Wide framing disposition effect: An empirical study*

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Abstract

We estimate the disposition effect for active traders in a large discount brokerage dataset containing US households' trading records between 1991 and 1996. We apply a *wide framing perspective,* focusing on portfolios rather than individual stocks. We find that the disposition effect varies inversely with the proportion of stocks trading at a gain in the portfolio, nearly vanishing when this proportion reaches 50%. This is driven by how the realisation of gains and losses depends on the percentage of gains in the account. The probability to realise a loss increases with the percentage of gains in the account. The relation between the probability of realising a gain and the percentage of gains in the bank account follows a U-shape. We also estimate the change in the disposition effect when an investor realises more than one stock on a trading day. We find when investors sell a stock, they are much more likely to also realise another stock on the same day. In particular, selling a loss increases an investor's propensity to sell a gain and vice versa. This key finding provides an explanation for the observed dependency of the disposition effect on the portfolio composition. We also propose several psychological explanations for our findings.

Keywords: Disposition Effect; Wide Framing; Portfolio Disposition Effect; Stock Market

JEL Codes: C55, D90, G40

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1 Introduction

Our work sheds new light on the disposition effect. The disposition effect is the tendency for investors to sell stocks that have increased in price since purchase at a faster rate than stocks that have decreased in price (Shefrin and Statman, 1985). It was first documented in a trading dataset by Odean (1998). Over twenty years later, the disposition effect has been studied empirically (Odean, 1998; Dhar and Zhu, 2006; Ben-David and Hirshleifer, 2012 amongst others), documented in the laboratory (for eg. Weber and Camerer, 1998; Frydman and Rangel, 2014; Song, 2016; Ploner, 2017) and explained by theoretical models (for eg. Barberis and Xiong, 2009; Kaustia, 2010; Hens and Vlcek, 2011; Henderson, 2012; Meng and Weng, 2018).

In the extant literature, the disposition effect has been considered in tandem with an assumption of narrow framing[1]. Narrow framing, in this context, is the tendency to treat investments separately at the individual stock level. Narrow framing has been linked to many empirical findings. For example, Barberis et al. (2006) argue that the widespread aversion to a 50:50 bet to win $110 or lose $100 is evidence not only of loss aversion but of narrow framing, and such framing is frequently invoked in applications of prospect theory.

We ask the question whether a wide framing perspective might help our understanding of the disposition effect. In a wide framing perspective, investment decisions may depend on the overall portfolio composition. If investors were really adopting narrow framing, their decisions should not be influenced by the composition of the portfolio. It is worth noting that wide framing, in the sense of considering the entire portfolio when taking decisions, is a standard assumption for classical finance models and it has already been treated by behavioural empirical researchers (Grinblatt and Keloharju, 2001; Hartzmark, 2015). We focus on a very specific implication of wide framing, the possibility that the percentage of stocks trading at a gain or loss in the portfolio, influences selling decisions.

We study the well established Large Discount Brokerage (LDB) dataset, which contains trading activities of individual traders in the USA from 1991 to 1996 (Barber and Odean, 2013 for a review). We focus our attention on the 5% most active traders (Richards and Willows, 2018), who account for around 35% of the trades. We do so, in order to look at bank accounts where several stocks are traded at the same time.

Our main finding concerns how the disposition effect varies as the number of stocks

[1]Whilst the term "narrow framing" was first used by Kahneman and Lovallo (1993), the more general concept of "decision framing" dates back to Tversky and Kahneman (1981). It is well known that decision makers take different decisions if they focus on each of them in isolation from the others versus taking into account more than one at the same time (Read et al., 1999).

trading at a gain or at a loss in a bank account changes[2]. We find that the disposition effect is much weaker when the percentage of stocks trading at a gain in the account of an investor is higher. Conversely, we observe the disposition effect is strongest when there is a low percentage of stocks trading at a gain in the investor's account. Investors tend to sell one of their few stocks at a gain, rather than one of their many stocks at a loss, in this case. A comparison of the relative magnitudes of the propensities to realise gains and losses, which together drive the disposition effect, shows the propensity to realise a gain varies far more than that to realise a loss. This effect holds even after controlling for the overall portfolio return.

In addition, we analyse the impact that the realisation of other gains or losses in an account has on the propensity to sell a stock, and on the disposition effect itself. Investors' propensity to realise a stock is dramatically increased if they are realising another stock on the same day. Baseline propensities to sell on days where other trades do not take place are around 1%-2%. However, propensities to sell a stock at a gain (loss) rise to around 50% on days where another stock in the account is sold at a gain (loss), and to around 10% when another stock is sold at a loss (gain). This result can help to explain why the disposition effect varies with portfolio composition. Take a day when an investor has a low proportion of stocks trading at a gain in their account. Since investors have a preference for realising a gain and a loss on the same day, the propensity to realise a gain will be relatively high, whilst the propensity to realise a loss will be relatively low, giving a strong disposition effect. As the proportion of stocks trading at a gain is increased, the propensity to realise a gain will drop, and the propensity to realise a loss will rise, leading to a decrease in the strength of the disposition effect. This is indeed consistent with our main finding that the disposition effect is much weaker when the percentage of stocks trading at a gain in the account of an investor is higher. Apart from this mechanism, which we document, we also explore several possible economic and psychological explanations for our main finding.

To sum up, whilst it has been documented that the magnitude of the disposition effect can differ across types of investors (Grinblatt and Keloharju, 2001; Dhar and Zhu, 2006), and the propensity to realise the stocks is influenced by the portfolio composition (Grinblatt and Keloharju, 2001; Hartzmark, 2015), we find that the strength of the disposition effect changes at the individual level, within the same bank account, when we measure it for different account compositions. In particular, we show that in portfolios where the percentage of stocks at a gain is above 50%, the disposition effect is either not present or very weak.

The paper is organised as follows. In Section 2 we review the related literature. In Section 3 we describe the LDB data used and our models. Our results are given in Section 4,

[2]In our analysis, each bank account is treated separately and investors may hold more than one account.

we discuss some potential explanations in Section 5 and Section 6 gives some concluding remarks.

2 Literature Review

There is a large empirical literature documenting the disposition effect under the implicit assumption of narrow framing at the stock level. Odean (1998) examines trading records for 10,000 accounts at a large US discount brokerage for the period 1987–1993. He compares the rate at which investors sell winners (realised gains) and losers (realised losses) and compares the realization of gains and losses to the opportunities to sell winners and losers. He finds that, relative to opportunities, investors realise their gains at about a 50% higher rate than their losses and that this difference is not explained by informed trading, a rational belief in mean reversion, transactions costs, or rebalancing. Odean (1999) observes that, in the majority of cases, winning stocks go on to earn positive returns after being sold and losing stocks continue making poor returns. Hence, the disposition effect contradicts profit maximization. Several studies also investigate the presence of the disposition effect among different types of investors. It has been shown that the disposition effect is stronger among individuals and institutional investors (Barber et al., 2007). Dhar and Zhu (2006) show that wealthier individuals, individuals employed in professional occupations and frequent traders exhibit a lower disposition effect.

One explanation of the disposition effect is framed in terms of Prospect Theory (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992) where each of the S-shaped utility, loss aversion, and use of a reference point play a role (Barberis and Xiong, 2009; Henderson, 2012; Ingersoll and Jin, 2013). Kőszegi and Rabin (2006) and Kőszegi and Rabin (2007) propose that the reference point does not need to be fixed exogenously but can be determined endogenously based on rational expectations about future outcomes.

In an experimental setting, Arkes et al. (2008) show that investors tend to update their reference point upwards after a good outcome realises and downwards after a bad outcome realises. They find that the magnitude of reference point adaptation following a price change is not as large as the magnitude of price change itself, and any adaptation is asymmetric with a greater adjustment after good, than after bad outcomes. Several theoretical models suggest an important role for the reference point in explaining the disposition effect (for eg. Meng and Weng, 2018; Andrikogiannopoulou and Papakonstantinou, 2020).

Our work is focused on the importance of two factors: the composition of the portfolio and days when multiple stocks are realised. We investigate how they shape the propensity of frequent traders (5% most active) to sell a stock for a gain and for a loss. It is known that traders who execute more trades on the same day are less disposition effect prone (Kumar and Lim, 2008). Other works have taken into account the composition of the portfolio in the decision to realise stocks. Two notable examples are Grinblatt and Keloharju (2001), who take into account several variables in estimating the decision to realise a stock and among them the value of the portfolio and, more recently, Hartzmark (2015), who finds that investors have a higher propensity to realise the stock with the highest and the one with the lowest return in their portfolio, with respect to the others.

Recent works that are closest to ours are those of Sakaguchi et al. (2019) and An et al. (2019). Sakaguchi et al. (2019) analyse data from a laboratory experiment and two datasets from trading activity: the LDB dataset and a dataset of UK based investors from the 2010's. They estimate how the disposition effect changes as the number of stocks in the gain and loss domain in a given portfolio changes. In particular in the LDB and UK datasets, they find that the disposition effect is highest when there is only one stock trading at a loss and two or more stocks trading at a gain in a portfolio. The effect decreases with the number of stocks at a gain. When there is one stock at a gain and two or more stocks trading at a loss in a portfolio, the propensity to realise gains is lower than the propensity to realise losses. The main conclusion of Sakaguchi et al. (2019) is that the probability that a stock in the gain domain is sold is relatively constant across portfolios with different numbers of stocks in gain and in loss. However, they reach this conclusion after restricting the analysis to the set of sell-days when exactly one stock was sold. This influences by construction the measure of the disposition effect they obtain. In contrast, we show that investors have a strong preference for realizing more than one stock on the same trading day. Sakaguchi et al. (2019) cannot capture this effect.

