Turning With The Tide

A time-series study conducted on the presence of herd behaviour in the Nordic financial markets

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Abstract:

This paper explores the presence of herding behaviour in the Nordic stock markets, i.e. the tendency of investors to mimic each other and follow the herd whilst disregarding their own beliefs and abilities to make rational investment decisions. We examine this effect during multiple global financial crises over the last 50 years to assess how both endogenous and exogenous shocks impact herding behaviour. Further, we analyse differences in herding behaviour between times of growth and recessions in the Nordic stock exchanges and show to what extent herding is affected by macroeconomic factors. We find that herding is detected within all five Nordic countries except for Norway, and that herding is more prominent during bearish days on the stock markets. Additionally, we conclude that on an international level an exogenous shock generates more consistent support for herding, but specific endogenous shocks can to a greater extent create herding within a single country. Controversially, we do not find sufficient support to assess whether herding is more likely to exist in periods preceding, during, or succeeding a crisis, however, herding is recorded consistently during longer periods in-between large endogenous shocks in the financial markets.

Key words:

Herd behaviour, Nordic capital markets, Equity return dispersion, Investor sentiment

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1. Introduction

"*Herding is a form of convergent social behaviour that can be broadly defined as the alignment of the thoughts or behaviours of individuals in a group (herd) through local interaction and without centralised coordination.*" - Herding in humans, RM Raafat, N 6.2.3 – Norway. Chater, C Frith 2009

Generally, the concept of herding behaviour refers to the tendency of people to mimic the behaviours of others, disregarding their own beliefs and information. It is the alignment of thoughts, behaviours, and actions among individuals within a group, colloquially known as a 'herd'. Experimental evidence in social psychology on behaviour of individuals in groups suggest that individuals abide by group decisions, even in instances in which the individual believes the group to be wrong (Asch, 1952). In the context of financial markets, the presence of herding occurs when investors choose to emulate the trading actions of others, disregarding their own beliefs and basing their investment decisions solely on the collective acts of others. In this sense, herding suggests that investors are drawn to the consensus of the market, implying that individual returns should not stray far away from the market return (Christie & Huang, 1995). Depending on the structure of herding, it is argued to be either a rational or irrational form of investor behaviour (Chang, Cheng & Khorana, 1999). The irrational view is focused on investor psychology where investors follow others blindly, disregarding their own beliefs (Devenow & Welch, 1996). Contrastingly, the rational view focuses on managers' mimicking of each other to maintain reputational capital in the market, hence relating to the classical principal-agent problem (Scharfstein & Stein, 1990; Rajan, 1994). Some authors (Bikhchandani, Hirshleifer & Welch, 1990; Welch, 1992) refers to this behaviour as an informational cascade.

Considerable time and effort have been put into understanding investment behaviour of market participants and its ensuing impact on security prices by academic researchers. This paper aims to answer the questions "*Do Nordic investors engage in herding behaviour and, if so, does their propensity to engage in such behaviour depend on the macroeconomic environment in which they operate and the nature of any turbulence?*". It follows that our aim with this study is threefold. Firstly, we examine the potential presence of herding. This is of interest as in the presence of herding, market efficiency is arguably reduced as investors choose to invest based on the collective actions of others rather than their own rational beliefs. As such, the behaviour of market participants, and by extension asset prices, will no longer effectively reflect all available information and price accordingly. For instance, Wermers (2002) finds that stocks that are bought by herds outperform stocks are sold by herds by 4 percent over a 6-month period, an outperformance that is even more pronounced amongst smaller stocks.

The second aim of this study is to analyse whether general economic environment can influence the potential presence of herding in the Nordic capital markets. We will examine whether herding is more likely to occur before, during, or after periods of economic distress in the national financial markets. We also differentiate between bullish and bearish days, which are defined as days in which the aggregate market return is positive or negative, respectively. This study applies two proposed measures of herding, discussed below, across various time frames. These time frames are defined based on periods with limited economic growth, as determined by the rate of the GDP growth in conjunction with indices development, and during which international crisis have occurred. Specifically, this study evaluates the presence of herding during the 1990's recession, the Dot-com Pre, the global financial crisis, the Greek government-debt crisis, and the global Covid-19 pandemic.

Finally, the third aim of this study is to investigate whether investors' propensity to engage in herding behaviour is affected by the nature of the event affecting the macroeconomic environment. Arguably, the periods included in this study represent both endogenous disturbances (such as the DotCom period) as well as exogenous ones (Covid-19 pandemic). We use this to investigate whether there is a difference in investor sentiment depending on the nature of the chock, i.e. whether it is endogenous or exogenous to the capital markets.

Many proposals are given as to the reasons behind institutional investor herding. These include reputational risk that may come from acting differently than others and having wrong, hence causing investors to disregard their own information in favour of mimicking other investors' behaviours (Scharfstein & Stein, 1990). Another reason proposed is given by Froot, Scharfstein, and Stein (1992) and Hirshleifer, Subrahmanyam, and Titman (1994) who argue that investors may herd around market consensus simply because they receive correlated private information. It is also possible that investors may share a similar aversion in the sense that they all dislike stocks with certain characteristics such as low volatility Falkenstein (1996). Herding has been observed in extreme market conditions characterised by increased uncertainty (Kurz & Kurz-Kim, 2013, (Schmitt & Westerhoff, 2017). Unarguably, the recent global pandemic of Covid represented such a situation, with entire societies changing their ways of living and working. It is therefore interesting to examine the presence of herding during the pandemic, which is something that the authors Ferreruela & Mallor (2021) have done in the context of the Spanish and Portuguese markets. The authors find evidence supporting the presence of herding in both markets. Hence, there is indeed preceding literature investigating the presence of herding. Apart from Ferreruela & Mallor (2021), Chang, Cheng, & Khorana (1999), finds presence of herding for South Korea and Taiwan. There are, however, also examples of other results which are inconsistent with the presence of herding, including Christie & Huang (1995).

As above examples illustrate, there is indeed previous literature examining herding in capital markets. However, this phenomenon has been scarcely researched in a Nordic-specific context. Exceptions include Mobarek, Mollah & Keasey (2014) who examines herding in a European context between the years 2001-2012 and finds that herding effect is most pronounced in the Nordic countries during the Eurozone crisis and in the continental countries during the global financial crisis. We extend on this expanding the time frame and comparing between different time periods as defined by macroeconomic factors.

This study builds on the work performed by Christie & Huang (1995) who propose the use of cross-sectional standard deviation to detect herding in the United States from December 1925 to December 1998. This measure is said to capture the presence of herding behaviour by effectively quantifying the degree to which asset returns increase and decrease along with the portfolio return. The authors argue that, if market participants supress their individual beliefs and predictions about asset prices and base their behaviours on that of others during periods of market stress (i.e., herd), individual security returns will not deviate substantially from the market return which would be reflected as lower values of the cross-sectional standard deviation. Whilst dispersions are predicted to be low in the presence of herd behaviour, they do not in their own have implications for the presence of herding as low dispersions could be triggered by other things including a lack of new information during a trading interval. As is presented by the authors, it is therefore not enough to simply search for periods of low dispersions and attribute these to herding. Equity dispersions share similarities with standard measures of volatility, but they bear an important distinction in that they employ the portfolio return rather than the expected returns of individual assets. Rational asset pricing models predict that periods of market stress induce increased levels of dispersion, which stands in stark contrast to herding of individual returns around the market, which would translate to particularly low levels of dispersions during periods of market stress. It is worth mentioning that Christie & Huang (1995) define periods of market stress as times with abnormally large average price movements and differentiates between the hypothesis of herding and that of traditional rational asset pricing models by constructing dummy variables defined depending on whether market return is in the upper or lower 5% (1%) of the return distribution. Further, the authors also investigate differences across industries and periods of market stress (which is defined as periods of abnormally large price movements) and normal market conditions. Dispersions were found to increase significantly during periods in which the average price changes were large. These results imply that individual returns do not cluster around the market return nor the industry returns, speaking against the presence of herding. We apply the cross-sectional standard deviation measure to the Nordic countries but fail to find support for the presence of herding before conducting robustness checks.

Further, we consult and extend on the work of Chang, Cheng & Khorana (1999) and their proposed cross-sectional absolute deviation measure. The empirical model proposed by the authors builds on the provided demonstration that rational asset pricing models predict that equity returns are not only an increasing function of the market return, but importantly also that the *relation is linear*. Provided that investors tend to herd during periods of large aggregated price movements, the linear and increasing relation will no longer hold and can instead become increasingly non-linear or even decrease. Chang, Cheng, & Khorana (1999) examine the investment behaviour from an international perspective in both developed and developing countries. They collect data on the U.S., Hong Kong, Japan, South Korea, and Taiwan form the 1970s to the 1990s. They base their study on the herding measure suggested by Christie & Huang (1995) but create interesting and important extensions. They propose a new method for detecting herding based on a non-linear regression specification, the cross-sectional absolute deviation (CSAD) which examines the relationship between the overall market return and the level of equity dispersion. Besides applying the newly crafted model to their sample they also test for shifts in herding following the liberalization of Asian financial markets. The authors find results consistent with those of Christie & Huang for the U.S. and Hong Kong but find significant non-linear relationships in the emerging markets Taiwan and South Korea, indicating a presence of herding.

Chiang and Zheng investigate herding behaviour in a global context from 1988 to 2009 across 18 countries, but there is a notable absence of the Nordic markets. The authors develop the cross-sectional absolute deviation measure further by including a dummy variable which divides the data into two subsets depending on whether the overall market is up or down. They find evidence of herding in advanced stock markets, excluding the U.S., and in Asian markets. Moreover, the authors also investigate herding behaviour across periods of time characterised by extraordinary circumstances. They find that crisis trigger herding in the country of origin, and then spreads to neighbouring countries. Additionally, they also find evidence suggesting that herding is, as intuition would suggest, more present in turbulent than it is during tranquil market conditions.

We will extend on these previous papers by investigating herding in a Nordic context, where investor sentiment and behaviour may differ from the regions studied previously due to culture or otherwise nation specific factors. Studying the Nordic markets is also of interest as the study effectively is done in an international context, but between nations which are neighbouring countries engaging in cross-country cooperation and which therefore has great influence on the economies of the other countries. This will allow us to answer the first aim of our research question, that is, whether herding is present in Nordic capital markets.

This study also extends on previous literature by extending the analysis to be conducted over a longer time-period and includes data from 1986 and onwards. We also conduct our analysis in different time periods and include one year prior as well as one year post each time frame characterised by extraordinary circumstances to be able to draw conclusions regarding the presence of herding under different market characteristics. That is, once the period which is deemed to be the time during which turbulence can be observed in the different Nordic capital markets is set, one year prior to that is also taken out as a separate period defined as the *pre period*, and one year after the period is deemed to be over is included as the *post period.* Additionally, we also include "normal states" which we define by the time between the aforementioned periods of receding economic growth, as well as a current period ranging from the end of the "post-Covid" period until October 13th 2023 where our dataset ends. This is done to address the second and third aim of this study. Because investing in a market in which herding behaviour occurs differs from investing in an otherwise normal market in the sense that a larger number of securities is required to achieve the same level of diversification (Chang, Cheng & Khorana, 1999), our research contributes to the important understanding of underlying market characteristics for Nordic investors.

2. Data and Methodology

3.1 Data

3.1.1 Data Description

We obtain our data from the Compustat - Capital IQ at the Wharton Research Data Services (WRDS) at University of Pennsylvania. We collect company names, daily data on closing prices, global company key, and two calculative factors. These factors are used to calculate daily market returns using the definition provided by WRDS. With these, the returns are adjusted for stock splits and includes cash equivalent distributions and reinvestments of dividends. These factors are the "*total daily return factor*" and the "*adjustment factor*", and the calculations are performed as per below.

$$\frac{(Closing\ Price \div Adjustment\ Factor) \times Return\ Factor}{((Closing\ Price_{Previous\ Day} \div Adjustment\ Factor_{Previous\ Day}\ ) \times Return\ Factor_{Previous\ Day})}$$

To counter the potential survivorship bias that may occur we construct five survivor-bias free datasets by including every stock that has ever been listed from 1986-2023 on any of the Nordic exchanges. This enables us to study the herding effect around stocks that are no longer public or have been liquidized, during the time when they were listed. We note that, due to data limitations further discussed below, we are not able to collect data during the same dates for each country as there are national public holidays and other factors which influence the markets. The specific dates used for each country are presented in table 1.

We use data on the daily closing price of the national indices for all Nordic countries. These are OMXS30, OMXC20, OBX, OMXH25 and OMXI10 (for Sweden, Denmark, Norway, Finland, and Iceland, respectively). These indices are constructed with the n (n = 30, 20, 25, 25, 10) most liquid companies listed in their respective exchanges. We collect this data from Nasdaq Nordic for all countries excluding Norway which is instead collected from Euronext, as Nasdaq does not have operations in Norway.

Lastly, we have collected national GDP growth data for each of the countries under observation from the Organization for Economic Co-Operation and Development (OECD) which is used to define our time periods.

3.1.2 Definition of time periods

We use daily data of the national indices in conjunction with the GDP growth to define when a time-period starts. The periods we are interested in are the 1990's recession, the DotCom pre period, the global financial crisis, the Greek government-debt crisis, and the Covid-19 pandemic. Additionally, we also include a current period. To determine when each period commences in the individual countries, we investigate which quarters have negative growth during a period in which we are interested (i.e., the periods mentioned above) and specify the period for our analysis as when there is a vital amount of negative GDP growth within at least 1.5 years without significant positive GDP growth in between. The gap between negative quarters is also of interest and we limit the accepted length of a gap to be two quarters. As such, we allow the GDP to slightly increase in-between adjacent quarters of negative growth. This increase has limited implications regarding general economic well-being as an increase from an already abnormally low level would still be considered part of a generally receding market. We allow for a positive growth for no more than two consecutive quarters. Furthermore, we also take the country's index development into account. We compare the initial GDP evaluation with the growth in figure 1 to find further support for our defined time periods. Looking at figure 1 we note that, compared to several of the periods as defined by the GDP growth rates solely (presented in figures 2-6), the indices growth rates indicate that economic recessions start at an earlier date. This is not surprising, as we only have GDP growth per quarter, which means that the GDP data may be lagged compared to the daily prices we have collected on the indices. This poses a potential issue as the data may capture macroeconomic trends "too late". Therefore, we define all periods to counter the lags by setting the start date one quarter earlier.

A suitable example for our period-definition-rule is the period for the global financial crisis of 2007-2009 in Sweden. Looking at figure 2, there are four clearly negative quarters during this period, with the most prominent downwards spike occurring in late 2008. Looking closely, we note that within this one year and nine-month period from Q1 2008 to Q3 2009 there are a total of six negative quarters. Hence, we have a period defined of more than 1,5 years as well as a negative GDP quota of 66.67%. Therefore, with the additional countering for lagged values, the 2008 financial crisis period is defined with the start date of 2007-10-01 to 2009-09-30 (2007 Q4 to 2009 Q3).

However, a few exceptions to this rule have been made. Most are country-specific, further discussed below, but in addition to such adjustments one major exception is made with regards to the Covid-19 pandemic period. This period is defined as Q1 2020 - Q4 2020. This is done since the global outbreak was in Q1 2020, which is clearly depicted in figure 2 – 6. Additionally, the Covid-19 pandemic was also unique in the sense that it was a sudden exogenous chock to all financial markets, rather than an endogenous one occurring in one (or a few) and then spreading to others. It is therefore deemed to be more suitable to have the same start date for all countries, regardless of country specific data. Moreover, we note that the Covid-19 pandemic did not end by 2021, but for this study we set the period of Covid-19 to be the year of 2020 which, according to our rule, implies that the pre- and post-periods are 2019 and 2021 respectively. This is done as it was the first year of the global pandemic, therefore arguably the period during which market uncertainty was at its peak. The 'Current' period is also commonly defined for all countries with the start date of Q1 2022 with Russia's war of aggression against Ukraine, which is also an exogeneous chock with no country-specific characteristics. The period ends with our dataset, i.e., October 2023.

Figure 1 – Nordic indices growth

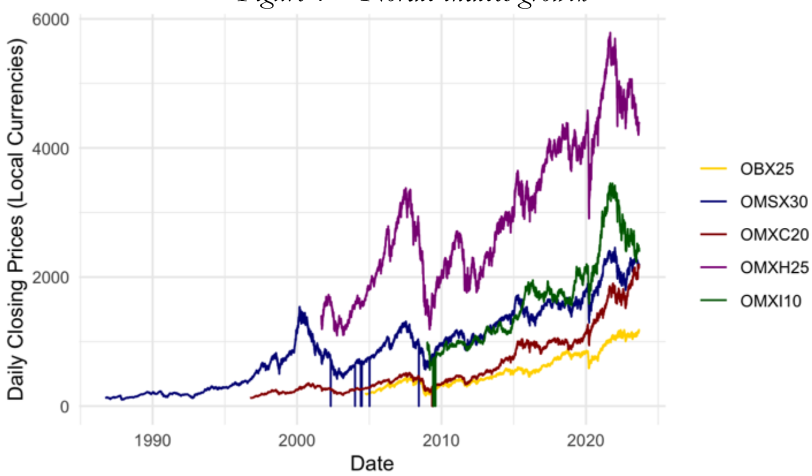

Figure 1 represents the daily return of each of the national indices which represent the top traded securities on that day. Source: Nasdaq Nordic, Euronext

Apart from the exceptions mentioned above, we set the time-periods separately for each country to account for the fact that not all international events have affected the national markets during the same dates. Because our analysis is inherently dependent on dividing the periods depending on factors that may influence investor sentiment (i.e., such as general economic factors), the time periods have been assessed individually for all countries included in the analysis using the quarterly GDP growth in conjunction with the national index development. The actual periods used in the analysis are provided in table 1 in the appendix. Below are brief explanations regarding the individual countries period definitions.

Figure 2 – Sweden quarterly GDP growth (%)

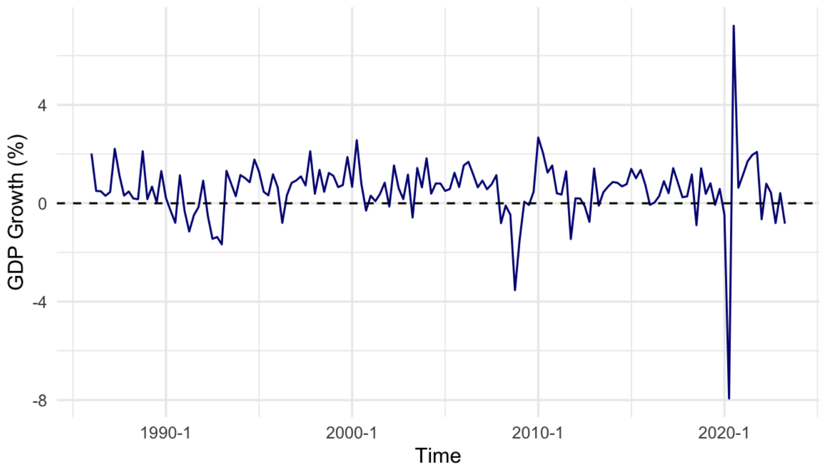

Figure 2 represents the quarterly percentual GDP growth. 0% quarterly growth is represented by a dotted line. Source: OECD

For Sweden, we note that the first negative GDP growth (the development of which can be found in Figure 2) for this sample occurs in the beginning of 1990. Looking more closely at the data, the first negative growth is more specifically in Q2. Therefore, taking our corrections of lagged values into account we use 1990 Q1 as starting point for the more turbulent period which was to follow due to the 1990's recession. The development can also be observed, although not as clearly, in figure 1 with the OMXS30 index declining. The end date has been set as Q1 1993, as the GDP growth following that quarter is positive for a longer period. It should be noted, however, that during the time-period which is included in the definition of the 1990's crisis, there have been some quarters which display a positive growth. Because the growth is based on the levels observed during the previous quarter, this provides limited insight as it may have increased from an already very low level. Therefore, for the period to be concluded as over, it is necessary to see that the development is positive for several succeeding quarters, as defined by the period-definition-rule described above.

For the DotCom period, the same reasoning as above has been followed. That is, the starting date for the period is set to be Q3 in 2000, since Q4 displays negative GDP growth which can be seen in Figure 2. Looking at figure 2, this period does not seem to have negative GDP growth. However, considering that the previous years all had positive GDP growth we still find this period interesting enough to examine given that it has some negative GDP growth, and that the growth rate has decreased significantly. This is also clearly visible in Figure 1, with the OMXS30 index dropping significantly during this period. The period is concluded to be over in Q1 2002, as the development of the index as well as the GDP growth begins to exhibit positive development at that time. For the global financial crisis, the start date for the period under observation in Sweden is set to be Q4 2007, which is clearly visible as a time with negative development in Figure 1. Arguably more interesting to note is the end date, which is set to be Q3

2009 as the development then turns to be positive once again. For the Greek government-debt crisis period, the starting date is set to be Q3 2011, and the end date is set to be Q2 2013. As aforementioned, the Covid and current periods are set to be the same for all countries included in the study.

Figure 3 – Denmark quarterly GDP growth (%)

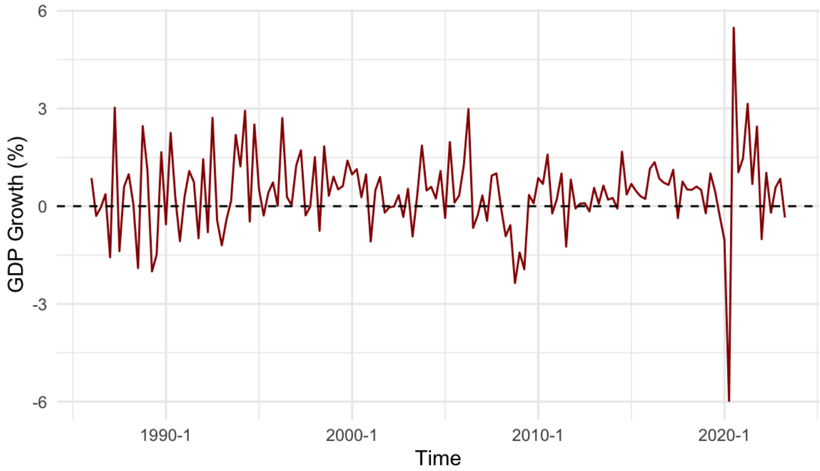

Figure 3 represents the quarterly percentual GDP growth. 0% quarterly growth is represented by a dotted line. Source: OECD

The 1990's recession for Denmark is defined as Q4 1991 – Q2 1993. Whilst we do note negative GDP growth during the sample before that, it is excluded from this study as there is a period of more than two consecutive quarters with positive growth in between. Hence, it is a period that breaks our rule, and the first period is therefore not considered part of the crisis we want to examine. Whilst there is sporadic negative GDP growth after 1993 as well, these occur after a period of two quarters has passed and are hence dismissed in this timeframe. For the DotCom period, the starting date has been set to Q4 2000 and the end date is defined as Q2 2003. These spikes are clearly visible in figure 3 during this period.

Figure 4 – Norway quarterly GDP growth (%)

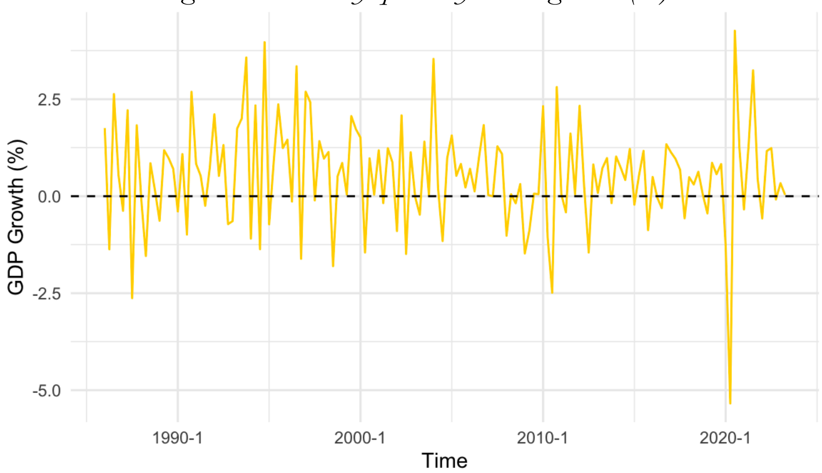

Figure 4 represents the quarterly percentual GDP growth. 0% quarterly growth is represented by a dotted line. Source: OECD

In Norway, we note that although the 1990's did display some periods of negative GDP growth, these did not reach our defined time-period criteria. However, Q2 1987 – Q1 1989 is a period that does fulfil our criteria. This is not surprising, as this was a period of economic disturbances in Norway (Moe, Solheim, & Vale, 2004). This is therefore the period which we have chosen to examine, and it is defined as the 1990's crash for the purposes of this study. For the other periods defined for Norway, no exceptions to the rules specified previously have been made.

