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FINANCIAL ADVISORS AND INVESTORS' BIAS

Marianne Andries
Maxime Bonelli
David Sraer

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ABSTRACT

We study an intervention by a brokerage firm providing 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 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 gains than losses, highly-advised investors see their bias significantly reduced afterward. Our paper shows that by appropriately manipulating advisors' information, financial firms can successfully reduce their clients' biases.

Marianne Andries
University of Southern California
marianne.andries@gmail.com

Maxime Bonelli
London Business School
mbonelli@london.edu

David Sraer
University of California, Berkeley
Haas School of Business
Department of Economics
and NBER
sraer@berkeley.edu

An online appendix is available at http://www.nber.org/data-appendix/w34130

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 investors to cash-in gains and avoid realizing losses (e.g. Odean, 1998a; Grinblatt and Han, 2005). Investment professionals often herald the view that financial advisors can help retail investors overcome these biases. For instance, on its webpage, Charles Schwab argues that "*advisors can play a valuable role in educating clients about these biases*".[1] However, research has cast doubt on this view. To start, investment professionals also suffer from behavioral biases: e.g., traders from the CBOT exhibit myopic loss aversion (Haigh and List 2005; Larson et al. 2016); professional traders and investment bankers exhibit overconfidence (Glaser et al., 2013). Further, financial advisors appear to transmit biases and investment preferences they display in their own portfolios, such as returns chasing, to their clients' (Linnainmaa et al., 2021). Finally, the "money doctor" view of financial advising suggests that even unbiased advisors may choose to pander to investors' beliefs when investors hold biased expectations (Gennaioli et al., 2015). Do these results imply that wealth management firms are destined to fail in helping clients overcome their investment biases?

We answer this question by evaluating an intervention conducted at a prominent French brokerage and financial advice service firm (hereafter, "the firm"). The firm specifically designed this intervention to help clients reduce their disposition effect bias. Before January 2018, financial advisors at the firm observed their clients' information from an online platform that displayed, among other variables, the average acquisition prices for all the assets in their clients' portfolios. The platform saliently highlighted with bold green/red color coding which

[1] 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).

positions were paper gains or losses. Clients also had direct access to this online platform, which they used to monitor their portfolios and make decisions. In January 2018, the firm launched a new advisors' platform where average purchase prices and all gain/loss information were removed.[2] In contrast, the clients' platform remained the same throughout the sample period, so the information directly available to them, including average purchase prices, was unchanged. The intervention's premise was that if financial advisors amplify their clients' disposition effect, removing their ability to observe acquisition prices would reduce this bias.

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.[3] 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. The portfolios in our sample represent only a small portion of investors' financial wealth: the firm estimates clients' average investable assets, not including pension savings, at 3 million euros.

A unique feature of our setting is the ability to observe whether investors receive advice from a personal financial advisor and, if so, who their advisors are and how frequently they interact. In our sample, 60% of investors have a financial advisor, while the remainder trade independently.[4] Despite their substantial net worth and access to financial advice, investors at the firm display a significant disposition effect. Before 2018, advised investors were 50% more likely to sell assets in paper gains than in paper losses, a bias similar to that observed by Odean (1998a) among U.S. retail investors. This finding highlights that the presence of advisors does not, on its own, appear to reduce clients' investment biases. It also helps explain why the firm

[2]The advisor platform's display was also modified to provide additional information, which we control for in our analysis (see Section 5.2).

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

[4]All investors in our sample retain the final decision on which assets to trade; even those receiving advice do not delegate portfolio management to their advisors.

designed its intervention in 2018. Was this intervention successful in limiting clients' disposition effect?

After the intervention, we observe a significant reduction in the average disposition effect among advised customers: the likelihood to realize gains rather than losses decreased to 20% after the intervention, compared to the 50% greater chance to sell gains over losses before 2018. However, this finding should be interpreted cautiously, as other shocks may have coincidentally influenced advised investors' trading behavior. To strengthen identification, we exploit heterogeneity within advised clients in their exposure to financial advisors. Some investors ("highly-advised") have frequent contact with their advisors (weekly or biweekly), while others ("lightly-advised") communicate less frequently. This allocation into different levels of advising "intensity" is determined by firm management during the client intake process, based on each client's expressed willingness to engage in regular discussions with their advisor, and is not disclosed to clients. We confirm in Section 4.1 that clients classified as "highly advised" rely more on the financial advise they receive, as they are significantly more likely to follow recommendations that the firm provides, via a list of "to buy" and "to sell" stocks released each week, in their trading decisions.

Using this classification, our primary empirical approach uses a standard difference-in-differences strategy, comparing the trading behavior of highly-advised and lightly-advised investors around the intervention. Identification relies on a standard parallel trends assumption: absent the intervention, the disposition effect in both group of clients would have evolved similarly after 2018. Visual inspection of pre-trends supports this assumption. We implement our difference-in-differences analysis using several methodologies. We first use data aggregated at the profile-month level. Following Odean (1998a), we measure the proportion of gains realized (PGR) for highly- vs. lightly-advised clients each month in our data, together with the proportion of losses realized (PLR). The ratio PGR/PLR captures the disposition effect for a given profile in a given month, with PGR/PLR -1 quantifying the bias's strength. We find

no significant difference in the PGR/PLR ratio between highly- and lightly-advised investors before January 2018: both exhibit a significant and identical bias (PGR/PLR = 1.5). After the intervention, the PGR/PLR for highly-advised investors decreases significantly (from 1.5 to 1.1, not significantly different from one, indicating no bias) and becomes significantly lower than that of lightly-advised clients.

We confirm this finding estimating a Cox hazard model at the investor-stock-day level, allowing the baseline hazard rate to be stratified by date, stock, advisor, and investor. Hazard models have become the standard specification for testing the disposition effect (e.g., Feng and Seasholes, 2005; Seru et al., 2010; Barber and Odean, 2013; An et al., 2023). Importantly, hazard models allow to control for the propensity of investors to sell stocks over time and are easily interpretable. We also use a matching estimator, pairing highly-advised clients with lightly-advised ones based on pre-2018 portfolio characteristics. Across all specifications, our primary result remains consistent: the intervention leads to a significant reduction in disposition effect among highly-advised investors. The finding that the intervention—the design change of the advisors' platform—significantly reduces the disposition effect of highly-advised clients rejects the null hypothesis that advisors use information about clients' gains and losses to reduce their disposition effect. More importantly, it demonstrates that financial firms can manipulate advisors' information to help reduce clients' investment biases.

We next analyze whether and how the firm's intervention affected clients' portfolio returns and overall investment in their account. In the post-intervention period, highly-advised investors experienced a significant increase in raw portfolio returns of approximately 20 basis points per month compared to lightly-advised clients. This increase in returns is primarily driven by greater exposure to momentum strategies and reduced exposure to value stocks: we no longer find a significant difference between the highly- and lightly-advised investors in the post-period once we consider risk-adjusted returns, measured against the four-factor model—comprising the

Fama-French three factors (Fama and French, 1992) and momentum.[5] We also find evidence of increased satisfaction among highly-advised clients, reflected in significantly higher inflows into their portfolios and a lower likelihood of account liquidation. These results suggest that the firm benefits from its decision to adjust the information provided to advisors.

Finally, we conduct ancillary analyses to validate the interpretation of our main finding. In addition to removing acquisition prices and paper gain/loss information, the new advisor platform's display added a (pre-exiting) proprietary stock-level momentum indicator, the past 3 month returns of each position, and its market capitalization. We show that adding this information to the platform did not drive the observed decline in the disposition effect among highly-advised clients. Another possible concern with interpretation is that the change in information display could have influenced other investment biases closely related to the disposition effect, potentially affecting our results. Empirically, we find that several well-documented investment biases are present in our data: the portfolio disposition effect (An et al., 2023), where the disposition effect is concentrated in portfolios with net paper losses and absent in portfolios with net paper gains; the rank effect (Hartzmark, 2015), whereby investors are more likely to sell stocks with the highest and lowest returns in a portfolio; and the V-shaped relationship between cumulative returns and the likelihood of a position being sold (Ben-David and Hirshleifer, 2012). However, we show that our main result is not driven by changes in these other biases. Finally, we reinforce our preferred interpretation by exploiting cross-sectional heterogeneity *within highly-advised clients*. Specifically, we find that the decline in the disposition effect post-intervention is more pronounced among (1) clients most likely to follow the firm's recommendations in their trading decisions, and (2) clients exhibiting a stronger disposition effect bias in the pre-period.

[5]The finding that the disposition effect bias reduces exposure to momentum aligns with Odean (1998a), who report that assets sold by retail investors at paper gains outperform those retained at paper losses by an average of 3.4 percentage points over the following year. Similarly, Choe and Eom (2009) document a significant performance decline due to the disposition effect. Furthermore, Odean (1998a) estimate an additional tax advantage of one percentage point per year from selling paper losses rather than gains. Comparable tax considerations likely apply in our sample, offering additional wealth gains to highly-advised investors who experience a reduction in their disposition effect.

Related literature. Our paper's main contribution is to show how financial firms can design interventions *targeting advisors* to limit their clients' investment biases.

While the literature on the inefficiencies of financial advising is mature, relatively few studies examine how financial firms can effectively design interventions to mitigate clients' investment biases.[6] Addressing this gap is the main contribution of our paper. D'Acunto et al. (2019) find that robo-advising can reduce certain investor biases, such as the disposition effect and the rank effect. Frydman and Rangel (2014) and Frydman and Wang (2020) show, through a lab experiment and a quasi-natural experiment at a Chinese brokerage firm, that increasing the salience of paper gains and losses reinforces the disposition effect. Our analysis differs in two key ways. First, we examine a setting where information about paper gains and losses is removed rather than emphasized. Second, and more fundamentally, our intervention targets financial advisors, not investors. To the best of our knowledge, our study is the first to demonstrate how financial firms can design interventions aimed at advisors to limit their clients' investment biases.

Because the intervention we study is mediated through financial advisors, our paper closely relates to the literature on financial advisors and their influence on investors' 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 highlights that they often provide suboptimal advice. Numerous studies document significantly lower returns for retail investors who rely on financial advisors (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). Using an audit study, Mullainathan et al. (2012) demonstrate that advisors frequently fail to de-bias clients, instead promoting returns-chasing behavior and recommending actively managed funds with high fees. Similarly, Célérier and Vallée (2017) find

[6] In a lab experiment, Rotaru et al. (2021) show that constructing an optimal portfolio for another person (e.g., a client) reduces one's own disposition effect. This suggests that advising clients may decrease financial advisors' disposition bias in their personal portfolios, a mechanism orthogonal to our study.

that banks exploit advisors' recommendations to sell risky and complex structured products with low returns for clients, and Egan et al. (2019) show that some financial firms target unsophisticated consumers to sustain higher levels of misconduct.

Using Canadian data, Foerster et al. (2017) reveal that advisors influence clients' portfolio choices by encouraging them to invest in similar assets and assume comparable portfolio risk. The closest study to ours is Linnainmaa et al. (2021), which provides causal evidence that trading biases (such as excessive trading, returns chasing, preference for high-cost funds, and under-diversification) can be attributed to advisors who display them in their own personal portfolios of investments, and fail to mitigate these biases in their clients' portfolios. However, our study differs in key aspects. Investors in our sample are orders of magnitude wealthier than those in Linnainmaa et al. (2021). While their advisors are limited to recommending mutual funds, advisors in our study primarily advise on individual stocks.[7] Advisors in their study make decisions for their own personal investment portfolios, concomitant to providing advice, whereas, to avoid conflict of interest, the advisors in our analysis are not allowed to own stock portfolios. Finally, Linnainmaa et al. (2021) do not examine the disposition effect, which is the central focus of our analysis. Our paper thus serves as a valuable complement to their contribution.

Finally, our paper also broadly relates to the abundant literature on behavioral biases in investment decisions (see Barber and Odean 2013; Liu et al. 2022 for recent reviews). This literature has documented ample evidence of a disposition effect (Shefrin and Statman, 1985, 2000) among retail investors (e.g. Odean 1998a for the U.S., Feng and Seasholes 2005 in China, Shapira and Venezia 2001 in Israel, Grinblatt and Keloharju 2001 and Seru et al. 2010 in Finland), and in professional traders and mutual fund investors (Heisler, 1994; Locke and Mann, 2005; Frazzini, 2006). Such a widespread trading bias may be driven by realization utility preferences (Barberis and Xiong, 2012; Ingersoll and Jin, 2013), by overconfidence building

[7] This aligns with Chang et al. (2016), who find that U.S. retail investors exhibit a significant disposition effect mainly for non-delegated assets, such as individually purchased stocks.

