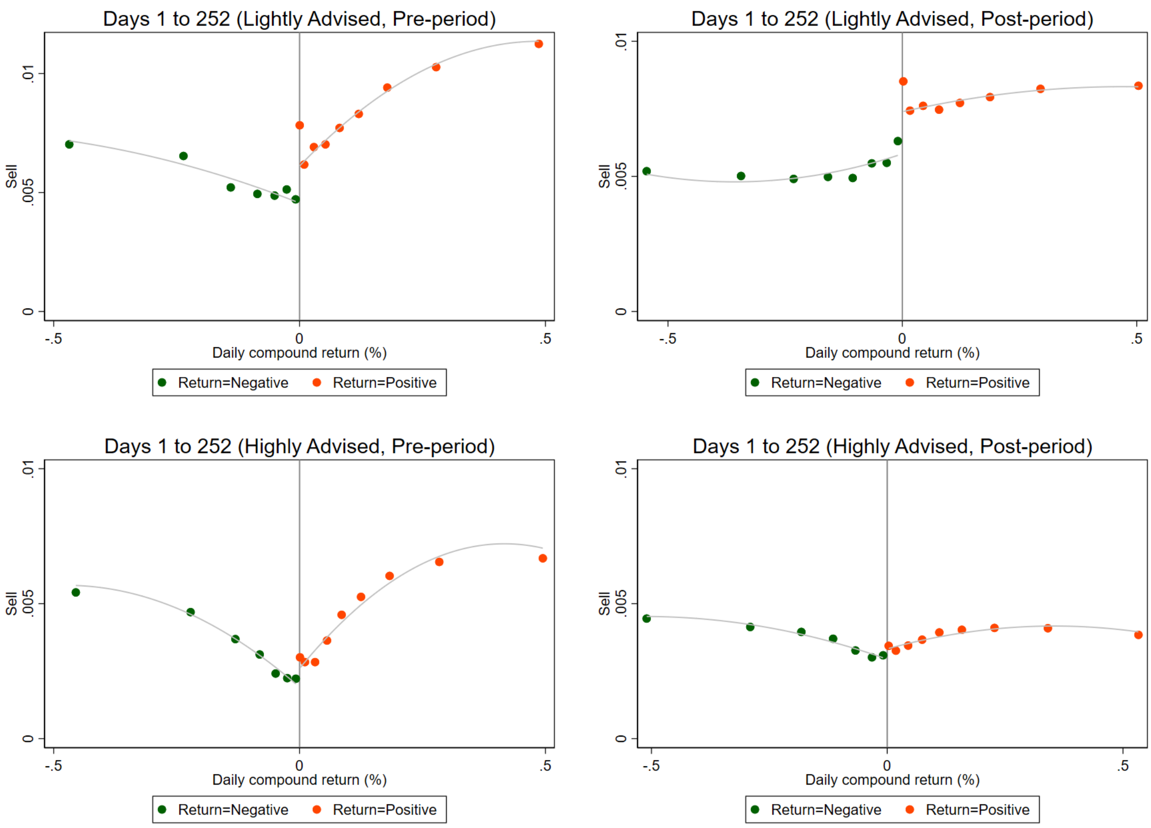


FIGURE 7: **Likelihood of Selling as a Function of Realized Return.** This figure assesses the influence of gain or loss magnitude on the likelihood of selling a stock by examining how the probabilities of selling a stock change based on the returns since the initial purchase. Our analysis closely follows the methodology employed by Ben-David and Hirshleifer (2012). Specifically, we focus on the year following investors' stock purchases and estimate the probabilities of stock sales as a function of the returns since the initial purchase. The figure presents bin scatter plots. In each panel, the horizontal axis represents the daily compounded return since the purchase, while the vertical axis represents the probability of selling the stock.

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Internet Appendix

Financial Advisors and Investors' Bias

Additional Tables

	Log(Nb. Calls)		Log(Nb. Calls In)		Log(Nb. Calls Out)	
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Nb. Clients)	0.510***		0.411***		0.876***	
	(0.105)		(0.144)		(0.146)	
Log(Nb. Highly Advised)		0.404***		0.360***		0.605***
		(0.079)		(0.114)		(0.114)
Log(Nb. Lightly Advised)		0.208***		0.144		0.375***
		(0.063)		(0.091)		(0.091)
Constant	2.652***	2.600***	2.637***	2.493***	-0.303	0.018
	(0.567)	(0.457)	(0.775)	(0.659)	(0.786)	(0.658)
Observations	34	33	34	33	34	33
R^2	0.42	0.56	0.20	0.30	0.53	0.61

TABLE A.1: **Relationship Between Calling Intensity and Number of Clients Across Advisors** Regressions are estimated at the advisor level. The dependent variable is the logarithm of the total number of calls (columns (1) and (2)), the number of incoming calls (columns (3) and (4)), and the number of outgoing calls (columns (5) and (6)) made by the advisor in September 2023. The independent variables comprise the logarithm of the total number of clients, along with the logarithm of the counts of highly advised and lightly advised clients associated with the respective advisors.