An et al. (2019) estimate the disposition effect separately for portfolios which are trading at a gain or at a loss. They observe that the disposition effect is weaker when the portfolio as a whole is trading at a gain (has positive paper return) than when it is trading at a loss.[3] There are some important differences in our analyses. An et al. (2019) use the entire dataset of investors regardless of whether they are frequent or infrequent traders. Furthermore, An et al. (2019) focus on the performance of the portfolio as a whole, disregarding the actual imbalance between the number of stocks which are trading at a gain or at a loss. Our analysis shows this is important. We estimate the propensity to sell gains and losses for various levels of the percentage of stocks trading at a gain. These estimates are used to

[3] An et al. (2019) propose two possible explanations for their findings. The first possible explanation is related to mental accounting. When the portfolio as whole is trading at a gain investors are more likely to realise losses since they frame the sale of the losing stock as the sale of a share of the entire portfolio, hence a share of an asset which is trading at a gain. Their second explanation builds on Barberis and Xiong (2009), extending realization utility to paper gains and losses.

compute the disposition effect across varying compositions of portfolio.

3 Data and Methodology

The dataset that will be used to estimate the models below consists of the trading records for investors in the U.S. during the period from January 1991 to November 1996. The data were obtained by Odean from a large discount brokerage and are commonly referred to in the literature as the LDB dataset. A detailed description of the dataset can be found in Barber and Odean (2000). Price data for the stocks traded by the sample of investors were obtained from the CRSP (Centre for Research in Security Prices) of WRDS (Wharton Research Data Services). We exclude those stocks for which we were not able to recover price information. We remove investment records if at least one of the entries has negative commissions (which may indicate that the transaction was reversed by the broker). We remove investments that include short-sale transactions or that have positions that were opened before the starting point of our dataset.

We define as the starting point of an investment episode the first time an investor buys a stock, or any time she buys it without the stock being present in the bank account at that time. The selling date is the first sale date after a buy date, and represents the end point of an investment episode (Shapira and Venezia, 2001; Chiyachantana and Yang, 2013; Brettschneider and Burgess, 2017). We define an episode as all the stock-day information between a buy and a sell date. An episode is classified as a gain if the selling price is higher than (or equal to) the buy price, and classified as a loss otherwise.

We restrict our attention to approximately 5% of the bank accounts present in the dataset which account for more than 35% of investment episodes. This corresponds to bank accounts where 24 or more investment episodes were started. After restricting our attention to this subset of accounts, we censor investment episodes. We only include investment episodes where the selling date is no later than 400 days from the buying date, in line with Brettschneider and Burgess (2017). We do this in order to capture active decisions of traders rather than buy and hold decisions. After imposing this condition and deleting (a very small number of) trades for which we suspected data were misreported, we retain bank accounts where at least 20 trading episodes were completed. This resulted in 114,441 episodes from 2,783 bank accounts (Table 1).

In this section, we give a preliminary estimate of the disposition effect that takes into account the percentage of stocks at a gain in the account. In other words, we calculate a disposition effect stratified by the current percentage of a stocks at a gain in the account. For each bank account, on each day when at least one stock is realised, we calculate PGR

Table 1: **Summary Statistics of the sample.**

Bank accounts	2,783
Episodes	114,441
Episodes per bank account (mean)	41.12
Episodes per bank account (median)	31
Percentage of gains in an account-stock-day (mean)	0.48
Percentage of gains in an account-stock-day (median)	0.50
Number of stocks in an account-stock-day (mean)	8.35
Number of stocks in an account-stock-day (median)	5

and PLR following Odean (1998), where PGR is the Proportion of Gains Realised

$$\text{PGR} = \frac{\text{Realised Gains}}{\text{Realised Gains} + \text{Paper Gains}}$$

and PLR is the Proportion of Losses Realised

$$\text{PLR} = \frac{\text{Realised Losses}}{\text{Realised Losses} + \text{Paper Losses}}.$$

For each such day, we calculate the disposition effect following Dhar and Zhu (2006) as the difference between PGR and PLR. We also determine the percentage of stocks which are trading at a gain in the bank account and classify it in one of four bins (0 to 0.25; 0.25 to 0.5; 0.5 to 0.75 and 0.75 to 1). Then, we calculate the disposition effect at account-gain-bin level. That is, we average the disposition effect, at account level, over all days in which a given account falls in a given gain bin. Finally, we calculate the disposition effect at the gain-bin level. That means, we average the disposition effect at account-gain-bin level over accounts, to obtain the average disposition effect for each of the four bins[4]. The output is shown in Table 2. We observe striking differences in the magnitude of the disposition effect, depending on the percentage of stocks at a gain. The disposition effect is ten times larger in bin 1 than in bin 4[5]. Finally, note we also estimate an average disposition effect of 0.15.[6]

[4]A more detailed derivation of the DE can be found in the Appendix A.1, together with a numerical example.

[5]A Jonckheere-Terpstra test confirms that the DE decreases when the percentage of gains increases ($p<0.001$, H_1 that the disposition effect is decreasing from bin 1 to bin 4, where bin 1 corresponds to gain percentage between 0 and 0.25 and bin 4 to gain percentage between 0.75 to 1).

[6]This is lower than the 0.21 estimated by Dhar and Zhu (2006) who used the entire sample of investors and found that the disposition effect decreases as the frequency of trading increases. Since we focus on a sample of frequent traders, it was to be expected that the disposition effect is lower than the estimate in Dhar and Zhu (2006). Plus, notice that here we only calculate the DE on selling days, while we will calculate it for all trading days in Section 4.

Table 2: **Disposition effect stratified by percentage of stocks at a gain.** Disposition effect (DE) was calculated in three steps. First, disposition effect was estimated as PGR-PLR within each account on any day where at least one stock is realised. Then, these account-day disposition effects were averaged over days, stratified by the percentage of stocks at gain within each account. Here, four equally sized bins were used for the stratification. Finally, within each of these gain bins, averages over accounts were taken resulting in the four quantities listed below. A Jonckheere trend test (also known as Jonckheere-Terpstra test) confirms that the disposition effect decreases with increasing percentage of stocks at a gain ($P < 0.001$).

Perc. of gains	DE
[0.00, 0.25]	0.20
(0.25 ,0.50]	0.18
(0.50, 0.75]	0.08
(0.75, 1.00]	0.02

We can go beyond these preliminary estimates by performing regression analyses to estimate the disposition effect. The unit of observation is an account-stock-day triple (An et al., 2019). The dependent variable takes the value of 1 for sell days and 0 otherwise. While earlier literature used logit models (Grinblatt and Keloharju, 2001; Birru, 2015), more recent works employ a linear probability model (Chang et al., 2016; An et al., 2019). In all these cases, the effects that covariates have on the different propensities to sell are mediated by an interaction with a dummy variable which indicates if a stock is trading at a gain on a specific day. Ai and Norton (2003) highlighted that the magnitude of the interaction effect in logit models does not equal the marginal effect of the interaction term and it can be of opposite sign. A linear probability model guarantees easier interpretation of marginal effects and a robust identification of the coefficients. Furthermore, a linear approximation is sufficient, because the range of the probabilities is small and the sample size is large enough to guarantee approximately normal residuals. We model heteroskedasticity by fitting robust clustered standard errors at bank account level (Arellano, 1987). We estimate three linear probability models. The first model focuses on the impact of the percentage of stocks at a gain in the account. It takes the following form:

$$y_{ijt} = \alpha + G_{ijt}\beta + D_{kijt}\delta_k + G_{ijt} \times D_{kijt}\gamma_k + \epsilon_{ijt} \tag{1}$$

where i refers to the bank account, j refers to the investment episode and t to the day. Then:

Response: y_{ijt} is equal to 1 on those days t when the stock traded in episode j in account i is sold, and 0 otherwise.

Gain: G_{ijt} is a dummy equal to 1 on those days t when the stock traded in episode j in account i is trading at a gain (closing price is higher than (or equal to) purchase price[7]).

Sextile percentage of gains: D_{kijt} with k $\in$ {1,2,4,5,6} are five dummies we obtained in the following way:

- Consider all days when more than one investment episode was open in a given bank account.
- Calculate the percentage of stocks trading at a gain[8] (excluding the stock for which we are estimating the probability of selling, traded in episode j).
- Split the percentage of stocks at a gain into six sextiles (based on the distribution of the percentage of gains at account-stock-day level). Observed sextile are marked by the following cut-points (these are the upper limits of each category): 0.10, 0.33, 0.50, 0.61, 0.80, 1.
- Each dummy D_k refers to one of the sextiles, imposing the third one as the reference category.

ϵ is the error term. The intercept α measures the probability of selling a loss when the percentage of gains in the account is in the third sextile. β captures the difference in the propensity to sell a gain and the propensity to sell a loss for the third sextile, the disposition effect. δ_k captures the difference in the propensity to realise a loss when the account is in the k^{th} sextile with respect to the third sextile. The sum of β and δ_k measures the disposition effect for the k^{th} sextile. We obtain out of sample prediction for the probability to sell a gain and the probability to sell a loss, for any of the gain percentage sextiles. The disposition effect is then calculated as the ratio between the probability of selling a gain and the probability of selling a loss, following the widely used definition of Odean (1998).

