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FINANCIAL ATTENTION AND THE DISPOSITION EFFECT

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Abstract

Using a novel brokerage dataset covering individual investors' login and stock trading behavior, we investigate the severity of the disposition effect as a function of attention. Our results show that more attentive investors trade less in line with the disposition effect, suggesting a comparative advantage in incorporating information into financial decision making. Furthermore, we find that high attention is related to a stronger tendency to sell moderate losses, as compared to large ones, while low attention increases an investor's likelihood to sell extreme, rather than moderate, profits. These results are in line with the theory of cognitive dissonance and saliency effects.

Keywords: Investor behavior, Disposition effect, Attention allocation
JEL Codes: G11, G41

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1 Introduction

Numerous studies over the past decades suggest that retail investors do not always behave in line with standard economic theory. They trade excessively, hold underdiversified portfolios and have a preference for stocks within their geographic proximity.[1] Potentially the most consistent trading behavior pertains to the disposition effect: investors are more likely to sell an asset that is trading at a profit than one that is trading at a loss (Shefrin et al., 1985; Odean, 1998; Weber and Camerer, 1998; Genesove and Mayer, 2001; Grinblatt and Keloharju, 2001; Kaustia, 2004; Frazzini, 2006; Chen et al., 2007).[2]

An interesting question that still remains, is whether investors who devote a lot of attention and time to monitor their portfolios, exhibit a similar level of the disposition effect. Do individuals who continuously monitor their portfolios make better financial decisions than those who do not? This is a pertinent question as attention is a limited and costly resource, but a definitive answer requires data that is often unavailable. In this regard, the increasing popularity of online trading platforms offers new avenues to measure how much attention retail investors pay to their financial assets through the use of login data.

In this paper, we use a novel dataset from the largest Belgian discount broker to investigate how strongly retail investors behave in line with the disposition effect, as a function of how much attention they allocate to their portfolios. Our data covers the login and trading activity of more than 65.000 clients between 2014 and 2016, with timestamps for when investors log in, when they last click on an item during a login session, and when the actual logout takes place. This allows us to measure, at the individual level, how frequently clients log in, how much time they spend on the investment platform, and whether they are consistently attentive throughout the sample period. We relate these different measures of attention to the retail investors' disposition effect with respect to stocks.

[1]See Barber and Odean (2013) for an excellent overview of the literature on individual investor behavior.

[2]In general, the academic literature considers the disposition effect to be a behavioral mistake, because it tends to be tax inefficient (Barber and Odean, 2013), and the stocks sold at a gain by individuals, go on to outperform the losing investments they keep in their portfolio (Odean, 1998; Seru et al., 2010; Duxbury et al., 2015).

We argue that the disposition effect differs between more and less attentive investors from two opposing perspectives. On the one hand, the higher attention allocation from more attentive investors likely results from a comparative advantage in understanding and incorporating financial information into their decision making. As a consequence, such investors should trade less in line with the disposition effect. Paying attention to your financial assets provides the opportunity to gather important financial information, which serves as an input in the investment process (Peress, 2004; Peng and Xiong, 2006; Andrei and Hasler, 2016). Rational investors will only allocate attention to their portfolios, up to the point where marginal benefits equal marginal costs. More sophisticated investors will have a greater payoff from monitoring their portfolios, because they are more well-suited to understand and interpret the information they obtain. Kacperczyk et al. (2016) present a similar notion in their three-period model, distinguishing between skilled and unskilled investment managers, in which only skilled managers allocate attention in the first period, thereby obtaining beneficial private information.

A negative relation between the disposition effect and financial attention can also be explained by myopic loss aversion. Higher financial attention could imply shorter evaluation periods, causing myopic loss aversion.[3] Benartzi and Thaler (1995) show that a short evaluation period makes investors unwilling to bear the risks associated with holding stocks unless they will be compensated by a sufficiently high equity risk premium.[4] Because investors focus too strongly on the short term, they react too negatively to recent losses, instead of focusing on the long-term benefits (see Thaler et al. (1997)). This could generate panic reactions, which might have a positive impact on the propensity to sell at a loss and hence a negative effect on the disposition effect. As a result, you could argue that the myopic loss aversion bias might prompt for a reduction in the disposition effect.[5]

On the other hand, Festinger's (1957) theory of cognitive dissonance predicts a positive

[3]See Duxbury (2015) for an excellent review of the experimental evidence on myopic loss aversion.

[4]Benartzi and Thaler (1995) use this argument to explain the equity risk premium puzzle.

[5]This interpretation is in a similar light to Duxbury et al. (2015)'s interpretation of the interaction between two behavioral biases, the house money effect and the disposition effect.

relationship between the disposition effect and the allocation of investors' attention. The theory suggests that the preference to sell stocks trading at a profit over those trading at a loss, manifests itself, because investors experience psychological discomfort when they are confronted with a loss. This discomfort stems from the difficulty to reconcile the loss with an individual's positive self-image and his ability to make proper investment decisions. To alleviate such dissonance, investors justify to themselves that the loss is only temporary and remains unrealized (Zuchel, 2001; Kaustia, 2010a; Lehenkari, 2012). Chang et al. (2016) formalize this reasoning, and explain how it can clarify the puzzling observation of a reverse disposition effect for mutual fund shares (see Calvet et al. (2009)).

The severity of cognitive dissonance depends on two factors: personal responsibility and commitment (Gilad et al., 1987). In this regard, individuals' attention allocation may act as a relative measure of commitment. Gilad et al. (1987, p. 64) defines commitment as the "ego-involvement for the decision maker, i.e., he or she cannot deny the significance of their behavior to the occurrence of subsequent events". Therefore, more attentive investors experience a heightened level of psychological discomfort when confronted with a poor investment decision. This results in a more severe disposition effect, due to a lower preference to sell a losing stock position. This prediction can also be more intuitively understood by considering a simple example. Investors choosing to closely monitor the performance of their investments have ample opportunity to respond quickly if their initial belief that a stock will appreciate turns out to be incorrect. At first, when a position starts to lose money, these attentive investors perceive the loss to be temporary. Subsequent news arrivals, leading to an aggravation of the loss, will confront the high-attention investors with the fact that they should have sold the stock sooner. This leads to more psychological discomfort, and a lower likelihood of realizing the loss. This is a concept Staw (1981) highlights as "the escalation of commitment". Investors who spend less time monitoring their portfolios, did not invest the same amount of costly resources into maintaining the position, resulting in a lower commitment and hence a higher probability to sell a stock trading at a loss.

Our empirical results are fourfold. First, the results from our baseline model show that more attentive investors exhibit a far smaller disposition effect. At the lowest decile of attention, the difference between the probability to sell a stock trading at a profit and one trading at a loss amounts to 13 to 14%, whereas this difference only equals 6 to 7% at the highest attention decile. Even after controlling for various measures of investor sophistication and trading experience, we find that the size of the disposition effect among low-attention investors significantly exceeds that of more attentive investors. These results provide evidence that financial attention may encompass a component of investor sophistication, or skill, that is not properly captured by alternative proxies.[6]

Second, to further investigate the potential role attention plays in the experience of cognitive dissonance, we extend our model, by allowing for a differential selling probability depending on the magnitude of one's return. This extension reveals a strong divergence between the probabilities to sell moderate and large losses as attention increases. At low levels of attention, the model-implied probabilities to sell a moderate or large loss do not differ significantly from one another. In contrast, among more attentive investors the likelihood to sell a loss monotonically decreases as the magnitude thereof increases. We attribute this finding to attentive investors being unable to deny to themselves that they are personally responsible for letting the loss build-up in their portfolios.

Third, our extended model also uncovers the role of saliency effects in investors' trading behavior in relation to the intensity of investors' monitoring activity. For less attentive investors, the likelihood to sell large profits significantly exceeds that of moderate ones, but among more attentive investors we find no significant difference. Individuals who monitor their portfolios on a continuous basis will, on average, perceive smaller changes in the stock position's capital gain each time they log in. This decreases the attention-grabbing nature

[6] We believe that our results are not driven by myopic loss aversion for two reasons. First, our results show that the propensity to sell at a loss decreases as attention gets higher. Second, there is some evidence that myopic loss aversion is less prevalent when investors have a higher degree of financial literacy (see e.g. Klos (2013)). As our measures of financial attention seem to proxy for sophistication, you could argue that the effect of myopic loss aversion is not predominant.

of such large gains relative to less attentive investors. As a consequence, the lower visibility for the high-attention investors leads to such positions being less likely to be sold.

Finally, we examine whether more attentive investors also exhibit a smaller return differential between stocks sold at a gain and those held in portfolio at a loss. When comparing the ex-post returns on realized gains and paper losses, we find stocks sold at a gain to outperform losses kept in portfolio for holding periods up to half a year. This pattern persists among more and less attentive individuals. Therefore, while more attentive investors trade less in line with the disposition effect, they too could have benefited from retaining their profitable stocks a while longer, and from more readily selling their losing ones.[7]

The remainder of this paper is structured as follows. Section 2 discusses the related literature. Section 3 describes our dataset and the different measures of attention used in this paper. Section 4 outlines the empirical model. Section 5 presents our empirical results and Section 6 concludes.

2 Literature

Our paper is related to the growing empirical literature investigating the role of investors' attention in financial markets. Attention matters for the strength of post-earnings announcement drift (DellaVigna and Pollet, 2009; Hirshleifer et al., 2009) and has predictive power for future stock returns (Gervais et al., 2001; Da et al., 2011; Yuan, 2015). It also plays a crucial role for the trading behavior of individual investors. Seasholes and Wu (2007) and Barber and Odean (2008) show that individuals tend to buy attention grabbing stocks. Sicherman et al. (2016) decompose 401(k) investors' trading behavior into separate patterns of investor attention and conditional trading.[8] Their results uncover that attention tends to be a positive function of past returns, whereas the reverse holds for conditional trading. Yuan (2015)

[7]For comparison, Gargano and Rossi (2018) show Odean's (1999) finding, i.e. the ex-post returns on stocks sold exceed those of purchases, to only be present among less attentive investors.

[8]Sicherman et al. (2016) define conditional trading as the decision to trade once the decision to log in and to gather information has already been made.

illustrates that, on days of positive market-wide attention, investors more readily sell their shares, and exhibit an increased preference towards realizing a gain over a loss. In contrast, Lu et al. (2016) find that hedge fund managers who are distracted by marital events, such as a divorce, tend to experience a strong fall in their funds' alphas, and trade more in line with the disposition effect. Birru (2015) finds that the disposition effect is not present for stocks who have recently experienced a stock split, because inattentive investors do not properly update their reference points.

Our research differs from these studies along several dimensions. First, we do not focus on the asset pricing implications of investor attention, but on its role for the quality of investors' trading behavior. Second, the empirical literature has largely relied on ingenious proxies of investor (in)attention. In contrast, our dataset allows us to construct accurate measures of how much time individuals spend monitoring their portfolios. To our knowledge, only four studies are able to construct measures of attention at the individual level. Karlsson et al. (2009) and Sicherman et al. (2016) employ login data from retirement accounts to illustrate that individuals behave like ostriches, reducing their portfolio monitoring behavior following negative market returns and heightened volatility. Using a sample of clients at Barclays Wealth & Investment Management, Gherzi et al. (2014) document that individual investors may act more like hyper-vigilant meerkats, who increase their attention allocation after both positive and negative market returns. Finally, Gargano and Rossi (2018) use login data from a brokerage house. They find that more attentive investors outperform low-attention investors, both at the portfolio level and the individual trade level. In contrast to these studies, our focus lies on the cross-sectional variation in the disposition effect, as a function of how much attention retail investors have allocated to their portfolios.

This research also contributes to the considerable literature on the heterogeneity in the disposition effect by providing novel results on its relationship with how much attention investors allocate to their portfolio. Investors trade less in line with this behavioral bias if they are more intelligent (Grinblatt et al., 2012), more diversified (Feng and Seasholes, 2005), and older (Korniotis and Kumar, 2011), as well as when financial advice is more readily available (Dhar and Zhu, 2006; Shapira and Venezia, 2001). Furthermore, Seru et al. (2010) show that investors learn to avoid the disposition effect, but such learning occurs only slowly.

Our study also contributes to the literature examining the underlying cause of the disposition effect, by offering further empirical evidence in favor of the theory of cognitive dissonance. Recently, the most cited explanation for the disposition effect, prospect theory, has been called into question (Barberis and Xiong, 2009; Kaustia, 2010b). Instead, Chang et al. (2016) propose cognitive dissonance, as this theory can clarify Calvet et al.'s (2009) puzzling observation of a reverse disposition effect among mutual fund shares. Their results are consistent with Summers and Duxbury (2012) and Lehenkari (2012), who document that individuals do not prefer to realize a gain over a loss, if they are not responsible for acquiring the asset in the first place. Furthermore, Jin and Scherbina (2011) show a lower tendency of mutual fund managers to continue to hold stocks with poor returns over the past 12 months if they are not responsible for the initial purchase decisions. Chang et al. (2016) also argue that the theory of cognitive dissonance may act as a "microfoundation" on the loss side for the realization utility model of Barberis and Xiong (2012), which more readily predicts a disposition effect.

Finally, our empirical results provide interesting new insights related to the literature on saliency effects for investors' decision making. Bordalo et al. (2012) develop a model in which the decision making of economic agents depends on the saliency of alternative payoffs. Jacobs and Hillert (2016) and Itzkowitz et al. (2016) find that if the first letter of a company's name is near the top of the alphabet, its stocks experience higher turnover and liquidity, because it is more likely to be seen by investors. Furthermore, the attention grabbing characteristics of a stock increase its likelihood of being bought by retail investors (Barber and Odean, 2008), and the overall rank of a share in retail investors or mutual fund managers portfolios determines its likelihood of being sold (Hartzmark, 2015). These results are consistent with investors employing basic heuristics to limit the set of stocks between which to choose. Our empirical results suggest the importance of such characteristics to depend upon how much attention investors pay to their portfolios, and financial markets in general.

3 Data

Our study employs a novel dataset from the largest Belgian discount broker, between January 2014 and December 2016, with more than 65.000 clients. The dataset consists of six files. A session file contains, for each account, login and logout timestamps, as well as timestamps for when investors have last committed an action during a particular login session. While logged in to the trading platform, investors have access to numerous sources of financial information. For example, they can monitor their stock portfolios, submit orders to trade, consult "analysts' forecasts & recommendations" and even conduct fundamental or technical analysis. A customer data file describes clients' demographic characteristics, including age, gender, and language spoken. A trade file contains the records of all transactions, complemented by a customer order file, which outlines all orders placed, both executed and non-executed, and their relevant characteristics. An account file includes a daily overview per account of the end-of-day value of all investments, as well as the amount of cash held on the account. Finally, a questionnaire file contains clients' responses to multiple choice test, which assess investors' financial literacy. This test is conducted in accordance with the Markets in Financial Instruments Directive (MiFID), to determine whether the different financial instruments offered by the broker, are appropriate for a particular investor.

For our empirical methodology, we follow Odean (1998) and Grinblatt and Keloharju (2001). We focus on each day a sale transaction takes place in a portfolio of at least two stocks in order to distinguish between the shares investors decide to sell and those they hold on to in their portfolios. To properly distinguish between capital gains and losses, we require an unambiguous reference price. For this reason we discard all sale transactions in stocks if the original purchase took place before the start of our sample period. This limits our sample of clients to 20,709. Descriptive statistics on the investors' demographic and stock portfolio characteristics are outlined in Table 1. Consistent with the most common dataset in the literature, investors are predominantly middle-aged males, who have been a client at the broker for an average of 6 years (see Barber and Odean (2001)). Throughout the sample period, these clients hold an average (median) of €59,933 (€19,000) on their brokerage account, of which 78% (86%) is invested in financial assets.[9] With respect to their stock portfolios, investors hold an average (median) of 9 (6) stocks, which slightly exceeds commonly observed levels (see for instance Ivković et al. (2008)). The investors trade actively for nonnegligible monetary values. The average (median) investor trades 62 (29) times in stocks throughout the entire sample period, and the average (median) value of such trades equals €4,518 (€2,348).

We use the login datafile to construct three different measures of attention at the individual investor level. First, *frequency* measures how often investors log in to the trading platform between January 2014 and December 2016. While *frequency* captures how often clients wish to consult their portfolio, it does not necessarily imply that they allocate a substantial amount of time to properly collect and analyze the financial information they gather. To address this, we also determine how much time investors spend on the trading platform, by calculating the total *duration* of their login sessions. To ensure that we genuinely measure login *duration*, we determine the difference between the time a client logs in and the time they last commit an action on the platform. Alternatively, we can use the logout timestamps, but this will lead to a strong upward bias of our second attention measure. A great deal of clients do not decide to logout actively, but choose to wait until

[9]For comparison, results from the most recent Household Finance and Consumption Survey show the average (median) value of total financial assets to equal €88,200 (€28,500) for Belgian households, while the median value invested in publicly traded stocks is €10,000. These figures are conditional on owning financial assets or publicly traded stocks for which participation rates are 98% and 11%, respectively (European Central Bank, 2017). These figures suggest the likelihood of investment accounts within our sample to be used for the sole purpose of trading for entertainment to be low. It also suggests that it is less likely that investors trade in stocks via multiple accounts at different brokers.

an automatic logout takes place after 2 hours. To illustrate this issue, the duration of an average login session lasts 1 hour and 53 minutes if we use the logout timestamps, but lasts just 28 minutes if we employ the last act timestamps. Finally, neither *frequency* nor *duration* record how consistently investors log in throughout the sample period. Therefore, our final measure of attention records the number of unique *days* a client logs in.

To ensure that our different measures of attention are comparable between investors, we first determine the total frequency, duration and days a client logs in during the time period that they own a stock portfolio. We subsequently normalize each attention measure by the number of days the client owns a stock portfolio. This circumvents the possibility that a client will be classified as devoting little attention to his portfolio, simply because he joins the broker at a later point during the sample period. Alternatively, we can focus on a subsample of investors, who were active throughout the entire sample, but this approach can raise the possibility of a survivorship bias seeping into our empirical results.

Panel A in Table 2 reports descriptive statistics on the amount of attention investors allocate to their portfolios. The average (median) investor logs in 1.07 (0.60) times a day for a total duration of 29 (5) minutes. Logins occur on average (median) on 36% (31%) of all days the investors hold a stock portfolio at the broker. Panel B illustrates that our different measures of attention are strongly, but imperfectly, correlated with one another. The correlation coefficients range from 0.47 to 0.79. Finally, the correlation coefficients together with the investor characteristics from Table 1 indicate that more attentive investors, have more wealth invested at the broker, hold more stocks in their portfolios and trade more actively in them. These statistics suggest that more attentive investors may be more sophisticated, consistent with the premise underlying our first prediction.