(Gödker et al., 2023), or by peer pressure (Heimer, 2016), and may be exacerbated by dynamic inconsistency (Heimer et al., 2023).[8] 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 trades from high net-worth retail investors and to document that they too display a significant disposition effect.[9] Our paper is also the first to measure the causal effect of the disposition effect on portfolio performance. Most studies analyzing the impact of the disposition effect on portfolio performance rely on constructing counterfactual scenarios—estimating which stocks investors would have held or sold in the absence of this behavioral bias (e.g., Odean, 1998a). In contrast, our study exploits an exogenous shift in the disposition effect, allowing us to directly measure its impact. We show that the disposition effect reduces portfolio raw returns, primarily by decreasing investors' exposure to the momentum factor.

2 Institutional Setting

2.1 Institution

Our dataset comes from Portzamparc, a French brokerage firm, hereafter referred to as "the firm". This firm is a division of the private wealth management branch of a leading banking group and provides brokerage services to high-net-worth individual investors in France. The firm also has a dedicated discretionary asset management subsidiary, which directly manages a €600 million portfolio on behalf of clients. Our analysis, however, solely focuses on the stock trading decisions of the 7,494 clients who use its brokerage services and does not use any information related to the asset management subsidiary.

Most assets traded by clients within our dataset are individual stocks (80% of total portfolio

[8] Heimer and Imas (2022) show, in lab experiments, that imposing leveraging constraints can limit traders' disposition effect.

[9] 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.

holdings). 10% of their portfolio holdings are mutual funds, and the remaining 10% is in cash. Investors in our study are wealthy: even though we observe only their financial wealth invested in direct stock holding at the firm, their average total assets held in the private wealth management branch of the bank are estimated to be around 3 million euros.[10]

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

A majority (60%) of the clients opt to be advised, in which case they are matched with one financial advisor. 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. One key dimension used for this profiling is the client's willingness to discuss with her advisor frequently. Accordingly, 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

[10]This estimate of clients' financial wealth does not include retirement savings. Retirement income in France mostly operates through the national pay-as-you-go pension system, such that less than 10% of the French population hold any type of stock portfolios (source AMF (Autorité des Marchés Financiers), November 2023).

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. 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, each assigned about 150 clients. 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]

2.2 Quasi-Experimental Setting

2.2.1 Clients' information

All the firm's clients 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, for each asset in their portfolios 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 clients' online platform and its display remained unchanged throughout the sample period we analyze.

[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"), and the current stock price ("Cours"). Clients can also see 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)).

2.2.2 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. 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 advisor platform.

In the new platform, advisors still see the list of assets in their clients' portfolios, their weights, and their current stock price ("Dernier cours de clôture"). In addition, they now observe for each asset: the realized returns over the past three months ("Rendement"), the market capitalization ("Capitalisation"), an ESG rating ("Note ESG"), a logo corresponding to the industry it belongs to (e.g., a picture of a credit card for banks), and 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). Some information previously available to the advisors no longer appears, such as, for each position, its market value and the number of stocks held in the portfolio.

Crucially, while the average acquisition price and the corresponding paper gains or losses appeared saliently in the old advisor platform, this information was entirely removed from the new platform.

2.2.3 Motivation behind the new platform

The primary rationale for introducing the new advisors' platform was to limit the disposition effect of clients. The firm's main worry was that the disposition effect increases the risk of extreme, negative returns. By keeping losers in the portfolio, clients with a strong disposition effect might end up losing large amounts on some positions, leading them to close their entire

[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.

portfolio and leave the firm. The firm also viewed the disposition effect as potentially detrimental to portfolio performance, as selling paper gains leads to higher taxes and may reduce exposure to momentum returns.[14]

Given these risks, the firm had been trying to reduce its clients' disposition effect for several years, both directly by sending "educational" material to clients and indirectly by telling its financial advisors that addressing their clients' bias should be a priority. However, the firm believed these outreach efforts were unsuccessful and thus decided to change the advisors' platform in 2018.[15] We thus view the introduction of the new advisors' platform as a quasi-natural experiment, in which the core treatment was to reduce advisors' information set.[16]

2.2.4 Client heterogeneity

40% of investors in our sample only use the brokerage service of the firm. They do not receive any advice, and, as such, are entirely unaffected by the advisors' platform change. These (*not-advised*) clients serve as a first control group in our quasi-natural experiment. However, as we show in Sections 3, they differ substantially from advised clients on observable characteristics. Thus, we also rely on heterogeneity *within advised investors* for identification purposes. Based on an intake questionnaire and on the frequency of advice they request, advised clients are sorted into different categories when they join the firm. The firm estimates that *highly-advised* investors talk to their advisors two to four times per month and that *lightly-advised* investors have less than one call per month.[17] Accordingly we analyze the two groups separately, assuming

[14] Section 4.4 quantifies how the intervention affects clients' realized performance and inflows/outflows, and provides supportive evidence on the firm's perceived cost of the disposition effect.

[15] The firm also considered removing gain-loss information from the clients' platform but renounced it when faced with the adverse reaction of clients they discussed it with.

[16] Since the clients' platform did not change, advisors could potentially avoid treatment by asking clients directly which positions in their portfolio are paper gains and losses. The results in Section 4 suggest they do not do so before providing advice.

[17] 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).

highly-advised (lightly advised) clients will be more heavily (lightly) "indirectly treated", in our quasi-natural experiment, via the information treatment on advisors.

2.2.5 Other considerations

Other features of the institutional setting may influence our analysis of client biases. First, a tax reform coincided with the platform change: in January 2018, capital gains began to be taxed at a flat 30% rate instead of the marginal income tax rate (45% for top earners). Since all clients are similarly affected by taxes, our difference-in-differences estimate effectively controls for this reform.[18] Importantly, by lowering the disincentive to realize paper gains, the tax reform should increase the average disposition effect in the post-period, in the absence of any treatment effect.[19]

Second, the firm's fee and compensation structure may shape advisor behavior, potentially influencing client biases. The firm earns revenue from transaction commissions and advisory fees, which are a fixed percentage of portfolio value. All advised clients—highly or lightly advised—pay the same fees. The firm benefits from having more advised clients, greater net inflows (including returns), and more transactions. Individual advisor compensation includes a fixed salary and a discretionary bonus, partly based on qualitative metrics such as perceived client satisfaction. The firm reports that bonuses are not tied to the number of transactions or to the mix of highly versus lightly advised clients. It is therefore unclear whether advisors have explicit incentives to address client biases. The firm also confirmed that there was no change in the compensation structure over the sample period.

Finally, although the stated goal of the platform redesign was to remove information on unrealized gains and losses, the new interface also introduced other features—such as the firm's proprietary BCAP ratings. While these ratings were already available before 2018, their more prominent display may have encouraged advisors to steer clients toward momentum strategies,

[18] According to the firm, all advised clients were previously taxed at the top marginal rate of 45%.

[19] We do not observe capital gains realized in other divisions of the bank or at other institutions, so we cannot directly assess tax optimization motives.

mechanically reducing the disposition effect. We show in Section 5 that this effect does not explain the observed decline in the disposition effect among highly-advised clients.

2.2.6 Financial advisors and investors' biases

The introduction of the new advisors' platform provides a quasi-natural experiment that is well-suited to identify the causal effect of advisors' information sets on their clients' disposition effect bias. A key advantage of our setting is that other important determinants of the disposition effect—such as the online platform interface for clients and the advisory fees—remain unchanged, allowing us to isolate the impact of the advisor-side information shock.[20]

While our design allows us to identify whether advisors influence clients' behavioral biases, it does not pin down the exact mechanism at play. For instance, advisors could be transmitting their own disposition effect bias in the advice they provide, similar to evidence of bias transmission in Linnainmaa et al. (2021). Because advisors in our study are precluded from trading their own stock portfolios, we cannot directly test for such a mechanism by analyzing their personal trading behaviors. Alternatively, advisors may prefer to cater to their clients' disposition effect because of other biases—e.g., their unwillingness to accept they may have given "bad" advice in the past;[21] because of agency issues—fearing that clients might be upset when realizing losses, or draw negative inference about their quality as advisors, resulting in potential complaints and lower bonuses; or to pander to their clients' beliefs so as to retain their trust and maintain their influence as "money doctors" (Gennaioli et al., 2015).[22] Because we lack variation in advisors' incentives and do not observe their beliefs, we cannot empirically disentangle these channels, which is a limitation of the paper.

[20] In Section 4, we also rule out confounding effects from changes in market conditions.

[21] 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.

[22] We note that these considerations would likely discourage advisors from asking their clients directly which of their positions are in a paper gain or loss, confirming our interpretation of the platform change as strictly decreasing the advisors' information set in the post period.

3 Data and Summary Statistics

3.1 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.[23]

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 in May 2021.[24] Our sample

[23]The trade file also includes transactions from incoming and outgoing bank transfers, which we use to compute inflows in Section 4.4.

[24]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 to a client in May 2021 was their advisor throughout the sample period.

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).

We compute portfolio returns using the trade and position files. For each client i and day t, we first determine portfolio weights for each stock at the end of the previous day $(t-1)$, then calculate the portfolio return on day t as the weighted average of stock returns. Monthly returns are obtained by compounding these daily returns over the month. To calculate expected returns, we calculate each stock's beta with respect to the Fama-French three factors (market, size, value) and momentum, using daily returns and factor data from Ken French's website. Betas are estimated via a three-year rolling regression of daily stock returns on the relevant factors.[25] Daily expected returns are computed as the product of stock betas and factor returns. A portfolio's daily expected return is the weighted average of its constituent stocks' expected returns. Monthly excess returns are defined as the difference between the portfolio's realized monthly return and its daily expected returns cumulated over one month.[26]

3.2 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

[25] We use either U.S. or European factors, depending on the stock's geographical location.

[26] Barber and Lyon (1997) note that compounding daily excess returns can introduce upward bias due to survivor bias, rebalancing effects, and skewness, which is why we analyze risk-adjusted performance as the difference in monthly buy-and-hold returns.

to lightly-advised investors. In total, out of the 45 financial advisors in our sample, 41 advise both types of clients.

Advised investors hold significantly larger portfolios than non-advised clients—144,000 on average versus €58,000. Among advised investors, the lightly-advised hold more on average than the highly-advised (€180,000 vs. €137,000). As expected, the distribution of portfolio sizes is right-skewed: the median is €71,000 for highly advised, €55,000 for lightly advised, and €18,000 for non-advised clients. There are 225 accounts exceeding €1 million. Appendix Figure A.1 shows a histogram of portfolio sizes across the three groups. According to our discussions with the firm's private wealth management arm, clients are advised to allocate no more than 5% of their financial wealth to direct stock investments, suggesting, based on the portfolios they hold at the firm, that advised clients have total financial wealth of around €3 million on average.

Client portfolios exhibit limited diversification. On average, highly-advised clients hold 11 stocks, lightly-advised 10, and non-advised 8. The medians are lower: 9, 7, and 4 stocks, respectively. Highly-advised clients trade about 11 times per year, compared to 18 for the lightly-advised and 19 for the non-advised. Stocks sold during the sample period were held for an average of 195 days (highly advised), 226 days (lightly advised), and 323 days (non-advised).[27] Appendix Figure A.2 reports the distribution of holding periods by investor type. On two key dimensions related to the disposition effect—the number of stocks held and the daily probability of selling—highly- and lightly-advised clients are more similar to each other than to non-advised clients. This motivates our focus on comparing these two groups in our main empirical analysis (Section 4).

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

[27]Holding periods are calculated from first purchase to full liquidation. Because intermediate trades are not accounted for, investors who trade more often can nonetheless have longer average holding periods.

higher for highly-advised investors (0.05% per month) than for the lightly-advised (-0.11% per month) and not advised clients (-0.39% per month).

We note that the firm's wealthy French investors have somewhat similar portfolio statistics as those reported in Odean (1998a); Barber and Odean (2000) in a different context: in their US retail brokerage data of 66,465 households, 28% of which own more than $100,000 in equity, the average number of stocks is 4.3, the median (average) holding period is 84 trading days (15 months), and the average risk-adjusted return is -0.3%/month.

