The Disposition Effect in Boom and Bust Markets

Sabine Bernard, Benjamin Loos, and Martin Weber*

Abstract

Most papers investigating the disposition effect implicitly assume it to be constant over time and use data that only cover boom periods. However, drivers of the disposition effect (preferences and beliefs) are rather countercyclical. We use individual investor trading data comprising several boom and bust periods (2001-2015). Our results show that the disposition effect also moves countercyclical, i.e. is higher in bust than in boom periods. Our findings are driven by individuals realizing more gains in bust periods. Investors are, in relative (absolute) terms, 25 (5) percent more likely to realize a gain in bust than in boom periods.

Keywords: *Disposition Effect, Market Cycles, Household Finance, Retail Investor*

JEL Classification: *D14, G11, G28*

* Sabine Bernard (sbernard@mail.uni-mannheim.de) and Martin Weber (weber@bank.bwl.uni-mannheim.de) are affiliated with the University of Mannheim (L9, 1-2, 68131 Mannheim, Germany).

** Benjamin Loos (benjamin.loos@uts.edu.au) is affiliated with the University of Technology Sydney (14-18 Ultimo Road, Sydney, Australia).

1. Introduction

The disposition effect, namely investors' tendency to sell winners more frequently than losers (Shefrin and Statman, 1985), is one of the most explored behaviors in finance. A large number of studies document the presence of the disposition effect among different investor types, in various asset classes, and across geographical regions.[1]

While there exists strong empirical evidence for the disposition effect, most papers investigating the disposition effect use data that only cover boom periods and implicitly assume that the disposition effect is constant over time.[2] Yet, recent literature on the proposed drivers of the disposition effect, preferences and beliefs, show that these drivers are changing with boom and bust cycles. Experimental literature exploring changes in investors' preferences shows that investors are more risk averse in bust periods (Cohn, Engelmann, Fehr, and Maréchal, 2015) or in negative emotional states such as anxiety (Loewenstein, Weber, Hsee, and Welch, 2001; Kuhnen and Knutson, 2011). Further, Guiso, Sapienza, and Zingales (2018) find empirical evidence that following the 2008 crisis, both qualitative and quantitative measures of risk aversion increased substantially. Likewise, investors' beliefs vary over time. Malmendier and Nagel (2011) find that investors who experienced low stock market returns throughout their lives are more pessimistic about future stock market returns and that more recent return experiences have stronger effects. In particular, recent events such as crises can trigger changes in investors' return expectations (Weber, Weber, and Nosic, 2013). The notion that macroeconomic conditions impact investors' beliefs is also found using survey data (Vissing-Jorgensen, 2003; Dominitz and Manski, 2010). Greenwood and Shleifer (2014) as well as Amromin and Sharpe (2014) find investors' expectations to be extrapolative and influenced by economic conditions, i.e., are positively correlated with past stock market returns.

The aim of this paper is to investigate if the disposition effect is indeed constant over time or if the disposition effect moves with market cycles (i.e., boom and bust periods). We analyze a large German retail investor data set containing private investor trading and portfolio data from 2001 to 2015 and show that the disposition effect is not time-invariant. In particular, we demonstrate that the disposition effect moves countercyclical with the market (Figure 1).

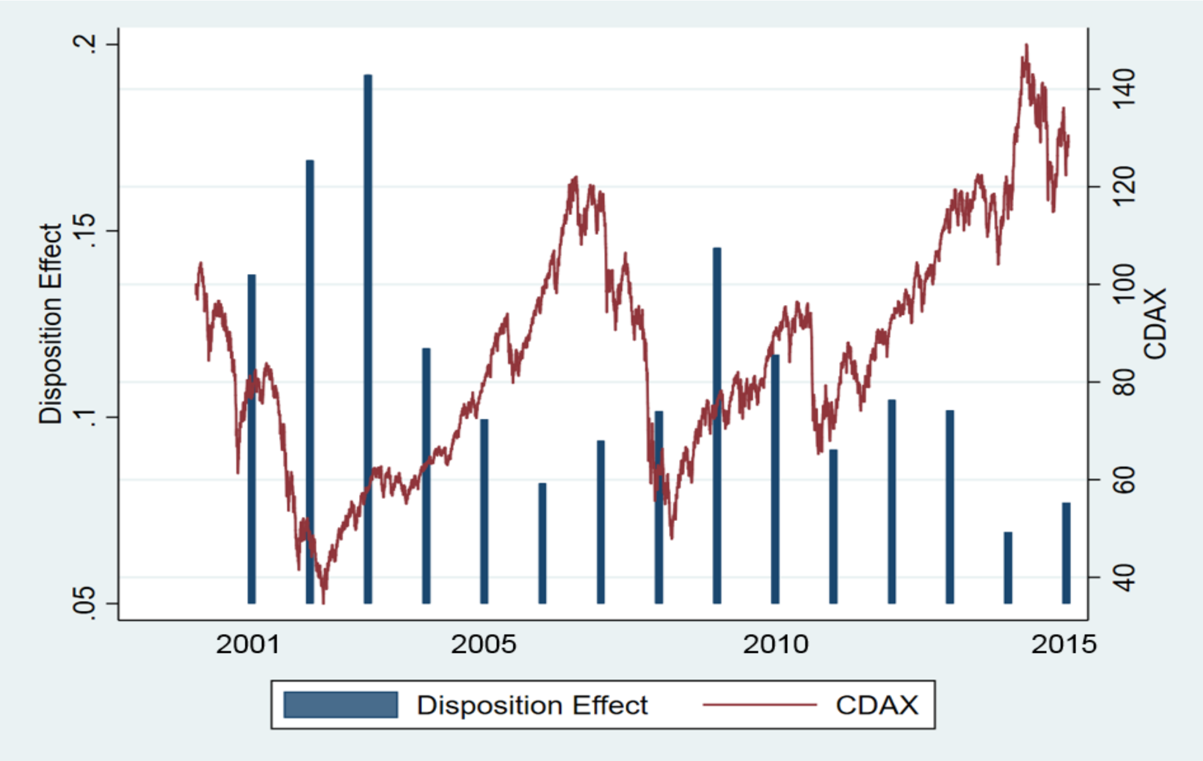
---

[1] For related literature see Appendix A Panel 1.

[2] For papers and time periods see Appendix A Panel 2.

Figure 1: The Disposition effect over time

This figure shows the evolution of the disposition effect from January 2001 to December 2015. The 15 blue bars represent the disposition effect at the end of each year over almost 100,000 German investors. The red line represents the broadest German market index (CDAX), which is indexed at 100 at the first trading day in 2001.



In other words, the disposition effect is highest in periods when the market is down and lowest in periods when the market is up. In order to assess whether a market is in a down or up state, we use a bear market indicator that equals one if the excess (of risk free rate) cumulative CDAX[3] return in the past 24 months is negative and zero otherwise (Daniel and Moskowitz, 2016). The disposition effect is the difference in the propensity to sell a stock at a gain (PGR) and the propensity to sell a stock at a loss (PLR). In bust periods the disposition effect is equal to 10.6% (=23.9-13.3) and in boom periods the disposition effect is equal to 5.42% (=18.9-13.48). In absolute terms, the disposition effect is 5.18 percentage points higher in bust than in boom periods. This difference in the disposition effect between boom and bust cycles is entirely driven by investors' increased propensity to realize gains in bust periods. Investors are in

[3] The CDAX is a German stock market index that comprises all stocks traded on the Frankfurter Stock Exchange that are listed in the Prime or General Standard market segment.

relative terms, more than 25% more likely to realize a winner asset in bust than in boom periods. The realization of losses does not change across boom and bust markets.

To further understand investors' change in selling behavior across boom and bust markets and to shed light on the channel (i.e. beliefs and preferences) that drives our results, we analyze the impact of the magnitude and the timing of gain and loss realizations in boom and bust markets.

If investors are Prospect Theory investors and if risk aversion increases in bust periods, then we expect to see a higher number of gain realizations in bust than in boom periods irrespective of the gains magnitude. We further expect the magnitude effect (PGR and gain's magnitude are positively correlated) to be stronger in boom than in bust periods since the slope of the value function decreases over the gain domain and is always smaller for high risk averse investors than for low risk averse investors. Lastly, the change in preferences should only effect the gain realization and not the loss realization since risk aversion exclusively affects the shape of the value function over gains and not losses. We find empirical evidence for all three hypothesize. On average, investors are 3.8 percentage points more likely to sell a gain in bust than in boom periods irrespectively of the gain's magnitude. In line with existing literature on the disposition effect, we find that investors' likelihood to sell a gain increases with its magnitude (Kaustia, 2010; Barber and Odean, 2013). However, we observe that the response to the size of gains is amplified in bust periods: The likelihood of selling a gain asset increases by around 4 percentage points over terciles within boom periods and increases by more than 7.6 percentage points within bust periods. Changes in PLR are rather small and hardly economically significant.

Turning to the belief channel, we investigate investors' timing of sales within and across boom and bust cycles. In contrast to changes in preferences, changes in beliefs do effect both, gain and loss realization. Research suggests that investors' beliefs are positively correlated with past stock market returns and thus investors become overly optimistic (pessimistic) in boom (bust) periods. Investors who are confronted with a bust period extrapolate their pessimistic views into the future and thus start to log in their gains as soon as possible and try to stop their losses to increase any further. Therefore, we expect to see a higher PGR and PLR at the beginning of a bust period than at the end of a bust period (within cycle comparison). Across cycles, we suppose PGR and PLR to be higher at the beginning of a bust than at the beginning of a boom period. In boom periods investors are assumed to be more optimistic and thus will "ride the bubble" (e.g. Harrison and Kreps, 1978; Vissing-Jorgensen, 2003) which should be reflected by a rather stable PGR over time. Our results show that within bust markets PGR and PLR is highest at the beginning of the cycle. Investors' PGR (PLR) at the beginning of a bust period decreases by more than 27% (19%) compared to invertors' PGR (PLR) at the end of a bust cycle. Across cycles, we find that investors are almost 22% (23.5%) more likely to sell a gain (loss) asset at the beginning of a bust than at the beginning of a boom period. Lastly, we find PGR in boom periods to be rather stable over time which suggested that investors tend to ride the bubble in boom periods.

