The disposition effect varies with portfolio composition because people take gain-loss-domain-level sell decisions

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The disposition effect is regarded as a property of an individual stock: If an investor has made a loss on a stock, he or she is less likely to sell it, whereas if an investor has made a gain on a stock, he or she is more likely to sell it. This means that the more stocks in a portfolio are in gain, the greater the probability that the stock sold will be in gain. But we show that the disposition effect is, in the large part, a gain-loss domain level decision, where investors first decide whether to sell a stock in the domain of gains or losses, and only then choose a stock to sell from within their chosen domain. The signature of this two-stage model is that the probability that the stock sold will be in gain is constant across portfolios with different numbers of stocks in gain and in loss. We see this pattern very clearly in two independent stockbroking datasets, one from the US investors from 1990s and another from UK investors from 2010s. We also see the pattern in a stockbroking experiment where we randomly vary the number of gains and losses in a portfolio. We conclude that sell decisions are taken at the gain-loss domain level, not just at the individual-stock level.

Key words: disposition effect, gains, losses, decision making, loss aversion
History:

1. Introduction

One of the most well-evidenced behavioral biases in finance is the disposition effect, in which people are more likely to sell stocks that have gained value since they bought them than stocks that have lost value (Odean 1998, Shefrin and Statman 1985). More generally, the idea that people treat gains and losses differently is well established in psychology and economics (Kahneman and Tversky 1979, Tversky and Kahneman 1991) and is embodied in the fundamental concept of loss aversion in behavioral economics (Camerer 2005). The idea that outcomes are evaluated against a reference level is also well established (Kőszegi and Rabin 2006, 2007, Lópes and Oden 1999), and the reference level is often taken to be the status quo (Kahneman and Tversky 1979). This paper shows that, in the domain of finance, whether a stock has gained or lost value is psychologically elemental, such that (a) stocks are grouped together, with decisions taken about selling at this category level without reference to the magnitudes of the gains and losses, and (b) stocks in gain are considered separately from stocks in loss, and vice versa. As such we demonstrate that the disposition effect is, at least in the large part, a gain-loss-domain-level effect and not only an individual-stock-level effect.

The disposition effect is robust, and has been demonstrated using real stock trading data for private investors (Brown et al. 2006, Grinblatt and Keloharju 2000, Odean 1998), professional traders (Garvey and Murphy 2004) and in laboratory experiments (Weber and Camerer 1998, Imas 2014). In many studies, the magnitude of the disposition effect is estimated using data from days upon which at least one stock is sold (sell-day portfolios) (e.g., Kaustia 2010, Odean 1998). Regression models are used to estimate the probability that a particular stock is sold while controlling for other properties of a given stock (e.g., past returns, price volatility, holding period). The disposition effect is observed when the probability that a stock is sold is higher when it is in gain than when it is in loss, other things being equal. The disposition effect is substantial. For example, Odean (1998) reported that gains are, on average, 1.5 times as likely to be sold as losses in the US retail investors' portfolios. Similarly, Kaustia (2010) showed that gains are twice as likely to be sold as losses when Finish investors sold a stock with a short holding period.

Here we propose that existing methods for estimating the disposition effect are inadequate because they make an erroneous assumption about the decision processes of individual investors. Consider an investor who is trying to decide on which stock to sell from his or her portfolio. The investor may consider all of the stocks in the portfolio, comparing their past performance and trying to predict their future outlook. If this investor exhibits the disposition effect, his or her decision will be swayed towards selling a stock in gain over a stock in loss. In this account, whether a stock is in gain or in loss is just one of many features used to assess each individual stock. This decision rule aligns well with the assumptions of the regression techniques used to estimate the disposition effect, in which the probability of each stock being sold is estimated simultaneously across domains of gains and losses. We refer to this approach as the one-stage model to reflect its implicit assumptions about the investors' decision process. Now, consider an alternative process in which an investor seeks to minimize the cognitive cost associated with the complex trade-offs of comparing stocks in gain with stocks in loss. Our investor therefore begins by answering a simple but important question: Do I sell a stock in gain or do I sell a stock in loss? This decision is exogenously made without any consideration of individual stocks in the portfolio and its composition, but can be influenced by the investor's tendency to sell gains over losses. In the second stage of the decision process, the investor is left with one of two possible choice contexts: If he or she initially decided to sell a gain then he or she must now decide which gain to sell. Alternatively, if he or she initially decided to sell a loss, he or she must now decide which loss to sell. We refer to this sequential process as the two-stage model, since the investors begin by selecting a domain from which they will sell in the first stage, and only then in the second stage do they evaluate the subset of stocks in the domain they chose in the first stage.

2. The Psychology of a Decision to Sell

When faced with a complex choice problem, individual decision makers tend to adapt and choose strategies that reflect a trade-off between decision accuracy and the cognitive cost of deciding-satisficing (Shah and Oppenheimer 2008, Simon 1955, 1956). As a result, decision makers are likely to use sequential and non-compensatory decision rules (Gigerenzer and Gaissmaier 2011, Payne et al. 1993). A common feature of these strategies is that people attempt to reduce size of a choice set (i.e., the number of alternatives in consideration) using a single criterion at a time (Brandstätter et al. 2006, Tversky 1972). Such models stand in stark contrast with the standard economic view, in which all available information is considered in making a decision. Here we focus on people's tendency to reduce the complexity of a decision context by first segregating choice objects into the domains of gains and losses, and then subsequently evaluating the options available within a domain.

The distinction between the positive and the negative is reflected in the psychological theories of language, attitude formation, attention allocation, reinforcement learning, and decision making (Cacioppo and Berntson 1994, Rozin and Royzman 2001). At the most rudimentary level, the common assumption is that people perceive different alternatives as gains and losses relative to some reference point (Kőszegi and Rabin 2006, 2007, Lópes and Oden 1999), often given by the current status quo (Kahneman and Tversky 1979, Novemsky and Kahneman 2005, Thaler and Johnson 1990, Tversky and Kahneman 1991). Much work has focused on the asymmetric weighting of gains and losses. It is widely accepted that the anticipated negative emotions associated with a loss are stronger than the anticipated positive emotions associated with a gain of an equal magnitude (Kermer et al. 2006). Demonstrations of such loss aversion (or negativity bias) apply to both monetary and nonmonetary domains (Baumeister et al. 2001). The existence of the disposition effect has been interpreted as support of the asymmetric weighing of gains and losses. People may avoid realizing a loss out of a concern for the intensity of negative feelings, and hence become more likely to sell a stock in gain (Weber and Camerer 1998). Here the label of loss aversion is a purely descriptive concept that does not come with any assumptions about the underlying decision processes. The goal of the present work is to flesh out the decision rule that may underpin the decision to sell a gain or a loss.

Psychological theory suggests that when people evaluate anticipated feelings of positive and negative events, they naturally engage in a within-domain comparison (Kahneman and Miller 1986, McGraw et al. 2010). That is, people may choose whether a given situation or an outcome falls into category of gains and losses, and only then proceed to compare it with outcomes within the same domain. Such mechanisms are also consistent with many models of relative judgment, where the relative comparison context is often constructed by separating outcomes using a natural anchor, such as zero point or other neutral value (Marsh and Parducci 1978, Parducci 1983, Stewart et al. 2006). Studies of loss aversion in risky choice support the idea that gains are evaluated only against other gains and that losses are evaluated only against other losses. For example, Walasek and Stewart (2015) showed that loss aversion, as evident in people's reluctance to accept mixed lottery gambles for equal gains and losses (e.g., a 50/50 chance of gaining \$100 or losing \$100), is greatly affected by the distribution of gains and losses in the set of choices they experience, and largely eliminated in a choice environment where the gains and losses have symmetrical distributions. This strong context-sensitivity of loss aversion could not occur if people were making gain-loss cross-domain comparisons.

In sum, whether something is a gain or a loss is a psychologically salient category. Here we demonstrate that sell decisions involve separating stocks in gains from stocks in loss, and choosing which domain to sell from.

3. Data and Method

We use empirical stock trading data provided by an US stock broker. In revising and resubmitting the paper, we obtained new data from a UK stock broker and replicated the results. We also replicated the findings in a new incentivized experiment.