	Sell × 100					
	(1)	(2)	(3)	(4)	(5)	(6)
Gain	3.279***	4.257***	4.335***	5.051***	4.330***	3.858***
	(0.794)	(1.291)	(0.834)	(1.227)	(0.595)	(0.740)
Gain × Purchased Following Recommendation	-1.320*	-0.285	-1.135*	-0.180	-0.426	0.112
	(0.701)	(0.731)	(0.671)	(0.703)	(0.614)	(0.579)
Gain × Highly Advised	0.689	1.260	0.503	0.943	0.829	0.458
	(0.957)	(0.965)	(0.981)	(0.928)	(0.698)	(0.675)
Highly Advised	1.167	0.783				
	(0.840)	(0.665)				
Purchased Following Recommendation	1.229*	4.372***	-0.144***	4.243***	2.303***	1.692***
	(0.658)	(0.537)	(0.419)	(0.509)	(0.507)	(0.499)
Highly Advised × Purchased Following Recommendation	-0.989	-1.184*	0.031	-0.837	-0.428	-0.653
	(0.778)	(0.664)	(0.557)	(0.587)	(0.552)	(0.558)
Gain × Highly Advised × Purchased Following Recommendation	-0.627	-1.018	-1.511*	-1.658**	-1.276*	-0.867
	(0.864)	(0.858)	(0.819)	(0.822)	(0.701)	(0.695)
Controls	No	Yes	No	Yes	No	Yes
Investor × Day FE	No	No	Yes	Yes	Yes	Yes
Stock × Day FE	No	No	No	No	Yes	Yes
Observations	304,470	304,470	304,470	304,470	304,470	304,470
R^2	0.00	0.05	0.09	0.13	0.46	0.46

TABLE A.2: **Propensity to Sell Gains when Stocks are Bought Following a Buy Recommendation.** The table provides estimation results from regressions estimated within the pre-treatment phase (from February 2016 to December 2017) using only advised clients. The dependent variable is equal to 100 if a stock is sold (fully or partially) on a given day and zero otherwise. Gain is a dummy variable equal to one if the return since purchase is positive and zero otherwise. Purchased Following Recommendation is a dummy variable equal to one if the investment recommendation from the firm's committee was "Buy" when the client initially bought the stock. Highly Advised is a dummy equal to 1 if the investor is in the *Highly Advised* group. The omitted category is the *Lightly Advised* group of investors. Control variables are the same as in Table 4. We include only days where investors have more than 2 assets in their portfolios and sell at least one stock. Standard errors are double clustered at the investor and day level. ***, ** and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Arcsinh(Nb. Shares Sold)		Arcsinh(Nb. Shares Purchased)	
	(1)	(2)	(3)	(4)
Sell Reco × Highly Advised	0.006***	0.006***	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Buy Reco × Highly Advised	-0.002**	-0.002*	0.006***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)
Sell Reco	0.012***	0.012***	-0.006***	-0.006***
	(0.001)	(0.001)	(0.001)	(0.001)
Buy Reco	-0.004***	-0.005***	0.010***	0.009***
	(0.001)	(0.001)	(0.001)	(0.001)
Investor × Day FE	No	Yes	No	Yes
Investor FE	Yes	No	Yes	No
Stock FE	Yes	Yes	Yes	Yes
Day FE	Yes	No	Yes	No
Observations	4.42e+07	4.42e+07	4.42e+07	4.42e+07
R^2	0.01	0.16	0.01	0.20

Table A.3: **Following Recommendations (Intensive Margin, number of shares).** Regressions are estimated at the investor-stock-day level. The dependent variable is the arcsinh of the number of shares sold (purchased) by the investor on that day. Sell (Buy) Reco is a dummy equal to 1 if the stock belongs to the list of the investment committee and its recommendation is to sell (buy) the stock. Highly Advised is a dummy equal to 1 if the investor is in the *Highly Advised* group. The omitted category is the *Lightly Advised* group of investors. Standard errors are double clustered at the investor and day level.

	Arcsinh(Sold Amount)		Arcsinh(Purchased Amount)	
	(1)	(2)	(3)	(4)
Sell Reco × Highly Advised	0.010***	0.011***	-0.004**	-0.003**
	(0.002)	(0.001)	(0.001)	(0.001)
Buy Reco × Highly Advised	-0.006***	-0.006***	0.007***	0.008***
	(0.002)	(0.002)	(0.002)	(0.002)
Sell Reco	0.022***	0.022***	-0.009***	-0.008***
	(0.001)	(0.001)	(0.002)	(0.001)
Buy Reco	-0.005***	-0.007***	0.022***	0.020***
	(0.002)	(0.002)	(0.002)	(0.002)
Investor × Day FE	No	Yes	No	Yes
Investor FE	Yes	No	Yes	No
Stock FE	Yes	Yes	Yes	Yes
Day FE	Yes	No	Yes	No
Observations	4.42e+07	4.42e+07	4.42e+07	4.42e+07
R^2	0.01	0.16	0.01	0.20

TABLE A.4: **Following Recommendations (Intensive Margin, Euro amount).** Regressions are estimated at the investor-stock-day level. The dependent variable is the arcsinh of the amount (number of shares times price) sold or purchased by the investor on that day. Sell (Buy) Reco is a dummy equal to 1 if the stock belongs to the list of the investment committee and its recommendation is to sell (buy) the stock. Highly Advised is a dummy equal to 1 if the investor is in the *Highly Advised* group. The omitted category is the *Lightly Advised* group of investors. Standard errors are double clustered at the investor and day level.