A recent paper by Engelberg, Henriksson, and Williams (2018) finds that investors who hold a portfolio with an overall positive value do not experience a disposition effect, while investors holding a portfolio with an overall negative value do so. Since it is plausible to assume that an investor's portfolio value and market conditions are positively correlated, one might argue that our results are driven by changes on the portfolio level but not by changes in market conditions. In the robustness section, we show that market cycles affect investors' selling behavior even after controlling for the portfolio driven disposition effect. Both effects seem to affect investors' degree of the disposition effect. Results are also robust against different definitions of boom and bust periods and various fixed effect models. Further, we show that mechanics such as an increased number of gain assets in a boom period do not drive our results.

Collectively, our findings cast doubt on the indirect assumption that the disposition effect is a time independent phenomenon. Taking up literature arguing that investors' preferences and beliefs vary with market cycles, we find that the disposition effect moves countercyclical to the market, i.e. is low in boom periods and high in bust periods. This change in investors' selling behavior across cycles is entirely driven by their increased gain realization in bust markets. Our paper contributes to the existing literature in several dimensions. We add new insights to the longstanding discussion on what drives disposition effect. As our results show both, preferences and beliefs, affect the strength of the disposition effect. Further, our results highlight that by using data from boom periods existing literature on average underestimates the disposition effect.

2. Data

The study is based on four data sets. The first data set comprises the trading history of 98,880 investors who hold accounts at a large German online bank from January 2001 until December 2015. Trades are reported on a daily frequency. Overall, the trade file has more than 20 million records. Each record provides the date of purchase/sale, the purchase/selling price, the volume traded, and the respective fees. The second data set comprises investors' portfolio holdings. It contains monthly positions for all accounts during the sample period. Each of the approximately 96 million records provide information about the account number, security number, year, month, the position's market value and the position's quantity. Accounts that are closed during the sample period are not replaced. In addition to investor's trading and holding data, the third data set contains information about investor's demographics such as age, gender, income, wealth, and zip code. The fourth data set comprises daily market data (from Thomson Reuters Datastream) of all the securities held or traded by the investors who are part of the first and second data set during the observation period.

According to Odean (1998) and Ben-David and Hirshleifer (2012), we filter the raw data set as follows: First, the analysis includes only securities that are identified as common shares that can be matched to market data downloaded from Thomson Reuters Datastream. Second, if an investor's trading history shows multiple trades in one security per day the transactions are netted. Third, we exclude securities that are purchased before January 2001 because the purchase prices of these assets are unknown and thus the disposition effect cannot be calculated. We confine our analysis to non-advised investors. We then construct each investor's portfolio on a monthly basis and calculate the investor's disposition effect. Consistent with Odean (1998) and Chang, Solomon, and Westerfield (2016), we only focus on observations in months when a sale takes place in an investor's portfolio. We end up with 80,860 accounts in the boom period and 69,439 accounts in the bust period. A bust period takes place whenever the excess cumulative CDAX return in the past 24 months is negative and zero otherwise (Daniel and Moskowitz, 2016). Information which month is being categorized as boom or bust month can be found in Appendix B. Overall, our data contains 18,280,493 records from January 2001 up to December 2015. Detailed information about the sample composition in boom and bust months is depicted in Table 1.

Table 1: Summary statistics in boom and bust periods

This table shows summary statistics for the filtered data used throughout this study, given that at least one sale took place in a given month. *Accounts* is the number of distinct accounts that were active in the boom and/or bust period. *Observations* records the account-stock-month triples. On the Portfolio Level the *Average number of trades, Portfolio holdings at a gain, Portfolio holdings at a loss, the Herfindahl-Hirschman index (HHI),* and the *Risk class* of an investor's position are reported monthly. The HHI is calculated following Dorn et al. (2008). The risk class classification is provided by the bank and ranges from 1 (low), 2 (increased), 3 (high) to 4 (very high). We report *Age, Gender, Education,* and *Wealth* on the account Level. The income category is provided by the bank and are midpoints of wealth brackets that given in Euro.

	Boom	Bust	Two sided t test (test statistic)
Sample Split			
Accounts	80,860	69,439	
Observations	11,633,923	6,646,570	
Portfolio Level			
Average # of trades (monthly)	3.07	3.12	11.97
Portfolio holdings at a gain (%)	38.07	20.73	
Portfolio holdings at a loss (%)	61.93	79.27	
Herfindahl-Hirschman Index (HHI)	48.3	46.6	14.28
Investor Level			
Age (Year)	52	53	-5.66
Gender (%)			3.72
Male	83	83	
Female	17	17	
Education (%)			-0.02
No title	94	93	
PhD or Professor	6	7	
Wealth (€)	45,400	46,400	1.63

On the portfolio level, we observe significant differences in boom and bust periods in terms of the average number of monthly trades, investors' portfolio diversification (measured by the Herfindahl-Hirschman index), and the fraction of portfolio holdings trading at a gain or loss. While the difference in the average number of monthly trades is highly statistically significant, it is hardly economically significant: The absolute difference in average number of monthly trades is only 0.05. In terms of portfolio diversification, investors are less diversified in bust than in boom periods. The Herfindahl-Hirschman Index (HHI) is equal to 48.3 in boom periods and 46.6 in bust periods. On average, investor's portfolio show a medium level of diversification. As can be expected, we find a higher fraction of gain assets in boom than in bust periods (38.07% versus 20.73%) and a smaller fraction of loss assets in boom than in bust periods (61.93% versus 79.27%). Note, that we simply count the absolute number of gain and loss assets in an investor's portfolio to calculate the fraction of portfolio holdings trading at a gain/loss. To account for these differences on the portfolio level, we control for potential portfolio driven effects such as the portfolio driven disposition effect (Engelberg et at., 2018) and the number of paper gains in our robustness tests. Turning to the investor level, differences between boom and bust periods become smaller. While there is no difference in investors' education and wealth between boom and bust periods, differences in age and gender are statistically significant. However, differences in age and gender are hardly economically significant. To account for differences on the investor level, we introduce account, month and account-month fixed effects to our models.

3. Methodology

While Odean (1998) proposes a simple proportion-based measure to calculate the disposition effect thereby neglecting other variables affecting the disposition effect, Birru (2015) develops a regression equation approach to control for other variables driving investors' selling behavior. We will follow Birru (2015) and Chang et al. (2016) in specifying our regression to measure the disposition effect as follows:

$$(1)\ Sale_{ijt} = \beta_0 + \beta_1 Gain_{ijt} + \epsilon_{ijt}$$

where observations occur at the account (i), stock (j), and month (t) level. *Sale* is a dummy variable that equals one if the cumulative volume of asset *j* decreases between the previous month and today in a particular account *i* and zero otherwise. *Gain* is a dummy variable that is equal to one if the average purchase price of stock *j* is smaller than the current market price of stock *j* and zero otherwise. The average purchase price is defined as the ratio of the cumulative purchase price and the cumulative volume for each security. In cases in which an investor sells off a position entirely and later repurchases the same security, the average purchase price is set to zero upon the total sale of the position. Furthermore, Odean (1998) states that fees and commissions should not have a significant influence on the calculation of the disposition effect. Thus, we do not consider fees and commission paid on each transaction. Consistent with contributors to the literature (e.g. Odean, 1998; Chang et al., 2016), we report gains and losses in each month a sale takes place in an investor's portfolio. Chang et al. (2016) argue that in months without a sale, investors' behavior might be driven by deliberate choice or simple inattention. They show that limiting the sample to months with at least one sale does not drive their results. To overcome intraclass correlation, we cluster standard errors at the account and date level in all regressions. We further run several models using account, month, and stock fixed effects to capture the aggregated effect of all unobservable, time-invariant explanatory variables for an investor's selling behavior. This is essential since unobservable, time-invariant variables such as an investor's characteristics (account level), seasonal trading patterns (month level), or industry specific trading strategies (stock level) might affect our results.

According to regression (1), the constant (β_0) measures investors' propensity to sell a stock at a loss (PLR), whereas, the sum of the constant and the gain coefficient (β_0+β_1) measures investor's propensity to sell a stock at a gain (PGR). Hence, β_1 measures the disposition effect (PGR – PLR).

Since we want to investigate whether market episodes have an impact on the selling behavior of private investors, we analyze this relationship by estimating the following regression equation:

$$(2)\ Sale_{ijt} = \beta_0 + \beta_1 Gain_{ijt} + \beta_2 Boom_t + \beta_3 Gain_{ijt} \times Boom_t + \epsilon_{ijt}$$

where observations are again on the account-stock-month level. Adding to the standard disposition effect regression, we introduce a boom dummy and interact it with the other regressor. Following Daniel and Moskowitz (2016), we use a *Boom* dummy that equals one if the excess cumulative CDAX return in the past 24 month is positive and zero otherwise. All following boom/bust specifications are based on the CDAX because we use German retail investor data. However, results are also robust to using the MSCI ACWI (see Appendix C). Again, the regression is two-way clustered at the account and date level and several fixed effect models are tested. The correlation between CDAX and MSCI ACWI during our sample period is equal to 0.763. Our coefficient of interest in regression (2) is β_3. The coefficient of the interaction term represents the difference in disposition effects between boom and bust markets.

4. The disposition effect across market cycles

There exists long-standing literature about the disposition effect of retail investors in finance. However, all of these studies implicitly assume the disposition effect to be constant over time. In addition, almost every paper investigating private investor's selling behavior uses trading data from a boom period (see Appendix A). The question at hand is whether investors' selling patterns are constant over time, and if not, whether selling behavior fluctuates with market cycles.

Figure 1 summarizes the result we document in this paper: The disposition effect moves countercyclical with the market index. Regression (2) estimates the average difference in the disposition effect across boom and bust periods. Results are reported in Table 2a. Simplifications of the results from regression equation (2) can be found in Table 2b.