3.1. US Empirical Data

The US empirical data are historical stock transactions for individual investors in the US. The trades were completed through a large discount brokerage between January 1991 and November 1996. These data were previously used in studies of disposition effect by Barber and Odean (2000, 2001, 2002) and Hartzmark (2015). We merged trades with the historical prices retrieved from the Center for Research in Security Price (CRSP).

3.2. UK Empirical Data

We replicated our analysis in a second dataset from a UK stockbroker. The UK empirical data are transaction histories for individual investors from April 2014 to June 2016, about 20 years after the US data. Gathergood et al. (2018) report naïve diversification in buying in these data, but selling has not been explored elsewhere. Unlike the US data, trades were almost exclusively placed using an online trading platform. We merged the transaction data with historical prices retrieved from the Datastream.

3.3. Data Preparation

Because the purchase prices of stocks bought before the beginning of the transaction data are unknown, we excluded all accounts which had positions before the start of the data period, so that we have complete price data for all portfolios. Multiple intra-day trades conducted by the same investor on the same stock were aggregated with quantity weighted prices. We extracted sell trades which changed a net position from positive to non-negative (i.e., sell trades leading to short positions were excluded), and reconstructed the portfolios held by the corresponding accounts on these sell dates (sell-day portfolios). Short positions and positions opened on sell days were excluded from the remaining portfolios. The return since purchase was calculated by using a quantity weighted average purchase price of a stock for a given account and a closing price of the stock as of one day prior to the sell date. Commissions and dividends were not included in the calculation of returns. If a sell-day portfolio contained one or more stocks with missing variables in either the price data or the transaction data, the whole sell-day portfolio was excluded. Because we are interested in the investors' choice of stock for sale, we extracted sell-day portfolios consisting of two or more stocks. Sell-day portfolios consisting of only gains or only losses and those including stocks at a zero return were excluded. Further, we extracted sell-day portfolios where exactly one stock was sold. (Note that a single stock was sold from a portfolio on more than 80% of sell-days both in the US and the UK data.) The summary statistics for the US and UK portfolios used are presented in Tables A1 and A2 in Appendix A. For the US data we were able to construct 35,663 sell-day portfolios for 10,668 accounts. For the UK data we were able to construct 20,695 sell-day portfolios for 4,923 accounts.

3.4. Notation

We describe notations used in Table 1. N_G is the number of gains in a portfolio and N_L is the number of losses in a portfolio. *Sell*, *Gain*, and *Loss* are 0/1 dummy variables indicating whether a stock is sold and whether it is in gain or loss. $P(A\ Gain)$ is the average value of *Sell* over the gains in a portfolio. That is, $P(A\ Gain) = E(Sell_i | Stock\ i\ is\ in\ gain)$. As such it represents the probability that a single, individual stock in gain is sold. Analogously, $P(A\ Loss)$ represents the probability that a single, individual stock in loss is sold. That is, $P(A\ Loss) = E(Sell_i | Stock\ i\ is\ in\ loss)$. $P(Any\ Gain) = P(A\ Gain) \times N_G$ is the probability that the stock sold is in gain (i.e., that the stock sold is *any* one of the stocks in gain). $P(Any\ Loss) = P(A\ Loss) \times N_L$ is the probability that the stock sold is in loss.

The measure of the disposition effect at the level of individual stocks is β. β reflects the relative probabilities of selling an individual, single gain, $P(A\ Gain)$, rather than an individual, single loss, $P(A\ Loss)$.

Table 1 Notation and Descriptions of Variables

Variable	Description
N_G	The number of gains in a sell-day portfolio
N_L	The number of losses in a sell-day portfolio
$Sell$	A dichotomous variable having a value of 1 if the stock was sold otherwise 0
$Gain$	A dichotomous variable having a value of 1 if the stock was in gain, otherwise 0
$Loss$	A dichotomous variable having a value of 1 if the stock was in loss, otherwise 0
$P(A\ Gain)$	The proportion of sold gains among all gains. In model predictions this is equivalent to the probability of the individual stock being sold, given it is in gain
$P(A\ Loss)$	The proportion of sold losses among all losses. In model predictions this is equivalent to the probability of the individual stock being sold, given it is in loss
$P(Any\ Gain)$	The proportion of sell-day portfolios where a gain was sold among all sell-day portfolios. In model predictions, this is equivalent to the probability of any gain being sold from a sell-day portfolio
$P(Any\ Loss)$	The proportion of sell-day portfolios where a loss was sold among all sell-day portfolios. In model predictions, this is equivalent to the probability of any loss being sold from a sell-day portfolio
β	$=\frac{P(A\ Gain)}{P(A\ Loss)}$, measuring a size of the disposition effect at individual stock level
B	$=\frac{P(Any\ Gain)}{P(Any\ Loss)}$, measuring a size of the disposition effect at portfolio level
$Return$	Return since purchase of a stock
$Return_{20}$	A stock's return for 20 days prior the sell day
$Volatility_{20}$	A stock's volatility for 20 days prior the sell day
$Holding\ Days$	Days for which the stock was hold since a first purchase

$$\beta = \frac{P(A\ Gain)}{P(A\ Loss)} \tag{1}$$

This β measure of individual-stock disposition effect is conventional in previous studies.

The measure of the disposition effect at the level of the gain-loss domain is B. B reflects the relative probability that the sale is of any gain, $P(Any\ Gain)$, rather than any loss, $P(Any\ Loss)$.

$$B = \frac{P(Any\ Gain)}{P(Any\ Loss)} \tag{2}$$

Because we select only the sell-day portfolios where exactly one stock was sold, the following *sell-day constraint* holds.

$$P(A\ Gain) \times N_G + P(A\ Loss) \times N_L = P(Any\ Gain) + P(Any\ Loss) = 1 \tag{3}$$

This allows us to derive the following relationship between β and B.

$$B = \frac{P(Any\ Gain)}{P(Any\ Loss)} = \frac{P(A\ Gain) \times N_G}{P(A\ Loss) \times N_L} = \beta \times \frac{N_G}{N_L} \tag{4}$$

We also include control variables in our multivariate analyses (Appendix B) for the return since purchase, $Return$, the return in the past 20 days, $Return_{20}$, the volatility in the past 20 days, $Volatility_{20}$, and the number of days that a stock has been held for, $Holding\ Days$.

4. Model Predictions

We introduce a *one-stage model*, where the disposition effect is at the level of individual stocks. In this model the parameter β measures how much more likely an individual stock is to be sold because it is in gain rather than loss. β is assumed to be constant across different portfolios. We also introduce a *two-stage model*, where the disposition effect is at gain-loss domain level. In this model the parameter B measures how much more likely it is that any of the stocks in gain are sold rather than any of the stocks in loss. B is assumed to be constant across different portfolios. Here we make predictions for how $P(Any\ Gain)$ will vary across portfolios under the one- and two-stage models.

4.1. The One-Stage Model

The disposition effect is typically estimated at the individual-stock level, by predicting the probability of selling each stock and including a dummy variable indicating whether the stock is in gain or loss. Our *one-stage model* captures this individual-stock level property by assuming that investors evaluate all stocks in their portfolio simultaneously to choose one stock to sell. In the one stage model, the disposition effect at the individual stock level, β, is assumed to be constant. Under the assumption of constant β, Equations 3 and 4 can be used to write $P(Any\ Gain)$ as a function of the portfolio composition N_G and N_L, and β.

$$P(Any\ Gain) = \frac{N_G}{N_G + \frac{N_L}{\beta}} \tag{5}$$

Thus, according to the one-stage model, $P(Any\ Gain)$ should be sensitive to both N_G and N_L. This is because investors are assumed to evaluate all of the stocks in a portfolio simultaneously, across both gains and losses when selecting a stock to sell. Panel A of Figure 1 shows the one-stage model predictions for $P(Any\ Gain)$ as a function of N_G and N_L (using the best-fitting value of $\beta = 2.08$ for the US Data, see Section 5.4). In the one-stage model, the more stocks in gain on a sell day, the more likely that the stock actually sold is in gain. And the more stocks in loss on a sell day, the more likely that the stock actually sold is in loss, and thus the less likely that the stock actually sold is in gain.