4 Methodology

To investigate the relationship between financial attention and the disposition effect, we follow a similar methodological approach as in Grinblatt and Keloharju (2001) and Grinblatt et al. (2012), which was recently also applied by Kaustia (2010b), Linnainmaa (2010) and Birru (2015). Each day a sale transaction takes place in a portfolio of at least two stocks, we categorize individuals' stock portfolio holdings in sale and hold decisions. We use a logistic regression model to estimate the probability that an investor sells a stock on these days. The empirical model takes the following form:

$$sale_{ijt} = \Lambda\left(\beta_0 + \beta_1\, gain_{ijt} + att_i'\,\delta_1 + gain_{ijt} \cdot att_i'\,\delta_2 + \mathrm{x}_{ijt}'\,\gamma\right) + \varepsilon_{ijt}. \tag{1}$$

In (1), $sale_{ijt}$ is a dummy variable that equals 1 if investor i sells stock j on day t. The indicator variable $gain_{ijt}$ is equal to 1 if the investor's capital gain since purchase on the stock was positive at the close of the prior trading day. To determine this, we use as a reference price, the volume-weighted average purchase price including transaction costs, expressed in euro. This serves as a natural benchmark for investors, because it coincides with the manner in which clients perceive their returns at the discount broker. We introduce financial attention in our baseline model by dividing all investors into attention deciles, and subsequently including a dummy variable for each attention decile but one, represented by the vector att_i. $\Lambda(.)$ represents the cumulative density function of the standard logistic distribution.

In line with the previous literature, we expect investors to trade in line with the disposition effect. In the abscence of interaction effects, this would manifest itself through a significantly positive β_1 coefficient. By interacting $gain_{ijt}$ with the different measures of financial attention, we allow the disposition effect to be a function of how much attention investors allocate to their portfolios. Given the nonlinear nature of our model, interpreting such interaction effects directly from model coefficients is less straightforward (Ai and

Norton, 2003). Unlike in linear models, the interaction effect leads to a more complicated dependency between the disposition effect and attention, and conducting inference based solely upon estimated coefficients may be inappropriate. As a consequence, we follow the suggestion of Greene (2010) by focusing our empirical analysis on the average predicted probabilities implied by our model coefficients, and by estimating the disposition effect as the average partial effect of $gain_{ijt}$ at each attention decile.

Within our model we also include a long list of control variables that may influence the decision to sell a stock, in line with Grinblatt and Keloharju (2001). This allows us to properly distinguish the disposition effect from alternative investment strategies such as contrarian or momentum trading behavior. First, we control for positive and negative market-adjusted returns for each stock j over 11 non-overlapping time intervals, for the market returns of the Eurostoxx 600 over the same periods and for their cross-products with $gain_{ijt}$ to account for a differential reaction to past market(-adjusted) returns if the position is trading at a profit in investors' portfolios. The 11 non-overlapping intervals for which we calculate returns are 0, 1, 2, 3, 4, [5 to 19], [20 to 39], [40 to 59], [60 to 119], [120 to 179], and [180 to 239] trading days before the date on which a sale transaction took place. Next, we account for potential reference price effects through two dummy variables, capturing whether the stock trades at a monthly high or low relative to the past 20 trading days. We further account for stock and market volatility by including the standard deviation of daily returns over the past 59 trading days for both the stock and the Eurostoxx 600. To account for potential calendar, industry, and life-cycle effects, we include dummies for each month, each level 6 Datastream industry classification, and each 5-year age interval in the sample. Finally, we control for the natural logarithm of the portfolio value and the holding period measured in days.

The logistic regression approach of Grinblatt and Keloharju (2001) also offers the important benefit that we can directly control for two factors that might confound our results: the number of stocks investors hold in portfolio each day they sell a stock position and their trading frequency. Feng and Seasholes (2005) show how Odean's (1998) PGR and PLR ratio analysis suffers from a potential mechanical relationship with these variables. Given their positive correlations with our different measures of attention, we may otherwise find a spurious negative relationship between financial attention and the disposition effect (see Table 2). We account for these potential concerns by including dummies for the number of stocks investors hold in portfolio[10], and the natural logarithm of investors' overall trading frequency.

We account for the nonnested clustering in our dataset with two-way standard error clustering at the individual and stock level. Under the assumption that our model is properly specified, consistent estimates for (1) can be obtained via maximum likelihood estimation. However, if the clustering is left unaccounted for, inference would potentially be based upon severely under-estimated standard errors (Petersen, 2009; Cameron and Miller, 2011; Cameron et al., 2011).

5 Empirical Results

5.1 Baseline Results

Table 3 reports estimated coefficients and two-way clustered standard errors for the empirical model described in Section 4. The estimated coefficients of attention, as well as the interactions, are significantly negative. This result holds regardless of which measure of attention is used. Intuitively, this result indicates that investors are less likely to sell a stock if they devote more attention to their portfolios, but this drop is more pronounced if a position is trading at a profit.

One potential issue that arises at this point pertains to our model being nonlinear. Ai and Norton (2003) illustrate that one needs to be careful when interpreting the size and sign of

[10] We include one dummy variable for each but one portfolio size up to 50 stocks, and one dummy variable for when investors hold 50 stocks or more in portfolio.

interaction effects in nonlinear models. To address this difficulty, we follow the suggestion by Greene (2010) and compute the average predicted probabilities of selling a stock at different attention deciles, while keeping all other explanatory variables constant. These results are reported in the top panel of Figure 1. In addition, we compute the disposition effect at each attention decile in the bottom panel of Figure 1, by calculating the average partial effect of $gain_{ijt}$ at each attention decile. In line with our initial interpretation, the size of the disposition effect falls significantly among more attentive investors. For instance, in the case we measure attention as the relative frequency with which investors log in, the difference between the average predicted probability of selling a profit and a loss amounts to 14.33 percentage points if attention is the lowest (i.e. at the first decile), and 6.20 percentage points when attention is the highest (i.e. at the tenth decile). Overall, the impact of attention also decreases the relative preference towards realizing a gain over a loss from 2.09 to 1.61 for the frequency measure. The model employing login duration and days lead to very similar estimates. The results in Figure 1 also indicate that the strongest attenuation of the disposition effect occurs at the lowest levels of attention.

Our results coincide with our first prediction whereby more attentive investors trade less in line with the disposition effect, because their higher attention allocation results from a comparative advantage at interpreting and incorporating information into their financial decision making process. In other words, they represent more skilled and sophisticated investors than those who monitor their portfolios on a less frequent basis. To shed further light on whether our initial results could also be captured by alternative measures of investor sophistication, we reestimate equation (1), and include different measures of financial sophistication, and their interaction with $gain_{ijt}$. First, after several years of investing, clients may become more financially sophisticated through experience, such that they learn to avoid the disposition effect (Feng and Seasholes, 2005; Seru et al., 2010; Korniotis and Kumar, 2011). We therefore include the number of years of experience the client has at the broker. Next, we include the average number of stocks an investor holds in his portfolio as a measure of diversification,[11] and the natural logarithm of the average wealth investors hold on their brokerage account (i.e. portfolio value), which is found to negatively correlate with the severity of the disposition effect.[12] Finally, we add a number of additional variables capturing individual investor heterogeneity, such as investors' age, age-squared, gender, and a dummy variable indicating whether the account is owned by more than one individual.

The estimated coefficients and standard errors from this extended specification are provided in Table 4, and a visualization of the model's implications for the disposition effect are shown in Figure 2. The magnitude of the estimated probabilities, and their difference appear largely unaffected by the inclusion of these sophistication controls. A reason for this outcome is that financial attention may capture a component of investor skill and sophistication unaccounted for by such other proxies. However, we also find that only the average wealth invested at the broker has a significantly negative coefficient on its interaction with $gain_{ijt}$. The coefficient on the interaction effect between portfolio diversification and $gain_{ijt}$ is even significantly positive. Nevertheless, the latter result may also reflect the ongoing discussion on whether underdiversification results from an informational advantage (see for instance Ivković et al. (2008), Van Nieuwerburgh and Veldkamp (2010) and Korniotis and Kumar (2013)).

It is important to note at this point that our empirical results may underestimate the relationship between financial attention and the disposition effect for two reasons. Firstly, it is not possible to observe the entire decision-making environment of individuals. They may pay attention to their portfolios, and financial markets in general, through an abundance of alternative sources (e.g. Reuters, Bloomberg, The Financial Times or Forbes), as opposed to using the broker's investment platform. Many such sources also offer the possibility to monitor the performance of self-selected stock portfolios which mimic the portfolios investors

[11]Feng and Seasholes (2005) employ a similar measure, but they focus on the number of stocks an investor initially holds in portfolio.

[12]Dhar and Zhu (2006) argue that investors with higher income levels and more wealth invested at a broker will more readily have access to, and make use of, financial advice. Korniotis and Kumar (2013) also find that income and wealth positively correlates with how well investors perform on verbal, quantitative and memory tests.

hold at the broker, reducing the need to consult the broker's platform. It is reasonable to assume that sophisticated investors more readily use such alternative sources to pay attention to their portfolios, which could result in our attention measures underestimating their actual attention allocation. Consequently, the estimated disposition effect among more attentive investors may be overestimated. Similarly, the disposition effect among less attentive investors may be underestimated, assuming these investors are less sophisticated and rely more readily on the broker's investment platform to pay attention to their portfolios. Second, our empirical results may be influenced by distracted attention behavior. Investors logging in to the brokerage platform may quickly glance at the state of their portfolio, and subsequently divert their attention to other sources (e.g. other tabs in the Internet browser, phone calls, or household activities). Such distracted behavior could lead to an overmeasurement of the login duration. However, if on average less sophisticated investors exhibit a higher tendency to engage in distracted attention behavior while being logged-in to the investment platform, then our estimation results would underestimate the negative relationship between financial attention and the disposition effect.

We test the robustness of our baseline results to a variety of different explanations and specifications. Firstly, while the descriptive statistics from Table 1 are in line with other datasets from the retail investor literature[13], they would suggest our sample to be composed of more active, and potentially speculative, investors. To explore whether our results differ for more speculative portfolios, we implement a subsample analysis for investors with high and low portfolio values relative to their age[14], and redetermine the attention deciles based upon investors' portfolio monitoring behavior within that subsample. Figure 3 shows the negative relationship between attention and the disposition effect to be the strongest among younger investors. We find no significant negative relationship among older investors in the high portfolio value group, which can be argued to be the least speculative traders.

[13] See for instance Barber and Odean (2000), Gargano and Rossi (2018) or Koestner et al. (2017)

[14] In particular, we split the sample in two based upon the median age of 49 and use the median portfolio value within each age group (€ 10,692 and € 34,875) to divide the sample further into a high and low portfolio value group.

Nevertheless, we still observe a significant decrease in the disposition effect among more attentive younger investors within the high portfolio value group. These results suggest that our findings are stronger among potentially more speculative portfolios. Second, our findings remain valid when we consider a limited sample of clients, who only traded in stocks throughout the entire sample period (Figure 4 and Table 6). Hence, we rule out that the investors' attention allocation was induced by nonstock investments. Next, we exclude the possibility of our results being driven by a stronger tendency to sell stocks in order to rebalance portfolios among the more attentive investors, by only focusing on sell transactions that completely liquidated a stock position (Figure 5 and Table 7). Linnainmaa (2010) finds that the dominant usage of limit orders among retail investors can lead to mechanical patterns in investors trading behavior. As a consequence, we test whether our results are robust to this limit order effect, by only considering sale transactions that were the result of market orders (Figure 6 and Table 9). Finally, our results are also robust across individual and shared investment accounts (Figure 7 and Table 9), and across yearly subsamples (Figure 8 and Tables 10 to 12).[15]

5.2 The Role of Return Magnitude

Our baseline results indicate that more attentive investors trade less in line with the disposition effect. Nevertheless, the estimated probabilities suggest that, as attention increases, the probability of realizing a loss falls as well. This coincides with the predictions based upon the theory of cognitive dissonance. The fall in the disposition effect, due to high-attention investors being more sophisticated, does not exclude a lower preference towards realizing a loss among more attentive investors. We test this proposition further by arguing that, while more attentive investors experience more psychological discomfort for a loss, this discomfort is even more pronounced if the loss is problematic. To investigate this, we reestimate our

[15] In Figure 8, we observe the disposition effect in 2016 to be below the observed levels for 2014 and 2015. This level difference can be attributed to the tax reform introduced by the Belgian regulator in 2016, whereby the sale of stocks trading at a capital gain were no longer exempt from taxes, but were taxed at a rate of 33% if held in portfolio for a period of less than 6 months.

model allowing for a differential sell probability depending on the magnitude of one's return on a stock position. More specifically, we construct dummy variables indicating whether the prior day capital gain (in absolute value) over the past holding period lies within the interval of [0, 5%), [5%, 10%), [10%, 15%), [15%, 20%), [20%, 25%), [25%, 30%), or [30%, $+\infty$). We include these new variables in the model and interact them with both att_i and $gain_{ijt}$.

An alternative expectation with respect to the larger return dummies may be argued based upon Hartzmark's (2015) recent discovery of a "rank effect" in retail investors' selling propensity. Hartzmark (2015) documents that investors tend to more readily sell assets, which hold an extreme rank within their portfolios. These positions appear more visible to investors and thus experience a higher probability of being sold. Barber and Odean (2008) raise and test a similar proposition whereby investors more readily buy stocks that have recently experienced high abnormal trading volume, extreme returns, and recently appeared in the news.

The average predicted probabilities based on our extended model for our three attention measures are presented in respectively Table 13a, 13b and 13c. For ease of interpretation, we also visualize the point estimates from these tables in Figure 9. In the bottom panel of Figure 9 we find no significant differences between the probabilities to sell a loss depending on the various return intervals. Consistent with our initial results, higher levels of attention decreases the probability of selling a loss, but a considerable divergence emerges between the propensity to sell losses of various magnitudes. For example, at the 10^{th} decile of attention, the average predicted probability of selling a loss between 0 and 5% is approximately three times as large as that for a loss exceeding 30% (13% against 4.4%, respectively). This result cannot be explained by saliency effects among investors' selling decisions, but is in line with the theory of cognitive dissonance. Each time an investor logs in to his account, he perceives a change in the returns for each of his stocks. The difference between how salient a large loss is, relative to a smaller one, would be less for an investor who logs in very frequently, because the change in the perceived capital loss will be smaller on average. A larger loss should be less salient to more attentive investors, and consequently, the probability of selling a larger loss should be closer to the probability of selling a moderate one. Vice versa, inattentive investors will perceive larger changes in the capital loss since purchase, making an extreme loss more salient than a moderate one. In contrast, the results in Figure 9 indicate an almost identical probability of selling larger losses if attention is low, but a far lower probability of selling larger loss if attention is high. These results are nevertheless consistent with the notion that investors who closely follow up on their investment results feel more responsible for not having discarded the extreme loss when they may have had frequent opportunity to do so. This leads to more psychological discomfort, and hence a lower probability of realizing more sizeable losses.

Interestingly, the top panel of Figure 9, which reports the same probabilities on the gain side, does highlight the potential role of saliency effects in investors' selling propensity of winning shares. When attention is low, the average estimated probability of selling a share that trades at a sizeable profit far exceeds that of a smaller one; yet they converge towards one another as attention increases. These results can be explained by larger gains being more visible for less attentive investors, but as more attention is allocated to their portfolios, the perceived changes in the capital gain on all winning positions will tend to become smaller. An extreme profit thereby becomes less attention-grabbing relative to a smaller one, and, as a consequence, high-attention investors exhibit a lower preference to realize more sizeable winners over smaller ones. Allowing for a differential sell probability depending on the magnitude of one's return thereby illustrates saliency effects in selling behavior to depend on the degree to which investors pay attention to their financial assets.

5.3 Investor Fixed Effects

In Section 5.1 we explore the potential role of investor level controls for our estimation results. Nevertheless, omitted variables at the investor level could strongly influence our estimation results, because of the limited set of variables we are able to control for within our dataset. As a consequence, we construct a time-varying measure of attention at the individual investor level and conduct OLS regressions with investor level fixed effects. Our approach is akin to the panel data regressions used by Gargano and Rossi (2018) to explore the relationship between financial attention and performance. More specifically, we estimate the following model:

$$sale_{ijt} = \alpha_i + \delta_m + \zeta_I + \beta_1\, gain_{ijt} + \beta_2\, att_{it} + \beta_3\, gain_{ijt} \cdot att_{it} + \mathrm{x}'_{ijt}\, \gamma + \varepsilon_{ijt}, \tag{2}$$

where $sale_{ijt}$ is a dummy variable equal to 1 if investor i sells stock j on day t, on a day when the investor sells at least a single stock position; $gain_{ijt}$ equals 1 if the investor's capital gain since purchase on the stock was positive at the close of the prior trading day; and att_{it} reflects the amount of attention an investor allocates to his portfolio over the 30 calendar days preceding the sale decision, as measured by login frequency, login duration or the number of days logged in. To improve interpretation of estimated coefficients and facilitate comparison between estimations, we standardize the time-varying attention measures to have zero mean and unit standard deviation. α_i, δ_m, and ζ_I denote investor, month and industry fixed effects. The vector x'_{ijt} retains the control variables from our model 1 with the exception of the investor level explanatory variables.

To estimate model 2, we implement the approach of Correia (2016), which accommodates the use of a large number of fixed effects.[16] In addition, when interpreting the economic significance of the models' coefficients, we focus on the relevant variation in att_{it} used to identify them. Within the presence of fixed effects, these coefficients are identified from the within unit variation in att_{it}, such that a realistic unit increase in att_{it} should correspond to the standard deviation of the residuals ($\tilde{\sigma}_{att_{it}}$) from an auxiliary regression of att_{it} on the fixed effects α_i, δ_m, and ζ_I (Mummolo and Peterson, 2018).

[16]This approach also avoids the downwards bias in cluster-robust standard errors by dropping singleton observations (i.e. individuals with only one observation) (Correia, 2015), but leads to a small decrease in the employed sample size. Retaining such singleton observations within our sample leaves estimated coefficient virtually unchanged.

The results from our estimated model with time-varying measures of attention are reported in Table 14. After controlling for investor level fixed effects, we find a significant negative relationship between financial attention and the disposition effect, irrespective of the attention measure used. The decrease in the disposition effect from a one standard deviation increase in attention ranges from 0.42 percentage points for login duration to 1.10 percentage points for login days ($= \tilde{\sigma}_{att_{it}} \times \hat{\beta}_3$). These figures are also significant from an economic perspective given an average disposition effect of approximately 8% within our sample.

We also present the extension of model 2 where we allow for a difference in the probability to sell depending on the return magnitude in Table 15. On the loss side, we find an investor to be less inclined to sell a more sizeable loss. Consistent with the theory of cognitive dissonance, we document this effect to be amplified by an investor being more attentive to his portfolio over the preceding 30 calendar days. For example, a one standard deviation increase in login frequency reduces the probability to sell a capital loss of 30% or more by 0.30 percentage points. On the gain side, an investor is more likely to sell a stock position as his return thereon increases. However, this effect is dampened by an investor paying more attention to his portfolio. A one standard deviation increase in the login frequency reduces the probability to sell a capital gain of 30% or more by 2 percentage points. This pattern is consistent with a reduced role for saliency effects when an investor allocates more attention to his financial assets.

