

UNIVERSITY OF GOTHENBURG SCHOOL OF BUSINESS, ECONOMICS AND LAW

Bachelor thesis in Financial Economics

Market efficiency and herding:

-A cross-country analysis

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Abstract

In this thesis we examine whether or not herd behavior, the act of market participants to ignore their own beliefs and instead follow the market consensus, is present in four different stock markets. To be able to establish if herd behavior is present, a measure based upon cross-sectional deviation are employed to a set of data covering stock markets returns. Furthermore, we decide to divide these four stock markets into a group of two emerging markets and compare the empirical results against two developed markets. We find significant evidence of herd behavior in the emerging stock markets. In addition, our results indicate that herd behavior is more profound when prices are decreasing than increasing. As a consequence of our results, investors need a larger set of stock to achieve the same level of diversification in markets with herd behavior.

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1. Introduction

1.1 Background

Financial theory rests upon the concept that market participants behave in a rational manner and that the prices of assets solely disclose relevant economic information. This concept is not a new invention; even as early as in the beginning of the 20th century financial markets were thought to be efficient. Bachelier (1900) found that financial markets obeyed by the principle of the random walk hypothesis. The random walk hypothesis states that stock prices should be completely random and unpredictable, hence following "a random walk". In extension this hypothesis implies that markets are efficient since efficiency requires no stock price predictability (Bachelier, 1900).

Modern financial theory builds on the work done by Markowitz's modern portfolio theory (1952) and Sharpe's capital asset pricing model (1964) claiming that market participants will to a great extent behave in a rational manner when investments are facilitated. Where the participants weigh and assess the risk return given by the optimal portfolio weight in accordance to the mean-variance optimization. Further research into efficiency in financial markets has been done. Fama (1970) formulated the famous hypothesis of efficient markets. According to the hypothesis, markets could be efficient in three different ways; weak-form efficient claiming that past information is already incorporated in the price, semi-strong-form efficient where all public information is included in the price and strong-form efficient when stock prices are including all information available. A number of research articles have investigated the degree of efficiency in different financial markets in the world.

However, issues are being raised questioning whether or not market participants are acting in a rational manner and if financial markets are efficient. New fields are emerging trying to find an answer to these questions of doubts. One of these fields are behavioral finance which tries to explain stock market bubble and crashes, market anomalies and biases affecting market participants. One of the interesting phenomenon's that are found in the financial market is herd behavior.

Herd behavior, when individual participants have the fallacy to imitate the actions undertaken by a larger group, is a clear deviation of the efficient market hypothesis which states that individuals are making rational and informed decisions. Many stock market bubbles and crashes have been explained by herd behavior, for instance the recent dot-com crash in the late 1990s and even as far back as the famous Tulip mania in the 17th century (Kapusuzoglu, 2011). Hence, herding is an important subject because of the potential impact it could have on investors and market participants acting in the financial market.

1.2 Purpose

The purpose of the thesis is to investigate the existence of herd behavior in different financial markets. Recent research into this area touches upon prevailing herd behavior in several markets. The aim of this thesis is hence to continue to explore herding by performing a cross-country investigation where emerging financial markets are compared to their developed equivalents. It is interesting to examine emerging markets, since they should in both theory and practice be less efficient than markets found in the developed world (Harvey, 1995). Two emerging markets are chosen for this task and as a contrast, this thesis further includes an additional group of two developed markets as a way to illustrate the difference. In order to examine the main question, three sub questions are outlined and the results are then studied.

- 1. Does herd behavior affect stock market performance in Brazil, Hong Kong, Sweden or Switzerland?
- 2. Is there any difference in the existence of herd behavior between emerging markets and more developed markets?
- 3. Was herding an element during the dot-com bubble?

The thesis is organized as following: Section Two provides an insight into underlying theory while Section Three outlines a review of the relevant literature. Section Four offers an overview of the methodology employed and provides a description over the data. Section Five presents the empirical results obtained. Section Six gives an interpretation and analysis of the regression results while Section Seven ends the thesis with a discussion about the major discoveries and gives additional suggestions for further research areas.

2. Theory

This section will outline the underlying theory needed to grasp the concept of herd behavior. First, the essential rationale behind the efficient market hypothesis is given. Second, a short introduction of herd behavior is covered together with its implication. The theory section ends with a presentation of the concept of behavioral finance and how it is related to herd behavior and rationality.

2.1 Efficient market hypothesis

The well-known efficient market hypothesis (EMH) dates back to the 1960s and is regarded as a fundamental building block in the modern financial theory. Its importance is reaffirmed by the sheer number of research articles evolved around this topic. EMH states that stock markets should be regarded as informational efficient; assuming that market participants cannot systematically beat the average market return on a risk adjusted basis given the information available at the time of the investment decision. There are three kinds of versions associated with EMH; the weak form, semi-strong form and strong form. Weak-form claims that all historical information is already included in the price, that is that participants could not benefit by utilizing historical information when deciding to invest or not. The semi-strong form argues that all information accessible to the general public are already incorporated into the price. Finally, the strong form states that all information available, even inside information is taken into consideration (Fama, 1970).

However, question has been put forward concerning the ability of EMH to handle market anomalies found inside the financial system. Stock market bubbles and crashes, psychological biases affecting investment decisions, as well as calendar effects and the weather effect have been reported. These effects should not be possible according to EMH. A brief review of the history of the financial system and financial markets depict another reality, where numerous crisis and bubbles from either a local or international perspective have been affecting markets since at least the beginning of the 17th century (Fenzl and Pelzmann, 2012).

2.2 Herd behavior

Bikhchandani and Sharma (2001) claim that according to the EMH market participants should take rational informed decisions given the available set of information when deciding upon investment objects. This decision should mirror the underlying expectation about the development of the market. However this is not always the case, in times of extreme market movements in either up or down direction some market participants have been deviating from what could be considered as rational behavior. Driven by their emotions, with for instance greed in stock market bubbles or fear in stock market crashes irrational participants follow or exit the market depending on market sentiment. There are at least three reasons, which are usually mentioned in the literature, why herd behavior exists in the financial markets. These reasons are broadly attributed to imperfect information, concern for reputation and compensation structure and will be reviewed below.

First, Bikhchandani and Sharma (2001) claim that information-based herding is one of the explanations for herd behavior in the financial market. This proposition states that market participants with access to sources of information which are less accurate, have a tendency to follow participants with access to higher quality information. Hence participants with low quality information will mimic the action performed by those individuals with high quality information while ignoring their own information. This will lead to herd formation, where the participants with low quality information waits until the individual with the highest quality source of information has done his investment decision and follow suit.

Second, Bikhchandani and Sharma (2001) reason that reputation based herding is another cause of herd behavior. Reputation based herding builds upon the idea that portfolio managers and the employees are uncertain about their ability to manage the portfolio. In this case will the portfolio manager with low ability follow the actions of the high ability portfolio manager in order to not be seen as inadequate even if his actions are correct in the first place. This is because low ability portfolio managers are unsure about their ability to interpret signals emitted by the financial market and rather trust high ability portfolio managers. Thus, the low ability portfolio manager feels it is better to imitate.

Lastly, Bikhchandani and Sharma (2001) argue that compensation-based herding could be seen as an explanation for herd behavior. If market participants' compensation depends solely on the performance compared to other participants' performance, it may shift the incentive

and lead to an inefficient held portfolio. If it is the case that the portfolio manager is rewarded by a performance benchmark and the manager in question underperforms, the incentive to mimic the benchmark index shifts in favor that might distort investment decisions.