4.2. The Two-Stage Model

In the *two-stage model*, investors first choose whether to sell from the gain domain or the loss domain, before then choosing a specific stock from their chosen domain. The disposition effect is at the level of the gain-loss domain, and not at the level of individual stocks as it is in the one-stage model. In the two-stage model, the disposition effect at the gain-loss domain level, B, is assumed to be constant. Under the assumption of constant B, Equations 3 and 4 can be used to eliminate $P(Any\ Loss)$ and write $P(Any\ Gain)$ as a function of B. N_G and N_L are eliminated.

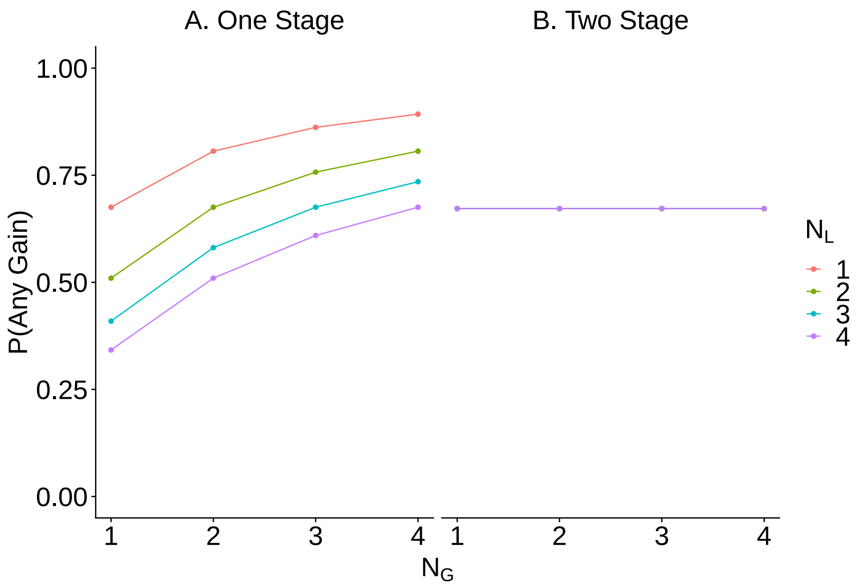


Figure 1 $P(Any\ Gain)$ **as a function of** N_G **and** N_L **in the one- and two-stage models. Note, lines coincide for the two-stage model.**

$$P(Any\ Gain) = \frac{B}{B+1} \tag{6}$$

Panel B of Figure 1 show the key signature of the two-stage model (using the best-fitting value of $B = 2.05$ for the US Data, see Section 5.4): $P(Any\ Gain)$ is independent of portfolio composition. $P(Any\ Gain)$ is constant, regardless of N_G and N_L.

To recap, if the one-stage model is correct, then β should be constant across portfolios. This means that $P(Any\ Gain)$ will increases as N_G increases or as N_L decreases. If the two-stage model is correct, then B should be a constant across portfolios. This means that $P(Any\ Gain)$ should be constant, regardless of N_G and N_L.

5. Results

In this section we test how the disposition effect in our US and UK data is sensitive to the number of stocks in gain and the number of stocks in loss in a portfolio. (We defer discussion of the experiment to the next section.) To preempt the findings, we see a pattern that looks remarkably like the signature from the two-stage model described above.

5.1. The Disposition Effect at the Individual Stock Level

Both the US and UK datasets show an individual stock level disposition effect. We estimate the effect simply by calculating $P(A\ Gain)$ and $P(A\ Loss)$, taking their ratio β, and averaging across all sell-days. For the US data $\beta = 1.8$, 95% CI [1.7, 1.9], which means that a given gain is about 1.8 times more likely to be sold than a given loss. For the UK data $\beta = 2.4$, 95% CI [2.2, 2.7].

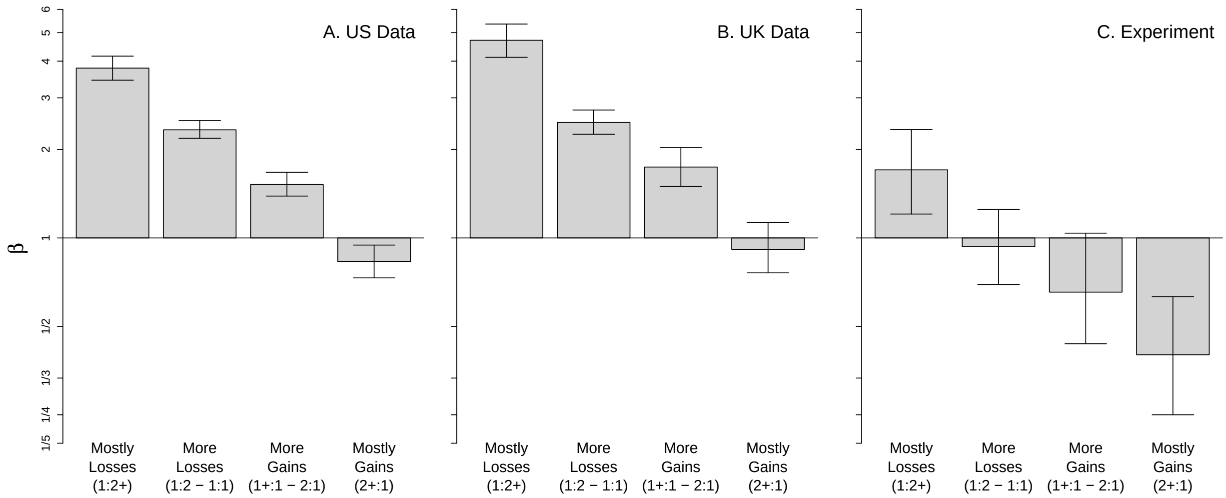


Figure 2 The disposition effect depends on the composition of the portfolio in the US empirical data (Panel A), the UK empirical data (Panel B), and the experimental data (Panel C). The error bars are 95% confidence intervals computed with the bootstrap method with 1,000 resamples, corrected for clustering by accounts and sell dates.

5.2. Portfolio-Composition Sensitivity of the Disposition Effect

Next, we show that the individual-stock-level disposition effect β depends on the composition of sell-day portfolios. Recall that, according to the one-stage model, β should be constant across portfolios of different compositions. Sell-day portfolios were divided into four bins depending on the ratio of N_G and N_L in the portfolio. The size of the disposition effect reduces considerably as the ratio of N_G over N_L increases. For the Mostly Losses bin, individual gains are on average about 3.8 times more likely to be sold as individual losses in the US data and 4.6 times more likely for the UK data. For the Mostly Gains bin, the disposition effect reversed in the US data, such that losses are now more likely to be sold than gains, and reversed, though not significantly, in the UK data.

This very simple calculation of proportions and ratios is complemented with and confirmed by a multivariate analysis of composition sensitivity in Appendix B, where we control for the returns, number of days held, and volatility of individual stocks, and include fixed effects for accounts and stock-by-dates.

5.3. Non-sensitivity of $P(Any\ Gain)$ to Portfolio Composition

Recall that, in the one-stage model where β is assumed to be constant across portfolios, the probability that the stock sold is a gain, $P(Any\ Gain)$, increases in the number of stocks in gain, N_G, and decreases with the number of stocks in loss, N_L. In contrast, recall that in the two-stage model, where instead B is assumed to be constant across portfolios, $P(Any\ Gain)$ is constant.

