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Herd Behaviour Myopia:
Problems with assessing market rationality on the US stock market based on conventional herding measures.

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Abstract

This paper aims to test the presence of herd behaviour in the seemingly rational US stock market by observing the behavioural tendencies at a sectoral-level. A model developed by Chang et al. (2000), where the measurement for herding is the dispersion between individual portfolio returns relative to the market return, is used. The results show evidence of irrational behaviour in six of the ten studied sectors during the time period 1/1/1990 - 22/3/2018. Furthermore, the study identifies two polarizing effects that may be driven by similar herding fundamentals – excessive homogenous dispersion and excessive heterogeneous dispersion. The opposing effects are studied further with the use of a rolling regression. The results from the rolling regression suggest that the effects may cancel each other out when the model is applied to an aggregate market-level. This flaw with the model questions the precision of previous studies conducted on an aggregate market-level, as the results may be misleading or even incorrect.

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1. Introduction

The concept of herd behaviour was introduced by the work of John Maynard Keynes in his famous *The General Theory Employment, Interest and Money* (1936). The Keynesian beauty contest tells the story of judges who instead of choosing the most beautiful contestant, rather chooses the person that they think the other judges will choose as the most beautiful. Keynes argued that this anecdote reflects the behaviour of participants in financial markets. Instead of relying on one's personal beliefs regarding the value of a security, investors invest in accordance with the belief of what others will do. These are the basic tenets of herd behaviour. Investors put their personal preferences and beliefs to the side and instead follow the strategy of other investors or the market in general.

During the 1980s the empirical results of the financial markets started to deviate from the conventional theories of efficient market hypothesis. Excess volatility was prevalent and prices of assets began to fluctuate in manners that seemed irrational. Behavioural finance emerged as an alternative explanation to the mispricing, claiming that the limits of arbitrage and psychology of investors where behind the phenomenon. Herd behaviour is a branch within behavioural finance that gained attention by being a possible explanation to the inefficient pricing. Prior studies of herd behaviour in a market setting has usually been based on the models developed by Christie & Huang (1995) and Chang et al. (2000), where they measure the degree of the dispersion between individual portfolio returns compared to the market return. The model developed by Christie & Huang (1995) argues that if the dispersion is below average during extreme market conditions - herd behaviour is present on the market. In contrast, Chang et al. (2000) who assumes that the returns can be derived from capital asset pricing models, proposes that the relationship between the dispersion of individual return and market return is linear. Thus, in presence of herding, dispersion only needs to decrease or increase at a decreasing rate relative to the market return.

Most of the previous research within this field has evaluated the behaviours of markets by observing the tendencies at a market-level. However, other studies investigate the behaviour of markets by looking at it from an industry or sectoral-level, providing a more nuanced picture of the overall market. According to Zheng et al. (2017) herding is more common at industry-levels compared to the domestic or international market-levels. Therefore, the inherent differences between industries might contribute to a further understanding of why the aggregate market herds or not. The results of herding in developed countries have been rather consistent, implying that countries such as the US do not provide any evidence of herding, suggesting that the participants of the market are rational. As the results have been conclusive on the US market, later studies have focused mostly on the behaviour of Asian markets, where strong indications of herding have been found.

Gebka & Wohar (2013) investigates whether herd behaviour is to be found on a national and sectoral-level on the global equity markets with the usage of the model developed by Chang et al. (2000). Furthermore, the authors suggest that one should not exclude the prevalence of irrationality if dispersion *increase* more than rational asset pricing models would predict. The irrationalities that might take form are localised herding, excessive flight-to-quality and overconfidence amongst investors. According to the authors, localised herding has been ignored by existing literature, where economists only speak of herding when returns are excessively homogenous and not when they are *heterogeneous* and caused by a homogenous view.

With this more broad-minded definition of herding, the research objective with this study is to examine if herd behaviour is to be found on the seemingly rational market of the US. This is conducted through examining the behaviour at sectoral-level and assessing whether the opposing effects of excessive heterogeneous and homogenous dispersion would cancel each other out when being measured on an aggregate market-level. Thus, this study aims to go beyond the traditional ways to investigate herd behaviour, by claiming that financial markets with previous evidence of non-herding may in fact be driven by polarizing irrationalities. Moreover, this questions the robustness of the previous literature that ignores these effects and simply investigates the behaviours at an aggregate market-level.

The US market is divided into eleven sectors in accordance with the S&P 500 indices and then evaluated by the model develop by Chang et al. (2000). The results obtained by the study suggest strong evidence of an excessive non-linear dispersion in the US market, as the behaviour in six of the eleven industries are driven by heterogeneous returns during 1/1/1990 through 3/22/2018. By observing the behaviours of the sectors on a yearly-basis, Healthcare, Information Technology and Utilities demonstrate tendencies of herd behaviour at different times. In contrast, sectors such as Financials, Materials and Industrials provides evidence of excessive dispersion in almost every year, highlighting the inherent differences between the sectors.

By applying a rolling window regression on the US market, several occasions of irrational dispersion are at the sector-level, but not on the aggregate market. Thus, with the use of the discussed method, researchers might have obtained an unrepresentative image of markets such as the US by only conducting research at the market level, ultimately creating a herd behaviour myopia within the field.

Our contribution to existing literature is twofold. Firstly, we are, to our knowledge, the first to study the implications of the opposing effects that are characterised by excessive heterogeneous dispersion (i.e. localised herding, excessive flight-to-quality and overconfidence) and excessive homogenous dispersion (i.e. herding). Second, our hope is to extend the literature of herd behaviour by conducting this study with a different time series and data points in comparison to previous research.