	Sell × 100							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gain	7.524***	7.881***	9.242***	9.657***	8.189***	8.361***	8.961***	8.264***
	(1.191)	(1.272)	(1.302)	(1.340)	(0.966)	(0.981)	(0.744)	(0.828)
Portfolio Gain × Gain	-6.361***	-5.530***	-8.185***	-7.148***	-7.263***	-6.216***	-7.383***	-6.615***
	(1.444)	(1.399)	(1.562)	(1.484)	(1.156)	(1.114)	(0.901)	(0.899)
Gain × Highly Advised	-0.333	0.025	-0.826	-0.323	0.098	-0.056	-0.252	-0.286
	(1.318)	(1.254)	(1.427)	(1.381)	(1.080)	(1.051)	(0.887)	(0.877)
Gain × Not Advised	0.786	0.585	0.750	0.587	0.715	0.666		
	(1.400)	(1.324)	(1.553)	(1.501)	(1.157)	(1.117)		
Highly Advised	1.128	0.837						
	(1.010)	(0.788)						
Not Advised	-0.865	-0.751						
	(1.044)	(0.825)						
Portfolio Gain × Highly Advised	-0.353	-0.013						
	(1.126)	(0.925)						
Portfolio Gain × Not Advised	-0.037	0.410						
	(1.139)	(0.920)						
Portfolio Gain × Gain × Highly Advised	0.981	0.776	1.292	0.876	0.622	0.450	1.063	0.943
	(1.582)	(1.527)	(1.698)	(1.625)	(1.273)	(1.232)	(1.051)	(1.040)
Portfolio Gain × Gain × Not Advised	1.336	1.253	1.632	1.422	1.140	0.963		
	(1.664)	(1.614)	(1.772)	(1.701)	(1.327)	(1.282)		
Portfolio Gain	1.290	0.354						
	(0.989)	(0.772)						
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Investor × Day FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Stock × Day FE	No	No	No	No	Yes	Yes	Yes	Yes
Advisor × Day FE	No	No	No	No	No	No	Yes	Yes
Observations	865,562	865,562	865,562	865,562	865,562	865,562	304,470	304,470
R^2	0.01	0.03	0.11	0.13	0.35	0.36	0.46	0.46

Table A.5: **Evaluating the portfolio disposition effect pre-treatment.** The table provides estimation results from regressions estimated within the pre-treatment phase (from February 2016 to December 2017). The dependent variable is equal to 100 if a stock is sold (fully or partially) on a given day and zero otherwise. Gain is a dummy variable equal to one if the return since purchase is positive and zero otherwise. Portfolio Gain is a dummy variable equal to one if the sum of the portfolio paper gains is greater than the sum of the portfolio paper losses since purchase and zero otherwise. Highly Advised and Not Advised are dummy variables indicating the client category. The omitted category is the *Lightly Advised* group of investors. Standard errors are double clustered at the investor and day level.

	Sell × 100							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Extreme	10.017***	12.246***	4.703***	7.029***	4.444***	5.867***	4.144***	4.487***
	(0.617)	(0.620)	(0.571)	(0.558)	(0.488)	(0.481)	(0.522)	(0.521)
Extreme × Highly Advised	-0.435	-0.127	0.571	0.720	-0.036	0.272	-0.354	0.136
	(0.746)	(0.714)	(0.702)	(0.639)	(0.581)	(0.561)	(0.597)	(0.574)
Extreme × Not Advised	0.829	1.040	-1.659**	-1.414**	-0.958	-1.038*		
	(0.918)	(0.850)	(0.685)	(0.633)	(0.584)	(0.569)		
Highly Advised	1.120*	1.114**						
	(0.589)	(0.520)						
Not Advised	-0.227	0.703						
	(0.709)	(0.645)						
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Investor × Day FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Stock × Day FE	No	No	No	No	Yes	Yes	Yes	Yes
Advisor × Day FE	No	No	No	No	No	No	Yes	Yes
Observations	865,562	865,562	865,562	865,562	865,562	865,562	304,470	304,470
R^2	0.01	0.04	0.10	0.13	0.35	0.36	0.46	0.46

TABLE A.6: **Evaluating the rank effect pre-treatment.** The table provides estimation results from regressions estimated within the pre-treatment phase (from February 2016 to December 2017). The dependent variable is equal to 100 if a stock is sold (fully or partially) on a given day and zero otherwise. Extreme is a dummy variable equal to one if the asset has had the highest paper return since purchase or the lowest paper return since purchase, and zero otherwise. Highly Advised and Not Advised are dummy variables indicating the client category. The omitted category is the *Lightly Advised* group of investors. Standard errors are double clustered at the investor and day level.

	Sell × 100							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Portfolio Gain × Gain × Post × Highly Advised	1.252	0.938	1.184	0.961	1.487	1.380	1.713	1.640
	(1.659)	(1.708)	(1.569)	(1.615)	(1.279)	(1.291)	(1.335)	(1.359)
Gain × Post × Highly Advised	-3.911***	-3.412**	-3.632***	-3.192**	-2.861**	-2.583**	-2.713**	-2.500*
	(1.471)	(1.514)	(1.401)	(1.474)	(1.231)	(1.246)	(1.302)	(1.332)
Gain × Post	0.096	0.621	-0.318	0.403	0.865	0.823	0.911	0.926
	(1.353)	(1.390)	(1.287)	(1.355)	(1.084)	(1.090)	(1.119)	(1.150)
Portfolio Gain	1.290	0.439	1.690**	1.103	1.370**	0.840		
	(0.989)	(0.740)	(0.758)	(0.686)	(0.586)	(0.549)		
Gain	7.524***	5.997***	8.388***	6.980***	8.291***	6.483***	8.961***	7.426***
	(1.190)	(1.230)	(1.158)	(1.198)	(0.701)	(0.722)	(0.743)	(0.772)
Portfolio Gain × Gain	-6.361***	-5.657***	-7.281***	-6.426***	-6.667***	-5.793***	-7.383***	-6.510***
	(1.443)	(1.479)	(1.402)	(1.408)	(0.844)	(0.858)	(0.901)	(0.921)
Post	-0.723	-1.018						
	(0.981)	(0.797)						
Portfolio Gain × Post	0.533	0.473	0.729	0.541	1.412**	1.147*		
	(1.049)	(0.850)	(0.778)	(0.719)	(0.656)	(0.603)		
Portfolio Gain × Gain × Post	0.249	0.261	0.537	0.402	-0.305	-0.479	-0.576	-0.792
	(1.510)	(1.568)	(1.425)	(1.484)	(1.173)	(1.188)	(1.214)	(1.243)
Highly Advised	1.128	0.692	-0.948	-1.076	-1.687***	-1.543***		
	(1.009)	(0.784)	(0.753)	(0.706)	(0.603)	(0.559)		
Portfolio Gain × Highly Advised	-0.353	0.072	1.018	1.310	1.082	1.055		
	(1.126)	(0.909)	(0.904)	(0.840)	(0.722)	(0.680)		
Gain × Highly Advised	-0.333	0.526	-0.517	0.415	0.018	-0.008	-0.252	-0.270
	(1.317)	(1.327)	(1.291)	(1.307)	(0.815)	(0.825)	(0.887)	(0.902)
Portfolio Gain × Gain × Highly Advised	0.981	0.601	1.152	0.663	1.025	0.846	1.063	0.893
	(1.581)	(1.605)	(1.542)	(1.543)	(0.984)	(0.982)	(1.050)	(1.055)
Post × Highly Advised	1.826*	1.417	2.951***	2.370***	2.609***	2.065***		
	(1.068)	(0.906)	(0.827)	(0.805)	(0.720)	(0.664)		
Portfolio Gain × Post × Highly Advised	-1.274	-1.141	-2.021**	-1.651*	-2.287***	-1.834**		
	(1.191)	(1.018)	(0.929)	(0.875)	(0.800)	(0.752)		
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Advisor × Day FE	No	No	Yes	Yes	Yes	Yes	No	No
Stock × Day FE	No	No	No	No	Yes	Yes	Yes	Yes
Investor × Day FE	No	No	No	No	No	No	Yes	Yes
Observations	1582102	1582102	1582102	1582102	1582102	1582102	1582102	1582102
R^2	0.00	0.03	0.04	0.07	0.32	0.33	0.37	0.38