2.3 Behavioral finance, rationality and herd behavior

According to Banerjee (1992) there are several social and economic situations where our decision-making is influenced by how other people act. Behavioral finance evolved as an answer trying to explain why market participants deviate from what is considered to be rational behavior. Shefrin (2000) proposed that irrational behavior attributes to the fact that psychology affects motivation and aspiration amongst humans. Furthermore, the author argues that psychology also is to blame for human miscalculations and misjudgments. Relating to the market participants in the financial system, Shefrin (2000) notes that psychological factors such as overconfidence and optimism play a great part in forming of stock market bubbles. Where market participants get caught up with their emotions, departing from what should be considered as rational behavior and choose to follow their emotions affected by psychological factors. Chang et al. (2009) define herd behavior as when market participants disregard their own believes and follow other market participant's actions in what is perceived as the market consensus, deviating from the rational path.

3. Literature review

An insight into relevant literature related to herd behavior and financial markets are given in this section. Section three ends with a brief summarizing of the literature review.

3.1 Literature review

This thesis is based upon the work conducted by Chang et al. (2000), where the authors are trying to estimate the level of herd behavior in different international markets. In this case the US, Hong Kong, Japanese, South Korean and Taiwanese stock market. The authors conclude that when return dispersion is measured by the cross-sectional absolute deviation of returns then rational asset pricing models predict not only that dispersion is an increasing function of the market return, but also that the relation between is linear. Moreover, the authors found that there is an increased tendency by markets participants to herd around what is "market consensus" in times with significant price movements. In addition to this, the authors also find that during periods of large fluctuations in stock prices the return dispersion for the US, Hong Kong and Japanese markets are increasing rather decreasing. This suggests evidence in the opposition of any persistent herd behavior in these markets. However, by looking at the South Korean and the Taiwanese markets the outcome is different. Both these markets provide evidence in favor of present herd behavior.

Lakonishok et al. (1992) used low frequency portfolio holding data in order to establish the degree of correlation in trades performed by investors and to which extent they are following each other in buying and selling. Moreover, the evidence regarding institutional investors was mixed as they were found to suffer from modest levels of herd behavior. Notably pension funds were less likely to herd compared to other financial institutions.

Avery and Zemsky (1998) conducted a study of the relationship between asset prices and herd behavior. According to the authors, herding arises when there are two dimensions of uncertainty, the existence and effect of a shock. However, this need not distort prices because the market discounts the information that trades reveals during herding. With a third dimension of uncertainty, the quality of trader's information, herd behavior can lead to a significant mispricing in the short-term.

Continuing on the path outlined by Chang et al. (2000), Demirer and Kutan (2006) investigated the Chinese stock market for herding activities among market participants on an individual firm level as well as on a sector level. Accordingly, it was concluded that the

Chinese market did not show any herding formation. Although it was noted that stock return dispersion was significantly higher during times of large fluctuations in market index. Comparing the return dispersion for upside and downside movements, the return dispersion was lower during extreme downside movements than it was during upside movements.

Tan et al. (2008) also studied the Chinese stock market for evidence of herd behavior but followed up on the suggestions presented by Demirer and Kutan (2006) by looking at dual-listed Chinese A-share and B-share stocks. The authors found present herd behavior within both Shanghai and Shenzhen A-share markets. Furthermore, herding occurred during both rising and falling market conditions. Investors investing in A-shares in the Shanghai stock market were more active during rising market conditions, high trading volume and high volatility compared to investor investing in B-shares.

Bowe and Domuta (2004) investigated the Jakarta Stock Exchange for herd behavior before, during and after the Asian crisis of 1997. Results indicate that foreign investors herd more than local investors. Furthermore, foreign herding increased more following the crisis, while local herding did not increase and diminished in the post-period following the crisis. Interestingly, domestic herding was positively connected to firm size. Foreign herding had no connection to firm size.

Saumitra and Siddharth (2013) looked into the Indian stock market after evidence of herd behavior between 2003 and 2008. Empirical results gave support to the fact that the Indian stock market investors are affected by herd behavior, since during times of extreme price movements, stock return dispersions tended to decrease rather than increase. Moreover, the authors found that herd behavior was more pronounced during major crashes.

From a European perspective, Gleason et al. (2003) and Gleason et al. (2004) studied the European commodity market and the European exchange of Exchange Traded Funds (ETFs). The overall findings were in favor of rational asset pricing and market efficiency and as a result, herd behavior was determined to not be an issue in the European market during times of price fluctuations and market stress.

Economou et al. (2011) examined herd behavior in the Portuguese, Italian, Spanish and Greek markets. The authors found that herd behavior was mainly present in the Greek and the Italian market, while evidence was mixed for the Spanish and Portuguese counterpart. An important

discovery made was the fact that markets showed significant degree of co-movement between these four markets.

Henker et al. (2006) investigated the presence of herd behavior in the Australian stock market between 2001 and 2002 using intraday data on the 160 most actively traded stocks. The empirical results gave no support of herd behavior tendencies in the Australian stock market when applying intraday data, both on market level as well as on sector level. In accordance with their findings, the authors concluded that information is communicated efficiently to market participants in the Australian stock market.

Chang (2010) set out to examine the relationship between herding and foreign institutions in emerging stock markets and determined that there is herd behavior present in these markets. Taking a different approach compared to Chang et al. (2000), the author investigate what he classifies as key players in the financial market, specifically foreign institutions, dealers, margin traders, and mutual funds. Instead of the applying the same research methodology as to Chang et al. (2000) two tests based upon the order flow and overshooting were computed as this enables a more closer tracking of individual actors. Results show that they trade closely connected and that foreign institutions seem to lead the way.

Kim et al. (2004) looked for herd behavior in the Korean stock market and the foreign exchange market and indeed found herding tendencies in both the won-dollar market and the equity market. However, the authors debated that further analysis is necessary to determine the true level of herding in the Korean financial market.

Nakagawa et al. (2012) studied the Japanese loan market for evidence of herd activities among market participants and the potential impact to the economy as whole. First, it was reported that Japanese financial institutions followed herd behavior across different types of financial institutions. Secondly, it was observed that herd behavior by financial institutions generated negative correlation with the GDP and land prices for several periods. As an interpretation of these results, the authors argued that the unstable correlation between herding and the economy might imply that loans made by herding of financial institutions could cause inefficiency of financial markets and destabilizing the real economy in the form of decline in GDP and land prices.

Boyson (2010) investigated reputational herding among hedge fund managers between 1994 and 2004. As an underlying hypothesis, career progression by hedge fund managers is used as

a motivation. Furthermore, the author argues that senior managers that deviate from the herd have a higher probability of failure than their less-senior counterparts and do not experience higher fund inflows. These incentives should encourage managers to herd more as their careers progress. The evidence gives wide attribution to this hypothesis as experienced managers were found to herd more than less-experienced managers.

Regarding the information based herding hypothesis, Spiwoks et al. (2008) took an experimental approach when connecting information signaled by markets actors to herd behavior. The corollary from the empirical laboratory experiment gave support to the fact that subjects showed propensity to herd and base their actions given signals from other research subjects.