The second and third models focus on the impact of realizations of stocks other than the one in question, distinguishing gains and losses. They take the following form:

$$y_{ijt} = \alpha + G_{ijt}\beta + I_{ijt}\delta + G_{ijt} \times I_{ijt}\gamma + \epsilon_{ijt} \tag{2}$$

In the second (third) model, I_{ijt} is a dummy equal to 1 if, on a given day t, at least one stock at a gain (loss), (apart from the stock traded in episode j) is realised in the bank

[7]On the selling day it is 1 if selling price is higher or equal to the purchase price.

[8]The percentage of gains is considered at the beginning of the trading day. So if a position is sold on day t, that contributes to our definition of the percentage of gains on day t. This reflects the idea that a selling decision on day t is influenced by what was present at the start of the day t in the account.

account i. β captures the disposition effect and δ the difference in the propensity to realise a loss when a gain (a loss) is realised in the account, apart from the stock traded in episode j. The sum of β and γ captures the disposition effect on days when a stock at a gain (loss), apart from the stock traded in episode j, is realised in bank account i. ϵ is the error term.

For each model described, we fit three regressions. First, the baseline model as defined in (1) and (2). Second, a Fixed Effects OLS regression with fixed effects at the account level. We do this to control for the propensity to sell a stock that is unique to each account. The propensity to sell may be linked to trading frequency, size or other account specific characteristics. Third, a Fixed Effects OLS regression with fixed effects at the account level and control variables for month and year (and respective interactions with the gain dummy). This is to control for differences in the propensity to sell due to time.

4 Results

4.1 Variation in the Disposition Effect with Portfolio Composition

Our key finding is that from a wide framing perspective, the disposition effect vanishes for some portfolio compositions. Our first set of results are summarised in Table 3, which reports the estimation of model (1). From these estimates, we obtain out-of-sample predictions displayed in Figure 1 and summarised in Table 4. We will discuss these first. Table 4 reports propensities to sell for each sextile of the distribution of the percentage of stocks trading at a gain in an account day. For example, we can see that the propensity to sell when the percentage of gains is in the first sextile and the stock is trading at a gain (gain dummy equal to 1) is 2.7%. These propensities are presented graphically in the lower panel of Figure 1. The disposition effect, based on the relative propensities to sell, is also reported in Table 4, and in the upper panel of Figure 1.

From the top panel of Figure 1, we see that the disposition effect is largest when the percentage of stocks trading at a gain in the account is lowest. The observations in the lower panel of Figure 1 show that the spread between the propensity to realise a gain and the propensity to realise a loss is largest when the percentage of gains in the account is in the first sextile. In other words, investors tend to sell one of their few stocks at a gain, rather than one of the many they hold at a loss. Table 4 examines this in more detail by estimating the disposition effect for any sextile of the distribution of the percentage of gains in the account. It demonstrates that the disposition effect broadly decreases as the percentage of stocks trading at a gain increases. The disposition effect increases slightly from the fifth to the sixth sextile, but is quite close to one from the fourth sextile onwards, when the percentage of positions at a gain in the account is higher than 50%.

If we compare our estimates of the magnitude of the disposition effect to the estimate of 1.51 reported by Odean (1998), we see a pattern. Where the percentage of stocks at a gain is below the median of the distribution, the disposition effect is much larger in magnitude than Odean's. Conversely, where the percentage of stocks at a gain is above the median, we see the disposition effect is much smaller than Odean's, and indeed, close to one.

The lower panel of Figure 1 displays the relative magnitudes of the propensities to realise gains and losses, which together drive the disposition effect. Our first observation is that the propensity to realise a gain varies much more than the propensity to realise a loss, for any level of the percentage of stocks at a gain in the account. In particular, the propensity to realise a loss lies between 1.08% and 1.7%, whilst the propensity to realise a gain is between 1.3% and 2.7%. The reduction of the disposition effect we describe above, is largely driven by a reduction in the propensity to realise a gain as the percentage of stocks trading at a gain in the account increases.

Two technical observations arise from the more detailed analysis of the estimation of model (1) presented in Table 3. First, the effect of the percentage of stocks at a gain is not linear, hence stratifying by sextiles was appropriate. Second, estimates are fairly stable when we control for bank account and time fixed effects. The direction and magnitude of the effects are fairly stable across all specifications.

We have shown that investors are not prone to the disposition effect, when the overall situation of their portfolio is positive. Other authors have demonstrated considerable variation in estimates of the disposition effect for different types of investors. Grinblatt and Keloharju (2001) observed that the disposition effect is weaker for institutional and foreign investors than for domestic investors in Finland. Dhar and Zhu (2006) found that the disposition effect is weaker for more experienced investors. What we see is different. We observe that the disposition effect varies significantly as the account composition changes. Our finding that the disposition effect decreases as the percentage of stocks trading at a gain increases is almost counter-intuitive. When the number of paper gains is higher, the gap in the propensity to realise gains and losses is smaller. When times are good, the disposition effect becomes almost non-existent.

We emphasise that it is very important to focus on the propensity to realise a gain and the propensity to realise a loss separately, as we do (lower panel in Figure 1). We are not only interested in estimating changes in the disposition effect, but also in unraveling whether they are linked to the variation in the propensity to realise a gain or the propensity to realise a loss.

Table 3: **Sextile of gains regression.** Linear probability model (given in (1)) where the dependent variable takes the value of 1 for sale days and 0 for hold days. Each observation is at account-stock-day level. Gain dummy is equal to 1 on those days when the stock is trading at a gain. Sextiles of stocks trading at a gain are obtained as follows: we calculate the percentage of stocks trading at a gain (excluding the stock for which we are estimating the probability of selling) in a given account-day, we split it into sextiles. Observed sextile are marked by the following cut-points (these are the upper limits of each category): 0.10, 0.33, 0.50, 0.61, 0.80, 1. The third sextile is the reference category.

	(1)	(2)	(3)
Gain	0.00404***	0.00484***	0.00766***
	(0.000411)	(0.000498)	(0.000708)
Sextile percentage of gains (ref. Third)			
First	0.000998***	-0.00492***	-0.00530***
	(0.000302)	(0.000354)	(0.000353)
Second	-0.00139***	-0.00232***	-0.00235***
	(0.000296)	(0.000292)	(0.000294)
Fourth	-0.000406	0.00173***	0.00179***
	(0.000405)	(0.000373)	(0.000397)
Fifth	0.00115***	0.00249***	0.00258***
	(0.000260)	(0.000307)	(0.000304)
Sixth	0.00442***	0.00169***	0.00154***
	(0.000367)	(0.000370)	(0.000366)
Gain × Sextile percentage of gains (ref. Third)			
Gain × First	0.00989***	0.0110***	0.0112***
	(0.000587)	(0.000653)	(0.000654)
Gain × Second	0.00422***	0.00469***	0.00479***
	(0.000484)	(0.000522)	(0.000527)
Gain × Fourth	-0.00321***	-0.00376***	-0.00386***
	(0.000487)	(0.000512)	(0.000512)
Gain × Fifth	-0.00418***	-0.00471***	-0.00484***
	(0.000412)	(0.000438)	(0.000441)
Gain × Sixth	-0.00145**	-0.00144*	-0.00148*
	(0.000510)	(0.000574)	(0.000574)
Account FE	NO	YES	YES
Time FE	NO	NO	YES
N	6611755	6611755	6611755

Standard errors clustered at bank account level in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 1: **Disposition effect and sextile of gain percentages.** Out of sample predictions of the linear probability model (first column in Table 3) where the dependent variable takes the value of 1 for sale days and 0 for hold days (observations at account-stock-day level, clustered se at bank account level). Sextiles of stocks trading at a gain are obtained as follows: we calculate the percentage of stocks trading at a gain (excluding the stock for which we are estimating the probability of selling) in a given account-day, and split it into sextiles. Observed sextiles are marked by the following cut-points (these are the upper limits of each category): 0.10, 0.33, 0.50, 0.61, 0.80, 1. The third sextile is the reference category.
Top: Disposition effect (propensity to realise a gain divided by the propensity to realise a loss) for each level of the sextiles of the distribution of the percentage of gain stocks in the portfolio. Grey line line is drawn at 1 (no disposition effect).
Bottom: Probability of sale for gains and losses for each level of the sextiles of the distribution of the percentage of gain stocks in the portfolio.