4 Empirical Analysis

4.1 Advisors' Influence on Clients' Stock Selection

Our empirical strategy requires that highly-advised clients are more influenced by their advisors than the lightly-advised. We provide direct evidence for this hypothesis 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). 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. We estimate the following regression model on the set of advised customers:

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

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

where i, j, and t denote investor, stock, and day. $Sell_{i,j,t}$ ($Buy_{i,j,t}$) equals one if i sells (buys)

j on t, and zero otherwise.[28] $SellReco_{j,t}$ ($BuyReco_{j,t}$) equals one if the investment committee recommends selling (buying) stock j during the week of day t. $HighlyAdvised_i$ equals one if investor i is highly advised. FE_i, FE_j, and FE_t denote investor, stock, and day fixed effects. Standard errors are double-clustered at the investor and day level. A positive β_s (γ_b) indicates that investors tend to sell (buy) stocks on the sell (buy) recommendation list. A positive β_{sh} (γ_{bh}) suggests a stronger effect for highly advised investors. We hypothesize 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 report estimates of Equations (1) and (2), respectively. Columns (2) and (4) add investor-by-day fixed effects. Column (1) shows that lightly advised investors are 0.23 percentage points (p.p.) more likely to sell stocks on the sell list and 0.05 p.p. less likely to sell stocks on the buy list, both significant at the 1% level. These effects may partly reflect stock-level omitted variables—stocks favored by both retail investors and the firm's investment committee. To isolate the impact of advisor intensity, we focus on the interaction terms β_{sh}, γ_{sh}, β_{bh}, and γ_{bh}, which capture how more frequent advice influences behavior, assuming similar responsiveness to information across investor types. Relative to lightly-advised clients, the highly-advised are 0.1 p.p. more likely to sell stocks on the sell list and 0.06 p.p. less likely to sell those on the buy list. Column (3) shows they are also 0.08 p.p. more likely to buy stocks on the buy list and 0.1 p.p. less likely to buy those on the sell list. All effects are significant at the 1% level and remain robust when adding investor-day fixed effects (columns (2) and (4)). We find similar results on the intensive margin: Appendix Table A.3 uses the number of shares traded, and Appendix Table A.4 the transaction amounts, as dependent variables. These results confirm that the highly vs. lightly advised distinction captures meaningful variations in how advisors influence portfolio decisions.

We confirm this interpretation using an event-study design. Specifically, for Sell recommen-

[28] $Sell_{i,j,t}$ and $Buy_{i,j,t}$ are defined over the same sample, implying that for the sell analysis, we focus on stocks already in investors' portfolios. The buy analysis includes both first-time purchases and additional-share purchases.

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

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

where i, j, and t denote investor, stock, and day. k measures the weeks between day t and the recommendation event: $SellReco(k)_{j,t}$ is an indicator variable equal to one if the recommendation on stock j switches to "Sell" 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. We use a similar specification for Buy recommendations.

Figure 3 plots the coefficients $\beta_{s,k}$ and $\beta_{sh,k}$. Panel A of Figure 3 shows a sharp increase in the likelihood that lightly-advised clients sell a stock immediately after it is added to the Sell list. Panel B shows this effect is significantly stronger for highly-advised clients, whose probability of selling rises by an additional 0.03 percentage points more in the first week post-recommendation, with the difference remaining statistically significant for up to eight weeks. The response is even more pronounced for Buy recommendations (Figure 4): highly-advised clients are 0.25 percentage points more likely than lightly-advised ones to buy a newly-recommended stock in the first week, with the effect gradually reverting to zero over the following eight weeks.[29] In both cases, the influence of investment committee recommendations on trading behavior is nearly twice as strong for highly advised clients. This pattern provides strong support for our empirical design.

[29] One plausible explanation for the asymmetry is that clients can act on a Buy recommendation regardless of their current holdings, whereas responding to a Sell recommendation requires already owning the stock.

4.2 Disposition Effect Bias

4.2.1 Aggregate analysis

To measure the effect of our quasi-natural experiment on clients' disposition effect biases, we start with the methodology of Odean (1998a) in a simple difference-in-differences analysis with data aggregated at the investor type-month level. 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 total number of paper gains and losses, as well as the number of realized gains and realized losses, each month and for each client type — highly advised, lightly advised and not advised. 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) as:

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

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, which quantifies the disposition effect bias.

We estimate the following model to evaluate the effect of the intervention on the disposition

effect:

$$PGR/PLR_{i,t} = \alpha_l + \alpha_h HighlyAdvised_i + \alpha_n NotAdvised_i + \beta_l Post_t \tag{4}$$
$$+ \beta_h \{HighlyAdvised_i \times Post_t\} + \beta_n \{NotAdvised_i \times Post_t\} + \epsilon_{i,t},$$

where i and t denote investor profile and month, $HighlyAdvised_i$ ($NotAdvised_i$) is a dummy equal to one if profile i corresponds to the highly-advised (not-advised), where the omitted category is the lightly-advised, and $Post_t$ is a dummy equal to one after January 2018.[30] Table 3 presents the coefficient estimates.

The not-advised, i.e., clients who use the firm only for its brokerage services, have a high disposition effect bias: when selling a stock, they are about twice more likely to sell among their paper gains than among their paper losses, in both the pre- and post-period—their bias does not change around the firm's intervention. Advised clients display significantly less bias in the pre-period: their average PGR/PLR ratio is around 1.5, with no significant difference between the highly- and lightly-advised. This cross-sectional comparison with non-advised clients might suggest that financial advisors help mitigate biases in the pre-period. However, it does not account for selection: clients who choose not to be advised may differ systematically in their biases from those who choose to be. Moreover, the average PGR/PLR ratio of 1.5 among advised clients closely matches that found by Odean (1998a) for U.S. retail investors, casting doubt on the idea that advisors are actively de-biasing clients in the pre-period.

The *causal* effect of financial advisors can, instead, be clearly identified from the decrease in the disposition effect of highly-advised clients in the post period: relative to the lightly-advised, their PGR/PLR ratio drops by a significant .6 to .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)

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

interacted with a highly-advised dummy.[31] Appendix Table A.5 shows this result is robust to excluding the pilot phase (January 2018 to May 2018).

Figure 5 shows the evolution of the monthly PGR/PLR ratios of portfolios held by highly-advised (green) and lightly-advised (red) clients over the sample period. The shaded areas correspond to 95% confidence intervals computed through a bootstrap procedure.[32] The vertical shaded line marks the start of the treatment period. Both categories of advised 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: their PGR/PLR ratio becomes indistinguishable from one, corresponding to unbiased trading, in most months post January 2018, while it remains around 1.5 for the lightly-advised.

4.2.2 Investor-stock-day level analysis

Because of its aggregation at the investor type-month level, the previous analysis can conceal significant heterogeneity within client types (highly- vs. lightly-advised), e.g., in terms of the stocks they hold. To ensure our results are robust to such heterogeneity, we follow Feng and Seasholes (2005), Seru et al. (2010), Frydman and Wang (2020), and An et al. (2023) and estimate the following Cox hazard model at the investor-stock-day level:

$$\frac{h_{i,j}(t)}{h_0(t)} = e^{\{\beta\{Gain_{i,j,t-1}\times\ Post_t\times\ HighlyAdvised_i\}+\psi Z_{i,j,t}+\gamma X_{i,j,t}+\epsilon_{i,j,t}\}} \quad (5)$$

where i, j, and t denote investor, stock, and day, respectively. $h_{i,j}(t)$ is investor i's probability of selling some or all of position j on day t conditional on not having sold any of asset j prior

[31] The disposition effect of the lightly-advised appears to (weakly) increase in the post-intervention period, although the increase is small (less than 0.15) and not significant at the 5% threshold (see the "Post" coefficient in columns (1) and (4)). This increase could be due to the lower capital gain tax in the post period, as discussed in Section 2. However, because all advised clients are in the same tax bracket, tax considerations cannot explain the decrease in the PGR/PLR ratio of highly- versus lightly-advised clients in the post period.

[32] 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.

to day t, with $h_0(t)$ the baseline hazard rate.[33] $Gain_{i,j,t-1}$ is a dummy variable equal to one if investor i has a gain on stock j on day $t-1$, $Post_t$ is a dummy variable equal to one if day t is after January 2018, and $HighlyAdvised_i$ is a dummy equal to one if investor i is highly-advised. $Z_{i,j,t}$ encompasses all the single and double interaction terms of $Gain_{i,j,t-1}$, $Post_t$ and $HighlyAdvised_i$. $X_{i,j,t}$ is a vector of 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 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)). Standard errors are clustered at the investor level.[34]

Table 4 presents the estimation results. Columns (1-2) present the results without stratification of the baseline hazard rate. Columns (3-10) include baseline hazard rate stratification by date, by stock, by advisor, and by investor. Across all specifications, we estimate a significant and negative β coefficient, confirming that the intervention causes a reduction in clients' disposition effect. Quantitatively, using column (10) (account stratification and controls included), we find that: (1) lightly advised clients exhibit a significant disposition effect in the pre-period, with a ratio of the proportion of gains realized (PGR) to the proportion of losses realized (PLR) estimated at 1.56 ($=e^{0.447}$) (2) the disposition effect is similar for highly and lightly-advised clients in the pre-period (insignificant -.053 coefficient on Gain $\times$ Highly Advised) (3) the disposition effect of lightly-advised clients does not change following the intervention (insignificant .010 coefficient on Gain $\times$ Post) but (4) the relative disposition effect of highly-advised clients declines significantly after the intervention, with their relative PGR/PLR falling from 1.48 ($= e^{.447-.053}$)

[33] The same analysis can be conducted for full liquidation of position j on day t conditional on not having sold asset j prior to day t. The results are presented in Appendix Table A.6.

[34] The hazard model does not allow for clustering standard errors across multiple dimensions. As discussed in Section 4.3, our results remain unchanged when using a linear probability model with standard errors double-clustered at the investor and day levels.

to 1.21 ($=e^{0.447-.053-0.211+0.010}$). These findings qualitatively confirm the analysis in Table 3, although the reduction in highly-advised clients disposition effect is somewhat smaller in this individual-month-level analysis.

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

$$\frac{h_{i,j}(t)}{h_0(t)} = e^{\left\{\sum_{k=-2,k\neq-1}^{3} \beta_k \{Gain_{i,j,t-1} \times\ TreatY(k)_t \times\ HighlyAdvised_i\} + \psi Z_{i,j,t} + \gamma X_{i,j,t} + \epsilon_{i,j,t}\right\}},$$

where i, j, and t denote investor, stock, and day, respectively. $TreatY(k)_t$ is a dummy equal to one if month t is part of year k before/after the new platform introduction in 2018. $Z_{i,j,t}$ encompasses all the single terms and double interactions of $Gain_{i,j,t-1}$, $TreatY(k)_t$ and $HighlyAdvised_i$. We use year -1 as the (omitted) baseline year. We also reproduce this analysis at the semester frequency, where we use the second half of 2017 as the omitted baseline.

Figure 6 reports the estimated β_k coefficients, along with 95% confidence intervals. The impact of the intervention—the change in advisors' platform—on the disposition effect of highly-advised investors, measured via the propensity to sell assets when in paper gain, appears immediately and is entirely captured within the first year of implementation.[35]

4.3 Robustness

4.3.1 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 based on portfolio characteristics in the pre-treatment period.

First, we perform a coarse matching exercise. Specifically, for each highly-advised client, we identify the set of lightly-advised clients that are in the same quartile of the pre-treatment

[35] The t-stat for the β_k coefficients on the 1st semester of 2018 is -5.35.

distribution of (i) assets (logarithm of average total assets), (ii) average number of stocks held, and (iii) average daily likelihood of selling one of several stocks. Using this matched sample of treated and controls, we re-estimate the Cox model analysis (5). The results are reported in Appendix Table A.7. They are similar to Table 4 and leave our conclusion unchanged.

Second, we implement a propensity score matching approach. Specifically, we estimate a logit model at the individual level, where 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 held in the portfolio, and the client's average daily likelihood of selling one or more stocks—all measured during the pre-treatment period. For each highly-advised client, we identify between one and five lightly-advised clients with the closest propensity score, allowing lightly-advised clients to be matched to multiple highly-advised clients.[36] Using these matched samples of treated and control investors, we re-estimate the Cox model in Equation (5). The results, reported in Appendix Table A.8, are similar to those in Table 4 and, again, leave our conclusion unchanged.[37]

4.3.2 Not-advised as controls

Appendix Table A.9 reproduce our baseline finding in Table 4 but consider various definitions for the treatment and control groups. Columns (1) and (2) correspond to our baseline result where lightly-advised serve as a control group for the highly-advised. Columns (3) and (4) use the not advised as the sole control group. Columns (5) and (6) bunch the lightly-advised and the not-advised together in the control group. Finally, columns (7) and (8) bunch all advised clients together in the treated group and compare the evolution of their disposition effect relative to the not-advised. Across all specifications, we continue to find a significant, negative causal effect of the intervention on the disposition effect of clients "treated" through their advisors.