To briefly summarize our literary review. There seems to be a scientific consensus that herding is more likely to occur during large market movements and in undeveloped markets. Therefore, this thesis will only search for herding during great price fluctuations and further investigate the differences between developed and undeveloped markets.

4. Methodology

Section four presents the methodology used in this study of herd behavior. Furthermore, we present the data, investigated sample and how the data was treated. The model for studying herd behavior is also presented to the reader. Section four ends with a brief discussion about variables in the model.

4.1 Data Collection

The sample constitutes of daily price changes for each share gathered from four stock markets. The stock markets used are located in Hong Kong, Brazil, Sweden and Switzerland. Relating to the article by Chang et al. (2000), this study will narrow in on one factor; cross-sectional absolute deviation. The sample constitutes of both overall stock market performance as well as individual firm performance. Our base sample includes 2.873.831 daily returns.

Historical daily stock market data and other financial data essential for the statistical analysis and modeling were gathered from *Bloomberg*¹. This was done for all four markets included in this thesis. Furthermore, adjusted historical closing prices were used since this would clearly circumvent the issue concerning stock splits and dividends.

Our samples only include stocks that were actively traded in April 2014, this is true for all markets investigated. This approach made it easier and more time efficient to obtain reliable data in a large quantity. This method makes our base sample smaller the further back we go in time. We were concerned that the dilution of stocks would affect the derived variables. However, we had a limit at a minimum of 40 stocks in any given time frame. At this level our sample had no significant relationship between the amount of stocks included and the degree of extreme values for our variables. Therefore, we think that our approach gave reliable data which can be used to infer the conditions of the markets examined and thus produce a comprehensive analysis which will open doors for further research. Although our sample is not a perfect mirror of the underlying markets examined.

In the dataset collected from Bloomberg, the observations for any give stock was typically either perfect or totally erroneous when compared to other sources². Observations were deleted if they did not match the actual price movements. Stocks in our sample that had ten or more errors were removed from the analysis.

¹ Bloomberg Professional service. Data Wizard for excel. Historical prices.

² www.finance.yahoo.com, www.avanza.se, Thomson Reuters Datastream.

4.2 Description of stock markets

A brief description over the stock markets used in this study is outlined below. The markets are selected with the intention to reflect the market performance for each country to as great extension as possible. The choice of which markets to include are influenced by the research questions posed in the introduction to this thesis, where two emerging markets are compared to two developed markets. The stock markets are as follows:

The Hong Kong Stock Exchange³ (SEHK) is one of largest stock exchanges in Asia in terms of market capitalization and market participants. Data gathered from SEHK yields a good overview of the market performance in Hong Kong. Consequently, data from 388 stocks were downloaded.

BM&F Bovespa⁴ found in Sao Paulo, is the primary stock exchange for Brazilian stocks. As one of the largest stock markets in the South American region it will serve as a good indicator regarding the market development in Brazil. In the light of this, data relating to 195 companies were acquired.

SIX Swiss Exchange⁵ housed in Zurich is the foremost stock exchange in Switzerland. Stock data gathered from this stock exchange will be used as a proxy over market performance in Switzerland. A sample consisting of 177 Swiss shares were collected.

NasdaqOMX Nordic Stockholm⁶ is the leading stock exchange in the Nordic region in terms of market capitalization and listed companies. The development of the stocks traded at SSE will thus provide a sound summary of the overall market performance in Sweden. Stock data from 250 Swedish stocks were used.

Throughout this thesis, we will refer to each stock market by the country in which it is located.

4.3 Specification of the main model

The model used for investigating herd behavior in the different financial markets is a standard multivariate regression model which aim to control for cross-sectional absolute deviation

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³ www.hkex.com.hk/eng/index.htm

⁴ www.bmfbovespa.com.br/en-us/home.aspx?idioma=en-us

⁵ www.six-swiss-exchange.com/index.html

⁶ www.nasdaqomxnordic.com/

(CSAD). This approach is influenced by the work Chang et al. (2000). CSAD is a non-linear approach to investigate the relation between the level of equity return dispersions and the general market return. Only data during extreme market movements are included in the regressions, since large price movement is considered a catalyst for herding and market irrationality (Forbes, 2009:221-34, Chen et al. 2003, Gyllenram, 2001:94-106, Guo and Shih, 2008). Moreover, if we were to add all observations in the regression and CSAD is increasing at an increasing rate during small market movements, this could hamper our ability to find an increase at a decreasing rate during large market movements. We will study both the highest and lowest 5% and 10% market returns for each market. As the regression model will be performed on both extreme market advances and market declines the two market conditions will be compared to each other.

4.4 Cross-sectional absolute deviations

The measure used in this thesis employs a strategy concerning absolute deviation of returns. CSAD is calculated as follows:

$$CSAD_t = \frac{1}{N} \sum_{i=1}^{N} |r_{i,t} - r_{m,t}|$$
 Eq. 1

where $r_{i,t}$ is the observed return on firm i at time t and $r_{m,t}$ is the equally weighted average market return and N is the total amount of firms in the sample. Chang et al. (2000) argues that one could expect the return dispersion to be a non-linearly increasing function of absolute market returns. But during herding, investors will ignore their own believes and instead try to follow the market consensus. This will cause the return dispersion to decrease or increase at a decreasing rate. This is a clear challenge to the CAPM assumption that return dispersions are an increasing function of the market return and that this relationship is a linear one. The following regression model will be used:

$$CSAD_t = \alpha + \gamma_1 |r_{m,t}| + \gamma_2 r_{m,t}^2 + \varepsilon_t$$
 Eq. 2

where α is the intercept, γ_1 the coefficient for the absolute equally weighted market return and ε_t is the customary error-term, γ_2 is the coefficient for the squared equally weighted market return and will show the non-linear relationship between CSAD and the market. Herd behavior in this model would be indicated by lower or less than proportional increase in the CSAD in times of extreme movements in the market. Accordingly, the non-linear coefficient γ_2 will be negative and statistically significant. A γ_2 that is not negative and statistically significant would imply no evidence of herding behavior. A positive γ_2 would indicate that

the dispersion is increasing at an increasing rate, which is to be expected in during normal market conditions, while a γ_2 that equals zero indicates a linear relationship, in parity to the CAPM, between the dispersion and the market return (Chang et al. 2000).

5. Data description

In section five we present the empirical results for each stock market investigated. Graphs and descriptive statistics are provided with interpretations.

5.1 Descriptive statistics

The descriptive statistics of the variables used in this study are presented below. Table 1 depicts daily average mean, standard deviation, maximum and minimum value together with an overview of the serial correlation lags and the Dickey-Fuller test.

Table 1 – Descriptive statistics

Summary statistics of returns (r_{mt}) and cross-sectional absolute deviation $(CSAD_t)$ for Brazil, Hong Kong, Sweden, Switzerland and our Dot-com analysis.