Figure 5 – Finland quarterly GDP growth (%)

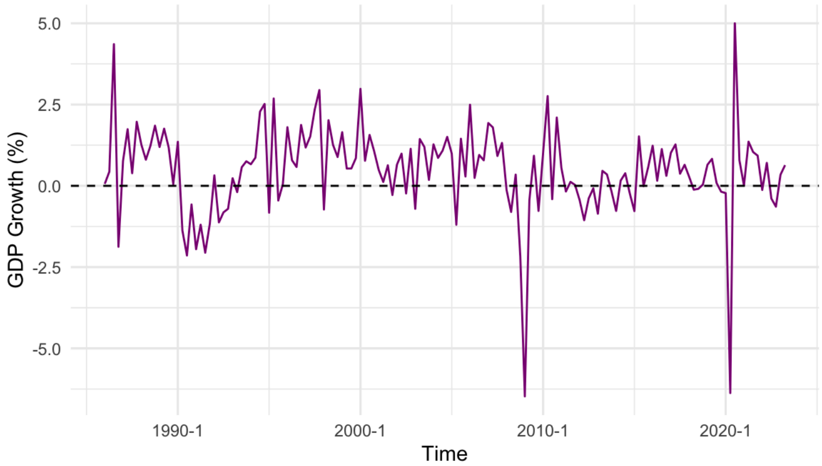

Figure 5 represents the quarterly percentual GDP growth. 0% quarterly growth is represented by a dotted line. Source: OECD

Above is the visual presentation of the Finnish GDP development. Here, we have chosen to disobey our rule in one instance, with the other periods following the logic previously presented. Specifically, the negative growth recorded in Q3 2010 is excluded as it has been affected by the large and positive development during the previous quarter. Hence, we make an exception and exclude it as we deem that it is not part of the period which we wish to analyse.

Figure 6 – Iceland quarterly GDP growth (%)

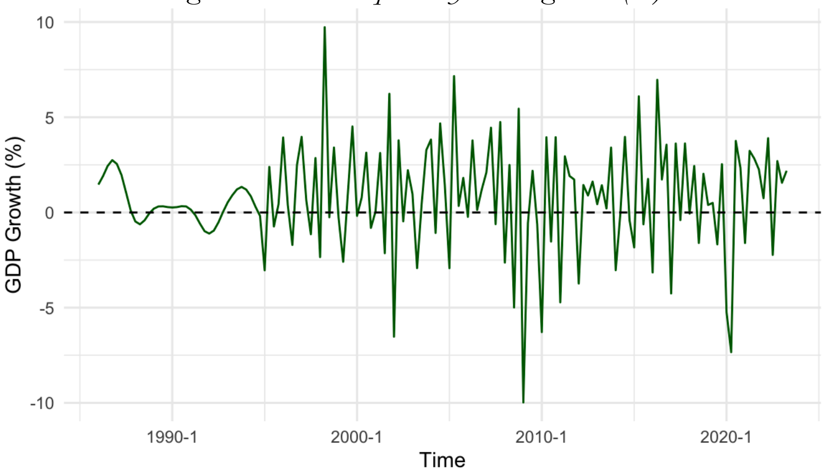

Figure 6 represents the quarterly percentual GDP growth. 0% quarterly growth is represented by a dotted line. Source: OECD

We note that the left-hand side of the graph displaying the Icelandic GDP growth differs in visible characteristics compared to the others, as well as to itself during more recent years. Due to lack of reliable data, this period contains estimated GDP growth from OECD rather than the actual development. Whilst this is unwanted, it bears little significance to us as the data we have for the Icelandic stock exchange is also limited in the earlier years, and hence the first period we analyse for Iceland is the DotCom period.

An exception to our rule has been made with regards to the Greek government-debt crisis, as it is also excluded from investigation in Iceland. This is due to the Icelandic financial crisis, which was an effect of the global financial crisis of 2008-2009 and which had a severe impact on

Iceland's economy. The aftermath of the 2008 crash led to the default of Iceland's three largest privately owned banks which destabilised the economic environment for several years (Önnudóttir, Helgason, Harðarson, & Thórisdóttir, 2021). Therefore, we have chosen to exclude the Greek government debt crisis since this occurs during a period where all three of these crises would have an effect in Iceland. Hence, we have chosen to include all this in the Icelandic crisis period which is defined as Q4 2007 – Q1 2012.

3.1.3 Data Limitations and Manipulation

Limitations in the data include a lack of observations for Iceland prior to 1995, which excludes Iceland from the analysis of the 1990s recession. Furthermore, Denmark's main index was switched from OMXC20 to OMXC25 in 2015 and therefore contains no data prior to 2015, which is why we have chosen to use the OMXC20 as the benchmark instead, despite it no longer being the main index of the Danish stock exchange. Whilst this may bear limited implications, an index which includes a larger number of assets would be preferred for our purposes, as we aim to examine market characteristics. Further, data on OMXI10 is limited with regards to its sample size (both the number of stocks included as well as the dates during which data is available) due to reasons unknown.

Additionally, data for quarterly GDP growth is not available for all countries during the entire time-period. OECD provides estimations for some periods during which data is limited or non-existent. These periods are as follows:
Sweden: Q1 1986 – Q4 1992,
Denmark: Q1 1986 – Q4 1994,
Finland: Q1 1986 – Q4 1989,
Iceland: Q1 1986 – Q4 1994.

Cleaning the data also exposed an underlying issue with the samples as some companies were listed in the dataset multiple times with different prices. It was concluded that this is explainable by certain companies having multiple stocks listed, as is common for large corporations to have. These issues were present in all countries and in some instances dropping the duplicates would not suffice since a second version of a stock could be listed on a day during which the first version was not. To combat these issues and counter potential cases of unplausible movements a restriction was added to the data to separate the versions of the same stock into two, by giving them suffixes based on the starting date of the next iteration of the Company Key in the dataset. The total number of listed stocks at any time across all countries therefore increased from 3178 to 5800.

Lastly, we note that a potential limitation of this study is the sheer sizes of the samples. Neither country included in the analysis is very large and hence the actions of a few investors may have a profound influence on the indices as well as the market return with which we have conducted this study. This may limit the conclusions that can confidently be drawn.

3.2 Method

We commence by testing for the presence of herding using the cross-sectional standard deviation,

$$s = \sqrt{\frac{\sum_{i=1}^{n}(r_i - \bar{r})^2}{n-1}}, \qquad (1)$$

where r_i is the observed return of firm *i*, and $\bar{r}$ is the cross-sectional average of the *n* returns in the portfolio. Further, we construct dummy variables, defined as per below, which we use to capture the days of extreme market movements. This allows us to test the hypothesis proposed by Christie & Huang (1995), that herding behaviour is more likely to emerge during periods of market stress which is defined as abnormal market movements. We run the following regression:

$$S_t = \alpha + \beta_1 D_t^L + \beta_2 D_t^U + \varepsilon_t \tag{2}$$

Here, α denotes the average dispersion of the sample when excluding the regions covered by the dummy variables, which are defined as:

$D_t^L = 1$ if the market return on day *t* is in the lowest 5 (1) percentile of the return distribution and 0 otherwise and,

$D_t^U = 1$ if the market return on day *t* is in the highest 5 (1) percentile of the return distribution.

Rational asset pricing models predict that periods of market stress induce increased levels of dispersion because individual assets differ in their sensitivity to market return, contrasting to herding of individual returns around the market which would translate to lower levels of dispersion (Christie & Huang, 1995). Thus, we use this equation to distinguish between the two hypothesises.

In addition to the analysis on the cross-sectional standard deviation regression presented above, a second measure of herding is consulted namely the cross-sectional absolute deviation (CSAD) as proposed by Chang, Cheng & Khorana. This builds on the provided demonstration that rational asset pricing models predict that equity returns are not only an increasing function of the market return, but importantly also that the relation is linear. We illustrate the relation between the market return and CSAD using a conditional version of the capital asset pricing model (Jensen, Black & Scholes, 1972):

$$E_t = \gamma_0 + \beta_i E_t(R_m - \gamma_0), \tag{3}$$

where γ_0 is the return of the zero-beta portfolio, β_i is the time invariant systematic risk measure of security *i*. Therefore, by setting β_m as the systematic risk of an equally weighted market portfolio yields:

$$\beta_m = \frac{\sum_{i=1}^{N} \beta_i}{N}. \tag{4}$$

Moreover, expressing the absolute value of the deviation of security *i*'s expected return in period *t* from the portfolio expected return as $|D|_{i,t} = |\beta_i - \beta_m| E_t(R_m - \gamma_0)$ allows for defining the expected value of CSAD as per below:

$$E(CSAD)_t = \frac{\sum_{i=1}^{N} |D|_{i,t}}{N} = \frac{\sum_{i=1}^{N} |\beta_i - \beta_m| E_t(R_m - \gamma_0)}{N}. \tag{5}$$

We show the increasing and linear relation between dispersions and time varying expected market returns as per below:

$$\frac{\partial E(CSAD)_t}{\partial E_t(R_m)^2} = \frac{\sum_{i=1}^{N} |\beta_i - \beta_m| E_t}{N} > 0, \tag{6}$$

$$\frac{\partial E(CSAD)_t}{\partial E_t(R_m)^2} = 0 \quad (7)$$

To allow for the possibility that herding propensity may differ in the up- and down-markets respectively, the following specifications are made:

$$CSAD_t^{UP} = \alpha + \gamma_1^{UP}\left|R_{m,t}^{UP}\right| + \gamma_2^{UP}{R_{m,t}^{UP}}^2 + \varepsilon_t \quad (8)$$
$$CSAD_t^{DOWN} = \alpha + \gamma_1^{DOWN}\left|R_{m,t}^{DOWN}\right| + \gamma_2^{DOWN}{R_{m,t}^{DOWN}}^2 + \varepsilon_t \quad (9)$$

Where $CSAD_t$ is the average $|D|_t$ of each stock relative to the return of the equally weighted market portfolio $R_{m,t}$ in period *t* and $\left|R_{m,t}^{UP}\right|$ and $\left|R_{m,t}^{DOWN}\right|$ are the absolute values of an equally weighted realised return of all securities listed on the market on day *t* when the market is up or down, respectively.

To estimate the dispersion levels across the sample the following simplification of equation (7) is used with market return and CSAD used as proxies for the unobservable $E_t(R_{m,t})$ and $E(CSAD_t)$:

$$CSAD_t = \frac{\sum_{i=1}^{N}\left|R_{i,t} - R_{M,t}\right|}{N} \quad (10)$$

This equation is based on the notion that, as opposed to the CSSD measure, herding around the market consensus during periods with sharp price changes will cause the linear and increasing relationship between market return and CSAD to destabilize into a non-linear and in some instances a decreasing relationship. With this in mind, we implement a nonlinear specification:

$$CSAD_t = \alpha + \gamma_1\left|R_{M,t}\right| + \gamma_2\left(R_{M,t}^2\right) + \varepsilon_t \quad (11)$$

We separate the markets based on bullish vs. bearish days to see if there are any differences to investors' propensity to herd, as suggested by Chiang and Zheng (2010) using the regression:

$$CSAD_t = \alpha + \gamma_1 D^{up}\left|R_{M,t}\right| + \gamma_2(1 - D^{up})\left|R_{M,t}\right| + \gamma_3 D^{up}\left(R_{M,t}\right)^2 + \gamma_4(1 - D^{up})\left(R_{M,t}\right)^2 + \varepsilon_t \quad (12)$$

Lastly, we conduct Breusch-Pagan tests for heteroscedasticity to examine the robustness of our models. Thereafter we also include supplemental White's variance and covariance matrixes in order to modify our regressions to adjust for heteroscedasticity.

3. Main empirical analysis

4.1 – Investigating the presence of Herding

4.1.1 – Descriptive Statistics

Descriptive statistics are presented in the appendix (table 2). Firstly, we note that the distribution for Norway, Finland, and Iceland all display high skewness and kurtosis values for their respective market returns compared to Sweden and Denmark, implying that the sample data for these countries contains a relatively larger quantity of extreme values compared to Sweden and Denmark. For Iceland, this is also highlighted by much larger max-values whilst the min-values are less extreme. Many of these max values are obtained because of the extreme daily returns of "penny stocks", coupled with there being fewer listed stocks on certain days during which the penny stocks have had a significant return. Because we weigh our daily aggregate market returns based on the number of stocks listed on a particular date, and not the absolute value of these returns, such instances impact our upper extreme values significantly.

Furthermore, the mean and median are both very close to zero for all countries, which is not surprising as one would expect that the daily market returns for the market are not going to be extreme. The biggest deviation from this is the mean of Iceland of 0.002 which is twice as large as its median, indicating the presence of a more extreme upper half than lower in terms of returns. Examining the mean and maximum values, Iceland has the largest maximum value but not the lowest minimum value, further supporting the presence of more extreme values in the upper half of the distribution of returns.

We note that the skewness levels are high for most of our variables. Moreover, skewness for CSSD and CSAD are more similar in between the different countries than the measures are for the other variable (market return). The measure for Denmark is approximately half as large compared to the next smallest observation for the other countries. Iceland exhibits the highest skewness for both CSSD and CSAD. The mean for Iceland and Denmark is the same for CSSD and their medians are also similar, at 0.032 for Iceland and 0.033 for Denmark. The substantial difference in skewness is therefore interesting and as we also note a significant difference in their respective max values, we conclude that Denmark is far more symmetrically distributed around its median, which is highlighted by its skewness level. The same conclusions are drawn from the CSAD measure, where we note larger but similar relations between the sizes of the descriptive statistics. Furthermore, for the descriptive statistics for market return we note that Denmark and Finland exhibit significantly more symmetric distributions around their respective medians, with 2.92 and 2.37 in skewness for the countries, respectively. The same can be noted for these two countries kurtosis values for their market returns, where they exhibit significantly lower values. We do note that the kurtosis for all countries and statistics is positive, reflecting that our data has a leptokurtic distribution rather than a normal one. The values for which the kurtosis is the lowest compared to the other countries for the same variable are the ones where skewness is relatively low. This is expected given that a lower skewness would resemble a normal distribution bell curve closer.

4.1.2 – Cross-Sectional Standard Deviation analysis

We employ equation 2 for the first part of the analysis which allows for an analysis on dispersion in days of extreme market movement, where a dispersion lower than expected indicates the presence of herding. We graphically visualize the relationship between the market return and the

CSSD measure. Following the logic of Christie & Huang (1995), we look for a descending line in the ends of the graph which would indicate low dispersion during moments of extreme or abnormal market movements (i.e., the aggregate return of that day is in the top or bottom 5% (1%) percentile. To be able to conclude that the relationship in the graphs supports the presence of herding the ends of the "funnel-shaped" cloud must curve down as the market returns grow more positive (negative). The relationships between market return and CSSD are visualised in the figures below.

Figure 7 – Sweden CSSD Cloud Graph

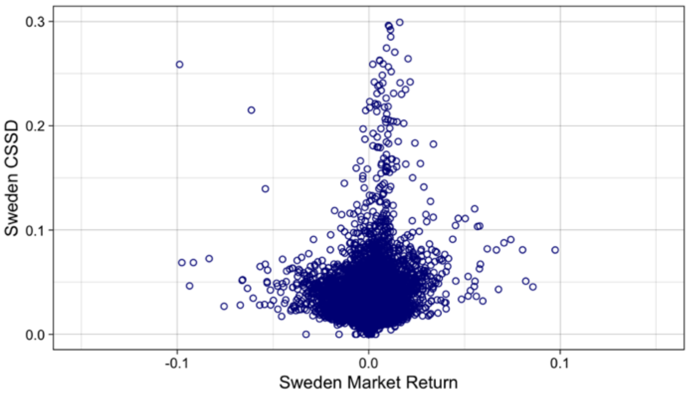

Figure 7 represents the daily CSSD as calculated in equation (1), and the corresponding daily market return in absolute values for Sweden across the complete sample period (1986-01-01 to 2023-10-13)

Figure 8 – Denmark CSSD Cloud Graph

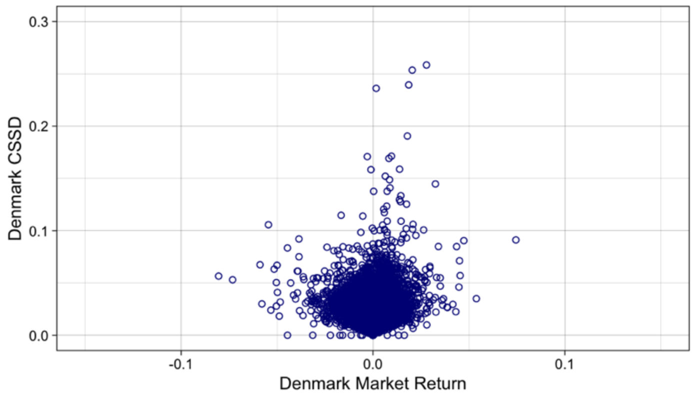

Figure 8 represents the daily CSSD as calculated in equation (1), and the corresponding daily market return in absolute values for Denmark across the complete sample period (1986-01-01 to 2023-10-13)

Figure 9 – Norway CSSD Cloud Graph

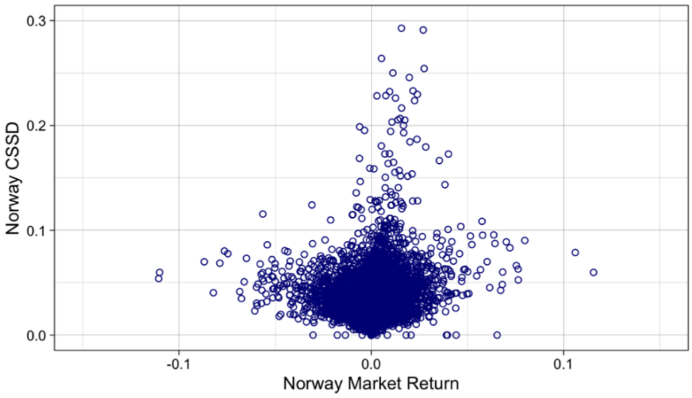

Figure 9 represents the daily CSSD as calculated in equation (1), and the corresponding daily market return in absolute values for Norway across the complete sample period (1986-01-01 to 2023-10-13)

Figure 10 – Finland CSSD Cloud Graph

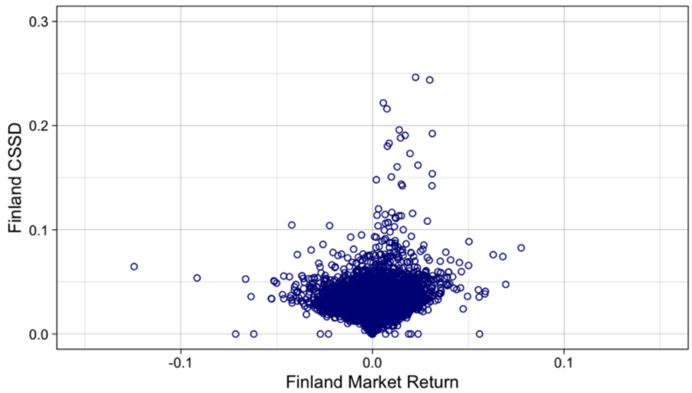

Figure 10 represents the daily CSSD as calculated in equation (1), and the corresponding daily market return in absolute values for Finland across the complete sample period (1986-01-02 to 2023-10-13)

Figure 11 – Iceland CSSD Cloud Graph

Figure 11 represents the daily CSSD as calculated in equation (1), and the corresponding daily market return in absolute values for Iceland across the complete sample period (1995-11-14 to 2023-10-13)

The relationship between the variables depicts a funnel shape for all countries around the zero percent daily market return, supporting the rational asset pricing models. We note outliers south of this shape for some countries (primarily Iceland, Denmark, and Norway, but less evident for Sweden and Finland) which imply that although the market return was in the extreme upper or lower tail of the distribution of market returns observed during the period, the dispersion has not increased during these instances. However, since the majority of the observations in the graphs pertaining to these countries do point to the aforementioned general "funnel shape", and because there are no clear descending lines from the ends of the graphs, we cannot argue herding is present at this stage. For Iceland we can also observe that the observations below the "herding-lines" are mostly due to CSSD values equal to 0, which can be explained due to the lack of data on Iceland and the fact that equation (1) divides by $n-1$, meaning that observations with only one listed company will automatically return a CSSD equal to 0. It should be noted that Sweden is the only country where the descending line in the end of the negative market returns could be argued for. The evidence of such descending line is not obvious, but around -0.5 on the x-axis one could argue the dispersions move in a descending trend, pointing to potential evidence of herding on days with negative market return.

At first glance, the figures point to a lack of herding presence in the complete sample using the CSSD measure for all countries, but there are a few important things to note. First, the results point to noticeable differences in dispersion between countries. For instance, Finland and Denmark seem to have less dispersion in general as indicated by the cluster being slightly flatter and lower compared to Sweden and Norway. Sweden also has greater dispersion at "normal" movement days, since the "peak" of the plot is slightly more crowded with observations and higher. Moreover, we note that Iceland's dispersion is more scattered and seemingly more random than the other countries', which can partially be explained by the lower number of companies listed in Iceland, due to the denominator taking on small values and therefore will not "stabilize" the CSSD value in instances where market return has been abnormal for one or a few stocks. Furthermore, it is also interesting to note that across all countries (except Iceland), the dispersion for days with slightly positive market returns are significantly higher than those days with slightly negative returns, as seen by the "points" of the graphs leaning to the right. This is indicative of a consensus that investors are more prone take positions different to that of the market on slightly bullish days as compared to slightly bearish days, which could potentially indicate that investors become more confident with their own abilities to make rational investment decisions and therefore chooses to steer away from other market participants. Arguably, this effect in turn creates a situation where herding around the market consensus in slightly bullish days would be considered unfavourable given that dispersions are high and scattered.

The regression model output based on equation (2) for the CSSD measure are reported in table 3-7 with both the 5% and 1% quantile restrictions. The results confirm the anticipation from the graphs that the presence of herding cannot be confirmed using the CSSD measure since the estimations are either non-negative or non-significant for all countries based on both the 5% and 1% quantile restrictions. This lack of negative and significant β values supports the traditional rational asset pricing models and does not indicate the presence of herding. Analysing the returned values of the regressions in the tables provide some insight as to why. For almost all periods/subsamples both the $\alpha_{5\%}$ and $\alpha_{1\%}$ are largely significant, whereas only a few of the dummy variables are significant. We note that for Sweden's Normal State 3 the $\alpha_{5\%}$ and $U_{upper,5\%}$ are the same (0.027) and significant at the 1% level. Therefore, we conclude that for this period the CSSD in aggregate is 0. This does not hold true for any other country or period, although we note that for some instances the coefficients are quite similar indicating a small cross sectional standard deviation. Hence, in general the dummy variables do not have significant impact on the dependent variable CSSD. The reason for this can be derived from the issue with the CSSD measure as argued by Chang et al. (1999), which is that it is too restrictive. Given that it focuses on the extremes of the return distribution, the risk that it excludes the herding effect in different subsamples becomes increasingly large when the quantile restrictions become narrower. For the CSSD measure to detect herding, the dispersions must fit the requirements that it is decreasing specifically on an extreme movement, which disregards potential herding in the remaining 90% (98%) of the sample.

Furthermore, the quantiles also need to be defined within the subsample, since defining them based on the complete sample could result in missing values for the dummy variables in some periods if a 5% (1%) extreme movement is missing within the sample. This makes the CSSD model further insignificant and unapplicable since it fails to compare the potential herding effect between periods in the sample. Had the CSSD measure been less restrictive, the model could potentially detect herding but since the dummy would stay unactive in the entire subsample the value would be missing, and the dummy is disregarded for the subsample. Comparably, with quantiles defined within each subsample as done in this analysis, the estimations for the β coefficients are likely to be more similar within the variables for a wider range of the return distributions, resulting in insignificant quantile restrictions.

The CSSD model is therefore problematic since potential herding effects around less extreme movements go unseen. With this in mind, not detecting herding with the CSSD measure is not unexpected and is in line with results of previous researchers e.g. Chang et al. (

). These authors do manage to find support for herding using other, less restrictive, measures. It is to those we turn to next.

4.1.3– Cross-Sectional Absolute Deviation analysis

The cross-sectional absolute deviation measure does not fixate only on the upper and lower percentiles of the distribution of returns, and therefore inherently includes more observations in the analysis. The underlying assumption of the CSAD measure that it quantifies the average proximity of individual returns to the realized average, as Chang et. al proposes, allows us to test for the presence of herding based solely on the dispersion as opposed to testing the dummy variables as previously explained by the CSSD measure. Similar to the CSSD graphs we are looking for a relationship between the CSAD measure and the daily market returns where the dispersion between the two starts to decrease as returns grow more extreme. Whilst the "funnel shape" is not as prominent in these plots, the indicative expected dispersion line is visible. This is the line we will use to examine a potential decreasing dispersion and non-linear relationship.