Table 2a: The disposition effect across market cycles – Regression results

This table examines the variation in the disposition effect between market cycles, i.e. boom and bust periods. We report the results of various regressions on the sample of 18,280,493 account-stock-month triples of individual investors from a German bank. Observations are taken monthly in months when at least one asset was sold in an investor's portfolio. The observation period ranges from January 2001 to December 2015. The dependent variable *Sale* is a dummy variable equal to one if the investor sells an asset within a particular month. *Gain* is a dummy variable equal to one if an asset's market price at the end of the month is above the reference point (here: defined as the average purchase price). *Boom* is a dummy variable that equals one if the excess cumulative CDAX return in the past 24 months is positive. Standard errors (in parentheses) are two-way clustered by account and month. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Dependent Variable: Sale	Model 1	Model 2	Model 3	Model 4	Model 5
Gain	0.106***	0.0973***	0.0999***	0.0900***	0.0855***
	(0.00595)	(0.00529)	(0.00580)	(0.00532)	(0.00484)
Boom	0.00184	0.0131***	0.00551	0.0158***	
	(0.00408)	(0.00322)	(0.00379)	(0.00322)	
Gain*Boom	-0.0518***	-0.0417***	-0.0502***	-0.0392***	-0.0284***
	(0.00660)	(0.00587)	(0.00639)	(0.00586)	(0.00485)
Constant	0.133***				
	(0.00340)				
Observations	18,280,493	18,277,565	18,279,680	18,276,753	18,236,138
R-squared	0.009	0.092	0.025	0.101	0.147
Cluster account-month	YES	YES	YES	YES	YES
Account FE		YES	YES	YES	YES
Stock FE				YES	YES
Month FE					YES
Account-month FE					YES

Table 2b: The disposition effect – Summary of regression results

This table depicts the probabilities of selling a gain (loss) in boom and bust periods as estimated by the regression equation (2). Numbers in this table are selling probabilities from Table 2a. Differences in selling a gain (loss) across boom and bust markets are stated by the test statistic in column 4 of the matrix. Differences in selling a gain and loss asset within a boom (bust) period are stated in row 3.

	Boom	**Bust**	**Significance**
Gain	18.90%	23.90%	***
Loss	13.48%	13.30%	
Disposition Effect	5.42%	10.60%	***
Significance	***	***	

The regression in Model 1 Table 2a shows that on average the disposition effect in boom periods is 5.42%, while in bust periods it is 10.6%. Thereby, the disposition effect in bust periods is nearly doubled in bust periods relative to the disposition effect in boom periods. In absolute terms, the difference in the disposition effect between boom and bust periods equals 5.18 percentage points. This effect is robust and holds even after introducing account and stock fixed effects (see Model 2, Model 3, Model 4 in Table 2a). To ensure that our results are not driven by different investor types being active in boom and bust period, we further introduce account-month fixed effects to our model (Model 5). As can be seen in Table 2a column 5, this conservative model specification does also not alter our main result. The boom-bust interaction term equals – 0.0284 and is statistically significant to the one percent level. Across all models, the difference in the disposition effect between boom and bust periods varies between 5.18 and 2.84 percentage points. The difference remains highly significant across all model specifications.

Since the disposition effect is the difference between PGR and PLR, either changes in gain realization and/or loss realization can drive our main result. Analyzing the difference in the disposition effect between boom and bust periods in more detail, we find that differences in the selling behavior are entirely driven by the gain side. In bust periods, investors' propensity to sell a gain asset is equal to 23.90%. In contrast, the likelihood to sell a gain asset in boom periods is only 18.90%. Hence, investors are in absolute terms 5 percentage points more likely to sell their gains in bust rather than in boom periods. This difference is highly statistically significant at the one percent level. Another channel driving the difference in the disposition effect across market cycles could be the loss domain. The difference in realizing a loss in boom versus bust periods is depicted by the boom coefficient (β_2). Investors are 0.184 percentage points less likely to realize losses in bust than in boom periods. However, this difference is not statistically significant. Interestingly, after introducing account FE to our regression, the difference in investors' loss selling behavior becomes significant. The boom coefficient increases in both, magnitude and significance, indicating that investors' characteristics affect their loss selling behavior.

Overall, results from regression equation (2) support our descriptive evidence from Figure 1. The disposition effect almost doubles in bust periods relative to boom periods and this is entirely driven by investors' increased gain realization.

One might argue that an investor's portfolio will per se contain more gain assets in boom periods than in bust periods and thus PGR in bust periods is higher than PGR in boom periods since PGR purely measures the fraction of realized gains over all gains in an investors' portfolio. Therefore, the observed difference in PGR between boom and bust markets may not reflect a change in investors' selling behavior but may rather be mechanically driven. For example, think of an investor who always sells exactly one asset per month. If the number of paper gains in the investor's portfolio increases, PGR will decrease, whereas, if the number of paper gains decreases, PGR will increase. Since the number of gains in an investor's portfolio will increase in boom and decrease in bust periods, this investor will show a higher PGR in bust than in boom periods even though his selling behavior did not change with market cycles. To ensure that our results are not driven by any mechanics, we further run our base regression (2) while controlling for the absolute number of paper gains in an investor's portfolio. As can be seen in Appendix D, after controlling for the number of paper gains the difference in disposition effect across market cycles is still economically and statistically significant. In fact, after controlling for the number of paper gains and various interactions, we observe a difference in the disposition effect across boom and bust period ranging from 4.97 % up to 8.43%.

Since we are the first to report a countercyclical movement of the disposition effect with the market and since we are using a proprietary data set, one might cast doubt on the representativeness of our results. We use a data set that is different from the classical Odean (1998) data set in two dimensions: Firstly, we deal with German investors instead of U.S. investors and secondly, we analyze data from 2001 to 2015 instead of analyzing data from the 1990's. Hence, differences between U.S. and German investors and/or different time periods might affect our results. By running the standard disposition effect regression (i.e. equation (1)), we show that our results are comparable to existing studies. As shown below in Table 3 column (1), on average a German investor suffers from a disposition effect of 6.83%. The average investor sells a gain with probability one-fifth (20.33%) and sells a loss with probability 13.5%. The ratio of selling a gain versus selling a loss is equal to 1.5.

Table 3: The disposition effect on the aggregated market level over the entire time period

This table examines the disposition effect on the aggregated market level over the entire time period (2001-2015). We report the results of various regressions on the sample of 18,280,493 account-stock-month triples of individual investors from a German bank. Observations are taken monthly in months when at least one asset was sold in an investor's portfolio. The fixed date is the last trading day in each month. The observation period ranges from January 2001 to December 2015. The dependent variable *Sale* is a dummy variable equal to one if the investor sells an asset within a particular month. *Gain* is a dummy variable equal to one if an asset's market price at the end of the month is above the reference point (here: defined as the average purchase price). Standard errors (in parentheses) are two-way clustered by account and month. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Dependent Variable: Sale	Model 1	Model 2	Model 3	Model 4	Model 5
Gain	0.0683***	0.0690***	0.0738***	0.0650***	0.0657***
	(0.00340)	(0.00324)	(0.00350)	(0.00366)	(0.00330)
Constant	0.135***				
	(0.00223)				
Observations	18,280,493	18,277,565	18,280,493	18,279,680	18,276,753
R-squared	0.008	0.092	0.012	0.024	0.102
Cluster account-month	YES	YES	YES	YES	YES
Account FE		YES			YES
Month FE				YES	YES
Stock FE			YES		YES

These results are in line with existing literature on the disposition effect. For example, Odean (1998) finds that the U.S. investors' disposition effect in the 1990's ranges between 5% and 8% and that the ratio between PGR and PLR is equal to 1.5. Moreover, our results are also in line with German disposition effect studies. Using German trading data from January 1991 to May 2000, Dorn and Strobl (2009) show German investors have a disposition effect of 7.7% and that the ratio of PGR/PLR is 1.52. Conclusively, results are not driven by country or time specific features of our data set and demonstrate external validity.

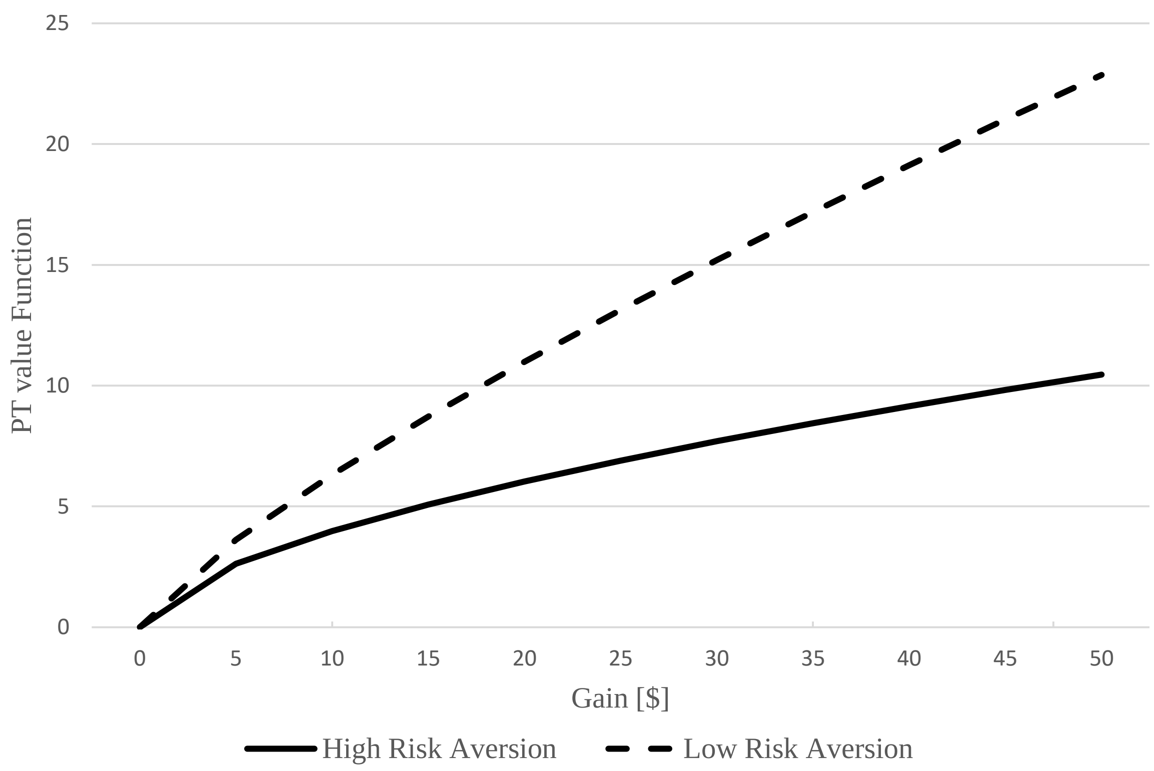
5. Selling pattern in boom and bust periods

5.1 The role of magnitude

We find that the change in the disposition effect between boom and bust periods is entirely driven by investors' change in gain realization. The question at hand is if changes in investors' preferences, i.e. changes in risk aversion, can explain our finding. As previous experimental studies show, investors' risk aversion increases in bust periods (e.g. Cohn et al., 2015).