Table A.7: **Evaluating the portfolio disposition effect pre vs. post-treatment.** The dependent variable is equal to 100 if a stock is sold (fully or partially) on a given day and zero otherwise. Gain is a dummy variable equal to one if the return since purchase is positive and zero otherwise. Portfolio Gain is a dummy variable equal to one if the sum of the portfolio paper gains is greater than the sum of the portfolio paper losses since purchase and zero otherwise. Highly Advised is a dummy equal to 1 if the investor is in the *Highly Advised* group. The omitted category is the *Lightly Advised* group of investors. Post is a dummy equal to 1 for months following January 2018. Standard errors are double clustered at the investor and day level.

	Sell × 100							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Extreme × Post × Highly Advised	-1.768**	-1.735**	-1.598**	-1.631**	-1.201*	-1.117	-0.374	-0.407
	(0.755)	(0.739)	(0.762)	(0.707)	(0.704)	(0.705)	(0.648)	(0.638)
Extreme × Post	-0.815	-0.398	0.188	0.577	0.551	0.658	-0.380	-0.165
	(0.634)	(0.628)	(0.630)	(0.587)	(0.640)	(0.629)	(0.556)	(0.545)
Extreme	10.017***	10.953***	7.140***	8.227***	6.644***	7.184***	4.144***	4.696***
	(0.616)	(0.584)	(0.615)	(0.546)	(0.583)	(0.540)	(0.522)	(0.501)
Post	-0.352	0.216						
	(0.521)	(0.485)						
Highly Advised	1.120*	1.291**	0.093	0.469	-0.466	-0.339		
	(0.588)	(0.533)	(0.505)	(0.459)	(0.427)	(0.367)		
Extreme × Highly Advised	-0.435	-0.439	0.132	0.056	-0.875	-0.468	-0.354	0.021
	(0.745)	(0.703)	(0.747)	(0.661)	(0.633)	(0.605)	(0.596)	(0.572)
Post × Highly Advised	-0.276	-0.712	0.329	-0.080	0.276	0.047		
	(0.557)	(0.533)	(0.513)	(0.486)	(0.426)	(0.386)		
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Advisor × Day FE	No	No	Yes	Yes	Yes	Yes	No	No
Stock × Day FE	No	No	No	No	Yes	Yes	Yes	Yes
Investor × Day FE	No	No	No	No	No	No	Yes	Yes
Observations	1582102	1582102	1582102	1582102	1582102	1582102	1582102	1582102
R^2	0.01	0.04	0.04	0.07	0.32	0.33	0.37	0.38

Table A.8: **Evaluating the rank effect pre vs. post-treatment.** The dependent variable is equal to 100 if a stock is sold (fully or partially) on a given day and zero otherwise. Extreme is a dummy variable equal to one if the asset has had the highest paper return since purchase or the lowest paper return since purchase, and zero otherwise. Highly Advised is a dummy equal to 1 if the investor is in the *Highly Advised* group. The omitted category is the *Lightly Advised* group of investors. Post is a dummy equal to 1 for months following January 2018. Standard errors are double clustered at the investor and day level.

	PGR / PLR		
	(1)	(2)	(3)
Highly Advised × Year -1			-0.178
			(0.143)
Highly Advised × Post	-0.630***	-0.630***	-0.723***
	(0.129)	(0.092)	(0.118)
Highly Advised	0.032	0.032	0.125
	(0.101)	(0.072)	(0.103)
Post	0.167*		
	(0.091)		
Constant	1.526***	1.628***	1.628***
	(0.071)	(0.032)	(0.031)
Year-Month FE	No	Yes	Yes
Observations	118	118	118
R^2	0.35	0.83	0.84

TABLE A.9: **Disposition Effect by Investors' Profile Excluding the Pilot Testing Period (Jan-May 2018).** Regressions are estimated at the profile-month level. The dependent variable is the Ratio of the Proportion of Gain Realized (PGR) to the Proportion of Loss Realized (PLR) for a given profile-month. Highly Advised is a dummy equal to 1 if the investor is in the *Highly Advised* group. The omitted category is the *Lightly Advised* group of investors. Post is a dummy equal to 1 for months following January 2018. Year -1 is a dummy equal to 1 for all months from January 2017 to December 2017. All months where $PLR = 0$ are excluded from the sample. Standard errors are not clustered.