Figure 12 – Sweden CSAD Cloud Graph

Figure 12 represents the daily CSAD as calculated in equation (10), and the corresponding daily market return in absolute values for Sweden across the complete sample period (1986-01-01 to 2023-10-13)

Figure 13 – Denmark CSAD Cloud Graph

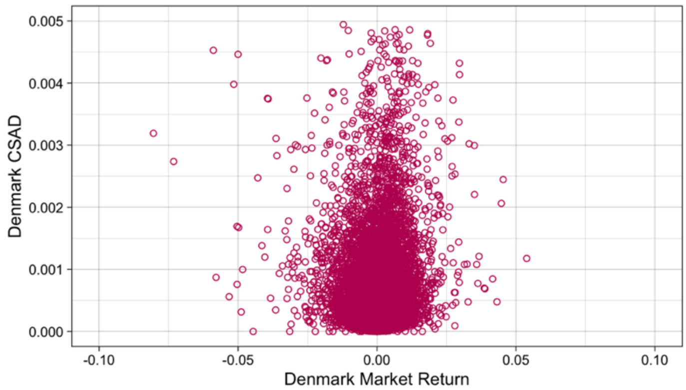

Figure 13 represents the daily CSAD as calculated in equation (10), and the corresponding daily market return in absolute values for Denmark across the complete sample period (1986-01-01 to 2023-10-13)

Figure 14 – Norway CSAD Cloud Graph

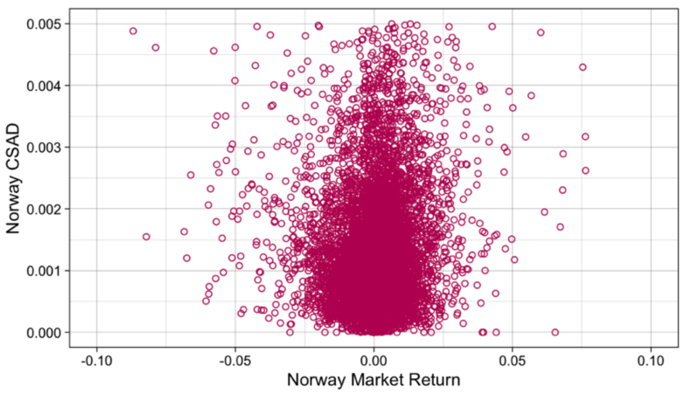

Figure 14 represents the daily CSAD as calculated in equation (10), and the corresponding daily market return in absolute values for Norway across the complete sample period (1986-01-01 to 2023-10-13)

Figure 15 – Finland CSAD Cloud Graph

Figure 15 represents the daily CSAD as calculated in equation (10), and the corresponding daily market return in absolute values for Finland across the complete sample period (1986-01-02 to 2023-10-13)

Figure 16 – Iceland CSAD Cloud Graph

Figure 16 represents the daily CSAD as calculated in equation (10), and the corresponding daily market return in absolute values for Iceland across the complete sample period (1995-11-14 to 2023-10-13)

Figure 12 – 16 provides visualisation of the relationship between the cross-sectional absolute deviation and market return for each of the Nordic countries. We note that these, compared to the same displays for the CSSD measure, are much more concentrated around the respective origo. Even when accounting for the differences in the axis, that is, that they portray a much more restrictive interval for the CSAD measure, there are still notable differences in their shapes. Specifically, the CSSD figures display greater dispersions across all market returns, as seen by numerous observations at y-values of more than 0.1, whilst the CSAD figures are consistently not reaching y-values of more than 0.005. Important to note is that we have restricted the axis, and hence excluded some outliers, to be able to visualise any potential relationships. This has been done for both the CSSD and the CSAD graphs. This allows for presentation of the data uncorrupted by outliers, so the plots are readable. However, prior to this adjustment the CSAD figures looked significantly flatter than the CSSD measures, indicating that this measure suggests a far lower dispersion from the daily market returns.

Comparing this to the figures in which the relationship between the CSSD measure and the market return is portrayed, we note that the concentration of observations is much higher for CSAD. Moreover, the point clouds are flatter for the Finnish and Icelandic point cloud, pointing to lower dispersions for the same return levels. As for the CSSD cloud graphs, we note that the distribution of observations leans slightly towards right, suggesting that investors are more prone to take on additional risk then the overall market return is slightly positive. There are no prominent indications suggesting a non-linear relationship in the "expected dispersion line" for any of the figures, however, one could argue that there is a small indication for this feature in Sweden's plot (figure 12) in the negative side of the x-axis, suggesting that the CSAD measure might predict herding around the negative market returns.

Table 8 in the appendix displays the results obtained for Sweden. We note a negative (-0.032) and significant at the 5% level value for the coefficient of α for the complete sample. Further, the coefficient for γ_2 is noticeably positive and significant at the 1% level, supporting the theory behind rational asset pricing models. Other interesting observations regard a few of the coefficients for the γ_2 variable, as we note several large positive and significant at the 1% level values. Specifically, all three periods pertaining to the Covid-19 pandemic as well as the period Normal state 4. Comparing the large differences to other estimations in different periods of the γ_2 coefficient this would imply that there are distinct outliers which increase the estimation significantly. Important to note is that these are "positive" outliers with a large dispersion from the market return, given that they yield a non-negative coefficient estimation which therefore suggests they are located above the line of "expected dispersion". This, and the fact that they are significant consequently means the model fails to indicate herding in these periods, and instead supports the rational asset pricing model. It is also of great importance to mention that these large outliers are mainly recorded in the periods pertaining to the Covid-19 pandemic, since this time had a severe impact on the Swedish (and global) economy as represented in both figure (1) and (12). In the event of a large recession in both the stock market and GDP development from an exogeneous shock of that size it is not unlikely that dispersions from the market return would grow significantly large, especially on the negative side of the spectrum.

Across the entire table, there are limited observations which speak for the presence of herding, in which instance we would expect the γ_2 variable to be negative and significant. The periods that do indicate a herding behaviour are the Greek crisis post period and the current state. As for the other periods, we do not have evidence supporting the presence of herding in Sweden with this measure. We also find that the coefficients on the linear $|R_{m,t}|$ term for the current period is positive and significant, which is in line with Chang, Cheng & Khorana's results where $CSAD_t$

increases with $R_{m,t}$. Moreover, during the Covid-periods we note positive and significant values for the ${R_{m,t}}^2$ coefficients, but negative and significant values for the $|R_{m,t}|$ term.

Denmark displays some similarities to Sweden (table 9). Whilst the large positive and significant values for the ${R_{m,t}}^2$ term are not as large, they are also significant at the 1% level. Moreover, they also correlate in terms of the periods in which they are observed. For Denmark, we note coefficients with these characteristics for the Covid-19 pre period, the Greek post and pre periods, the global financial crisis crash and post and the DotCom post, respectively. Interestingly, the large and positive (and significant at the 1% level) observation is also made for the entire sample. Regarding the presence of herding, we note negative and significant observations of the coefficient for the ${R_{m,t}}^2$ variable in only three instances. Firstly, in the period named Normal state 2 we observe a value of -0.678 which is significant at the 10% level. Secondly, in the Normal state 2 period, we have a value of -2.832 which is significant at the 5% level and, finally, in the current state we note -3.047 which is also significant at the 5% level. This fails to support that the presence of herding is most prominent during periods of abnormal market conditions, as it therefore should not occur to the same extent in periods which we have deemed to be "normal". However, we note that the Normal 2 period is one of the longest periods (1992/01/02 - 1999/09/29) we have for our sample and therefore it is not surprising that this period manages to deliver values of significance, nor that there may have been presence of herding during this time. Moreover, we note some significant and positive values for the $|R_{m,t}|$ coefficient but primarily negative ones. Specifically, there are negative and significant values in the DotCom crash and post periods, the Global financial crisis crash, the Greek post period, and the Covid-19 pre period. For the positive and significant estimations, these are not as large in terms of absolute values and are never recorded at the 1% significance level.

In the Norwegian market, there is no period in which γ_2 takes on a negative and significant value. Hence, no support is found for the presence of herding. Instead, we note positive and significant values for γ_2 in most subsamples examined, supporting the rational asset pricing model and displaying similarities to the results already discussed for Sweden and Denmark. That is, CSAD in general increases (decreases) with the realised average market return for each day. Moreover, we find that most coefficients for $|R_{m,t}|$ are negative and significant, speaking against the prediction that CSAD increases (decreases) linearly with $|R_{m,t}|$. This is in line with the results reported by Chang et al. (1999). These results are not observed to the same extent for Sweden and Denmark. Hence, we conclude that Norway's dispersions do, to a greater extent relative to those of Sweden and Denmark, have a positive correlation to the market returns. That is, when the market return is larger in absolute terms, so is the dispersion.

For Finland, we note a negative and significant value of γ_2 for the complete sample. This result is consistent with herding in the Finnish capital markets. We note, however, that there is only one subperiod during which similar results are observed, namely the Normal state 2 period which is defined as (1994/07/02 – 2000/06/29). Other than that, we find no negative and significant coefficients for the γ_2 variable.

Further, we note several positive and significant values for the γ_1 variable, supporting the prediction that CSAD increases (decreases) linearly with $|R_{m,t}|$. These results are not in line with the results reported by Chang et al. (1999). Given that the dispersion increases with the absolute value of the market return, this result implies that, on aggregate, people choose to invest different from other investors to a larger extent on days when the market return is positive, and less so when the market return is negative. This, however, does not imply much about the presence of herding as we cannot connect these results with negative and significant values for the γ_2 variable which are necessary as herding would be shown by a slower increasing, or even decreasing, non-linear relationship which is not captured by the $|R_{m,t}|$ coefficient.

The coefficient for the $|R_{m,t}|$ is negative and significant at the 1% level for Iceland for the entire sample. We also note a positive and significant value for the γ_2 variable for the entire sample, as well as for the periods between the global financial crisis pre-period and Normal state 4. These results contrast to those we would expect during periods with herding. However, we do observe negative and significant values for the γ_2 variable during Normal state 2 and the DotCom pre period.

Another interesting observation is that the alpha variable is zero between the DotCom post and the current period, spanning over more than 17 years with the exceptions being the global financial crisis crash during which the observed coefficient was -0.001 and Normal state 4 during which the observed coefficient was 0.001, the latter significant at the 1% level.

4.1.4 – Cross-Sectional Absolute Deviation: Bullish vs. Bearish

In general, we note more extreme values when conducting the analysis based on whether the market, in aggregate, had positive or negative returns during a specific day the results of which are presented in tables 13-17. This is not unexpected due to a couple of reasons. Firstly, when we apply equitation 12 and conduct a regression based on it, we effectively divide the data into much smaller subsamples as we utilise dummy variables which divide our data depending on the market movements. For simplicity, if we assume that there are an equal number of bullish and bearish days, this will give us twice as many and thus half as large subsamples. Therefore, the respective outliers in each subsample will carry much more weight relative to other observations. Secondly, when sub-setting the sample based on the observations in this way, the outliers are bound to be more visible as they are now included in dummy samples containing only positive (negative) values where they are no longer mirrored by outliers on the opposite side of the spectrum. Hence, we will see larger (smaller) values than we did previously.

Bearing the above in mind, the very large (small) values obtained for several of the coefficients pertaining to Sweden are explained. Looking back at the descriptive statistics we note that the standard deviation for market return in Sweden is the second largest. The only country with a higher standard deviation is Iceland, which as previously discussed is explained as the sample size is much smaller and hence outliers affect the deviation much more intensely. Whilst standard deviation is not the same as cross-sectional absolute deviation, there are similarities, and this deviation does explain the presence of the more extreme values observed. This being the case for Sweden could be as it is the largest sample that we have and hence, it is bound to have more extreme outliers because there are simply just more stocks and days during which such extreme values can be observed.

For Sweden, we observe negative and significant values for the $|R_{m,t}|$ coefficient both on days during which market return is up and down but note that they are more prominent during bullish days. Specifically, during Normal state 4 and the Covid periods these results are especially negative whilst being significant at the 1% level. This occurs during the same period as we have largely positive and significant values for the coefficients for the γ_3 variable, which are results that reoccur in other periods and countries as well.

We noted previously that the CSAD measure implied the presence of herding in both Sweden and Denmark during the current period. This regression allows us to detect whether this herding differs between bullish and bearish days. Interestingly, we find that herding occurs during days of positive market returns in Denmark, but during days of negative market returns in Sweden. These results are significant at the 1% and 5% level, respectively. Hence, there seem to be a difference in investor sentiment where Swedish investors are more prone to mimic the behaviours of their peers during bearish days whereas Danish investors are more prone to such behaviour during bullish days. Further, we note that we find support for the presence of herding in Sweden during bearish days for the complete sample. However, this could be an effect of the largely negative measure in the current state. Additionally, we also note that the negative and significant coefficient obtained during the Greek crisis post period is still negative, however no longer significant. This is likely due to the limited data that is included in the sub-sample created with the dummy variables, limiting the observations that the model has access to and hence its ability to generate significant results. Lastly, there are still some large and positive values included in the results.

We observe a negative and significant value during positive periods for the 1990s crash in Denmark during days of positive market returns, in line with the results discussed above. However, during the Normal state 2 we do note results suggesting the presence of herding during days of negative market returns significant at the 10% level. Moreover, there are several periods during which the coefficients for the $|R_{m,t}|$ variable is negative and significant, especially when the overall market return is positive.

We note the absence of evidence supporting the presence of herding in Norway which is in line with the results obtained for the original CSAD measure. There are several periods during which the coefficients for the $|R_{m,t}|$ variable is negative and significant, especially when the overall market return is positive but here there are more periods when the market return is negative than was observed for Denmark.

For Finland, we note a negative and significant at the 1% level value for the complete sample during bullish days. This is also in line with previously reported results. Moreover, we obtain results supporting the presence of herding during bullish days in Normal state 2. We note the absence of negative coefficients during bearish days. Moreover, we note that there are more positive and significant values for the $|R_{m,t}|$ variable in Finland than there is negative. Most of these are observed during days in which the overall market return is positive.

Lastly, for Iceland, we note a negative and significant at the 10% level coefficient for the γ_4 coefficient during the DotCom pre period. Interestingly, during the DotCom crash we note negative and significant coefficients for both bearish and bullish days, whereas the pre-period only had significance during days in which the complete market return was negative. In Iceland, during the Covid-19 pre period, we also note negative and significant coefficient during days in which the overall market is up.

4.2 – Robustness tests

Due to findings of heteroscedasticity in the majority of the data using the Breusch-Pagan test we have conducted White's Variance and Covariance Matrixes on our samples in order to estimate robust versions of the regression models. Below are the analyses for the robust regressions with the adjustment for potential heteroskedasticity. Whilst it is of interest to conduct robustness checks, the analysis inherently comes with limitations as it alters the original model and hence, one must be cautions with the interpretations thereof. In our instance, we find that there are numerous observations that are no longer significant but that previously were. We do, however also find that the CSSD measure, which failed to provide us with observations of significance suggesting herding previously, now suggests that herding is present. The results and their differences in significance are presented and discussed below.

4.2.1 – Robust CSSD

As seen in tables 18-22 there has been a few considerable changes with regards to the regression based on equation 2. The previous regression on the CSSD measure provided no evidence for herding in any of the markets or periods under examination in this study. Whilst this mostly holds true for the robust versions as well, there is now slight indication of herding presence in the Swedish market for two subsamples as can be seen when looking at the 1% dummy low variable's coefficients. These are the Greek government-debt crisis period and the Covid-19 pre-period. However, these two observations are quite different with the Greek pre period result being significant at the 1% level whilst the Covid is significant in the 10% level. Moreover, the Greek government had -0.011 whilst Covid was -0.005, hence Covid is less negative as well. What is interesting about these results are that they are in line with the cloud graph analysis in section 4.1.2 where we note a slight potential indication of a descending line in the negative end of the graph. Given the high levels of heteroscedasticity in the Swedish CSSD regression model these results were unrecorded before, but with the additional test using White's Variance and Covariance Matrix we do find some, although modest and limited, indication of herding in Sweden using the CSSD measure as well. However, taking into consideration that this herding effect was not captured until heteroscedasticity was accounted for, we cannot based solely on these results conclude that herding is present.

We note similar results for Finland and Iceland. Specifically, for Finland we note a negative (-0.001) and significant at the 10% level value for the lower dummy variable (1%) during the Covid-19 post period. For Iceland, similar results are obtained for both the 1% dummy variables during the DotCom pre-period. These are both recorded as -0.02 with significance at the 5% level. This could imply that the data exhibits perfect multicollinearity for this period. Whilst this is quite an extraordinary result, it is not something that we are able to draw hard conclusions based on as the data for Iceland is limited due to its size.

4.2.2 – Robust CSAD

The coefficients for the robust versions of the CSAD coefficients are provided in table 23 – 27. We note that, for Sweden, the coefficient for the γ_2 in the current period is no longer significant. Hence, with the CSAD measure, and when accounting and adjusting the model with regards to heteroscedasticity, we no longer find support for the presence of herding. However, for the Greek crisis post period we note that the significance of the γ_2 coefficient has increased and is now significant at the 10% level. Moreover, many of the large and positive observations previously recorded are no longer significant. There is however an exception during the Covid-pre period.

For Denmark, we note that the negative and significant value for the γ_2 coefficient was observed in the current period at a 5% significance level. This holds true after conducting the White's Variance and Covariance Matrixes, with the same significance level, supporting the previous results which suggested the presence of herding. The same can be said for the Normal state 3 period.

In the Norwegian market, we find no support for the presence of herding using the CSAD measure alone, which still holds true after conducting the robustness test.

For Finland, we no longer find evidence of herding. Hence, the negative and significant at the 10% level coefficient for γ_2 that we observed for the normal state 2 period is no longer significant. The same is true for the γ_2 coefficient for the complete sample. We do note that we still have a positive and significant at the 1% level value for the same coefficient in the current state. This result supports the rational asset pricing models.

Lastly, for Iceland, we note that the negative and statistically significant coefficient of γ_2 for the Covid-19 pre and post periods becomes significant at the 10% level after conducting robustness checks, which was not the case previously. However, for the γ_2 coefficient in the Normal 2 and DotmCom pre period, the significance does not remain.

For the $|R_{m,t}|$ variables we note that in general, for all countries, we have lost some significance for several observations. This is expected for the same reasons as discussed above.

4.2.3 – Robust CSAD Bullish vs Bearish

The regression output for the robust CSAD analysis on bullish and bearish days are found in tables 28 – 32. For Sweden, we note the absence of negative and significant values for the γ_4 coefficient, failing to support the presence of herding during the days in which the market in aggregate exhibits negative returns in that subsample. The same is true for the γ_3 variable, and hence we cannot speak for the presence of herding during days of positive market returns either. The large and significant positive value observed for the γ_3 variable during the pre-period to Covid-19 does remain. We note positive and significant values for γ_1 in several periods – supporting that CSAD increases with $|R_{M,t}|$ on days in which the market exhibits positive aggregate returns. However, during the Covid-19 pre period the coefficient is negative and significant at the 5% level, implying that the dispersion decreases when the absolute value of returns during bearish days become more extreme. Whilst this result fails to provide insight as to the presence of herding as this would necessities that the dispersion increases at a lower rate or even decreases which is measured by the coefficients on ${R_{M,t}}^2$ variable. For γ_2 we note a negative and significant value during the Normal state 4. Sweden also exhibits positive and significant values for the coefficient of α for the 1990's recession post period, the DotCom crash and post periods, the Greek crisis post period as well as the Covid-19 period.

For Denmark, we note negative and significant values for the γ_3 coefficient in the current period, suggesting the presence of herding in days where the overall market return is positive. Moreover, in the same period we note positive and significant values for the γ_2 coefficient, suggesting that CSAD increases with $|R_{M,t}|$ on days during which the overall market is down. Hence, it supports the presence of herding in the current period on days in which the market is up but supports the prediction that CSAD increases with $|R_{M,t}|$ on days during which the market is down. Similarly, support for CSAD increasing with $|R_{M,t}|$ during days in which the market is up is found for the normal state 2 and the current period. However, for the complete sample both the γ_1 and γ_2 are negative and significant. Hence, we find no support for CSAD increasing with the absolute value of the market return for Denmark in aggregate.

For Norway, we note the absence of negative and significant values for the coefficients for the ${R_{M,t}}^2$ variable. Hence, we find no support for herding during any period in which the market return in aggregate is positive nor negative. Moreover, during several periods we note a positive and significant value for the coefficients of $|R_{M,t}|$ during days in which the overall market return is positive. We also note that we have in general a lot fewer significant estimations, which is most evident in the more recent period for the γ_3 variable.

For the capital market in Finland, we fail to find support for the presence of herding in either of the different subsamples when the market is up (down) as evident by the absence of negative and significant values for the γ_3 (γ_4) coefficient. We note that the $\gamma_3$is positive and significant for the current period, supporting the rational asset pricing model. In this period, it is also noteworthy that we observe a negative and significant value for the γ_1 coefficient. We also note positive and significant values for the coefficients for the absolute market return in the following periods: normal state 1, 1990's recession pre and during periods, normal state 2, DotCom pre period and the global financial crisis.

We note a negative and significant value for the $\left(R_{M,t}\right)^2$ coefficient during the DotCom crash and the Covid-19 pre period in the Icelandic market during days in which the market is up, supporting the presence of herding. Further, we observe positive and significant values for the absolute market return variable in the DotCom crash and post periods, the global financial crisis crash, and the Covid-19 crash. Moreover, we note positive and significant values for the $\left(R_{M,t}\right)^2$ coefficient when the market is down during and the global financial crisis post period, and for days in which the market is up for the global financial crisis crash period as well as the current period. Moreover, the largely positive and significant at the 1% level estimations for normal state 4 in both bearish and bullish days are no longer significant.

4. Interpretation of empirical findings

The results obtained by the CSSD measures fails to provide us with support for the presence of herding. This is arguably not very surprising, as the measure in its nature only focuses on herding when market returns are very extreme (i.e., in the first or fifth percentiles) and therefore fails to account for herding that may occur in the middle range of market returns. With the CSSD measure we do find multiple positive and significant at the 1% level values for the dummy coefficients. This holds true for all countries indicating the lack of evidence for herding and therefore the initial standpoint of rational asset pricing holds true. Moreover, the 1% criterion produces larger estimates than the 5% criterion across all countries. Hence, we can conclude that the predictions of rational asset pricing are most apparent when confined to the 1% most extreme market returns. We found dispersions to increase significantly during periods of large average price changes, i.e., when the market return was abnormally large in absolute terms. This implies that individual returns do not cluster around the market return during periods of market stress, and therefore speaks against the presence of herding.

We find support of herding behavior within several of the countries in the Normal State 2 period. Specifically, we find this support with differing significant levels in Denmark, Finland, and Iceland. This result contradicts that herding would be more prominent in times of market stress and economic downturns. Apart from the normal states we also find support of herding in a few of the periods relating to different market stresses. Within the Swedish sample we find slight presence of herding in the post period of the Greek government-debt crisis, and in Iceland we notice a small significance during the pre-period of the DotCom crash as well. We do not find any further support around other crises, and we therefore cannot answer our question regarding if herding is more prominent before or after severe stress. There are several positive and significant values for the γ_2 coefficient, some of which are larger than others. During the Covid periods in Sweden we record the largest positive estimations in any model, which all yield a significance at the 1% level. These results imply a strong and positive relationship between the dispersion and market returns further supporting rational asset pricing. It is of great importance to note that a lack of positive and significant coefficient estimates does not suggest that rational asset pricing models are wrong, however the presence of them further proves their underlying assumption within asset pricing.

When examining the results depending on bullish and bearish days, we note some differences to the previously mentioned results. Specifically, we now find support for herding in the crisis period of the 1990s recession in Denmark, the pre-period of Covid-19 in Iceland, and we also note that support for herding in Iceland during the Normal state 2 period is no longer present. Regarding Iceland, the support for herding has also shifted from the period before the DotCom crash to the crisis period. We also note that a majority of the support for herding is found in the days related to negative market return across all countries, indicating that herding is more prominent during days when the market recedes. This suggests that herding would be prominent during days of negative market returns because investors are more prone to mimic the behaviors of their peers in bad times.

We note that there are some differences in our results when conducting the regressions for robustness with White's variance and covariance matrix. It is essential to keep in mind that whilst these tests are favorable to run in order to receive heteroscedastic-adjusted estimations, the underlying regression has been altered with. The output interpreted in the robust versions therefore no longer represents the initial model specifications which must be taken into account when interpreting and analyzing the results. With that said, the robust model results yield some interesting values which we will turn to next to compare with the non-robust regression outputs.

The most interesting findings are related to the CSSD measure. With the additional adjustments for heteroskedasticity we are now able to find, somewhat limited, but still prominent support for herding using this measure. As previously discussed, there are now two periods for Sweden and one for Finland during which our data indicates that herding did occur. During the Greek government-debt crisis, we find that the coefficient of the lower dummy variable at 1% percentile is negative and significant at the 1% level in Sweden. This suggests that herding occurs during the days in which market return is particularly negative, which is in line with our previously set out expectations. Interestingly, we do find that herding occurs in the Covid-19 pre period as well. Whilst we have defined this period as a "pre" period, it can be questioned whether this really applies to the pandemic as no one knew that it was coming and hence, there was no way for investors to use this information and adapt their investments accordingly. However, looking at figure 2 displaying the GDP growth for Sweden we note that this period does exhibit some quarters with negative growth. Hence, investors may have used this as sentiment to opt their investments to better correlate with those of their peers.