As shown in Figure 2, an increase in risk aversion exclusively affects PT investor's value function in the gain domain. This increase has several effects on investors' selling behavior of gains. Firstly, for any given amount of gain, the value function of the less risk averse investor will always be steeper than for the more risk averse investor. Therefore, the marginal utility of an additional unit of gain is lower for investors with high risk aversion than for investors with low risk aversion in any given gain x. Thus, investors who are more risk averse realize gains more frequently than less risk averse investors. Secondly, the change in the slope of the value function decreases over the gain domain and is always smaller for high risk averse investors than for low risk averse investors. Therefore, the selling probability of gains is positively correlated with a gains magnitude and this effect is stronger in bust periods than in boom periods. Lastly, if the increase risk aversion is the main driver of the differences in investors' selling behavior in boom and bust periods, then loss realization should not be affected by this change in preferences. Meaning that loss realization should not be significantly different in boom than in bust periods.

Figure 2: PT investor's value function



To test our hypothesis about how the increase in risk aversion affects investors' selling behavior, we separately sort investors' gains and losses into terciles given their magnitude on a monthly basis. The best performing gain (loss) assets belong to tercile 3, the medium performing gain (loss) assets belong to tercile 2, and the worst performing gain (loss) assets belong to tercile 1. This approach restricts our sample to investors who hold at least three gain and three loss assets in one month. Overall, roughly six million observations drop out due to this sample restriction. We ensure that our sample restriction does not tamper our results, by re-running regression equation (2) on the restricted sample. As can be seen in Appendix E, our coefficient of interest, i.e. the interaction term of boom and gain, is equal to 5.35 percent, which is close to the estimated coefficient (5.18 percent) when using the unrestricted sample. To investigate the role of magnitude on investors' selling decision in boom and bust periods, we run regression equation (3). We separately estimate regression (3) over the gain and loss assets, to avoid three-way interactions:

$$(3)\ Sale_{ijt} = \beta_0 + \beta_1 Boom_t + \beta_2 Tercile2_{ijt} + \beta_3 Tercile3_{ijt} + \beta_4 Boom_t \times Tercile2_{ijt} + \beta_5 Boom_t \times Tercile3_{ijt} + \epsilon_{ijt}$$

where observations occur at the account (i), stock (j), and month (t) level. The *Sale* and *Boom* variables are defined as in regression equation (1) and (2). *Tercile2* and *Tercile3* are dummy variables that equal one if the asset belongs to tercile 2 or tercile 3 respectively and zero otherwise. Tercile 1 as base tercile is subsumed in the constant. Further, we introduce two interaction regressors. The regression is again two-way clustered at the account and date level and several fixed effect models are estimated. Regression results are shown in Table 4a below. A summary of the regression results of Model 1 is given in Table 4b.

We find that regardless of the market cycle and in line with existing literature, investors' likelihood to sell a gain asset increases with its magnitude, whereas, the likelihood of selling a loss asset is less strongly affected by its magnitude (Kaustia, 2010; Barber and Odean, 2013). This asymmetric response to gains and losses is grounded by preference-based explanations of the disposition effect. Investors with prospect theory preferences are risk averse over gains and risk seeking over losses. In addition, investors derive a burst utility (disutility) from realizing gains (losses). In this set up, investors likelihood to sell a gain increases with the gains' magnitude, whereas, loss realizations are deferred and thus PLR is not affected by magnitude.

Table 4a: The magnitude effect – Regression results

This table examines the effect of the gain (loss) magnitude on investors' selling pattern in boom and bust markets. We report the results of various regressions for Panel A (Gains) and Panel B (Losses), i.e. Panel A contains all assets trading at a gain, while Panel B contains all assets trading at a loss. The sample is restricted to investors who hold at least three gain and three loss assets within month t. The dependent variable *Sale* is a dummy variable equal to one if the investor sells an asset within a particular month. *Gain* is a dummy variable equal to one if an asset's market price at the end of the month is above the reference point (here: defined as the average purchase price). *Boom* is a dummy variable that equals one if the excess cumulative CDAX return in the past 24 month is positive and zero otherwise. *Tercile 2* and *Tercile 3* (best performing) are dummy variables that equal one if the asset belongs to tercile 2 or tercile 3 respectively and zero otherwise. Standard errors (in parentheses) are two-way clustered by account and month. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Gains				
Dependent Variable: Sale	Model 1	Model 2	Model 3	Model4
Boom	-0.0198***	0.00532	-0.0104***	0.0104***
	(0.00447)	(0.00356)	(0.00361)	(0.00369)
Tercile 2	0.0374***	0.0407***	0.0379***	0.0403***
	(0.00250)	(0.00245)	(0.00240)	(0.00241)
Tercile 3	0.0755***	0.0807***	0.0754***	0.0795***
	(0.00472)	(0.00460)	(0.00458)	(0.00457)
Boom*Tercile 2	-0.0185***	-0.0183***	-0.0182***	-0.0181***
	(0.00260)	(0.00257)	(0.00251)	(0.00253)
Boom*Tercile 3	-0.0357***	-0.0348***	-0.0352***	-0.0346***
	(0.00498)	(0.00487)	(0.00485)	(0.00482)
Constant	0.156***			
	(0.00387)			
Observations	5,088,445	5,088,445	5,086,258	5,086,255
R-squared	0.005	0.095	0.024	0.105
Panel B: Losses				
Dependent Variable: Sale	Model 1	Model 2	Model 3	Model4
Boom	0.0111***	0.0165***	0.00852**	0.0167***
	(0.00386)	(0.00262)	(0.00381)	(0.00256)
Tercile 2	-0.00552***	-0.00320**	-0.0181***	-0.0139***
	(0.00132)	(0.00135)	(0.00110)	(0.00109)
Tercile 3	-0.0156***	-0.0109***	-0.0339***	-0.0250***
	(0.00201)	(0.00206)	(0.00196)	(0.00192)
Boom*Tercile 2	-0.00211	-0.00211	-0.000235	-0.000182
	(0.00152)	(0.00155)	(0.00127)	(0.00133)
Boom*Tercile 3	-0.00770***	-0.00796***	-0.00538**	-0.00560**
	(0.00223)	(0.00227)	(0.00212)	(0.00220)
Constant	0.108***			
	(0.00341)			
Observations	6,873,035	6,873,035	6,871,432	6,871,429
R-squared	0.001	0.097	0.018	0.106
Cluster account-month	YES	YES	YES	YES
Account FE		YES		YES
Stock FE			YES	YES

Table 4b: The magnitude effect – Summary of regression results

This table depicts the probabilities of selling a gain (loss) in boom and bust periods as estimated by the regression equation (3). Numbers in this table are selling probabilities from Table 4a. Differences in selling a gain (loss) across boom and bust markets are stated by the test statistic in column 4 of each matrix.

Gain	Boom	Bust	Difference (test statistic)	Loss	Boom	Bust	Difference (test statistic)
Tercile 1	13.62%	15.60%	19.64	**Tercile 1**	11.91%	10.80%	8.35
Tercile 2	15.51%	19.34%	34.55	**Tercile 2**	11.15%	10.25%	5.71
Tercile 3	17.60%	23.15%	42.04	**Tercile 3**	9.58%	9.24%	1.24

With regard to our first hypothesis, we find that investors are always more likely to sell a gain asset in a bust period than in a boom period across magnitude terciles. Holding the gain magnitude constant, we find that investors are 3.8 percentage points more likely to realize a gain in bust than in boom periods. This difference in PGR is highly statistically significant at the one percent level.

Investigating the boom-bust split in more detail, we see that the asymmetric response to the gain magnitude is amplified in bust periods: While the likelihood of selling a gain asset increases by around 4 percentage points over terciles within the boom periods, it increases by more than 7.6 percentage points within the bust periods. Thus, the magnitude effect in bust periods is nearly doubled compared to the effect in boom periods.

Our last hypothesis states that an increase in risk aversion does not affect PLR. We find that PLR decreases over terciles in boom and bust periods. These differences are statistically significant bur they are not economically significant. Further, if we compare loss realizations in boom and bust periods across magnitude tercile, we find no significant difference in the loss realization of the best performing loser (i.e. tercile 3).

The above mentioned results are robust against several fixed effect models. They remain economically and statistically significant after introducing stock and account fixed effects (see Model 2 to 4).

Collectively, the observed investor behavior is in line with a preference based explanation of the disposition effect. Differences in investors' selling pattern of gains in boom and bust periods, can be linked to an increase in investors' risk aversion during bust periods (e.g. Cohn et al., 2015). The observed changes in PLR are statistically but hardly economically significant.