Market/ variables	Sample period (number of	Number of stocks	Mean (%)	S.D (%)	Maximum (%) (Date)	Minimum (%) (Date)	Serial cor	relation at	lag			
	observations)	included	(, -,		(====)			2	3	5	20	DF-test
<u>Brazil</u>	11/01/94-14/04/14	195										
$r_{m,t}$	(5011)		0,1486	1,8551	18,7574 (15/1/99)	-13,9301 (10/9/98)	0,1448	0,0245	0,0164	0,0004	0,0511	-61,166*
$CSAD_t$			2,0018	0,87	24,32394	0,61685	0,4738	0,4335	0,3942	0,3649	0,3395	-42,283*
Hong Kong	01/04/86-14/04/14	388										
$r_{m,t}$	(6944)		0,0838	1,6663	12,6956 (27/01/98)	-36,2135 (10/10/87)	0,1219	0,0313	0,0635	0,0018	0,0151	-73,709*
$CSAD_t$			2,6238	1,3366	18,3192	0,2624	0,5982	0,5373	0,5241	0,4994	0,4293	-41,773*
Sweden	02/01/90-14/04/14	250										
$\overline{r_{m,t}}$	(6098)		0,06375	1,1555	10,1295 (20/11/92)	-7,6072 (11/09/01)	0,1738	0,06	0,0238	0,0279	0,0013	-65,498*
$CSAD_t$			1,8458	0,7198	10,6493	0,1221	0,7284	0,6974	0,6698	0,6574	0,5593	-30,939*
Switzerland	24/10/89-14/04/14	177										
$r_{m,t}$	(6154)		0,0438	0,8114	5,8534 (13/10/08)	-5,5205 (28/10/97)	0,2246	0,1518	0,0843	0,0853	0,0644	-62,387*
$CSAD_t$			1,6561	0,5699	7,8156	0,031	0,7229	0,6926	0,6748	0,6504	0,5673	-31,446*
Dot-com	02/01/98-28/12/2001	153										
$r_{m,t}$	(1003)		0,0534	1,2730	7,7787	-7,6072	0,1846	0,0206	0,0672	-0,0412	-0,0267	-26,202*
$CSAD_t$			2,3352	0,6574	5,8346	0,7229	0,7071	0,6765	0,6302	0,6067	0,4104	-13,100*

This table reports the daily mean, standard deviation, and the maximum and minimum values of returns $(r_{m,t})$ and the Cross-sectional absolute deviation $(CSAD_t)$ for each sample period for all countries including our dot-com analysis. It also contains the number of stock included from each market and the date of the most extreme market up and down movement. In addition, the serial correlation of $r_{m,t}$ and $CSAD_t$ is reported for lags 1, 2, 3, 5 and 20 along with the t-stat of the Dickey-Fuller test.

^{*} Significant at the 1% level.

From table 1 several conclusions can be drawn. First, the market with the highest daily average market return is the Brazil stock market, reporting a daily average of 0.15%. The Swiss stock market had the lowest return, with an average daily return of 0.04%. Standard deviation was found to have a wide spread during the investigated time period. The largest standard deviation was found in the Hong Kong market, 1.66, while the Swiss market has a corresponding standard deviation of 0.81. Efficiency increases with economic development and developed markets should be more efficient in terms of market infrastructure, openness to foreign investments and regulation (Chang et al. 2000). Hence, it is reasonable that the Swiss market has both the lowest daily average return together with the fact that it has the lowest standard deviation.

Second, looking at the maximum values for the sample we can establish that the Brazilian market has the highest maximum market return on one day during the sample period with a value of 18.75%. Hong Kong market had the second highest maximum value of 12.69%, while the Swedish and Swiss stock market reported the lowest maximum value with the corresponding values of 10.12% and 5.85%.

Looking at extreme negative values for market movement in our sample, Hong Kong stands out with a one day market crash of above 36%. This occurred on what has been labeled the Black Monday. This historical global market crash occurred in October 1987 and had its epicenter in Hong Kong. While a lot of research has been done, no clear reason has been singled out as the origin of the crash. Overvaluation caused by speculation leading up to the crash has been suggested as a likely cause (Sornette, 2002).

Other extreme values in the dataset were the terrorist attack of September 11th for Sweden and the Global mini-crash of 1997 for Switzerland. Brazil saw its greatest one day fall on 10th September 1998, caused by capital flight from foreign investors due to huge currency fluctuation and fueled by an enormous budget deficit for the Brazilian government as reported on CNN Money (1998).

Briefly commenting on the CSAD statistics, the highest averages is found in the emerging markets. This is true for standard deviation and maximum values as well.

For each market CSAD seems to be highly autocorrelated with an average first order autocorrelation of 0.63. Because of this, all coefficient standard errors throughout this thesis are adjusted for autocorrelation and heteroscedasticity with the method presented by Newey and West (1987) to mitigate any concern related. Failing to account for serial correlation would make our results unreliable. Moreover, the Dickey-Fuller test indicates that both market returns and CSAD follows a stationary process. The high degree of significance in stationarity shown for market returns are in line with Malkiels (1973) discussion in *a random walk down Wall Street* that stock markets follow a random walk. But as further explained in section six, price movements in stock markets appear to be less "random" than Malkiels would suggest at the time when his classical book was published.

5.2 Graphs of CSAD and market return

We included graphs to illustrate the relationship between CSAD and market returns for developed versus undeveloped markets. Figure 1 includes a scatterplot for the Swiss market and figure 2 for the Hong Kong market. (The same scatterplots for Switzerland and Sweden can be found in the appendix.) We see that in the emerging market the dispersion is greater relative to the developed market were CSAD values are more clustered and centric. Furthermore, this also becomes apparent when looking at slopes in up-market and downmarket in each country. Hong Kong has a far steeper slope than the Swiss market has. Moreover, the distribution of the developed market tends to exhibit a clearer "V" or heart looking-pattern as the dispersion increases with greater market movements.



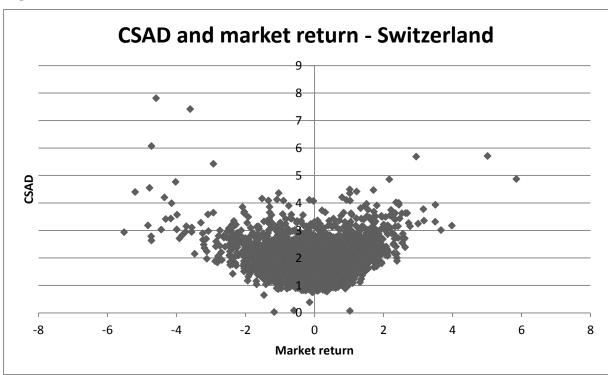


Figure. 1. Relationship between the daily cross-sectional absolute deviation (CSAD) and the corresponding equally-weighted market return for Switzerland (24/10/89-14/04/14)

Figure 2

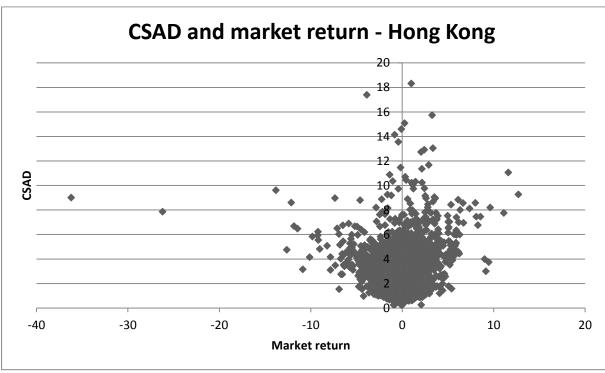


Figure. 2. Relationship between the daily cross-sectional absolute deviation (CSAD) and the corresponding equally-weighted market return for Hong Kong (01/04/86-14/04/14)

6. Regression results and analysis

In this section we analysis the results obtained for each market and try to distinguish if there are tendencies of herd behavior in the markets. First, we interpret the regression results. Second, we analyze if there is any difference in behavior in up-market compared to downmarket and survey the cross-country comparison. Finally, we analyze the dot-com bubble.