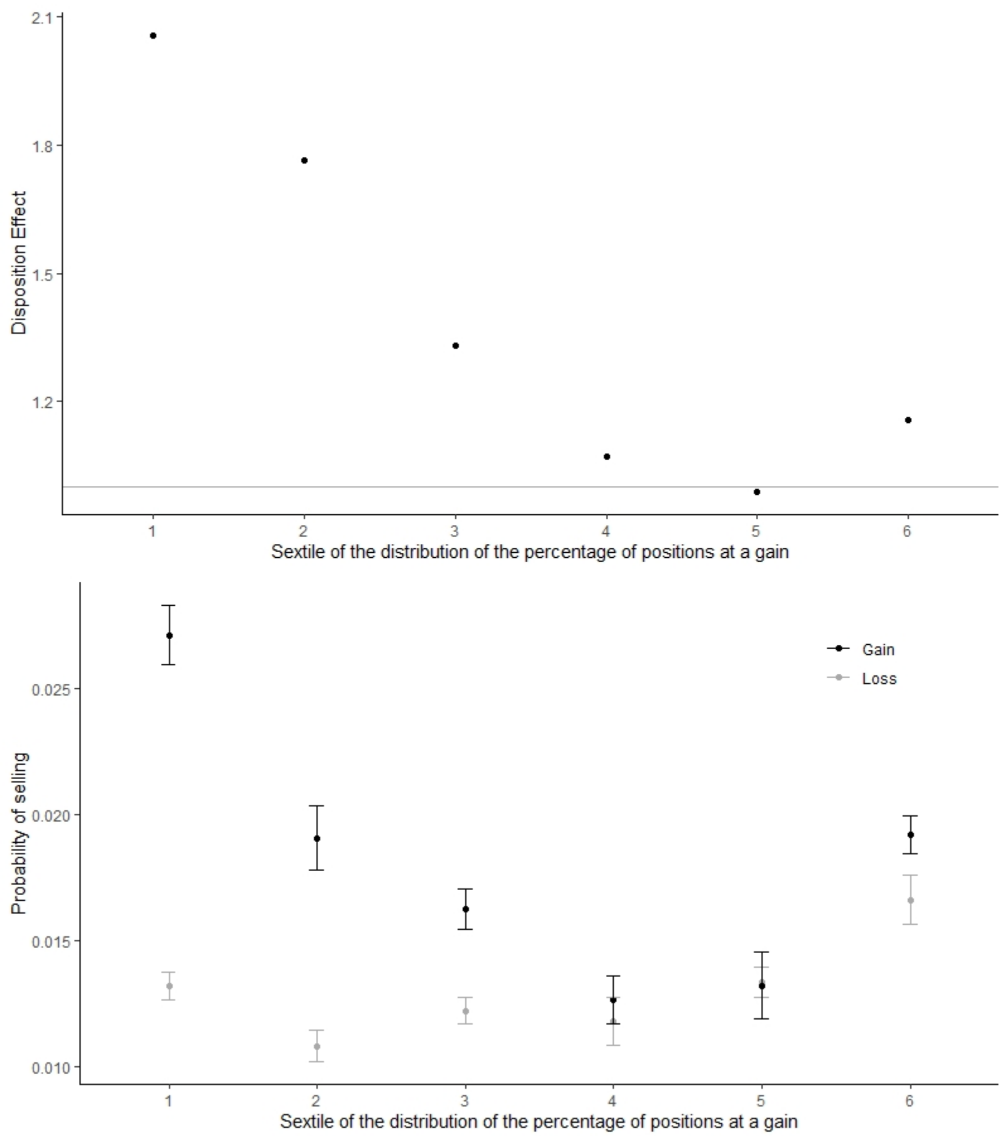


Table 4: **Disposition effect and sextile of gain percentages.** Estimated propensity to sell a gain and propensity to sell a loss for each sextile of the distribution of the percentage of stocks trading at a gain in an account-day. Disposition effect is calculated as the propensity to realise a gain divided by the propensity to realise a loss. Out of sample predictions of the linear probability model (first column in Table 3) where the dependent variable takes the value of 1 for sale days and 0 for hold days (observations at account-stock-day level, clustered se at bank account level). Sextiles of stocks trading at a gain are obtained as follows: we calculate the percentage of stocks trading at a gain (excluding the stock for which we are estimating the probability of selling) in a given account-day, and split it into sextiles. Observed sextiles are marked by the following cut-points (these are the upper limits of each category): 0.10, 0.33, 0.50, 0.61, 0.80, 1. The third sextile is the reference category.

Sextile of gain perc.	1	2	3	4	5	6
Propensity to sell gain	0.027	0.019	0.016	0.013	0.013	0.019
Propensity to sell loss	0.013	0.011	0.012	0.012	0.013	0.017
Disposition effect	2.056	1.775	1.332	1.071	0.990	1.156

4.2 The Impact of Realising Other Gains and Losses on the Propensity to Sell

In our second set of results, we investigate the impact that the realisation of *other gains or losses* in the account has on the propensity to realise a stock. Tables 5 and 7 report the results from the estimation of the linear probability models given in (2), where another loss or gain, respectively, is realised. From these estimates, we obtain out-of-sample predictions which are given in Tables 6 and 8, again, for the situation of another loss or gain, respectively.

Our first striking observation from Tables 6 and 8 is that investors have a high propensity to realise a stock if they are already realising another one, on a given day. In particular, the propensity to realise a loss is around 50% and the propensity to realise a gain is slightly higher than 10% on those days when another stock at a loss in the account is realised. The propensity to realise a loss is slightly smaller than 10% and the propensity to realise a gain is around 50% on those days when another stock at a gain in the account is sold. These magnitudes should be compared to baseline propensities to sell on days when another loss or gain is not realised, which are all in the region of 1%-1.7%.

Portfolio or bank account effects are very relevant. In particular, investors have a much higher propensity to realise another stock, once they have realised one. Furthermore, realising a gain makes it more likely to realise another gain than to realise a loss, and realising a loss makes it more likely to realise another loss than to realise a gain. We note that this effect cannot be captured using the framework adopted by Sakaguchi et al. (2019), since they restrict their analysis to sale days where only one stock is realised in a portfolio.

How might we explain the observed behavior? The notion of investor attention (Barber and Odean, 2008) may be relevant. If investors only pay attention to their portfolio on some days, then they also trade more on those days. Another possible explanation may be related to reference point updating, particularly for investors' realising multiple losses on the same day. Upon realising the sale of one stock trading just below it's reference point, an investor may update (downgrade) her reference points on other stocks trading at paper losses as well, leading to further sales. A further possibility is simply that since realising losses is difficult, it may be a defense mechanism to realise more than one at the same time. We return to this point in Section 5.

Whilst we demonstrate that the realisation of a gain (loss) significantly increases the propensity to realise another gain (loss), we also find that it increases the propensity to realise a loss (gain). For example, the propensity to sell a gain rises sixfold when a loss is realised on the same day (in the same account). One possible explanation for this is that once the investor realises a gain, she might find it more acceptable realising a loss at the same time for psychological or tax reasons. A psychological explanation relies on the idea that realising a loss might be more acceptable, once also a gain is realised since the two positions will balance each other out. Another possibility is that the investor is willing to realise a loss together with a gain to lower the tax she has to pay on the capital gain. However, apart from being interested in this finding per se, we are very much intruiged as to how this can help to shed light on why the disposition effect varies with portfolio composition.

If investors have a preference for realising a gain and a loss on the same day, on days when there is a low percentage of gains, the propensity to realise a gain will be high and the propensity to realise a loss will be low. This follows from the fact that, on those days, the investor can choose from a small pool of stocks at a gain, and a larger pool of losing stocks. PGR, as defined in Odean (1998) will have a very low denominator and PLR will have a high denominator. As the percentage of gains in the account increases, we expect the propensity to realise a loss to increase, and the propensity to realise a gain to decrease. This describes well the pattern we observe in Figure 1[9] and leads the disposition effect to decrease as the percentage of stocks at a gain increases. Hence, the finding that investors tend to realise more than one stock on a given day, contributes to partially explain the mechanism which leads the disposition effect to change with the account composition.

The fact that the realisation of a gain (loss) has a dramatic impact on the propensity to realise another gain (loss) does not affect this explanation. Let's focus on the case where

[9]The probability of realising a loss increases as the percentage of gains increases, while the probability of realising a gain follows a U-shape. It is lower in sextile 6 than in sextile 1 but it does reach the minimum in sextile 4. We are not suggesting that preference for realising multiple stocks on the same day alone leads to the variation in the disposition effect that we observe, but it potentially contributes to it.

the percentage of gains is high. We know that realising a gain will increase the probability of realising another gain, and will also increase the probability of realising a loss, albeit to a lesser extent. Hence, there will be variation in the disposition effect due to changes in both PGR and PLR. However, since the denominator of PGR is high, the marginal (increasing) contribution that any realisation of gains has on the disposition effect, will be less than the marginal (decreasing) contribution that any loss has on the disposition effect, since the denominator of PLR is low.

Table 5: **Other loss indicator regression.** Linear probability model (given in (2)) where the dependent variable takes the value of 1 for sale days and 0 for hold days. Each observation is at account-stock-day level. Gain dummy is equal to 1 on those days when the stock is trading at a gain. Other loss realised indicator is a dummy which takes the value of 1 if, on a given account-day, a stock at a loss is realised (other than the stock whose propensity is being estimated).

	(1)	(2)	(3)
Gain dummy	0.00701***	0.00876***	0.0107***
	(0.000328)	(0.000416)	(0.000642)
Other loss realised indicator	0.488***	0.487***	0.486***
	(0.0291)	(0.0276)	(0.0275)
Gain dummy × Other loss realised indicator	-0.399***	-0.399***	-0.399***
	(0.0273)	(0.0263)	(0.0263)
Account FE	NO	YES	YES
Time FE	NO	NO	YES
N	7133537	7133537	7133537

Standard errors clustered at bank account level in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: **Disposition Effect and other loss indicator.** Disposition effect when a loss is realised in the account on a given day or not. Disposition Effect is calculated as the propensity to realise a gain divided by the propensity to realise a loss. Out of sample predictions of a linear probability model (first column of Table 5) where the dependent variable takes the value of 1 for sale days and 0 for hold days (obervations at account-stock-day level). Other loss realised refers to those day when, in a given account, a stock at a loss is realised (other than the stock whose propensity is being estimated).

Propensity to sell gain	Propensity to sell loss	Other loss realised	Disposition Effect
0.017	0.010	NO	1.717
0.105	0.497	YES	0.212

Table 7: **Other gain indicator regression.** Linear probability model (given in (2)) where the dependent variable takes the value of 1 for sale days and 0 for hold days. Each observation is at account-stock-day level. Gain dummy is equal to 1 on those days when the stock is trading at a gain. Other gain realised indicator is a dummy which takes the value of 1 if, on a given account-day, a stock at a gain is realised (other than the stock whose propensity is being estimated).