For the CSAD measure, it becomes apparent that the robustness checks have removed the significance of some of the results reported with the normal CSSD measure. As aforementioned, this is not surprising and does not inherently entail that these results were not correct. The ones that we do still obtain are, however, concluded to bear a higher importance as they are not only significant using the measure on its own but also when conducting robustness checks. Additionally, the two new significant values we obtain in Iceland during the covid pre and post periods are also interesting to bear in mind. The fact that these were not recorded as significant previously may be since the sample size was larger prior to it being adjusted with the robustness checks, meaning that the returns that are left after such checks will bear more weight in the model. The covid pre period can be argued for with the same logic presented for CSSD in Sweden, as Iceland exhibits descending GDP growth during that time.

Having conducted the robustness checks, it is also worth mentioning that the previously discussed significant results for Sweden are no longer significant. As is the case for Finland. For Denmark, we note that there is still significance for some negative values of the coefficients for the $(R_{M,t})^2$ coefficient, particularly during days in which the overall market return is positive. This suggests that investors' propensity to herd becomes more prominent during days of positive economic returns. For Iceland, the only negative and significant results reported for the $(R_{M,t})^2$ coefficient are reported at the 5% significance level during the DotCom crash and the Covid pre period, both of which during bullish days. Overall, the conclusions from this test would be that investors herd more when returns are positive, suggesting that they may believe that others are more informed than they themselves are and hence, they mimic their investments to try and get a piece of the positive returns. With these results, we conclude that with regards to our second aim of the research question, herding is present in the Nordic capital markets and that its occurrence is more likely during days of negative market return. Regarding the specific periods during which it is observed, we cannot conclude that it is more prominent during periods of economic distress, as we have observed herding during periods which are deemed to be normal. We do, however conclude that herding is more prominent during bearish days. Arguably, this effect could have further implications for the capital markets as the presence of herding could contort asset prices such that the market is no longer efficient. This would then make the general market conditions even worse, and therefore spur investors to engage in herding further.

Finally, addressing the third part of our research question we find somewhat conflicting results. We find that the period during which we could find most evidence suggesting the presence of herding (within the crisis periods) was the DotCom crash which would suggest that endogenous shocks bear the most importance. However, all five of these were recorded in Iceland. Therefore, it is deemed to be of interest that the second most impactful period was the Covid-19 crisis during which Sweden, Finland and Iceland all had herding in their respective financial markets, supporting that exogenous shocks bear significance. It is also the only period where more than two countries had herding in the same crisis period. This suggests that in a Nordic context, an exogenous shock like the Covid-19 pandemic is more likely to cause herding behavior within the capital markets than an endogenous one. However, we acknowledge that endogenous shocks can have a larger impact in specific countries as implied by the support found for herding in Iceland during the DotCom periods using multiple measures and model regressions.

5. Conclusion

In this study, we find support for the presence of herding using the cross-sectional standard deviation after conducting robustness checks. We also find support when using the cross-sectional absolute deviation, both pre and post robustness checks, and when conducting the analysis depending on whether overall market return is positive or negative on a specific day. We find evidence supporting herding in all countries except Norway. Further, we find that herding is more prominent during days in which the overall market return is negative.

Herding appears to not be influenced by macroeconomic factors to the extent that we previously thought. Whilst we do find herding to be present during periods with negative national economic growth, we also find evidence supporting the presence of herding during periods defined as normal. Hence, we are not able to conclude that herding is more prominent during periods of economic distress, as we fail to find that it is not as frequently observed during periods with national economic growth.

Apart from Iceland in which we find most evidence supporting the presence of herding during the DotCom crash, Covid-19 is by far the period during which most herding has occurred. Hence, we conclude that exogenous shocks to the financial markets are more significance in terms of their influence on investors' sentiment.

Finally, one could extend on this study by investigating whether it is possible to say anything about the overall market efficiency during periods in which herding appears to be present. By utilizing a rational asset pricing model, it would be possible to test whether it is able to successfully price assets during these times. With this, it would be possible to further underline the findings of this study.

As final remarks, we propose that potential extensions of this literature may benefit by including a segmentation based on industries, hence looking for potential differences therebetween as we consider it of interest to further map the characteristics herding, and because we believe the differences in investor sentiment and culture between industries could cause significant differences in herding prominence. Further, as mentioned under data limitations, because the Nordic countries all have exchanges with limited sizes, the functionality of the models and their degree of adoption may improve by conducting the same analysis on a joint sample containing all Nordic countries to ensure that there are sufficiently large samples available. One could argue that the sheer sizes of these makes institutional investors' investments move the index in such a way that they themselves impact it, and the market return used in this study, to such a large extent that it becomes less meaningful to speak of herding in this sense. This additional analysis could then be compared to the analyses of the individual countries in order to make the results more robust. Lastly, it could also be of interest to explore potential herding across international borders. For instance, one could investigate whether any of the Nordic countries herd around the U.S. or Chinese markets.

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AI disclaimer

Artificial intelligence (AI) has been used in the writing of this thesis. Specifically, ChatGPT has been used as aid when writing the code with which the study has been made. This includes rewriting already existing code to better fit with our purposes, as well as help formulate completely new code based on certain inputs provided. No other help has been received and no other AI tools have been used in the writing of this thesis.

Appendix

Table 1: *Definition of time periods*

Normal 1

	During
Sweden	1986/01/01 - 1988/12/30
Denmark	1986/01/01 – 1987/03/30
Norway	Excluded[1]
Finland	1986/01/02 - 1998/12/30
Iceland	Excluded[2]

Early 1990's recession

	Pre	During	Post
Sweden	1988/12/31 - 1989/12/31	1990/01/01 - 1993/03/31	1993/04/01 - 1994/04/01
Denmark	1987/03/31 - 1988/03/31	1988/04/01 - 1990/12/31	1991/01/01 - 1992/01/01
Norway	1986/03/31 - 1987/03/31	1987/04/01 - 1989/03/31	1989/04/01 - 1990/04/01
Finland	1988/12/31 - 1989/12/31	1990/01/01 - 1993/06/30	1993/07/01 - 1994/07/01
Iceland	Excluded[3]		

Normal 2

	During
Sweden	1994/04/02 - 1999/06/29
Denmark	1992/01/02 - 1999/09/29
Norway	1990/04/02 - 1999/12/30
Finland	1994/07/02 - 2000/06/29
Iceland	1995/11/14 - 1997/12/30

The dot-com pre

	Pre	During	Post
Sweden	1999/06/30 - 2000/06/30	2000/07/01 - 2002/03/31	2002/04/01 - 2003/04/01
Denmark	1999/09/30 - 2000/09/30	2000/10/01 - 2003/06/30	2003/07/01 - 2004/07/01
Norway	1999/12/31 - 2000/12/31	2001/01/01 - 2003/06/30	2003/07/01 - 2004/07/01
Finland	2000/06/30 - 2001/06/30	2001/07/01 - 2003/03/31	2003/04/01 - 2004/04/01
Iceland	1997/12/31 - 1998/12/31	1999/01/01 - 2003/06/30	2003/07/01 - 2004/07/01

Normal 3

	During
Sweden	2003/04/02 - 2006/09/29
Denmark	2004/07/02 - 2006/09/29
Norway	2004/07/02 - 2006/09/29
Finland	2004/04/02 - 2006/09/29
Iceland	2004-07-02 - 2006/09/29

Global financial crisis of 2007-2009

	Pre	During	Post
Sweden	2006/09/30 - 2007/09/30	2007/10/01 - 2009/09/30	2009/10/01 - 2010/10/01
Denmark	2006/09/30 - 2007/09/30	2007/10/01 - 2009/06/30	2009/07/07 - 2010/07/07
Norway	2006/09/30 - 2007/09/30	2007/10/01 - 2009/06/30	2009/07/01 - 2010/07/01
Finland	2006/09/30 - 2007/09/30	2007/10/01 - 2009/12/31	2010/01/01 - 2011/01/01
Iceland	2006/09/30 - 2007/09/30	2007/10/01 - 2012/03/31	2012/04/01 - 2013/04/01

[1] Excluded due to limited data between 1986/01/01 and 1986/03/30
[2] Excluded due to no data available prior to 1995/11/14
[3] Excluded due to no data available prior to 1995/11/14

Greek government debt-crisis

	Pre	During	Post
Sweden	2010/06/30 - 2011/06/30	2011/07/01 - 2013/06/30	2013/07/01 - 2014/07/01
Denmark	2010/03/31 - 2011/03/31	2011/04/01 - 2012/12/31	2013/01/01 - 2014/01/01
Norway	2011/03/31 - 2012/03/31	2012/04/01 - 2013/12/31	2014/01/01 - 2015/01/01
Finland	2010/09/30 - 2011/09/30	2011/10/01 - 2015/03/31	2015/04/01 - 2016/04/01
Iceland	Excluded[4]		

Normal 4

	During
Sweden	2014/07/02 - 2018/12/30
Denmark	2014/01/02 - 2018/12/30
Norway	2015/01/02 - 2018/12/30
Finland	2016/04/02 - 2018/12/30
Iceland	2013/04/02 - 2018/12/30

Covid-19 pandemic

	Pre	During	Post
Sweden	2019/01/01 - 2019/12/31	2020/01/01 - 2020/12/31	2021/01/01 - 2021/12/31
Denmark	2019/01/01 - 2019/12/31	2020/01/01 - 2020/12/31	2021/01/01 - 2021/12/31
Norway	2019/01/01 - 2019/12/31	2020/01/01 - 2020/12/31	2021/01/01 - 2021/12/31
Finland	2019/01/01 - 2019/12/31	2020/01/01 - 2020/12/31	2021/01/01 - 2021/12/31
Iceland	2019/01/01 - 2019/12/31	2020/01/01 - 2020/12/31	2021/01/01 - 2021/12/31

Current

	During
Sweden	2022/01/01 - October 2023
Denmark	2022/01/01 - October 2024
Norway	2022/01/01 - October 2025
Finland	2022/01/01 - October 2026
Iceland	2022/01/01 - October 2027

Table 1 provides specifications of the different time periods used in the analysis. It displays the periods under investigation as "pre", "during" and "post" the different turbulent periods, respectively. For the "Normal States" and the "Current" period the dates are presented under "during" as these periods do not have a "pre" or "post" period given that they are defined as the periods in-between the shocks to the market we are examining.

Table 2: *Descriptive statistics –market return, CSSD and CSAD*

Market return

Country	Mean	Median	Max	Min	SD	Skewness	Kurtosis
Sweden	0.001	0.000	0.958	-0.375	0.019	17.888	1050.812
Iceland	0.002	0.001	2.638	-0.184	0.035	58.362	4022.438
Denmark	0.001	0.001	0.288	-0.099	0.012	2.920	66.029
Finland	0.001	0.001	0.232	-0.080	0.008	2.366	86.914
Norway	0.001	0.001	0.786	-0.236	0.013	21.394	1284.204

CSSD

Country	Mean	Median	Max	Min	SD	Skewness	Kurtosis
Sweden	0.014	0.011	4.173	0.000	0.054	68.674	5285.039
Iceland	0.049	0.031	67.675	0.000	0.758	78.885	6694.723
Denmark	0.049	0.033	7.981	0.000	0.203	22.537	627.215
Finland	0.026	0.023	3.149	0.000	0.041	52.852	3585.566
Norway	0.028	0.024	4.472	0.000	0.058	56.984	3949.000

[4] Excluded due to longer period of economic recession already included in the "*Global financial crisis of 2007-2009"*

CSAD

Country	Mean	Median	Max	Min	SD	Skewness	Kurtosis
Sweden	0.003	0.000	16.585	0.000	0.202	82.151	6751.540
Iceland	0.576	0.001	4572.944	0.000	47.027	94.088	9086.641
Denmark	0.043	0.001	63.647	0.000	1.044	41.128	2056.550
Finland	0.002	0.001	9.868	0.000	0.104	87.737	8137.477
Norway	0.004	0.001	19.952	0.000	0.212	87.183	8029.292

In table 2, the descriptive statistics for the daily market return, CSSD and CSAD, are displayed based on the complete samples for each country. The statistics calculated are the mean, median, maximum-value, minimum-value, standard deviation, skewness and kurtosis. The CSSD measure is calculated using equation (1):

$$s = \sqrt{\frac{\sum_{i=1}^{n}(r_i - \bar{r})^2}{n-1}},$$

And the CSAD measure is calculated using equation (10):

$$CSAD_t = \frac{\sum_{i=1}^{N}\left|R_{i,t} - R_{M,t}\right|}{N}$$

Table 3: *Sweden CSSD*

	$\alpha_{5\%}$		D_{Lower} *5%*		D_{Upper} *5%*		$\alpha_{1\%}$		D_{Lower} *1%*		D_{Upper} *1%*	
Total Sample												
Coefficient	0.036	***	0.004		0.256	***	0.039	***	0.013		0.998	***
T-stat	17.457		0.403		28.355		21.676		0.702		55.978	
Normal State 1												
Coefficient	0.019	***	0.009		0.011		0.019	***	0.021		0.022	
T-stat	47.941		5.074		6.365		51.657		5.656		5.936	
1990s Recession Pre												
Coefficient	0.015	***	0.004		0.035		0.016	***	0.005		0.124	***
T-stat	11.517		0.755		6.057		14.667		0.455		12.462	
1990s Recession Crash												
Coefficient	0.024	***	0.011		0.029	***	0.026	***	0.017	***	0.037	
T-stat	48.677		4.919		13.604		50.248		3.465		7.488	
1990s Recession Post												
Coefficient	0.032	***	-0.002		0.024		0.033	***	-0.008		0.034	***
T-stat	31.122		-0.516		5.563		32.403		-0.890		3.604	
Normal State 2												
Coefficient	0.021	***	0.009		0.009		0.021	***	0.029	***	0.021	
T-stat	67.986		6.758		7.145		74.106		10.447		7.360	
DotCom Pre												
Coefficient	0.035	***	0.008		0.055	***	0.037	***	0.005		0.113	***
T-stat	27.926		1.446		10.304		30.451		0.407		9.861	
DotCom Crash												
Coefficient	0.041	***	0.010	***	0.021		0.042	***	0.019	**	0.036	
T-stat	62.703		3.695		7.494		65.614		3.125		6.057	
DotCom Post												
Coefficient	0.046	***	0.019	***	0.038		0.048	***	0.061		0.036	**
T-stat	36.922		3.540		7.137		38.693		5.274		3.136	
Normal State 3												
Coefficient	0.027	***	0.002		0.027	***	0.027	***	0.003		0.084	***
T-stat	45.263		0.658		10.447		52.045		0.669		16.892	
Global Crisis Pre												
Coefficient	0.028	***	-0.002		0.028		0.029	***	0.000		0.106	***
T-stat	21.509		-0.264		4.900		25.528		-0.044		10.247	
Global Crisis Crash												
Coefficient	0.043	***	0.011	**	0.020		0.044	***	0.031	***	0.034	
T-stat	48.372		2.948		5.088		51.465		3.853		4.267	

Global Crisis Post												
Coefficient	0.046	***	0.002		0.035		0.048	***	0.001		0.009	
T-stat	28.154		0.291		5.105		29.232		0.048		0.585	
Greek Crisis Pre												
Coefficient	0.049	***	-0.001		0.021		0.050	***	0.000		0.030	**
T-stat	39.232		-0.207		4.092		40.895		0.028		2.623	
Greek Crisis Crash												
Coefficient	0.060	***	-0.002		0.118	***	0.063	***	-0.011		0.249	***
T-stat	24.771		-0.191		11.355		27.374		0.000		11.589	
Greek Crisis Pre												
Coefficient	0.046	***	-0.003		0.024	***	0.047	***	-0.001		0.001	
T-stat	29.995		0.000		3.780		31.285		0.000		0.086	
Normal State 4												
Coefficient	0.033		0.004		0.205	***	0.035	***	0.004		0.825	***
T-stat	6.862		0.199		9.841		8.512		0.099		20.438	
Covid-19 Pre												
Coefficient	0.038		-0.002		0.197		0.040		-0.005		0.771	***
T-stat	5.661		0.000		6.962		8.382		0.000		17.475	
Covid 19 Crash												
Coefficient	0.046		0.024		0.588		0.048	*	0.017		2.692	***
T-stat	1.493		0.181		4.497		1.919		0.075		11.573	
Covid 19 Post												
Coefficient	0.044	*	-0.007		0.571		0.049		-0.007		2.269	***
T-stat	2.527		0.000		7.735		4.527		0.000		22.777	
Current State												
Coefficient	0.131		-0.072		3.042	***	0.232	***	-0.186		4.970	***
T-stat	7.067		-0.903		38.401		8.571		-0.716		19.101	

This table reports the estimated coefficients for the OLS regression on Eq (2):
$\mathrm{CSSD}_t = \alpha + \beta_1 \mathrm{D}_t^L + \beta_2 \mathrm{D}_t^U + \varepsilon_t$,
where $\mathrm{D}_t^L(\mathrm{D}_t^U)$ equals 1 if the market return on day t lied in the extreme lower (upper) tail of the return distribution, and 0 otherwise. The 5% and 1% refers to the percentage of observations in the upper and lower tail of the market distribution. Heteroskedasticity consistent t-statistics are also reported.
* The coefficient is significant at the 10% level
** The coefficient is significant at the 5% level
*** The coefficient is significant at the 1% level

Table 4: *Denmark CSSD*

	$\alpha_{5\%}$		D_{Lower} *5%*		D_{Upper} *5%*		$\alpha_{1\%}$		D_{Lower} *1%*		D_{Upper} *1%*	
Total Sample												
Coefficient	0.024	***	0.007	***	0.028	***	0.025	***	0.012	**	0.099	***
T-stat	55.165		3.783		14.933		60.213		3.028		24.404	
Normal State 1												
Coefficient	0.014	***	0.006		0.009	***	0.014	***	0.011		0.015	
T-stat	63.838		5.988		9.778		67.753		5.627		7.204	
1990s Recession Pre												
Coefficient	0.012	***	0.008		0.008		0.013	***	0.015		0.015	
T-stat	32.134		4.760		5.050		34.379		4.174		4.187	
1990s Recession Crash												
Coefficient	0.018	***	0.019	***	0.012		0.019	***	0.023		0.018	***
T-stat	35.875		8.777		5.724		37.224		4.688		3.659	
1990s Recession Post												
Coefficient	0.021	***	-0.001		0.022		0.022	***	0.003		0.018	
T-stat	31.503		-0.225		8.124		31.169		0.429		2.731	
Normal State 2												
Coefficient	0.019	***	0.007		0.011	***	0.019	***	0.010		0.022	***
T-stat	70.948		6.127		9.775		75.421		3.963		8.597	
DotCom Pre												
Coefficient	0.028	***	0.009	**	0.016		0.028	***	0.021	**	0.044	
T-stat	37.229		2.792		5.199		41.407		3.229		6.908	

DotCom Crash						
Coefficient	0.029***	0.006*	0.032***	0.030***	0.009	0.072***
T-stat	41.316	2.113	10.488	45.222	1.529	11.581
DotCom Post						
Coefficient	0.024***	0.006	0.131	0.025	-0.002	0.562***
T-stat	3.707	0.216	4.815	4.734	0.000	11.479
Normal State 3						
Coefficient	0.022***	0.002	0.017***	0.022***	0.008*	0.023
T-stat	46.946	0.880	8.731	48.651	1.727	4.994
Global Crisis Pre						
Coefficient	0.021***	0.003	0.005*	0.022***	0.007	0.006
T-stat	36.853	1.133	2.039	38.693	1.383	1.117
Global Crisis Crash						
Coefficient	0.037	0.019	0.165	0.039	0.038	0.658***
T-stat	5.300	0.629	5.384	6.325	0.656	11.244
Global Crisis Post						
Coefficient	0.037***	-0.002	0.064	0.038***	-0.002	0.198***
T-stat	17.585	-0.192	7.230	21.508	0.000	11.953
Greek Crisis Pre						
Coefficient	0.036***	0.001	0.049	0.037***	-0.001	0.171***
T-stat	16.751	0.096	5.400	19.933	-0.034	9.992
Greek Crisis Crash						
Coefficient	0.036***	0.005	0.028	0.037***	0.015*	0.081***
T-stat	38.538	1.227	6.982	43.039	1.886	10.040
Greek Crisis Post						
Coefficient	0.030	0.001	0.077	0.030***	0.006	0.344***
T-stat	7.710	1.068	4.674	9.644	0.202	11.727
Normal State 4						
Coefficient	0.024***	0.007***	0.012	0.024***	0.013**	0.034***
T-stat	56.247	3.606	6.270	60.564	3.275	8.860
Covid-19 Pre						
Coefficient	0.022	0.003	0.077	0.023	0.000	0.333***
T-stat	5.851	0.190	4.768	7.385	0.003	11.606
Covid 19 Crash						
Coefficient	0.027***	0.009*	0.008*	0.027***	0.023**	0.013
T-stat	29.857	2.515	2.076	31.889	2.916	1.694
Covid 19 Post						
Coefficient	0.027***	0.003	0.004	0.027***	0.002	0.005
T-stat	37.276	1.068	1.384	39.294	0.274	0.843
Current State						
Coefficient	0.033***	0.003	0.005*	0.033***	0.005	0.004
T-stat	66.494	1.362	2.377	69.724	1.086	0.852

This table reports the estimated coefficients for the OLS regression on Eq (2):

$$CSSD_t = \alpha + \beta_1 D_t^L + \beta_2 D_t^U + \varepsilon_t,$$

where $D_t^L(D_t^U)$ equals 1 if the market return on day t lied in the extreme lower (upper) tail of the return distribution, and 0 otherwise. The 5% and 1% refers to the percentage of observations in the upper and lower tail of the market distribution. Heteroskedasticity consistent t-statistics are also reported.