Figure 3 shows the probability that the stock sold is a gain $P(Any\ Gain)$ as a function of the number of stocks in gain N_G and the number of stocks in loss N_L. The empirical results look like

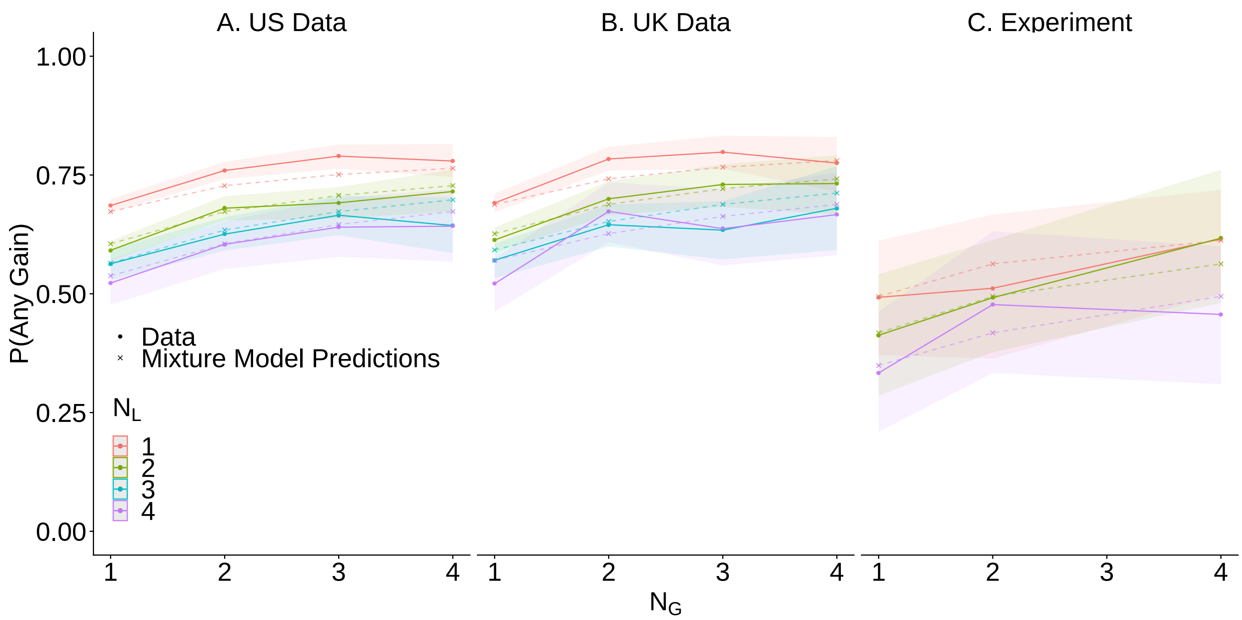


Figure 3 **Solid lines show $P(Any\ Gain)$ as a function of N_G and N_L in the US empirical data (Panel A), the UK empirical data (Panel B), and the experimental data (Panel C). The shaded areas represent 95% confidence intervals computed with the bootstrap method with 1,000 resamples, corrected for clustering by accounts and sell dates. Dashes lines are mixture model fits.**

a mixture of the one- and two-stage model predictions from Figure 1. $P(Any\ Gain)$ is roughly constant, increasing only a little with N_G and decreasing only a little with N_L. The increase with N_G and decrease with N_L is weaker than predicted in the one-stage model.

5.4. Estimating a Mixture Of the One- and Two-Stage Models.

We have estimated the maximum likelihood one-stage model (Equation 5), two-stage model (Equation 6), and a mixture of one- and two-stage models (Equation 7).

$$P(Any\ Gain) = (1-w)\,\frac{N_G}{N_G + \frac{N_L}{\beta}} + (w)\,\frac{B}{B+1} \tag{7}$$

The parameter w in the mixture model can be understood as: (a) a given individual's weighting of two-stage model over the one-stage model in a sell decision, or (b) the probability that a given individual follows the two-stage model over the one-stage model in any single sell day. We used the Nelder-Mead simplex algorithm find the maximum likelihood values of β, B, and w. We optimized $log(\beta)$, $log(B)$, and $logit(w)$ so that β and B were constrained to be non-negative and w was constrained to be between 0 and 1.

The maximum likelihood parameter values and model selection criteria are presented in Tables 2. For the US data, we estimate $\beta = 1.96$, 95% CI [1.36, 2.81], $B = 2.13$, 95% CI [1.70, 2.67], and the mixture parameter weights the two-stage model 59%, 95% CI [54%, 64%]. For the UK data, we

Table 2 Model Parameter and Selection Criteria for Three Optimized Models

Dataset	Parameter/Criteria	One Stage	Two Stage	Mixture
	β	2.08		1.96
		[2.03, 2.13]		[1.36, 2.81]
	B		2.05	2.13
			[2.01, 2.10]	[1.70, 2.67]
US	w			0.59
				[0.54, 0.64]
	LogLik	-23,067	-22,552	-22,220
	AIC	46,136	45,106	44,447
	BIC	46,145	45,114	44,472
	β	2.61		1.51
		[2.53, 2.69]		[0.95, 2.40]
	B		2.06	2.80
			[2.00, 2.12]	[2.13, 3.68]
UK	w			0.64
				[0.60, 0.68]
	LogLik	-13,433	-13,071	-12,883
	AIC	26,869	26,144	25,773
	BIC	26,877	26,152	25,797
	β	0.93		1.42
		[0.77, 1.12]		[0.06, 35.51]
	B		0.98	0.72
			[0.82, 1.16]	[0.06, 9.12]
Experiment	w			0.55
				[0.26, 0.81]
	LogLik	-354	-347	-340
	AIC	709	695	686
	BIC	718	703	711

estimate $\beta = 1.51$, 95% CI [0.95, 2.40], $B = 2.80$, 95% CI [2.13, 3.68], and the mixture parameter weights the two-stage model 64%, 95% CI [60%, 68%]. The optimized model fits show that for both the US and UK data, the two-stage model fits the data better than the one-stage model, but that the mixture model fits the data better than either model. The predictions of the mixture model are presented as a dashed lines in Figure 3, and are similar to the results from the empirical data.

The model comparison and the estimation of the mixture parameter demonstrates that, for both the US and UK data, a substantial contribution from the two-stage model is required to fit the data.

6. Experiment

We conducted an experiment to assess how the portfolio composition influences the disposition effect. The experiment complements the analysis of the UK and US stockbroking transactions, because we can randomly assign the number of stocks in gain and loss in the portfolio, and thus make a causal claim about the effects of portfolio composition. Participants watched the value of

$100-per-stock investments in a set of stocks unfold over six months before selecting one of the stocks to sell. Participants received the value of the stock they selected for sale, before watching the remaining stocks unfold for a further six months and receiving the value of these remaining stocks at 1 year. Of key interest is whether the stock selected for sale at the six-month point is in gain or in loss, and how this depends upon the number of stocks in gain and in loss in the portfolio at the six-month point.

6.1. Method

6.1.1. Design. In nine trials, participants were shown portfolios consisting of at set of $100 stock investments in hypothetical companies. They saw how the prices of these stocks changed over the course of six months. We varied the number of stocks that had gained value and the number of stocks that had lost value at the six-month point. We used a 3×3 within-subject design, with varying numbers of stocks in gain (1, 2, or 4) and varying numbers of stocks in loss (1, 2, or 4) at the six month point. The nine possible combinations of the numbers of stocks in gain and in loss give us nine trials, which were presented to the participants in a random order. Our dependent variable was the choice of stock that a participant chose to sell after six month period. Our study design, sample size, exclusion criteria and analysis plan were preregistered on the Open Science Framework (https://osf.io/fd5vh/).

6.1.2. Participants. As per our preregistration, we collected data from 500 participants on Amazon Mechanical Turk (MTurk). We did not collect demographic information. We required participants to be US workers fluent in English with over a 99% approval rating for over 1,000 HITs. Participants' choices were incentivized, such that their decision from one randomly selected trial determined their bonus payment. Specifically, participants earned the money equivalent to the value of the stock sold at six months and the value of the remaining stocks at 12 months divided by 100, added to a $2.00 flat participation fee. Median pay was $5.02 and maximum pay was $5.68.

6.1.3. Stimuli. We generated 1,000 trajectories for stocks that were in gain at the six month point and 1,000 trajectories for stocks in loss at the six month point. Trajectories followed a random walk with 1,000 time steps in the year. The starting value V_0 for a stock was $100. The change in value at each time step was distributed normally mean 0 and standard deviation 1: $\Delta V_t \sim N(0,1)$ and $V_t = V_0 + \sum_{i=1}^{t} \Delta V_i$. We generated many trajectories and discarded any that fell below $50 or rose above $150 or where the final value was outside the range $75–$125. To ensure reasonably smooth trajectories only retained the 10% of trajectories with the highest R^2 value from a value-by-time linear model. We selected, at random, 1,000 gain trajectories with $V_{six\ months}$ between $130 and $110 and 1,000 loss trajectories with $V_{six\ months}$ between $70 and $90.