5.4 Performance Analysis

Our main empirical results show that more attentive investors trade less in line with the disposition effect. In general, the academic literature considers the disposition effect to be a behavioral mistake for two reasons. Firstly, trading in line with the disposition effect tends to be tax inefficient (Barber and Odean, 2013). Second, Odean (1998) finds that when investors sell winner stocks, these go on to outperform the losing investments they keep in portfolio.

Investors could therefore have benefited from retaining their profitable stock investments, while more readily having sold their losing ones. Barber and Odean (2013) explain this difference in returns to be attributable to investors losing out on returns, because of the momentum effect (Jegadeesh and Titman, 1993). In this section, we examine whether more attentive investors, in addition to trading less in line with the disposition effect, also exhibit a smaller return differential between stocks sold at a gain and those held in portfolio at a loss. We thereby follow prior studies such as Odean (1998), Seru et al. (2010), and Duxbury et al. (2015), who compare the ex-post returns on realized gains and paper losses.

Using the dataset of sell and hold decisions, we form transaction-based calendar-time portfolios which mimic the returns acquired by investing in a portfolio of stocks investors decide to sell at a gain or hold in portfolio at a loss. This allows us to account for the cross-sectional correlation between the ex-post returns of realized gains and paper losses by aggregating them in a single daily time series. In addition, value-weighting realized gains or paper losses addresses the potential concern of trades in smaller stocks overly influencing our results (Seasholes and Zhu, 2010).[17] Each day an investor realizes a gain (retains a loss), we add the amount of shares sold (held) to our portfolio for a holding period of 30, 90, 180 or 365 calendar days. Next, we compute the daily value-weighted returns of the realized gains (paper losses) portfolio.[18] This approach produces a single time-series of returns for a portfolio of realized gains (paper losses) between January 2014 and December 2016.

As a first step, we report in Table 16 the average raw daily returns of the transaction-based calendar-time portfolio for realized gains, paper losses, and their difference. We find the average ex-post returns on realized gains to significantly exceed those of paper losses for holding periods up to half a year. For example, winner stocks sold outperform paper losses by 4 basis points (bp) a day in the 30 days following the sell or hold decision. This

[17]See Seasholes and Zhu (2010) for a full discussion on how the use of transaction-based calendar-time portfolios address these pitfalls which emerge when evaluating the performance of individual investors' trading behavior.

[18]To further reduce potential concerns about small stocks influencing our results, we winsorize stock-day returns at the 0.5% level. In unreported results, we document our findings to be robust to the use of alternative winsorizing levels.

corresponds to a difference in returns of 10.5 percentage points per annum (p.a.). Hence, investors in our sample could have benefited from retaining their profitable investments, and more readily selling their losing ones.

In Table 16, we also investigate the extent to which this return differential can be explained by the momentum effect. We regress the difference in returns between realized gains and paper losses on the Fama-French-Carhart factors.[19] Our results show the outperformance of winning stocks sold over losers kept to be reasonably well-captured by the performance of the Carhart momentum factor. The significantly positive exposure to the momentum factor ranges from 0.198 to 0.318. The Carhart momentum factor performed very well relative to the market factor during our sample period (26% versus 7.2% respectively). Nevertheless, we still find a significantly positive alpha for holding periods up to 30 days. We can therefore not fully attribute the return differential between realized gains and paper losses to momentum effects.

Next, we split our sample into two groups based upon the median investor's attention allocation. In Table 17, we report the average return differential between the realized gains and paper losses portfolios for the low- (Panel A) and high-attention (Panel B) groups, as well as the estimated alpha coefficient from a regression on the Fama-French-Carhart factors. In line with the results from Table 16, we find stocks sold at a gain to outperform losses held in portfolio for holding periods up to half a year. For two out of three attention measures, the return differential between realized gains and paper losses is smaller in magnitude and significance for the high-attention group. For a holding period of 30 calendar days, low-attention investors in terms of login frequency and days, experience a significant opportunity cost of respectively 5.3 and 5.6 bp per day (14.5% and 15.3% p.a.), as compared to only respectively 3.4 and 3.5 bp per day (9.0% and 9.3% p.a.) among high-attention investors. When measuring investor attention by login duration, we observe the same return differen-

[19]Daily returns of the value-weighted market portfolio, the risk-free rate, and the Fama-French-Carhart factors are downloaded from Kenneth French's website. We obtain the EUR-USD exchange rate from Datastream to convert all factor returns to euro.

tial among high and low-attention investors for a holding period of 30 days, but a smaller one among low-attention investors for holding periods of 90 and 180 days. These patterns remain consistent when evaluating performance on the alpha from the Fama-French-Carhart regressions. In Panel C of Table 17, we test statistically whether the difference in returns between the realized gains and paper losses portfolios significantly differs between the high- and low-attention groups. For all attention measures, we do not find the difference in returns to be significantly lower in the high-attention group. While more attentive investors trade less in line with the disposition effect, our results suggest that when they sell gains, those go on to outperform losing investments held in portfolio, and this opportunity cost is of a similar magnitude as among less attentive investors.[20]

6 Conclusion

In this paper, we present the novel finding that investors who more closely monitor their portfolios, behave less in line with the disposition effect. We propose that this result stems from more attentive investors allocating higher attention as they have a comparative advantage in understanding and incorporating financial information into their decision making. They therefore behave less in line with the disposition effect. We also uncover that the underlying dynamics driving this result may be more complex. We show that higher levels of attention are associated with both lower propensities to sell a stock at a gain and at a loss. However, the fall in the gain probability dominates, resulting in an overall negative relationship between the disposition effect and financial attention. We reason that the fall in the loss region is consistent with cognitive dissonance, and show that the decrease in the probability to sell a loss is even more pronounced if the loss is severe. More attentive investors are less likely to realize a loss, because they cannot deny to themselves that they are responsible for letting the loss build-up in their portfolios. Such individuals may therefore benefit from the active

[20] Interestingly, Gargano and Rossi (2018) show Odean's (1999) finding that the ex-post returns of stocks sold exceeds those of purchases, to only be present among less attentive investors.

use of stop-loss orders to proactively commit to selling a loss (Fischbacher et al., 2017). We also find that less attentive investors exhibit a higher propensity to sell extreme gains than more attentive investors, consistent with the notion that such positions are more salient for investors who devote less attention to their portfolios. This result suggests the importance of such attention grabbing characteristics to depend on how much attention investors pay to their portfolios. Finally, we show that, while more attentive investors trade less in line with the disposition effect, they too could have benefited from retaining their profitable stocks a while longer, and more readily selling their loser shares.

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Table 1: Descriptive statistics on investors' characteristics

	Mean	Stdev	P1	P25	P50	P75	P99
Panel A: Account information							
Male (in %)	87.81						
Individual account (in %)	76.75						
Age	49.16	14.72	22.00	37.00	49.00	60.00	82.00
MiFID test score (in %)	52.60	20.82	0.00	37.50	50.00	68.75	93.75
Number of years at broker	6.09	2.21	3.09	5.66	7.32	9.11	10.78
Panel B: Portfolio information							
Portfolio value (in €)	59,933	164,547	220	6,248	19,000	54,593	629,508
Proportion of assets (in %)	78	23	7	70	86	94	100
Proportion of cash (in %)	22	23	0	6	14	30	93
Panel C: Stock transactions							
Number of stocks in portfolio	9	12	1	3	6	11	55
Trading frequency	62	143	3	14	29	63	527
Transaction value (in €)	4,518	8,812	110	1,194	2,348	4,619	39,627

Table 1 reports descriptive statistics on clients' account characteristics (Panel A), their portfolios (Panel B) and their trading behavior in stocks (Panel C) for 20,709 clients at a large Belgian discount broker between January 2014 and December 2016. The summary statistics in Panel B and C are calculated based upon the average across time for each client, with the exception of the number of transactions. MiFID test scores are based on a subsample of 17,320 clients' first attempt at completing the survey.

Table 2: Descriptive statistics on financial attention measures

	Frequency	Duration	Days
Panel A: Summary statistics			
Mean	1.07	29	0.36
Stdev	1.31	64	0.26
P1	0.03	0	0.01
P25	0.22	1	0.12
P50	0.60	5	0.31
P75	1.45	21	0.59
P99	5.94	311	0.86
Panel B: Pairwise correlations			
Frequency	1.00		
Duration	0.47^{***}	1.00	
Days	0.79^{***}	0.49^{***}	1.00
Age	0.14^{***}	0.11^{***}	0.19^{***}
MiFID test score	-0.01^{*}	0.06^{***}	-0.02^{**}
No. Years at broker	-0.02^{***}	0.07^{***}	0.00
Portfolio value	0.11^{***}	0.09^{***}	0.14^{***}
Proportion of assets	0.03^{***}	-0.02^{**}	0.10^{***}
Proportion of cash	-0.03^{***}	0.02^{**}	-0.10^{***}
Number of stocks in portfolio	0.12^{***}	0.08^{***}	0.22^{***}
Trading frequency	0.30^{***}	0.24^{***}	0.28^{***}
Transaction value	0.05^{***}	0.06^{***}	0.04^{***}

Table 2 reports summary statistics on the amount of attention clients devote to their portfolios (Panel A), and the pairwise correlations with other individual level characteristics (Panel B). Attention is measured by how frequently a client logs in to the trading platform (*frequency*), how long the client has spent logged-in (*duration*), measured in minutes, and how many unique days a client has logged in (*days*). The duration of each login session is calculated as the difference between the last-click timestamp and the begin timestamp. To ensure comparability, all attention measured are normalized by the number of days a client owned a stock portfolio.

Table 3: Financial attention and the disposition effect

	Frequency		Duration		Days	
Gain	1.009***	(0.068)	0.975***	(0.075)	1.000***	(0.067)
Attention						
Decile 2	-0.213***	(0.061)	-0.147**	(0.058)	-0.140**	(0.058)
Decile 3	-0.257***	(0.061)	-0.205***	(0.059)	-0.242***	(0.058)
Decile 4	-0.370***	(0.060)	-0.196***	(0.066)	-0.292***	(0.058)
Decile 5	-0.364***	(0.058)	-0.229***	(0.057)	-0.333***	(0.052)
Decile 6	-0.304***	(0.058)	-0.189***	(0.063)	-0.257***	(0.053)
Decile 7	-0.360***	(0.057)	-0.270***	(0.059)	-0.336***	(0.054)
Decile 8	-0.333***	(0.059)	-0.235***	(0.057)	-0.297***	(0.057)
Decile 9	-0.411***	(0.059)	-0.224***	(0.059)	-0.363***	(0.056)
Decile 10	-0.329***	(0.062)	-0.239***	(0.060)	-0.303***	(0.058)
Attention × Gain						
Decile 2	-0.124	(0.077)	-0.091	(0.083)	-0.216***	(0.078)
Decile 3	-0.194**	(0.075)	-0.116	(0.082)	-0.136*	(0.074)
Decile 4	-0.110	(0.075)	-0.186**	(0.093)	-0.181**	(0.075)
Decile 5	-0.241***	(0.073)	-0.221***	(0.079)	-0.244***	(0.072)
Decile 6	-0.317***	(0.074)	-0.376***	(0.093)	-0.362***	(0.071)
Decile 7	-0.328***	(0.074)	-0.284***	(0.086)	-0.278***	(0.074)
Decile 8	-0.382***	(0.073)	-0.363***	(0.081)	-0.355***	(0.080)
Decile 9	-0.294***	(0.077)	-0.313***	(0.088)	-0.250***	(0.075)
Decile 10	-0.443***	(0.083)	-0.352***	(0.087)	-0.434***	(0.081)
Additional Controls	No		No		No	
Pseudo R^2	14.88		14.86		14.87	
N	1,883,239		1,883,239		1,883,239	

Table 3 reports estimated coefficients and standard errors from the logistic regression described in Section 4, where the dependent variable takes the value of one if an investor sells a stock position on a day when he sells at least some stock, and 0 if otherwise. Observations are obtained for 20,709 unique clients, who traded in common equity at the Belgian discount broker between January 2014 and December 2016. Coefficients marked with ***, **, and * indicate significance at the 1, 5, and 10 percent level, respectively. Standard errors are clustered at the investor and stock level and are reported in parenthesis.

Table 4: Financial attention and the disposition effect, controlling for investor sophistication

	Frequency		Duration		Days	
Gain	0.434*	(0.263)	0.438*	(0.261)	0.468*	(0.263)
Age	-0.018	(0.016)	-0.021	(0.016)	-0.019	(0.016)
Age × Gain	0.036***	(0.008)	0.036***	(0.008)	0.035***	(0.008)
Age^2	0.000	(0.000)	0.000	(0.000)	0.000	(0.000)
Age^2 × Gain	-0.000***	(0.000)	-0.000***	(0.000)	-0.000***	(0.000)
Female	-0.103***	(0.035)	-0.101***	(0.036)	-0.102***	(0.035)
Female × Gain	0.226***	(0.049)	0.226***	(0.050)	0.225***	(0.049)
Individual	-0.030	(0.032)	-0.032	(0.031)	-0.032	(0.031)
Individual × Gain	0.049	(0.051)	0.057	(0.051)	0.053	(0.051)
Experience	0.037***	(0.005)	0.038***	(0.005)	0.037***	(0.005)
Experience × Gain	-0.000	(0.009)	-0.000	(0.009)	-0.000	(0.009)
Diversification	-0.059**	(0.026)	-0.068***	(0.026)	-0.056**	(0.025)
Diversification × Gain	0.133***	(0.029)	0.131***	(0.029)	0.140***	(0.028)
ln(Portf Value)	0.036**	(0.018)	0.042**	(0.018)	0.040**	(0.018)
ln(Portf Value) × Gain	-0.053**	(0.023)	-0.056**	(0.023)	-0.055**	(0.023)
Attention						
Decile 2	-0.214***	(0.061)	-0.155***	(0.059)	-0.140**	(0.058)
Decile 3	-0.249***	(0.061)	-0.207***	(0.059)	-0.227***	(0.058)
Decile 4	-0.359***	(0.061)	-0.191***	(0.065)	-0.280***	(0.058)
Decile 5	-0.350***	(0.059)	-0.232***	(0.058)	-0.330***	(0.053)
Decile 6	-0.291***	(0.059)	-0.192***	(0.063)	-0.238***	(0.055)
Decile 7	-0.338***	(0.058)	-0.275***	(0.061)	-0.330***	(0.055)
Decile 8	-0.329***	(0.060)	-0.244***	(0.058)	-0.283***	(0.059)
Decile 9	-0.399***	(0.060)	-0.237***	(0.059)	-0.345***	(0.058)
Decile 10	-0.325***	(0.059)	-0.255***	(0.057)	-0.302***	(0.052)
Attention × Gain						
Decile 2	-0.117	(0.078)	-0.082	(0.085)	-0.219***	(0.078)
Decile 3	-0.201***	(0.077)	-0.108	(0.084)	-0.150**	(0.075)
Decile 4	-0.110	(0.077)	-0.179*	(0.093)	-0.185**	(0.076)
Decile 5	-0.230***	(0.078)	-0.208**	(0.082)	-0.228***	(0.073)
Decile 6	-0.305***	(0.079)	-0.341***	(0.095)	-0.368***	(0.076)
Decile 7	-0.331***	(0.079)	-0.263***	(0.092)	-0.277***	(0.079)
Decile 8	-0.366***	(0.080)	-0.328***	(0.087)	-0.362***	(0.085)
Decile 9	-0.271***	(0.083)	-0.281***	(0.090)	-0.249***	(0.081)
Decile 10	-0.407***	(0.077)	-0.317***	(0.080)	-0.413***	(0.073)
Pseudo R^2	15.07		15.05		15.07	
N	1,883,236		1,883,236		1,883,236	

Table 4 reports coefficients and standard errors from an extended logistic regression model with additional controls for investor sophistication and heterogeneity. Observations are obtained for 20,709 unique clients, who traded in common equity at the Belgian discount broker between January 2014 and December 2016. Coefficients marked with ***, **, and * indicate significance at the 1, 5, and 10 percent level, respectively. Standard errors are clustered at the investor and stock level and are reported in parenthesis.

Table 5a: Login frequency and the disposition effect for age and portfolio value subsamples

	Age and portfolio value subsample							
	Age < 50 Portfolio < €10,692		Age < 50 Portfolio ≥ €10,692		Age ≥ 50 Portfolio < €34,875		Age ≥ 50 Portfolio ≥ €34,875	
Gain	0.136	(0.722)	0.509	(0.910)	−1.445	(1.612)	2.600	(1.834)
Attention								
Decile 2	−0.001	(0.115)	−0.126	(0.115)	−0.233**	(0.104)	−0.233**	(0.103)
Decile 3	−0.287**	(0.113)	−0.218*	(0.116)	−0.257***	(0.099)	−0.379***	(0.103)
Decile 4	−0.195	(0.119)	−0.368***	(0.114)	−0.391***	(0.114)	−0.389***	(0.093)
Decile 5	−0.258**	(0.117)	−0.286**	(0.113)	−0.314***	(0.105)	−0.353***	(0.095)
Decile 6	−0.179	(0.122)	−0.185*	(0.108)	−0.314***	(0.101)	−0.324***	(0.098)
Decile 7	−0.151	(0.113)	−0.193*	(0.107)	−0.347***	(0.106)	−0.473***	(0.097)
Decile 8	−0.322***	(0.108)	−0.208*	(0.106)	−0.381***	(0.104)	−0.492***	(0.093)
Decile 9	−0.284**	(0.111)	−0.324***	(0.107)	−0.323***	(0.101)	−0.455***	(0.092)
Decile 10	−0.211**	(0.106)	−0.208*	(0.112)	−0.201**	(0.098)	−0.438***	(0.095)
Attention × Gain								
Decile 2	−0.038	(0.161)	−0.149	(0.132)	−0.054	(0.149)	0.130	(0.134)
Decile 3	0.057	(0.161)	−0.097	(0.131)	−0.141	(0.148)	0.231*	(0.135)
Decile 4	−0.295*	(0.158)	−0.006	(0.131)	−0.106	(0.148)	0.165	(0.125)
Decile 5	−0.204	(0.151)	−0.204	(0.130)	−0.223	(0.142)	0.096	(0.130)
Decile 6	−0.455***	(0.167)	−0.296**	(0.126)	−0.254*	(0.145)	0.005	(0.136)
Decile 7	−0.546***	(0.146)	−0.432***	(0.125)	−0.246*	(0.148)	0.141	(0.133)
Decile 8	−0.410***	(0.143)	−0.445***	(0.124)	−0.243*	(0.143)	0.211*	(0.127)
Decile 9	−0.447***	(0.149)	−0.209*	(0.123)	−0.388***	(0.145)	0.089	(0.131)
Decile 10	−0.615***	(0.149)	−0.423***	(0.135)	−0.531***	(0.135)	0.071	(0.126)
Pseudo R^2	13.69		15.1		13.27		11.77	
N	99,787		443,335		236,455		1,103,595	

Table 5a reports coefficients and standard errors from the logistic regression model described in Section 4, where the dependent variable takes the value of one if an investor decides to sell a stock position on a day when he decides to sell at least some stock, and 0 if otherwise. Each regression model is estimated for a subsample of investors dependent upon their portfolio value relative to their age, and login frequency deciles are based upon investors login frequency within each subsample. Coefficients marked with ***, **, and * indicate significance at the 1, 5, and 10 percent level, respectively. Standard errors are clustered at the investor and stock level and are reported in parenthesis.