* The coefficient is significant at the 10% level

** The coefficient is significant at the 5% level

*** The coefficient is significant at the 1% level

Table 5: *Norway CSSD*

	$\alpha_{5\%}$	D_{Lower} *5%*	D_{Upper} *5%*	$\alpha_{1\%}$	D_{Lower} *1%*	D_{Upper} *1%*
Total Sample						
Coefficient	0.033	0.007	0.310***	0.035	0.014	1.407***
T-stat	4.126	0.189	8.862	4.569	0.180	18.696
1990s Recession Bubble						
Coefficient	0.018***	0.013	0.008**	0.019***	0.014*	0.000
T-stat	28.946	5.076	3.257	30.364	2.410	-0.057

1990s Recession Crash												
Coefficient	0.022	***	0.011		0.012		0.022	***	0.019	***	0.032	
T-stat	37.584		4.438		4.738		40.773		3.753		6.321	
1990s Recession Recovery												
Coefficient	0.035	***	0.007	*	0.009	**	0.036	***	0.006		0.016	*
T-stat	45.505		1.961		2.701		47.703		0.812		2.285	
Normal State 2												
Coefficient	0.027	***	0.011	***	0.027	***	0.028	***	0.018		0.045	***
T-stat	89.557		8.684		21.107		94.123		5.997		15.166	
DotCom Bubble												
Coefficient	0.036	***	0.007		0.033		0.038	***	0.012		0.032	**
T-stat	33.021		1.609		7.140		33.613		1.173		3.092	
DotCom Crash												
Coefficient	0.043	***	0.007	*	0.025	***	0.044	***	0.013	*	0.034	
T-stat	64.609		2.406		8.802		67.485		2.183		5.503	
DotCom Recovery												
Coefficient	0.036	***	0.000		0.026		0.037	***	0.000		0.019	*
T-stat	38.845		0.041		6.559		39.162		0.000		2.086	
Normal State 3												
Coefficient	0.026	***	0.005		0.035		0.026	***	0.016		0.126	***
T-stat	20.792		0.991		6.476		23.820		1.469		11.587	
Global Crisis Bubble												
Coefficient	0.024	***	0.002		0.028		0.024	***	0.002		0.108	***
T-stat	18.263		0.291		5.002		22.127		0.225		10.836	
Global Crisis Crash												
Coefficient	0.041	***	0.021	**	0.054		0.044	***	0.030	*	0.036	*
T-stat	26.310		3.104		7.967		27.707		1.996		2.362	
Global Crisis Recovery												
Coefficient	0.046		0.003		2.341		0.050		0.008		10.534	***
T-stat	0.383		0.006		4.666		0.526		0.009		11.871	
Greek Crisis Bubble												
Coefficient	0.044		0.011		0.238	***	0.048	***	0.023		0.742	***
T-stat	7.713		0.441		9.975		12.051		0.631		19.951	
Greek Crisis Crash												
Coefficient	0.034	***	0.007		0.125	***	0.035	***	0.010		0.495	***
T-stat	10.145		0.464		8.568		14.248		0.406		21.035	
Greek Crisis Recovery												
Coefficient	0.030	***	0.009		0.420	***	0.038		-0.004		1.339	***
T-stat	3.393		0.031		11.182		7.181		0.000		27.282	
Normal State 4												
Coefficient	0.033		0.003		0.175		0.035		0.004		0.673	***
T-stat	6.376		0.137		7.839		7.552		0.089		15.057	
Covid-19 Bubble												
Coefficient	0.033		0.001		0.095		0.034	***	0.006		0.379	***
T-stat	7.258		0.043		4.984		8.939		0.167		10.839	
Covid 19 Crash												
Coefficient	0.044	***	0.012		0.083		0.045	***	0.029		0.278	***
T-stat	12.272		0.813		5.567		14.696		1.020		9.714	
Covid 19 Recovery												
Coefficient	0.033		0.004		0.740		0.034		0.003		3.345	***
T-stat	1.057		0.031		5.638		1.544		0.015		16.169	
Current State												
Coefficient	0.043		-0.002		3.179		0.051		-0.007		14.562	***
T-stat	0.288		-0.003		4.939		0.391		-0.005		11.727	

This table reports the estimated coefficients for the OLS regression on Eq (2):
$\mathrm{CSSD}_t = \alpha + \beta_1 D_t^L + \beta_2 D_t^U + \varepsilon_t$,
where $D_t^L(D_t^U)$ equals 1 if the market return on day t lied in the extreme lower (upper) tail of the return distribution, and 0 otherwise. The 5% and 1% refers to the percentage of observations in the upper and lower tail of the market distribution. Heteroskedasticity consistent t-statistics are also reported.
* The coefficient is significant at the 10% level
** The coefficient is significant at the 5% level

*** The coefficient is significant at the 1% level

Table 6: *Finland CSSD*

	$\alpha_{5\%}$		D_{Lower} 5%		D_{Upper} 5%		$\alpha_{1\%}$		D_{Lower} 1%		D_{Upper} 1%	
Total Sample												
Coefficient	0.025	***	0.009	***	0.042	***	0.026	***	0.016	**	0.151	***
T-stat	41.594		3.503		15.791		45.941		2.850		26.610	
Normal State 1												
Coefficient	0.024	***	0.010		0.018	***	0.024	***	0.016	***	0.036	***
T-stat	52.250		4.931		9.298		55.811		3.845		8.474	
1990s Recession Pre												
Coefficient	0.021	***	0.007	***	0.016		0.022	***	0.006		0.019	
T-stat	46.681		3.522		8.330		46.023		1.446		4.323	
1990s Recession Crash												
Coefficient	0.030	***	0.011		0.018	***	0.031	***	0.017	***	0.015	***
T-stat	65.274		5.754		8.862		67.773		3.651		3.307	
1990s Recession Post												
Coefficient	0.025	***	0.004		0.022		0.026	***	0.002		0.017	*
T-stat	33.740		1.142		7.000		33.975		0.324		2.441	
Normal State 2												
Coefficient	0.025	***	0.011		0.019	***	0.026	***	0.027		0.031	
T-stat	56.902		5.679		10.105		60.959		6.437		7.237	
DotCom Pre												
Coefficient	0.035	***	0.011	***	0.012	***	0.036	***	0.012	*	0.010	
T-stat	46.218		3.454		3.784		47.956		1.782		1.524	
DotCom Crash												
Coefficient	0.033	***	0.005		0.019		0.034	***	0.005		0.049	
T-stat	39.793		1.294		5.342		42.860		0.731		6.530	
DotCom Post												
Coefficient	0.026	***	0.005		0.027		0.028	***	0.002		0.026	**
T-stat	26.578		1.117		6.544		27.471		0.255		2.731	
Normal State 3												
Coefficient	0.021	***	0.004	**	0.007		0.021	***	0.004		0.008	**
T-stat	73.624		3.152		5.790		76.675		1.488		3.117	
Global Crisis Pre												
Coefficient	0.021	***	0.003	*	0.011		0.022	***	0.007		0.022	
T-stat	44.867		1.699		5.374		47.497		1.568		5.202	
Global Crisis Crash												
Coefficient	0.030	***	0.011		0.016		0.031	***	0.024		0.021	
T-stat	55.829		4.772		6.717		58.801		4.677		4.045	
Global Crisis Post												
Coefficient	0.027	***	0.001		0.034		0.027	***	0.003		0.141	***
T-stat	14.844		0.099		4.453		17.736		0.226		9.954	
Greek Crisis Pre												
Coefficient	0.025	***	0.007		0.047		0.026	***	0.011		0.143	***
T-stat	14.151		1.009		6.383		16.944		0.791		9.980	
Greek Crisis Crash												
Coefficient	0.024	***	0.005		0.044		0.024	***	0.006		0.156	***
T-stat	13.957		0.665		6.039		15.575		0.389		10.584	
Greek Crisis Post												
Coefficient	0.022	***	0.007	**	0.009	***	0.022	***	0.012	*	0.023	
T-stat	39.063		2.883		3.722		42.123		2.472		4.641	
Normal State 4												
Coefficient	0.021	***	0.004	*	0.011		0.021	***	0.011	**	0.032	***
T-stat	51.968		2.325		6.571		56.612		3.277		9.169	
Covid-19 Pre												
Coefficient	0.024	***	0.002		0.008	*	0.024	***	-0.001		0.014	
T-stat	21.663		0.458		1.687		22.987		0.000		1.471	
Covid 19 Crash												

Coefficient	0.026	***	0.012	***	0.016		0.027	***	0.019	*	0.012	
T-stat	30.501		3.346		4.576		32.026		2.484		1.531	
Covid 19 Post												
Coefficient	0.023	***	0.000		0.040		0.025	***	-0.001		0.092	***
T-stat	19.572		0.053		8.019		21.944		0.000		8.903	
Current State												
Coefficient	0.027	*	0.003		0.446	***	0.029		0.006		1.912	***
T-stat	2.417		0.064		9.350		4.210		0.084		28.516	

This table reports the estimated coefficients for the OLS regression on Eq (2):
$\mathrm{CSSD}_t = \alpha + \beta_1 D_t^L + \beta_2 D_t^U + \varepsilon_t$,
where $D_t^L(D_t^U)$ equals 1 if the market return on day t lied in the extreme lower (upper) tail of the return distribution, and 0 otherwise. The 5% and 1% refers to the percentage of observations in the upper and lower tail of the market distribution. Heteroskedasticity consistent t-statistics are also reported.
* The coefficient is significant at the 10% level
** The coefficient is significant at the 5% level
*** The coefficient is significant at the 1% level

Table 7: *Iceland CSSD*

	$\alpha_{5\%}$		D_{Lower} *5%*		D_{Upper} *5%*		$\alpha_{1\%}$		D_{Lower} *1%*		D_{Upper} *1%*	
Total Sample												
Coefficient	0.012	***	0.016		0.034	***	0.013	***	0.051		0.114	***
T-stat	17.311		5.294		11.277		19.609		8.049		17.888	
Normal State 2												
Coefficient	0.003		0.004		0.014		0.004		-0.004		0.035	
T-stat	5.428		1.321		4.890		6.669		-0.670		5.915	
DotCom Pre												
Coefficient	0.001	*	0.008	**	0.006	*	0.002	***	-0.002		-0.002	
T-stat	2.149		2.691		2.212		3.373		-0.480		-0.393	
DotCom Crash												
Coefficient	0.012	***	-0.001		0.002		0.012	***	-0.005		0.010	*
T-stat	29.176		-0.609		0.967		30.504		-1.304		2.576	
DotCom Post												
Coefficient	0.013	***	0.000		0.009		0.014	***	0.003		0.011	**
T-stat	29.418		0.036		4.881		30.621		0.654		2.599	
Normal State 3												
Coefficient	0.013	***	0.005	***	0.012		0.013	***	0.006	*	0.011	***
T-stat	38.598		3.526		8.361		40.396		1.867		3.535	
Global Crisis Pre												
Coefficient	0.010	***	0.004		0.012		0.010	***	0.007		0.040	***
T-stat	18.052		1.511		5.121		21.087		1.580		9.007	
Global Crisis Crash												
Coefficient	0.012	***	0.064	***	0.074	***	0.016	***	0.168	***	0.160	***
T-stat	14.621		17.643		20.426		21.422		23.178		22.064	
Global Crisis Post												
Coefficient	0.007	***	0.010		0.023	***	0.008	***	0.021		0.051	***
T-stat	13.892		4.767		10.503		17.003		4.740		11.519	
Normal State 4												
Coefficient	0.011	***	0.016		0.077		0.011		0.053	*	0.337	***
T-stat	3.640		1.239		6.023		4.216		1.986		12.624	
Covid-19 Pre												
Coefficient	0.011	***	0.005	***	0.007		0.012	***	0.011	***	0.006	*
T-stat	33.168		3.558		4.850		34.878		3.427		1.791	
Covid 19 Crash												
Coefficient	0.015	***	0.012		0.012		0.016	***	0.027		0.017	**
T-stat	25.078		4.801		4.643		27.206		4.971		3.125	
Covid 19 Post												
Coefficient	0.014	***	0.012		0.014		0.015	***	0.008		0.018	**
T-stat	22.102		4.440		5.211		23.496		1.335		3.116	
Current State												

Coefficient	0.018 ***	0.010 **	0.029 ***	0.019 ***	0.016 *	0.068 ***
T-stat	24.393	3.102	9.355	27.461	2.398	10.317

This table reports the estimated coefficients for the OLS regression on Eq (2):
$CSSD_t = \alpha + \beta_1 D_t^L + \beta_2 D_t^U + \varepsilon_t$,
where $D_t^L (D_t^U)$ equals 1 if the market return on day t lied in the extreme lower (upper) tail of the return distribution, and 0 otherwise. The 5% and 1% refers to the percentage of observations in the upper and lower tail of the market distribution. Heteroskedasticity consistent t-statistics are also reported.
* The coefficient is significant at the 10% level
** The coefficient is significant at the 5% level
*** The coefficient is significant at the 1% level

Table 8: *Sweden CSAD*

	α		γ_1		γ_2	
Total Sample						
Coefficient	-0.032	**	-2.804	*	673.830	***
T-stat	-3.179		-2.558		73.918	
Normal State 1						
Coefficient	0.000		0.010	*	0.304	***
T-stat	7.650		1.916		3.577	
1990s Recession Pre						
Coefficient	-0.001		0.196	*	1.659	
T-stat	-1.336		2.036		0.923	
1990s Recession Crash						
Coefficient	0.000		0.058		-0.030	
T-stat	4.606		5.999		-0.174	
1990s Recession Post						
Coefficient	0.001		0.004		2.795	*
T-stat	4.859		0.112		1.969	
Normal State 2						
Coefficient	0.001	***	-0.106	***	4.443	***
T-stat	17.755		-14.677		34.225	
DotCom Pre						
Coefficient	0.003		-0.554		30.293	
T-stat	3.980		-4.396		6.956	
DotCom Crash						
Coefficient	0.001	***	0.044	***	0.602	*
T-stat	12.788		3.430		2.238	
DotCom Post						
Coefficient	0.002		-0.036		4.087	
T-stat	6.135		-0.875		4.632	
Normal State 3						
Coefficient	0.000		0.217	**	-0.367	
T-stat	-0.211		3.046		-0.181	
Global Crisis Pre						
Coefficient	0.000		0.271		-3.123	
T-stat	-0.099		1.497		-0.450	
Global Crisis Crash						
Coefficient	0.002		0.065	*	0.384	
T-stat	8.128		2.166		0.574	
Global Crisis Post						
Coefficient	0.001		0.537	*	-11.533	
T-stat	0.674		2.408		-1.565	
Greek Crisis Pre						
Coefficient	0.002	***	0.328	*	-11.137	
T-stat	3.633		2.058		-1.126	
Greek Crisis Crash						
Coefficient	0.002		0.117		84.417	***
T-stat	0.685		0.178		3.319	
Greek Crisis Post						

	α		γ1		γ2	
Coefficient	0.001	*	0.524	**	-18.210	*
T-stat	2.530		3.227		-1.746	
Normal State 4						
Coefficient	0.008	*	-4.585		452.813	***
T-stat	2.348		-5.370		14.275	
Covid-19 Pre						
Coefficient	0.025	***	-15.880	***	1584.526	***
T-stat	10.033		0.000		77.855	
Covid 19 Crash						
Coefficient	0.402		-82.062	***	1658.775	***
T-stat	7.798		-16.493		61.926	
Covid 19 Post						
Coefficient	0.099		-36.072	***	1995.490	***
T-stat	7.752		0.000		82.425	
Current State						
Coefficient	-1.056	***	151.265	***	-110.931	**
T-stat	-8.869		18.694		-2.650	

This table reports the estimated coefficients for the OLS regression on Eq (11):
$CSAD_t = \alpha + \gamma_1 |R_{M,t}| + \gamma_2 (R_{M,t}^2) + \varepsilon_t$.
Heteroskedasticity consistent t-statistics are also reported.
* The coefficient is significant at the 10% level
** The coefficient is significant at the 5% level
*** The coefficient is significant at the 1% level

Table 9: *Denmark CSAD*

	α		γ_1		γ_2	
Total Sample						
Coefficient	0.016	***	-5.048	***	194.269	***
T-stat	46.828		-101.957		383.653	
Normal State 1						
Coefficient	0.000	***	0.008		0.257	
T-stat	13.439		4.017		4.971	
1990s Recession Pre						
Coefficient	0.000		0.018		-0.041	
T-stat	6.727		4.988		-0.506	
1990s Recession Crash						
Coefficient	0.000		0.029	**	0.755	*
T-stat	4.205		2.748		2.028	
1990s Recession Post						
Coefficient	0.000	**	0.073		-0.684	
T-stat	2.884		4.194		-0.943	
Normal State 2						
Coefficient	0.000		0.061		-0.678	*
T-stat	7.679		6.940		-1.802	
DotCom Pre						
Coefficient	0.001		-0.004		5.629	**
T-stat	6.746		-0.114		3.163	
DotCom Crash						
Coefficient	0.001		-0.234	***	20.096	
T-stat	4.100		-3.444		7.839	
DotCom Post						
Coefficient	0.004	***	-1.912	***	155.480	***
T-stat	12.132		-26.809		294.726	
Normal State 3						
Coefficient	0.000	*	0.134		-2.832	**
T-stat	1.973		5.201		-2.728	
Global Crisis Pre						
Coefficient	0.000		0.019		-0.295	
T-stat	6.842		0.937		-0.334	

Global Crisis Crash						
Coefficient	0.041	***	-8.583	***	216.952	***
T-stat	13.561		-31.627		144.503	
Global Crisis Post						
Coefficient	0.006		-2.013		132.785	***
T-stat	5.272		-8.244		16.720	
Greek Crisis Pre						
Coefficient	0.006		-2.103		134.316	***
T-stat	5.399		-8.197		16.495	
Greek Crisis Crash						
Coefficient	0.002		-0.478		47.716	***
T-stat	7.720		-5.451		10.134	
Greek Crisis Post						
Coefficient	0.004	***	-2.399	***	296.200	***
T-stat	14.774		2.406		236.710	
Normal State 4						
Coefficient	0.001		0.061	*	1.492	
T-stat	4.329		1.822		0.995	
Covid-19 Pre						
Coefficient	0.008	***	-4.857	***	406.853	***
T-stat	11.418		0.000		91.451	
Covid 19 Crash						
Coefficient	0.001	***	0.045	*	-0.233	
T-stat	3.662		1.737		-0.497	
Covid 19 Post						
Coefficient	0.001		0.105	*	-4.822	
T-stat	4.770		2.406		0.000	
Current State						
Coefficient	0.001	***	0.098		-3.047	**
T-stat	10.716		4.462		-2.726	

This table reports the estimated coefficients for the OLS regression on Eq (11):
$CSAD_t = \alpha + \gamma_1 |R_{M,t}| + \gamma_2 (R^2_{M,t}) + \varepsilon_t$.
Heteroskedasticity consistent t-statistics are also reported.
* The coefficient is significant at the 10% level
** The coefficient is significant at the 5% level
*** The coefficient is significant at the 1% level

Table 10: *Norway CSAD*

	α		γ_1		γ_2	
Total Sample						
Coefficient	3.722	***	-504.377	***	782.110	***
T-stat	27.121		-50.137		178.583	
1990s Recession Pre						
Coefficient	0.000		0.024	***	-0.047	
T-stat	4.308		3.715		-0.338	
1990s Recession Crash						
Coefficient	0.000		0.019		0.082	*
T-stat	6.797		4.810		2.326	
1990s Recession Post						
Coefficient	0.001	***	0.031	**	-0.043	
T-stat	13.477		3.240		-0.367	
Normal State 2						
Coefficient	0.001	***	0.052	***	0.273	
T-stat	9.964		9.591		4.791	
DotCom Pre						
Coefficient	0.001	*	0.140	**	-1.457	
T-stat	2.310		3.050		-1.296	
DotCom Crash						
Coefficient	0.002	***	0.081	***	-0.182	

T-stat	11.345		3.821		-0.378	
DotCom Post						
Coefficient	0.001		0.121	**	-2.102	
T-stat	4.921		3.144		-1.518	
Normal State 3						
Coefficient	0.008		-2.077	***	79.148	***
T-stat	6.612		-9.829		16.141	
Global Crisis Pre						
Coefficient	0.003		-1.022		66.537	***
T-stat	4.664		-7.503		11.716	
Global Crisis Crash						
Coefficient	0.000		0.344	*	-2.821	
T-stat	0.189		2.004		-0.782	
Global Crisis Post						
Coefficient	0.013		-4.674	***	264.857	***
T-stat	7.282		-22.527		2414.631	
Greek Crisis Pre						
Coefficient	0.023		-6.888	***	322.452	***
T-stat	7.141		-14.719		43.312	
Greek Crisis Crash						
Coefficient	0.005		-2.401	***	246.952	***
T-stat	7.029		-16.831		126.844	
Greek Crisis Post						
Coefficient	0.005		-3.566		334.524	***
T-stat	1.533		0.000		51.675	
Normal State 4						
Coefficient	0.017	***	-6.607	***	367.974	***
T-stat	15.496		-37.311		501.094	
Covid-19 Pre						
Coefficient	0.016	***	-9.417	***	843.177	***
T-stat	9.533		0.000		64.695	
Covid 19 Crash						
Coefficient	-0.004		1.248	*	-8.516	
T-stat	-0.953		2.387		-1.014	
Covid 19 Post						
Coefficient	0.050	***	-15.483	***	618.068	***
T-stat	13.566		0.000		407.260	
Current State						
Coefficient	0.017	***	-8.197	***	660.044	***
T-stat	3.499		-15.639		3324.440	

This table reports the estimated coefficients for the OLS regression on Eq (11):
$CSAD_t = \alpha + \gamma_1 |R_{M,t}| + \gamma_2 (R_{M,t}^2) + \varepsilon_t$.
Heteroskedasticity consistent t-statistics are also reported.
* The coefficient is significant at the 10% level
** The coefficient is significant at the 5% level
*** The coefficient is significant at the 1% level

Table 11: *Finland CSAD*

	α		γ_1		γ_2	
Total Sample						
Coefficient	-0.044	***	7.102	***	-6.891	***
T-stat	-15.673		25.455		-13.698	
Normal State 1						
Coefficient	0.000		0.050	***	-0.110	
T-stat	7.326		9.318		-1.499	
1990s Recession Pre						
Coefficient	0.000		0.024	*	0.218	
T-stat	7.393		2.277		0.510	
1990s Recession Crash						

Coefficient	0.001	***	0.034	***	0.235	
T-stat	10.215		3.435		1.080	
1990s Recession Post						
Coefficient	0.001	**	-0.001		2.432	*
T-stat	2.855		-0.036		2.341	
Normal State 2						
Coefficient	0.000		0.155	***	-0.191	***
T-stat	-1.464		20.805		-18.024	
DotCom Pre						
Coefficient	0.001		0.057	**	-0.459	
T-stat	8.472		2.722		-0.621	
DotCom Crash						
Coefficient	0.001	***	0.038		2.058	
T-stat	3.481		0.787		1.196	
DotCom Post						
Coefficient	0.000		0.105	*	0.776	
T-stat	1.631		1.673		0.264	
Normal State 3						
Coefficient	0.000	***	0.029	**	-0.176	
T-stat	11.005		3.296		-0.584	
Global Crisis Pre						
Coefficient	0.000		0.025	*	0.134	
T-stat	8.090		2.126		0.266	
Global Crisis Crash						
Coefficient	0.001	***	0.025	*	0.745	
T-stat	9.064		1.662		1.644	
Global Crisis Post						
Coefficient	-0.001		0.235		10.783	*
T-stat	-0.550		1.158		2.124	
Greek Crisis Pre						
Coefficient	0.003	*	-0.764	**	41.761	
T-stat	2.323		-3.241		5.551	
Greek Crisis Crash						
Coefficient	0.013	***	-5.366	***	306.227	***
T-stat	18.291		-43.148		130.058	
Greek Crisis Post						
Coefficient	0.000		0.024	*	0.103	
T-stat	7.275		1.885		0.210	
Normal State 4						
Coefficient	0.000	***	0.070	**	-0.199	
T-stat	3.427		2.851		-0.167	
Covid-19 Pre						
Coefficient	0.000		0.195	*	-5.495	
T-stat	0.808		1.906		-0.995	
Covid 19 Crash						
Coefficient	0.001	***	0.057	**	-0.419	
T-stat	3.487		2.992		-1.354	
Covid 19 Post						
Coefficient	0.001	*	-0.216		35.111	
T-stat	1.688		0.000		4.293	
Current State						
Coefficient	0.018		-7.568	***	443.896	***
T-stat	6.885		-23.078		246.330	

This table reports the estimated coefficients for the OLS regression on Eq (11):
$CSAD_t = \alpha + \gamma_1 |R_{M,t}| + \gamma_2 (R_{M,t}^2) + \varepsilon_t.$
Heteroskedasticity consistent t-statistics are also reported.
* The coefficient is significant at the 10% level
** The coefficient is significant at the 5% level
*** The coefficient is significant at the 1% level

Table 12: *Iceland CSAD*

	α		γ_1		γ_2	
Total Sample						
Coefficient	0.014	***	-2.460	***	20.165	***
T-stat	30.548		-68.852		373.846	
Normal State 2						
Coefficient	0.000	*	0.014		-0.036	**
T-stat	-2.518		5.134		-2.643	
DotCom Pre						
Coefficient	0.000		0.015	*	-0.163	*
T-stat	-1.584		2.589		-1.752	
DotCom Crash						
Coefficient	0.000	***	0.010		-0.041	
T-stat	8.618		5.439		-3.907	
DotCom Post						
Coefficient	0.000		0.025	***	-0.082	
T-stat	4.506		3.483		-0.201	
Normal State 3						
Coefficient	0.000	***	0.026		-0.232	
T-stat	3.704		6.303		-1.620	
Global Crisis Pre						
Coefficient	0.000		-0.111		6.380	***
T-stat	5.619		-8.093		14.064	
Global Crisis Crash						
Coefficient	-0.001		0.137	***	0.739	***
T-stat	-4.526		17.504		21.921	
Global Crisis Post						
Coefficient	0.000	**	-0.056		8.664	***
T-stat	3.155		0.000		18.802	
Normal State 4						
Coefficient	0.001	***	-0.285	***	18.376	***
T-stat	16.793		-42.436		2574.104	
Covid-19 Pre						
Coefficient	0.000	***	0.029	***	-0.804	
T-stat	3.776		3.871		-1.560	
Covid 19 Crash						
Coefficient	0.000	***	0.011		0.587	*
T-stat	3.828		1.162		2.563	
Covid 19 Post						
Coefficient	0.000		0.070	*	-0.278	
T-stat	0.354		2.367		0.000	
Current State						
Coefficient	0.000	*	-0.008		5.862	
T-stat	2.355		-0.256		4.874	

This table reports the estimated coefficients for the OLS regression on Eq (11):
$CSAD_t = \alpha + \gamma_1 |R_{M,t}| + \gamma_2 (R_{M,t}^2) + \varepsilon_t$.
Heteroskedasticity consistent t-statistics are also reported.
* The coefficient is significant at the 10% level
** The coefficient is significant at the 5% level
*** The coefficient is significant at the 1% level

Table 13: *Sweden CSAD bullish vs bearish*

	α		γ_1		γ_2		γ_3		γ_4	
Total Sample										
Coefficient	-0.093	***	13.844	***	9.762		624.937	***	-132.559	**
T-stat	-9.295		11.111		5.094		68.046		-3.162	
Normal State 1										