6.1 Interpretation of the regression results

In table 2 we find our regression results for Hong Kong. The γ_2 parameter is negative and highly significant during market decline. This means that during extreme market movement the dispersion is increasing at a decreasing rate, indicating that investors are suppressing their own believes and following the market consensus. Hence, they are herding.

Table 2 - Hong Kong
Regression results of the daily cross-sectional absolute deviation on the linear and squared term of the market portfolio. Values are reported for up and down market at the extreme 5 and 10 percent.

	α	γ ₁	γ ₂	R^2	F	Observations
5% extreme market advance	2.529573***	.4876042**	.0018294	0.1353	27.78	348
10% extreme market advance	1.711969***	.7954465***	0213527	0.1764	68.39	695
5% extreme market decline	1.716628***	.5021971***	0086754***	0.2502	83.27	348
10% extreme market decline	1.805405	.4777475***	0079649***	0.2217	127.16	695

This table reports the estimated coefficients of the following regression model:

 $CSAD_{t} = \alpha + \gamma_{1} |r_{m,t}| + \gamma_{2} r_{m,t}^{2} + \varepsilon_{t}$

where $r_{m,t}$ is the absolute value of an equally-weighted realized return of all available securities on day t and $r_{m,t}^2$ is the squared value of this term. A negative $r_{m,t}^2$, or and increase at a decreasing rate, would according to our model imply herding. Standard errors are robust.

The results from our regressions for Brazil are listed in table 3. Just as in Hong Kong we find a significant negative γ_2 during market decline but no significant γ_2 during market advance. In fact, in Brazil there is no suggestion of herding during market advance.

Table 3 - Brazil
Regression results of the daily cross-sectional absolute deviation on the linear and squared term of the market portfolio. Values are reported for up and down market at the extreme 5 and 10 percent.

	α	γ_1	γ_2	R^2	F	Observations
5% extreme market advance	1.621663***	.3034306	.015432	0.3073	8.04	251
10% extreme market advance	1.705431***	.2834208***	.0164073	0.3259	14.51	501
5% extreme market decline	1.461644***	.3452974***	0109215	0.1109	18.52	251
10% extreme market decline	1.196853***	.4310426***	0166396**	0.1955	55.75	501

This table reports the estimated coefficients of the following regression model:

 $CSAD_{t} = \alpha + \gamma_{1} |r_{m,t}| + \gamma_{2} r_{m,t}^{2} + \varepsilon_{t}$

where $r_{m,t}$ is the absolute value of an equally-weighted realized return of all available securities on day t and $r_{m,t}^2$ is the squared value of this term. A negative $r_{m,t}^2$, or and increase at a decreasing rate, would according to our model imply herding. Standard errors are robust. Number of observations and F-statistics is also reported.

^{*} Significant at the 10% level

^{**} Significant at the 5% level

^{***}Significant at the 1% level

^{*} Significant at the 10% level

^{**} Significant at the 5% level

^{***}Significant at the 1% level

In table 4 we have the results of the Switzerland regressions. The Swiss market does display negative γ_2 parameters but they are insignificant. Hence, our results suggest that there is no herding on the Swiss stock exchange.

Table 4 - Switzerland
Regression results of the daily cross-sectional absolute deviation on the linear and squared term of the market portfolio. Values are reported for up and down market at the extreme 5 and 10 percent.

	α	γ ₁	γ ₂	R^2	F	Observations
5% extreme market advance	1.08223***	.8994253***	0360358	0.3120	55.40	308
10% extreme market advance	1.004108***	.9578044***	0450545	0.3336	117.18	616
5% extreme market decline	1.392136***	.3725168	.0381332	0.3126	28.32	308
10% extreme market decline	1.539489***	.263362	.0554999	0.2744	52.28	616

This table reports the estimated coefficients of the following regression model:

 $CSAD_{t} = \alpha + \gamma_{1} |r_{m,t}| + \gamma_{2} r_{m,t}^{2} + \varepsilon_{t}$

where $r_{m,t}$ is the absolute value of an equally-weighted realized return of all available securities on day t and $r_{m,t}^2$ is the squared value of this term. A negative $r_{m,t}^2$, or and increase at a decreasing rate, would according to our model imply herding. Standard errors are robust. Number of observations and F-statistics is also reported.

Regression results for Sweden are shown in table 5. Interestingly, Sweden does show signs of herding in both up and down markets. The results are only weakly significant. The suggestion of herding during market advance is, as we shall see later on, driven to a large extent by the occurrences during the dot-com bubble.

Table 5 - Sweden

Regression results of the daily cross-sectional absolute deviation on the linear and squared term of the market portfolio. Values are reported for up and down market at the extreme 5 and 10 percent.

	α	γ_1	γ_2	R^2	F	Observations
5% extreme market advance	1.038494**	.9253935***	0462952	0.2926	32.91	305
10% extreme market advance	1.091314***	.9026366***	0442853*	0.3426	71.43	610
5% extreme market decline	.6941594	.8851673***	0619396*	0.1670	18.35	305
10% extreme market decline	1.250126***	.5533809***	0267629	0.1906	34.07	610

This table reports the estimated coefficients of the following regression model:

 $CSAD_{t} = \alpha + \gamma_{1} |r_{m,t}| + \gamma_{2} r_{m,t}^{2} + \varepsilon_{t}$

where $r_{m,t}$ is the absolute value of an equally-weighted realized return of all available securities on day t and $r_{m,t}^2$ is the squared value of this term. A negative $r_{m,t}^2$, or and increase at a decreasing rate, would according to our model imply herding. Standard errors are robust. Number of observations and F-statistics is also reported.

^{*} Significant at the 10% level

^{**} Significant at the 5% level

^{***}Significant at the 1% level

^{*} Significant at the 10% level

^{**} Significant at the 5% level

^{***}Significant at the 1% level

6.2 Comparing up-market with down-market

Comparing our results from an up-market and down-market perspective, we find that herd behavior are more profound in markets where price movements are decreasing. This result is in accordance with previous studies showing that during times of great negative market movements, such as the financial crisis of 2008 and dotcom-crash etc. there is great uncertainty about the fundamental underlying value of an asset (Lux, 1995). Naturally, this is mirrored by our results as well. Examining the difference across our markets, we find that in a down-market the Hong Kong stock market together with its Brazilian counterpart was affected to a greater extent than the more developed markets. During up-market movements, the result is generally found to be insignificant across markets.

6.3 Cross-country comparison

Overall herding in the emerging markets are found to be more statistical significant than their developed counterparts. The Hong Kong market is the market with the highest statistical significant coefficients. The Brazilian stock market is second in terms of significant γ_2 coefficient and is significant at the 5% level. Ranked third is Sweden, which only shows weak significance (10% level). Lastly, Swiss stock market has no statistical significant estimated γ_2 coefficients. This indicates that herd behavior is less of an issue in developed markets. This is consistent with what other studies have shown. For example, Chang et al. (2000) gave broad support to the fact that herd behavior is more severe and persistent in emerging market than developed ones. Similar findings are reported by Saumitra and Siddharth (2013). Chang et al. (2000) argues one possible reason why emerging markets are more afflicted by herd behavior is that they are less efficient in terms of financial regulation, infrastructure and openness to foreign capital. Thus, the quality of information transferred between investors about the underlying value of the assets is less adequate and more uncertain relative to developed markets, where appropriate infrastructure exists and the uncertainties tends to be reduced.