[36] We do not perform matching without replacement, as there are more highly advised than lightly advised clients in our sample. When restricting the match to a single closest neighbor, the 1,302 highly advised clients in the pre-treatment period are matched to 305 distinct lightly advised clients.

[37] Reducing the number of matched neighbors lowers the statistical significance of the coefficient on $Gain_{i,j,t-1} \times Post_t \times HighlyAdvised_i$, but its magnitude remains stable.

4.3.3 Linear Probability Model

One limitation of the Cox specification is that it does not allow to control for high-dimensional fixed effects. To ensure the robustness of our finding to the inclusion of such fixed effects, we follow Ben-David and Hirshleifer (2012) and estimate the following linear probability model at the investor-stock-day level:

$$\begin{aligned} 100 \times Sell_{i,j,t} = \beta Gain_{i,j,t-1} &+ \beta_h \{Gain_{i,j,t-1} \times HighlyAdvised_i\} \\ &+ \beta_p \{Gain_{i,j,t-1} \times Post_t\} \\ &+ \beta_{ph} \{Gain_{i,j,t-1} \times Post_t \times HighlyAdvised_i\} \\ &+ \gamma X_{i,j,t} + FE_{i\times t} + FE_{j\times t} + \epsilon_{i,j,t}, \end{aligned} \tag{6}$$

where i, j, and t denote investor, stock, and day, respectively. $FE_{i\times t}$ and $FE_{j\times t}$ denote investor-day and stock-day fixed effects. Standard errors are double-clustered at the investor and day levels.

Appendix Table A.10 presents estimation results using a sample restricted to days on which a sale occurs within portfolios containing two or more stocks. Columns (1–2) report results without fixed effects, columns (3–10) include various sets of fixed effects: day, stock, investor, stock-day, advisor-day, and investor-day. Note that investor fixed effects subsume advisor fixed effects, as client–advisor pairs remain constant throughout the sample.

Across all specifications, the triple interaction coefficient β_{ph} is negative and statistically significant at the 1% level: relative to lightly-advised clients, the highly-advised become significantly less likely to sell paper gains in the post period even when controlling for stock-level covariates or including advisor-day, investor-day, or stock-day fixed effects. Appendix Table A.11 replicates the analysis on the full set of investor-stock-day observations, including portfolio-days with no sales. The results are again similar.

4.4 Effect on Flows and Portfolio Returns

4.4.1 Portfolio Returns

We evaluate how the disposition effect affects portfolio performance in our sample by leveraging the same natural experiment and identification strategy as in Section 4.2.

Using data on U.S. retail investors, Odean (1998a) finds that, comparing stocks sold while in paper gains to stocks in paper loss investors held on to in their portfolio, the stocks sold in paper gain outperform paper-loss stocks by 3.4 percentage points over the following year. This suggests that the disposition effect may be costly to investors. We replicate this analysis by estimating regression (4) at the profile-month level, using as the dependent variable the ex-post return difference between paper-gain stocks that were sold and paper-loss stocks that were kept. We consider four investment horizons: three months, six months, one year, and two years.

Table 5, Panel A, presents the results. In the post-intervention period, highly-advised clients experience a significant decline in this return difference—the "opportunity cost" they pay when selling stocks in paper gains—relative to the lightly-advised: 2 p.p. at the 3- and 6-month horizons, and 3 p.p. at the 1-year horizon. This indicates a reduction in the potential cost of the disposition effect for highly-advised investors following the platform intervention.

Our unique setting allows us to extend our analysis beyond cost-benefit estimations of counterfactual scenarios—estimating which stocks investors would have held or sold if they were unbiased. We also directly assess the effect of the intervention and measure its impact on portfolio performance. To do so, we estimate the following investor-month level regression:

$$\text{Monthly Return}_{i,t} = \beta \{HighlyAdvised_i \times Post_t\} + FE_i + FE_t + \epsilon_{i,t}, \tag{7}$$

where i and t denote investor and month, respectively. FE_i and FE_t are investor and month fixed effects. In some specifications, we also include advisor $\times$ month fixed-effects and cohort $\times$

month fixed-effects.[38] Panel B of Table 5 presents the estimation results when the dependent variable is the portfolio monthly raw return. Panel C presents the risk-adjusted monthly returns, using the four factor risk model (three Fama-French factors and momentum).

Following the introduction of the new platform, highly-advised clients experience an increase in portfolio returns of approximately 20 basis points per month relative to the lightly-advised (Panel B). This improvement is both quantitatively significant and statistically robust at the 5% level, controlling for year-month, investor, advisor × year-month, and cohort × year-month fixed effects. In contrast, the risk-adjusted returns of highly-advised investors remain statistically unchanged in the post-period (Panel C), suggesting that the observed improvements in raw portfolio returns stem from changes in portfolio exposures to common risk factors. We confirm this interpretation in Table 6, where we estimate regression (7) using portfolio loadings on the four factors as dependent variables. Relative to the lightly-advised, the portfolios of highly-advised clients experience a reduction in their exposure to market risk and value, and an increase in exposure to size and momentum. Given the substantial cumulative return of the momentum factor (71%) and insignificant size premium (cumulative return of 1.15%) over our sample period, the increase in raw returns performance for highly-advised investors in Table 5 is driven by their portfolios' increased exposure to momentum.[39]

Our finding that reducing the disposition effect bias increases exposure to momentum aligns with the counterfactual analysis results documented above and in Odean (1998a). However, the greater loadings on the momentum factor of highly-advised portfolios in the post-period may also reflect advisors deliberately shifting their recommendations toward momentum strategies following the platform redesign, which included a more salient display of the firm's proprietary BCAP momentum rating. In Section 5, we analyze whether such a momentum shift occurred and whether it disproportionately affected highly-advised clients. Our analysis provides limited

[38] Cohort is defined as the initial semester in which the client is first recorded in our database

[39] Over the sample period, the momentum (size) premium is about 80 (0.06) basis points monthly for French stocks. Calculations are available upon request.

evidence of such an effect: highly-advised investors are not more likely than the lightly-advised to purchase stocks with high momentum ratings in the post-period.[40] This suggests that the increase in momentum exposure in the post-period is not driven by more aggressive buying of momentum stocks, but rather by highly-advised investors being more reluctant to sell recent winners: portfolio positions gain dummies (i.e., the driver of the disposition effect) have a strong association with momentum factor betas, with a correlation of approximately 0.18.[41] Taken together, these findings are consistent with a decline in the disposition effect leading to a tilt toward momentum exposure (increased retention of recent winners), which in turn enhances portfolio performance over our sample period.

4.4.2 Client Inflows

Does the firm benefit from its clients' reduced disposition effect, and the greater portfolio returns they obtain? Given the firm's fee structure (custody and advisory fee), the firm mechanically receives a share of the higher portfolio returns in the post-period, but additional profits could arise via increased net inflows into clients' accounts.

Using transaction-level data, we construct three measures of monthly inflows. The first is gross inflows, which is simply the total amount of incoming bank transfers into an account in a given month normalized by the previous month's total portfolio value.[42] The second is a measure of net inflows, which corresponds to gross inflows minus outflows, where outflows are defined as the total flows out of the account in a given month, normalized again by the previous month's total portfolio value. Finally, 87 accounts are closed over our sample period. We thus define an extended measure of net inflows that accounts for clients' exits: when an account is closed, we assign an outflow of -100% to that account-month observation.

[40] See Appendix Table A.16 and Section 5 for further details.

[41] As we discuss in Section 5, there is some evidence that highly-advised investors are also less likely to sell stocks with high BCAP momentum ratings or high past-3 month returns in the post-period, but these characteristics are only weakly correlated with stocks' momentum betas. At the stock-day level, the correlation between the firm's proprietary BCAP momentum indicator and a stock's momentum beta is just 0.007, likely because the indicator aggregates across multiple return horizons. Similarly, the correlation between a stock's trailing three-month returns and its momentum beta is -0.005.

[42] To remove outlier observations, we winsorize normalized inflows above 100%.

We assess the effect of the intervention by estimating regression (7) with inflows as the dependent variable. Panels A of Table 7 present the coefficient estimates for gross inflows. Following the new platform's introduction, inflows from highly-advised clients increase significantly by .23 p.p. relative to lightly-advised clients (Column (4)), which corresponds to approximately 80% of the dependent variable's mean and 0.1 standard deviation. Panel B uses net inflows and finds a similar result. Finally, Panel C account for clients' exits, and, again, shows that there is a significant increase in net inflows of about .28 percentage points for highly-advised accounts after the intervention.

The results in Table 7 are consistent with increased client satisfaction following the intervention. A natural explanation is that clients reward the firm for the improved portfolio returns documented in Table 5. We examine this hypothesis in Appendix Table A.12, and find that the sensitivity of inflows and account liquidation to past portfolio performance is modest and mostly insignificant, with no statistical difference between highly- and lightly-advised clients.[43] Another possibility is that clients—especially highly advised ones—may be responding to other concurrent changes at the firm leading to increased satisfaction. However, Appendix Table A.13 shows that the rise in inflows is concentrated among clients with a high pre-period disposition effect, i.e., those who benefit most from the intervention through a reduction in their trading bias (see Table 9 and the discussion in Section 5.1).

While our analysis does not conclude decisively on what drives clients' inflows following the intervention, the results above provide supportive evidence that the positive impact of the firm's intervention on clients' satisfaction was mediated by the decrease in disposition effect. This interpretation matches the firm's view. In an informal anonymous survey we conducted among its advisors, we asked what they believed drove their clients to increase their inflows in the post-period.[44] 57% of advisors attribute increased client satisfaction to the greater time and

[43] Unreported regressions show that the results documented in Table 7 are unchanged when controlling for clients' realized portfolio returns across various horizons. This finding echoes Egan et al. (2019), who document that financial advisors engaging in misconduct often remain unpunished by unsophisticated clients.

[44] The complete survey questions and answers are available upon request.

effort invested each time they convince them to sell paper losses. Among these advisors, two third answer that, following the display change, clients came to value their advisors' willingness to make "difficult" recommendations (e.g., holding gains and selling losses), which built trust. By comparison, only 11% of advisors answer that higher portfolio returns explain the higher observed inflows.

5 Further Discussions

This section discusses a series of additional analyses conducted to test the interpretation of our findings.

5.1 Cross-sectional Splits

A potential issue with our identification strategy is that highly- and lightly-advised clients might differ in unobservable ways that may explain why their trading behaviors differ after the 2018 intervention. To strengthen our interpretation, we conduct two additional tests that exploits only *within highly-advised clients* identification.

First, if, as we posit, the intervention's impact on clients' disposition effect was mediated by financial advisors, we should expect the effect to be stronger among those who were ex ante more likely to follow advisor recommendations within the group of highly-advised clients. To measure this propensity in the pre-period, we again leverage the fact that we observe, for each day in our sample, the stocks included in the firm's investment committee's Buy and Sell lists (see Section 2.1). For each highly-advised client, we estimate a regression—using only pre-period data—of a dummy equal to one if the client buys stock i on day t on an indicator equal to one if the committee recommends buying stock i on that day. Clients with estimated coefficients above the median (across all clients) are classified as "High Followers."

We then re-estimate our baseline specification (Equation 5) within the sample of highly-advised clients, replacing the highly-advised dummy with a "High Follower" dummy. Table 8

reports the results. The coefficient on the triple interaction $\{HighFollower \times Post \times Gain\}$ is negative and statistically significant in most specifications, indicating that—within highly-advised clients—the reduction in the disposition effect post-intervention is concentrated among those who are more likely to follow advisor recommendations. This finding further supports our interpretation that the change in advisors' information display is the primary driver of the decrease in disposition effect we observe following the firm's intervention.