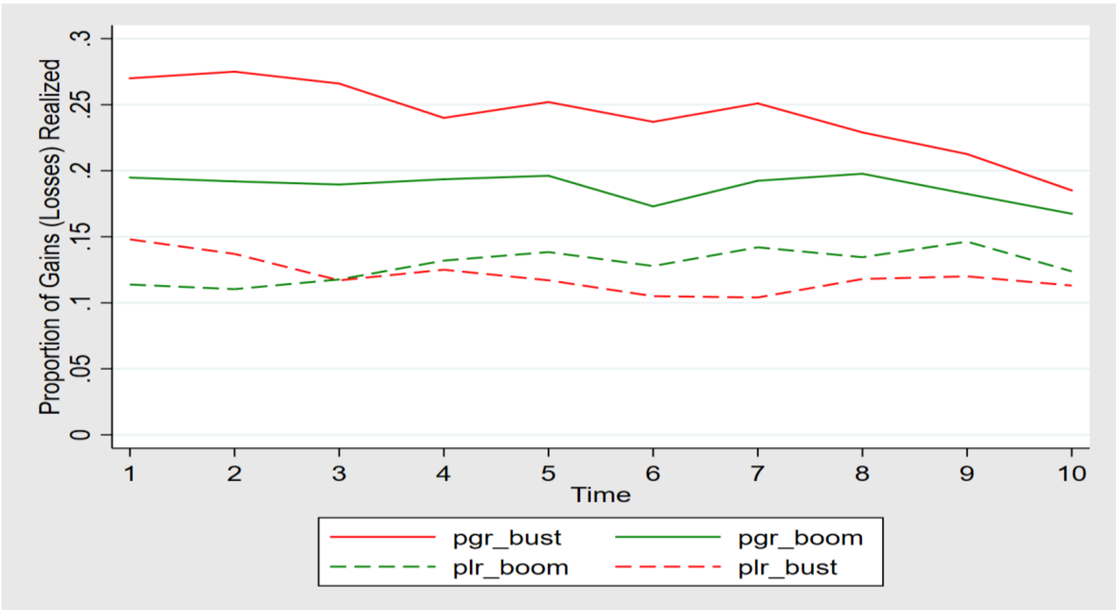
5.2 The role of time

Besides changes in investors' risk aversion, literature suggests changes in investors' beliefs as another potential driver of the disposition effect. Since investors' beliefs are positively correlated with past stock market returns (Weber et al. 2013; Greenwood and Shleifer, 2014; Amromin and Sharpe, 2014), investors become overly pessimistic (optimistic) about future returns in bust (boom) markets.

To investigate the effect of changes in beliefs on investors' selling behavior, we look at the timing of sales within a boom and bust cycle. In contrast to our preference section above, changes in beliefs do effect both, gain and loss realization. If investors are overly pessimistic in a bust period, we expect to see a higher PGR and PLR at the beginning of a bust period than at the end of a bust period (within cycle comparison). Further, we expect PGR and PLR to be higher at the beginning of a bust than at the beginning of a boom period (across cycle comparison). Investors who are confronted with a bust period extrapolate their pessimistic views into the future and thus start to log in their gains as soon as possible and try to stop their losses to increase any further. In boom periods investors are assumed to be more optimistic. We hypothesize that investors "ride the bubble" (e.g. Harrison and Kreps, 1978; Vissing-Jorgensen, 2003) and expect PGR in boom periods to be stable over time.

Figure 3: PGR and PLR in boom and bust markets

This figure shows the propensity to sell a stock at a gain (PGR) and the propensity to sell a stock at a loss (PLR) over time. Booms and busts are subdivided into deciles to account for differences in length across cycles. Observations at the beginning of a boom (bust) period are part of decile 1, whereas observations at the end of a boom (bust) period are part of decile 10.



As illustrated in Figure 3, investors show a higher probability to sell gains (PGR) at the beginning of busts as compared to booms. The probability to realize gains in busts is decreasing by 8.5% over time while the likelihood to realize gains in booms stays relatively constant over time. Turning to loss realization, PLR slightly increases (decreases) over time in boom (bust). Changes in PGR appear more substantial than changes in PLR.

To investigate this relationship more formally, we estimate the following regression equation:

$$(4)\ Sale_{ijt} = \beta_0 + \beta_1 Boom_t + \beta_2 Inbetween_{ijt} + \beta_3 End_{ijt} + \beta_4 Boom_t \times Inbetween_{ijt} + \beta_5 Boom_t \times End_{ijt} + \epsilon_{ijt}$$

where observations occur at the account (i), stock (j), and month (t) level. The *Sale* and *Boom* variables are defined as in regression equation (1) to (3). To account for the different time length of boom and bust periods, we decompose each market cycle intro three periods: Beginning, In-between, End.[4] We use this partition to track investors' selling behavior over time in different market cycles. To ensure that each month in our sample period can be assigned to exactly one time bucket (beginning, in-between or end), the minimum length of a cycle has to be at least six month. Note, that we do not assume investors to be able to time the market. Meaning that the *End* dummy captures the advanced stage of the boom or bust period and not investors' timing ability. *Beginning (End)* is a dummy variable that equals one if the observation belongs to the first (last) three month of a boom or bust period. *In-between* is a dummy variable that is equal to one if an observation is not part of the *Beginning* or *End* period. *Beginning* as base category is subsumed in the constant. We introduce two interaction regressors to capture differences in the timing of gain (loss) realizations in a boom or a bust period. The standard errors are again two-way clustered at the account and date level and we include several fixed effects models. To ensure that our results are not affected by changes in the absolute number of assets over time, we control for the number of assets in an investors' portfolio throughout every regression equation specification. To avoid three-way interactions, we separately estimate regression (4) for the gain and loss assets. Results are shown in Table 5a and Table 5b.

[4] An alternative time partition of boom and bust periods using quartiles can be found in Appendix F.

Table 5a: The time effect – Regression results

This table examines the effect of time on investors' selling pattern in boom and bust markets. We report the results of various regressions for Panel A (Gains) and Panel B (Losses), i.e. Panel A contains all assets trading at a gain, while Panel B contains all assets trading at a loss. *Sale*, *Gain*, and B*oom* are defined as in regression (1) to (3). Beginning (End) is a dummy variable that equals one if the observation belongs to the first (last) three month of a boom or bust period. In-between is a dummy variable that is equal to one whenever and observation is not part of the Beginning or End period. Standard errors (in parentheses) are two-way clustered by account and month. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Gains				
Dependent Variable: Sale	Model 1	Model 2	Model 3	Model4
Boom	-0.0631***	-0.0238	-0.0406**	-0.0130
	(0.0182)	(0.0200)	(0.0189)	(0.0213)
In-between	-0.0174	0.000135	-0.00547	0.00679
	(0.0199)	(0.0204)	(0.0195)	(0.0214)
End	-0.0786***	-0.0302	-0.0537***	-0.0193
	(0.0205)	(0.0215)	(0.0206)	(0.0228)
Boom*In-between	0.00604	0.00335	-0.00287	0.000295
	(0.0194)	(0.0208)	(0.0199)	(0.0220)
Boom*End	0.0381*	0.0187	0.0215	0.0129
	(0.0226)	(0.0238)	(0.0228)	(0.0247)
Constant	0.288***			
	(0.0194)			
Observations	6,573,960	6,568,494	6,571,745	6,566,272
R-squared	0.016	0.122	0.035	0.132
Cluster account-month	YES	YES	YES	YES
Account FE		YES		YES
Stock FE			YES	YES
Number of Assets in PF	YES	YES	YES	YES
Panel B: Losses				
Dependent Variable: Sale	Model 1	Model 2	Model 3	Model4
Boom	-0.0316***	-0.0180*	-0.0282***	-0.0140
	(0.00841)	(0.00919)	(0.00862)	(0.00958)
In-between	-0.0176*	-0.0131	-0.0155*	-0.0113
	(0.00926)	(0.00967)	(0.00935)	(0.00995)
End	-0.0314**	-0.0168	-0.0288**	-0.0135
	(0.0123)	(0.0102)	(0.0123)	(0.0105)
Boom*In-between	0.0348***	0.0321***	0.0319***	0.0316***
	(0.00945)	(0.00973)	(0.00945)	(0.0100)
Boom*End	0.0358***	0.0312***	0.0291**	0.0284***
	(0.0122)	(0.0104)	(0.0123)	(0.0107)
Constant	0.166***			
	(0.00881)			
Observations	11,149,108	11,145,217	11,147,636	11,143,753
R-squared	0.008	0.109	0.024	0.120
Cluster account-month	YES	YES	YES	YES
Account FE		YES		YES
Stock FE			YES	YES
Number of Assets in PF	YES	YES	YES	YES

Table 5b: The time effect – Summary of regression results

This table depicts the probabilities of selling a gain (loss) in boom and bust periods as estimated by the regression equation (4). Numbers in this table are selling probabilities from Table 5a. Differences in selling a gain (loss) across boom and bust markets are stated by the test statistic in column 4 of each matrix.

Gain	Boom	Bust	Difference (test statistic)	Loss	Boom	Bust	Difference (test statistic)
Beginning	22.49%	28.80%	12.02	**Beginning**	13.44%	16.60%	14.10
In-between	21.35%	27.06%	69.00	**In-between**	15.16%	14.84%	0.55
End	18.44%	20.94%	3.53	**End**	13.88%	13.46%	0.23

As results show, investors' selling patterns between boom and bust markets are more heterogeneous in the gain than in the loss domain. We find that in bust periods investors are more likely to realize a gain or a loss at the beginning of the cycle relative to any later point in time. Investors' PGR (PLR) at the beginning of a bust period decreases by more than 27% (19%) compared to invertors' PGR (PLR) at the end of a bust cycle. Comparing PGR and PLR across market cycles, we further find that PGR (PLR) at the beginning of a bust is higher than PGR (PLR) at the beginning of the boom. In relative terms, investors are 22% (23.5%) more likely to sell a gain (loss) at the beginning of a bust period than at the beginning of a boom period. These findings are in line with our hypothesis that investors who are overly pessimistic extrapolate their negative views into the future and therefore log in their gains or prevent their losses to increase any further.

Moreover, we find that the gain realization in boom cycles is rather stable over time. On average PGR changes by only 2% over time (compared to 3.93% in bust cycle). By keeping the selling probability rather constant, we find evidence for investors tendency to ride the bubble which is in line with existing literature (Harrison and Kreps, 1978; Vissing-Jorgensen, 2003).

Collectively, the observed differences in investors' selling pattern over time within and across market cycles can be linked to changes in investors' beliefs. Investors become more optimistic in boom periods and therefore tend to ride the bubble, whereas, they become overly pessimistic in bust periods and thus start to sell off their gains and losses as soon as possible.