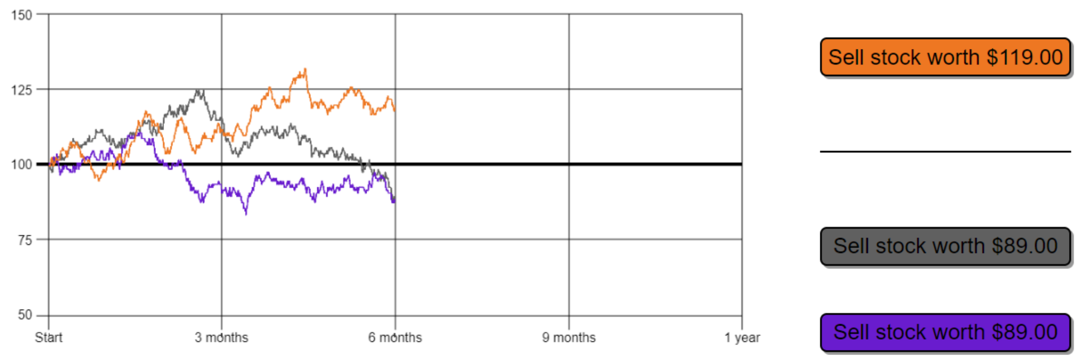
6.1.4. Procedure. The welcome screen explained to the participants that they are going to be making the type of decisions stock brokers make every day. In particular, they were informed that they will be shown a portfolio of stocks, and their task will be to choose which stock they would like to sell and which ones they would like to keep in that portfolio. The exact wording of the instructions is available on the Open Science Framework (https://osf.io/qw2k5/). The experiment began with a practice trial. First, they were shown an example portfolio, consisting of several $100 investment in stocks of hypothetical companies (identified by a random string of unique three alphabetical characters). Then, participants saw an empty plot with values ranging from 50 to 150 on the y-axis and evenly spaced values ”Start”, ”3 months”, ”6 months”, ”9 months” and ”1 year” on the x-axis. Participants were instructed that they are going to see how the values of all stocks changed over the course of six months. They saw an animation of price trajectories moving from the starting position up until they reached the six month mark (see Figure 4). At this point, participants were informed that they can now select exactly one stock to sell from their portfolio. For practice purposes, they were asked to select a specific stock worth $112. They were told that the are next going to observe how the price of remaining stocks changed in the next six months. After the animation ended, all gains and losses were summarized, combining the gain/loss made from the sale of the stock after six months with the gains/losses made from the sale of all remaining stocks after one year. At this stage, the incentive structure was explained. In particular, participants were told that if this portfolio was selected at the end of their study, their earnings would be based on the combined gain or loss from the trial (at one cent per every experiment dollar). Participants were then given the choice of starting the experiment or repeating the practice trial. The experimental trials had the exact same structure as the practice trial. After completing all nine trials, participants were thanked and given their completion code to submit on MTurk.

6.1.5. Exclusions. In 9 of 4500 trials (500 participants $\times$ 9 choices per participant), stock names were erroneously duplicated. These choices were excluded from the analysis (this makes almost no difference to the results.) Thus we have 4,491 choices in remaining. As per our preregistration, we primarily focus on the analysis of the first choice for each participant in order to avoid an influence of participants learning how to win the game over trials. The effects of portfolio composition are very similar in the analysis of all choices (see Appendix D).

6.2. Experiment Results

To preempt the fuller description of results below, while we do not observe an aggregate individual-stock-level disposition effect when averaging over portfolio composition, we do observe that the individual-stock-level disposition effect varies greatly over different portfolios, which is inconsistent

Portfolio 2



Six months have passed, and you can see the current value of each stock on the graph above. Stocks that are above $100.00 are currently in profit, and stocks below $100.00 are in loss.

This is where you need to make a decision. As a stock broker who owns this portfolio, which stock would you choose to sell at this point? Your task is to choose exactly one stock to sell.

Figure 4 **A screenshot from the experiment. In this example, one stock is in gain at six months and two stocks are in loss.**

with the one-stage model. We also see that $P(Any\ Gain)$ is quite constant across portfolio composition, consistent with the two-stage model. Overall, the experimental results are consistent with the two-stage model with B less than 1.

6.2.1. The Disposition Effect at the Individual-Stock Level. We find $P(A\ Loss)$ is similar to $P(A\ Gain)$—participants were equally likely to sell a stock in gain and stocks in loss. The individual stock level disposition effect β is 0.9, 95% CI [0.8, 1.1]. We return to this lack of disposition effect in the experiment in the General Discussion.

6.2.2. Portfolio-Composition Sensitivity of the Disposition Effect. Panel C of Figure 2 shows that the degree of the disposition effect depends on the composition of sell-day portfolios. These results confirm the findings in the stockbroking data seen in Panels A and B.

6.2.3. Non-Sensitivity of $P(Any\ Gain)$ to Portfolio Composition. Panel C of Figure 3 shows that $P(Any\ Gain)$ is quite constant, regardless of N_G and N_L. $P(Any\ Gain)$ is in the range 0.3–0.4 across different values of N_G and N_L. The result confirms the finding from the stockbroking data seen in Panels A and B.

6.2.4. Estimating a Mixture of the One- and Two-Stage Models. Table 2 reports the fit of the mixture model. The w parameter indicates that a mixture of one- and two-stage models is required to fit the data. BIC values favor the two-stage model over the one-stage model and the mixture model.

7. General Discussion

How do investors choose which stock to sell from their portfolio? We propose a two-stage sequential decision rule, in which investors first decide whether to sell a stock in gain or a stock in loss. Only then, having selected a domain, do individual select a stock from their chosen domain. The signature of this two-stage model is that the probability that the stock sold is in gain should be independent of portfolio composition. More specifically, the two-stage model predicts, given a stock is sold, that the probability that the stock is in gain is constant regardless of the number of stocks in gain and the number of stocks in loss in the portfolio. We first found this effect in US stock broking data first used by Barber and Odean (2000). In revising the paper we extended this finding to UK data (see Gathergood et al. 2018, for analysis of buying behavior). Despite large differences in investor types (investors from the UK data trade about 10 times more often than the investors from the US data) and methods (the US trades were most executed on the telephone whereas the UK trades were executed using an online platform), the effect of portfolio composition is very similar. Finally, in revising the paper, we ran a trading experiment where we randomly assigned portfolio composition, again finding that the probability that the stock sold is in gain is constant across portfolios with different numbers of stocks in gain and loss. This double replication gives us great confidence in the evidence for the two-stage account.

7.1. The Origin of the Disposition Effect

Here we have shown that the selling decision is taken first at the gain-loss domain level before individual stocks are considered. This result does have some implications for existing explanations of the disposition effect. The disposition effect could be caused by a belief in mean-reversion (Shefrin and Statman 1985). Accordingly, investors could believe that the stock in loss will regress towards the purchase value, and thus hold on to the stock. Such a mean reversion belief could apply to the gain-loss domain level as well as the individual stock level.

The disposition effect could be caused by the pain of realizing a loss at the point of sale (Shefrin and Statman 1985). This explanation could apply at the gain-loss level too—people may simply select to avoid the pain of realizing a loss and thus choose to sell from the set of stocks in gain, without considering individual stocks.

The disposition effect could also be caused by a reference point shift, such that stocks are evaluated on the concave loss part of the prospect theory value function rather than the convex gain part, which means that people will become risk seeking for stocks in loss and prefer the stock in loss to its cash value (Grinblatt and Keloharju 2001). It is harder to see this as an explanation of the gain-loss domain-level disposition effect, as evaluating individual stocks would appear to be important here (but note, we do see some individual-stock level disposition effect in the mixture modelling, so we cannot rule out some shift in risk preference as a contributing factor to the individual-stock level disposition effect).