Second, under our interpretation, the firm's intervention should mostly affect clients who exhibit a higher disposition effect in the first place. We thus estimate, for each highly-advised client, a regression—using only pre-period data—of a dummy equal to one if the client sells stock i on day t on an indicator equal to one if stock i is in a paper gain on that day. Clients with estimated coefficients above the median (across all clients) are classified as "High Disposition". We then follow the same procedure as above. We re-estimate our baseline specification (Equation 5) within the sample of highly-advised clients, replacing the highly-advised dummy with the "High Disposition" dummy. Table 9 reports the results. The coefficient on the triple interaction $\{HighDisposition \times Post \times Gain\}$ is negative and statistically significant throughout all specifications. This confirms that the reduction in the disposition effect post-intervention is mostly driven by clients with a strong disposition effect ex ante, further strengthening our interpretation.

5.2 Other Changes to the Information Display

While our interpretation emphasizes the removal of the gain/loss information, the new advisor platform introduced and removed other relevant information that may have affected how advisors form recommendations (see Section 2.2). If this information correlates with positions being in gains or losses, it could be responsible for changing clients' trading behavior in a way consistent with a reduction in the disposition effect. While the cross-sectional splits in Section 5.1 attenuates these concerns, they do not directly address them. We do so in this section.

As previously discussed, the new platform design displays the "BCAP" ratings—a proprietary grading system quantifying a stock's momentum. This index was already communicated to advisors prior to 2018, but it became more salient after the intervention. If paper gains are more likely to be high BCAP stocks (i.e., high momentum stocks), and if the display change made advisors less likely to recommend selling high BCAP stocks, the adding of BCAP information, rather than the removing gain/loss information, may have caused the reduction in disposition effect.

Using data on stock-level BCAP ratings, we first 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).[45] 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.14).

We then directly test whether highly-advised clients' decreased propensity to sell paper gains in the post-period is driven by a decreased propensity to sell high-BCAP stocks. To do so, we re-estimate the Cox model of Equation (5), adding controls for all interactions between $HighBCAP_{j,t}$, $Post_t$, and $HighlyAdvised_i$, where $HighBCAP_{j,t}$ is a dummy equal to one if stock j has a high BCAP rating (A or P) on day t. Appendix Table A.15 presents the estimation results.

We find that highly-advised clients are, in fact, less likely to sell high-BCAP stocks in the post-period, as indicated by the negative and mostly significant coefficients on $HighBCAP \times Post_t \times HighlyAdvised$. However, controlling for the change in the propensity to sell high-BCAP stocks does not affect our main result: the coefficient on $Gain \times Post \times HighlyAdvised$ remains

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

negative and statistically significant throughout, with a magnitude similar to that reported in Table 4. Relatedly, Appendix Table A.16 shows that highly-advised clients are not more likely to *buy* high-BCAP stocks in the post-period, suggesting that the inclusion of BCAP ratings on the advisor platform had a limited impact on client trading behavior.

Information beyond the BCAP ratings was added to the new advisor platform—most notably, the past three-month return and the market capitalization of each stock in the portfolio—which could have also influenced advisors and altered clients' trading behavior.[46] In Appendix Table A.17, we augment our baseline specification by controlling for all interactions of *Post*, *HighlyAdvised*, and a "High Past-3M Return" dummy, which equals one if a stock's past three-month return is above the median for that day. We find that highly-advised clients became significantly less likely to sell high past-return stocks after the intervention. However, once again, our baseline result remains largely unchanged in this augmented specification: the coefficient on $Gain \times Post \times HighlyAdvised$ remains negative and statistically significant throughout. We repeat this exercise using stock market capitalization instead of past returns. The results, reported in Appendix Table A.18, show a marginal increase in the likelihood that highly-advised clients sell larger stocks post-intervention. Once again, this effect appears orthogonal to our main finding, which remains unchanged.

Taken together, these results support our interpretation that the observed reduction in the disposition effect is primarily driven by the removal of average acquisition prices, i.e., gain/loss information, from the advisor platform.

5.3 Did the Intervention Affect Other Biases?

Another interpretation concern is that when the firm introduced the new platform, it more generally put in place (unobservable) policies that increased the *overall* quality of advising, and therefore improved the investment strategies of highly-advised investors. If this were the case,

[46] Other information removed from or added to the platform at the intervention, such as an industry symbol for each stock, its ESG rating, or the number of shares and $ value, rather than their weight in the portfolio, are assumed orthogonal to disposition effect considerations and therefore not analyzed.

we would perhaps expect to see an improvement in other trading biases beyond the disposition effect. This section checks whether this is the case.

We first consider the rank effect of Hartzmark (2015), i..e, the higher propensity to sell extreme positions. We re-estimate the Cox model of Equation (5), replacing $Gain_{i,t-1}$ 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 rank in the portfolio, using closing market prices at $t-1$, and zero otherwise. Appendix Table A.19 presents the estimation results. As in Hartzmark (2015), investors have a significantly greater probability of selling "extreme" positions than other assets in their portfolios (the coefficients on the *Extreme* dummy are significant and positive, though significantly less so for the highly-advised). However, the firm's intervention—the change in advisor platform—had no significant impact on the relative rank effect of highly advised investors: the estimated coefficient on $Extreme \times Post \times HighlyAdvised$ is small and insignificant throughout.

We also investigate changes in under-diversification and return chasing behavior—the two main trading biases highlighted in Linnainmaa et al. (2021)—using investor-month-level data. Appendix Table A.20 presents our findings. In column (1), we regress the log of the number of stocks held in portfolio against $Post \times HighlyAdvised$ controlling for year-month and investor fixed-effects. Column (2) uses instead the portfolio's Herfindahl–Hirschman Index (HHI) as the dependent variable. In both cases, we estimate a small, insignificant coefficient, showing highly-advised clients did not become more diversified after the intervention. Column (3) uses return chasing as the dependent variable, where, to measure return chasing, we compute, for each investor and each month, the loading of the average percentile of stocks purchased during the month on the one year past return.[47] We find a significant increase in highly-advised clients' return chasing, indicating that they become *more biased* in this dimension.

These results bring additional support to the interpretation that the change in trading behav-

[47]When an investor does not purchase a stock in a month, we use the last available value. Our regression clusters standard errors at the investor level so this back-filling does not affect the significance of our findings.

ior we observe in the post-period can be attributed to the documented firm's intervention—the change in advisor platform display and the removal of gain/loss information—with precisely its intended consequence: a reduction in clients' disposition effect.

5.4 Further Exploring the Disposition Effect

An et al. (2023) show that the disposition effect is significantly weaker when portfolios are at a gain, and operates mostly for portfolios in net losses: the portfolio disposition effect. We assess the robustness of our findings to this result. To do so, we re-estimate the Cox model in Equation (5), controlling for $\{PortfolioGain \times Post_t \times HighlyAdvised_i\}$, and all corresponding interaction terms, where $PortfolioGain_{i,t-1}$ is a dummy 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. Appendix Table A.21 presents the estimation results. 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.[48] However, controlling for the portfolio disposition effect does not affect our main result: the coefficient on $\{Gain \times Post_t \times HighlyAdvised_i\}$ is negative and significant throughout our specifications. We also observe no change in the relative composition of portfolios in paper gains versus losses: the coefficient on $\{PortfolioGain \times Post_t \times HighlyAdvised_i\}$ is insignificant throughout, i.e., the highly-advised investors are not more likely to sell assets from portfolios in paper gain in the post-period than the lightly advised.

Ben-David and Hirshleifer (2012) show that beyond a simple dummy for gains and losses, the magnitude of the realized paper gains and losses affects the probability that a position is sold. We assess the robustness of our findings to this effect. We re-estimate the Cox model in Equation (5), controlling for the compounded returns of assets in paper gain (loss), $Return(+)_{i,t-1}$

[48] The highly-advised have a slightly, but significantly, lower portfolio disposition effect than the lightly advised: the loading on $PortfolioGain \times Gain \times HighlyAdvised_i$ is positive (and significant) and offsets almost entirely the negative (and significant) coefficient on the $Gain \times HighlyAdvised_i$ dummy variable.

($Return(-)_{i,t-1}$). Appendix Table A.22 presents the estimation results. Similarly to Ben-David and Hirshleifer (2012), we find the probability of selling a position is "V-shaped" in the pre-period, with no statistical difference across advised clients: we find a significant positive (negative) loading on $Return(+)_{i,t-1}$ ($Return(-)_{i,t-1}$), i.e., large positive and large negative returns are more likely to be sold. However, while the shape partly "flattens" in the post-period, there is no significant difference in this change between highly and lightly-advised clients.[49] Most importantly, controlling for the "V-shape" does not affect our main result: the coefficient on $\{Gain \times Post_t \times HighlyAdvised_i\}$ remains negative and significant throughout our specifications.

6 Conclusion

This paper evaluates an intervention conducted by a large brokerage and financial services firm in France aimed at reducing its clients' disposition effect. A key feature of the intervention is that it targeted *financial advisors* by removing their ability to directly observe clients' unrealized gains and losses. Exploiting cross-sectional variation in advising intensity, we show that the intervention significantly reduced the *clients'* disposition effect.

Our findings lend support to the view that financial advisors do not, in general, mitigate their clients' behavioral biases. On the contrary, when advisors have access to information about paper gains and losses—information directly relevant to the disposition effect—clients exhibit *more*, not less, biased trading behavior. More broadly, our results demonstrate that financial firms can effectively limit trading biases by reshaping the information available to their advisors.

While our empirical analysis rules out several alternative explanations, important questions remain that our data and quasi-natural experiment cannot fully address. Perhaps the most critical is why advisors fail to attenuate their clients' biases without firm interventions. Recent

[49] The change in the V-shape is illustrated in Appendix Figure A.3, where we show binscatter plots 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.

work suggests that advisors may simply transmit their own biases (Linnainmaa et al., 2021), but agency frictions could also play a role—particularly in our setting, which differs substantially from that of Linnainmaa et al. (2021).

Two additional questions left unanswered are: (1) Can brokerage firms design similar interventions to reduce other investment biases, such as return chasing or under-diversification? (2) Can the design of this intervention be improved to eliminate the disposition effect of all investors while preserving client satisfaction? We leave these questions for future work.

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	42.5
Holding Period (Days)	.	195.72	151.9	15	82	159	273	504
Holding Period Before 1st Sale (Days)	.	190.17	151.52	15	79	149	265	501
Monthly Return (%)	.	1.05	1.7	-1.06	.44	.9	1.59	3.77
Monthly Risk-Adjusted Return (%)	.	.05	1.62	-2.24	-.25	.22	.64	1.89
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	73.5
Holding Period (Days)	.	226.04	148.63	22	106	201.25	332	501.5
Holding Period Before 1st Sale (Days)	.	214.38	149.31	21	95.25	185.75	311	501
Monthly Return (%)	.	.57	1.8	-2.09	.04	.69	1.17	2.81
Monthly Risk-Adjusted Return (%)	.	-.11	1.83	-2.73	-.33	.16	.61	1.72
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
Holding Period Before 1st Sale (Days)	.	308.65	201.1	30	133	285	478.5	659
Monthly Return (%)	.	.25	1.94	-2.86	-.28	.62	1.1	2.42
Monthly Risk-Adjusted Return (%)	.	-.39	1.99	-3.64	-.83	.11	.56	1.41

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 purchase date and the liquidation of the position. Holding Period Before 1st Sale corresponds to the number of days between the purchase date and any sale of the position including partial sales. 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					
	(1)	(2)	(3)	(4)	(5)	(6)
Highly Advised × Year -1			-0.166			-0.166
			(0.136)			(0.139)
Not Advised × Year -1						0.388***
						(0.139)
Highly Advised × Post	-0.629***	-0.629***	-0.712***	-0.629***	-0.629***	-0.712***
	(0.124)	(0.087)	(0.110)	(0.115)	(0.093)	(0.112)
Not Advised × Post				-0.149	-0.149	0.045
				(0.115)	(0.093)	(0.112)
Highly Advised	0.030	0.030	0.113	0.030	0.030	0.113
	(0.098)	(0.068)	(0.096)	(0.091)	(0.074)	(0.099)
Not Advised				0.522***	0.522***	0.328***
				(0.091)	(0.074)	(0.099)
Post	0.147*			0.147*		
	(0.088)			(0.081)		
Constant	1.517***			1.517***		
	(0.069)			(0.064)		
Year-Month FE	No	Yes	Yes	No	Yes	Yes
Observations	128	128	128	192	192	192
R^2	0.36	0.84	0.85	0.57	0.81	0.83

TABLE 3: **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 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. 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.