6. Robustness test

6.1 The disposition effect on the portfolio level

A recent study by Engelberg et al. (2018) finds that investors who hold a portfolio with an overall positive value do not exhibit a disposition effect, while investors holding a portfolio with an overall negative value do so. It is plausible to assume that there is a link between the value of an investor's portfolio and market cycles. In boom periods, one would expect to see the majority of investors holding a portfolio with an overall positive value, while, in bust periods, one would expect it to be the other way around. Hence, our results might be driven by changes on the portfolio level but not by changes in macroeconomic conditions affecting investors' selling behavior. To control for this alternative explanation, we run regression equation (1) on two subsamples: (Panel A) portfolio trading at a gain in a boom market and (Panel B) portfolio trading at a gain in a bust market. If the portfolio driven disposition effect - and not changes in the macroeconomic cycles - is the underlying source of the difference in the disposition effect, there should be no disposition effect in any of the two subsamples since both portfolios are trading at a gain. As shown in Table 6, the disposition effect for subsample (A) is marginal (1.2%) while the disposition effect for subsample (B) is considerably stronger (4.6%). The disposition effect almost quadruples from subsample A to B. This shows that macroeconomic cycles do have an impact on investor's selling behavior even after controlling for portfolio level effects. Relatively speaking this effect is even stronger than the doubling of the disposition effect observed in regression (2) Model 1. Collectively, both effects seem to affect investors' degree of the disposition effect.

Table 6: The portfolio driven disposition effect

This table examines the variation in the disposition effect between market cycles, i.e. boom and bust periods while controlling for the portfolio driven disposition effect. The main difference to previous tables is that: Panel A comprises the sample of investors who hold a portfolio with an overall positive portfolio value in boom periods. Panel B comprises the sample of investors who hold a portfolio with an overall positive portfolio value in bust periods. Standard errors (in parentheses) are two-way clustered by account and month. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Dependent Variable: Sale	Panel A	Panel A	Panel B	Panel B
Gain	0.0121***	0.00928***	0.0462***	0.0422***
	(0.00238)	(0.00284)	(0.00506)	(0.00583)
Constant	0.139***	0.141***	0.153***	0.155***
	(0.00288)	(0.00303)	(0.00539)	(0.00562)
Observations	6,748,820	6,748,820	1,681,310	1,681,310
R-squared	0.000	0.018	0.004	0.028
Cluster account-month	YES	YES	YES	YES
Stock FE		YES		YES

6.2 Sensitivity of the boom definition

Our main analyses relies on the commonly used boom and bust classification by Daniel and Moskowitz (2016). To confirm that our results are robust, we test several alternative boom and bust classifications. As a first alternative measure (*Model 1*) we define a boom dummy at month t equal to one if the excess cumulative CDAX return in the past 12 month is strictly greater than zero. In *Model 2* the boom dummy equals one if the excess cumulative 12 month lagged CDAX return falls into the top 30% of the market return over our sample period. The boom dummy is zero if the 12 month lagged return of the CDAX falls into the bottom 30% of the market return. If the return falls neither into the top nor bottom 30% the dummy *Neutral* equals one. In *Model 3* the boom dummy equals one (zero) if the excess cumulative CDAX return in the past 12 month is greater (small or equal) than zero for at least three month in a row. For *Model 2* and *Model 3* regression equation (2) has to be modified because the alternative boom definitions in these models allow each month t to be either a boom, bust, or neutral month. To account for months that are neither boom nor bust month (i.e. neutral months) the regressor *Neutral* and the interaction term *Neutral*Gain* are added to regression equation (2). Lastly, *Model 4* uses the NBER bust period definition and therefore focuses more on macroeconomic developments than financial markets. As we use German investor data, the boom dummy is equal to zero if the German GDP decreases in two consecutive quarters. We rerun our main regression equation (2) using all alternative definitions. Results are displayed in Table 7.

As shown in Table 7, our main result is not sensitive to changes in the definition of boom and bust periods. The change in the disposition effect is again displayed by the Gain-Boom interaction term. The difference in the disposition effect across market cycles ranges from -5.54 percentage points (Model 3) to -2.22 percentage points (Model 4). Models 1 to 3 use a stock return based boom/bust definition and show that the magnitude of our coefficient of interest in our baseline regression (2) (-5.18 percentage points) fits well within in the range of the alternative definitions. Model 4 is based on the NBER boom/bust definition that focuses on changes in GDP as a measure of macroeconomic trends. Even though macroeconomic cycles react more slowly to changes of economic conditions than market cycles (see Appendix G) our effect persists.

Table 7: Various boom and bust definitions

This table examines the variation in the disposition effect between market cycles, i.e. boom and bust periods using various different boom and bust definitions. *Gain* is a dummy variable equal to one if an asset's market price at the end of the month is above the reference point (here: defined as the average purchase price). *Boom* is a dummy variable that equals one if the market is in a boom period given the boom definition for the respective model. In *Model 1* the boom dummy equals one if the excess cumulative CDAX return in the past 12 month is strictly greater than zero. In *Model 2* the boom dummy equals one if the excess cumulative CDAX return (12 month lagged) falls into the top 30% of the market return over the sample period. The boom dummy is zero if the excess cumulative CDAX return (12 month lagged) falls into the bottom 30% of the market return. If the return falls neither into the top nor bottom 30% the *Neutral* dummy equals one. In *Model 3* the boom dummy equals one (zero) if the excess cumulative CDAX return over the past 12 month is greater than (small or equal to) zero for at least three month in a row. Finally, *Model 4* uses the NBER bust period definition. The boom dummy is equal to zero if the German GDP decreases in two consecutive quarters. Standard errors (in parentheses) are two-way clustered by account and month. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable: Sale	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4
Gain	0.108***	0.112***	0.111***	0.0891***
	(0.00724)	(0.00751)	(0.00753)	(0.0129)
Boom	0.00178	0.00737	0.00224	0.0112*
	(0.00427)	(0.00516)	(0.00446)	(0.00585)
Neutral		-0.00515	-0.0170***	
		(0.00466)	(0.00574)	
Gain*Boom	-0.0504***	-0.0532***	-0.0554***	-0.0222*
	(0.00780)	(0.00864)	(0.00806)	(0.0132)
Gain*Neutral		-0.0536***	-0.0160	
		(0.00850)	(0.0136)	
Constant	0.133***	0.135***	0.134***	0.124***
	(0.00375)	(0.00388)	(0.00392)	(0.00562)
Observations	18,280,493	18,280,493	18,280,493	18,280,493
R-squared	0.009	0.010	0.009	0.008
Cluster account-month	YES	YES	YES	YES

7. Conclusion

While the disposition effect is one of the most explored behavioral phenomena, most papers investigating the disposition effect implicitly assume the effect to be constant over time and use data that only cover boom periods. However, proposed drivers of the disposition effect (preferences and beliefs) are rather countercyclical.

We use novel data that contains trade records and portfolio holdings of approximately 100,000 private investors in Germany throughout several boom and bust markets (2001–2015) and show that the disposition effect is not time-invariant. In particular, we demonstrate that the disposition effect moves countercyclical with the market, i.e. is low in boom markets and high in bust markets. These differences in the disposition effect across market cycles are entirely driven by investors’ increased gain realization in bust periods compared to boom periods. Investors are 5 percentage points more likely to realize a gain in bust than in boom periods.

We find evidence that both, preferences and beliefs, drive investors’ change in selling behavior across market cycles. By analyzing how the magnitude of a gain/loss affects investors’ selling behavior, we are able to test how changes in risk aversion (i.e. preferences) account for our findings. We find that investors are always more likely to sell a gain asset in bust than in boom periods irrespectively of the gain’s magnitude. Further, the magnitude effect in bust periods is almost twice as strong as in boom periods. Changes in PLR are rather small and hardly economically significant. All these findings can be explained by investors being more risk averse in boom than in bust periods and thus changes in preferences can explain our findings. By analyzing the timing of sale within and across market cycles, we test how changes in beliefs can account for our findings. We find that investors PGR and PLR is higher at the beginning than at the end of a bust period. Across cycles, PGR and PLR are higher at the beginning of a bust period than at the beginning of a boom period. In boom periods, PGR is rather constant over time. These results coincide with literature arguing that investors becoming overly optimistic (pessimistic) in boom (bust) markets.

Collectively, our findings cast doubt on the indirect assumption that the disposition effect is a time-independent phenomenon and take up literature arguing that investors’ preferences and beliefs vary with market cycles. Our results show that the disposition effect moves countercyclical with the market just as the proposed driver of the disposition effect do. Both channels, the preference and the belief channel, affect investors’ selling behavior in boom and bust markets and hence the degree of the disposition effect. Our analysis further shows that by solely using retail investor trading data from boom periods existing literature on average underestimates the disposition effect since the phenomenon becomes even more severe in bust periods.

References

Amromin, G./Sharpe, S. A., 2014, From the Horse's Mouth: Economic Conditions and Investor Expectations of Risk and Return, *Management Science* 60, 845 – 66.

Barber, B. M./Lee, Y./Liu, Y. Odean, T., 2007, Is the Aggregate Investor Reluctant to Realize Losses? Evidence from Taiwan, *European Financial Management* 13, 423 – 447.

Barber, B. M./odean, T., 2000, Trading Is Hazardous to Your Wealth: The Common Stock Investment Performance of Individual Investors, *The Journal of Finance* 55, 773-806.

Barber, B. M./Odean, T., 2013, The Behavior of Individual Investors, Handbook of the Economics of Finance, Elsevier, Amsterdam, pp. 1533 – 1570.

Ben-David, I./Hirshleifer, D., 2012, Are Investors Really Reluctant to Realize Their Losses? Trading Responses to Past Returns and the Disposition Effect, *Review of Financial Studies* 25, 2485 – 2532.

Birru, J., 2015, Confusion of Confusion: A Test of the Disposition Effect and Momentum, *Review of Financial Studies* 28, 1849 – 1873.

Boolell-Gunesh, S./Broihann, M. H./Merli, M., 2009, Disposition effect, investor sophistication and taxes: Some French Specificities, Finance, Presses univ. de Grenoble, Grenoble, 51 – 87.

Brown P./ Chappel, N./ da Silva Rosa R./Walter, T., 2006, The reach of the disposition effect: Large sample evidence across investor classes, *International Review of Finance*, 6(1-2), 43-78.