While we saw strong disposition in both our US and UK stockbroking datasets we did not see the disposition effect in our trading experiment. We have several explanations as to why the disposition effect was absent from the trading experiment. Participants did not choose their own stocks, so realizing a loss may not have the pain associated with admitting one was mistaken. Consistent with this idea, Chang et al. (2016) find the disposition effect in trading stocks, where the individual investor is to blame for bad decisions, but not mutual funds where it is the fund manager, not the individual, who is to blame. A second explanation is that, although we told participants about their gain or loss from their sale at the half-way point, perhaps participants treated this as a paper loss, for which people do not show a disposition effect, rather than an actual cash loss, for which people do show a disposition effect (Imas 2014).

Whatever the cause of the absence of the disposition effect in the experiment, we did find that the individual-stock level disposition effect varies over portfolios, in contrast to the predictions of the one-stage model, and that the probability of selling any gain was invariant over the composition of gains and losses in the portfolio as we saw in the US and UK stockbroking data. It is this invariance that is the key signature of the two-stage model, and means that, whatever the origin of the disposition effect, it is, at least in a larger part, a gain-loss domain level phenomenon.

7.2. Alternative Explanations of Portfolio Composition Invariance

We have deferred until now the discussion of other possible accounts of the insensitivity of the probability that the stock sold is a gain to the gain-loss composition of the portfolio. For example, consider an alternative version of the two-stage model in which investors first evaluate each gain by comparing with other gains to identify one candidate gain to be sold. They also evaluate each loss by comparing with other losses and pick one candidate loss to be sold. Then, in the second stage, the candidate gain and the candidate loss are compared with one another and exactly one of them ends up being sold. Essentially, in this alternate model, the two stages are reversed. We cannot distinguish these two ordering of the steps in the two-stage model. But the prediction is the same—the probability that the stock sold is in gain will be independent from the number of gains and losses in the portfolio, because, in part, the decision to sell is a gain-loss domain level decision.

Barberis and Xiong (2012) proposed a model of realization utility, which, when combined with myopic preferences, leads to investors sell stocks in gain for immediate realization utility but holding stocks in loss (i.e., to the disposition effect). A reviewer suggested that this might be combined with the notion that investors compensate for the disutility of paper losses in a portfolio by realising stocks in gain. This might explain why investors would be more likely to sell stocks in gain in portfolios with more losses, as we see in Figure 2, but also makes the prediction that as soon as a portfolio is in a paper loss state, all gains will be sold very fast, because every gain sold leaves the portfolio in an even worse paper-loss state leading to more realisation of gains. We also show, in Appendix E, that the propensity to realize a gain is not associated with the returns on the unrealized gains or losses in the portfolio.

7.3. Conclusion

The disposition effect is typically described as the tendency of an investor to hold on to an individual stock if he or she has made a loss on it. That is, the disposition effect is due to the individual stock being in loss. In two stockbroking datasets and in an experiment, we demonstrate that the probability that the stock sold on a sell day is in gain is independent of the number of stocks in gain and the number of stocks in loss in the portfolio. Intuitively, if there are twice as many stocks in gain in an investor's portfolio, he or she should be more likely to choose a gain as the stock to sell. We propose a two-stage model, in which investors first choose whether to sell a stock from the set of those in gain or a stock from the set of those in loss before considering any of the individual stocks. This two-stage model fits the three datasets more closely than the typical one-stage model in which individual stocks are considered directly for sale. We conclude that the disposition effect is, in large part, a gain-loss domain level phenomenon.

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Table A1 Descriptive Statistics

Statistics	US Data	UK Data
Num.of Sell-Day Portfolios	35,663	20,695
Num.of Stocks	181,380	106,605
Num.of Accounts	10,668	4,923
Num.Unique Sell-Dates	1,467	1,012

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Appendix A: Summary Statistics for the Sell-Day Portfolios

Table A2 Summary of Control Variables

US Data	Mean	Std. Dev.	25th Pctile	Median	75th Pctile
Return	0.06	0.40	-0.11	0.01	0.15
Holding Days	248	290	50	142	333
UK Data					
Return	-0.01	0.27	-0.10	-0.01	0.06
Holding Days	138	173	22	71	188

Appendix B: A Multivariate Analysis of Composition Sensitivity in the Disposition Effect

In order to confirm the composition-sensitivity of the disposition effect in multivariate setting, a linear regression was conducted. The dependent variable is the dichotomous variable *Sell* taking the value of 1 if a stock was sold, otherwise 0. The independent variables are $Gain \times Gain\ Loss\ Ratio\ Bin$, $Best$, $Worst$, $\sqrt{HoldingDays}$, $Gain \times Retrun$, $Loss \times Return$, $Gain \times Return_{20}$, $Gain \times Volatility_{20}$, $Gain \times Return \times \sqrt{HoldingDays}$, and $Loss \times Return \times \sqrt{HoldingDays}$. *Gain Loss Ratio Bin* includes four bins: Mostly Losses (N_G:N_L=1 : 2+), More Losses (N_G:N_L=1 : 2 to 1 : 1), More Gains (N_G:N_L=1+ : 1 to 2 : 1), and Mostly Gains (N_G:N_L=2+:1). *Best* and *Worst* are dummies for the best and worst performing stocks in a sell-day portfolio. Hartzmark (2015) showed, the best and worst performing stocks in a portfolio are more likely to be sold than other middle performing stocks (the rank effect). Fixed effects of accounts and stock-by-dates were included. The standard errors were clustered by accounts and sell dates. A regression was conducted separately on the US and the UK data.

Tables B1 and B2 report the coefficients from the US and the UK data, respectively.

In the both US and UK data, the first four rows show the effect of *Gain* (i.e., the disposition effect) interacting with *Gain Loss Ratio Bin*. Comparing the coefficients and corresponding confidence intervals among the four bins, it is clear that the disposition effect decreases from Mostly-Losses-Bin (the first row) to Mostly-Gains-Bin (the fourth row), showing that the larger the number of gains relative to the number of losses in a portfolio the smaller the disposition effect. The results are consistent with the composition-sensitivity of the disposition effect seen in Panels A and B of Figure 2.

Table B1 **A Linear Regression for Composition-Sensitivity of the Disposition Effect (US data)**

	Estimate	Cluster s.e.	t value	p value
$Gain \times Mostly\ Losses\ Bin$	0.145	0.057	2.557	0.011
$Gain \times More\ Losses\ Bin$	0.096	0.047	2.047	0.041
$Gain \times More\ Gains\ Bin$	0.030	0.043	0.685	0.493
$Gain \times Mostly\ Gains\ Bin$	0.007	0.045	0.157	0.875
Best	0.145	0.031	4.621	0.000
Worst	0.034	0.027	1.271	0.204
$\sqrt{HoldingDays}$	-0.001	0.002	-0.707	0.480
$Gain \times Return$	0.025	0.098	0.257	0.797
$Loss \times Return$	0.192	0.254	0.755	0.450
$Gain \times Return_{20}$	0.050	0.159	0.311	0.756
$Gain \times Volatility_{20}$	0.470	1.315	0.357	0.721
$Gain \times Return \times \sqrt{HoldingDays}$	-0.003	0.004	-0.706	0.480
$Loss \times Return \times \sqrt{HoldingDays}$	-0.010	0.012	-0.858	0.391
R^2	0.94			
Num. Observations	181,380			

Table B2 **A Linear Regression for Composition-Sensitivity of the Disposition Effect (UK data)**

	Estimate	Cluster s.e.	t value	p value
$Gain \times Mostly\ Losses\ Bin$	0.138	0.032	4.380	0.000
$Gain \times More\ Losses\ Bin$	0.096	0.024	3.939	0.000
$Gain \times More\ Gains\ Bin$	0.042	0.024	1.762	0.078
$Gain \times Mostly\ Gains\ Bin$	0.015	0.026	0.569	0.569
Best	0.227	0.024	9.325	0.000
Worst	0.037	0.018	2.040	0.041
$\sqrt{HoldingDays}$	-0.005	0.002	-3.078	0.002
$Gain \times Return$	-0.089	0.106	-0.839	0.402
$Loss \times Return$	0.601	0.152	3.957	0.000
$Gain \times Return_{20}$	0.018	0.042	0.434	0.664
$Gain \times Volatility_{20}$	-0.408	0.448	-0.911	0.362
$Gain \times Return \times \sqrt{HoldingDays}$	0.000	0.007	0.006	0.995
$Loss \times Return \times \sqrt{HoldingDays}$	-0.020	0.008	-2.523	0.012
R^2	0.86			
Num. Observations	106,193			

Appendix C: Robustness Check

C.1. Tax Exempt Accounts

Investors might have tax motivations to realize a gain or realize a loss, and thus, might evaluate only gains or only losses in their portfolio on the sell day. For checking whether our findings are robust without tax-motivated investors, we repeated the analysis with a sample of tax-exempt accounts (i.e., IRA and Keogh accounts). The results are shown in Figures C1 and C2.