Table 5b: Login duration and the disposition effect for age and portfolio value subsamples

	Age and portfolio value subsample							
	Age < 50 Portfolio < €10,692		Age < 50 Portfolio ≥ €10,692		Age ≥ 50 Portfolio < €34,875		Age ≥ 50 Portfolio ≥ €34,875	
Gain	0.381	(0.714)	0.485	(0.875)	−0.844	(1.547)	3.205*	(1.882)
Attention								
Decile 2	−0.082	(0.117)	−0.037	(0.109)	0.077	(0.103)	−0.114	(0.095)
Decile 3	−0.067	(0.106)	−0.144	(0.109)	−0.208*	(0.109)	−0.054	(0.118)
Decile 4	−0.072	(0.109)	−0.179*	(0.106)	0.013	(0.103)	−0.223**	(0.091)
Decile 5	−0.164	(0.106)	−0.040	(0.103)	−0.119	(0.100)	−0.154	(0.103)
Decile 6	−0.010	(0.108)	−0.063	(0.104)	−0.034	(0.098)	−0.262***	(0.087)
Decile 7	−0.207**	(0.099)	−0.104	(0.116)	−0.232**	(0.095)	−0.230***	(0.088)
Decile 8	−0.153	(0.103)	−0.177*	(0.102)	−0.037	(0.095)	−0.296***	(0.095)
Decile 9	−0.122	(0.098)	−0.105	(0.103)	0.054	(0.093)	−0.282***	(0.084)
Decile 10	−0.103	(0.104)	−0.101	(0.101)	−0.002	(0.093)	−0.285***	(0.085)
Attention × Gain								
Decile 2	−0.174	(0.183)	−0.141	(0.131)	−0.489***	(0.135)	−0.089	(0.145)
Decile 3	−0.372**	(0.150)	−0.099	(0.124)	−0.138	(0.154)	−0.234	(0.172)
Decile 4	−0.461***	(0.165)	−0.063	(0.128)	−0.533***	(0.143)	−0.177	(0.137)
Decile 5	−0.414***	(0.151)	−0.260**	(0.115)	−0.351***	(0.130)	−0.292*	(0.165)
Decile 6	−0.718***	(0.161)	−0.364***	(0.123)	−0.496***	(0.141)	−0.144	(0.132)
Decile 7	−0.503***	(0.146)	−0.418***	(0.150)	−0.254*	(0.132)	−0.174	(0.138)
Decile 8	−0.602***	(0.151)	−0.254**	(0.118)	−0.632***	(0.135)	−0.159	(0.149)
Decile 9	−0.660***	(0.157)	−0.349***	(0.125)	−0.649***	(0.127)	−0.087	(0.130)
Decile 10	−0.781***	(0.148)	−0.293**	(0.119)	−0.740***	(0.135)	−0.198	(0.127)
Pseudo R^2	13.64		15.06		13.3		11.78	
N	99,787		443,335		236,455		1,103,595	

Table 5b reports coefficients and standard errors from the logistic regression model described in Section 4, where the dependent variable takes the value of one if an investor decides to sell a stock position on a day when he decides to sell at least some stock, and 0 if otherwise. Each regression model is estimated for a subsample of investors dependent upon their portfolio value relative to their age, and login duration deciles are based upon investors login duration within each subsample. Coefficients marked with ***, **, and * indicate significance at the 1, 5, and 10 percent level, respectively. Standard errors are clustered at the investor and stock level and are reported in parenthesis.

Table 5c: Login days and the disposition effect for age and portfolio value subsamples

	Age and portfolio value subsample							
	Age < 50 Portfolio < €10,692		Age < 50 Portfolio ≥ €10,692		Age ≥ 50 Portfolio < €34,875		Age ≥ 50 Portfolio ≥ €34,875	
Gain	0.330	(0.733)	0.540	(0.913)	−1.303	(1.637)	2.325	(1.781)
Attention								
Decile 2	−0.056	(0.119)	−0.129	(0.111)	−0.252**	(0.105)	−0.252**	(0.100)
Decile 3	−0.234*	(0.126)	−0.207*	(0.113)	−0.240**	(0.109)	−0.432***	(0.095)
Decile 4	−0.192*	(0.113)	−0.291**	(0.113)	−0.272***	(0.096)	−0.403***	(0.096)
Decile 5	−0.170	(0.127)	−0.249**	(0.104)	−0.371***	(0.101)	−0.402***	(0.089)
Decile 6	−0.235**	(0.118)	−0.199*	(0.103)	−0.297***	(0.101)	−0.498***	(0.094)
Decile 7	−0.140	(0.112)	−0.166*	(0.100)	−0.312***	(0.099)	−0.471***	(0.092)
Decile 8	−0.255**	(0.118)	−0.230**	(0.102)	−0.252**	(0.099)	−0.495***	(0.098)
Decile 9	−0.272**	(0.118)	−0.207*	(0.110)	−0.313***	(0.098)	−0.524***	(0.093)
Decile 10	−0.231**	(0.110)	−0.221**	(0.101)	−0.257***	(0.090)	−0.437***	(0.094)
Attention × Gain								
Decile 2	−0.051	(0.180)	−0.070	(0.151)	0.061	(0.144)	0.226*	(0.133)
Decile 3	−0.162	(0.181)	0.009	(0.155)	−0.194	(0.151)	0.239*	(0.132)
Decile 4	−0.248	(0.165)	−0.017	(0.159)	−0.077	(0.133)	0.179	(0.136)
Decile 5	−0.442**	(0.176)	−0.109	(0.151)	−0.112	(0.145)	0.166	(0.129)
Decile 6	−0.464***	(0.168)	−0.237	(0.149)	−0.238*	(0.142)	0.167	(0.139)
Decile 7	−0.597***	(0.158)	−0.291**	(0.146)	−0.188	(0.145)	0.195	(0.130)
Decile 8	−0.487***	(0.161)	−0.256*	(0.150)	−0.264*	(0.147)	0.230	(0.142)
Decile 9	−0.528***	(0.162)	−0.222	(0.165)	−0.300**	(0.140)	0.223	(0.135)
Decile 10	−0.567***	(0.162)	−0.269*	(0.151)	−0.450***	(0.131)	0.020	(0.132)
Pseudo R^2	13.63		15.05		13.26		11.79	
N	99,787		443,335		236,455		1,103,595	

Table 5c reports coefficients and standard errors from the logistic regression model described in Section 4, where the dependent variable takes the value of one if an investor decides to sell a stock position on a day when he decides to sell at least some stock, and 0 if otherwise. Each regression model is estimated for a subsample of investors dependent upon their portfolio value relative to their age, and login days deciles are based upon investors days logged-in within each subsample. Coefficients marked with ***, **, and * indicate significance at the 1, 5, and 10 percent level, respectively. Standard errors are clustered at the investor and stock level and are reported in parenthesis.

Table 6: Financial attention and the disposition effect among stock only traders

	Frequency		Duration		Days	
Gain	0.318	(0.311)	0.317	(0.314)	0.316	(0.307)
Attention						
Decile 2	-0.248***	(0.074)	-0.153*	(0.080)	-0.190***	(0.072)
Decile 3	-0.218***	(0.072)	-0.204***	(0.078)	-0.273***	(0.068)
Decile 4	-0.433***	(0.079)	-0.172*	(0.097)	-0.306***	(0.076)
Decile 5	-0.390***	(0.070)	-0.178**	(0.078)	-0.415***	(0.064)
Decile 6	-0.351***	(0.073)	-0.286***	(0.080)	-0.273***	(0.068)
Decile 7	-0.333***	(0.073)	-0.304***	(0.084)	-0.383***	(0.073)
Decile 8	-0.344***	(0.076)	-0.252***	(0.080)	-0.323***	(0.073)
Decile 9	-0.427***	(0.075)	-0.336***	(0.082)	-0.427***	(0.070)
Decile 10	-0.368***	(0.070)	-0.205***	(0.078)	-0.289***	(0.067)
Attention × Gain						
Decile 2	-0.051	(0.103)	-0.151	(0.114)	-0.134	(0.099)
Decile 3	-0.189*	(0.098)	-0.113	(0.116)	-0.109	(0.096)
Decile 4	-0.012	(0.109)	-0.209	(0.144)	-0.154	(0.104)
Decile 5	-0.125	(0.100)	-0.320***	(0.112)	-0.142	(0.096)
Decile 6	-0.264**	(0.105)	-0.188	(0.119)	-0.344***	(0.101)
Decile 7	-0.298***	(0.108)	-0.242*	(0.124)	-0.152	(0.106)
Decile 8	-0.318***	(0.108)	-0.285**	(0.120)	-0.266**	(0.105)
Decile 9	-0.211*	(0.110)	-0.105	(0.117)	-0.156	(0.103)
Decile 10	-0.296***	(0.109)	-0.384***	(0.116)	-0.425***	(0.105)
Additional Controls	Yes		Yes		Yes	
Pseudo R^2	14.13		14.11		14.14	
N	370,725		370,725		370,725	

Table 6 reports coefficients and standard errors from the logistic regression model described in Section 4, where the dependent variable takes the value of one if an investor sells a stock position on a day when he sells at least some stock, and 0 if otherwise. Observations are obtained for a subsample of clients, who only traded in common equity at the Belgian discount broker between January 2014 and December 2016. Each attention decile is constructed based upon the stock investors' portfolio monitoring behavior. Coefficients marked with ***, **, and * indicate significance at the 1, 5, and 10 percent level, respectively. Standard errors are clustered at the investor and stock level and are reported in parenthesis.

Table 7: Financial attention and the disposition effect, excluding rebalancing decisions

	Frequency		Duration		Days	
Gain	0.380	(0.273)	0.363	(0.272)	0.403	(0.275)
Attention						
Decile 2	-0.211***	(0.063)	-0.169***	(0.059)	-0.144**	(0.061)
Decile 3	-0.264***	(0.063)	-0.244***	(0.061)	-0.245***	(0.060)
Decile 4	-0.366***	(0.064)	-0.207***	(0.067)	-0.298***	(0.061)
Decile 5	-0.379***	(0.061)	-0.276***	(0.059)	-0.360***	(0.056)
Decile 6	-0.316***	(0.062)	-0.244***	(0.066)	-0.273***	(0.058)
Decile 7	-0.376***	(0.062)	-0.331***	(0.064)	-0.375***	(0.059)
Decile 8	-0.369***	(0.063)	-0.292***	(0.061)	-0.336***	(0.063)
Decile 9	-0.460***	(0.064)	-0.289***	(0.062)	-0.403***	(0.062)
Decile 10	-0.366***	(0.061)	-0.327***	(0.059)	-0.354***	(0.056)
Attention × Gain						
Decile 2	-0.128	(0.082)	-0.073	(0.086)	-0.237***	(0.083)
Decile 3	-0.217***	(0.080)	-0.078	(0.088)	-0.159**	(0.078)
Decile 4	-0.142*	(0.080)	-0.176*	(0.095)	-0.204**	(0.079)
Decile 5	-0.227***	(0.080)	-0.182**	(0.085)	-0.226***	(0.076)
Decile 6	-0.311***	(0.082)	-0.308***	(0.100)	-0.359***	(0.080)
Decile 7	-0.323***	(0.084)	-0.224**	(0.097)	-0.271***	(0.084)
Decile 8	-0.367***	(0.084)	-0.285***	(0.090)	-0.340***	(0.090)
Decile 9	-0.239***	(0.087)	-0.239**	(0.094)	-0.222**	(0.087)
Decile 10	-0.387***	(0.081)	-0.245***	(0.084)	-0.393***	(0.077)
Additional Controls	Yes		Yes		Yes	
Pseudo R^2	15.21		15.18		15.2	
N	1,515,387		1,515,387		1,515,387	

Table 7 reports coefficients and standard errors from the logistic regression model described in Section 4, where the dependent variable takes the value of one if an investor decides to sell a stock position on a day when he decides to sell at least some stock, and 0 if otherwise. Observations are obtained for a subsample, which excludes observations that are possibly due to the rebalancing of the stock portfolio. Coefficients marked with ***, **, and * indicate significance at the 1, 5, and 10 percent level, respectively. Standard errors are clustered at the investor and stock level and are reported in parenthesis.

Table 8: Financial attention and the disposition effect among market order sales

	Frequency		Duration		Days	
Gain	0.246	(0.368)	0.270	(0.382)	0.278	(0.375)
Attention						
Decile 2	-0.369***	(0.124)	-0.254**	(0.115)	-0.192*	(0.114)
Decile 3	-0.297**	(0.120)	-0.219**	(0.103)	-0.256**	(0.109)
Decile 4	-0.487***	(0.120)	-0.326***	(0.108)	-0.256**	(0.108)
Decile 5	-0.479***	(0.121)	-0.270***	(0.103)	-0.404***	(0.101)
Decile 6	-0.346***	(0.118)	-0.243**	(0.114)	-0.293***	(0.102)
Decile 7	-0.459***	(0.117)	-0.337***	(0.109)	-0.367***	(0.102)
Decile 8	-0.475***	(0.120)	-0.344***	(0.101)	-0.346***	(0.105)
Decile 9	-0.525***	(0.118)	-0.298***	(0.107)	-0.372***	(0.106)
Decile 10	-0.433***	(0.121)	-0.330***	(0.104)	-0.373***	(0.103)
Attention × Gain						
Decile 2	-0.053	(0.163)	0.037	(0.170)	-0.074	(0.162)
Decile 3	-0.166	(0.155)	-0.047	(0.152)	-0.109	(0.145)
Decile 4	-0.008	(0.149)	-0.022	(0.154)	-0.131	(0.145)
Decile 5	-0.158	(0.149)	-0.180	(0.149)	-0.112	(0.141)
Decile 6	-0.334**	(0.147)	-0.335*	(0.183)	-0.293**	(0.141)
Decile 7	-0.246*	(0.147)	-0.233	(0.166)	-0.236*	(0.140)
Decile 8	-0.311**	(0.153)	-0.215	(0.147)	-0.274*	(0.150)
Decile 9	-0.270*	(0.162)	-0.247	(0.160)	-0.278*	(0.159)
Decile 10	-0.394**	(0.153)	-0.287*	(0.150)	-0.327**	(0.147)
Additional Controls	Yes		Yes		Yes	
Pseudo R^2	14.54		14.52		14.51	
N	328,543		328,543		328,543	

Table 9 reports coefficients and standard errors from the logistic regression model described in Section 4, where the dependent variable takes the value of one if an investor decides to sell a stock position on a day when he decides to sell at least some stock, and 0 if otherwise. Observations are obtained for a subsample, which only includes observations that are the result of a market order sale. Coefficients marked with ***, **, and * indicate significance at the 1, 5, and 10 percent level, respectively. Standard errors are clustered at the investor and stock level and are reported in parenthesis.

Table 9: Financial attention and the disposition effect among market order sales

	Frequency		Duration		Days	
Gain	0.246	(0.368)	0.270	(0.382)	0.278	(0.375)
Attention						
Decile 2	-0.369***	(0.124)	-0.254**	(0.115)	-0.192*	(0.114)
Decile 3	-0.297**	(0.120)	-0.219**	(0.103)	-0.256**	(0.109)
Decile 4	-0.487***	(0.120)	-0.326***	(0.108)	-0.256**	(0.108)
Decile 5	-0.479***	(0.121)	-0.270***	(0.103)	-0.404***	(0.101)
Decile 6	-0.346***	(0.118)	-0.243**	(0.114)	-0.293***	(0.102)
Decile 7	-0.459***	(0.117)	-0.337***	(0.109)	-0.367***	(0.102)
Decile 8	-0.475***	(0.120)	-0.344***	(0.101)	-0.346***	(0.105)
Decile 9	-0.525***	(0.118)	-0.298***	(0.107)	-0.372***	(0.106)
Decile 10	-0.433***	(0.121)	-0.330***	(0.104)	-0.373***	(0.103)
Attention × Gain						
Decile 2	-0.053	(0.163)	0.037	(0.170)	-0.074	(0.162)
Decile 3	-0.166	(0.155)	-0.047	(0.152)	-0.109	(0.145)
Decile 4	-0.008	(0.149)	-0.022	(0.154)	-0.131	(0.145)
Decile 5	-0.158	(0.149)	-0.180	(0.149)	-0.112	(0.141)
Decile 6	-0.334**	(0.147)	-0.335*	(0.183)	-0.293**	(0.141)
Decile 7	-0.246*	(0.147)	-0.233	(0.166)	-0.236*	(0.140)
Decile 8	-0.311**	(0.153)	-0.215	(0.147)	-0.274*	(0.150)
Decile 9	-0.270*	(0.162)	-0.247	(0.160)	-0.278*	(0.159)
Decile 10	-0.394**	(0.153)	-0.287*	(0.150)	-0.327**	(0.147)
Additional Controls	Yes		Yes		Yes	
Pseudo R^2	14.54		14.52		14.51	
N	328,543		328,543		328,543	

Table 9 reports coefficients and standard errors from the logistic regression model described in Section 4, where the dependent variable takes the value of one if an investor decides to sell a stock position on a day when he decides to sell at least some stock, and 0 if otherwise. Observations are obtained for a subsample, which only includes observations that are the result of a market order sale. Coefficients marked with ***, **, and * indicate significance at the 1, 5, and 10 percent level, respectively. Standard errors are clustered at the investor and stock level and are reported in parenthesis.