Calvet, L. E./Campbell, J. Y./Sodini P., 2009, Fight or Flight? Portfolio Rebalancing by Individual Investors, *Quarterly Journal of Economics* 124, 301 – 348.

Chang, C. H., 2008, The Impact of Behavioral Pitfalls on Investors’ Decisions: The Disposition Effect in the Taiwanese Warrant Market, *Social Behavior and Personality* 36, 617 – 634.

Chang, T. Y/Solomon, D. H./Westerfield M., 2016, Looking for Someone to Blame: Delegation, Cognitive Dissonance and the Disposition Effect, *The Journal of Finance* 71, 267 – 302.

Chen, F./Figlewskiz, S./Heisler, J./Weigend, A. S., 1998, Uncovering Hidden Structure in Bond Futures Trading, Leonard N. Stern School of Business, New York University, Working Paper, 98-01, March 1998.

Choe, H./Eom, Y., 2009, The disposition effect and investment performance in futures market, *Journal of Futures Markets* 29, 496 – 522.

Chui, M. W., 2001, An Experimental Study of the Disposition Effect: Evidence From Macau, *Journal of Psychology and Financial Markets* 2, 215-21.

Cici, G., 2012, The Prevalence of the Disposition Effect in Mutual Funds' Trades*, Journal of Financial and Quantitative Analysis* 47, 795 – 820.

Cohn, A./Engelmann, J./Fehr, E./Maréchal, M. A., 2015, Evidence for Countercyclical Risk Aversion: An Experiment with Financial Professionals, *American Economic Review* 105, 860 – 885.

Daniel, K./Moskowitz, T. J., 2016, Momentum crashes, *Journal of Financial Economics* 122, 221 -247.

Dhar, R./Zhu, N., 2006, Up Close and Personal: Investor Sophistication and the Disposition Effect, *Management Science* 52, 726-740.

Dominitz, J./Manski, C. F., 2011, Measuring and interpreting expectations of equity returns, *Journal of applied econometrics* 26, 352 – 370.

Dorn, D,/Huberman, G./Sengmueller, P., 2008, Correlated Trading and Returns, *The Journal of Finance* 63, 885 – 920.

Dorn, D./Strobl, G., 2009, Rational disposition effects: Theory and evidence, Drexel University, Working Paper.

Engelberg, J./Henriksson, M./Williams, J., The Portfolio-Driven Disposition Effect (May 4, 2018). Available at SSRN: https://ssrn.com/abstract=3126997 or http://dx.doi.org/10.2139/ssrn.3126997

Feng, L./Seasholes, M. S., 2005, Do Investor Sophistication and Trading Experience Eliminate Behavioral Biases in Financial Markets?, *Review of Finance* 9, 305 – 351.

Frazzini, A., 2006, The Disposition Effect and Underreaction to News, *The Journal of Finance* 61, 2017 – 2046.

Garvey, R./Murphy, A., 2004, Are Professional Traders too Slow to Realize their Losses?, *Financial Analysts Journal* 60, 35 – 43.

Genesove, D./Mayer, C., 2001, Loss Aversion and Seller Behavior: Evidence from the Housing Market, National Bureau of Economic Research (NBER), Working Paper, 8143, March 2001.

Guiso, L./Sapienza, P./ Zingales, L., 2018, Time varying risk aversion, *Journal of Financial Economics* 128, 403 – 421.

Greenwood, R./Shleifer, A., 2014, Expectations of Returns and Expected Returns, *Review of Financial Studies* 27, 714 – 746.

Grinblatt, M./Keloharju M., 2001, What Makes Investors Trade?, *The Journal of Finance* 56, 589 – 616.

Hartzmark, S. M./Solomon, D. H., 2012, Efficiency and the Disposition Effect in NFL Prediction Markets, *The Quarterly Journal of Finance* 2, 1 – 42.

Heath, C./Huddart, S./Lang, M., 1999, Psychological Factors and Stock Options Exercises, *The Quarterly Journal of Finance* 114, 601 – 627.

Heisler, J., 1994, Loss Aversion in a Futures Market: An Empirical Analysis, *The Review of Futures Markets* 13, 793 – 822.

Kaustia, M., 2010, Prospect Theory and the Disposition Effect, *Journal of Financial and Quantitative Analysis* 45, 791 – 812.

Kaustia, M. 2004, Market-wide impact of the disposition effect: evidence from IPO trading volume, Journal of Financial Markets 7, 207 – 235.

Kuhnen, C. A./Knutson, B., 2011, The Influence of Affect on Beliefs, Preferences and Financial Decisions, *Journal of Financial and Quantitative Analysis* 45, 605 – 626.

Kumar, A. , 2009, Hard-to-Value Stocks, Behavioral Biases, and Informed Trading, *Journal of Financial and Quantitative Analysis* 44, 1375 – 1401.

Loewenstein, G. F./Weber, E. U. / Hsee, C. K. /Welch, N. Risk as Feelings, 2001, Risk as feelings, *Psychological Bulletin* 127, 267-286

Malmendier, U./Nagel, S., 2011, Depression Babies: Do macroeconomic experiences affect risk taking?, *The Quarterly Journal of Economics* 126, 373 – 416.

Odean, T., 1998, Are Investors Reluctant to Realize Their Losses?, *The Journal of Finance* 53, 1775 – 1798.

Shapira, Z./Venezia, I., 2001, Patterns of behavior of professionally managed and independent investors, *Journal of Banking and Finance* 25, 1573 – 1587.

Shefrin, H./Statman, M., 1985, The Disposition to Sell Winners Too Early and Ride Losers Too Long: Theory and Evidence, *The Journal of Finance* 40, 777 – 790.

Vissing-Jorgensen, A., 2003, Perspectives on behavioral finance: does “irrationality” disappear with wealth? Evidence from expectations and actions, NBER Macroeconomics Annual 2003, Volume 18, Mark Gertler and Kenneth Rogoff, MIT Press, Cambridge, MA, 189 – 297.

Weber, M./Camerer, C.F., 1998, The disposition effect in securities trading: an experimental analysis, *Journal of Economic Behavior & Organization* 33, 167 – 184.

Weber, M./Weber, E. U./Nosic, A., 2013, Who takes risks when and why: Determinates of changes in investor risk taking, *Review of Finance* 17, 847 - 883.

Wermers, R., 2003, Is Money Really ‘Smart’? New Evidence on the Relation Between Mutual Fund Flows, Manager Behavior, and Performance Persistence, Working Paper, University of Maryland.

Appendix

Appendix A: Literature on the disposition effect

Panel 1:

This table lists prominent papers on the disposition effect among different investor types, in various asset classes, and across geographical regions.

The disposition effect among different investors types	
Retail investors	Odean (1998), Kumar (2009), Feng and Seasholes (2005), Dhar and Zhu (2006)
Institutional investors	Wermers (2003), Frazzini (2006), Garvey and Murphy (2004), Cici (2012)
The disposition effect in various asset classes	
Stocks	Odean (1998)
Executive stock options	Heath et al. (1999)
Stock index futures	Heisler (1994), Chen et al. (1998), Choe and Eom (2009)
Warrants	Chang (2008)
Online betting	Hartzmark and Solomon (2012)
Housing	Genesove and Mayer (2001)
The disposition effect across geographical regions	
USA	Odean (1998), Frazzini (2006), Cici (2012)
Europe	Grinblatt and Keloharju (2001), Boolell-Gunesh et al. (2009), Calvet et al. (2009), Weber and Camerer (1998), Dorn and Strobl (2009)
Asia	Chui (2001), Feng and Seasholes (2005), Chang (2008), Barber et al. (2007)
Middle East	Shapira and Venezia (2001)

Panel 2:

This table lists prominent papers on the disposition effect and the sample period used in the paper. Corresponding to the country specific trading pattern analyzed in one paper, we calculate the average p.a. market return. The market index applied is indicated in column (3).

Articles	Sample Period	Market Index	Arithmetic average (p.a.)
Odean (1998)	1987 -1993	S&P 500	13.3%
Barber and Odean (2000)	1991 -1996	S&P 500	21.8%
Grinblatt and Keloharju (2001)	1995 - 2000	OMX Helsinki 25	39.0%
Feng and Seasholes (2005)	1999 - 2000	SSE Composite Index	42.5%
Brown et al. (2006)	1995 - 2000	All Ordinaries	8.0%
Dhar and Zu (2006)	1991 - 1996	S&P 500	21.8%
Weber and Welfens (2006)	1997 - 2001	DAX 30	23.5%
Barber et al. (2007)	1995 - 1999	TAIEX	4.1%
Dorn and Strobl (2009)	1995 -2000	DAX 30	45.2%
Kaustia (2010)	1995 - 2000	OMX Helsinki 25	39.0%
Chang et al. (2016)	1991 -1996	S&P 500	21.8%

Appendix B: Categorization of months being a boom or bust month

This table shows the exact split between boom and bust periods using the Daniel and Moskowitz (2016) boom and bust definition. The sample period ranges from January 2001 (2001m1) until December 2015 (2015m12). The market index is the CDAX and the MSCI ACWI.