Coefficient	0.000		0.002		0.013	*	0.612		0.160	
T-stat	7.976		0.346		2.158		4.911		1.574	
1990s Recession Pre										
Coefficient	0.001		-0.372	***	-0.013		29.380	***	0.202	
T-stat	1.263		-3.668		-0.145		10.337		0.126	
1990s Recession Crash										
Coefficient	0.000		0.086		0.047	***	-0.272		-0.351	
T-stat	4.300		7.799		3.519		-1.468		-1.061	
1990s Recession Post										
Coefficient	0.001		-0.003		0.042		4.198	**	-1.761	
T-stat	4.930		-0.077		0.896		2.764		-0.854	
Normal State 2										
Coefficient	0.001	***	-0.024	**	-0.149	***	1.120		6.019	***
T-stat	18.943		-3.284		-21.551		6.827		48.322	
DotCom Pre										
Coefficient	0.002	***	-0.628		-0.172		40.867	***	6.103	
T-stat	3.621		-5.246		-1.109		9.420		1.019	
DotCom Crash										
Coefficient	0.002	***	0.001		0.021		2.768		0.387	
T-stat	14.554		0.070		1.559		5.707		1.402	
DotCom Post										
Coefficient	0.002		0.096	*	-0.233		-0.044		10.493	***
T-stat	7.667		2.235		-5.168		0.000		9.402	
Normal State 3										
Coefficient	0.000		0.033		0.056		16.597		-0.788	
T-stat	0.888		0.374		0.652		4.532		-0.347	
Global Crisis Pre										
Coefficient	0.002	*	-0.730	**	-0.110		81.814		2.778	
T-stat	1.877		-2.608		-0.546		4.709		0.383	
Global Crisis Crash										
Coefficient	0.002		0.154		-0.035		-1.247		2.604	**
T-stat	8.173		4.584		-0.968		-1.610		2.827	
Global Crisis Post										
Coefficient	0.001		0.735	**	0.289		-12.673		-7.421	
T-stat	0.499		3.053		1.034		0.000		0.000	
Greek Crisis Pre										
Coefficient	0.002	***	0.364	*	0.119		-7.009		-4.998	
T-stat	3.798		1.940		0.637		-0.507		0.000	
Greek Crisis Crash										
Coefficient	0.013		-6.781	***	-1.574	*	625.201	***	40.554	*
T-stat	5.460		-9.874		-2.509		16.964		1.790	
Greek Crisis Post										
Coefficient	0.001	**	0.595	*	0.122		-19.723		-2.676	
T-stat	2.618		2.475		0.545		0.000		0.000	
Normal State 4										
Coefficient	0.018	***	-14.466	***	-2.992		1337.085	***	73.137	**
T-stat	8.455		-21.810		-4.586		43.842		3.039	
Covid-19 Pre										
Coefficient	0.017		-13.345	***	-6.597		1537.365	***	436.411	**
T-stat	7.424		0.000		-4.136		83.221		3.073	
Covid 19 Crash										
Coefficient	0.096	***	-34.895	***	-6.597		1479.170	***	65.547	**
T-stat	9.709		-27.559		-4.514		240.860		3.168	
Covid 19 Post										
Coefficient	0.086		-34.993	***	-21.576	***	1986.720	***	983.726	*
T-stat	6.395		0.000		0.000		74.275		2.475	
Current State										
Coefficient	-0.968		162.135	***	155.653		-161.180		-4203.196	**
T-stat	-7.388		20.247		4.289		-3.926		-2.899	

This table reports the estimated coefficients for the OLS regression on Eq (12):

$$CSAD_t = \alpha + \gamma_1 D^{up}\left|R_{M,t}\right| + \gamma_2(1 - D^{up})\left|R_{M,t}\right| + \gamma_3 D^{up}\left(R_{M,t}\right)^2 + \gamma_4(1 - D^{up})\left(R_{M,t}\right)^2 + \varepsilon_t$$

Heteroskedasticity consistent t-statistics are also reported.
* The coefficient is significant at the 10% level
** The coefficient is significant at the 5% level
*** The coefficient is significant at the 1% level

Table 14: *Denmark CSAD bullish vs bearish*

	α		γ_1		γ_2		γ_3		γ_4	
Total Sample										
Coefficient	0.008	***	-3.780	***	-1.020	***	193.234	***	19.658	***
T-stat	33.174		-88.332		-16.592		526.479		10.908	
Normal State 1										
Coefficient	0.000	***	0.007	*	0.002		0.506		0.315	
T-stat	14.003		2.530		0.750		5.058		5.609	
1990s Recession Pre										
Coefficient	0.000		0.016	***	0.020		0.042		-0.112	
T-stat	6.717		3.759		4.334		0.392		-1.104	
1990s Recession Crash										
Coefficient	0.000	***	0.048		0.048		-0.539	*	-0.025	
T-stat	3.561		6.553		6.769		-2.334		-0.115	
1990s Recession Post										
Coefficient	0.000	**	0.089		0.068	*	-1.063		-2.735	
T-stat	2.732		4.982		2.153		-1.449		-1.259	
Normal State 2										
Coefficient	0.000		0.047		0.063		0.753		-1.027	*
T-stat	7.975		4.086		5.935		1.072		-2.380	
DotCom Pre										
Coefficient	0.001		-0.012		0.033		6.860	***	1.354	
T-stat	6.634		-0.328		0.714		3.557		0.453	
DotCom Crash										
Coefficient	0.002		-0.535		-0.100		43.339	***	3.577	
T-stat	5.453		-7.189		-1.426		13.722		1.271	
DotCom Post										
Coefficient	0.004	***	-1.883	***	-1.151		155.298	***	82.061	**
T-stat	10.330		-24.745		-4.602		278.310		3.209	
Normal State 3										
Coefficient	0.000	**	0.094	**	0.038		2.762		-0.538	
T-stat	2.807		2.916		1.058		1.354		-0.414	
Global Crisis Pre										
Coefficient	0.000		0.050		0.001		-2.618		0.417	
T-stat	5.961		1.369		0.029		-0.822		0.406	
Global Crisis Crash										
Coefficient	0.025	***	-7.712	***	-2.560		214.086	***	46.404	
T-stat	9.028		-25.500		-5.399		142.280		3.997	
Global Crisis Post										
Coefficient	0.004		-1.725		-0.496		141.966	***	15.683	
T-stat	4.117		-7.576		-1.628		19.923		1.096	
Greek Crisis Pre										
Coefficient	0.004	***	-1.625		-0.481		139.814	***	15.940	
T-stat	3.909		-6.332		-1.584		18.601		1.116	
Greek Crisis Crash										
Coefficient	0.002	***	-0.682	***	-0.218	*	86.074	***	12.716	*
T-stat	9.375		-8.633		-2.566		18.261		2.585	
Greek Crisis Post										
Coefficient	0.003	***	-2.170	***	-0.893		292.832	***	78.921	**
T-stat	12.667		2.330		0.000		241.160		2.886	
Normal State 4										
Coefficient	0.001		0.023		0.014		8.515	**	0.950	
T-stat	4.791		0.524		0.378		3.271		0.570	
Covid-19 Pre										

Coefficient	0.005		-3.983	***	-1.657		393.838	***	94.435	***
T-stat	8.208		0.000		-4.618		102.810		3.450	
Covid 19 Crash										
Coefficient	0.001	**	0.116	*	0.018		-2.964		0.210	
T-stat	2.741		2.425		0.588		-1.332		0.401	
Covid 19 Post										
Coefficient	0.001		0.127	*	0.064		-5.953		-2.590	
T-stat	4.755		2.330		1.240		0.000		0.000	
Current State										
Coefficient	0.001	***	0.171		0.065	**	-7.532	***	-1.469	
T-stat	9.934		5.260		2.689		-3.330		0.000	

This table reports the estimated coefficients for the OLS regression on Eq (12):

$$CSAD_t = \alpha + \gamma_1 D^{up}\left|R_{M,t}\right| + \gamma_2(1 - D^{up})\left|R_{M,t}\right| + \gamma_3 D^{up}\left(R_{M,t}\right)^2 + \gamma_4(1 - D^{up})\left(R_{M,t}\right)^2 + \varepsilon_t$$

Heteroskedasticity consistent t-statistics are also reported.
* The coefficient is significant at the 10% level
** The coefficient is significant at the 5% level
*** The coefficient is significant at the 1% level

Table 15: *Norway CSAD bullish vs bearish*

	α		γ_1		γ_2		γ_3		γ_4	
Total Sample										
Coefficient	3.491	***	-644.468	***	-273.226	***	839.739	***	2318.983	
T-stat	25.219		-58.152		-12.211		176.249		6.802	
1990s Recession Pre										
Coefficient	0.000		0.024	***	0.024	**	-0.023		-0.088	
T-stat	4.292		3.402		2.962		-0.146		-0.439	
1990s Recession Crash										
Coefficient	0.000		0.022	***	0.014	**	0.090		0.108	**
T-stat	6.559		3.885		2.907		1.063		2.812	
1990s Recession Post										
Coefficient	0.001	***	0.009		0.009		0.849	***	0.049	
T-stat	14.726		0.785		0.734		3.447		0.360	
Normal State 2										
Coefficient	0.000	***	0.079	***	0.040		0.181	**	-0.111	
T-stat	8.878		12.804		4.676		3.084		-0.665	
DotCom Pre										
Coefficient	0.001	*	0.220		0.069		-2.236		-0.546	
T-stat	2.054		4.155		1.352		-1.573		0.000	
DotCom Crash										
Coefficient	0.002	***	0.095		0.078	**	0.010		-0.938	
T-stat	11.297		4.047		3.007		0.018		-1.361	
DotCom Post										
Coefficient	0.001		0.091	*	0.019		0.904		-0.320	
T-stat	5.690		2.164		0.371		0.493		0.000	
Normal State 3										
Coefficient	0.005		-1.784	***	-0.646	**	101.764	***	14.274	*
T-stat	5.121		-9.571		-2.778		23.541		2.257	
Global Crisis Pre										
Coefficient	0.003		-1.415	***	-0.356	***	114.590	***	11.358	*
T-stat	8.096		-17.082		-3.601		30.000		2.546	
Global Crisis Crash										
Coefficient	0.001		0.261		0.112		7.639		-0.610	
T-stat	0.551		1.057		0.596		1.075		-0.157	
Global Crisis Post										
Coefficient	0.007		-3.344	***	-1.001	*	264.155	***	31.623	
T-stat	4.977		-17.798		-1.908		2659.300		1.418	
Greek Crisis Pre										
Coefficient	0.009		-4.048	***	-1.105	*	300.280	***	29.295	
T-stat	4.197		-11.163		-2.066		57.626		1.606	

Greek Crisis Crash					
Coefficient	0.003	-1.755 ***	-0.468	240.344 ***	30.086
T-stat	4.178	-11.629	-1.275	122.990	1.065
Greek Crisis Post					
Coefficient	0.002	-2.490	-0.168	323.787 ***	9.983
T-stat	0.473	0.000	-0.100	45.779	0.091
Normal State 4					
Coefficient	0.006 ***	-3.817 ***	-0.793	358.152 ***	19.276 ***
T-stat	12.202	-42.617	-5.518	1008.941	3.562
Covid-19 Pre					
Coefficient	0.008	-6.766 ***	-1.894	806.329 ***	100.168 **
T-stat	8.059	0.000	-4.201	111.890	2.993
Covid 19 Crash					
Coefficient	0.012 **	-4.780	-0.788	261.496 ***	9.471
T-stat	3.088	-6.135	-1.452	9.902	1.169
Covid 19 Post					
Coefficient	0.045 ***	-15.866 ***	-9.587	619.283 ***	358.081
T-stat	11.628	0.000	0.000	370.630	4.304
Current State					
Coefficient	0.007	-5.580 ***	-0.950	659.053 ***	27.640
T-stat	1.603	-11.261	-0.678	3510.664	0.433

This table reports the estimated coefficients for the OLS regression on Eq (12):

$$CSAD_t = \alpha + \gamma_1 D^{up}\left|R_{M,t}\right| + \gamma_2(1-D^{up})\left|R_{M,t}\right| + \gamma_3 D^{up}\left(R_{M,t}\right)^2 + \gamma_4(1-D^{up})\left(R_{M,t}\right)^2 + \varepsilon_t$$

Heteroskedasticity consistent t-statistics are also reported.
* The coefficient is significant at the 10% level
** The coefficient is significant at the 5% level
*** The coefficient is significant at the 1% level

Table 16: *Finland CSAD bullish vs bearish*

	α	γ_1	γ_2	γ_3	γ_4
Total Sample					
Coefficient	-0.047 ***	10.615 ***	3.813 ***	-11.267 ***	-18.382
T-stat	-16.602	32.011	8.992	-20.609	-4.308
Normal State 1					
Coefficient	0.000 ***	0.025 ***	0.035	0.983	-0.089
T-stat	9.269	3.490	5.109	5.761	-1.110
1990s Recession Pre					
Coefficient	0.000 ***	-0.031 *	0.022 *	3.853	-0.216
T-stat	9.002	-2.176	1.981	4.910	0.000
1990s Recession Crash					
Coefficient	0.001 ***	0.043	0.008	0.000	1.015 *
T-stat	10.476	4.010	0.593	-0.001	2.332
1990s Recession Post					
Coefficient	0.000 *	0.007	0.035	2.696 *	-0.867
T-stat	2.572	0.218	0.819	2.446	-0.465
Normal State 2					
Coefficient	0.001	0.075 ***	-0.010	-0.097 ***	1.516 ***
T-stat	8.207	9.890	-1.003	-9.426	26.015
DotCom Pre					
Coefficient	0.001	0.090 ***	0.032	-1.696	0.384
T-stat	8.525	3.500	1.407	-1.649	0.457
DotCom Crash					
Coefficient	0.001 ***	0.081	0.027	2.069	-0.131
T-stat	3.454	1.472	0.477	1.017	-0.056
DotCom Post					
Coefficient	0.001 *	0.045	0.074	6.292 *	-2.282
T-stat	2.091	0.650	0.904	1.720	-0.597
Normal State 3					
Coefficient	0.000 ***	0.033 **	0.021 *	0.033	-0.177

T-stat	10.897		3.131		2.045		0.080		-0.482	
Global Crisis Pre										
Coefficient	0.000	***	0.002		0.020		2.422	***	-0.329	
T-stat	9.085		0.148		1.461		3.449		0.000	
Global Crisis Crash										
Coefficient	0.001	***	0.042	*	0.010		0.448		1.004	*
T-stat	9.008		2.368		0.603		0.770		1.756	
Global Crisis Post										
Coefficient	-0.002		0.680	**	0.496		4.881		-16.870	
T-stat	-1.508		2.891		1.323		0.921		0.000	
Greek Crisis Pre										
Coefficient	0.004		-1.905		-0.499	*	117.834	***	13.080	*
T-stat	4.501		-8.639		-2.540		14.340		2.042	
Greek Crisis Crash										
Coefficient	0.009	***	-5.020	***	-2.118		304.451	***	90.232	
T-stat	13.523		-37.098		-7.711		133.250		5.529	
Greek Crisis Post										
Coefficient	0.000		0.017		0.013		1.187		0.221	
T-stat	7.307		0.850		0.903		1.191		0.426	
Normal State 4										
Coefficient	0.001		-0.135	**	0.003		23.764		0.664	
T-stat	5.630		-2.955		0.126		5.974		0.546	
Covid-19 Pre										
Coefficient	0.000		0.288	**	0.109		-8.345		-6.394	
T-stat	0.646		2.604		0.576		0.000		-0.382	
Covid 19 Crash										
Coefficient	0.000	*	0.117	**	0.033		-2.107		-0.079	
T-stat	2.445		3.198		1.487		-1.514		-0.232	
Covid 19 Post										
Coefficient	0.002		-1.032	***	-0.232	*	140.982	***	9.455	
T-stat	4.894		0.000		0.000		17.306		1.451	
Current State										
Coefficient	0.005	**	-4.828	***	-0.827		431.153	***	22.499	
T-stat	2.960		-19.569		-1.575		328.655		1.127	

This table reports the estimated coefficients for the OLS regression on Eq (12):

$$CSAD_t = \alpha + \gamma_1 D^{up}\left|R_{M,t}\right| + \gamma_2(1 - D^{up})\left|R_{M,t}\right| + \gamma_3 D^{up}\left(R_{M,t}\right)^2 + \gamma_4(1 - D^{up})\left(R_{M,t}\right)^2 + \varepsilon_t$$

Heteroskedasticity consistent t-statistics are also reported.

* The coefficient is significant at the 10% level

** The coefficient is significant at the 5% level

*** The coefficient is significant at the 1% level

Table 17: *Iceland CSAD bullish vs bearish*

	α		γ_1		γ_2		γ_3		γ_4	
Total Sample										
Coefficient	0.005	***	-1.414	***	-0.232	***	19.469	***	1.511	***
T-stat	24.321		-72.140		-9.046		757.637		13.016	
Normal State 2										
Coefficient	0.000		0.001		0.003		0.158		-0.012	
T-stat	-0.006		0.181		0.928		4.553		-0.778	
DotCom Pre										
Coefficient	0.000		0.012	*	0.017	**	-0.130		-0.199	*
T-stat	-1.609		1.905		2.655		-1.124		-1.739	
DotCom Crash										
Coefficient	0.000		0.019		0.007	*	-0.188	**	-0.026	*
T-stat	7.441		5.745		2.531		-3.294		-2.120	
DotCom Post										
Coefficient	0.000		0.030		0.008		-0.335		0.306	
T-stat	4.732		4.167		0.665		0.000		0.280	
Normal State 3										

Coefficient	0.000 ***	0.030	0.013 *	-0.218	0.054
T-stat	3.861	6.092	2.570	-1.009	0.319
Global Crisis Pre					
Coefficient	0.000	-0.115 ***	-0.036 *	7.627 ***	1.309 *
T-stat	5.270	-9.250	-2.361	18.465	2.061
Global Crisis Crash					
Coefficient	0.000	0.130 ***	0.122 ***	0.952 ***	0.741 ***
T-stat	-3.927	11.195	12.513	13.286	19.561
Global Crisis Post					
Coefficient	0.000 **	-0.073	-0.071 *	9.159 ***	15.344 ***
T-stat	3.160	0.000	-2.155	19.098	3.483
Normal State 4					
Coefficient	0.000 ***	-0.255 ***	-0.122 ***	18.345 ***	12.533 ***
T-stat	11.179	-34.244	-9.588	2333.922	37.326
Covid-19 Pre					
Coefficient	0.000 ***	0.036	0.021 *	-1.320 *	-0.002
T-stat	3.783	4.180	2.270	0.000	0.000
Covid 19 Crash					
Coefficient	0.000 ***	0.014	0.002	0.666	0.730 **
T-stat	3.654	0.905	0.217	0.999	2.857
Covid 19 Post					
Coefficient	0.000	0.051	0.048	-0.345	4.128
T-stat	0.725	1.641	1.000	0.000	1.186
Current State					
Coefficient	0.000 ***	-0.130 ***	0.010	16.527 ***	0.508
T-stat	3.805	-3.859	0.351	10.684	0.417

This table reports the estimated coefficients for the OLS regression on Eq (12):

$$CSAD_t = \alpha + \gamma_1 D^{up}|R_{M,t}| + \gamma_2(1 - D^{up})|R_{M,t}| + \gamma_3 D^{up}(R_{M,t})^2 + \gamma_4(1 - D^{up})(R_{M,t})^2 + \varepsilon_t$$

Heteroskedasticity consistent t-statistics are also reported.
* The coefficient is significant at the 10% level
** The coefficient is significant at the 5% level
*** The coefficient is significant at the 1% level

Table 18: *Sweden CSSD robust*

	$\alpha_{5\%}$	D_{Lower} *5%*	D_{Upper} *5%*	$\alpha_{1\%}$	D_{Lower} *1%*	D_{Upper} *1%*
Total Sample						
Coefficient	0.036 ***	0.004 **	0.256	0.039 ***	0.013 **	0.998
T-stat	105.435	2.816	6.588	72.329	2.977	5.847
Normal State 1						
Coefficient	0.019 ***	0.009	0.011	0.019 ***	0.021 ***	0.022 **
T-stat	49.008	4.601	5.028	52.632	3.905	2.688
1990s Recession Pre						
Coefficient	0.015 ***	0.004 *	0.035	0.016 ***	0.005	0.124
T-stat	26.937	2.541	1.417	28.025	1.107	1.056
1990s Recession Crash						
Coefficient	0.024 ***	0.011	0.029	0.026 ***	0.017 ***	0.037 ***
T-stat	54.665	5.335	6.192	50.752	3.582	3.879
1990s Recession Post						
Coefficient	0.032 ***	-0.002	0.024 **	0.033 ***	-0.008	0.034
T-stat	32.272	-0.778	3.188	32.893	-1.598	1.202
Normal State 2						
Coefficient	0.021 ***	0.009 *	0.009	0.021 ***	0.029 *	0.021
T-stat	88.564	2.431	6.061	92.084	1.702	4.124
DotCom Pre						
Coefficient	0.035 ***	0.008 ***	0.055 **	0.037 ***	0.005	0.113
T-stat	45.120	3.455	2.834	38.938	0.772	1.125
DotCom Crash						
Coefficient	0.041 ***	0.010 **	0.021	0.042 ***	0.019 **	0.036 *
T-stat	64.873	3.270	5.232	66.560	2.969	2.569

DotCom Post						
Coefficient	0.046 ***	0.019	0.038 ***	0.048 ***	0.061	0.036 **
T-stat	46.188	1.518	3.932	42.097	0.937	2.771
Normal State 3						
Coefficient	0.027 ***	0.002	0.027 **	0.027 ***	0.003 *	0.084 *
T-stat	89.734	1.483	2.704	90.786	1.981	1.947
Global Crisis Pre						
Coefficient	0.028 ***	-0.002	0.028	0.029 ***	0.000	0.106
T-stat	49.602	-1.104	1.148	52.721	-0.088	0.847
Global Crisis Crash						
Coefficient	0.043 ***	0.011 **	0.020	0.044 ***	0.031 *	0.034
T-stat	47.928	2.752	6.373	51.869	2.108	3.958
Global Crisis Post						
Coefficient	0.046 ***	0.002	0.035	0.048 ***	0.001	0.009
T-stat	43.171	0.799	1.447	28.962	0.359	1.357
Greek Crisis Pre						
Coefficient	0.049 ***	-0.001	0.021 *	0.050 ***	0.000	0.030
T-stat	40.698	-0.272	2.394	40.527	0.213	5.017
Greek Crisis Crash						
Coefficient	0.060 ***	-0.002	0.118 **	0.063 ***	-0.011 ***	0.249 *
T-stat	43.935	-0.458	3.052	33.969	-3.430	1.732
Greek Crisis Post						
Coefficient	0.046 ***	-0.003	0.024 *	0.047 ***	-0.001	0.001
T-stat	32.002	-0.691	1.884	31.030	-0.152	0.131
Normal State 4						
Coefficient	0.033 ***	0.004 **	0.205 *	0.035 ***	0.004	0.825 *
T-stat	63.395	2.897	2.243	47.311	1.558	1.937
Covid-19 Pre						
Coefficient	0.038 ***	-0.002	0.197	0.040 ***	-0.005 *	0.771
T-stat	28.796	-0.717	1.578	21.746	-2.568	1.367
Covid 19 Crash						
Coefficient	0.046 ***	0.024	0.588	0.048 ***	0.017	2.692
T-stat	19.930	1.262	1.003	20.221	5.331	0.839
Covid 19 Post						
Coefficient	0.044 ***	-0.007	0.571	0.049 ***	-0.007	2.269
T-stat	21.452	-2.444	1.733	14.792	-1.177	1.728
Current State						
Coefficient	0.131 ***	-0.072	3.042 ***	0.232 ***	-0.186	4.970 ***
T-stat	12.635	-4.194	10.177	8.636	-6.859	8.623

This table reports the estimated coefficients for the OLS regression after increasing robustness using White's Variance and Covariance Matrix on Eq (2):

$$CSSD_t = \alpha + \beta_1 D_t^L + \beta_2 D_t^U + \varepsilon_t,$$

where $D_t^L(D_t^U)$ equals 1 if the market return on day t lied in the extreme lower (upper) tail of the return distribution, and 0 otherwise. The 5% and 1% refers to the percentage of observations in the upper and lower tail of the market distribution. Heteroskedasticity consistent t-statistics are also reported.