	Sell									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Gain × Post × Highly Advised	-0.251***	-0.195***	-0.258***	-0.200***	-0.249***	-0.226***	-0.266***	-0.216***	-0.245***	-0.211***
	(0.065)	(0.065)	(0.064)	(0.065)	(0.065)	(0.064)	(0.065)	(0.065)	(0.071)	(0.075)
Gain × Post	-0.034	0.053	-0.076	0.038	-0.079	0.012	-0.054	0.045	-0.098	0.010
	(0.056)	(0.055)	(0.053)	(0.054)	(0.058)	(0.057)	(0.056)	(0.055)	(0.062)	(0.065)
Gain × Highly Advised	-0.120*	-0.098	-0.120*	-0.094	-0.056	-0.048	-0.094	-0.055	-0.107	-0.053
	(0.072)	(0.072)	(0.072)	(0.072)	(0.072)	(0.072)	(0.074)	(0.074)	(0.086)	(0.091)
Post × Highly Advised	0.175**	0.169**	0.174**	0.169**	0.168**	0.152**	0.221***	0.231***	0.123**	0.162***
	(0.078)	(0.077)	(0.075)	(0.074)	(0.074)	(0.073)	(0.070)	(0.070)	(0.058)	(0.060)
Gain	0.455***	0.387***	0.419***	0.389***	0.511***	0.487***	0.461***	0.394***	0.481***	0.447***
	(0.062)	(0.063)	(0.060)	(0.060)	(0.067)	(0.066)	(0.064)	(0.066)	(0.078)	(0.084)
Post	0.137*	0.130*			0.201***	0.128*	0.178***	0.169***	0.229***	0.193***
	(0.070)	(0.069)			(0.070)	(0.068)	(0.060)	(0.059)	(0.046)	(0.048)
Highly Advised	-0.342***	-0.298***	-0.318***	-0.280***	-0.366***	-0.317***	-0.294***	-0.244***		
	(0.099)	(0.097)	(0.095)	(0.093)	(0.093)	(0.092)	(0.087)	(0.086)		
Log(Buy Price)		-0.021***		-0.025***		-0.121***		-0.023***		-0.026***
		(0.006)		(0.006)		(0.018)		(0.006)		(0.004)
Volatility(+)		0.011		0.007		-0.005		0.012*		0.012*
		(0.008)		(0.008)		(0.014)		(0.007)		(0.007)
Volatility(-)		-0.003		-0.003		-0.008		-0.001		0.001
		(0.005)		(0.005)		(0.011)		(0.005)		(0.004)
Return(+)		-0.166***		-0.062***		-0.577***		-0.145***		0.066***
		(0.016)		(0.012)		(0.029)		(0.015)		(0.012)
Return(-)		0.912***		0.632***		0.757***		0.880***		0.477***
		(0.048)		(0.047)		(0.059)		(0.046)		(0.051)
Buy Reco		-0.487***		-0.576***		-0.334***		-0.579***		-0.650***
		(0.021)		(0.020)		(0.024)		(0.019)		(0.016)
Sell Reco		0.640***		0.593***		0.699***		0.618***		0.622***
		(0.021)		(0.019)		(0.024)		(0.019)		(0.016)
Stratified by date	No	No	Yes	Yes	No	No	No	No	No	No
Stratified by stock	No	No	No	No	Yes	Yes	No	No	No	No
Stratified by advisor	No	No	No	No	No	No	Yes	Yes	No	No
Stratified by account	No	No	No	No	No	No	No	No	Yes	Yes
Observations	35014237	35014237	35014237	35014237	35014237	35014237	35014237	35014237	35014237	35014237
Pseudo R^2	0.002	0.011	0.004	0.025	0.004	0.015	0.002	0.017	0.002	0.036

TABLE 4: **Cox Model Estimates.** This table presents estimates of the Cox hazard model in equation (5) analyzing selling decisions, at the investor-stock-day level. The dependent variable is a dummy variable that equals one if there is sale (including partial sale), and zero otherwise. Gain is a dummy variable equal to one if the return since purchase is positive and zero otherwise. Highly Advised is a dummy variable indicating whether the client belongs to that 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. 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 stratify the baseline hazard function by date in columns (3)-(4), by stock in columns (5)-(6), by advisor in columns (7)-(8), and by account in columns (9)-(10). Standard errors are clustered at the account 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)	
Year-Month FE	No	Yes	No	Yes	No	Yes	No	Yes
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)
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

	Monthly Alpha (%)			
	(1)	(2)	(3)	(4)
Highly Advised × Post	0.105	0.065	0.098	0.059
	(0.075)	(0.080)	(0.076)	(0.081)
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	0.37	0.43	0.38	0.44

TABLE 5: **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.

	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)
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 6: **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.

Panel A: Asset Inflows

	Inflow (%)			
	(1)	(2)	(3)	(4)
Highly Advised × Post	0.162*	0.217***	0.169**	0.228***
	(0.083)	(0.081)	(0.082)	(0.080)
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	0.19	0.24	0.20	0.26

Panel B: Asset Net Flows

	Net Flow (%)			
	(1)	(2)	(3)	(4)
Highly Advised × Post	0.206**	0.232***	0.216**	0.247***
	(0.089)	(0.083)	(0.089)	(0.083)
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	0.19	0.25	0.20	0.26

Panel C: Asset Net Flows including Client Exits

	Net Flow (% incl. Exit)			
	(1)	(2)	(3)	(4)
Highly Advised × Post	0.252***	0.264***	0.263***	0.283***
	(0.098)	(0.093)	(0.098)	(0.093)
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	0.18	0.24	0.20	0.25

TABLE 7: **Effects on Flows.** Regressions are estimated at the investor-month level. In Panels A, B and C, the dependent variables are the percentage inflow, the net percentage flow, and the net percentage flow considering it equals -100% when a 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.

	Sell									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Gain × Post × High Follower	-0.244***	-0.191**	-0.245***	-0.208**	-0.247***	-0.212***	-0.260***	-0.218**	-0.124	-0.080
	(0.087)	(0.087)	(0.086)	(0.087)	(0.083)	(0.082)	(0.091)	(0.093)	(0.090)	(0.096)
Gain × Post	-0.062	0.068	-0.095	0.070	-0.120	-0.005	-0.091	0.058	-0.253***	-0.111
	(0.080)	(0.080)	(0.078)	(0.079)	(0.078)	(0.075)	(0.084)	(0.085)	(0.083)	(0.087)
Gain × High Follower	0.220**	0.238**	0.195**	0.221**	0.240***	0.223**	0.202**	0.233**	0.082	0.136
	(0.095)	(0.097)	(0.093)	(0.096)	(0.093)	(0.091)	(0.099)	(0.102)	(0.110)	(0.116)
Post × High Follower	0.364***	0.343***	0.332***	0.332***	0.345***	0.316***	0.319***	0.307***	0.201**	0.202**
	(0.087)	(0.086)	(0.079)	(0.079)	(0.080)	(0.079)	(0.091)	(0.091)	(0.082)	(0.087)
Gain	0.131	0.118	0.114	0.124	0.246***	0.305***	0.172*	0.179*	0.311***	0.322***
	(0.089)	(0.090)	(0.087)	(0.090)	(0.090)	(0.086)	(0.092)	(0.096)	(0.103)	(0.109)
Post	0.123	0.105			0.197**	0.095	0.178**	0.176**	0.198***	0.187**
	(0.081)	(0.080)			(0.079)	(0.077)	(0.086)	(0.086)	(0.073)	(0.077)
High Follower	-0.470***	-0.454***	-0.454***	-0.460***	-0.490***	-0.459***	-0.422***	-0.420***		
	(0.120)	(0.116)	(0.109)	(0.106)	(0.107)	(0.106)	(0.122)	(0.117)		
Log(Buy Price)		-0.018**		-0.027***		-0.159***		-0.029***		-0.029***
		(0.008)		(0.008)		(0.025)		(0.007)		(0.006)
Volatility(+)		0.036***		0.357***		-0.009		0.025***		0.333***
		(0.008)		(0.089)		(0.022)		(0.009)		(0.095)
Volatility(-)		-0.000		0.003		-0.001		0.003		0.005
		(0.010)		(0.008)		(0.020)		(0.008)		(0.007)
Return(+)		-0.144***		-0.062***		-0.665***		-0.121***		0.067***
		(0.028)		(0.019)		(0.053)		(0.022)		(0.016)
Return(-)		0.640***		0.470***		0.393***		0.592***		0.278***
		(0.058)		(0.062)		(0.080)		(0.059)		(0.072)
Buy Reco		-0.412***		-0.520***		-0.252***		-0.560***		-0.644***
		(0.033)		(0.030)		(0.046)		(0.027)		(0.021)
Sell Reco		0.808***		0.742***		0.833***		0.757***		0.768***
		(0.031)		(0.028)		(0.044)		(0.028)		(0.026)
Stratified by date	No	No	Yes	Yes	No	No	No	No	No	No
Stratified by stock	No	No	No	No	Yes	Yes	No	No	No	No
Stratified by advisor	No	No	No	No	No	No	Yes	Yes	No	No
Stratified by account	No	No	No	No	No	No	No	No	Yes	Yes
Observations	17665451	17665451	17665451	17665451	17665451	17665451	17665451	17665451	17665451	17665451
Pseudo R^2	0.001	0.013	0.001	0.032	0.002	0.016	0.002	0.022	0.002	0.046

TABLE 8: **Cox Model Estimates: Only Highly-Advised Depending on Propensity to Follow Recommendations Pre-Period.** This table presents estimates of the Cox hazard model analyzing selling decisions, at the investor-stock-day level. The dependent variable is a dummy variable that equals one if there is sale (including partial sale), and zero otherwise. This table presents estimations of specifications similar to those presented in Table 4, but uses only the sample of highly-advised clients. We separate highly-advised clients according their likelihood of following the recommendations of the firm (corresponding to the "High Follower" dummy variable). To identify *High Follower* investors, we estimate, for each individual in the pre-period, a regression in which the dependent variable is a dummy indicating whether the investor buys stock i on day t, and the independent variable is an indicator that equals one if the investment committee recommends buying stock i on that day. We then extract the estimated regression coefficient and classify investors with an above-median coefficient as *High Followers*. Standard errors are clustered at the account level. ***, ** and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Sell									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Gain × Post × High Disposition	-0.786***	-0.764***	-0.819***	-0.852***	-0.822***	-0.794***	-0.820***	-0.826***	-0.831***	-0.870***
	(0.075)	(0.077)	(0.076)	(0.077)	(0.077)	(0.077)	(0.077)	(0.078)	(0.079)	(0.084)
Gain × Post	0.419***	0.581***	0.399***	0.627***	0.367***	0.517***	0.413***	0.600***	0.409***	0.621***
	(0.067)	(0.068)	(0.067)	(0.068)	(0.069)	(0.070)	(0.068)	(0.069)	(0.070)	(0.075)
Gain × High Disposition	1.010***	1.102***	0.986***	1.085***	1.053***	1.038***	1.024***	1.122***	1.032***	1.090***
	(0.073)	(0.074)	(0.073)	(0.074)	(0.074)	(0.075)	(0.075)	(0.077)	(0.078)	(0.081)
Post × High Disposition	-0.342***	-0.336***	-0.361***	-0.349***	-0.319***	-0.318***	-0.346***	-0.321***	-0.082	-0.062
	(0.073)	(0.074)	(0.070)	(0.073)	(0.074)	(0.074)	(0.078)	(0.080)	(0.078)	(0.085)
Gain	-0.506***	-0.596***	-0.534***	-0.593***	-0.376***	-0.405***	-0.512***	-0.586***	-0.542***	-0.552***
	(0.063)	(0.065)	(0.063)	(0.065)	(0.066)	(0.066)	(0.065)	(0.067)	(0.066)	(0.070)
Post	0.693***	0.663***	0.000	0.000	0.748***	0.633***	0.713***	0.680***	0.417***	0.388***
	(0.066)	(0.067)	(.)	(.)	(0.070)	(0.070)	(0.071)	(0.073)	(0.067)	(0.074)
High Disposition	1.025***	1.024***	1.007***	0.998***	0.937***	0.954***	0.856***	0.822***	0.000	0.000
	(0.071)	(0.072)	(0.068)	(0.070)	(0.072)	(0.072)	(0.075)	(0.076)	(.)	(.)
Log(Buy Price)		-0.015**		-0.022***		-0.134***		-0.024***		-0.029***
		(0.008)		(0.008)		(0.025)		(0.007)		(0.006)
Volatility(+)		0.039***		0.272***		0.005		0.022**		0.328***
		(0.008)		(0.086)		(0.023)		(0.009)		(0.094)
Volatility(-)		0.006		0.008		0.016		0.005		0.004
		(0.008)		(0.007)		(0.021)		(0.008)		(0.007)
Return(+)		-0.009		0.004		-0.329***		-0.009		0.085***
		(0.019)		(0.017)		(0.043)		(0.017)		(0.016)
Return(-)		0.671***		0.531***		0.410***		0.623***		0.326***
		(0.064)		(0.064)		(0.084)		(0.065)		(0.071)
Buy Reco		-0.546***		-0.614***		-0.369***		-0.616***		-0.644***
		(0.033)		(0.031)		(0.047)		(0.027)		(0.021)
Sell Reco		0.752***		0.702***		0.799***		0.733***		0.766***
		(0.031)		(0.028)		(0.045)		(0.029)		(0.027)
Stratified by date	No	No	Yes	Yes	No	No	No	No	No	No
Stratified by stock	No	No	No	No	Yes	Yes	No	No	No	No
Stratified by advisor	No	No	No	No	No	No	Yes	Yes	No	No
Stratified by account	No	No	No	No	No	No	No	No	Yes	Yes
Observations	17445954	17445954	17445954	17445954	17445954	17445954	17445954	17445954	17445954	17445954
Pseudo R^2	0.010	0.024	0.022	0.054	0.019	0.032	0.010	0.031	0.003	0.048