	(1)	(2)	(3)
Gain dummy	0.00358***	0.00486***	0.00640***
	(0.000294)	(0.000349)	(0.000556)
Other gain realised indicator	0.0762***	0.0738***	0.0735***
	(0.00317)	(0.00306)	(0.00307)
Gain dummy × Other gain realised indicator	0.409***	0.407***	0.407***
	(0.0296)	(0.0287)	(0.0286)
Account FE	NO	YES	YES
Time FE	NO	NO	YES
N	7133537	7133537	7133537

Standard errors clustered at bank account level in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8: **Disposition Effect and other gain indicator.** Disposition effect when a gain is realised in the account on a given day or not. Disposition Effect is calculated as the propensity to realise a gain divided by the propensity to realise a loss. Out of sample predictions of a linear probability model (first column of Table 7) where the dependent variable takes the value of 1 for sale days and 0 for hold days (observations at account-stock-day level). Other gain realised refers to those day when, in a given account, a stock at a gain is realised (other than the stock whose propensity is being estimated).

Propensity to sell gain	Propensity to sell loss	Other gain realised	Disposition Effect
0.015	0.011	NO	1.319
0.500	0.087	YES	5.716

4.3 Wide framing disposition for positive and negative portfolios

In this section we perform additional robustness tests, taking into account the return of the entire portfolio, to address the possibility that there may be a "wealth effect" at work. Also, the magnitude of portfolio return (be it positive or negative) may play a role for tax considerations. If, for example, the portfolio contains mainly (large) paper gains, the investor might find it worthwhile realising some losses in order to offset taxes coming from the future gain realisations. Or, she might find it worthwhile realising some gains when she mainly has losses since she knows she will probably be able to offset the taxes coming from those gains by selling one of the many losses in the future.

To address these concerns, we consider if the overall paper return of the bank account is positive or negative. The overall account return is calculated as the total dollar gains/losses across all stocks held in the account on day t, divided by the sum of the total purchase costs of those stocks.

In Table 9 we control for a dummy which takes the value of 1 on any day the portfolio return is (weakly) positive. To aid comparability with the analysis reported in Table 3 we reproduce the first column of Table 3 in the first column of Table 9. We can see that after controlling for the direction of the portfolio return, our main conclusion still holds. In particular, the coefficients for the interactions of the Gain dummy with the sextiles of the percentage of gains are extremely stable across the several specifications. Those are our coefficients of interest since, as we explained in Section 3, they capture the magnitude of the disposition effect in the different sextile categories. We control for account and time fixed effects as before, and in column 5 of Table 9 we also look at the interaction of the Gain dummy and the positive portfolio dummy and see that this is positive and significant. This means that the disposition effect is a bit stronger, overall, when the portfolio is at a paper gain.

The fact that our main conclusion holds is visualised very clearly by looking at Figure 2. It plots the predicted disposition effect for any gain percentage sextile, calculated when the account is at a paper loss or gain. We can see that the pattern we observed in Figure 1 is perfectly replicated in both cases. If wealth effects were having any influence on our findings, we would have expected this to be reflected in these estimates.

In Appendix A.2 we perform some additional robustness checks. First, we take into account the magnitude of the portfolio return. Hence, we go beyond the simple fact that it is positive or negative and we repeat our estimates, whilst controlling for the magnitude of the positive or negative portfolio return. Second, we repeat our main estimate using a proportional hazard model (Cox, 1972; Moore, 2016). Survival analysis models are widely used in medical research and they are relatively popular in demography and labour economics. They

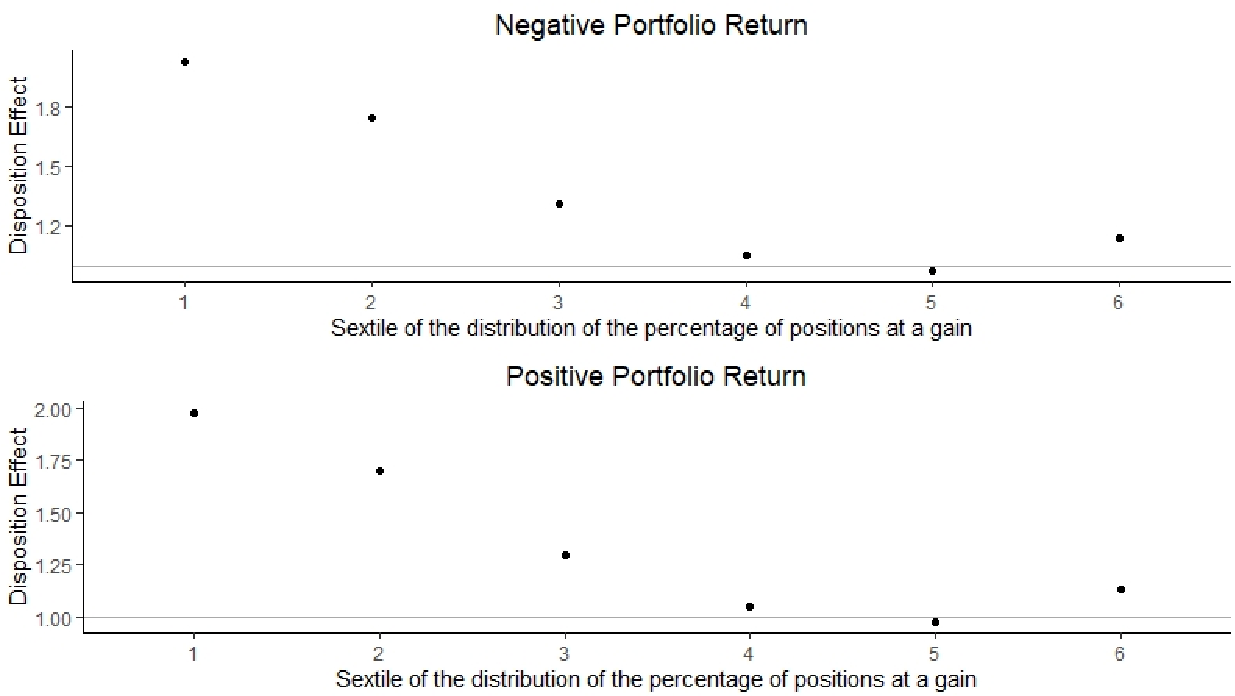
Table 9: **Positive/negative portfolio regression.** Linear probability model where the dependent variable takes the value of 1 for sale days and 0 for hold days. Each observation is at account-stock-day level. Gain dummy is equal to 1 on those days when the stock is trading at a gain. Sextiles of stocks trading at a gain are obtained as follows: we calculate the percentage of stocks trading at a gain (excluding the stock for which we are estimating the probability of selling) in a given account-day, we split it into sextiles. Observed sextile are marked by the following cut-points (these are the upper limits of each category): 0.10, 0.33, 0.50, 0.61, 0.80, 1. The third sextile is the reference category. Positive portfolio return is a dummy which is equal to 1 if the overall return of the bank account is greater or equal than 0. Portfolio return is calculated as the total dollar gains/losses across all stocks held by an investor on day t, divided by the total purchase costs of these stocks.

	(1)	(2)	(3)	(4)	(5)
Gain	0.00404***	0.00376***	0.00407***	0.00686***	0.00339***
	(0.000411)	(0.000446)	(0.000483)	(0.000689)	(0.000558)
Sextile percentage of gains (ref. Third)					
First	0.000998***	0.00117***	-0.00445***	-0.00482***	-0.00462***
	(0.000302)	(0.000305)	(0.000359)	(0.000359)	(0.000359)
Second	-0.00139***	-0.00127***	-0.00200***	-0.00202***	-0.00214***
	(0.000296)	(0.000291)	(0.000292)	(0.000294)	(0.000284)
Fourth	-0.000406	-0.000596	0.00120**	0.00125**	0.00140***
	(0.000405)	(0.000410)	(0.000376)	(0.000397)	(0.000367)
Fifth	0.00115***	0.000854**	0.00166***	0.00174***	0.00200***
	(0.000260)	(0.000272)	(0.000303)	(0.000299)	(0.000291)
Sixth	0.00442***	0.00414***	0.000927*	0.000756*	0.00127***
	(0.000367)	(0.000370)	(0.000369)	(0.000365)	(0.000357)
Gain × Sextile percentage of gains (ref. Third)					
Gain × First	0.00989***	0.00987***	0.0110***	0.0112***	0.0114***
	(0.000587)	(0.000587)	(0.000654)	(0.000654)	(0.000656)
Gain × Second	0.00422***	0.00429***	0.00490***	0.00500***	0.00524***
	(0.000484)	(0.000480)	(0.000524)	(0.000529)	(0.000504)
Gain × Fourth	-0.00321***	-0.00314***	-0.00356***	-0.00366***	-0.00391***
	(0.000487)	(0.000488)	(0.000510)	(0.000508)	(0.000502)
Gain × Fifth	-0.00418***	-0.00410***	-0.00449***	-0.00461***	-0.00507***
	(0.000412)	(0.000417)	(0.000435)	(0.000437)	(0.000420)
Gain × Sixth	-0.00145**	-0.00146**	-0.00147*	-0.00151**	-0.00210***
	(0.000510)	(0.000508)	(0.000571)	(0.000572)	(0.000552)
Positive portfolio return		0.000751**	0.00218***	0.00226***	0.00131***
		(0.000253)	(0.000230)	(0.000240)	(0.000283)
Gain × Positive portfolio return					0.00165***
					(0.000390)
Account FE	NO	NO	YES	YES	YES
Time FE	NO	NO	NO	YES	NO
N	6611755	6611755	6611755	6611755	6611755