	PGR / PLR			
	(1)	(2)	(3)	(4)
Highly Advised × Post	-0.339***	-0.313***	-0.352***	-0.324***
	(0.097)	(0.102)	(0.098)	(0.102)
Constant	1.146***	1.129***	1.153***	1.136***
	(0.057)	(0.060)	(0.057)	(0.060)
Year-Month FE	Yes	No	No	No
Investor FE	Yes	Yes	Yes	Yes
Advisor × Year-Month FE	No	Yes	No	Yes
Cohort × Year-Month FE	No	No	Yes	Yes
Observations	28,102	28,102	28,102	28,102
R^2	0.32	0.38	0.33	0.40

TABLE A.10: **Disposition Effect by Investors Excluding the Pilot Testing Period (Jan-May 2018).** Regressions are estimated at the investor-month level. The dependent variable is the Ratio of the Proportion of Gain Realized (PGR) to the Proportion of Loss Realized (PLR) for a given advisor-profile-month. Highly Advised is a dummy equal to 1 if the investor is in the *Highly Advised* group. The omitted category is the *Lightly Advised* group of investors. Cohort is defined as the initial semester in which the client is first recorded in our database. Post is a dummy equal to 1 for months following January 2018. All months where $PLR = 0$ are excluded from the sample. Standard errors are clustered at the investor level.

	PGR - PLR			
	(1)	(2)	(3)	(4)
Highly Advised × Post	-0.025***	-0.030***	-0.025***	-0.031***
	(0.009)	(0.009)	(0.009)	(0.009)
Constant	0.042***	0.044***	0.042***	0.045***
	(0.005)	(0.005)	(0.005)	(0.005)
Year-Month FE	Yes	No	No	No
Investor FE	Yes	Yes	Yes	Yes
Advisor × Year-Month FE	No	Yes	No	Yes
Cohort × Year-Month FE	No	No	Yes	Yes
Observations	53,281	53,281	53,281	53,281
R^2	0.29	0.35	0.29	0.36

TABLE A.11: **Disposition Effect by Investors: Difference instead of the Ratio.** Regressions are estimated at the investor-month level. The dependent variable is the Proportion of Gain Realized (PGR) minus the Proportion of Loss Realized (PLR) for a given advisor-profile-month. Highly Advised is a dummy equal to 1 if the investor is in the *Highly Advised* group. The omitted category is the *Lightly Advised* group of investors. Cohort is defined as the initial semester in which the client is first recorded in our database. Post is a dummy equal to 1 for months following January 2018. Standard errors are clustered at the investor level.

	PGR				PLR			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Highly Advised × Post	-0.019***	-0.024***	-0.019***	-0.023***	0.004	0.006	0.004	0.007
	(0.006)	(0.007)	(0.006)	(0.007)	(0.005)	(0.005)	(0.005)	(0.005)
Constant	0.174***	0.176***	0.174***	0.176***	0.132***	0.130***	0.132***	0.130***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
Year-Month FE	Yes	No	No	No	Yes	No	No	No
Investor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Advisor × Year-Month FE	No	Yes	No	Yes	No	Yes	No	Yes
Cohort × Year-Month FE	No	No	Yes	Yes	No	No	Yes	Yes
Observations	55,306	55,306	55,306	55,306	54,343	54,343	54,343	54,343
R^2	0.39	0.44	0.40	0.45	0.30	0.36	0.31	0.37

Table A.12: **Disposition Effect by Investors: PGR and PLR separately.** Regressions are estimated at the investor-month level. The dependent variables are the Ratio of the Proportion of Gain Realized (PGR) and the Proportion of Loss Realized (PLR) for a given advisor-profile-month. Highly Advised is a dummy equal to 1 if the investor is in the *Highly Advised* group. The omitted category is the *Lightly Advised* group of investors. Cohort is defined as the initial semester in which the client is first recorded in our database. Post is a dummy equal to 1 for months following January 2018. Standard errors are clustered at the investor level.

	PGR / PLR			
	(1)	(2)	(3)	(4)
Highly Advised × Post	-0.448***	-0.433***	-0.452***	-0.432***
	(0.122)	(0.128)	(0.120)	(0.126)
Constant	1.556***	1.544***	1.558***	1.543***
	(0.069)	(0.073)	(0.069)	(0.072)
Year-Quarter FE	Yes	No	No	No
Investor FE	Yes	Yes	Yes	Yes
Advisor × Year-Quarter FE	No	Yes	No	Yes
Cohort × Year-Quarter FE	No	No	Yes	Yes
Observations	21,499	21,499	21,499	21,499
R^2	0.39	0.44	0.40	0.44

TABLE A.13: **Disposition Effect by Investors: Investor-Quarter level Regressions.** Regressions are estimated at the investor-quarter level. The dependent variable is the Ratio of the Proportion of Gain Realized (PGR) to the Proportion of Loss Realized (PLR) for a given advisor-profile-month. Highly Advised is a dummy equal to 1 if the investor is in the *Highly Advised* group. The omitted category is the *Lightly Advised* group of investors. Cohort is defined as the initial semester in which the client is first recorded in our database. Post is a dummy equal to 1 for months following January 2018. All quarters where $PLR = 0$ are excluded from the sample. Standard errors are clustered at the investor level.