Figure C1 shows that the composition sensitivity of the disposition effect seen in Figure 2 is observed in the sample consisting of tax-exempt accounts. Figure C2 shows $P(Any\ Gain)$ as a function of N_G and N_L

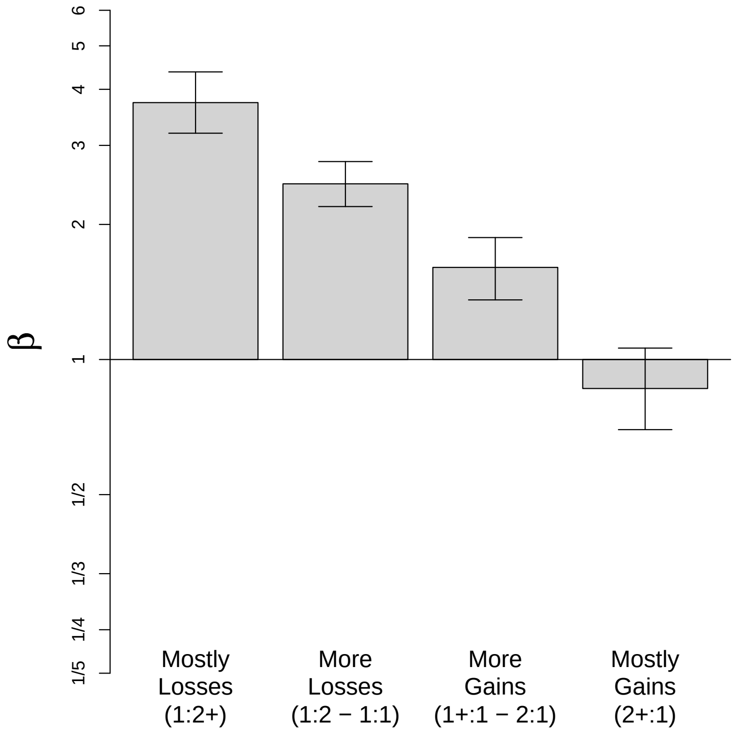

Figure C1 The disposition effect depends on the composition of the portfolio (tax-exempt accounts). This figure corresponds to Figure 2 reducing the sample to observations for IRA and Keogh accounts. The error bars are 95% confidence intervals computed with the bootstrap method with 1,000 resamples, corrected for clustering by accounts and sell dates.

on the sample of tax-exempt accounts. The constant $P(Any\ Gain)$, seen in Panel C of Figure 3, is mostly confirmed.

To recap, the findings of the main analysis are robust with the sample consisting of only tax-exempt accounts.

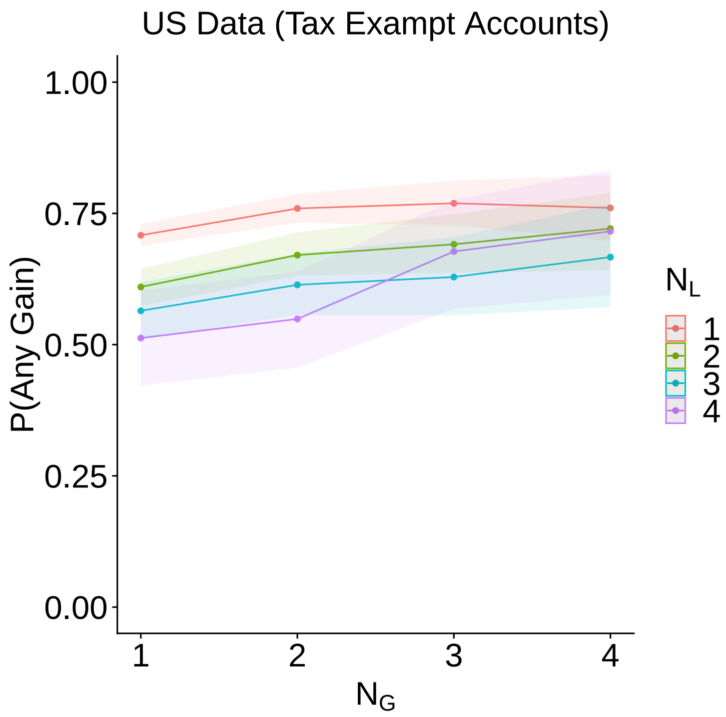

Figure C2 **P(Any Gain) as a function of N_G and N_L in the empirical data (tax-exempt accounts). This figure corresponds to the third panel of Figure 3 reducing the sample to observations for IRA and Keogh accounts. The shadow area represents 95% confidence intervals computed with the bootstrap method with 1,000 resamples, corrected for clustering by accounts and sell dates.**

Appendix D: Analysis of all Experimental Trials

Because we selected low volatility trajectories, stocks in loss at the time when participants were asked to sell one tended to stay in loss until the end of the trial. Conversely stocks in gain at the decision stage tended to stay in gain until the end of the trial. Participants appear to have become aware of this design feature over the course of the repeated trials: $P(Any\ Gain)$ sharply decreased after the first trial, eventually leading to a reversal of the disposition effect. Because of this order effect, we report our preregistered between-subject analysis in the main text. We also preregistered a within-subjects analysis of all trials, which report here: Throughout all trials, the insensitivity of $P(Any\ Gain)$ to portfolio composition was preserved, supporting the two-stage model (see Figures D1 and D2).

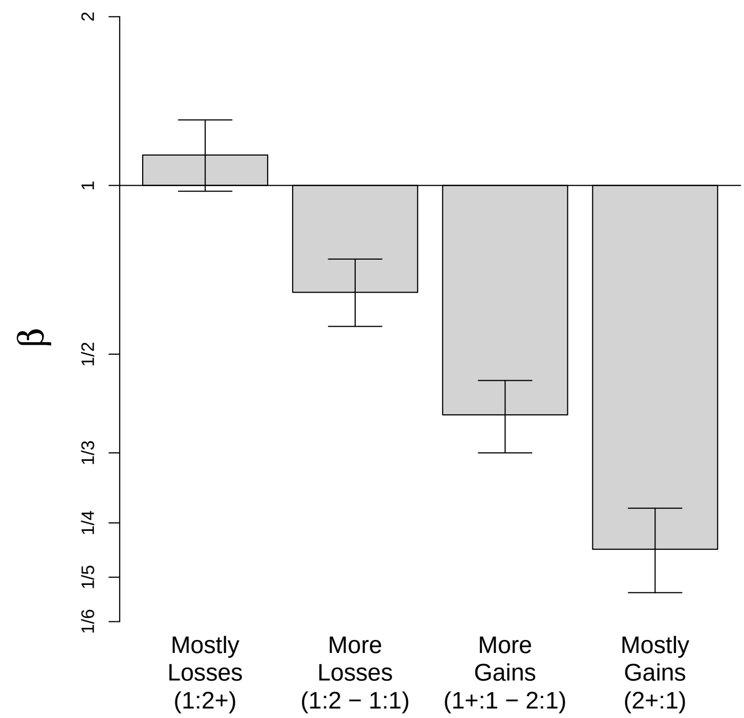

Figure D1 The disposition effect depends on the composition of the portfolio in the whole experimental data. The error bars are 95% confidence intervals computed with the bootstrap method with 1,000 resamples, corrected for clustering by accounts and sell dates.