TABLE 9: **Cox Model Estimates: Only Highly-Advised Depending on Disposition Effect Pre-Period.** This table presents estimates of the Cox hazard model analyzing selling decisions, at the investor-stock-day level. The dependent variable is a dummy variable that equals one if there is sale (including partial sale), and zero otherwise. This table presents estimations of specifications similar to those presented in Table 4, but uses only the sample of highly-advised clients. We separate highly-advised clients according to their disposition effect biases (corresponding to the "High Disposition" dummy variable). To identify *High Disposition* investors, we estimate a regression for each individual in the pre-period, where the dependent variable is a dummy indicating whether the investor sells stock i on day t, and the independent variable is an indicator that equals one if stock i is in a paper gain on that day. Investors with an above-median estimated regression coefficient are classified as *High Disposition* investors. Standard errors are clustered at the account level. ***, ** and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Figures

Position du **28/02/2023**	Valorisation titres	**275 177,02 EUR**
	Valorisation espèces	**13 798,90 EUR**
	Valeur totale	**288 975,92 EUR**

Espèces

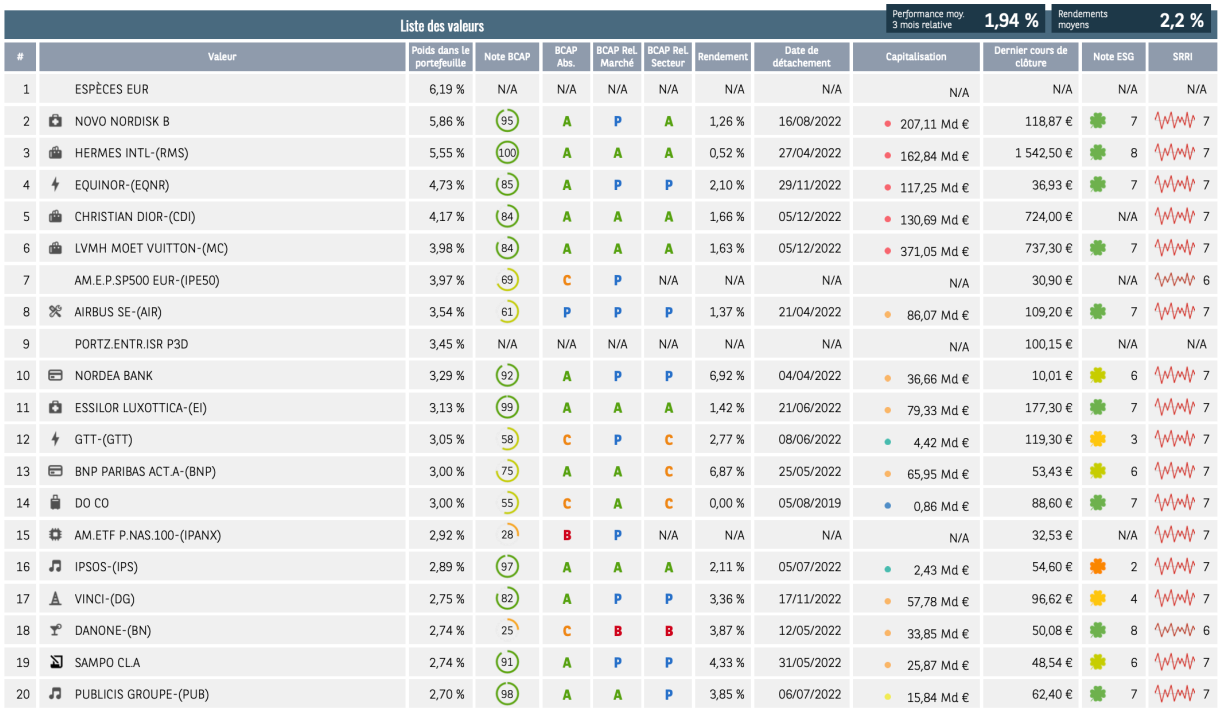
Regroupement	Libellé	Solde	Valorisation	Poids (%)
Total espèces			**13 798,90**	**4,78**
ESPECES				
Espèces EUR	**Espèces EUR**		**13 798,90**	**4,78**
. Espèce Compte Titre	. Espèce Compte	13 798,90 EUR	13 798,90 EUR	4,78

Titres

Regroupement	Libellé valeur	HG	BL	Quantité	PAM	Cours	Date Cours	PMVL	Valorisation	Poids (%)	Secteur économique
ACTIONS									**256 085,32**	**88,62**	
NL0000235190	**AIRBUS SE-(AIR)**			90	105,3960 EUR	124,0200 EUR	28/02/2023	1 676,16 EUR	11 161,80 EUR	**3,86**	**Divers**
FR0013412285	**AM.P.SP500 SCR.ACC-(IPE50)**			357	31,9910 EUR	30,3360 EUR	28/02/2023	-590,84 EUR	10 829,95 EUR	**3,75**	**Divers**
FR0013412269	**AM.P.US T.SCR.ACC-(IPANX)**			249	38,0750 EUR	33,0890 EUR	28/02/2023	-1 241,51 EUR	8 239,16 EUR	**2,85**	**Divers**
NL0010273215	**ASML HOLDING-(ASML)**			17	289,9460 EUR	584,0000 EUR	28/02/2023	4 998,92 EUR	9 928,00 EUR	**3,44**	**Divers**
FR0000120628	**AXA-(CS)**			349	27,8360 EUR	29,8500 EUR	28/02/2023	702,89 EUR	10 417,65 EUR	**3,61**	**Divers**
IE00BD1RP616	**BANK IRELAND GRP**								**9 939,79**	**3,44**	**Divers**
. DUBLIN	Divers			953	6,7070 EUR	10,4300 EUR	28/02/2023	3 548,02 EUR	9 939,79 EUR	3,44	Divers
FR0000131104	**BNP PARIBAS ACT.A-(BNP)**			156	55,2820 EUR	66,1500 EUR	28/02/2023	1 695,41 EUR	10 319,40 EUR	**3,57**	**Divers**
ES0140609019	**CAIXABANK**								**8 497,04**	**2,94**	**Divers**
. MADRID	Divers			2 097	3,3170 EUR	4,0520 EUR	28/02/2023	1 541,29 EUR	8 497,04 EUR	2,94	Divers
FR0000130403	**CHRISTIAN DIOR-(CDI)**			16	641,6050 EUR	787,0000 EUR	28/02/2023	2 326,32 EUR	12 592,00 EUR	**4,36**	**Divers**
AT0000818802	**DO CO**								**7 732,80**	**2,68**	**Divers**
. Vienne	Divers			72	88,8190 EUR	107,4000 EUR	28/02/2023	1 337,83 EUR	7 732,80 EUR	2,68	Divers
FR0000035818	**ESKER-(ALESK)**			39	163,4800 EUR	151,9000 EUR	28/02/2023	-451,62 EUR	5 924,10 EUR	**2,05**	**Divers**
FR0000121667	**ESSILOR LUXOTTICA-(EL)**			49	168,6560 EUR	164,4000 EUR	28/02/2023	-208,54 EUR	8 055,60 EUR	**2,79**	**Divers**
FR0014008VX5	**EUROAPI-(EAPI)**			3	12,5000 EUR	15,5000 EUR	28/02/2023	9,00 EUR	46,50 EUR	**0,02**	**Divers**
FR0000052292	**HERMES INTL-(RMS)**			10	477,1260 EUR	1 715,5000 EUR	28/02/2023	12 383,74 EUR	17 155,00 EUR	**5,94**	**Divers**
DE0006231004	**INFINEON TECHN.**								**6 770,03**	**2,34**	**Divers**
. XETRA	Divers			202	36,6090 EUR	33,5150 EUR	28/02/2023	-624,99 EUR	6 770,03 EUR	2,34	Divers
FR0000073298	**IPSOS-(IPS)**			147	50,9140 EUR	58,1000 EUR	28/02/2023	1 056,34 EUR	8 540,70 EUR	**2,96**	**Divers**
FR0000121014	**LVMH MOET VUITTON-(MC)**			15	427,9200 EUR	789,0000 EUR	28/02/2023	5 416,20 EUR	11 835,00 EUR	**4,10**	**Divers**
LU1834988781	**LY.I.L.S.E.600TRAV-(TRV)**			216	28,0080 EUR	28,0620 EUR	28/02/2023	11,66 EUR	6 061,39 EUR	**2,10**	**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, "quantité"= number of stocks, "valorisation" = value, "poids"=weight, "cours"= market value, "PAM"= average buy price, "PMVL" = average gain/loss.