	PGR/PLR (Profile-Month)		PGR/PLR (Investor-Month)	
	(1)	(2)	(3)	(4)
Highly Advised × Post	-0.629***	-0.629***	-0.338***	-0.348***
	(0.115)	(0.093)	(0.090)	(0.091)
Not Advised × Post	-0.149	-0.149	-0.007	0.108
	(0.115)	(0.093)	(0.130)	(0.147)
Highly Advised	0.030	0.030		
	(0.091)	(0.074)		
Not Advised	0.522***	0.522***		
	(0.091)	(0.074)		
Post	0.147*			
	(0.081)			
Constant	1.517***	1.609***	1.672***	1.645***
	(0.064)	(0.032)	(0.059)	(0.061)
Year-Month FE	No	Yes	Yes	No
Investor FE	No	No	Yes	Yes
Cohort × Year-Month FE	No	No	No	Yes
Observations	192	192	49,006	49,006
R^2	0.57	0.81	0.37	0.38

TABLE A.14: **Disposition Effect by Investors: Including Not Advised Investors.** Regressions are estimated at the profile-month (columns 1 and 2) and at the investor-month (columns 3 and 4) levels. The dependent variable is the Ratio of the Proportion of Gain Realized (PGR) to the Proportion of Loss Realized (PLR). Highly Advised and Not Advised are dummy variables indicating the client category. The omitted category is the *Lightly Advised* group of investors.

	BCAP Index				High BCAP			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gain	4.518***	9.865***	9.854***	9.749***	0.070***	0.151***	0.151***	0.149***
	(0.748)	(0.563)	(0.563)	(0.549)	(0.012)	(0.009)	(0.009)	(0.008)
Investor FE	No	Yes	Yes	No	No	Yes	Yes	No
Stock FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Day FE	No	Yes	No	No	No	Yes	No	No
Investor × Day FE	No	No	No	Yes	No	No	No	Yes
Advisor × Day FE	No	No	Yes	No	No	No	Yes	No
Observations	4.29e+07	4.29e+07	4.29e+07	4.29e+07	4.29e+07	4.29e+07	4.29e+07	4.29e+07
R^2	0.01	0.35	0.35	0.43	0.01	0.29	0.29	0.36

Table A.15: **The Relationship Between the BCAP Index and Gains** Regressions are estimated at the investor-stock-day level. In columns (1)-(4), the dependent variable is the BCAP Index, the firm's proprietary momentum indicator for the stock (between 0 and 100). In columns (5)-(8), the dependent variable is High BCAP, a dummy variable equal to one is the rating letter for the stock is A or P. Standard errors are clustered at the stock and day level.

	PHBR / PLBR			
	(1)	(2)	(3)	(4)
Highly Advised × Post	-0.018	-0.001	-0.029	-0.006
	(0.063)	(0.068)	(0.063)	(0.068)
Constant	0.890***	0.881***	0.896***	0.884***
	(0.036)	(0.039)	(0.036)	(0.039)
Year-Month FE	Yes	No	No	No
Investor FE	Yes	Yes	Yes	Yes
Advisor × Year-Month FE	No	Yes	No	Yes
Cohort × Year-Month FE	No	No	Yes	Yes
Observations	37,277	37,277	37,277	37,277
R^2	0.12	0.20	0.13	0.21

TABLE A.16: **Proportion of High Momentum Versus Low Momentum Realized.** The dependent variable is the Ratio of the Proportion of High BCAP Realized (PHBR) to the Proportion of Low BCAP Realized (PLBR) for a given investor-month. The BCAP is a proprietary momentum indicator developed by the firm. We obtained the methodology employed by the firm to compute the BCAP index and applied it to the stocks within our sample. We compute the PHBR/PLBR ratio by aggregating realized High BCAP and Low BCAP as well as paper High BCAP and Low BCAP, within each investor and month. Highly Advised is a dummy equal to 1 if the investor is in the *Highly Advised* group. The omitted category is the *Lightly Advised* group of investors. Cohort is defined as the initial semester in which the client is first recorded in our database. Post is a dummy equal to 1 for months following January 2018. Standard errors are clustered at the investor level. ***, ** and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Sell × 100							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
High BCAP × Gain × Post × Highly Advised	-0.220	-0.210	-0.372	-0.479	-0.427	-0.752	-0.613	-1.003
	(0.740)	(0.714)	(0.735)	(0.723)	(0.729)	(0.719)	(0.753)	(0.743)
Gain × Post × Highly Advised	-3.793***	-3.408***	-3.528***	-3.094***	-3.689***	-3.052***	-3.409***	-2.819***
	(0.958)	(0.956)	(0.883)	(0.881)	(0.860)	(0.857)	(0.931)	(0.944)
Gain × Post	0.814	1.311	0.615	1.253	0.892	1.490**	0.406	1.145
	(0.867)	(0.872)	(0.805)	(0.803)	(0.759)	(0.750)	(0.817)	(0.822)
High BCAP	-0.267	0.230	-0.271	0.111	-0.182	0.271	-0.082	0.365
	(0.330)	(0.319)	(0.316)	(0.320)	(0.310)	(0.313)	(0.326)	(0.329)
Gain	2.406***	1.111	2.953***	1.683**	3.332***	1.711**	3.890***	2.376***
	(0.682)	(0.873)	(0.687)	(0.818)	(0.643)	(0.778)	(0.685)	(0.819)
High BCAP × Gain	1.709***	1.465***	1.806***	1.667***	1.460***	1.535***	1.365**	1.460**
	(0.535)	(0.538)	(0.538)	(0.563)	(0.534)	(0.547)	(0.559)	(0.571)
Post	-0.576	-0.727	0.000	0.000	0.000		0.000	0.000
	(0.714)	(0.599)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)
High BCAP × Post	-0.243	-0.541	-0.058	-0.335	-0.246	-0.462	-0.108	-0.342
	(0.396)	(0.394)	(0.349)	(0.353)	(0.343)	(0.349)	(0.348)	(0.354)
High BCAP × Gain × Post	0.153	0.269	-0.180	-0.278	-0.301	-0.313	-0.154	-0.140
	(0.546)	(0.532)	(0.522)	(0.537)	(0.511)	(0.524)	(0.536)	(0.552)
Highly Advised	1.299*	1.107*	0.254	0.273	-0.569	-0.218	0.000	0.000
	(0.734)	(0.611)	(0.583)	(0.524)	(0.602)	(0.545)	(0.000)	(0.000)
High BCAP × Highly Advised	-1.040**	-1.105**	-1.128**	-1.134**	-1.215***	-1.143***	-1.404***	-1.287***
	(0.467)	(0.437)	(0.461)	(0.443)	(0.456)	(0.440)	(0.475)	(0.459)
Gain × Highly Advised	-0.061	0.619	-0.113	0.550	0.606	0.694	0.140	0.226
	(0.807)	(0.807)	(0.789)	(0.757)	(0.735)	(0.716)	(0.791)	(0.767)
High BCAP × Gain × Highly Advised	0.636	0.807	0.690	0.813	0.423	0.715	0.605	0.909
	(0.708)	(0.696)	(0.724)	(0.721)	(0.721)	(0.714)	(0.743)	(0.732)
Post × Highly Advised	1.469*	0.956	2.179***	1.703***	2.688***	1.883***	0.000	0.000
	(0.787)	(0.688)	(0.648)	(0.607)	(0.667)	(0.617)	(0.000)	(0.000)
High BCAP × Post × Highly Advised	-0.247	-0.021	-0.406	-0.322	-0.447	-0.221	-0.643	-0.465
	(0.536)	(0.512)	(0.504)	(0.482)	(0.499)	(0.483)	(0.514)	(0.499)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Advisor × Day FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	No	No	No	No	Yes	Yes	Yes	Yes
Investor × Day FE	No	No	No	No	No	No	Yes	Yes
Observations	1565981	1565981	1565981	1565981	1565981	1565981	1565981	1565981
R^2	0.00	0.03	0.04	0.07	0.05	0.08	0.11	0.13