* The coefficient is significant at the 10% level

** The coefficient is significant at the 5% level

*** The coefficient is significant at the 1% level

Table 19: *Denmark CSSD robust*

	$\alpha_{5\%}$	D_{Lower} *5%*	D_{Upper} *5%*	$\alpha_{1\%}$	D_{Lower} *1%*	D_{Upper} *1%*
Total Sample						
Coefficient	0.024 ***	0.007 ***	0.028 ***	0.025 ***	0.012	0.099 **
T-stat	169.782	10.056	3.614	171.961	6.376	2.598
Normal State 1						
Coefficient	0.014 ***	0.006	0.009	0.014 ***	0.011 *	0.015
T-stat	67.756	4.109	7.131	69.867	2.382	4.086
1990s Recession Pre						
Coefficient	0.012 ***	0.008 **	0.008	0.013 ***	0.015	0.015 **

T-stat	33.157		3.173		4.899		34.318		4.211		2.909	
1990s Recession Crash												
Coefficient	0.018	***	0.019		0.012		0.019	***	0.023		0.018	**
T-stat	38.465		4.652		5.864		38.286		1.601		2.771	
1990s Recession Post												
Coefficient	0.021	***	-0.001		0.022		0.022	***	0.003		0.018	*
T-stat	33.612		-0.401		4.012		31.074		0.413		2.237	
Normal State 2												
Coefficient	0.019	***	0.007		0.011		0.019	***	0.010		0.022	**
T-stat	78.929		4.231		5.418		78.547		4.805		2.704	
DotCom Pre												
Coefficient	0.028	***	0.009	*	0.016	**	0.028	***	0.021		0.044	*
T-stat	41.094		2.000		2.777		43.692		0.919		2.126	
DotCom Crash												
Coefficient	0.029	***	0.006		0.032	**	0.030	***	0.009	***	0.072	*
T-stat	63.280		4.819		3.017		55.912		3.444		1.804	
DotCom Post												
Coefficient	0.024	***	0.006		0.131		0.025	***	-0.002		0.562	
T-stat	41.016		1.275		1.073		39.284		-1.034		0.833	
Normal State 3												
Coefficient	0.022	***	0.002		0.017	**	0.022	***	0.008		0.023	*
T-stat	57.017		1.225		3.244		49.690		4.156		1.757	
Global Crisis Pre												
Coefficient	0.021	***	0.003		0.005	***	0.022	***	0.007	**	0.006	**
T-stat	35.600		1.545		3.775		38.350		2.915		2.851	
Global Crisis Crash												
Coefficient	0.037	***	0.019		0.165		0.039	***	0.038		0.658	
T-stat	38.567		5.143		1.202		40.801		4.332		0.961	
Global Crisis Post												
Coefficient	0.037	***	-0.002		0.064	*	0.038	***	-0.002		0.198	
T-stat	36.521		-1.175		1.805		34.629		-1.012		1.094	
Greek Crisis Pre												
Coefficient	0.036	***	0.001		0.049		0.037	***	-0.001		0.171	
T-stat	34.315		0.557		1.353		35.276		-0.320		0.870	
Greek Crisis Crash												
Coefficient	0.036	***	0.005	*	0.028	*	0.037	***	0.015		0.081	
T-stat	49.645		1.717		2.341		50.324		1.539		1.624	
Greek Crisis Post												
Coefficient	0.030	***	0.001		0.077		0.030	***	0.006	*	0.344	
T-stat	36.713		0.628		1.060		39.388		1.896		0.872	
Normal State 4												
Coefficient	0.024	***	0.007		0.012	**	0.024	***	0.013	**	0.034	*
T-stat	61.747		4.350		3.030		66.268		2.767		2.088	
Covid-19 Pre												
Coefficient	0.022	***	0.003		0.077		0.023	***	0.000		0.333	
T-stat	39.027		1.331		1.073		41.625		0.051		0.853	
Covid 19 Crash												
Coefficient	0.027	***	0.009	**	0.008	**	0.027	***	0.023	***	0.013	*
T-stat	29.047		2.800		3.295		31.671		3.930		2.237	
Covid 19 Post												
Coefficient	0.027	***	0.003	**	0.004	**	0.027	***	0.002	***	0.005	*
T-stat	36.503		1.255		1.619		38.987		0.606		1.132	
Current State												
Coefficient	0.033	***	0.003	*	0.005	**	0.033	***	0.005		0.004	*
T-stat	64.664		1.989		2.970		69.338		1.072		1.846	

This table reports the estimated coefficients for the OLS regression after increasing robustness using White's Variance and Covariance Matrix on Eq (2):

$$CSSD_t = \alpha + \beta_1 D_t^L + \beta_2 D_t^U + \varepsilon_t,$$

where $D_t^L (D_t^U)$ equals 1 if the market return on day t lied in the extreme lower (upper) tail of the return distribution, and 0 otherwise. The 5% and 1% refers to the percentage of observations in the upper and lower tail of the market distribution. Heteroskedasticity consistent t-statistics are also reported.

* The coefficient is significant at the 10% level
** The coefficient is significant at the 5% level
*** The coefficient is significant at the 1% level

Table 20: *Norway CSSD robust*

	$\alpha_{5\%}$		D_{Lower} 5%		D_{Upper} 5%		$\alpha_{1\%}$		D_{Lower} 1%		D_{Upper} 1%	
Total Sample												
Coefficient	0.033	***	0.007	***	0.310	*	0.035	***	0.014		1.407	*
T-stat	149.887		8.547		2.033		114.052		7.399		1.866	
1990s Recession Pre												
Coefficient	0.018	***	0.013	***	0.008		0.019	***	0.014		0.000	
T-stat	32.897		3.594		1.571		30.857		1.575		-0.021	
1990s Recession Crash												
Coefficient	0.022	***	0.011	**	0.012	**	0.022	***	0.019	*	0.032	*
T-stat	41.146		3.111		2.745		42.642		1.955		2.073	
1990s Recession Post												
Coefficient	0.035	***	0.007	*	0.009	*	0.036	***	0.006		0.016	
T-stat	46.039		1.684		2.331		48.448		0.696		0.805	
Normal State 2												
Coefficient	0.027	***	0.011	***	0.027	***	0.028	***	0.018		0.045	
T-stat	104.401		9.613		8.833		97.111		7.092		5.499	
DotCom Pre												
Coefficient	0.036	***	0.007	*	0.033		0.038	***	0.012		0.032	*
T-stat	34.373		2.395		4.020		33.466		1.490		2.567	
DotCom Crash												
Coefficient	0.043	***	0.007	**	0.025		0.044	***	0.013	***	0.034	
T-stat	64.781		2.981		7.175		67.244		3.462		5.104	
DotCom Post												
Coefficient	0.036	***	0.000		0.026	**	0.037	***	0.000		0.019	
T-stat	41.683		0.066		3.194		39.083		-0.001		1.415	
Normal State 3												
Coefficient	0.026	***	0.005	*	0.035		0.026	***	0.016	*	0.126	
T-stat	81.435		2.448		1.511		77.108		1.769		1.037	
Global Crisis Pre												
Coefficient	0.024	***	0.002		0.028		0.024	***	0.002		0.108	
T-stat	46.609		1.286		1.151		50.109		0.571		0.873	
Global Crisis Crash												
Coefficient	0.041	***	0.021		0.054	*	0.044	***	0.030	*	0.036	***
T-stat	42.357		4.372		2.221		27.544		2.422		3.367	
Global Crisis Post												
Coefficient	0.046	***	0.003		2.341		0.050	***	0.008		10.534	
T-stat	23.127		0.725		1.037		17.058		0.768		0.857	
Greek Crisis Pre												
Coefficient	0.044	***	0.011		0.238	*	0.048	***	0.023		0.742	*
T-stat	24.970		1.639		2.322		18.487		4.966		1.885	
Greek Crisis Crash												
Coefficient	0.034	***	0.007	*	0.125	*	0.035	***	0.010	*	0.495	*
T-stat	40.062		1.863		1.956		38.557		1.919		1.908	
Greek Crisis Post												
Coefficient	0.030	***	0.009	**	0.420	*	0.038	***	-0.004		1.339	**
T-stat	28.517		3.150		2.501		9.093		-0.629		3.160	
Normal State 4												
Coefficient	0.033	***	0.003	*	0.175	*	0.035	***	0.004		0.673	
T-stat	58.533		2.054		1.795		43.651		1.414		1.437	
Covid-19 Pre												
Coefficient	0.033	***	0.001		0.095		0.034	***	0.006		0.379	
T-stat	33.222		0.351		1.135		30.211		1.467		0.820	
Covid 19 Crash												
Coefficient	0.044	***	0.012	*	0.083		0.045	***	0.029		0.278	

T-stat	23.163		2.501		1.434		24.566		7.063		0.870	
Covid 19 Post												
Coefficient	0.033	***	0.004	*	0.740		0.034	***	0.003		3.345	
T-stat	34.654		1.753		1.256		24.896		0.859		1.171	
Current State												
Coefficient	0.043	***	-0.002		3.179		0.051	***	-0.007		14.562	
T-stat	39.648		-0.913		1.110		14.771		-1.248		0.982	
Current State												
Coefficient	0.043	***	-0.002		3.179		0.051	***	-0.007		14.562	
T-stat	39.648		-0.913		1.110		14.771		-1.248		0.982	

This table reports the estimated coefficients for the OLS regression after increasing robustness using White's Variance and Covariance Matrix on Eq (2):

$\mathrm{CSSD}_t = \alpha + \beta_1 \mathrm{D}_t^L + \beta_2 \mathrm{D}_t^U + \varepsilon_t$,

where $\mathrm{D}_t^L(\mathrm{D}_t^U)$ equals 1 if the market return on day t lied in the extreme lower (upper) tail of the return distribution, and 0 otherwise. The 5% and 1% refers to the percentage of observations in the upper and lower tail of the market distribution. Heteroskedasticity consistent t-statistics are also reported.

* The coefficient is significant at the 10% level
** The coefficient is significant at the 5% level
*** The coefficient is significant at the 1% level

Table 21: *Finland CSSD robust*

	$\alpha_{5\%}$		D_{Lower} *5%*		D_{Upper} *5%*		$\alpha_{1\%}$		D_{Lower} *1%*		D_{Upper} *1%*	
Total Sample												
Coefficient	0.025	***	0.009	***	0.042	***	0.026	***	0.016		0.151	**
T-stat	191.521		11.029		3.712		193.983		4.755		2.730	
Normal State 1												
Coefficient	0.024	***	0.010	***	0.018		0.024	***	0.016	*	0.036	
T-stat	58.303		3.656		4.811		57.098		1.954		4.308	
1990s Recession Pre												
Coefficient	0.021	***	0.007		0.016		0.022	***	0.006	*	0.019	*
T-stat	47.105		5.408		5.669		45.988		2.413		2.458	
1990s Recession Crash												
Coefficient	0.030	***	0.011		0.018		0.031	***	0.017	*	0.015	*
T-stat	71.615		4.239		4.987		68.977		2.001		1.842	
1990s Recession Post												
Coefficient	0.025	***	0.004	*	0.022	*	0.026	***	0.002	*	0.017	*
T-stat	42.141		1.978		2.343		33.747		1.949		2.247	
Normal State 2												
Coefficient	0.025	***	0.011	**	0.019		0.026	***	0.027		0.031	*
T-stat	74.045		2.620		4.838		72.512		1.388		2.066	
DotCom Pre												
Coefficient	0.035	***	0.011	***	0.012		0.036	***	0.012	***	0.010	*
T-stat	45.176		3.621		5.481		47.600		3.651		1.859	
DotCom Crash												
Coefficient	0.033	***	0.005	*	0.019	**	0.034	***	0.005		0.049	
T-stat	41.852		2.462		2.813		45.475		0.754		1.575	
DotCom Post												
Coefficient	0.026	***	0.005		0.027	*	0.028	***	0.002		0.026	
T-stat	32.761		0.837		2.542		27.727		0.410		1.046	
Normal State 3												
Coefficient	0.021	***	0.004	***	0.007	*	0.021	***	0.004	*	0.008	*
T-stat	84.718		3.777		2.421		76.699		1.708		2.298	
Global Crisis Pre												
Coefficient	0.021	***	0.003	***	0.011	**	0.022	***	0.007		0.022	*
T-stat	45.777		3.350		3.233		47.975		6.486		1.916	
Global Crisis Crash												
Coefficient	0.030	***	0.011		0.016		0.031	***	0.024		0.021	
T-stat	55.055		4.935		8.248		58.618		4.618		4.669	
Global Crisis Post												

Coefficient	0.027	***	0.001		0.034		0.027	***	0.003		0.141	
T-stat	28.689		0.343		1.139		30.754		0.813		0.877	
Greek Crisis Pre												
Coefficient	0.025	***	0.007	*	0.047		0.026	***	0.011	*	0.143	
T-stat	27.678		2.581		1.628		28.478		1.798		0.892	
Greek Crisis Crash												
Coefficient	0.024	***	0.005	***	0.044		0.024	***	0.006	*	0.156	
T-stat	72.478		3.459		1.390		66.844		2.569		1.033	
Greek Crisis Post												
Coefficient	0.022	***	0.007	***	0.009	*	0.022	***	0.012		0.023	
T-stat	40.093		3.577		2.358		42.752		8.489		1.533	
Normal State 4												
Coefficient	0.021	***	0.004	**	0.011	*	0.021	***	0.011	**	0.032	
T-stat	64.287		2.911		2.383		68.256		3.136		1.517	
Covid-19 Pre												
Coefficient	0.024	***	0.002		0.008	**	0.024	***	-0.001		0.014	
T-stat	20.793		0.816		2.749		22.823		-0.574		1.491	
Covid 19 Crash												
Coefficient	0.026	***	0.012	**	0.016		0.027	***	0.019	*	0.012	*
T-stat	30.551		3.039		4.425		31.842		2.498		2.051	
Covid 19 Post												
Coefficient	0.023	***	0.000	**	0.040		0.025	***	-0.001	*	0.092	*
T-stat	34.469		0.108		2.132		26.528		-0.323		1.123	
Current State												
Coefficient	0.027	***	0.003	*	0.446	*	0.029	***	0.006		1.912	*
T-stat	37.345		1.688		2.104		19.455		1.364		2.443	

This table reports the estimated coefficients for the OLS regression after increasing robustness using White's Variance and Covariance Matrix on Eq (2):

$CSSD_t = \alpha + \beta_1 D_t^L + \beta_2 D_t^U + \varepsilon_t$,

where $D_t^L (D_t^U)$ equals 1 if the market return on day t lied in the extreme lower (upper) tail of the return distribution, and 0 otherwise. The 5% and 1% refers to the percentage of observations in the upper and lower tail of the market distribution. Heteroskedasticity consistent t-statistics are also reported.

* The coefficient is significant at the 10% level

** The coefficient is significant at the 5% level

*** The coefficient is significant at the 1% level

Table 22: *Iceland CSSD robust*

	$\alpha_{5\%}$		D_{Lower} 5%		D_{Upper} 5%		$\alpha_{1\%}$		D_{Lower} 1%		D_{Upper} 1%	
Total Sample												
Coefficient	0.012	***	0.016		0.034	**	0.013	***	0.051		0.114	*
T-stat	94.475		6.198		2.677		85.128		4.869		1.852	
Normal State 2												
Coefficient	0.003		0.004		0.014		0.004		-0.004		0.035	
T-stat	7.733		1.023		1.520		7.875		-7.875		0.733	
DotCom Pre												
Coefficient	0.001	***	0.008		0.006		0.002	**	-0.002	**	-0.002	**
T-stat	3.673		0.786		1.107		3.327		-3.327		-3.327	
DotCom Crash												
Coefficient	0.012	***	-0.001		0.002		0.012	***	-0.005		0.010	
T-stat	31.093		-0.426		0.671		31.172		-0.861		1.198	
DotCom Post												
Coefficient	0.013	***	0.000		0.009	***	0.014	***	0.003		0.011	*
T-stat	30.091		0.033		3.622		30.522		1.440		1.716	
Normal State 3												
Coefficient	0.013	***	0.005	**	0.012		0.013	***	0.006		0.011	
T-stat	41.234		2.824		5.074		41.991		0.781		1.332	
Global Crisis Pre												
Coefficient	0.010	***	0.004	***	0.012		0.010	***	0.007	*	0.040	
T-stat	29.665		3.548		1.348		30.757		2.579		0.892	

Global Crisis Crash						
Coefficient	0.012 ***	0.064	0.074	0.016 ***	0.168	0.160
T-stat	28.976	6.091	8.036	25.050	5.087	6.524
Global Crisis Post						
Coefficient	0.007 ***	0.010 ***	0.023 **	0.008 ***	0.021 *	0.051
T-stat	26.124	3.602	2.876	22.153	1.877	1.336
Normal State 4						
Coefficient	0.011 ***	0.016 ***	0.077	0.011 ***	0.053 **	0.337
T-stat	67.564	3.474	1.373	63.928	2.630	1.191
Covid-19 Pre						
Coefficient	0.011 ***	0.005 **	0.007 ***	0.012 ***	0.011 *	0.006 *
T-stat	34.176	2.717	3.895	34.982	1.660	2.362
Covid 19 Crash						
Coefficient	0.015 ***	0.012 **	0.012	0.016 ***	0.027 *	0.017 *
T-stat	25.645	3.287	4.957	27.437	2.458	1.867
Covid 19 Post						
Coefficient	0.014 ***	0.012 **	0.014	0.015 ***	0.008 *	0.018 *
T-stat	31.604	1.486	3.321	23.515	4.674	1.568
Current State						
Coefficient	0.018 ***	0.010 **	0.029 ***	0.019 ***	0.016 *	0.068 *
T-stat	30.855	2.954	3.362	29.450	1.908	2.324

This table reports the estimated coefficients for the OLS regression after increasing robustness using White's Variance and Covariance Matrix on Eq (2):

$$CSSD_t = \alpha + \beta_1 D_t^L + \beta_2 D_t^U + \varepsilon_t,$$

where $D_t^L(D_t^U)$ equals 1 if the market return on day t lied in the extreme lower (upper) tail of the return distribution, and 0 otherwise. The 5% and 1% refers to the percentage of observations in the upper and lower tail of the market distribution. Heteroskedasticity consistent t-statistics are also reported.
* The coefficient is significant at the 10% level
** The coefficient is significant at the 5% level
*** The coefficient is significant at the 1% level

Table 23: *Sweden CSAD robust*

	α	γ_1	γ_2
Total Sample			
Coefficient	-0.032	-2.804	673.830
T-stat	-0.153	-0.062	0.763
Normal State 1			
Coefficient	0.000	0.010	0.304
T-stat	7.849	1.207	1.374
1990s Recession Pre			
Coefficient	-0.001	0.196	1.659
T-stat	-0.426	0.358	0.081
1990s Recession Crash			
Coefficient	0.000	0.058 ***	-0.030
T-stat	5.095	3.660	-0.103
1990s Recession Post			
Coefficient	0.001 ***	0.004	2.795
T-stat	3.518	0.051	0.671
Normal State 2			
Coefficient	0.001 *	-0.106	4.443
T-stat	2.092	-0.912	1.097
DotCom Pre			
Coefficient	0.003	-0.554	30.293
T-stat	1.401	-0.865	1.016
DotCom Crash			
Coefficient	0.001	0.044	0.602
T-stat	4.554	0.637	0.266
DotCom Post			
Coefficient	0.002 ***	-0.036	4.087

	α		γ_1		γ_2	
T-stat	3.856		-0.273		0.931	
Normal State 3						
Coefficient	0.000		0.217		-0.367	
T-stat	-0.122		1.231		-0.062	
Global Crisis Pre						
Coefficient	0.000		0.271		-3.123	
T-stat	-0.097		1.052		-0.396	
Global Crisis Crash						
Coefficient	0.002	***	0.065	*	0.384	
T-stat	11.042		2.054		0.395	
Global Crisis Post						
Coefficient	0.001		0.537		-11.533	
T-stat	0.617		1.368		-1.337	
Greek Crisis Pre						
Coefficient	0.002		0.328	*	-11.137	
T-stat	5.666		1.761		-1.141	
Greek Crisis Crash						
Coefficient	0.002		0.117		84.417	
T-stat	0.325		0.043		0.478	
Greek Crisis Post						
Coefficient	0.001		0.524	***	-18.210	**
T-stat	3.987		3.478		-3.092	
Normal State 4						
Coefficient	0.008		-4.585		452.813	
T-stat	0.708		-0.768		1.078	
Covid-19 Pre						
Coefficient	0.025	*	-15.880	*	1584.526	**
T-stat	2.226		-2.484		3.159	
Covid 19 Crash						
Coefficient	0.402		-82.062		1658.775	
T-stat	0.896		-0.929		0.995	
Covid 19 Post						
Coefficient	0.099		-36.072		1995.490	
T-stat	1.001		-1.221		1.966	
Current State						
Coefficient	-1.056		151.265		-110.931	
T-stat	-0.964		0.883		-0.061	

This table reports the estimated coefficients for the OLS regression after increasing robustness using White's Variance and Covariance Matrix on Eq (11):
$CSAD_t = \alpha + \gamma_1|R_{M,t}| + \gamma_2(R_{M,t}^2) + \varepsilon_t$
Heteroskedasticity consistent t-statistics are also reported.
* The coefficient is significant at the 10% level
** The coefficient is significant at the 5% level
*** The coefficient is significant at the 1% level

Table 24: *Denmark CSAD robust*

	α		γ_1		γ_2	
Total Sample						
Coefficient	0.016	*	-5.048	*	194.269	**
T-stat	2.332		-2.428		2.885	
Normal1						
Coefficient	0.000	***	0.008	*	0.257	
T-stat	10.646		1.965		1.618	
1990s Recession Pre						
Coefficient	0.000		0.018	***	-0.041	
T-stat	6.557		3.917		-0.330	
1990s Recession Crash						
Coefficient	0.000	**	0.029		0.755	
T-stat	2.688		0.907		0.453	

1990s Recession Post						
Coefficient	0.000		0.073		-0.684	
T-stat	1.242		0.933		-0.141	
Normal State 2						
Coefficient	0.000		0.061	***	-0.678	
T-stat	6.565		3.807		-1.022	
DotCom Pre						
Coefficient	0.001		-0.004		5.629	
T-stat	5.092		-0.057		0.993	
DotCom Crash						
Coefficient	0.001	*	-0.234		20.096	
T-stat	1.677		-0.694		0.978	
DotCom Post						
Coefficient	0.004		-1.912		155.480	
T-stat	1.090		-0.957		0.999	
Normal State 3						
Coefficient	0.000		0.134	**	-2.832	*
T-stat	1.502		2.705		-2.357	
Global Crisis Pre						
Coefficient	0.000		0.019		-0.295	
T-stat	7.263		1.307		-0.367	
Global Crisis Crash						
Coefficient	0.041		-8.583		216.952	
T-stat	1.011		-0.981		1.000	
Global Crisis Post						
Coefficient	0.006		-2.013		132.785	
T-stat	1.183		-0.891		0.943	
Greek Crisis Pre						
Coefficient	0.006		-2.103		134.316	
T-stat	1.181		-0.910		0.945	
Greek Crisis Crash						
Coefficient	0.002	*	-0.478		47.716	
T-stat	2.398		-0.906		1.117	
Greek Crisis Post						
Coefficient	0.004		-2.399		296.200	
T-stat	1.306		-0.975		1.008	
Normal State 4						
Coefficient	0.001		0.061		1.492	
T-stat	3.976		1.566		0.564	
Covid-19 Pre						
Coefficient	0.008		-4.857		406.853	
T-stat	1.038		-0.982		0.995	
Covid 19 Crash						
Coefficient	0.001		0.045	*	-0.233	
T-stat	6.837		2.036		-0.325	
Covid 19 Post						
Coefficient	0.001		0.105	*	-4.822	
T-stat	8.134		2.459		-1.841	
Current State						
Coefficient	0.001	***	0.098		-3.047	**
T-stat	16.431		4.134		-2.680	

This table reports the estimated coefficients for the OLS regression after increasing robustness using White's Variance and Covariance Matrix on Eq (11):

$CSAD_t = \alpha + \gamma_1 |R_{M,t}| + \gamma_2 (R_{M,t}^2) + \varepsilon_t$

Heteroskedasticity consistent t-statistics are also reported.