Standard errors clustered at bank account level in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 2: **Disposition effect and sextile of gain percentages.** Out of sample predictions of the linear probability model (second column in Table 9) where the dependent variable takes the value of 1 for sale days and 0 for hold days (observations at account-stock-day level, clustered se at bank account level). Sextiles of stocks trading at a gain are obtained as follows: we calculate the percentage of stocks trading at a gain (excluding the stock for which we are estimating the probability of selling) in a given account-day, and split it into sextiles. Observed sextiles are marked by the following cut-points (these are the upper limits of each category): 0.10, 0.33, 0.50, 0.61, 0.80, 1. The third sextile is the reference category. Portfolio return is calculated as the total dollar gains/losses across all stocks held by an investor at the end of day t, divided by the total purchase costs of these stocks. Disposition effect is calculated as the propensity to realise a gain divided by the propensity to realise a loss.



have recently been used in a series of financial applications (Feng and Seasholes, 2005; Ivković and Weisbenner, 2005; Deville and Riva, 2007; Jiao, 2015; Brettschneider and Burgess, 2017). This type of model measures the probability of realizing a gain/loss, conditional on the fact that the position was not sold the day before. The benefit of this model is that it is not only showing probability of realizing a loss or a gain, it also takes into account how long, and so how reluctant an investor is to realise a position. The time is important to allow, for example, reference updating and re-framing to take place (see Section 5). In both cases our main conclusion remains valid and stable: the disposition effect is higher when the percentage of gains is low and it is lower when the percentage of gains is high.

5 Discussion

Mental accounting (Thaler, 1980; Thaler, 1985; An et al., 2019) is a potential explanation for our main finding that the disposition effect is weaker for portfolios with a higher proportion of gains. The explanation relies on the fact that realising a loss when having many gains, can be seen as realising part of a gain, since the overall situation of the portfolio is positive. However, we will now propose some alternative explanations for our result.

A first possibility entails reference point updating. Arkes et al. (2008) showed in an experimental setting that investors update upwards (downwards) their reference point after an asset increases (decreases) in price. Investors only partially update the reference point, and they update asymmetrically, by more in the gain than in the loss domain. Chiyachantana and Yang (2013) propose a reference point updating mechanism to explain the disposition effect. They argue that, when the stock is trading below the reference point, the investor is in the risk seeking region of the S-shaped utility function. Hence, choosing between a sure loss and a risky loss she will prefer the risky loss and hold on to the stock. If she adapted her reference point down to the current price, she would stop to perceive it as belonging to the loss domain and sell it (since it would be a choice between a sure gain and a risky gain and the investors would be in the risk averse portion of the S-shaped utility function).

We now apply this line of reasoning to our results and start with the loss domain. Suppose that the effect found by Arkes et al. (2008) holds. When the stock enters the loss domain, the investor does not immediately update the reference point downwards and the price will be lower than investor's reference point. We see in Figure 1 that the propensity to realise a loss is relatively constant and only increases when the percentage of stocks at a gain is very high. One possible driver for the increased propensity to realise a loss is the following: when there are only a small number of losing stocks in the account, they are evaluated as being relatively worse since the investor compares them to the large number of winning stocks. Hence, she is willing to adjust the reference point of that loss downwards to the current price and to realise losses. The propensity to realise a gain is at its highest when the percentage of stocks trading at a gain is really low (Figure 1). Using a similar line of reasoning, an investor considers those few gains to be relatively valuable as compared to a large number of losing stocks. She adjusts the reference points of the winning stocks upwards, closer to the running prices, which leads to a higher propensity to realise gains.

We can suggest some other explanations for the pattern we observe which connects our work to classical research in decision making. Regret (Loomes and Sugden, 1982) or disappointment (Bell, 1985; Loomes and Sugden, 1986; Jia et al., 2001; Delquié and Cillo, 2006) might play a role. Anticipated regret might explain why investors realise gains when they have relatively few winning positions. Regret refers to the idea that a decision maker would regret obtaining an outcome which is ex-post sub-optimal. When the percentage of gains is low, the worst possible outcome would be that those few gains end up in the loss domain. Hence, the investor chooses to sell them now, before their price decreases. On the other hand, when the proportion of positions at a paper gain is higher, the investor would not be as concerned that she may not realise any gain at all and would not necessarily rush to sell. The central idea of disappointment theory is that an individual forms an expectation about a risky alternative, and may experience disappointment if the outcome obtained falls short of this expectation. If investors have a well defined expectation regarding their future earnings, it is likely that their expectation will be positive, otherwise they would have not bought the stock in the first place. Hence, when the percentage of gains in the account is low, the probability of the final outcome falling short of expectations is high. Then, individuals rush to realise the few gains they have, in order to meet their ex-ante expectations.

This explanation is linked to the reasonable belief that if the investor has more stocks in the gain domain, then the likelihood that she will have a loss is smaller. On the other hand, if the investor has only a few stocks in the gain domain, then the likelihood that she will have a gain is small. This automatically leads to a higher propensity to realise gains when there is only a few of them in the account. If the objective of the investor is to maximise the number of investments sold for a gain, she will sell one of the few gains when she mainly has losses on her account, since the likelihood that many of those losses will turn into gains is small.

Along similar lines, having many losses might lead the investor to update her beliefs on the future trajectory of her stocks (see among the others Barberis (2018) for a review on belief formation in markets). When the majority of the stocks are trading at a paper loss, the investor might be more pessimistic on all her stocks and realise the few gains, which she expects to become losses soon otherwise.

A further possibile explanation is that the investor updates her confidence on her own stock selection ability. Perceived stock selection ability and the need to keep a good self-image has been a leading explanation for the disposition effect (Kaustia, 2011). As Barber et al. (2007) write:

> For some investors, the tendency to hold losers may be driven on a more basic level than probabilities of gains and losses. We live in a world in which most decisions are judged ex post and most people find it psychologically painful to acknowledge their mistakes. When a stock is sold for a loss, it becomes, irrevocably, an (ex post) mistake. A stock that one continues to hold for a loss, however, still might turn out to be a good (ex post) decision. Thus by continuing to hold onto their losers, investors postpone, and potentially avoid, admitting their mistakes.

Hence, the finding that they are disposition effect prone. The idea is that they realise gains and keep losses because realising gains corresponds to a good *obtained* performance. We propose that this mechanism might be stronger in our setting. When the investor has many paper losses in her portfolio she might be very disappointed by her investments and she might need an even bigger boost to her spirits than at other times. Hence, the disposition effect is even larger when she has only a few gains. On the other hand, when she has many paper gains she might already hold a good idea of her own stock selection ability and be less prone to the disposition effect.

A final psychological explanation might rely upon investor attention (Barber and Odean, 2008; Dierick et al., 2019). We see that the propensity to realise a gain is lower for balanced compositions of the bank account. It might be the case that unbalanced compositions of the portfolio lead the investor to focus their attention on their investments, and to be more active, by realising positions.

We can also relate our findings to those of Hartzmark (2015) who finds that investors tend to sell extreme winners and losers in their portfolio. Empirically, he finds both a direct rank order effect and a relative size effect. In common with Hartzmark (2015), we observe investors tend to realise salient stocks, at least, they sell gains which are salient. A gain in a portfolio where most of the stocks are losses is more salient than a gain in a portfolio with a more balanced ratio between gains and losses. This is consistent with what we observe in Figure 1 for portfolios with many losses, and leads to a strong disposition effect in that situation[10]. However, our result differs from the ranking finding of Hartzmark (2015) for

[10]However, our observation is more general and points to the fact that "gains" in a portfolio with a small percentage of gains are more likely to be sold than in a portfolio with higher percentage of gains. This effect is only partially driven by the single extreme "gain".

the situation with a salient, or extreme loss, in a portfolio with many gains. In this case, the rank effect says the extreme loss would be sold, whilst our findings show a much weaker disposition effect and more balance in the propensities to sell gains and losses, when there is a high proportion of gains. Salience is a relevant feature for decision making and it is widely studied both in psychology (Towal et al., 2013), economics (Bordalo et al., 2012) and finance (Bose et al., 2020).

Moving beyond our main findings, one interesting implication of our work might be that whilst people dislike realising losses, when they do, they prefer to sell more than one loss position at a time. Psychologically, this can be linked to the idea that it is better concentrating all painful experiences at once. This is consistent with the psychological evidence on adaptation. Nelson and Meyvis (2008) show that interrupting a consumption experience can make pleasant experiences more enjoyable and unpleasant experiences more irritating. As a parallel, we suggest that realising two losses in two days (hence interrupting the unpleasant experience of selling losses) is more irritating than realising two of them on the same day (hence having a longer unpleasant experience which allows adaptation).

Prospect theory can provide another potential explanation for why more than one loss is taken simultaneously. This preference arises from the convexity of the value function in the loss region. Convexity leads to a preference for realizing multiple losses simultaneously. In a portfolio setting without narrow framing, Henderson (2012) models asset sales under prospect theory and demonstrates that an investor would sell multiple units of asset at a loss under the preference specification of Tversky and Kahneman (1992).