TABLE A.17: **Propensity to Sell High Momentum and Gains.** Regressions are estimated at the investor-stock-day level. The dependent variable is equal to 100 if the stock is sold (fully or partially) on a day and zero otherwise. High BCAP is a dummy variable equal to one if the BCAP rating is A or P. Gain is a dummy variable equal to one if the return since purchase is positive and zero otherwise. Highly Advised and Not Advised are dummy variables indicating the client category. The omitted category is the *Lightly Advised* group of investors. Post is a dummy equal to 1 for months following January 2018. Control variables are the same as in Table 7. We include only days where investors have more than 2 assets in their portfolios and sell at least one stock. Standard errors are double-clustered at the investor and day level. ***, ** and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Mkt-RF	SMB	HML	Mom
	(1)	(2)	(3)	(4)
Highly Advised × Post	-0.024***	0.048***	-0.038***	0.040***
	(0.007)	(0.013)	(0.012)	(0.007)
Constant	0.788***	-0.425***	-0.103***	-0.015***
	(0.004)	(0.007)	(0.007)	(0.004)
Year-Month FE	Yes	Yes	Yes	Yes
Investor FE	Yes	Yes	Yes	Yes
Observations	56,381	56,381	56,381	56,381
R^2	0.59	0.78	0.59	0.59

Table A.18: **Effects on Client Portfolios' Factor Exposures.** Regressions are estimated at the investor-month level. The dependent variables are the portfolio beta loadings on the Fama-French 3 factors: market (Mkt-RF), size (SMB), value (HML), as well as the momentum factor (Mom). Highly Advised is a dummy equal to 1 if the investor is in the *Highly Advised* group. The omitted category is the *Lightly Advised* group of investors. Post is a dummy equal to 1 for months following January 2018. Standard errors are clustered at the investor level. ***, ** and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Arcsinh(Nb. Trades)			
	(1)	(2)	(3)	(4)
Highly Advised × Post	0.046*	0.045	0.046*	0.045
	(0.026)	(0.027)	(0.026)	(0.027)
Constant	1.951***	1.952***	1.951***	1.952***
	(0.015)	(0.016)	(0.015)	(0.016)
Year-Month FE	Yes	No	No	No
Investor FE	Yes	Yes	Yes	Yes
Advisor × Year-Month FE	No	Yes	No	Yes
Cohort × Year-Month FE	No	No	Yes	Yes
Observations	56,381	56,381	56,381	56,381
R^2	0.48	0.52	0.48	0.53

Table A.19: **Effects on Client Portfolios' Turnover.** Regressions are estimated at the investor-month level. The dependent variable is the arcsinh of the number of transactions made by the investor in the month. Highly Advised is a dummy equal to 1 if the investor is in the *Highly Advised* group. The omitted category is the *Lightly Advised* group of investors. Post is a dummy equal to 1 for months following January 2018. Standard errors are clustered at the investor level. ***, ** and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Additional Figures