* The coefficient is significant at the 10% level

** The coefficient is significant at the 5% level

*** The coefficient is significant at the 1% level

Table 25: *Norway CSAD robust*

	α		γ_1		γ_2	
Total Sample						
Coefficient	3.722		-504.377		782.110	
T-stat	0.728		-0.740		1.473	
1990s Recession Pre						
Coefficient	0.000		0.024	**	-0.047	
T-stat	4.425		2.878		-0.274	
1990s Recession Crash						
Coefficient	0.000		0.019	**	0.082	*
T-stat	5.870		3.043		2.388	
1990s Recession Post						
Coefficient	0.001		0.031		-0.043	
T-stat	7.029		0.976		-0.043	
Normal State 2						
Coefficient	0.001		0.052	*	0.273	
T-stat	4.461		2.069		0.522	
DotCom Pre						
Coefficient	0.001	***	0.140	*	-1.457	
T-stat	3.387		2.262		-1.156	
DotCom Crash						
Coefficient	0.002	***	0.081	***	-0.182	
T-stat	13.763		3.789		-0.337	
DotCom Post						
Coefficient	0.001		0.121	**	-2.102	
T-stat	5.466		2.825		-1.481	
Normal State 3						
Coefficient	0.008		-2.077		79.148	
T-stat	1.067		-0.976		0.981	
Global Crisis Pre						
Coefficient	0.003		-1.022		66.537	
T-stat	1.171		-0.925		0.930	
Global Crisis Crash						
Coefficient	0.000		0.344		-2.821	
T-stat	0.201		1.382		-1.028	
Global Crisis Post						
Coefficient	0.013	*	-4.674	**	264.857	
T-stat	2.589		-3.036		5.445	
Greek Crisis Pre						
Coefficient	0.023		-6.888		322.452	
T-stat	1.039		-1.030		1.287	
Greek Crisis Crash						
Coefficient	0.005	*	-2.401	**	246.952	
T-stat	2.160		-2.763		6.899	
Greek Crisis Post						
Coefficient	0.005		-3.566		334.524	***
T-stat	0.423		-0.939		3.453	
Normal State 4						
Coefficient	0.017		-6.607		367.974	*
T-stat	1.471		-1.641		2.353	
Covid-19 Pre						
Coefficient	0.016		-9.417		843.177	
T-stat	1.030		-0.969		0.988	
Covid 19 Crash						
Coefficient	-0.004		1.248		-8.516	
T-stat	-0.669		1.087		-0.712	
Covid 19 Post						
Coefficient	0.050		-15.483		618.068	
T-stat	1.153		-1.485		4.052	

Current State					
Coefficient	0.017		-8.197		660.044
T-stat	0.721		-1.547		7.138

This table reports the estimated coefficients for the OLS regression after increasing robustness using White's Variance and Covariance Matrix on Eq (11):
$CSAD_t = \alpha + \gamma_1 |R_{M,t}| + \gamma_2 (R_{M,t}^2) + \varepsilon_t$
Heteroskedasticity consistent t-statistics are also reported.
* The coefficient is significant at the 10% level
** The coefficient is significant at the 5% level
*** The coefficient is significant at the 1% level

Table 26: *Finland CSAD robust*

	α		γ_1		γ_2
Total Sample					
Coefficient	-0.044		7.102		-6.891
T-stat	-0.613		0.535		-0.038
Normal State 1					
Coefficient	0.000		0.050		-0.110
T-stat	5.284		3.964		-0.371
1990s Recession Pre					
Coefficient	0.000		0.024		0.218
T-stat	6.030		1.254		0.224
1990s Recession Crash					
Coefficient	0.001	***	0.034	*	0.235
T-stat	9.366		2.529		0.713
1990s Recession Post					
Coefficient	0.001	***	-0.001		2.432
T-stat	3.443		-0.021		0.754
Normal State 2					
Coefficient	0.000		0.155		-0.191
T-stat	-0.111		0.846		-0.139
DotCom Pre					
Coefficient	0.001	***	0.057	**	-0.459
T-stat	9.839		2.718		-0.623
DotCom Crash					
Coefficient	0.001		0.038		2.058
T-stat	4.783		0.540		0.535
DotCom Post					
Coefficient	0.000	*	0.105		0.776
T-stat	1.989		1.156		0.120
Normal State 3					
Coefficient	0.000	***	0.029	*	-0.176
T-stat	8.790		1.675		-0.461
Global Crisis Pre					
Coefficient	0.000		0.025		0.134
T-stat	7.946		1.584		0.150
Global Crisis Crash					
Coefficient	0.001		0.025		0.745
T-stat	7.421		1.474		1.403
Global Crisis Post					
Coefficient	-0.001		0.235		10.783
T-stat	-0.097		0.101		0.089
Greek Crisis Pre					
Coefficient	0.003		-0.764		41.761
T-stat	1.200		-0.876		0.925
Greek Crisis Crash					
Coefficient	0.013		-5.366		306.227
T-stat	1.032		-0.989		1.000
Greek Crisis Post					

	α		γ_1		γ_2	
Coefficient	0.000		0.024		0.103	
T-stat	4.971		0.869		0.070	
Normal State 4						
Coefficient	0.000	*	0.070		-0.199	
T-stat	2.576		1.327		-0.064	
Covid-19 Pre						
Coefficient	0.000		0.195		-5.495	
T-stat	1.351		1.382		-0.700	
Covid 19 Crash						
Coefficient	0.001		0.057	*	-0.419	
T-stat	4.977		2.225		-0.557	
Covid 19 Post						
Coefficient	0.001		-0.216	*	35.111	
T-stat	0.773		-0.342		0.618	
Current State						
Coefficient	0.018	*	-7.568		443.896	***
T-stat	2.414		-4.174		25.401	

This table reports the estimated coefficients for the OLS regression after increasing robustness using White's Variance and Covariance Matrix on Eq (11):
$CSAD_t = \alpha + \gamma_1 |R_{M,t}| + \gamma_2 (R_{M,t}^2) + \varepsilon_t$
Heteroskedasticity consistent t-statistics are also reported.
* The coefficient is significant at the 10% level
** The coefficient is significant at the 5% level
*** The coefficient is significant at the 1% level

Table 27: *Iceland CSAD robust*

	α		γ_1		γ_2	
Total Sample						
Coefficient	0.014		-2.460		20.165	
T-stat	0.960		-0.954		1.035	
Normal State 2						
Coefficient	0.000		0.014		-0.036	
T-stat	-0.611		0.706		-0.166	
DotCom Pre						
Coefficient	0.000		0.015		-0.163	
T-stat	-1.268		1.415		-1.268	
DotCom Crash						
Coefficient	0.000		0.010	*	-0.041	
T-stat	7.447		2.120		-0.509	
DotCom Post						
Coefficient	0.000		0.025	**	-0.082	
T-stat	5.258		2.920		-0.130	
Normal State 3						
Coefficient	0.000	**	0.026	**	-0.232	
T-stat	3.008		3.048		-0.563	
Global Crisis Pre						
Coefficient	0.000		-0.111		6.380	
T-stat	1.132		-0.862		0.941	
Global Crisis Crash						
Coefficient	-0.001		0.137	*	0.739	
T-stat	-1.642		2.578		1.559	
Global Crisis Post						
Coefficient	0.000		-0.056		8.664	
T-stat	0.923		-0.621		1.088	
Normal State 4						
Coefficient	0.001		-0.285	*	18.376	***
T-stat	1.453		-1.646		3.448	
Covid-19 Pre						
Coefficient	0.000		0.029		-0.804	*

T-stat	5.453	4.177	-1.733	
Covid 19 Crash				
Coefficient	0.000	0.011	0.587	***
T-stat	4.296	1.481	3.404	
Covid 19 Post				
Coefficient	0.000	0.070	-0.278	***
T-stat	0.246	0.950	-0.052	
Current State				
Coefficient	0.000	-0.008	5.862	
T-stat	1.042	-0.057	0.714	

This table reports the estimated coefficients for the OLS regression after increasing robustness using White's Variance and Covariance Matrix on Eq (11):

$$CSAD_t = \alpha + \gamma_1 |R_{M,t}| + \gamma_2 (R_{M,t}^2) + \varepsilon_t$$

Heteroskedasticity consistent t-statistics are also reported.
* The coefficient is significant at the 10% level
** The coefficient is significant at the 5% level
*** The coefficient is significant at the 1% level

Table 28: *Sweden CSAD bullish vs bearish robust*

	α		γ_1		γ_2	γ_3		γ_4
Total Sample								
Coefficient	-0.093		13.844		9.762	624.937		-132.559
T-stat	-0.504		0.268		0.511	0.646		-0.504
Normal State 1								
Coefficient	0.000		0.002		0.013	0.612		0.160
T-stat	6.825		0.149		1.073	0.994		0.601
1990s Recession Pre								
Coefficient	0.001		-0.372		-0.013	29.380		0.202
T-stat	0.652		-0.575		-0.116	0.659		0.134
1990s Recession Crash								
Coefficient	0.000		0.086	***	0.047	-0.272		-0.351
T-stat	4.685		3.515		4.296	-0.716		-1.162
1990s Recession Post								
Coefficient	0.001	***	-0.003		0.042	4.198		-1.761
T-stat	3.855		-0.033		0.834	0.865		-0.991
Normal State 2								
Coefficient	0.001	*	-0.024		-0.149	1.120	*	6.019
T-stat	2.375		-0.602		-0.947	1.730		1.046
DotCom Pre								
Coefficient	0.002		-0.628		-0.172	40.867		6.103
T-stat	1.510		-0.878		-0.669	1.058		0.782
DotCom Crash								
Coefficient	0.002	***	0.001		0.021	2.768	**	0.387
T-stat	10.228		0.051		0.627	3.265		0.323
DotCom Post								
Coefficient	0.002	**	0.096		-0.233	-0.044		10.493
T-stat	2.964		1.048		-0.797	-0.028		0.925
Normal State 3								
Coefficient	0.000		0.033		0.056	16.597		-0.788
T-stat	0.379		0.070		0.468	0.454		-0.315
Global Crisis Pre								
Coefficient	0.002		-0.730		-0.110	81.814		2.778
T-stat	1.580		-0.842		-0.686	0.905		0.628
Global Crisis Crash								
Coefficient	0.002	***	0.154	***	-0.035	-1.247		2.604
T-stat	9.475		3.403		-0.682	-1.145		1.201
Global Crisis Post								
Coefficient	0.001		0.735		0.289	-12.673		-7.421
T-stat	0.255		0.559		0.775	-0.110		-0.643

Greek Crisis Pre					
Coefficient	0.002	0.364	0.119	-7.009	-4.998
T-stat	5.961	1.460	1.282	-0.515	-1.122
Greek Crisis Crash					
Coefficient	0.013	-6.781	-1.574	625.201	40.554
T-stat	1.274	-0.999	-0.915	1.199	0.841
Greek Crisis Post					
Coefficient	0.001	0.595 *	0.122	-19.723	-2.676
T-stat	5.039	2.089	0.778	-0.528	-0.155
Normal State 4					
Coefficient	0.018	-14.466	-2.992 ***	1337.085	73.137 *
T-stat	4.457	-4.207	-3.752	4.173	2.557
Covid-19 Pre					
Coefficient	0.017 *	-13.345 **	-6.597 *	1537.365 ***	436.411 *
T-stat	2.043	-2.607	-1.852	3.888	1.798
Covid 19 Crash					
Coefficient	0.096	-34.895	-6.597	1479.170	65.547
T-stat	0.973	-0.969	-0.789	0.992	0.424
Covid 19 Post					
Coefficient	0.086	-34.993	-21.576	1986.720	983.726
T-stat	0.782	-0.965	-0.766	1.832	0.761
Current State					
Coefficient	-0.968	162.135	155.653	-161.180	-4203.196
T-stat	-0.982	0.924	0.984	-0.088	-0.966

This table reports the estimated coefficients for the OLS regression after increasing robustness using White's Variance and Covariance Matrix on Eq (12):

$$CSAD_t = \alpha + \gamma_1 D^{up}\left|R_{M,t}\right| + \gamma_2(1 - D^{up})\left|R_{M,t}\right| + \gamma_3 D^{up}\left(R_{M,t}\right)^2 + \gamma_4(1 - D^{up})\left(R_{M,t}\right)^2 + \varepsilon_t$$

Where D^{up} equals 1 if the aggregate market return on any given day is positive (>0).
Heteroskedasticity consistent t-statistics are also reported.
* The coefficient is significant at the 10% level
** The coefficient is significant at the 5% level
*** The coefficient is significant at the 1% level

Table 29: *Denmark CSAD bullish vs bearish robust*

	α	γ_1	γ_2	γ_3	γ_4
Total Sample					
Coefficient	0.008 **	-3.780 **	-1.020 *	193.234	19.658 *
T-stat	2.623	-3.019	-2.327	4.377	2.210
Normal1					
Coefficient	0.000 ***	0.007	0.002	0.506 *	0.315
T-stat	9.953	1.219	0.290	1.759	1.350
1990s Recession Pre					
Coefficient	0.000	0.016 **	0.020	0.042	-0.112
T-stat	4.744	2.747	1.008	0.209	-0.066
1990s Recession Crash					
Coefficient	0.000 *	0.048	0.048	-0.539 *	-0.025
T-stat	1.873	4.381	1.243	-2.080	-0.012
1990s Recession Post					
Coefficient	0.000	0.089	0.068	-1.063	-2.735
T-stat	1.261	0.925	1.168	-0.172	-0.617
Normal State 2					
Coefficient	0.000 ***	0.047	0.063 **	0.753	-1.027 *
T-stat	3.632	0.743	3.024	0.121	-2.290
DotCom Pre					
Coefficient	0.001	-0.012	0.033	6.860	1.354
T-stat	4.151	-0.114	0.340	0.750	0.153
DotCom Crash					
Coefficient	0.002 *	-0.535	-0.100	43.339	3.577
T-stat	1.913	-0.977	-0.737	1.175	0.934

DotCom Post					
Coefficient	0.004	-1.883	-1.151	155.298	82.061
T-stat	1.079	-0.950	-0.859	1.001	0.844
Normal State 3					
Coefficient	0.000 *	0.094	0.038	2.762	-0.538
T-stat	1.698	0.906	1.124	0.265	-0.564
Global Crisis Pre					
Coefficient	0.000	0.050 *	0.001	-2.618	0.417
T-stat	6.878	1.733	0.061	-1.101	0.934
Global Crisis Crash					
Coefficient	0.025	-7.712	-2.560	214.086	46.404
T-stat	0.967	-0.945	-0.901	0.996	0.927
Global Crisis Post					
Coefficient	0.004	-1.725	-0.496	141.966	15.683
T-stat	1.282	-0.843	-0.743	0.943	0.548
Greek Crisis Pre					
Coefficient	0.004	-1.625	-0.481	139.814	15.940
T-stat	1.222	-0.830	-0.727	0.933	0.557
Greek Crisis Crash					
Coefficient	0.002 **	-0.682	-0.218	86.074	12.716 *
T-stat	3.092	-1.139	-1.292	1.434	1.665
Greek Crisis Post					
Coefficient	0.003	-2.170	-0.893	292.832	78.921
T-stat	1.402	-0.986	-0.872	1.036	0.858
Normal State 4					
Coefficient	0.001	0.023	0.014	8.515	0.950
T-stat	4.967	0.272	0.509	0.751	0.688
Covid-19 Pre					
Coefficient	0.005	-3.983	-1.657	393.838	94.435
T-stat	1.042	-0.973	-0.913	0.999	0.878
Covid 19 Crash					
Coefficient	0.001	0.116	0.018	-2.964	0.210
T-stat	5.618	1.596	1.193	-0.716	0.611
Covid 19 Post					
Coefficient	0.001	0.127	0.064	-5.953	-2.590
T-stat	7.965	1.906	2.248	-1.204	-1.577
Current State					
Coefficient	0.001 ***	0.171	0.065 ***	-7.532 **	-1.469
T-stat	14.353	4.010	3.031	-3.124	-1.456

This table reports the estimated coefficients for the OLS regression after increasing robustness using White's Variance and Covariance Matrix on Eq (12):

$$CSAD_t = \alpha + \gamma_1 D^{up}|R_{M,t}| + \gamma_2(1 - D^{up})|R_{M,t}| + \gamma_3 D^{up}(R_{M,t})^2 + \gamma_4(1 - D^{up})(R_{M,t})^2 + \varepsilon_t$$

Where D^{up} equals 1 if the aggregate market return on any given day is positive (>0).
Heteroskedasticity consistent t-statistics are also reported.
* The coefficient is significant at the 10% level
** The coefficient is significant at the 5% level
*** The coefficient is significant at the 1% level

Table 30: *Norway CSAD bullish vs bearish robust*

	α	γ_1	γ_2	γ_3	γ_4
Total Sample					
Coefficient	3.491	-644.468	-273.226	839.739	2318.983
T-stat	0.719	-0.727	-0.702	1.388	0.574
1990s Recession Pre					
Coefficient	0.000 ***	0.024 *	0.024	-0.023	-0.088
T-stat	3.737	2.396	1.356	-0.156	-0.111
1990s Recession Crash					
Coefficient	0.000	0.022 *	0.014	0.090	0.108
T-stat	5.131	1.983	1.490	0.355	0.655

1990s Recession Post									
Coefficient	0.001		0.009		0.009		0.849		0.049
T-stat	8.766		0.185		0.427		0.348		0.079
Normal State 2									
Coefficient	0.000		0.079	**	0.040		0.181		-0.111
T-stat	5.767		3.219		4.872		0.386		-0.937
DotCom Pre									
Coefficient	0.001	*	0.220	*	0.069	*	-2.236		-0.546
T-stat	2.557		2.237		2.112		-1.084		-0.624
DotCom Crash									
Coefficient	0.002	***	0.095	***	0.078	***	0.010		-0.938
T-stat	14.077		3.723		3.426		0.016		-1.531
DotCom Post									
Coefficient	0.001		0.091		0.019		0.904		-0.320
T-stat	5.836		1.343		0.532		0.213		-0.287
Normal State 3									
Coefficient	0.005		-1.784		-0.646		101.764		14.274
T-stat	1.104		-0.947		-0.983		0.933		1.040
Global Crisis Pre									
Coefficient	0.003		-1.415		-0.356		114.590		11.358
T-stat	1.221		-0.975		-0.932		0.992		0.916
Global Crisis Crash									
Coefficient	0.001		0.261		0.112		7.639		-0.610
T-stat	0.837		1.020		1.379		0.602		-0.465
Global Crisis Post									
Coefficient	0.007	*	-3.344	**	-1.001		264.155	***	31.623
T-stat	2.197		-3.036		-1.590		11.922		1.628
Greek Crisis Pre									
Coefficient	0.009		-4.048		-1.105		300.280	*	29.295
T-stat	0.865		-0.958		-0.669		1.722		0.679
Greek Crisis Crash									
Coefficient	0.003		-1.755		-0.468		240.344		30.086
T-stat	1.167		-1.552		-0.612		5.390		0.710
Greek Crisis Post									
Coefficient	0.002		-2.490		-0.168		323.787	**	9.983
T-stat	0.138		-0.524		-0.050		3.083		0.064
Normal State 4									
Coefficient	0.006		-3.817		-0.793	*	358.152	***	19.276
T-stat	4.250		-6.141		-1.982		14.919		0.829
Covid-19 Pre									
Coefficient	0.008		-6.766		-1.894		806.329		100.168
T-stat	1.097		-0.972		-0.946		1.011		0.939
Covid 19 Crash									
Coefficient	0.012		-4.780		-0.788		261.496		9.471
T-stat	1.105		-0.903		-0.900		0.934		0.920
Covid 19 Post									
Coefficient	0.045		-15.866		-9.587		619.283		358.081
T-stat	0.811		-0.996		-0.789		3.305		0.782
Current State									
Coefficient	0.007		-5.580		-0.950		659.053	***	27.640
T-stat	0.484		-1.354		-0.353		14.201		0.331

This table reports the estimated coefficients for the OLS regression after increasing robustness using White's Variance and Covariance Matrix on Eq (12):

$$CSAD_t = \alpha + \gamma_1 D^{up}|R_{M,t}| + \gamma_2(1-D^{up})|R_{M,t}| + \gamma_3 D^{up}(R_{M,t})^2 + \gamma_4(1-D^{up})(R_{M,t})^2 + \varepsilon_t$$

Where D^{up} equals 1 if the aggregate market return on any given day is positive (>0).

Heteroskedasticity consistent t-statistics are also reported.

* The coefficient is significant at the 10% level

** The coefficient is significant at the 5% level

*** The coefficient is significant at the 1% level

Table 31: *Finland CSAD bullish vs bearish robust*

	α		γ_1		γ_2		γ_3		γ_4
Total Sample									
Coefficient	-0.047		10.615		3.813		-11.267		-18.382
T-stat	-0.566		0.480		0.561		-0.032		-0.311
Normal State 1									
Coefficient	0.000		0.025		0.035	*	0.983		-0.089
T-stat	5.476		0.990		1.992		0.945		-0.194
1990s Recession Pre									
Coefficient	0.000	***	-0.031		0.022	*	3.853	**	-0.216
T-stat	9.748		-1.642		2.277		2.892		-0.723
1990s Recession Crash									
Coefficient	0.001	***	0.043	**	0.008		0.000		1.015
T-stat	8.855		2.599		0.347		0.000		0.921
1990s Recession Post									
Coefficient	0.000	**	0.007		0.035		2.696		-0.867
T-stat	2.988		0.104		1.246		0.654		-0.971
Normal State 2									
Coefficient	0.001	**	0.075	*	-0.010		-0.097		1.516
T-stat	3.017		2.046		-0.135		-0.357		0.617
DotCom Pre									
Coefficient	0.001	***	0.090	**	0.032		-1.696		0.384
T-stat	9.686		3.069		1.446		-1.473		0.468
DotCom Crash									
Coefficient	0.001		0.081		0.027		2.069		-0.131
T-stat	4.551		0.711		0.851		0.332		-0.133
DotCom Post									
Coefficient	0.001	**	0.045		0.074		6.292		-2.282
T-stat	2.792		0.365		1.160		0.578		-1.130
Normal State 3									
Coefficient	0.000		0.033		0.021		0.033		-0.177
T-stat	7.597		1.355		1.244		0.071		-0.189
Global Crisis Pre									
Coefficient	0.000		0.002		0.020		2.422		-0.329
T-stat	8.484		0.089		1.208		1.329		-0.563
Global Crisis Crash									
Coefficient	0.001		0.042	*	0.010		0.448		1.004
T-stat	7.230		2.429		0.424		1.018		0.955
Global Crisis Post									
Coefficient	-0.002		0.680		0.496		4.881		-16.870
T-stat	-0.293		0.248		0.410		0.030		-0.400
Greek Crisis Pre									
Coefficient	0.004		-1.905		-0.499		117.834		13.080
T-stat	1.189		-0.958		-0.995		0.986		1.045
Greek Crisis Crash									
Coefficient	0.009		-5.020		-2.118		304.451		90.232
T-stat	1.034		-0.979		-0.970		0.998		0.972
Greek Crisis Post									
Coefficient	0.000		0.017		0.013		1.187		0.221
T-stat	5.819		0.571		0.487		0.545		0.148
Normal State 4									
Coefficient	0.001		-0.135		0.003		23.764		0.664
T-stat	4.444		-0.819		0.145		1.035		0.927
Covid-19 Pre									
Coefficient	0.000		0.288		0.109		-8.345		-6.394
T-stat	1.110		1.568		1.528		-0.961		-1.332
Covid 19 Crash									
Coefficient	0.000		0.117	*	0.033	**	-2.107		-0.079

	α	γ_1	γ_2	γ_3	γ_4
T-stat	5.537	2.422	2.642	-1.235	-0.452
Covid 19 Post					
Coefficient	0.002	-1.032 *	-0.232 **	140.982	9.455
T-stat	1.359	-1.006	-0.808	1.210	0.779
Current State					
Coefficient	0.005	-4.828 ***	-0.827	431.153 ***	22.499
T-stat	1.474	-3.462	-1.265	53.755	1.242

This table reports the estimated coefficients for the OLS regression after increasing robustness using White's Variance and Covariance Matrix on Eq (12):
$CSAD_t = \alpha + \gamma_1 D^{up}|R_{M,t}| + \gamma_2(1 - D^{up})|R_{M,t}| + \gamma_3 D^{up}(R_{M,t})^2 + \gamma_4(1 - D^{up})(R_{M,t})^2 + \varepsilon_t$
Where D^{up} equals 1 if the aggregate market return on any given day is positive (>0).
Heteroskedasticity consistent t-statistics are also reported.
* The coefficient is significant at the 10% level
** The coefficient is significant at the 5% level
*** The coefficient is significant at the 1% level

Table 32: *Iceland CSAD bullish vs bearish robust*

	α	γ_1	γ_2	γ_3	γ_4
Total Sample					
Coefficient	0.005	-1.414	-0.232	19.469	1.511
T-stat	0.951	-0.950	-0.796	1.068	1.556
Normal State 2					
Coefficient	0.000	0.001	0.003	0.158	-0.012
T-stat	-0.005	0.054	0.775	0.523	-0.258
DotCom Pre					
Coefficient	0.000	0.012	0.017	-0.130	-0.199
T-stat	-1.188	1.615	1.124	-1.061	-1.052
DotCom Crash					
Coefficient	0.000 ***	0.019 ***	0.007 *	-0.188 **	-0.026
T-stat	9.334	3.785	1.810	-2.583	-1.117
DotCom Post					
Coefficient	0.000	0.030 ***	0.008	-0.335	0.306
T-stat	5.710	3.472	1.011	-0.524	0.506
Normal State 3					
Coefficient	0.000 **	0.030 *	0.013	-0.218	0.054
T-stat	2.726	2.356	1.104	-0.275	0.090
Global Crisis Pre					
Coefficient	0.000	-0.115	-0.036	7.627	1.309
T-stat	1.164	-0.822	-0.790	0.918	0.958
Global Crisis Crash					
Coefficient	0.000	0.130 **	0.122	0.952 **	0.741
T-stat	-1.319	2.837	1.346	2.666	0.769
Global Crisis Post					
Coefficient	0.000	-0.073	-0.071	9.159	15.344 *
T-stat	1.135	-0.763	-1.054	1.131	1.655
Normal State 4					
Coefficient	0.000 *	-0.255 *	-0.122	18.345	12.533
T-stat	1.651	-2.546	-0.608	4.809	0.996
Covid-19 Pre					
Coefficient	0.000	0.036	0.021 *	-1.320 **	-0.002
T-stat	5.328	4.409	2.069	-2.703	-0.002
Covid 19 Crash					
Coefficient	0.000 ***	0.014	0.002	0.666	0.730 *
T-stat	3.936	0.681	0.241	0.597	2.441
Covid 19 Post					
Coefficient	0.000 ***	0.051	0.048	-0.345	4.128 *
T-stat	0.801	1.043	0.637	-0.081	0.408
Current State					
Coefficient	0.000 **	-0.130	0.010	16.527 *	0.508

T-stat	2.620	-1.016	0.258	1.830	0.258

This table reports the estimated coefficients for the OLS regression after increasing robustness using White's Variance and Covariance Matrix on Eq (12):

$CSAD_t = \alpha + \gamma_1 D^{up}|R_{M,t}| + \gamma_2(1 - D^{up})|R_{M,t}| + \gamma_3 D^{up}(R_{M,t})^2 + \gamma_4(1 - D^{up})(R_{M,t})^2 + \varepsilon_t$

Where D^{up} equals 1 if the aggregate market return on any given day is positive (>0).

Heteroskedasticity consistent t-statistics are also reported.

* The coefficient is significant at the 10% level

** The coefficient is significant at the 5% level

*** The coefficient is significant at the 1% level