Table 9: Financial attention and the disposition effect among shared and individually-owned accounts

	Frequency				Duration				Days			
	Shared		Individual		Shared		Individual		Shared		Individual	
Gain	0.136	(0.722)	0.509	(0.910)	0.381	(0.714)	0.485	(0.875)	0.330	(0.733)	0.540	(0.913)
Attention												
Decile 2	−0.001	(0.115)	−0.126	(0.115)	−0.082	(0.117)	−0.037	(0.109)	−0.056	(0.119)	−0.129	(0.111)
Decile 3	−0.287**	(0.113)	−0.218*	(0.116)	−0.067	(0.106)	−0.144	(0.109)	−0.234*	(0.126)	−0.207*	(0.113)
Decile 4	−0.195	(0.119)	−0.368***	(0.114)	−0.072	(0.109)	−0.179*	(0.106)	−0.192*	(0.113)	−0.291**	(0.113)
Decile 5	−0.258**	(0.117)	−0.286**	(0.113)	−0.164	(0.106)	−0.040	(0.103)	−0.170	(0.127)	−0.249**	(0.104)
Decile 6	−0.179	(0.122)	−0.185*	(0.108)	−0.010	(0.108)	−0.063	(0.104)	−0.235**	(0.118)	−0.199*	(0.103)
Decile 7	−0.151	(0.113)	−0.193*	(0.107)	−0.207**	(0.099)	−0.104	(0.116)	−0.140	(0.112)	−0.166*	(0.100)
Decile 8	−0.322***	(0.108)	−0.208*	(0.106)	−0.153	(0.103)	−0.177*	(0.102)	−0.255**	(0.118)	−0.230**	(0.102)
Decile 9	−0.284**	(0.111)	−0.324***	(0.107)	−0.122	(0.098)	−0.105	(0.103)	−0.272**	(0.118)	−0.207*	(0.110)
Decile 10	−0.211**	(0.106)	−0.208*	(0.112)	−0.103	(0.104)	−0.101	(0.101)	−0.231**	(0.110)	−0.221**	(0.101)
Attention × Gain												
Decile 2	−0.038	(0.161)	−0.149	(0.132)	−0.174	(0.183)	−0.141	(0.131)	−0.051	(0.180)	−0.070	(0.151)
Decile 3	0.057	(0.161)	−0.097	(0.131)	−0.372**	(0.150)	−0.099	(0.124)	−0.162	(0.181)	0.009	(0.155)
Decile 4	−0.295*	(0.158)	−0.006	(0.131)	−0.461***	(0.165)	−0.063	(0.128)	−0.248	(0.165)	−0.017	(0.159)
Decile 5	−0.204	(0.151)	−0.204	(0.130)	−0.414***	(0.151)	−0.260**	(0.115)	−0.442**	(0.176)	−0.109	(0.151)
Decile 6	−0.455***	(0.167)	−0.296**	(0.126)	−0.718***	(0.161)	−0.364***	(0.123)	−0.464***	(0.168)	−0.237	(0.149)
Decile 7	−0.546***	(0.146)	−0.432***	(0.125)	−0.503***	(0.146)	−0.418***	(0.150)	−0.597***	(0.158)	−0.291**	(0.146)
Decile 8	−0.410***	(0.143)	−0.445***	(0.124)	−0.602***	(0.151)	−0.254**	(0.118)	−0.487***	(0.161)	−0.256*	(0.150)
Decile 9	−0.447***	(0.149)	−0.209*	(0.123)	−0.660***	(0.157)	−0.349***	(0.125)	−0.528***	(0.162)	−0.222	(0.165)
Decile 10	−0.615***	(0.149)	−0.423***	(0.135)	−0.781***	(0.148)	−0.293**	(0.119)	−0.567***	(0.162)	−0.269*	(0.151)
Pseudo R^2	13.69		15.58		13.66		15.57		13.74		15.58	
N	598,306		1,284,930		598,306		1,284,930		598,306		1,284,930	

Table 9 reports coefficients and standard errors from the logistic regression model described in the Section 4, where the dependent variable takes the value of one if an investor decides to sell a stock position on a day when he decides to sell at least some stock, and 0 if otherwise. Each regression model is estimated for a subsample of investors dependent upon whether the account was owned by an individual or shared with someone else. Attention deciles are based upon investors attention allocation within each subsample. Coefficients marked with ***, **, and * indicate significance at the 1, 5, and 10 percent level, respectively. Standard errors are clustered at the investor and stock level and are reported in parenthesis.

Table 10: Financial attention and the disposition effect for the 2014 subsample

	Frequency		Duration		Days	
Gain	-0.026	(0.393)	-0.266	(0.371)	-0.023	(0.389)
Attention						
Decile 2	-0.320*	(0.170)	-0.277*	(0.143)	-0.304*	(0.169)
Decile 3	-0.345**	(0.171)	-0.380***	(0.129)	-0.374**	(0.161)
Decile 4	-0.505***	(0.165)	-0.482***	(0.128)	-0.529***	(0.151)
Decile 5	-0.569***	(0.165)	-0.403***	(0.130)	-0.519***	(0.153)
Decile 6	-0.573***	(0.161)	-0.480***	(0.128)	-0.588***	(0.149)
Decile 7	-0.536***	(0.161)	-0.558***	(0.127)	-0.562***	(0.151)
Decile 8	-0.596***	(0.158)	-0.512***	(0.123)	-0.590***	(0.149)
Decile 9	-0.595***	(0.161)	-0.572***	(0.126)	-0.598***	(0.152)
Decile 10	-0.607***	(0.161)	-0.531***	(0.124)	-0.600***	(0.150)
Attention × Gain						
Decile 2	-0.365	(0.258)	-0.025	(0.200)	-0.313	(0.244)
Decile 3	-0.261	(0.262)	-0.053	(0.190)	-0.318	(0.240)
Decile 4	-0.303	(0.246)	0.112	(0.186)	-0.347	(0.226)
Decile 5	-0.290	(0.240)	-0.134	(0.191)	-0.302	(0.225)
Decile 6	-0.381	(0.243)	-0.196	(0.189)	-0.407*	(0.222)
Decile 7	-0.414*	(0.246)	-0.083	(0.185)	-0.414*	(0.228)
Decile 8	-0.401*	(0.243)	-0.218	(0.179)	-0.354	(0.226)
Decile 9	-0.473*	(0.245)	-0.074	(0.181)	-0.408*	(0.231)
Decile 10	-0.470*	(0.242)	-0.195	(0.175)	-0.485**	(0.224)
Additional Controls	Yes		Yes		Yes	
Pseudo R^2	15.19		15.19		15.18	
N	430,541		430,541		430,541	

Table 10 reports coefficients and standard errors from the logistic regression model described in Section 4, where the dependent variable takes the value of one if an investor decides to sell a stock position on a day when he decides to sell at least some stock, and 0 if otherwise. Observations are obtained for the 2014 subsample, where each attention decile is constructed based upon investors' portfolio monitoring behavior in 2014. Coefficients marked with ***, **, and * indicate significance at the 1, 5, and 10 percent level, respectively. Standard errors are clustered at the investor and stock level and are reported in parenthesis.

Table 11: Financial attention and the disposition effect for the 2015 subsample

	Frequency		Duration		Days	
Gain	0.915***	(0.325)	0.864***	(0.322)	0.956***	(0.325)
Attention						
Decile 2	-0.252*	(0.133)	-0.210*	(0.113)	-0.250*	(0.128)
Decile 3	-0.474***	(0.126)	-0.221*	(0.115)	-0.448***	(0.127)
Decile 4	-0.478***	(0.129)	-0.342***	(0.111)	-0.496***	(0.128)
Decile 5	-0.568***	(0.128)	-0.334***	(0.112)	-0.527***	(0.127)
Decile 6	-0.512***	(0.126)	-0.265**	(0.111)	-0.506***	(0.127)
Decile 7	-0.572***	(0.129)	-0.332***	(0.111)	-0.519***	(0.130)
Decile 8	-0.507***	(0.126)	-0.369***	(0.111)	-0.611***	(0.127)
Decile 9	-0.641***	(0.128)	-0.381***	(0.110)	-0.560***	(0.127)
Decile 10	-0.579***	(0.127)	-0.326***	(0.109)	-0.597***	(0.129)
Attention × Gain						
Decile 2	-0.286*	(0.155)	-0.135	(0.149)	-0.337**	(0.154)
Decile 3	-0.281*	(0.150)	-0.344**	(0.153)	-0.288*	(0.153)
Decile 4	-0.364**	(0.153)	-0.310**	(0.149)	-0.394**	(0.153)
Decile 5	-0.359**	(0.148)	-0.357**	(0.151)	-0.439***	(0.150)
Decile 6	-0.504***	(0.146)	-0.542***	(0.150)	-0.489***	(0.151)
Decile 7	-0.426***	(0.151)	-0.443***	(0.149)	-0.563***	(0.154)
Decile 8	-0.596***	(0.149)	-0.467***	(0.152)	-0.432***	(0.151)
Decile 9	-0.451***	(0.151)	-0.429***	(0.151)	-0.499***	(0.157)
Decile 10	-0.521***	(0.148)	-0.519***	(0.149)	-0.556***	(0.151)
Additional Controls	Yes		Yes		Yes	
Pseudo R^2	14.74		14.71		14.74	
N	844,990		844,990		844,990	

Table 11 reports coefficients and standard errors from the logistic regression model described in Section 4, where the dependent variable takes the value of one if an investor decides to sell a stock position on a day when he decides to sell at least some stock, and 0 if otherwise. Observations are obtained for the 2015 subsample, where each attention decile is constructed based upon investors' portfolio monitoring behavior in 2015. Coefficients marked with ***, **, and * indicate significance at the 1, 5, and 10 percent level, respectively. Standard errors are clustered at the investor and stock level and are reported in parenthesis.

Table 12: Financial attention and the disposition effect for the 2016 subsample

	Frequency		Duration		Days	
Gain	0.901**	(0.350)	0.913***	(0.350)	0.961***	(0.356)
Attention						
Decile 2	-0.451**	(0.197)	-0.440**	(0.180)	-0.461**	(0.185)
Decile 3	-0.516***	(0.193)	-0.666***	(0.183)	-0.511***	(0.184)
Decile 4	-0.658***	(0.194)	-0.657***	(0.180)	-0.602***	(0.185)
Decile 5	-0.720***	(0.195)	-0.598***	(0.183)	-0.710***	(0.184)
Decile 6	-0.720***	(0.195)	-0.700***	(0.183)	-0.652***	(0.186)
Decile 7	-0.681***	(0.195)	-0.654***	(0.184)	-0.717***	(0.186)
Decile 8	-0.706***	(0.195)	-0.669***	(0.182)	-0.636***	(0.186)
Decile 9	-0.796***	(0.196)	-0.665***	(0.183)	-0.717***	(0.185)
Decile 10	-0.663***	(0.194)	-0.685***	(0.181)	-0.713***	(0.186)
Attention × Gain						
Decile 2	0.123	(0.214)	0.204	(0.197)	0.190	(0.202)
Decile 3	0.092	(0.204)	0.257	(0.193)	0.089	(0.194)
Decile 4	0.148	(0.204)	0.151	(0.191)	0.134	(0.197)
Decile 5	0.143	(0.204)	0.062	(0.195)	0.139	(0.193)
Decile 6	-0.010	(0.204)	0.037	(0.193)	-0.020	(0.196)
Decile 7	-0.083	(0.204)	-0.070	(0.194)	-0.068	(0.197)
Decile 8	-0.128	(0.202)	-0.177	(0.189)	-0.147	(0.197)
Decile 9	-0.101	(0.205)	-0.152	(0.191)	-0.075	(0.195)
Decile 10	-0.307	(0.201)	-0.137	(0.189)	-0.150	(0.195)
Additional Controls	Yes		Yes		Yes	
Pseudo R^2	14.76		14.72		14.72	
N	607,667		607,667		607,667	

Table 12 reports coefficients and standard errors from the logistic regression model described in Section 4, where the dependent variable takes the value of one if an investor decides to sell a stock position on a day when he decides to sell at least some stock, and 0 if otherwise. Observations are obtained for the 2016 subsample, where each attention decile is constructed based upon investors' portfolio monitoring behavior in 2016. Coefficients marked with ***, **, and * indicate significance at the 1, 5, and 10 percent level, respectively. Standard errors are clustered at the investor and stock level and are reported in parenthesis.

Table 13a: Sell probability, login frequency and return magnitude

Frequency	Return intervals						
decile	<5%	5%-10%	10%-15%	15%-20%	20%-25%	25%-30%	>30%
Panel A: Probabilities to sell a gain							
1	20.0 [18.0-21.9]	20.6 [18.4-22.8]	26.7 [23.8-29.5]	28.7 [24.9-32.5]	34.0 [29.5-38.5]	31.6 [27.2-36.0]	34.8 [31.4-38.3]
2	16.7 [15.3-18.1]	19.6 [17.9-21.3]	23.4 [21.5-25.3]	23.6 [21.0-26.1]	22.6 [20.2-25.1]	26.4 [23.6-29.2]	27.5 [25.0-30.0]
3	15.5 [14.3-16.8]	17.7 [16.3-19.1]	20.7 [19.0-22.4]	21.4 [19.5-23.3]	23.7 [21.3-26.1]	23.0 [20.4-25.6]	27.2 [25.0-29.5]
4	15.8 [14.8-16.9]	19.0 [17.7-20.3]	20.3 [19.0-21.6]	22.6 [21.0-24.3]	23.6 [21.7-25.6]	22.9 [20.5-25.3]	25.2 [23.0-27.3]
5	15.3 [14.4-16.2]	17.7 [16.6-18.8]	19.1 [17.9-20.2]	20.5 [19.0-22.0]	20.5 [18.6-22.3]	22.6 [20.5-24.7]	23.5 [21.6-25.4]
6	15.2 [14.3-16.0]	18.3 [17.2-19.3]	19.1 [17.9-20.2]	20.0 [18.6-21.4]	21.2 [19.3-23.0]	21.1 [19.0-23.3]	22.6 [20.9-24.4]
7	15.3 [14.4-16.1]	16.8 [15.7-17.8]	18.1 [16.9-19.3]	19.4 [18.2-20.7]	20.0 [18.5-21.5]	20.0 [18.3-21.7]	20.9 [19.3-22.5]
8	15.4 [14.6-16.3]	17.3 [16.4-18.2]	17.7 [16.5-18.9]	18.6 [17.2-20.0]	18.9 [17.6-20.2]	18.1 [16.5-19.7]	18.9 [17.2-20.5]
9	16.6 [15.8-17.4]	17.9 [17.0-18.8]	18.1 [17.0-19.1]	17.5 [16.3-18.7]	18.8 [17.5-20.1]	18.3 [16.9-19.6]	19.0 [17.5-20.6]
10	17.4 [16.6-18.3]	17.3 [16.4-18.3]	16.2 [15.3-17.2]	15.9 [14.9-16.8]	15.4 [14.3-16.5]	15.7 [14.5-17.0]	15.6 [14.4-16.9]
Panel B: Probabilities to sell a loss							
1	13.7 [12.0-15.3]	12.7 [10.7-14.6]	11.9 [9.8-14.0]	10.3 [8.0-12.6]	11.0 [8.5-13.5]	13.6 [10.3-16.9]	11.3 [9.7-12.8]
2	11.7 [10.8-12.6]	10.6 [9.4-11.8]	11.1 [9.7-12.4]	10.7 [9.1-12.4]	9.2 [7.5-10.8]	9.1 [7.4-10.9]	9.0 [7.8-10.1]
3	12.8 [11.8-13.8]	10.5 [9.4-11.5]	9.7 [8.5-11.0]	8.7 [7.5-9.9]	9.2 [7.8-10.6]	8.2 [6.7-9.7]	7.7 [6.6-8.8]
4	11.5 [10.6-12.3]	9.7 [8.7-10.6]	8.6 [7.7-9.4]	9.3 [8.3-10.3]	8.6 [7.4-9.7]	8.7 [7.5-9.9]	6.6 [5.7-7.4]
5	11.4 [10.6-12.2]	9.9 [9.1-10.6]	9.0 [8.2-9.9]	8.8 [7.9-9.7]	8.1 [7.2-9.0]	8.5 [7.4-9.5]	6.8 [6.1-7.6]
6	12.2 [11.4-12.9]	10.1 [9.4-10.8]	9.5 [8.7-10.3]	8.9 [8.0-9.7]	8.8 [7.8-9.8]	8.1 [6.9-9.2]	6.8 [6.0-7.6]
7	11.8 [11.1-12.5]	10.0 [9.2-10.7]	8.7 [8.0-9.3]	8.6 [7.8-9.3]	7.8 [7.0-8.6]	7.7 [6.9-8.5]	6.6 [5.9-7.4]
8	11.7 [11.1-12.4]	10.0 [9.3-10.7]	9.2 [8.5-10.0]	8.7 [8.0-9.5]	8.4 [7.5-9.3]	8.0 [7.1-8.8]	6.1 [5.4-6.7]
9	12.1 [11.4-12.7]	9.0 [8.5-9.6]	8.2 [7.7-8.8]	7.4 [6.8-8.0]	7.2 [6.5-7.9]	6.7 [6.0-7.4]	5.0 [4.4-5.6]
10	13.0 [12.4-13.7]	9.7 [8.9-10.4]	8.5 [7.8-9.1]	7.4 [6.8-7.9]	7.2 [6.6-7.7]	6.7 [6.1-7.4]	4.4 [3.9-4.9]

Table 13a reports average predicted probabilities of selling a stock position, on a day when an investors sells at least a single stock position, as a function of login frequency expressed in deciles, at different return intervals. Panel A reports probabilities for a stock position trading at a profit, and panel B for one that is trading at a loss. Figures in squared brackets represent 95% confidence intervals. Standard errors are clustered at the investor and stock level.

Table 13b: Sell probability, login duration and return magnitude

Duration	Return intervals						
decile	<5%	5%-10%	10%-15%	15%-20%	20%-25%	25%-30%	>30%
Panel A: Probabilities to sell a gain							
1	17.2 [15.6-18.9]	19.9 [17.8-22.0]	25.2 [22.6-27.7]	24.9 [21.7-28.0]	29.6 [25.9-33.3]	34.0 [29.4-38.6]	34.1 [31.0-37.2]
2	16.4 [15.0-17.8]	19.3 [17.6-20.9]	21.5 [19.7-23.2]	23.2 [21.1-25.3]	24.6 [22.1-27.0]	25.2 [22.2-28.1]	26.9 [24.4-29.4]
3	15.2 [14.1-16.3]	18.4 [17.2-19.6]	22.0 [20.4-23.6]	21.5 [19.7-23.3]	22.7 [20.5-24.9]	25.3 [22.9-27.7]	27.1 [24.8-29.4]
4	15.6 [14.7-16.6]	18.6 [17.2-20.0]	19.8 [18.4-21.1]	21.7 [20.3-23.2]	21.5 [19.8-23.2]	24.7 [22.2-27.1]	24.5 [22.3-26.7]
5	15.2 [14.3-16.1]	17.8 [16.7-18.8]	19.4 [18.1-20.6]	20.3 [18.8-21.8]	20.9 [19.3-22.6]	21.2 [19.4-23.0]	24.0 [22.1-25.9]
6	14.7 [13.8-15.6]	17.2 [16.0-18.4]	17.6 [16.3-18.9]	19.2 [17.8-20.6]	20.2 [18.6-21.8]	19.0 [17.2-20.9]	21.5 [19.9-23.2]
7	15.7 [14.7-16.7]	17.2 [16.2-18.3]	18.0 [16.9-19.0]	18.6 [17.3-19.8]	19.1 [17.6-20.6]	19.2 [17.6-20.9]	20.3 [18.6-21.9]
8	16.0 [15.2-16.9]	16.9 [16.0-17.7]	17.7 [16.5-18.8]	18.3 [17.0-19.7]	18.3 [16.7-19.8]	17.3 [16.0-18.6]	17.8 [16.1-19.4]
9	17.6 [16.5-18.6]	17.9 [16.9-19.0]	17.5 [16.5-18.6]	17.1 [16.0-18.3]	18.1 [16.8-19.3]	17.5 [15.9-19.1]	18.1 [16.6-19.6]
10	17.1 [16.2-17.9]	17.6 [16.6-18.6]	16.6 [15.6-17.7]	16.4 [15.3-17.5]	16.6 [15.3-17.8]	16.2 [14.8-17.6]	16.6 [15.3-17.8]
Panel B: Probabilities to sell a loss							
1	12.9 [11.3-14.5]	11.5 [9.9-13.1]	11.0 [9.3-12.8]	10.3 [8.2-12.3]	10.4 [8.1-12.7]	12.6 [9.7-15.4]	10.5 [8.6-12.4]
2	11.5 [10.5-12.4]	10.7 [9.5-11.9]	9.5 [8.4-10.7]	9.8 [8.5-11.1]	9.5 [8.0-11.0]	9.4 [7.4-11.3]	8.8 [7.7-9.9]
3	11.4 [10.5-12.3]	10.2 [9.2-11.2]	9.0 [8.0-10.1]	9.8 [8.5-11.2]	8.5 [7.2-9.8]	8.4 [7.2-9.6]	7.9 [6.9-9.0]
4	12.2 [10.9-13.6]	10.3 [9.4-11.3]	9.6 [8.6-10.6]	8.7 [7.7-9.7]	8.7 [7.6-9.9]	9.1 [7.7-10.4]	7.0 [6.2-7.9]
5	11.3 [10.6-12.0]	10.0 [9.2-10.8]	9.5 [8.6-10.4]	9.2 [8.2-10.1]	8.7 [7.7-9.6]	8.2 [7.1-9.3]	7.0 [6.2-7.8]
6	11.7 [10.8-12.6]	10.1 [9.2-11.0]	9.9 [9.0-10.8]	9.3 [8.3-10.3]	9.4 [8.4-10.3]	8.8 [7.8-9.9]	6.8 [6.1-7.5]
7	11.6 [10.9-12.2]	9.7 [8.8-10.5]	8.5 [7.9-9.2]	8.3 [7.6-9.1]	7.4 [6.6-8.2]	7.2 [6.4-8.1]	6.0 [5.3-6.7]
8	12.0 [11.3-12.7]	9.7 [9.0-10.3]	8.9 [8.3-9.6]	7.8 [7.1-8.4]	8.1 [7.3-8.9]	7.8 [7.0-8.5]	5.7 [5.1-6.3]
9	13.3 [12.4-14.2]	9.3 [8.6-9.9]	8.0 [7.4-8.6]	7.1 [6.6-7.7]	6.9 [6.3-7.5]	6.8 [6.1-7.6]	5.0 [4.4-5.6]
10	12.6 [12.0-13.2]	9.6 [8.9-10.3]	8.5 [7.8-9.2]	7.7 [7.1-8.4]	7.2 [6.5-7.8]	6.5 [5.8-7.1]	4.6 [4.1-5.1]

Table 13b reports average predicted probabilities of selling a stock position, on a day when an investors sells at least a single stock position, as a function of login duration expressed in deciles, at different return intervals. Panel A reports probabilities for a stock position trading at a profit, and panel B for one that is trading at a loss. Figures in squared brackets represent 95% confidence intervals. Standard errors are clustered at the investor and stock level.