Liste des valeurs

Performance moy. 3 mois relative 1,94 %

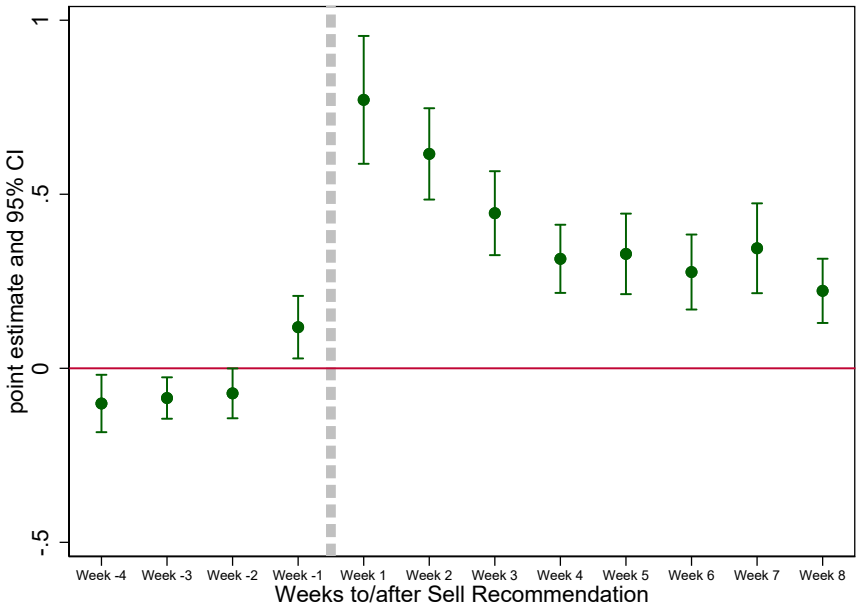
Rendements moyens 2,2 %

#	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

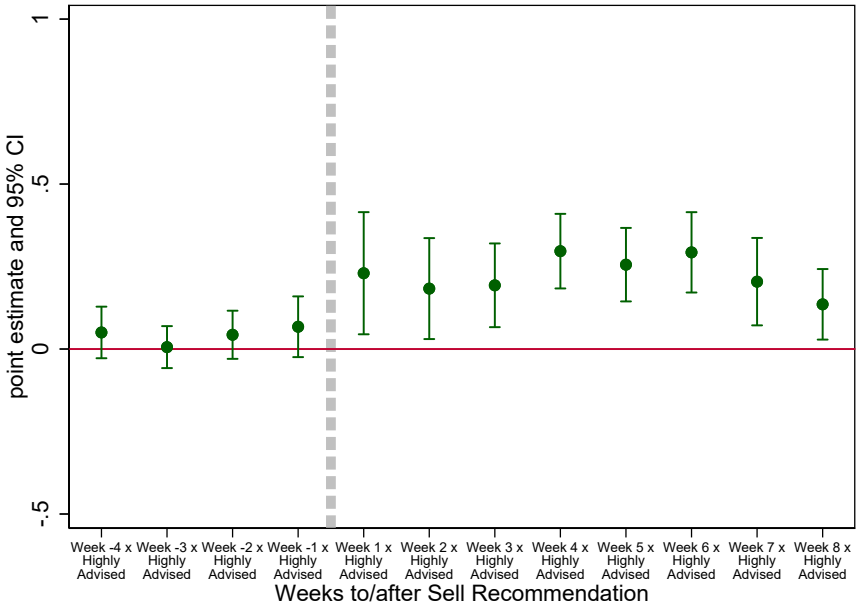
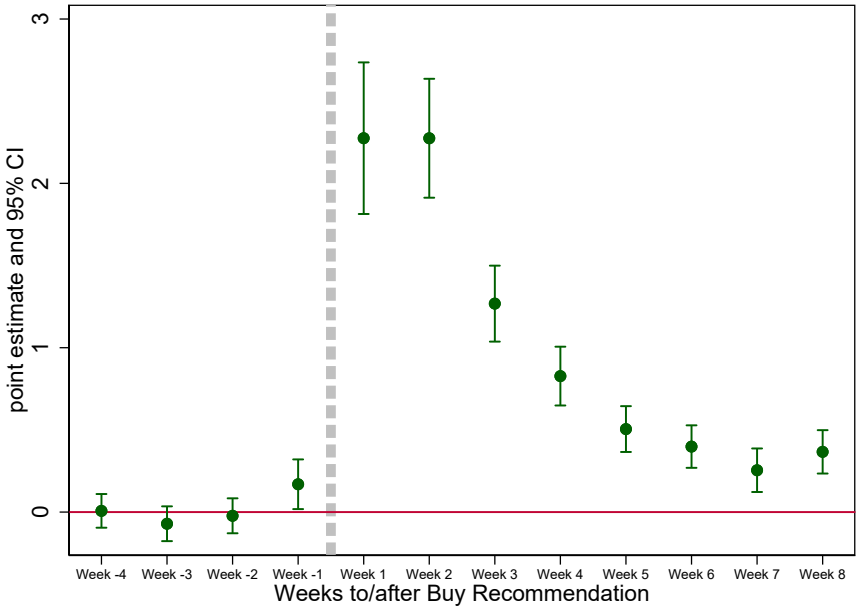


FIGURE 3: **Event Study: Following Sell Recommendations.** These figures plot the coefficient on the 4 weeks before and 8 weeks after the committee recommendation on a stock switches to "Sell". Panel A provides the coefficients $\beta_{s,k}$ and Panel B the coefficients $\beta_{sh,k}$ of regression (3): $100 \times Sell_{i,j,t} = \sum_{k=-4}^{+8} [\beta_{s,k} SellReco(k)_{j,t} + \beta_{sh,k} SellReco(k)_{j,t} \times HighlyAdvised_i] + FE_i + FE_j + FE_t + \epsilon_{i,j,t}$, 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

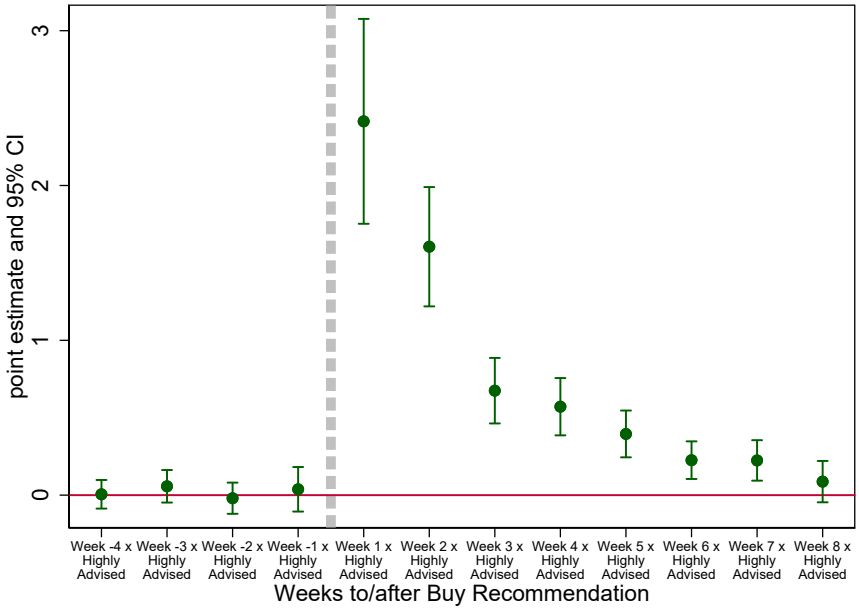


FIGURE 4: **Event Study: Following Buy Recommendations.** These figures plot the coefficient on the 4 weeks before and 8 weeks after the committee recommendation on a stock switches to "Buy". Panel A provides the coefficients $\beta_{b,k}$ and Panel B the coefficients $\beta_{bh,k}$ of regression: $100 \times Buy_{i,j,t} = \sum_{k=-4}^{+8} [\beta_{s,k} BuyReco(k)_{j,t} + \beta_{sh,k} BuyReco(k)_{j,t} \times HighlyAdvised_i] + FE_i + FE_j + FE_t + \epsilon_{i,j,t}$, 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.

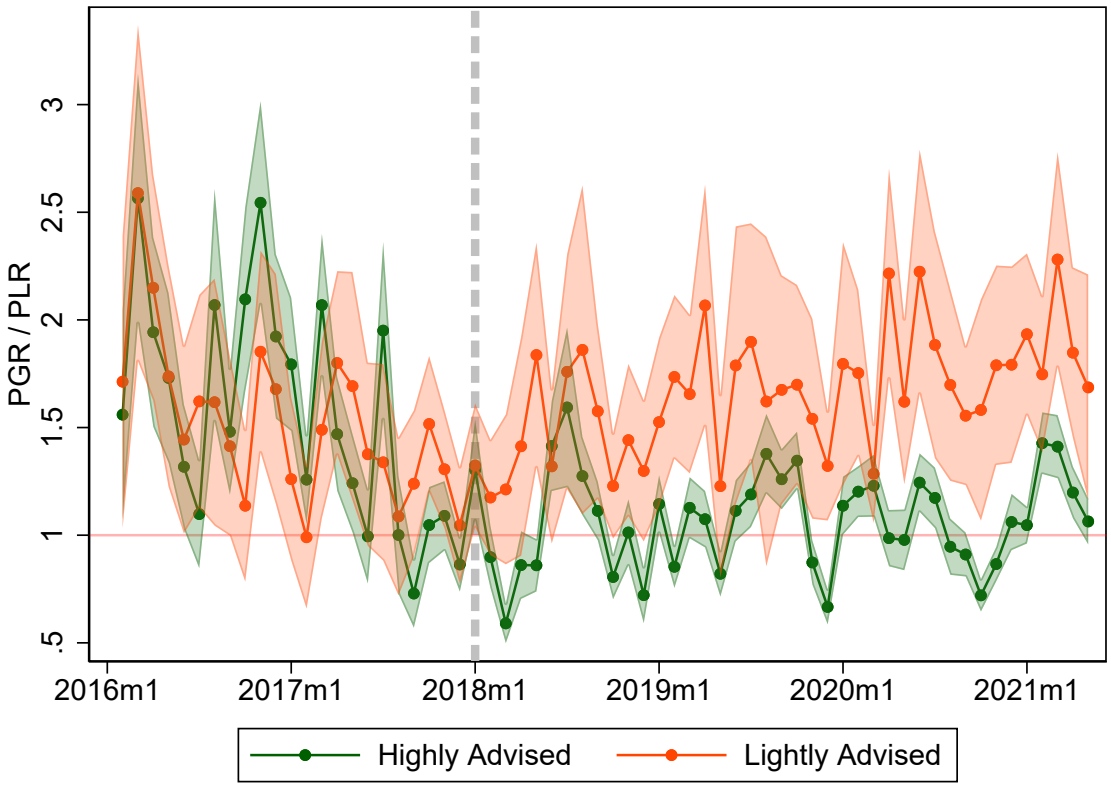
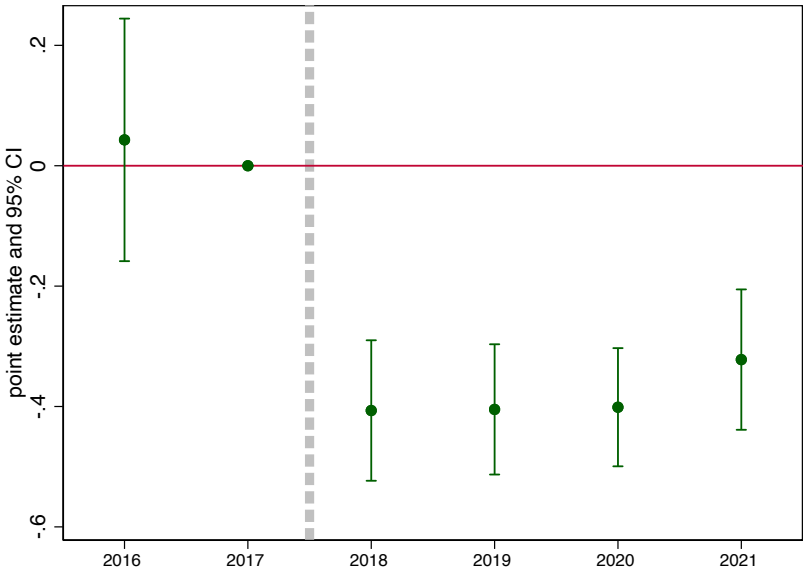


FIGURE 5: **Disposition Effect by Investors' Profile.** This figure displays the evolution of the ratio of the Proportion of Gain Realized (PGR) to the Proportion of Loss Realized (PLR). PGR is the number of realized gains divided by the number of realized gains plus the number of paper (unrealized) 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.

Panel A: Event Study with year dummies



Panel B: Event Study with half-year dummies

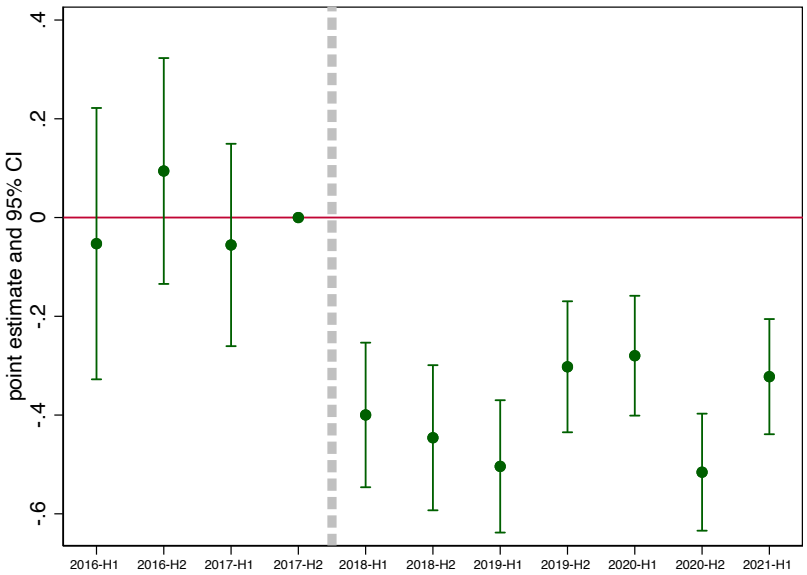


FIGURE 6: **Cox Model Event Study** This figure investigates the timing of the treatment effect. In Panel A, we estimate the event-study specification in equation (5) and plot the coefficients on the triple interaction terms $Gain \times HighlyAdvised \times TreatYear(k)$. We use year -1 as the (omitted) baseline year. In Panel B, we reproduce this analysis at the semester frequency, where we use the second half of 2017 as the omitted baseline. Standard errors are clustered at the account level.

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