6.4 The dot-com bubble

The dot-com bubble is regarded as one of the most spectacular equity market boom-bust in modern history. The period was distinguished by rapid growth in the information technology sector and related fields until ending a few years later with massive capital losses (Graham et al., 2006: 12).

As a new market emerged of commercial websites and information technology, capital flooded as investors anticipated unprecedented opportunity to invest in startups that would flourish in a new sector (Graham et al., 2006: 530). This lead to a deluge of IPOs during the dot-com bubble (Graham et al., 2006: 143).

At this time, many investors believed in a concept that in hindsight (partly misnomer) has been labeled "the new economy" in which the profit of a firm had lesser importance to the valuation (Graham et al., 2006: 15-16). A new market had opened and one of the most crucial things was to "be first" with a certain business idea in order to reap the first mover's advantage and tie customers who somewhere in the future could generate earnings.

We wanted to explore this epoch further and therefor chose to perform our CSAD-analysis on OMX Stockholm during this period specifically. The dot-com bubble is viewed to have had a big impact on the Swedish stock market, with a high level of speculation in tech and internet firms such as Boo.com, Framfab and Ericsson among many others (Lindstedt, 2012). At the height of the bubble, OMX Stockholm PI⁷ had a value of above 413, less than 3 years later OMX Stockholm PI was down below 125. Besides, the Stockholm stock exchange did not display herding at a 5% level of significance for the whole time period from early 1990 until 14th April 2014. Comparing the results from our analysis could form a good example about what was distinctive for the period during the dot-com bubble.

In our analysis of the dot-com bubble we choose the time-period between 1998 and 2002 since this is regarded as the pinnacle of the dot-com bubble (Browne and Walden, 2008). Moreover, this period was chosen since we want a restricted sample for comparison with the unrestricted sample.

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⁷ The OMX Stockholm PI (OMXSPI) is a stock market index of all shares that are traded on the Stockholm Stock Exchange.

The results from our regressions are displayed in Table 6. We found strong indication of herding when the market was advancing. We found weak significance when measuring the 10% most extreme market advances. When measuring the 5% most extreme market gains we found herding at a significance of the 5% level as oppose to the whole time period, which showed no statistical significant confirmation of herding at the 5% level of significance. Moreover, the coefficient indicating herding was the highest (-0.0704) in absolute terms in all of our regressions. Theses observerations leads us to conclude that the market activity and behavior of investors during the dot-com bubble was divergent from the market behavior in our total sample period of 1990 unto the early 2014.

Table 6 - Dot-com bubble
Regression results of the daily cross-sectional absolute deviation on the linear and squared term of the market portfolio. Values are reported for up and down market at the extreme 5 and 10 percent.

	α	γ_1	γ_2	R^2	F	Observations
5% extreme market advance	.8945987	1.18731***	070387**	0.5267	332.58	51
10% extreme market advance	1.479854***	.8821618***	0387883*	0.5121	168.41	101
5% extreme market decline	2.435954***	.0875375	.0265203	0.2642	33.15	51
10% extreme market decline	1.850262***	.3941598*	0063756	0.2891	25.36	101

This table reports the estimated coefficients of the following regression model:

 $CSAD_{t} = \alpha + \gamma_{1} |r_{m,t}| + \gamma_{2} r_{m,t}^{2} + \varepsilon_{t}$

where $r_{m,t}$ is the absolute value of an equally-weighted realized return of all available securities on day t and $r_{m,t}^2$ is the squared value of this term. A negative $r_{m,t}^2$, or and increase at a decreasing rate, would according to our model imply herding. Standard errors are robust. Number of observations and F-statistics is also reported.

An intresting thing with our dot-com analysis is that there were no signs of hering during market decline, as opposed to our emerging markets which only showed signs of hearding when the market was weakening. In the most extreme market declines of 5%, our reggression implies an increase in dispersion at an increasing rate. Throughout the 10% most extreme market declines the regression does indicate an increase in dispersion at an decreasing rate, but the squared market coefficient has a P-value of 0.788 - which makes it rather insipid. In conclusion, our model shows no inclination that herding took place during one of the greatest stock market declines in recent history of the Stockholm stock exchange.

We wanted to point mark the exact occurenses during the boom of the dot-com bubble and the bust. Therefore we performed two new regressions. One in which we only used data from the boom of the dot-com bubble and one in which we only used data during the bust of the dot-com bubble. The time period of the market boom was selected from the beginning of 1998 unto the 6th of Mars 2000, when OMX Stockholm PI peaked. The period of the bust was chosen

^{*} Significant at the 10% level

^{**} Significant at the 5% level

^{***}Significant at the 1% level

from 6th of Mars 2000 until the end of 2002, when the maket had begun to level out and recover.

The results, shown in Table 7, are consistent with our previous findings. There is significant herding upwards when the market was booming, as the negative γ_2 coefficient confirms, but no significant herding downwards when the bubble was eroding. The value of the γ_2 coefficient in the boom analysis, just as in our previous regression, was sizeable (even greater). The same coefficient in the bust regression was lower in absolute terms and insignificant.

Table 7 - Dot-com boom bust
Regression results of the daily cross-sectional absolute deviation on the linear and squared term of the market portfolio. Values are reported for up and down market at the extreme 5 and 10 percent.

	α	γ_1	γ ₂	R^2	F	Observations
Boom						
5% extreme market advance	.7912976	1.255504 **	0782083	0.4943	205.00	28
10% extreme market advance	.8412725*	1.232937 ***	0761803**	0.5124	448.17	55
Bust						
5% extreme market decline	1.279216	.8508676 **	0527406	0.3965	17.02	36
10% extreme market decline	1.855281***	.5761922**	025106	0.3846	41.22	71

This table reports the estimated coefficients of the following regression model:

 $CSAD_{t} = \alpha + \gamma_{1} |r_{m,t}| + \gamma_{2} r_{m,t}^{2} + \varepsilon_{t}$

where $r_{m,t}$ is the absolute value of an equally-weighted realized return of all available securities on day t and $r_{m,t}^2$ is the squared value of this term. A negative $r_{m,t}^2$, or and increase at a decreasing rate, would according to our model imply herding. Standard errors are robust. Number of observations and F-statistics is also reported.

Our model does not falsify that during this massive loss of the asset value, investors could have acted with value judgement of each security and independently from the expected actions of other investors. However, our sample does not include all stocks that were traded at OMX Stockholm at the time and the sample only consist of stocks that also were traded during 2014. Thus, excluding several companies that has been merged, acquired or gone bankrupt since. Herding during the bust of the dot-com bubble in the Stockholm stock exchange remains an intresting field for future studies.

^{*} Significant at the 10% level

^{**} Significant at the 5% level

^{***}Significant at the 1% level

7. Conclusion

In section seven we conclude our thesis, define our contribution and present additional suggestions concerning further research topics.

7.1 Conclusion

We find evidence for herd behavior in emerging markets while there is little support of herd activity in developed markets. Furthermore, our results show that herd behavior increases in severity in emerging markets compared to advanced economies. This is in line with what other studies have found, Chang et al. (2000) and Saumitra and Siddharth (2013). Naturally, during periods of extreme market movements there is uncertainty about the value of an asset. Our results clearly indicate this as we find that return dispersion increase at a decreasing rate during periods of market turmoil. Moreover, this is true only for the emerging markets Hong Kong and Brazil. The developed markets only demonstrate weak evidence at most in our full-scale analysis, implying that herd behavior is not a significant issue. However, the historical events during the dot-com bubble clearly contradict the perception that developed markets are totally efficient and free from herding.