Table 13c: Sell probability, login days and return magnitude

Login days decile	Return intervals <5%	5%-10%	10%-15%	15%-20%	20%-25%	25%-30%	>30%
Panel A: Probabilities to sell a gain							
1	19.7 [17.8-21.6]	20.7 [18.3-23.0]	26.6 [23.8-29.4]	27.6 [23.7-31.5]	33.0 [28.6-37.3]	29.9 [25.6-34.2]	34.5 [30.7-38.3]
2	16.5 [15.1-17.8]	18.2 [16.6-19.7]	21.7 [19.8-23.6]	22.6 [20.2-24.9]	23.1 [20.5-25.6]	25.8 [22.8-28.8]	26.9 [24.4-29.5]
3	16.3 [14.9-17.6]	19.0 [17.6-20.4]	21.5 [19.7-23.3]	22.5 [20.7-24.4]	22.5 [20.3-24.7]	25.2 [22.3-28.0]	26.9 [24.7-29.2]
4	16.3 [15.3-17.3]	18.5 [17.1-19.8]	19.9 [18.5-21.3]	21.7 [20.0-23.4]	23.1 [21.1-25.2]	21.1 [18.7-23.6]	24.8 [22.6-27.0]
5	15.3 [14.4-16.2]	18.5 [17.4-19.7]	19.1 [17.9-20.2]	19.9 [18.4-21.4]	20.0 [18.4-21.6]	20.3 [18.1-22.4]	22.5 [20.5-24.4]
6	15.7 [14.7-16.6]	17.1 [16.0-18.2]	18.2 [17.1-19.3]	19.2 [17.8-20.7]	20.4 [18.6-22.1]	21.2 [19.3-23.0]	20.7 [19.2-22.3]
7	15.9 [14.9-16.9]	18.0 [17.0-19.1]	18.2 [17.1-19.4]	19.0 [17.7-20.3]	20.0 [18.5-21.4]	20.1 [18.4-21.9]	19.9 [18.3-21.4]
8	16.1 [15.2-17.0]	16.8 [15.9-17.8]	18.0 [16.9-19.2]	18.6 [17.3-19.9]	18.9 [17.4-20.4]	18.2 [16.7-19.7]	19.7 [18.0-21.5]
9	16.9 [16.1-17.8]	18.1 [17.2-19.1]	18.3 [17.2-19.4]	18.5 [17.4-19.5]	19.0 [17.7-20.3]	19.0 [17.5-20.5]	19.8 [18.2-21.5]
10	16.6 [15.7-17.5]	17.1 [16.2-18.0]	16.3 [15.3-17.2]	16.1 [15.1-17.1]	16.3 [15.2-17.3]	16.2 [14.9-17.4]	16.7 [15.4-18.0]
Panel B: Probabilities to sell a loss							
1	13.5 [12.0-15.1]	12.1 [10.5-13.8]	11.7 [9.7-13.6]	10.8 [8.5-13.0]	10.1 [7.9-12.3]	11.9 [8.9-14.9]	10.9 [9.5-12.4]
2	12.9 [11.9-13.9]	10.8 [9.6-11.9]	10.6 [9.3-12.0]	10.3 [8.7-11.9]	9.4 [7.7-11.1]	9.7 [7.7-11.7]	8.9 [7.5-10.3]
3	12.5 [11.5-13.5]	10.6 [9.5-11.6]	10.2 [9.0-11.3]	8.9 [7.7-10.0]	9.0 [7.8-10.3]	8.6 [7.2-10.0]	7.1 [6.2-8.1]
4	12.4 [11.5-13.2]	10.2 [9.3-11.2]	9.1 [8.2-10.0]	9.2 [8.2-10.3]	8.2 [7.0-9.3]	8.3 [7.1-9.4]	6.1 [5.3-6.9]
5	11.4 [10.7-12.1]	9.6 [8.8-10.3]	8.6 [7.8-9.5]	8.1 [7.2-8.9]	9.2 [8.1-10.3]	7.9 [6.8-9.0]	6.5 [5.8-7.2]
6	12.6 [11.9-13.3]	10.2 [9.5-10.9]	9.3 [8.5-10.0]	9.2 [8.4-10.1]	7.8 [6.9-8.6]	8.4 [7.4-9.4]	6.9 [6.1-7.6]
7	11.6 [10.9-12.3]	9.2 [8.6-9.9]	8.5 [7.8-9.1]	8.3 [7.6-9.1]	7.8 [7.0-8.6]	7.8 [6.9-8.8]	6.6 [5.9-7.2]
8	12.4 [11.6-13.3]	10.0 [9.3-10.8]	8.8 [8.1-9.4]	8.3 [7.6-8.9]	7.6 [6.7-8.5]	7.4 [6.6-8.2]	5.7 [4.9-6.4]
9	12.1 [11.5-12.8]	9.2 [8.6-9.7]	8.5 [7.9-9.1]	7.2 [6.7-7.7]	7.3 [6.7-7.9]	6.8 [6.1-7.5]	5.1 [4.5-5.6]
10	12.6 [11.9-13.3]	9.7 [9.0-10.4]	8.6 [7.9-9.2]	7.7 [7.1-8.4]	7.4 [6.8-8.0]	6.8 [6.2-7.5]	4.7 [4.2-5.3]

Table 13c reports reports average predicted probabilities of selling a stock position, on a day when an investors sells at least a single stock position, as a function of login days expressed in deciles, at different return intervals. Panel A reports probabilities for a stock position trading at a profit, and panel B for one that is trading at a loss. Figures in squared brackets represent 95% confidence intervals. Standard errors are clustered at the investor and stock level.

Table 14: Time-varying financial attention model

	Frequency	Duration	Days
att_{it}	0.003	0.002	0.001
	(0.002)	(0.001)	(0.001)
$gain_{ijt}$	0.053^{***}	0.053^{***}	0.053^{***}
	(0.005)	(0.005)	(0.005)
$gain_{ijt} \times att_{it}$	-0.016^{***}	-0.01^{***}	-0.022^{***}
	(0.003)	(0.002)	(0.002)
N	1,881,416	1,881,416	1,881,416
Overall R^2	16.35	16.31	16.4
Within R^2	4.35	4.31	4.41
$\tilde{\sigma}_{att_{it}}$	0.46	0.42	0.50

Table 14 reports coefficients and standard errors from the OLS regression model described in Section 5.3, where the dependent variable takes the value of one if an investor decides to sell a stock position on a day when he decides to sell at least some stock, and 0 if otherwise. Financial attention is measured as the login frequency, login duration or login days over the 30 calendar days preceding the sale decision. All attention measures are standardized to have zero mean and unit standard deviation. $\tilde{\sigma}_{att_{it}}$ denotes the standard deviation of the residuals from an auxiliary regression of the attention measures on the investor, month and industry fixed effects. Coefficients marked with ***, **, and * indicate significance at the 1, 5, and 10 percent level, respectively. Standard errors are clustered at the investor and stock level and are reported in parenthesis.

Table 15: Time-varying financial attention and return magnitude

	Frequency		Duration		Days	
att_{it}	0.005***	(0.002)	0.005***	(0.001)	0.003**	(0.001)
$gain_{ijt}$	0.028***	(0.005)	0.029***	(0.005)	0.028***	(0.004)
$gain_{ijt} \times att_{it}$	−0.003	(0.002)	−0.002	(0.002)	−0.007***	(0.002)
Ret_{ijt}						
[5%, 10%)	−0.022***	(0.002)	−0.023***	(0.002)	−0.022***	(0.002)
[10%, 15%)	−0.031***	(0.003)	−0.031***	(0.003)	−0.031***	(0.003)
[15%, 20%)	−0.038***	(0.003)	−0.038***	(0.003)	−0.037***	(0.003)
[20%, 25%)	−0.042***	(0.003)	−0.043***	(0.003)	−0.041***	(0.003)
[25%, 30%)	−0.045***	(0.003)	−0.046***	(0.003)	−0.045***	(0.003)
[30%, +∞)	−0.066***	(0.004)	−0.066***	(0.004)	−0.065***	(0.004)
$Ret_{ijt} \times gain_{ijt}$						
[5%, 10%)	0.037***	(0.003)	0.037***	(0.003)	0.037***	(0.003)
[10%, 15%)	0.049***	(0.003)	0.050***	(0.004)	0.049***	(0.003)
[15%, 20%)	0.059***	(0.004)	0.061***	(0.004)	0.059***	(0.004)
[20%, 25%)	0.067***	(0.005)	0.069***	(0.005)	0.067***	(0.005)
[25%, 30%)	0.071***	(0.005)	0.073***	(0.005)	0.070***	(0.005)
[30%, +∞)	0.097***	(0.007)	0.099***	(0.007)	0.096***	(0.007)
$Ret_{ijt} \times att_{it}$						
[5%, 10%)	−0.006**	(0.002)	−0.004***	(0.002)	−0.003**	(0.001)
[10%, 15%)	−0.007***	(0.002)	−0.005***	(0.002)	−0.004***	(0.002)
[15%, 20%)	−0.009***	(0.002)	−0.008***	(0.002)	−0.006***	(0.002)
[20%, 25%)	−0.009***	(0.002)	−0.009***	(0.002)	−0.006***	(0.002)
[25%, 30%)	−0.010***	(0.002)	−0.012***	(0.002)	−0.009***	(0.002)
[30%, +∞)	−0.012***	(0.002)	−0.013***	(0.003)	−0.009***	(0.002)
$Ret_{ijt} \times att_{it} \times gain_{ijt}$						
[5%, 10%)	−0.007**	(0.003)	−0.004*	(0.002)	−0.007***	(0.002)
[10%, 15%)	−0.015***	(0.003)	−0.012***	(0.003)	−0.015***	(0.002)
[15%, 20%)	−0.021***	(0.003)	−0.013***	(0.003)	−0.020***	(0.003)
[20%, 25%)	−0.024***	(0.003)	−0.015***	(0.003)	−0.022***	(0.003)
[25%, 30%)	−0.025***	(0.004)	−0.013***	(0.004)	−0.022***	(0.004)
[30%, +∞)	−0.034***	(0.004)	−0.022***	(0.004)	−0.028***	(0.003)
N	1,881,416		1,881,416		1,881,416	
Overall R^2	16.62		16.56		16.65	
Within R^2	4.67		4.6		4.7	
$\tilde{\sigma}_{att_{it}}$	0.46		0.42		0.50	

Table 15 reports coefficients and standard errors from the OLS regression model described in Section 5.3. $\tilde{\sigma}_{att_{it}}$ denotes the standard deviation of the residuals from an auxiliary regression of the time-varying individual-level attention measures on the investor, month and industry fixed effects. Coefficients marked with ***, **, and * indicate significance at the 1, 5, and 10 percent level, respectively. Standard errors are clustered at the investor and stock level and are reported in parenthesis.

Table 16: Transactions-based calendar-time portfolios

	Raw Return			Factor Exposures				
Holding Period	RG	PL	Diff	Alpha	RmRF	SMB	HML	WML
30 Days	0.133	0.094	0.040***	0.030**	0.046**	0.046	0.001	0.288***
			(0.015)	(0.013)	(0.020)	(0.045)	(0.047)	(0.036)
90 Days	0.116	0.093	0.024**	0.013	0.032*	0.000	0.004	0.318***
			(0.013)	(0.011)	(0.017)	(0.032)	(0.037)	(0.030)
180 Days	0.109	0.092	0.018*	0.008	0.040***	−0.007	−0.028	0.291***
			(0.012)	(0.010)	(0.015)	(0.029)	(0.030)	(0.027)
365 Days	0.101	0.094	0.007	0.000	0.061***	−0.007	−0.054**	0.198***
			(0.010)	(0.009)	(0.015)	(0.026)	(0.025)	(0.023)

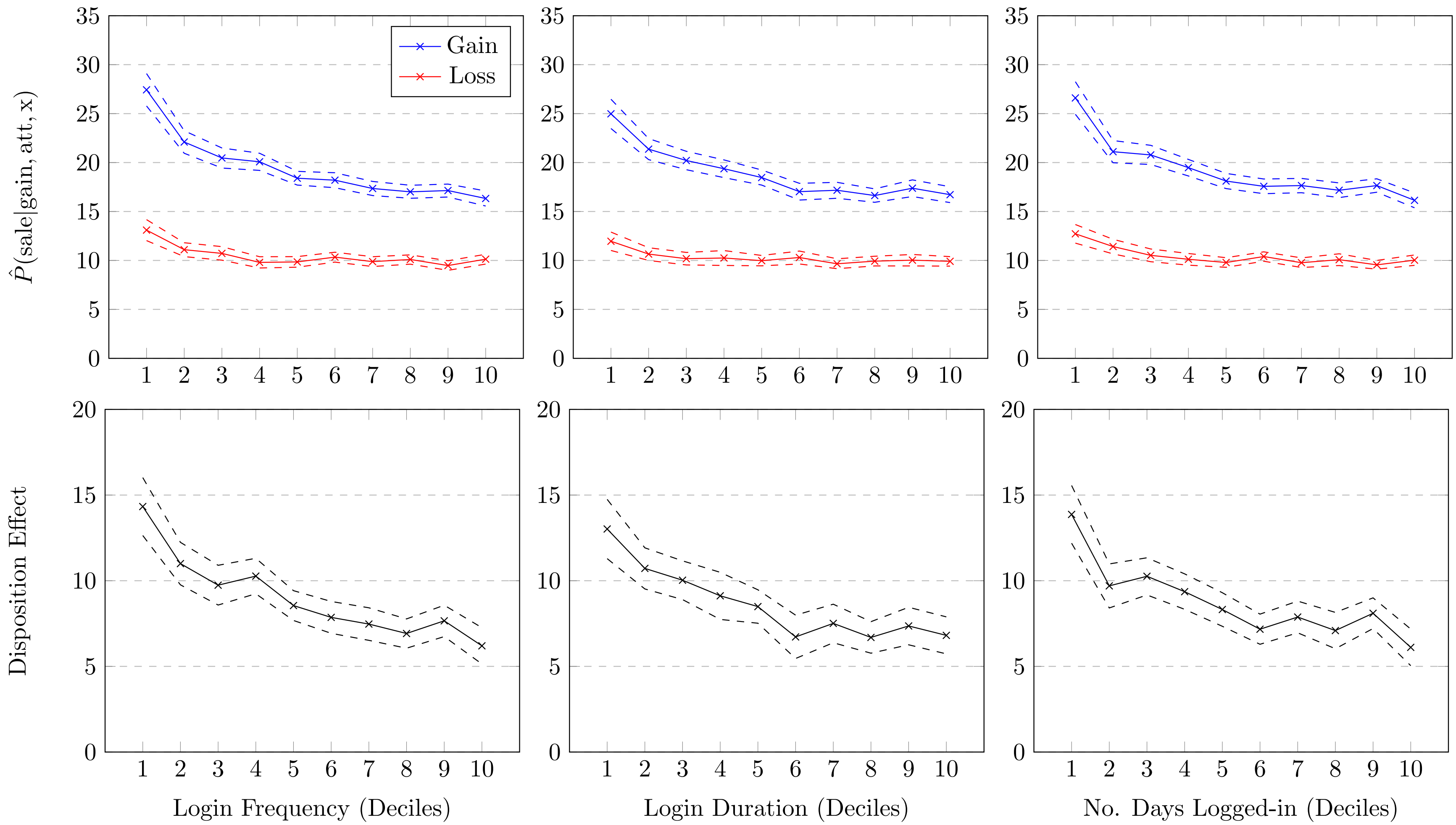
Table 16 reports the average raw returns of two transactions-based calendar-time portfolios, which mimic the returns acquired by investing in a portfolio of realized gains (RG) and paper losses (PL), and its difference. The sample covers all RG and PL observations between January 2014 and December 2016. Stock-day returns are winsorized at the 0.5% level. The right-hand side of Table 16 presents the alpha and factor exposures for the RG-minus-PL portfolio returns regressed on the Fama-French-Carhart factors. Coefficients marked with ***, **, and * indicate significance at the 1, 5, and 10 percent level, respectively. For The columns "Diff" and "Alpha", we assess statistical significance based upon a one-tailed t-test. Within parentheses, we report Newey-West heterokedasticity and autocorrelation robust standard errors with a lag length of five.