Appendix E: Ruling Out an Alternative Explanation on Realization Utility

Barberis and Xiong (2012) proposed a model of realization utility in which investors derive utility by realizing gains or losses from their portfolio. This model offers an explanation of the disposition effect. Combined with sufficient discounting, a stock in gain will be sold today because the immediate realisation utility is larger than the discounted utility from a later realisation. A stock in loss will not be voluntarily realised because of the disutility of realising it.

Here we consider whether an extension of the realization utility model proposed by a reviewer, in which an individual faced with the disutility of a portfolio with many paper loses might realise (i.e., sell) a gain to offset their paper loss disutility. We might assume that the desire to sell a gain is stronger when more stocks are in loss. Specifically we might assume that $\beta \propto \frac{N_L}{N_G}$. With c as the constant of proportionality, we can substitute for β into the one-stage model equation (Equation 5) and obtain $P(Any\ Gain) = \frac{c}{c+1}$. This result is identical to the two-stage model equation (Equation 6) where $c = B$. That is, if the disposition effect is not constant but varies with portfolio composition—exactly as we have been arguing—then the two stage model results.

We think it is simpler to view the two stage model as a constant probability to sell from the gain domain, rather than a varying probability to sell a particular gain as a function of portfolio composition. Further the motivation for variation in the desire to sell a gain in this realised-utility account ignores the actual size of losses. That is, investors' utility from unrealized gains and losses in a portfolio and the utility derived by

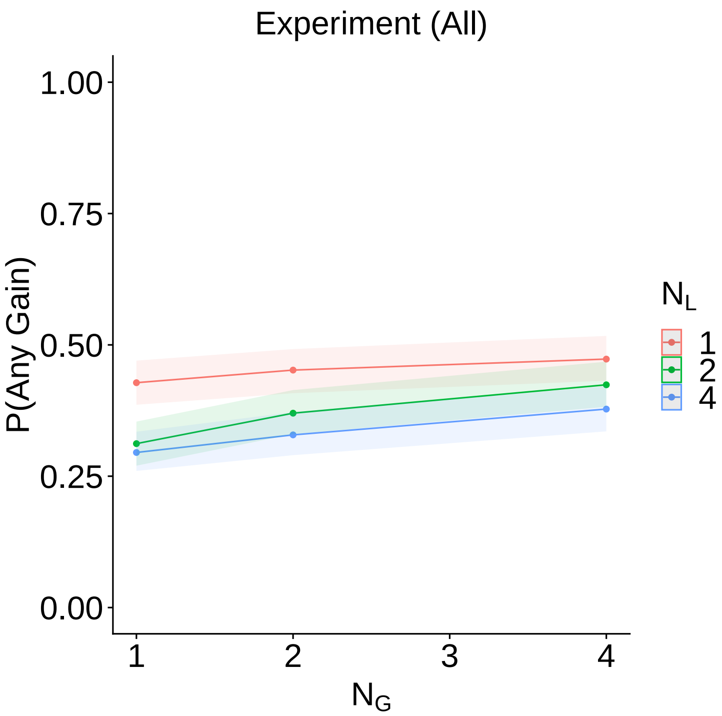

Figure D2 $P(Any\ Gain)$ **as a function of** N_G **and** N_L **in the whole experimental data. The shadow area in the third panel represents 95% confidence intervals computed with the bootstrap method with 1,000 resamples, corrected for clustering by accounts and sell dates.**

realizing gains or losses should be, at least partially, dependent on the size of gains and losses (instead of the number of gains and losses). More specifically, if the extended realization utility account is correct, we should expect that the larger the size of unrealized loss in the portfolio the larger the size of realized gain on the sell-day.

Figure E1 shows the size of realized gain or loss on the sell-day as a function of the size of unrealized gain or loss in the portfolio. The curve is flat for the portfolio-level losses and has an upward slope in the gain domain. This is not consistent with realized utility account, which predicts that large unrealised portfolio losses must be compensated by large realised gains.

The x-axis variable in Figure E1 correlates with N_G and N_L and may be confounded with the disposition effect where a stock with a large unrealized gain was realized on the day, and thus, one large gain contributes to both the x- and y- axes. In order to account for this, we extracted portfolios with N_G=1 and N_L=1 and calculated $P(A\ Gain)$ as a function of the size of unrealized gain/loss in the portfolio (i.e., the aggregation of a gain and a loss within a portfolio). If the alternative model is correct, we would expect that the larger the size of an unrealized loss in the portfolio the larger $P(A\ Gain)$. Figure E2 plots the results, showing no association between portfolio-level unrealized gain/loss and the likelihood of a gain being realized. This is again not consistent with the prediction of the myopic realization utility model.

Acknowledgments

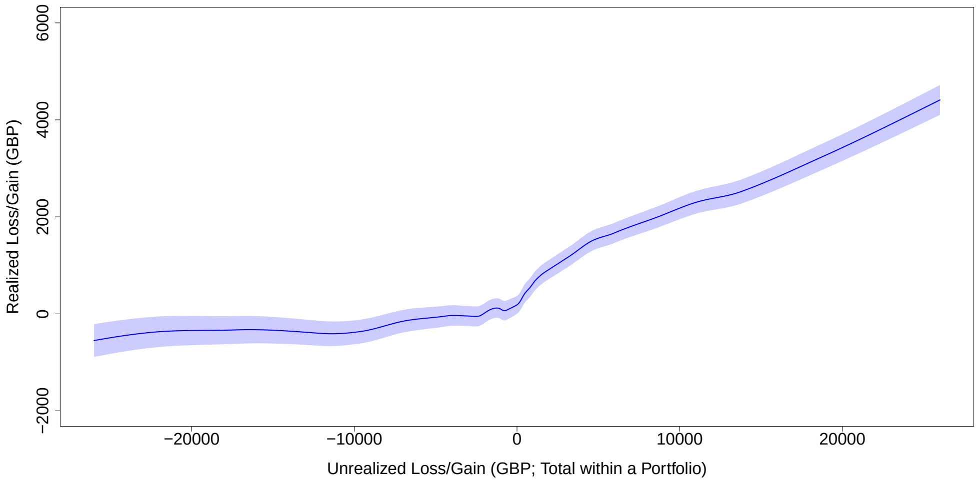

Figure E1 **The size of realized gain/loss on the sell-day as a function of the size of unrealized gain/loss in the portfolio. The blue line is a prediction form a local regression. The shaded areas are bootstrapped 95% confidence intervals.**

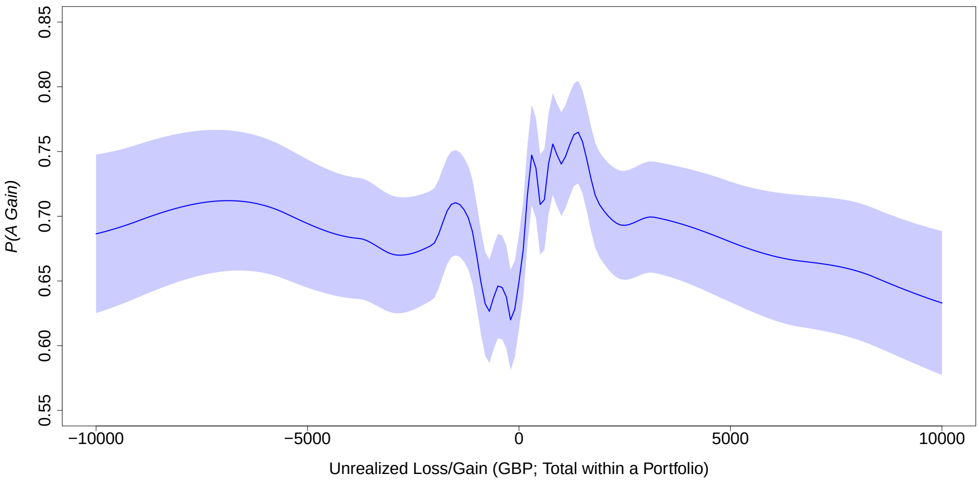

Figure E2 $P(A\ Gain)$ **as a function of the size of unrealized gain/loss in the portfolio. The blue line is a prediction form a local regression. The shaded areas are bootstrapped 95% confidence intervals.**

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