An important investment implication of our results is that an investor should use a larger set of stocks to achieve the same level of diversification in a market were participants herd.

7.2 Contribution

This thesis set out to investigate and contribute to the existing literature by narrowing in and illuminating on the herd behavior found inside different stock markets. Moreover, since the growing importance of emerging markets and their ever increasing role in the global financial market, it is sensible to include these kinds of markets into our analysis. We try to fill the gap in this thesis by including both stock markets that are considered to be mature and stock markets that are considered to be developing. In addition, the existing literature regarding the region of Latin America is weak at most. By incorporating this interesting part of the world into our analysis, we believe that this will shed more light on what role herd behavior play in stock markets.

7.3 Suggestions for future research

Previous studies have focused on market returns as a variable for measuring and assessing herd behavior. Admittedly, there are more interesting variables that could provide additional information. Variables constructed around the bid-ask spread or turnover volume might be suitable candidates for such application. The advantage of using either of these variables are similar to stock market return. The data is easily accessible. Furthermore, it is possible to incorporate more markets in the analysis and expand on the idea that developing markets should show greater tendencies of herd behavior than developed ones. Such expansion could yield good insight into different market characteristics among the stock markets in different regions. A third approach could be in the shape of an industry sector analysis where all the stocks are categorized in its corresponding industry sector. This approach would be more detailed since it is possible to investigate individual categories of stocks and derive potential herd behavior more specifically than an overall market analysis. Arguably a great deal of information of stock behavior is lost when performing a top-down approach. This would be mitigated using the bottom-up methodology. We found strong herding indications during the dot-com boom but none at dot-com bust; however we would like to suggest a more comprehensive study on this epoch of financial history. Herd behavior is both an intriguing and fascinating aspect of human behavior which requires further studies.

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Appendix

In this appendix we provide full regression statistics for all of our regressions. The following abbreviations were used:

mar: Market returns

mara or m: Absolute market returns mar2 or m2: Squared market returns

csad or c: Cross-sectional absolute deviation

l: extreme low market movement h: extreme high market movement

f: The 5% most extreme up or down market movement

t: The 10% most extreme up or down market movement

Regression results for Brazil

Linear	regression	Numl	oer	of ob	s =	501
		F(2,	498) =	55.75
		Prol	> >	F	=	0.0000
		R-s	quar	ed	=	0.1955
		Door	- 1/10	177	_	0 6 0 0 1

csadxlt	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
maraxlt	.4310426	.0776508	5.55	0.000	.278479	.5836062
mar2x1t	0166396	.0073388	-2.27	0.024	0310585	0022207
_cons	1.196853	.1505695	7.95	0.000	.901023	1.492682

Linear regression	Number of obs =	251
	F(2, 248) = 1	8.52
	Prob > F = 0.	0000
	R-squared = 0.	1109
	Root MSE = 1.	0658

csadxlf	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
maraxlf	.3452974	.1111492	3.11	0.002	.1263807	.5642142
mar2x1f	0109215	.0085578	-1.28	0.203	0277767	.0059337
_cons	1.461644	.3076292	4.75	0.000	.8557454	2.067543

T. (Number of obs		502
Linear regression	Number of obs	=	302
	F(2, 499)	=	14.51
	Prob > F	=	0.0000
	R-squared	=	0.3259
	Root MSE	=	1.3589

csadxht	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
maraxht	.2834208	.109555	2.59	0.010	.0681749	.4986668
mar2xht	.0164073	.0113948	1.44	0.151	0059803	.038795
_cons	1.705431	.2513376	6.79	0.000	1.21162	2.199241

Linear regression	Number of obs =	251
	F(2, 248) =	8.04

= 0.0004 Prob > F = 0.3073 R-squared Root MSE = 1.7571

csadxhf	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
maraxhf	.3034306	.1845274	1.64	0.101	0600101	.6668714
mar2xhf	.015432	.0118976	1.30	0.196	0080012	.0388651
_cons	1.621663	.5757661	2.82	0.005	.4876475	2.755678

Regression results for Hong Kong

Linear regression

Number of obs = F(2, 692) = 127.16 Prob > F = 0.0000 R-squared = 0.2217 = 1.3184 Root MSE

clt	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
mlt	.4777475	.0488946	9.77	0.000	.3817479	.5737471
m21t	0079649	.0013826	-5.76	0.000	0106795	0052503
_cons	1.805405	.1256404	14.37	0.000	1.558723	2.052087

Linear regression Number of obs =

F(2, 345) = 83.27Prob > F = 0.0000= 0.0000 = 0.2502 R-squared = 1.4105 Root MSE

clf	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
mlf	.5021971	.0648441	7.74	0.000	.3746576	.6297365
m21f	0086754	.0017752	-4.89	0.000	012167	0051838
_cons	1.716628	.2148013	7.99	0.000	1.294143	2.139113

Linear regression

Number of obs = 695F(2, 692) = 68.39Prob > F = 0.0000R-squared = 0.1764Root MSE = 1.7192

cht	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
mht	.7954465	.1559251	5.10	0.000	.4893035	1.101589
m2ht	0213527	.0164127	-1.30	0.194	0535774	.0108721
_cons	1.711969	.2838591	6.03	0.000	1.15464	2.269297

Linear regression Number of obs = Number of obs = 346 F(2, 345) = 27.78 Prob > F = 0.0000 R-squared = 0.1353 Root MSE = 1.965

Robust chf Coef. Std. Err. t P>|t| [95% Conf. Interval] .4876042 .0581313 mhf .2183541 2.23 0.026 .917077 .0018294 -.0355435 .0392023 m2hf .0190013 0.10 0.923 .5285584 2.529573 4.79 0.000 1.489971 3.569176 _cons

Regression results for Sweden

C					
Linear regress	sion				Number of obs = 610 F(2, 607) = 34.07 Prob > F = 0.0000 R-squared = 0.1906 Root MSE = .78914
csadxlt	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]
maraxlt mar2xlt _cons	.5533809 0267629 1.250126			0.000 0.162 0.000	.2914471 .8153147 0642856 .0107599 .8965849 1.603666
Linear regress	sion				Number of obs = 305 F(2, 302) = 18.35 Prob > F = 0.0000 R-squared = 0.1670 Root MSE = .9204
csadxlf	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]
maraxlf mar2xlf _cons	.8551673 0619396 .6941591	.3065006 .0374552 .5131037	2.79 -1.65 1.35	0.006 0.099 0.177	
. reg csadxht	maraxht mar2	xht, robust			
Linear regress	sion				Number of obs = 610 F(2, 607) = 71.43 Prob > F = 0.0000 R-squared = 0.3426 Root MSE = .84601
csadxht	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]
maraxht mar2xht _cons	.9026366 0442853 1.091314	.1646644 .0248079 .2119268	5.48 -1.79 5.15		093005 .0044344
Linear regress	sion				Number of obs = 305 F(2, 302) = 32.91 Prob > F = 0.0000 R-squared = 0.2926 Root MSE = .97984
csadxhf	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]
maraxhf mar2xhf _cons	.9253935 0462952 1.038494		3.45 -1.37 2.39	0.001 0.170 0.017	.3982913 1.452496 1125834 .019993 .1840125 1.892975