In addition, this finding has parallels in the accounting literature, where a company's management team knowingly manipulates its income statement to make poor results look even worse in order to make future results appear better (big bath). Banks can also engage in a big bath. Banks typically face rising delinquency and default rates on loans when the economy goes into recession and unemployment rises. These banks often write off the loans beforehand in anticipation of the losses and create a loan loss reserve. A bank can effectively create a big bath and be liberal with the loan loss provision as its earnings are hurt by tough economic times. While institutional factors might play role, there is room for a psychological explanation of this behaviour. For example, Moore (1973) finds that discretionary accounting decisions that reduce income are more likely to be made in a period of management changes. Big baths can be motivated by the desire to manipulate earnings. New management might have the desire to look better than it is with respect to the old one. Large accounting write-offs often follow CEO turnover (Strong and Meyer, 1987; Murphy and Zimmerman, 1993), as new CEOs can blame the losses taken on their predecessors and take credit for subsequent improvements in reported profitability. Along the same lines, selling all the losses at once, might lead to a subsequent better performance of the investor, in relative terms. She might look at her profits more favourably, after a stream of several losses than with respect to a few losses.

6 Conclusion

In this paper, we proposed a description of the disposition effect from a wide framing perspective. Our sample focused on relatively active traders (the 5% most active, who account for 35% of trades in the LDB dataset). We examined how the disposition effect changes when the percentage of stocks trading at a gain in a specific account-day changes. In addition, we estimated the propensity to realise gains and losses when more than one stock is realised on a given account-day. When the percentage of stocks trading at a gain on a given account-day increases, the disposition effect decreases and in some cases it disappears. Also, on those days when another stock is realised, the propensity to sell increases significantly. In particular, the propensity to realise a loss increases more than the propensity to realise a gain when another stock at a loss is sold and the propensity to realise a gain increases more than the propensity to realise a loss when another stock at a gain is sold. However, investors show a higher propensity to realise gains (losses) also when a loss (gain) is realised in their account. This can explain some of the the variation we see in the disposition effect, due to the portfolio composition.

Our main conclusion represents an important advance in the literature on the disposition effect. It is already well known that the disposition effect differs across various types of investors (Grinblatt and Keloharju, 2001; Dhar and Zhu, 2006). In our paper, we control for fixed effects at account and time level and find that the magnitude of the disposition effect changes from period to period at the individual level. When the percentage of stocks trading at a gain in a given account-day is higher, the disposition effect is lower. We conclude that investors do not exhibit the disposition effect in all situations. In particular, the effect is more likely to occur in bad times than in good times.

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A Appendix

A.1 Stratified disposition effect

In this Section we explain the reasoning and implementation of the estimation of the disposition effect stratified by percent of stocks at a gain given in Table 2 in Section 3. An example is given to demonstrate the method.

For each (bank) account A there is a sequence of days T_A where at least one stock is traded. For the number of days in this set we use $\# T_A$. For each of these days, using all the stocks held in the account, we calculate the disposition effect, DE, and the percentage of stocks trading at a gain (percentage of gains or PG). We index by At to highlight the dependency on both account and day.

We partition percentages into a (small) number of equally-sized gain bins and only distinguish bin numbers for PG_{At}, but they may change from day to day even within the same account. Given a particular bin number j, we can find all the days t for which PG_{At} belongs to j. We call this set of days $T_A^{(j)}$ and denote the number of days in this set by $\# T_A^{(j)}$.

We now calculate account level disposition effects restricted to days where the percent gain is in a particular bin. These disposition effects at account-gain bin level $\mathrm{DE}_A^{(j)}$ are constructed as follows. For each account A and each gain bin j, average the account-day-gain bin disposition effects $\mathrm{DE}_{At}^{(j)}$ over all days $T_A^{(j)}$. These are temporal averages and can be expressed via the formula:

$$\mathrm{DE}_A^{(j)} = \frac{1}{\# T_A^{(j)}} \sum_{\text{all days } t \text{ in } T_A^{(j)}} \mathrm{DE}_{At}. \tag{3}$$

We now aggregate over accounts to focus on dependency of the disposition effect on percent gain. The disposition effects at gain bin level $\mathrm{DE}^{(j)}$ are constructed as averages of the disposition effects at account-gain bin level $\mathrm{DE}_A^{(j)}$ over accounts. The collection of these over all gain bins is the percent gain stratified disposition effect. They are averages over accounts. Written as a formula, using # accounts for the total number of accounts in the data sets, we obtain

$$\mathrm{DE}^{(j)} = \frac{1}{\#\,\text{accounts}} \sum_{\text{all accounts A}} \mathrm{DE}_A^{(j)}. \tag{4}$$

Averaging first over days and then over accounts gives each account holder the same weight, regardless of how often and over what length of periods the account holder traded. This ensures that the estimates of the percent gain stratified disposition effect are not driven by a few particularly active traders. We include a numerical example based on the values in

Table A1.

Table A1: **Numerical example.** Numerical example data showing two accounts A and B with 3 and 5 trading days, respectively. DE and PG bin are both at account-day level. DE refers to the disposition effect. PG bin refers to the percent of stocks at gain, with 1 referring to $[0, 0.5]$ bin and 2 referring to $(0.5, 1]$ bin. From these we calculate summaries of the disposition effect at account-gain-bin level and at gain-bin level.

Account	Day	DE	PG bin	DE account-gain-bin	DE gain-bin
A	1	0.22	1	0.20	0.19
	2	0.18	1	0.20	0.19
	3	0.02	2	0.02	0.03
B	1	0.15	1	0.18	0.19
	2	0.05	2	0.04	0.03
	3	0.03	2	0.04	0.03
	4	0.20	1	0.18	0.19
	5	0.19	1	0.18	0.19

The calculations for the disposition effect at account-gain-bin and at gain-bin level were carried out as follows. The average disposition effects at account-gain-bin level are, using (3),

$$\begin{aligned}
\mathrm{DE}_A^{(1)} &= \frac{1}{2}(\mathrm{DE}_{A1}^{(1)} + \mathrm{DE}_{A2}^{(1)}) = \frac{1}{2}(0.22 + 0.18) = 0.20 \\
\mathrm{DE}_A^{(2)} &= \mathrm{DE}_{A3}^{(2)} = 0.02 \\
\mathrm{DE}_B^{(1)} &= \frac{1}{3}(\mathrm{DE}_{B1}^{(1)} + \mathrm{DE}_{B4}^{(1)} + \mathrm{DE}_{B5}^{(1)}) = \frac{1}{3}(0.15 + 0.20 + 0.19) = 0.18 \\
\mathrm{DE}_B^{(2)} &= \frac{1}{2}(\mathrm{DE}_{B2}^{(2)} + \mathrm{DE}_{B3}^{(2)}) = \frac{1}{2}(0.05 + 0.03) = 0.04
\end{aligned}$$

The average disposition effects at gain-bin level are, using (4),

$$\begin{aligned}
\mathrm{DE}^{(1)} &= \frac{1}{2}(0.20 + 0.18) = 0.19 \\
\mathrm{DE}^{(2)} &= \frac{1}{2}(0.02 + 0.04) = 0.03
\end{aligned}$$

The numbers in Table A1 were chosen to show the same message as the real data set considered in the paper. They show that the disposition effect is negatively associated with the percentage of stocks at gain in the account. A summary (in the style of Table 2) is given in Table A2.

Table A2: **Gain stratified disposition effect using results of Table A1.**

Perc. of gains	DE
[0,0.5]	0.19
(0.5,1]	0.03

A.2 Additional analyses

In Table A3 we extend our main analysis from Table 3, taking into account the overall return of the bank account. The overall account return is calculated as the total dollar gains/losses across all stocks held in the account on day t, divided by the sum of the total purchase costs of these stocks, as we explained at the beginning of Section 4.3. In this way, we can control not only for the number of position trading at gain or loss but also for their magnitude, since we take into account the quantities of each stock bought at the start of an investment episode[11]. More specifically, on any given day t we multiply the quantity of a stock purchased by the account holder by its purchase price and by the return of that stock on day t. This gives the dollar value of a position. We sum over all those dollar values and we divide that by the total amount of dollars invested to buy those stocks. This is just the sum of all the stocks purchase prices multiplied by the quantities purchased.

We split the overall return of the bank account in quintiles and we control for it. The result is presented in Table A3. To easily compare these estimates with the original ones, we reproduce the first column of Table 3 in the first column of Table A3. We can see that the main result is very stable and the coefficient of the interactions among the gain dummy and the percentage of gains are almost unchanged from one specification to another. Those capture the magnitude of the disposition effect in the different sextiles of the percentage of gains, as we explained in Section 3. The result then holds after controlling for the magnitude of the portfolio paper return, account fixed effects and time fixed effects. This further mitigates concerns on wealth effects affecting our main result.

As a final robustness check, we fit a proportional hazard (PH) model to our data. We first give more mathematical details on this model, developed by Cox (1972). The proportional hazard model is a semi-parametric model, aimed at describing the "time-to-event" of individuals. In our case the time to event is the time from the start to the end of an investment episode. It has the advantage of assessing the impact of the covariates over the entire time axis, while for example a logistic regression only evaluates the odds of the event/non

[11]Quantity is the number of stocks bought on the day an investment episode starts (multiple days purchases represent a negligible fraction of traders' activity). Moreover, quantity is considered at the beginning of the trading day. So if a position is sold on day t, that contributes to our definition of the portfolio return on day t. This reflects the idea that a selling decision on day t is influenced by what was present at the start of the day t in the account.