Table 17: Transactions-based calendar-time portfolios by attention

Holding Period	Frequency				Duration				Days			
	Raw Return		Alpha		Raw Return		Alpha		Raw Return		Alpha	
Panel A: Low Attention												
30 Days	0.053***	(0.021)	0.044***	(0.019)	0.040***	(0.017)	0.030**	(0.016)	0.056***	(0.021)	0.047***	(0.019)
90 Days	0.029**	(0.018)	0.020*	(0.016)	0.018	(0.015)	0.007	(0.014)	0.034**	(0.018)	0.025*	(0.016)
180 Days	0.023*	(0.016)	0.010	(0.014)	0.004	(0.014)	−0.005	(0.012)	0.025*	(0.016)	0.015	(0.014)
365 Days	0.003	(0.014)	0.000	(0.013)	−0.007	(0.012)	−0.013	(0.011)	0.012	(0.015)	0.005	(0.014)
Panel B: High Attention												
30 Days	0.034***	(0.015)	0.026**	(0.013)	0.039***	(0.015)	0.030**	(0.014)	0.035***	(0.015)	0.026**	(0.013)
90 Days	0.020*	(0.013)	0.011	(0.011)	0.024**	(0.013)	0.015*	(0.011)	0.020*	(0.013)	0.011	(0.011)
180 Days	0.013*	(0.012)	0.006	(0.010)	0.019*	(0.012)	0.010	(0.010)	0.015*	(0.012)	0.006	(0.009)
365 Days	0.000	(0.010)	−0.001	(0.009)	0.009	(0.010)	0.003	(0.009)	0.004	(0.010)	−0.001	(0.009)
Panel C: High-minus-Low												
30 Days	−0.019	(0.016)	−0.017*	(0.014)	−0.000	(0.013)	0.000	(0.014)	−0.021*	(0.016)	−0.021*	(0.014)
90 Days	−0.009	(0.012)	−0.008	(0.011)	0.006	(0.011)	0.007	(0.011)	−0.014	(0.013)	−0.013	(0.012)
180 Days	−0.010	(0.011)	−0.003	(0.010)	0.014	(0.010)	0.015*	(0.011)	−0.009	(0.012)	−0.009	(0.011)
365 Days	−0.002	(0.010)	−0.002	(0.009)	0.017	(0.009)	0.016**	(0.010)	−0.007	(0.011)	−0.007	(0.010)

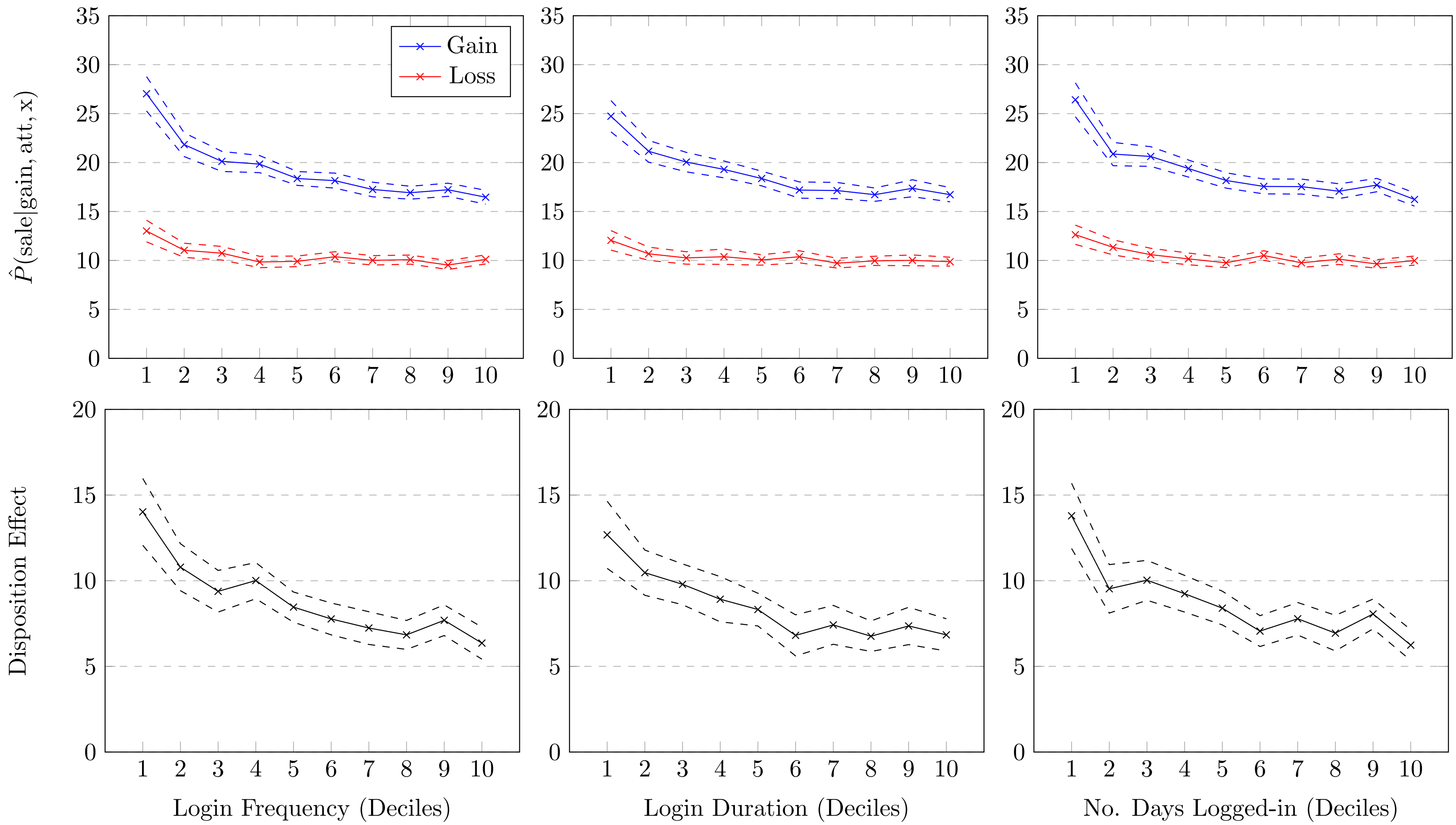
Table 17 reports the average difference in the raw returns between two transactions-based calendar-time portfolios, which mimic the returns acquired by investing in a portfolio of realized gains (RG) and paper losses (PL). Panel A and Panel B report the returns of the RG-minus-PL portfolio for groups of investors split by the median value of each attention measure. Panel C reports the difference in results between Panel A and B. The sample covers all RG and PL observations between January 2014 and December 2016. Stock-day returns are winsorized at the 0.5% level. The column Alpha in Table 17 presents the estimated constant from a regression of the RG-minus-PL portfolio returns on the Fama-French-Carhart factors. Coefficients marked with ***, **, and * indicate significance at the 1, 5, and 10 percent level, respectively, employing a one-tailed t-test. Within parentheses, we report Newey-West heterokedasticity and autocorrelation robust standard errors with a lag length of five.

Figure 1: Financial attention and the disposition effect



The top panel of Figure 1 reports the average predicted probabilities of selling a winning or a losing stock position, as a function of investors' financial attention, expressed in deciles. The probabilities are implied from the logistic regression described in Section 4, where the dependent variable takes the value of 1 if an investor sells a stock position on a day when he sells at least some stock, and 0 if otherwise. The bottom panel reports the change in the disposition effect, as a function of financial attention. The disposition effect at each decile of attention is calculated as the average partial effect of a dummy variable, taking the value of 1 if the stock position was trading at a gain in the investor's portfolio, and 0 if otherwise. Dotted lines represent 95% confidence intervals. Standard errors are clustered at the investor and stock level.

Figure 2: Financial attention and the disposition effect, controlling for investor sophistication



The top panel of Figure 2 reports the average predicted probabilities of selling a winning or a losing stock position, as a function of investors' financial attention, expressed in deciles. The probabilities are implied from an extended logistic regression model with additional controls for investor sophistication and heterogeneity. The dependent variable takes the value of one if an investor sells a stock position on a day when he sells at least some stock, and 0 if otherwise. The bottom panel reports the change in the disposition effect, as a function of financial attention. The disposition effect at each decile of attention is calculated as the average partial effect of a dummy variable, taking the value of 1, if the stock position was trading at a gain in the investors portfolio, and 0 if otherwise. Dotted lines represent 95% confidence intervals. Standard errors are clustered at the investor and stock level.

Figure 3: Estimated disposition effect by age and portfolio value subsamples

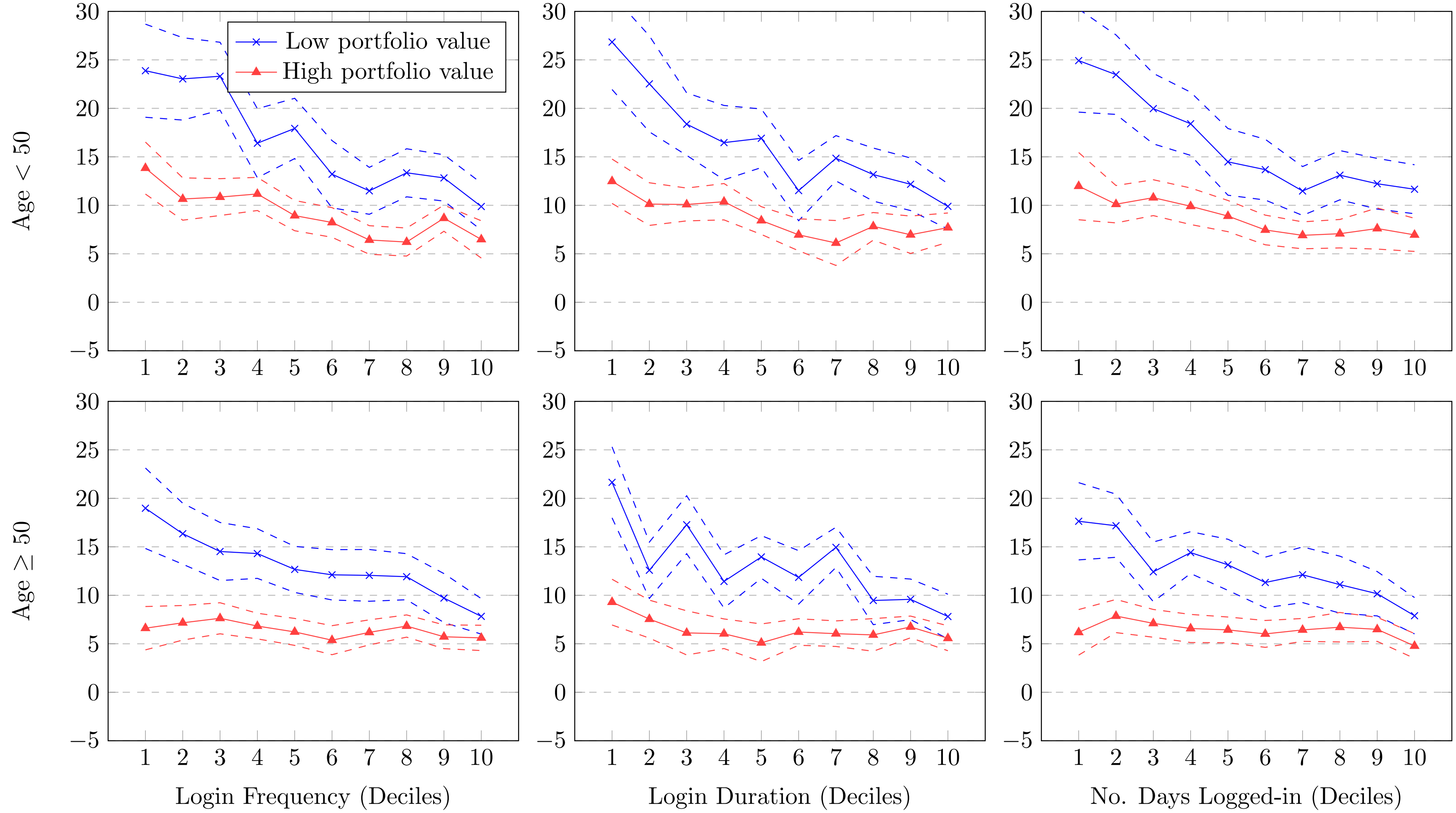
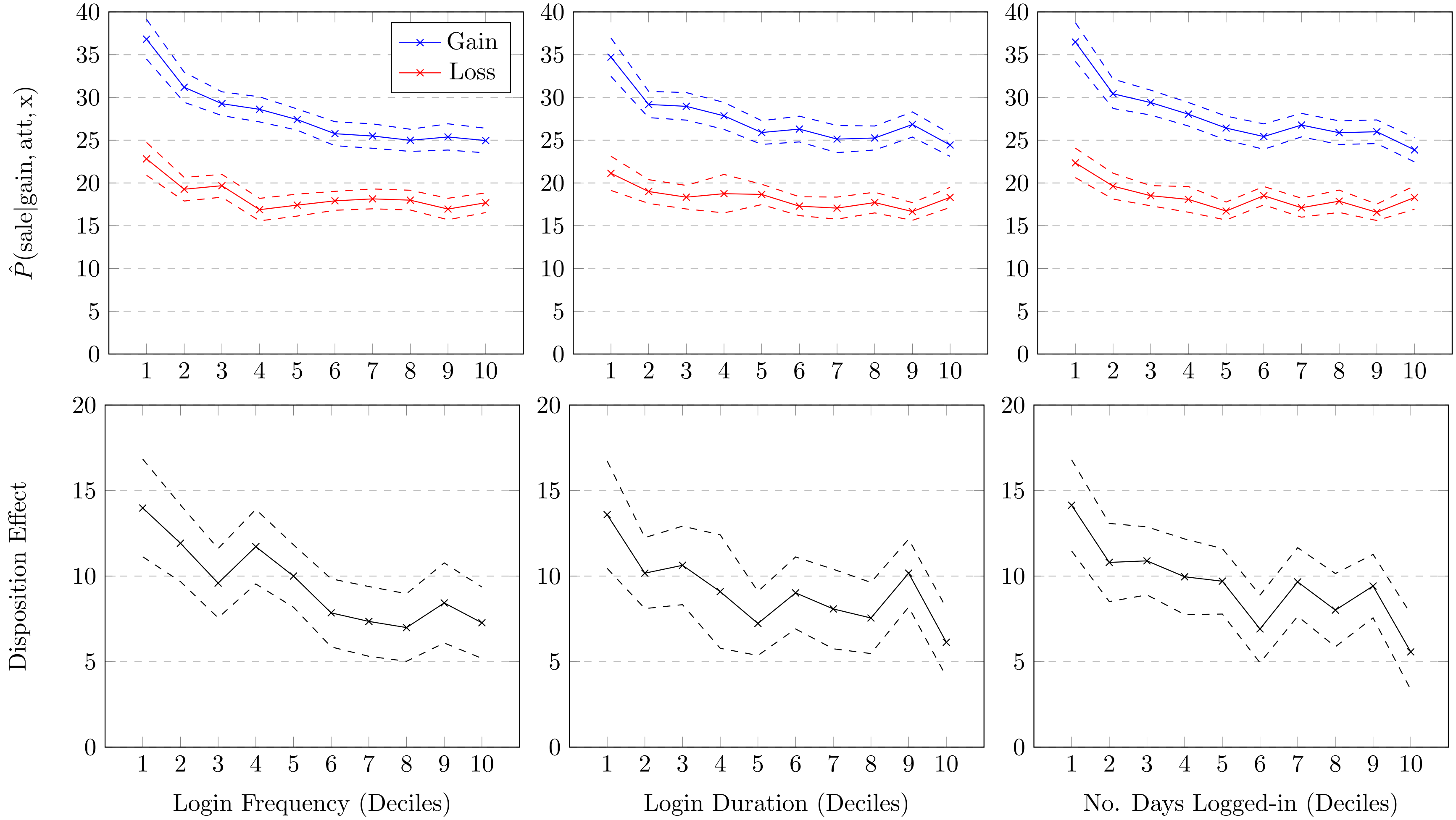


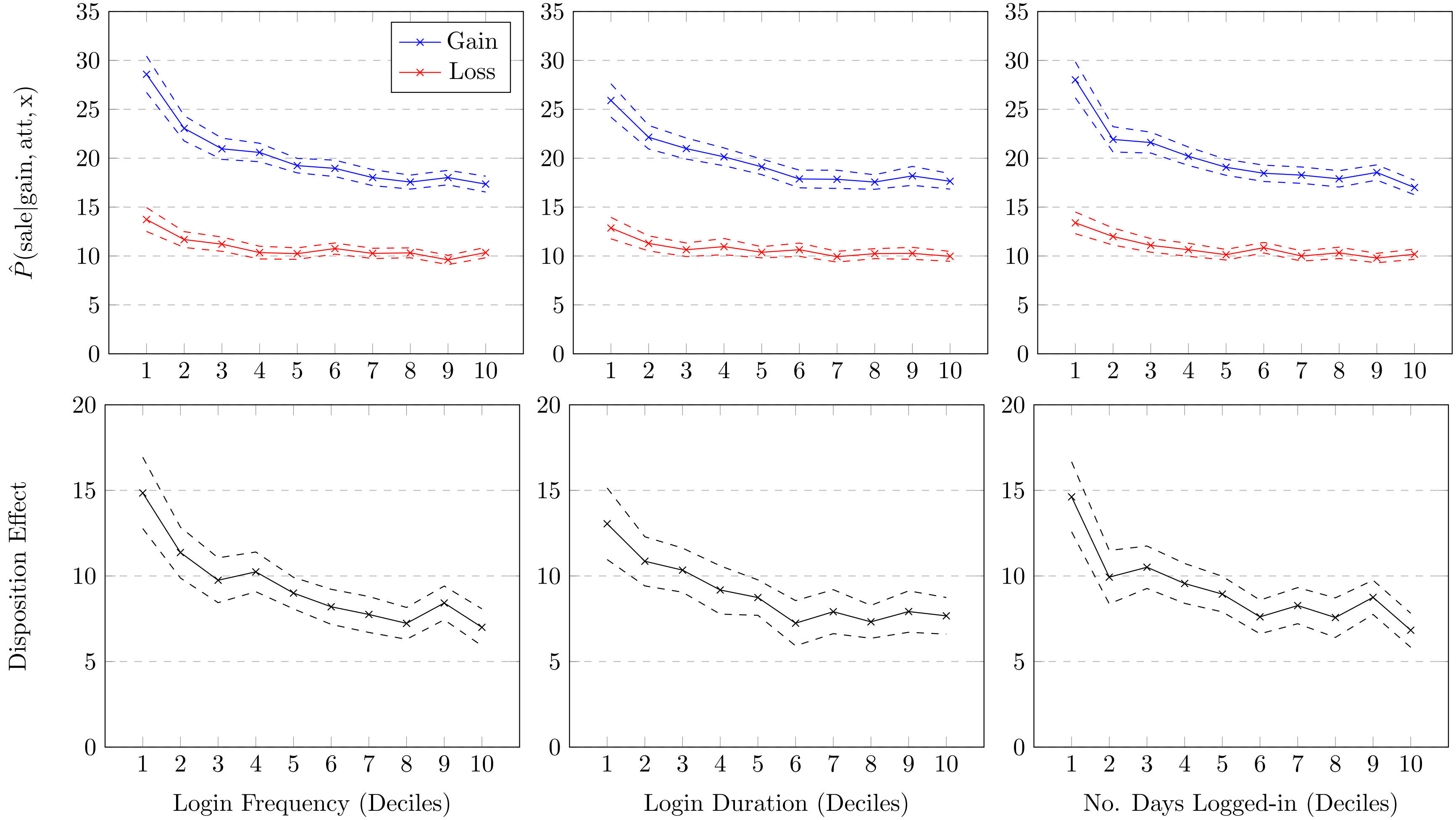
Figure 3 reports the disposition effect at each decile of attention, calculated as the average partial effect of a dummy variable, taking the value of 1 if the stock position was trading at a gain in the investor's portfolio, and 0 if otherwise. The results are implied from the logistic regression described in the Section Methodology for 4 subsamples. The sample is first split based upon the median investor's age. Subsequently, each subsample is split once more using the median portfolio value within each age group. Attention deciles are determined based upon investors' portfolio monitoring behavior within each one of the 4 subsamples. Dotted lines represent 95% confidence intervals. Standard errors are clustered at the investor and stock level.