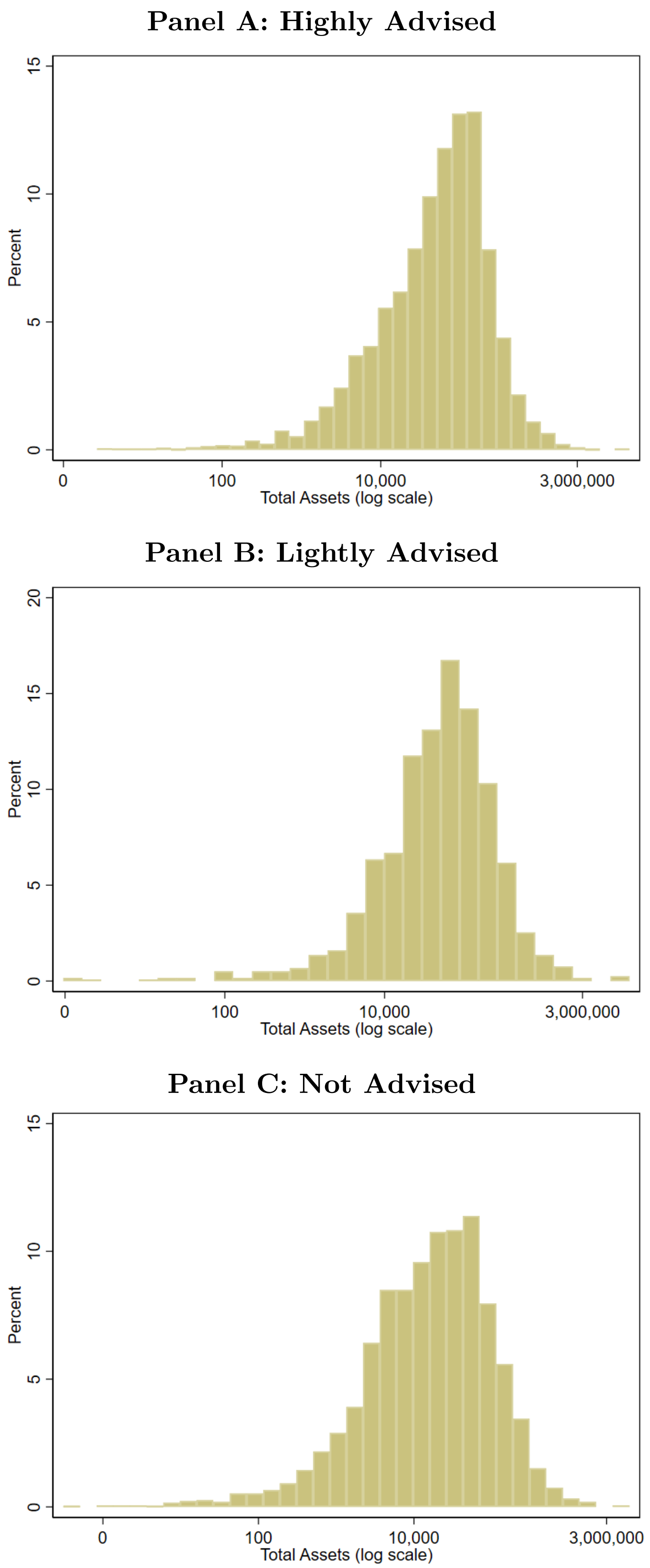

FIGURE A.1: **Portfolio Size Distributions**. For each profile, the figure presents the distribution of the log of investors' median total assets over the sample period.

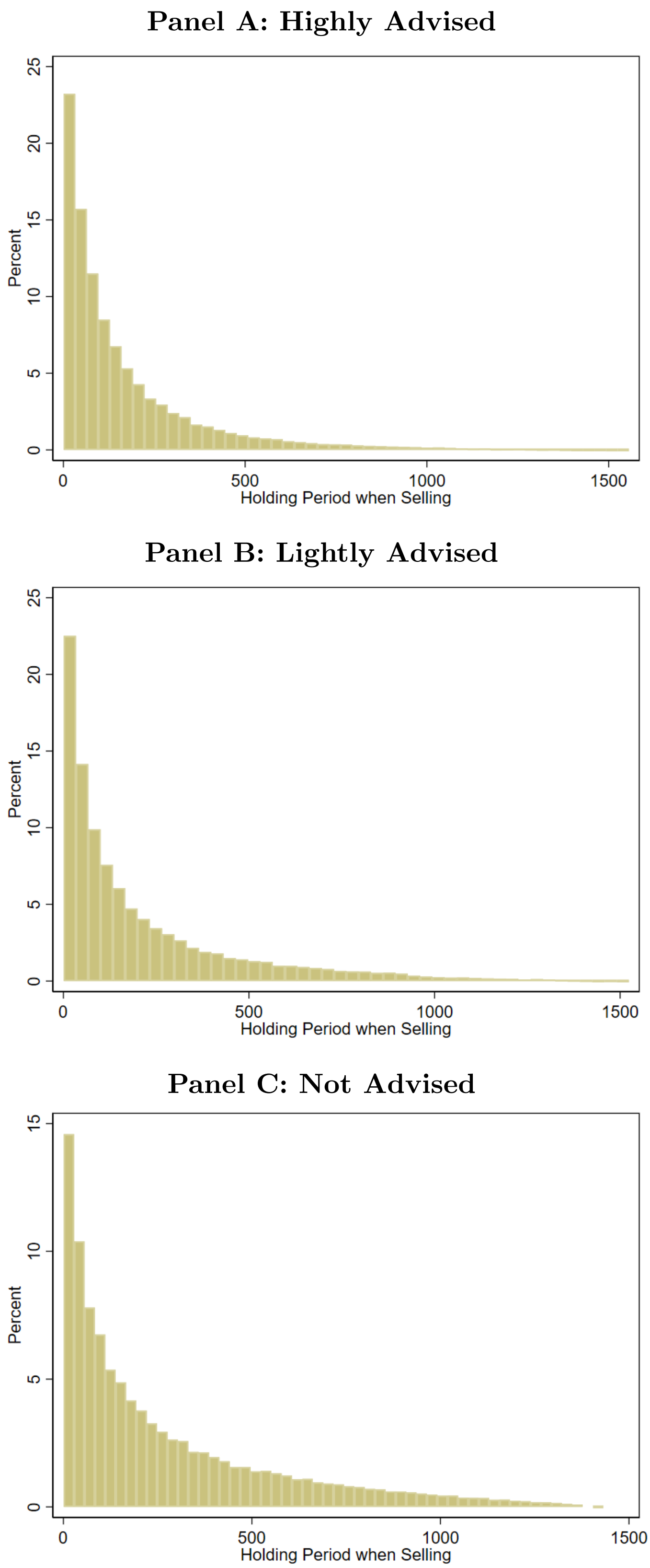

FIGURE A.2: **Holding Period Distributions**. For each profile, the figure presents the distribution of the investors' median holding periods for assets that were sold over the sample period.