CDAX	
Boom	**Bust**
2001m1 - 2001m3	
	2001m4 - 2004m9
2004m10 - 2008m3	
	2008m4
2008m5- 2008m8	
	2008m9 - 2010m10
2010m11 – 2011m9	
	2011m10
2011m11-2011m12	
	2012m1
2012m2-2012m5	
	2012m6
2012m7-2013m2	
	2013m3
2013m4	
	2013m5
2013m6 – 2015m12	
MSCI ACWI	
Boom	**Bust**
2001m1 - 2001m6	
	2001m7 - 2004m9
2004m10-2004m11	
	2004m12
2005m1-2008m1	
	2008m2-2010m9
2010m10-2015m12	

Appendix C: MSCI ACWI as market measure

This table examines the variation in the disposition effect between market cycles using the MSCI ACWI instead of the CDAX as market index. We report the results of various regressions on the sample of 18,280,493 account-stock-month triples of individual investors from a German bank. Observations are taken monthly in months when at least one asset was sold in an investor's portfolio. The fixed date is the last trading day in each month. The observation period ranges from January 2001 to December 2015. The dependent variable *Sale* is a dummy variable equal to one if the investor sells an asset within a particular month. *Gain* is a dummy variable equal to one if an asset's market price at the end of the month is above the reference point (here: defined as the average purchase price). Column (1) to (5) examines variation in the disposition effect using several boom/bust definitions. The boom definition at work is indicated by the column's title. For example, column's (1) title is "Table 2a (1)" meaning that the boom definition is identical to the boom definition used in Table 2a column (1), i.e. the Moskowitz definition is at work. Standard errors (in parentheses) are two-way clustered by account and month. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable: Sale	(1) Table 2a (1)	(2) Table 7 (1)	(3) Table 7 (2)	(4) Table 7 (3)
Gain	0.106***	0.110***	0.110***	0.115***
	(0.00604)	(0.00737)	(0.00737)	(0.00766)
Boom	0.00286	-0.00192	-0.00127	-0.000543
	(0.00404)	(0.00441)	(0.00553)	(0.00451)
Neutral			-0.00227	-0.00588
			(0.00463)	(0.00877)
Gain*Boom	-0.0514***	-0.0516***	-0.0476***	-0.0597***
	(0.00671)	(0.00791)	(0.00897)	(0.00817)
Gain*Neutral			-0.0540***	-0.0254**
			(0.00820)	(0.0127)
Constant	0.133***	0.136***	0.136***	0.135***
	(0.00333)	(0.00396)	(0.00396)	(0.00400)
Observations	18,280,493	18,280,493	18,280,493	18,280,493
R-squared	0.009	0.009	0.009	0.010
Cluster account-month	YES	YES	YES	YES

Appendix D: Change in the number of paper gains across market cycles

This table replicates the results of our baseline regression (regression equation (2)) while controlling for the absolute number of paper gains. Regressors are defined as is regression equation (2). In Panel A *Number paper gain* is the absolute number of paper gains in month t on the market level. In Panel B *Number paper gain* is the absolute number of paper gains in month t on the investors' portfolio level. Results are reported for various regressions on the sample of 18,280,493 investors. Standard errors (in parentheses) are two-way clustered by account and month. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Number of paper gains on the market level				
Dependent Variable: Sale	(1)	(2)	(3)	(4)
Gain	0.106***	0.113***	0.122***	0.144***
	(0.00589)	(0.00571)	(0.00758)	(0.0151)
Boom	0.00283	-0.0458***	-0.0501***	-0.0419***
	(0.00480)	(0.00911)	(0.00934)	(0.0106)
Paper gain	-4.86e-08	-1.68e-06***	-1.58e-06***	-1.33e-06***
	(1.40e-07)	(2.64e-07)	(2.72e-07)	(3.10e-07)
Gain*Boom	-0.0519***	-0.0610***	-0.0536***	-0.0843***
	(0.00659)	(0.00632)	(0.00648)	(0.0171)
Number paper gain*Boom		2.06e-06***	2.12e-06***	1.78e-06***
		(2.94e-07)	(2.95e-07)	(3.45e-07)
Gain*Paper gain			-3.87e-07**	-1.36e-06***
			(1.74e-07)	(5.14e-07)
Gain*Boom*Number Paper gain				1.18e-06**
				(5.44e-07)
Constant	0.134***	0.166***	0.164***	0.159***
	(0.00466)	(0.00660)	(0.00681)	(0.00777)
Observations	18,280,493	18,280,493	18,280,493	18,280,493
R-squared	0.009	0.010	0.010	0.010
Cluster account-month	YES	YES	YES	YES

Panel B: Number of paper gains on the individual level				
Dependent Variable: Sale	(1)	(2)	(3)	(4)
Gain	0.113***	0.116***	0.129***	0.144***
	(0.00630)	(0.00670)	(0.00838)	(0.00938)
Boom	0.00939**	0.00187	-0.00223	0.00256
	(0.00398)	(0.00411)	(0.00408)	(0.00420)
Paper gain	-0.00203***	-0.00305***	-0.00251***	-0.00190***
	(0.000604)	(0.000730)	(0.000530)	(0.000416)
Gain*Boom	-0.0510***	-0.0554***	-0.0497***	-0.0682***
	(0.00644)	(0.00672)	(0.00650)	(0.00817)
Number paper gain*Boom		0.00124***	0.00147***	0.000696***
		(0.000245)	(0.000286)	(0.000126)
Gain*Paper gain			-0.00166***	-0.00352***
			(0.000506)	(0.000718)
Gain*Boom*Number Paper gain				0.00222***
				(0.000416)
Constant	0.144***	0.150***	0.147***	0.144***
	(0.00404)	(0.00427)	(0.00387)	(0.00378)
Observations	18,280,493	18,280,493	18,280,493	18,280,493
R-squared	0.022	0.023	0.025	0.025
Cluster account-month	YES	YES	YES	YES

Appendix E: The disposition effect across market cycles – Sample Comparison

This table examines the variation in the disposition effect between market cycles, i.e. boom and bust periods, and compares the estimation results from regression equation (2) between the unrestricted and the restricted sample from our magnitude analyses. The dependent variable *Sale* is a dummy variable equal to one if the investor sells an asset within a particular month. *Gain* is a dummy variable equal to one if an asset's market price at the end of the month is above the reference point (here: defined as the average purchase price). *Boom* is a dummy variable that equals one if the excess cumulative CDAX return in the past 24 month is positive. Standard errors (in parentheses) are two-way clustered by account and month. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)
Dependent Variable: Sale	Unrestricted	Restricted
Gain	0.106***	0.104***
	(0.00595)	(0.00634)
Boom	0.00184	-0.00101
	(0.00408)	(0.00411)
Gain * Boom	-0.0518***	-0.0535***
	(0.00660)	(0.00686)
Constant	0.133***	0.133***
	(0.00340)	(0.00352)
Observations	18,280,493	11,961,480
R-squared	0.009	0.009
Cluster account-month	YES	YES

Appendix F: The impact of time on the selling pattern in boom and bust periods

This table examines the effect time on investors' selling pattern in boom and bust markets. We report the results of various regressions for Panel A (Gains) and Panel B (Losses), i.e. Panel A contains all assets trading at a gain, while Panel B contains all assets trading at a loss. *Sale*, *Gain*, and B*oom* are defined as in regression (1) to (3). *Quartile2, Quartile3*, and *Quartile4* are dummy variables that equal one if the asset belongs to the quartile respectively. Quartile 1 as base quartile is subsumed in the constant. Assets that are sold at the beginning of the boom (bust) period are part of quartile 1, whereas assets sold at the end of the boom (bust) period are part of quartile 4. Standard errors (in parentheses) are two-way clustered by account and month. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Gains

Dependent Variable: Sale	Model 1	Model 2	Model 3	Model4
Boom	-0.0775***	-0.0323***	-0.0566***	-0.0211**
	(0.0106)	(0.00937)	(0.0104)	(0.00975)
Quartile2	-0.0227	-0.00451	-0.0114	0.000718
	(0.0147)	(0.0109)	(0.0130)	(0.0107)
Quartile3	-0.0307*	-0.00324	-0.0179	0.00395
	(0.0167)	(0.0124)	(0.0147)	(0.0123)
Quartile4	-0.0679***	-0.0278**	-0.0510***	-0.0184
	(0.0136)	(0.0110)	(0.0125)	(0.0114)
Boom*Quartile2	0.0117	0.00455	0.00278	0.00209
	(0.0154)	(0.0130)	(0.0141)	(0.0129)
Boom*Quartile3	0.0217	0.0123	0.0120	0.00960
	(0.0172)	(0.0138)	(0.0153)	(0.0138)
Boom*Quartile4	0.0472***	0.0340***	0.0390***	0.0306**
	(0.0141)	(0.0127)	(0.0135)	(0.0133)
Constant	0.301***			
	(0.0118)			
Observations	6,573,960	6,568,494	6,571,745	6,566,272
R-squared	0.016	0.122	0.036	0.132
Cluster account-month	YES	YES	YES	YES
Account FE		YES		YES
Stock FE			YES	YES
Number of Assets in PF	YES	YES	YES	YES

Panel B: Losses

Dependent Variable: Sale	Model 1	Model 2	Model 3	Model4
Boom	-0.0236***	-0.00747	-0.0210***	-0.00340
	(0.00770)	(0.00646)	(0.00786)	(0.00665)
Quartile2	-0.0174*	-0.00911	-0.0163	-0.00784
	(0.0101)	(0.00685)	(0.0101)	(0.00684)
Quartile3	-0.0365***	-0.0215***	-0.0345***	-0.0192***
	(0.00773)	(0.00587)	(0.00800)	(0.00611)
Quartile4	-0.0264***	-0.0148**	-0.0242***	-0.0115*
	(0.00900)	(0.00672)	(0.00921)	(0.00690)
Boom*Quartile2	0.0203*	0.0139*	0.0195*	0.0142*
	(0.0109)	(0.00782)	(0.0108)	(0.00782)
Boom*Quartile3	0.0497***	0.0388***	0.0468***	0.0386***
	(0.00898)	(0.00727)	(0.00922)	(0.00752)
Boom*Quartile4	0.0300***	0.0258***	0.0243**	0.0235***
	(0.0103)	(0.00844)	(0.0106)	(0.00867)
Constant	0.169***			
	(0.00800)			
Observations	11,149,108	11,145,217	11,147,636	11,143,753
R-squared	0.008	0.109	0.025	0.120
Cluster account-month	YES	YES	YES	YES
Account FE		YES		YES
Stock FE			YES	YES
Number of Assets in PF	YES	YES	YES	YES

Appendix G: Categorization of boom and bust months using various definitions

This table shows the absolute number of months that are categorized as Boom, Bust, or Neutral months according to the definitions used in this paper. There are five different bust definitions: the main measure (Moskowitz) and four alternative measures (Model 1, Model2, Model 3, Model 4). The sample period ranges from January 2001 until December 2015. The market index is the CDAX.

		Boom	Bust	Neutral
Main measure	Moskowitz	107	71	0
Alternative measure	Model 1	114	66	0
	Model 2	45	63	72
	Model 3	108	60	12
	Model 4	165	15	0