Figure 4: Financial attention and the disposition effect among stock only traders



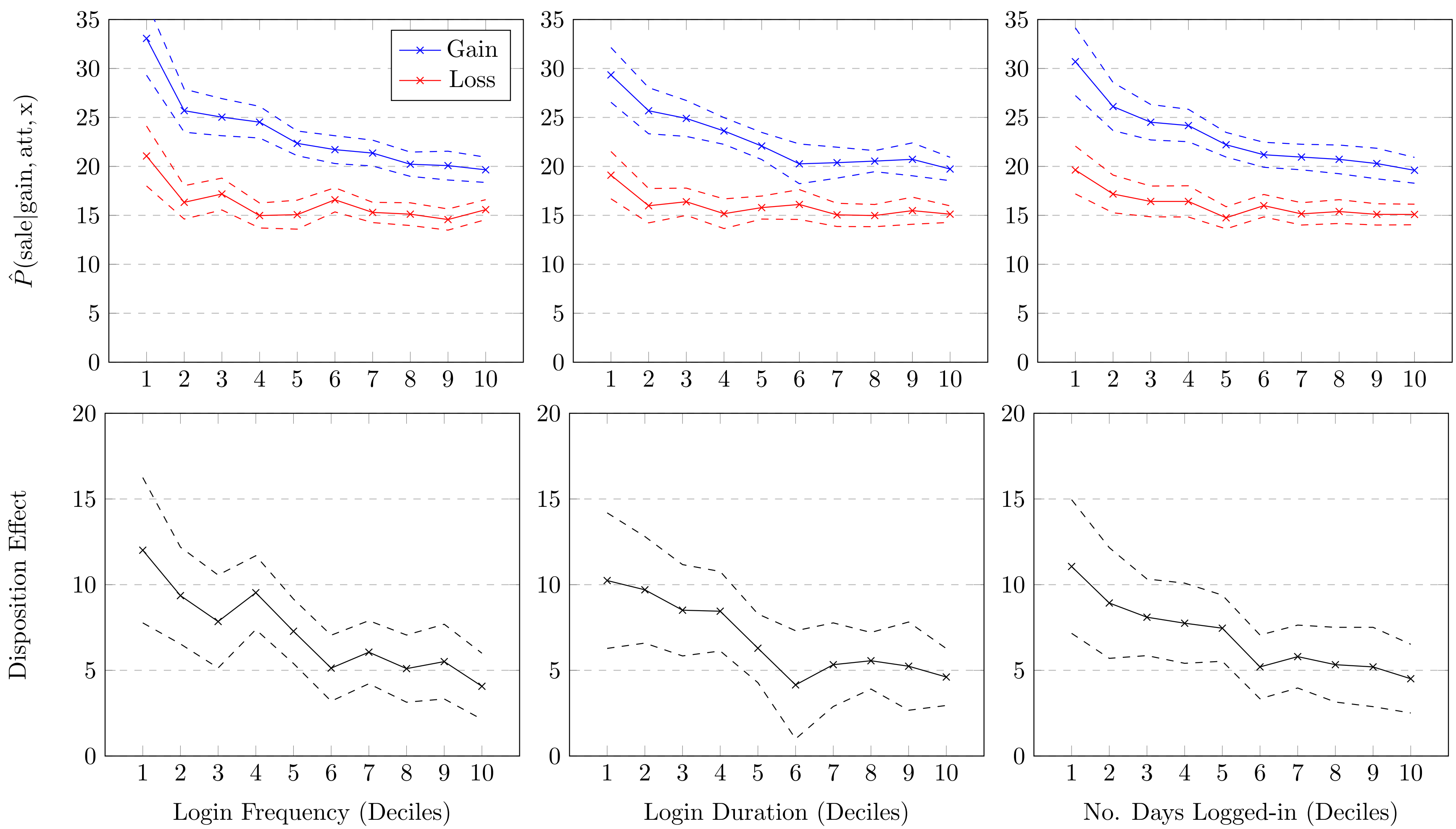
The top panel of Figure 4 reports the average predicted probabilities of selling a winning or a losing stock position, as a function of an investor's financial attention, expressed in deciles. The probabilities are implied from the logistic regression described in Section 4, where the dependent variable takes the value of 1 if an investor sells a stock position on a day when he sells at least some stock, and 0 if otherwise. The bottom panel reports the change in the disposition effect, as a function of financial attention. The disposition effect at each decile of attention is calculated as the average partial effect of a dummy variable, taking the value of 1 if the stock position was trading at a gain in the investors portfolio, and 0 if otherwise. Results are calculated for a subsample of clients, who only traded in equities throughout the sample period. Dotted lines represent 95% confidence intervals. Standard errors are clustered at the investor and stock level.

Figure 5: Financial attention and the disposition effect, excluding rebalancing decisions



The top panel of Figure 5 reports the average predicted probabilities of selling a winning or a losing stock position, as a function of an investor's financial attention, expressed in deciles. The probabilities are implied from the logistic regression described in Section 4, where the dependent variable takes the value of 1 if an investor sells a stock position on a day when he sells at least some stock, and 0 if otherwise. The bottom panel reports the change in the disposition effect, as a function of financial attention. The disposition effect at each decile of attention is calculated as the average partial effect of a dummy variable, taking the value of 1 if the stock position was trading at a gain in the investors portfolio, and 0 if otherwise. Results are calculated for a subsample, excluding observations that are possibly due to rebalancing efforts. Dotted lines represent 95% confidence intervals. Standard errors are clustered at the investor and stock level.

Figure 6: Financial attention and the disposition effect among market order sales



The top panel of Figure 6 reports the average predicted probabilities of selling a winning or a losing stock position, as a function of an investor's financial attention, expressed in deciles. The probabilities are implied from the logistic regression described in Section 4, where the dependent variable takes the value of 1 if an investor sells a stock position on a day when he sells at least some stock, and 0 if otherwise. The bottom panel reports the change in the disposition effect, as a function of financial attention. The disposition effect at each decile of attention is calculated as the average partial effect of a dummy variable, taking the value of 1 if the stock position was trading at a gain in the investors portfolio, and 0 if otherwise. Results are calculated for a subsample of observations, which are the result of a market sale order. Dotted lines represent 95% confidence intervals. Standard errors are clustered at the investor and stock level.

Figure 7: Individual vs shared accounts

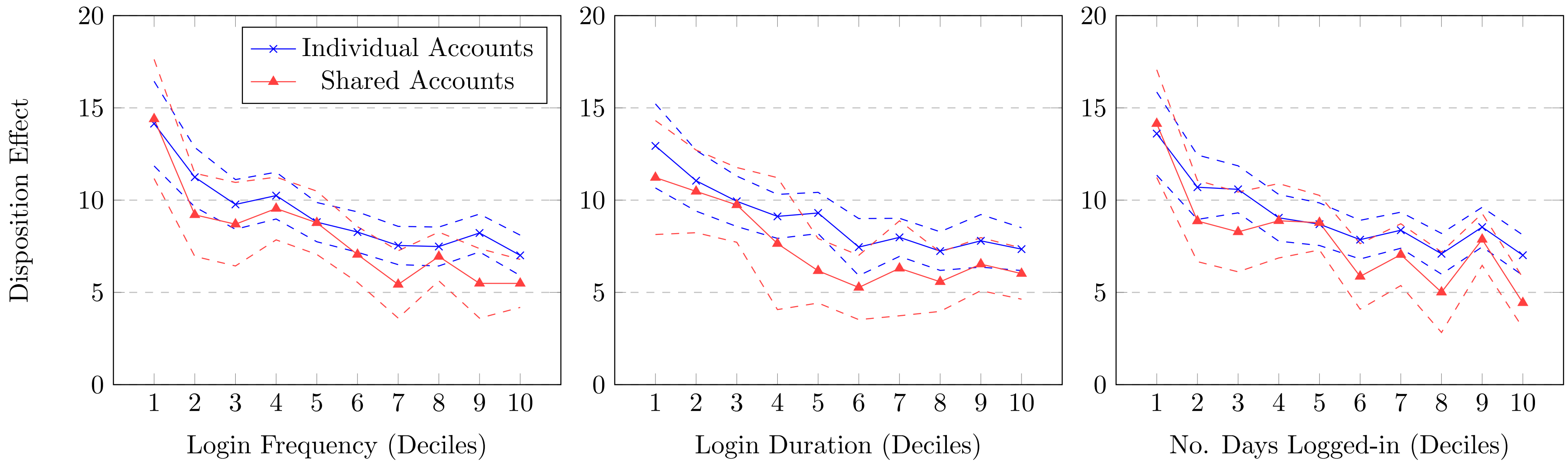


Figure 7 reports the disposition effect at each decile of attention, calculated as the average partial effect of a dummy variable, taking the value of 1 if the stock position was trading at a gain in the investors portfolio, and 0 if otherwise. The results are implied from the logistic regression described in Section 4, where the dependent variable takes the value of 1 if an investor sells a stock position on a day when he sells at least some stock, and 0 if otherwise. Results are calculated for subsamples of accounts held by an individual or accounts held by two clients (shared accounts). Attention deciles are determined conditional on the investors' portfolio monitoring behavior within each subsample. Dotted lines represent 95% confidence intervals. Standard errors are clustered at the investor and stock level.

Figure 8: Financial attention and the disposition effect across yearly subsamples

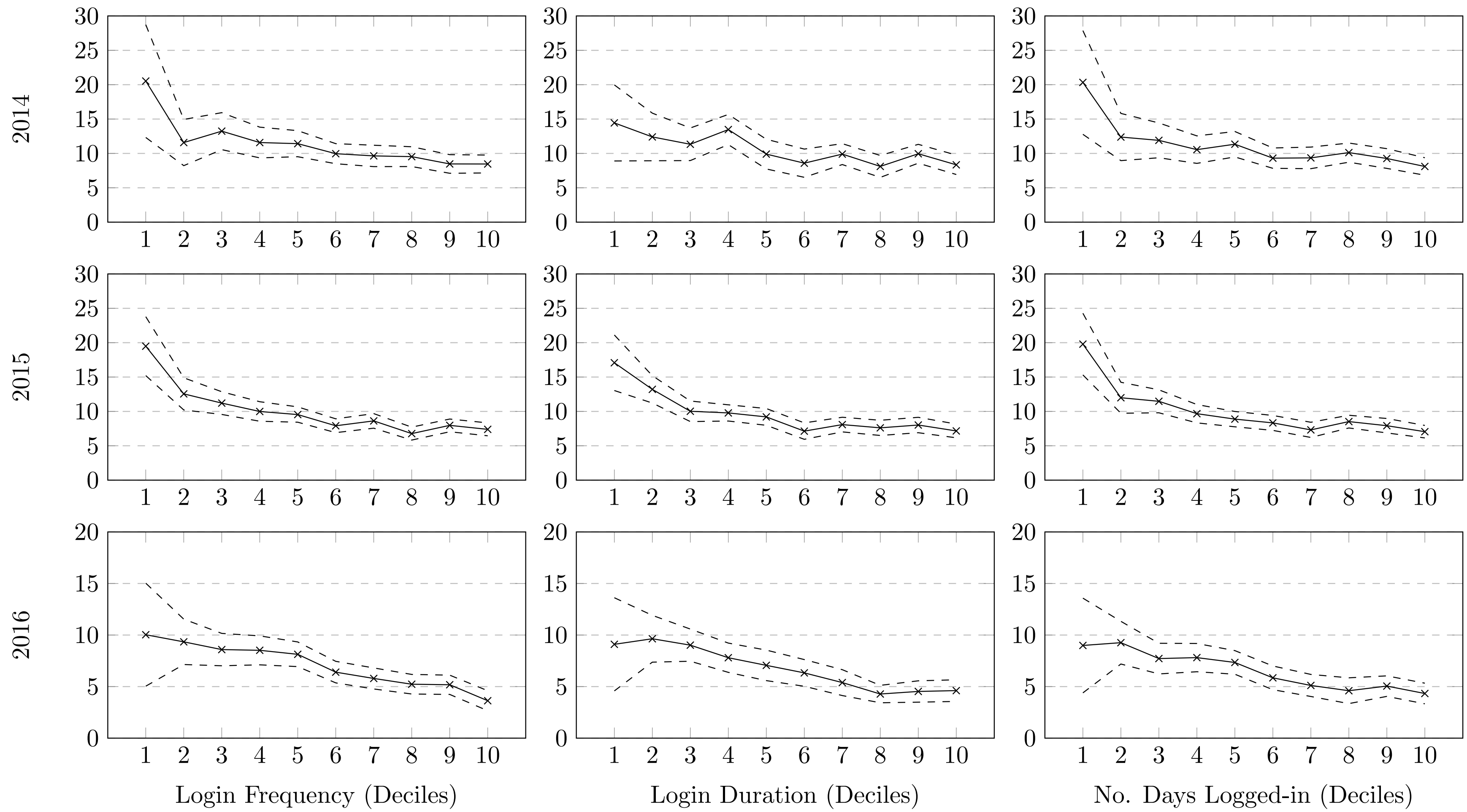


Figure 8 reports the disposition effect at each decile of attention, calculated as the average partial effect of a dummy variable, taking the value of 1 if the stock position was trading at a gain in the investors portfolio, and 0 if otherwise. The results are implied from the logistic regression described in Section 4, where the dependent variable takes the value of 1 if an investor sells a stock position on a day when he sells at least some stock, and 0 if otherwise. Results are calculated for subsamples of observations spanning each year, and where each attention decile is determined based upon investors' portfolio monitoring behavior in that year. Dotted lines represent 95% confidence intervals. Standard errors are clustered at the investor and stock level.

Figure 9: Sell probability, financial attention and return magnitude

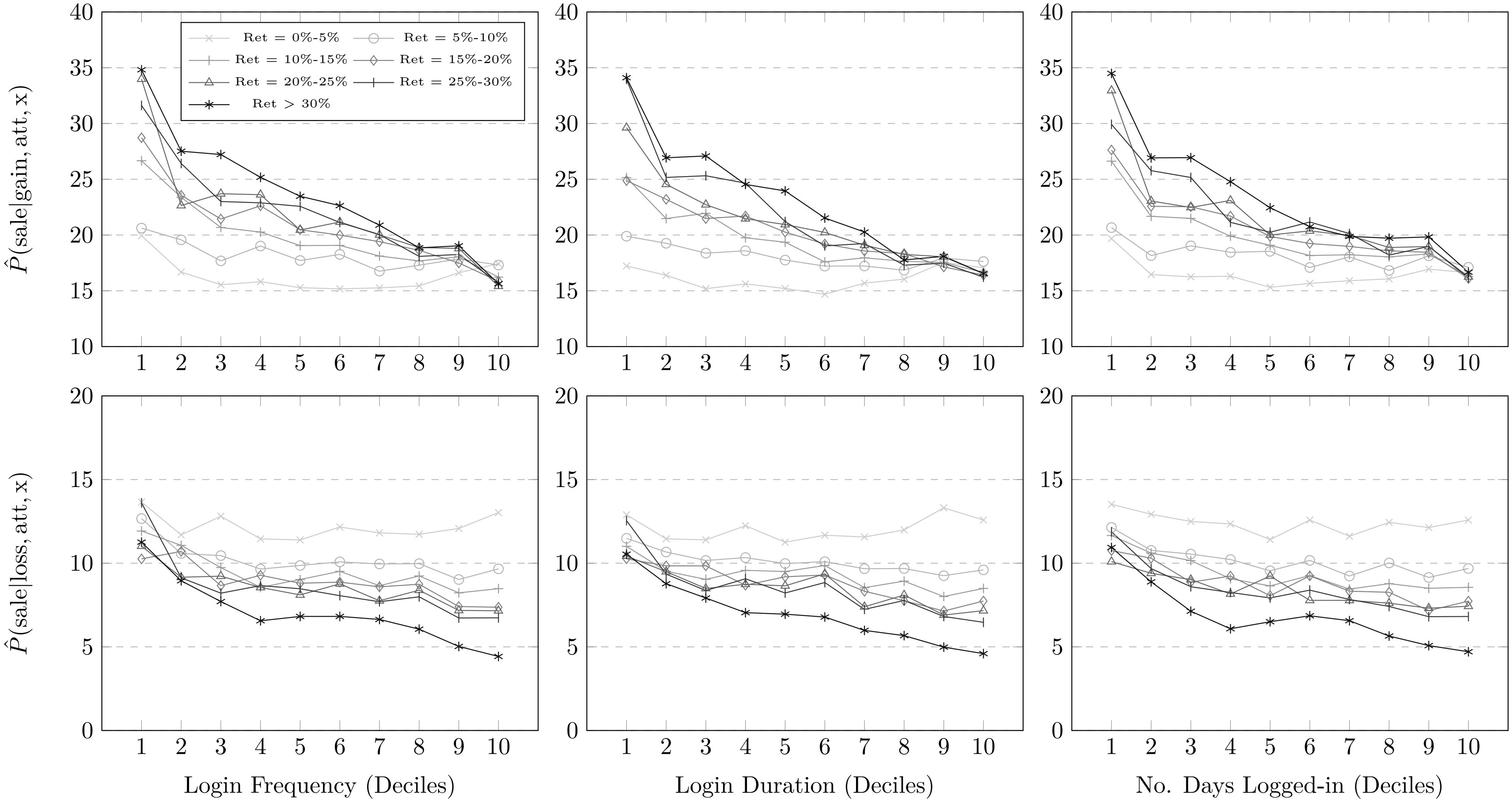


Figure 9 reports the average predicted probabilities of selling a stock position that is trading at a moderate or an extreme return in the investor's portfolio, as a function of an investor's financial attention, expressed in deciles. The average predicted probabilities are shown for subsamples of stocks trading in 5% return intervals and a return higher than 30%. The top panel reports the probabilities for a stock position that is trading at a profit, and the bottom panel for one that is trading at a loss. Standard errors are clustered at the investor and stock level.