Regression results for Switzerland

Linear regression	Number of obs =	616
	F(2, 613) =	52.28
	Prob > F =	0.0000
	R-squared =	0.2744
	Root MSE =	.65353

csadxlt	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
maraxlt	.263362	.1904141	1.38	0.167	1105812	.6373052
mar2xlt	.0554999	.0463929	1.20	0.232	0356083	.1466082
_cons	1.539489	.171789	8.96	0.000	1.202123	1.876855

Linear regression Number of obs = 308

Number of obs = 308 F(2, 305) = 28.32 Prob > F = 0.0000 R-squared = 0.3126 Root MSE = .69955

csadxlf	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
maraxlf	.3725168	.3499493	1.06	0.288	3161038	1.061137
mar2x1f	.0381332	.0687363	0.55	0.579	0971242	.1733905
_cons	1.392136	.4049688	3.44	0.001	.5952491	2.189022

Linear regression Number of obs = 616

F(2, 613) = 117.18 Prob > F = 0.0000= 0.3336 = .57225 R-squared Root MSE

Robust csadxht Coef. Std. Err. P>|t| [95% Conf. Interval] .9578044 .1309993 7.31 0.000 .7005426 maraxht -.0450545 .0294022 -1.53 0.126 -.1027957 mar2xht 1.004108 .1217092 8.25 0.000 .7650904 1.243126 _cons

Number of obs = Linear regression 308 F(2, 305) = 55.40 Prob > F = 0.0000 R-squared = 0.3120

= .60587 Root MSE

csadxhf	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
maraxhf	.8994253	.2004181	4.49	0.000	.5050482	1.293802
mar2xhf	0360358	.0372594	-0.97	0.334	1093539	.0372823
_cons	1.082223	.229104	4.72	0.000	.631398	1.533047

Dot-com bubble

Linear regression Number of obs =

F(2, 98) = 25.36 Prob > F = 0.0000 R-squared = 0.2891 = .57022 Root MSE

csadxlt	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
maraxlt	.3941598	.2075837	1.90	0.061	0177832	.8061029
mar2xlt	0063756	.023627	-0.27	0.788	0532627	.0405115
_cons	1.850262	.3305243	5.60	0.000	1.194347	2.506177

Number of obs = 51 Linear regression F(2, 48) = 33.15 Prob > F = 0.0000- 33.15 = 0.0000 = ^ R-squared Root MSE = .60323

Robust csadxlf Coef. Std. Err. P>|t| [95% Conf. Interval] t .0875375 .4147138 0.834 -.7463004 .9213754 maraxlf mar2x1f .0265203 .0423236 0.63 0.534 -.0585769 .1116175 _cons 2.435954 .7910462 3.08 0.003 .8454494 4.026459 Linear regression Number of obs =

F(2, 98) = 168.41 Prob > F = 0.0000 R-squared = 0.5121 Root MSE = .5296

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csadxht	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
maraxht	.8821618	.1891736	4.66	0.000	.5067529	1.257571
mar2xht	0387833	.0206839	-1.88	0.064	0798298	.0022631
_cons	1.479854	.3022382	4.90	0.000	.8800724	2.079636

Linear regression Number of obs = 51

F(2, 48) = 332.58 Prob > F = 0.0000 R-squared = 0.5267 Root MSE = .53263

Robust csadxhf Coef. Std. Err. t P>|t| [95% Conf. Interval] 1.18731 .3059129 3.88 0.000 .5722309 1.802389 mar2xhf -.0703875 .0311628 -2.26 0.028 -.1330445 -.0077304 -.2261079 2.015305 _cons .8945987 .5573895 1.60 0.115

Dot-com Boom

. reg csadxht maraxht mar2xht, robust

Linear regression Number of obs = 59

F(2, 52) = 448.17 Prob > F = 0.0000 R-squared = 0.5124 Root MSE = .64849

csadxht	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
maraxht mar2xht cons	1.232937 0761803	.2829034 .0293755	4.36 -2.59 1.95	0.000 0.012 0.057	.6652499 1351266 0255187	1.800624 017234 1.708064

R-squared = 0.4943 Root MSE = .64559

Robust Coef. Std. Err. t P>|t| [95% Conf. Interval] csadxhf 1.255504 .5828618 2.15 0.041 .0550773 2.45593 maraxhf -.0782083 .0578739 -.1974018 .0409852 mar2xhf -1.35 0.189 .7912976 1.044711 0.456 -1.360326 2.942921 _cons

Dot-com Bust

Linear regression

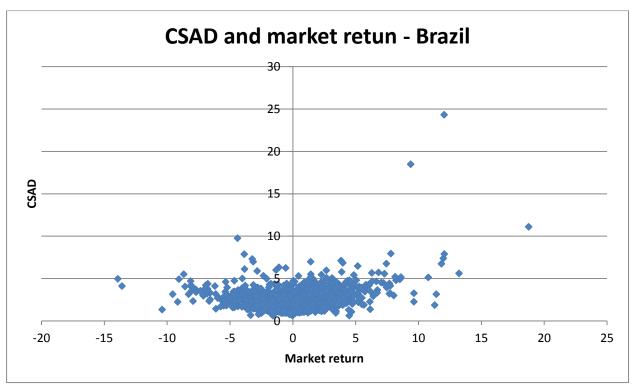
Number of obs = 23 F(2, 20) = 8.34 Prob > F = 0.0023 R-squared = 0.3741 R-squared = .60019

csadxht	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
maraxht	2.05076	1.216897	1.69	0.107	4876425	4.589163
mar2xht	190293	.1481765	-1.28	0.214	4993837	.1187977
_cons	63303	2.37704	-0.27	0.793	-5.591448	4.325388

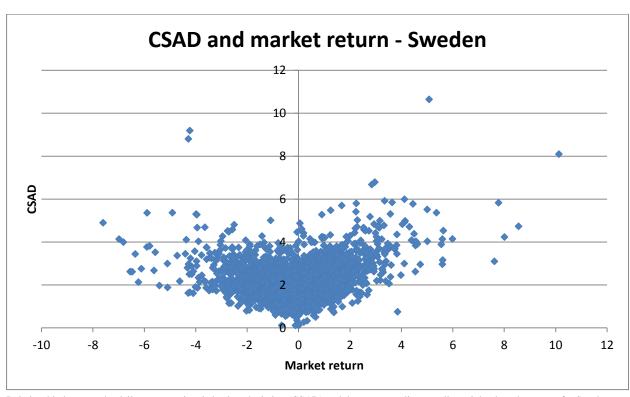
Linear regression

Number of obs = 36 F(2, 33) = 15.88 Prob > F = 0.0000 R-squared = 0.3852 Root MSE = .55179

csadxhf	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
maraxhf	1.179101	.7540116	1.56	0.127	3549472	2.713149
mar2xhf	0875073	.1005802	-0.87	0.391	2921393	.1171248
_cons	1.108565	1.306501	0.85	0.402	-1.549531	3.766662



Relationship between the daily cross-sectional absolute deviation (CSAD) and the corresponding equally-weighted market return for Brazil (11/01/94-14/04/14)



Relationship between the daily cross-sectional absolute deviation (CSAD) and the corresponding equally-weighted market return for Sweden (02/01/90-14/04/14)