Table A3: **Portfolio return regression.** Linear probability model where the dependent variable takes the value of 1 for sale days and 0 for hold days. Each observation is at account-stock-day level. Gain dummy is equal to 1 on those days when the stock is trading at a gain. Sextiles of stocks trading at a gain are obtained as follows: we calculate the percentage of stocks trading at a gain (excluding the stock for which we are estimating the probability of selling) in a given account-day, we split it into sextiles. Observed sextile are marked by the following cut-points (these are the upper limits of each category): 0.10, 0.33, 0.50, 0.61, 0.80, 1. The third sextile is the reference category. Portfolio return is calculated as the total dollar gains/losses across all stocks held by an investor on day t, divided by the total purchase costs of these stocks.

	(1)	(2)	(3)	(4)	(5)
Gain	0.00404***	0.00373***	0.00410***	0.00682***	0.00496***
	(0.000411)	(0.000455)	(0.000485)	(0.000689)	(0.000585)
Sextile percentage of gains (ref. Third)					
First	0.000998***	0.00162***	-0.00491***	-0.00507***	-0.00537***
	(0.000302)	(0.000334)	(0.000405)	(0.000402)	(0.000417)
Second	-0.00139***	-0.000996***	-0.00222***	-0.00214***	-0.00252***
	(0.000296)	(0.000301)	(0.000287)	(0.000289)	(0.000281)
Fourth	-0.000406	-0.000725	0.00134***	0.00134***	0.00157***
	(0.000405)	(0.000407)	(0.000370)	(0.000391)	(0.000364)
Fifth	0.00115***	0.000844**	0.00168***	0.00174***	0.00195***
	(0.000260)	(0.000279)	(0.000308)	(0.000304)	(0.000289)
Sixth	0.00442***	0.00421***	0.000803*	0.000646	0.00102**
	(0.000367)	(0.000376)	(0.000377)	(0.000373)	(0.000359)
Gain × Sextile percentage of gains (ref. Third)					
Gain × First	0.00989***	0.00953***	0.0113***	0.0114***	0.0122***
	(0.000587)	(0.000584)	(0.000665)	(0.000665)	(0.000687)
Gain × Second	0.00422***	0.00407***	0.00508***	0.00511***	0.00574***
	(0.000484)	(0.000476)	(0.000511)	(0.000515)	(0.000487)
Gain × Fourth	-0.00321***	-0.00298***	-0.00372***	-0.00377***	-0.00407***
	(0.000487)	(0.000484)	(0.000506)	(0.000503)	(0.000500)
Gain × Fifth	-0.00418***	-0.00383***	-0.00480***	-0.00484***	-0.00517***
	(0.000412)	(0.000409)	(0.000420)	(0.000422)	(0.000407)
Gain × Sixth	-0.00145**	-0.00103*	-0.00195***	-0.00188***	-0.00223***
	(0.000510)	(0.000503)	(0.000559)	(0.000558)	(0.000550)
Portfolio Return	NO	YES	YES	YES	YES
Portfolio Return × Gain	NO	NO	NO	NO	YES
Account FE	NO	NO	YES	YES	YES
Time FE	NO	NO	NO	YES	NO
N	6611755	6611755	6611755	6611755	6611755

Standard errors clustered at bank account level in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A4: **Cox model.** The dependent variable takes the value of 1 for sale days and 0 for hold days. Each observation is at account-stock-day level. Gain dummy is equal to 1 on those days when the stock is trading at a gain. Sextiles of stocks trading at a gain are obtained as follows: we calculate the percentage of stocks trading at a gain (excluding the stock for which we are estimating the probability of selling) in a given account-day, we split it into sextiles. Observed sextile are marked by the following cut-points (these are the upper limits of each category): 0.10, 0.33, 0.50, 0.61, 0.80, 1. The third sextile is the reference category. Positive portfolio return is a dummy which is equal to 1 if the overall return of the bank account is greater or equal than 0. Portfolio return is calculated as the total dollar gains/losses across all stocks held by an investor on day t, divided by the total purchase costs of these stocks.

	OLS	*Proportional Hazard*		
	(1)	(2)	(3)	(4)
Gain	0.004***	0.307***	0.257***	0.253***
	(0.0002)	(0.015)	(0.015)	(0.015)
Sextile percentage of gains (ref. Third)				
First	0.001***	−0.255***	−0.250***	−0.222***
	(0.0002)	(0.016)	(0.017)	(0.016)
Second	−0.001***	−0.195***	−0.187***	−0.173***
	(0.0002)	(0.016)	(0.016)	(0.016)
Fourth	−0.0004	0.122***	0.095***	0.083***
	(0.0003)	(0.023)	(0.023)	(0.023)
Fifth	0.001***	0.201***	0.146***	0.143***
	(0.0002)	(0.017)	(0.017)	(0.017)
Sixth	0.004***	0.143***	0.086***	0.091***
	(0.0002)	(0.017)	(0.018)	(0.018)
Quintile portfolio return (ref. Third)				
First			0.035***	
			(0.013)	
Second			−0.020	
			(0.011)	
Fourth			0.134***	
			(0.011)	
Fifth			0.208***	
			(0.013)	
Positive portfolio return				0.151***
				(0.009)
Gain × Sextile percentage of gains (ref. Third)				
Gain × First	0.010***	0.458***	0.478***	0.459***
	(0.0003)	(0.021)	(0.021)	(0.021)
Gain × Second	0.004***	0.329***	0.356***	0.347***
	(0.0003)	(0.022)	(0.022)	(0.022)
Gain × Fourth	−0.003***	−0.239***	−0.236***	−0.224***
	(0.0004)	(0.030)	(0.030)	(0.030)
Gain × Fifth	−0.004***	−0.333***	−0.338***	−0.316***
	(0.0003)	(0.022)	(0.023)	(0.022)
Gain × Sixth	−0.001***	−0.131***	−0.165***	−0.133***
	(0.0003)	(0.022)	(0.022)	(0.022)
N	6,611,755	6,611,755	6,611,755	6,611,755

Standard errors in parentheses. Strata fixed at the account level.
*p<0.05; **p<0.01; ***p<0.001

event with respect to a fixed time. Informally, a PH model incorporates all the information accumulated in time for a given episode. A logistic regression would evaluate the information in a given day independently from the information on other days of the same episode. We now add more details to our discussion. In particular, we need to define some objects (see e.g. Moore, 2016).

Definition 1. Let T be a non-negative continuous random variable, representing the time until the event of interest.

$F(t) = P(T \leq t)$ denotes the distribution function and $f(t)$ the probability density function of random variable T.

$S(t) = P(T > t) = 1 - F(t)$ is called survival function. It is the probability that a randomly selected individual will survive beyond time t. It is a decreasing function, taking values in $[0, 1]$ with $S(0) = 1$ and $S(t)$ goes to 0 as t goes to ∞.

$\mathrm{H(t)} = -\log \mathrm{S(t)}$ is the cumulative hazard function.

The derivative of H(t) with respect to t is the hazard function (or hazard rate) $h(t)$. This measures the instantaneous risk of dying right after time t given the individual is alive at time t.

We fit a regression model where we evaluate the change in the hazard rate with respect to a set of covariates. Given a set of covariates $\mathbf{x}_j = (x_{j1}, x_{j2}, ..., x_{jp})$ measured for subject j, the following model is fit to the data

$$h_j\left(t\right) = h_0\left(t\right) \exp\left(\beta^t \mathbf{x_j}\right);$$

with β, a $p \times 1$ vector of parameters and $h_0(t)$ which is the baseline hazard function (i.e. hazard for a subject j with $\mathbf{x_j} = \mathbf{0}$).
The proportional hazards assumption states that the ratio of the hazards of two subjects with covariates x_j and $x_{j'}$ is constant over time:

$$\frac{h_j\left(t\right)}{h_{j'}\left(t\right)} = \frac{\exp\left(\beta^t \mathbf{x}_j\right)}{\exp\left(\beta^t \mathbf{x}_{j'}\right)}$$

The Cox PH model is a semi-parametric model since it leaves the form of $h_0(t)$ completely unspecified. Then, to estimate the model we maximize a partial likelihood. In our case, it maximises that a given stock was sold in that time point (it was that specific stock). This is in contrast to a full likelihood that would include the time point of the sale itself. Finally, we should point out that we are estimating a model with time changing covariates so it is better to define it as

$$h_j(t) = h_0(t) \exp\left(\beta^t \mathbf{x}_{jt}\right)$$

To deal with unobserved heterogeneity we stratify the model based on the investor who holds the position. This means that each bank account has a different baseline hazard function, which can absorb any heterogeneity not captured by the model covariates. Hence, the hazard function for the j_{th} position of the i_{th} bank account is

$$h_{ij}(t) = h_{0i}(t) \exp\left(\beta^t \mathbf{x}_{ijt}\right);$$

where $\mathbf{x}_{ijt}$ is the covariate vector for the position. Possible reasons for there being a difference between investors include their preference for risk, their beliefs about the market (e.g. whether there is price momentum or not), their investment objectives and the particular strategy they are following. For example, some investors may trade very frequently and follow a strategy based on short term changes in stock prices. The holding periods of these investors will therefore be shorter than other investors in the sample. Differentiating investors' baseline hazards can separate out this kind of differences from the effects of the covariates included in the model, that are common across all investors.

The results are presented in Table A4 and once more we see that our main result holds. The coefficients reported do not represent the marginal effects on the propensity to realise a position but they should be exponentiated to obtain that. For example, the Gain dummy in column 2 of Table A4 has a coefficient of 0.307. This means that the probability of a sale when the stock is trading at a gain is 36% higher than the probability of a sale when the stock is not trading at a gain (exp(0.307) = 1.36). Hence, we should focus on the direction and the significance of all the coefficients and we can see that they are all consistent with our original estimates, reproduced in column 1 of Table A4.