2. Literature review

2.1 Theoretical Framework and related literature

2.1.1 Efficient Market Hypothesis

There are two schools of thought on investment behaviour in financial markets. First, the Efficient Market Hypothesis (EMH), developed by Fama (1970), proposes that the stock price already reflects all available information. Meaning that it is impossible to beat the overall market performance. According to Shleifer (2000) the hypothesis is built resting on three assumptions. First, most investors are rational and thus value financial securities rationally. Second, the investors that act irrational do not have an effect on the values of securities since their trades are random and cancel each other out. Lastly, if investors act irrational in similar ways, the market will be met by rational arbitrageurs who will take advantage of the deviations and once again create efficient pricing.

EMH was followed by successful empirical studies during the 1960s and 1970s. Michael Jensen, co-creator of the hypothesis stated:

"There is no other proposition in economics which has more solid empirical evidence supporting it than the Efficient Market Hypothesis" (Jensen 1978, p.95)

However, during the 1980s, empirical results began to differ from the theories of efficient markets. It appeared as the prices of securities had more volatility than what the efficient market hypothesis could explain (Schiller 2003). In connection to these discoveries new fields of study, such as Behavioural Finance, emerged as alternative explanation to the deviations.

2.1.2 Behavioural Finance

Behavioural finance claims that the value of securities can deviate from their fundamental values, caused by the presence of irrational agents (Shleifer 2000). Barberis and Thaler (2003) stated that behavioural finance rests on two legs: Limits to Arbitrage and Psychology.

A common critique towards market mispricing is that it would be met by arbitrageurs, attempting to take advantage of the mispricing and thus eliminating the deviation. However, this critique can be met by the theory of limited arbitrage which states that rational traders are unable to do anything about the mispricing caused by irrational investors due to the costs and risks associated with arbitrage.

The second leg of behavioural finance is psychology. People form irrationalities that can be distinguished into two categories: First, *Information Processing* is when people do not process information correctly, and thus incorrectly estimate the value of an asset. One example of this bias is *Conservatism*, when investors are not fast enough in updating their belief in response to recent evidence (i.e. news about a firm). Second, *Preferences* is when investors make suboptimal decisions even when they hold the "right information". An example of this behaviour is *Framing*. Framing is when an individual act differently regarding an investment or project depending on how it is presented, even if the probability for successful or failure are the same. *Herd behaviour* is another example of psychology induced action, where individuals suppress their personal beliefs in order to follow the actions of others.

2.1.3 Herd behaviour in financial markets

Herd behaviour emerged as a field of study as economists investigated the origination of inefficient pricing in the financial markets. Herd behaviour has since been a common explanation to the fact that prices may fluctuate from their fundamental values (Christie & Huang 1995). Herding has been granted with a lot of different definitions. Scharfstein & Stein (1990) claimed that herd behaviour is a form of mass psychology that weakens the relationship between information and market outcome, and thus stays in contrast to the efficient market hypothesis. Based on early notions on the phenomena the famous review of herd behaviour in financial markets written by Bikchandani & Sharma (2000) defined intentional herd behaviour in the following manner:

> *"An individual is said to herd if she would have made an investment without knowing other investors' decisions, but does not make that investment when she finds that others have decided not to do so. Alternatively, she herds when the knowledge that others are investing changes her decisions from not investing to making the investment"*
>
> *(*Bikchandani & Sharma, 2000, p. 280)

However, according to this definition, we assume that herding is something intentional and which may result in an inefficient market outcome, contributing to excess volatility and systemic risk. This should be distinguished from *spurious herding* - which occur when investors with similar news, independently of each other, makes similar decisions. Bikchandani & Sharma (2000) demonstrated this behaviour by exemplifying the actions made by investors following an increase in interest rates - where investors typically move from stocks to other securities. Investors act on the information similarly and together, causing a herd movement. However, they base their decisions on public information rather than observing each other, resulting in an efficient market outcome.

Devanow & Welch (1996) distinguished herd behaviour within financial markets by dividing them into *rational* and *non-rational herding*. The latter claims that herding prevails in situations imbedded by external factors. Non-rational herding focuses on the psychology of investors.

2.2 Rational Herding

Rational herding or *Intentional herding*, coined by Bikchandani & Sharma (2000) was their major topic in their review "Herd Behaviour in Financial Markets", who similarly to Devanow & Welch (1996) claims that there are three reasons for rational herding or *intentional herding*; 1) *Imperfect information*; 2) *Concern for reputation; 3) Compensation structures*

2.2.1 Imperfect information

Imperfect information, or *information cascades*, are according to Bikchandani & Sharma (2000, p. 609) when actions rather than private information are publicly visible. It is based on the fact that agents gain useful information by observing the previous actions of other agents and as a result ignores their own private information. This can be exemplified by an investor who has a negative attitude against the value of a certain security, but, by watching the actions of others, the investor chooses to put their private information to the side and invest in the security.

Banerjee (1992) also assessed the notion of *information cascades*. Banerjee developed and expressed a sequential model in order to show that following others and suppressing your private information can be rational. This model further suggests that the act of trying to use the previous information makes the agent less responsive to their own information and each action. As a result, the agent becomes less and less informative for others, causing the value of information to depreciate. This results in an inefficient equilibrium which could be solved if agents could trade signals with each other or if the first couple of agents were forced to use only their private information, creating an informational base which stabilises the final outcome.

This model, where people acquire information by observing actions of others in their group, was one of the two models that the Nobel laureate Schiller (1995) used to explain the origination of herding. He proposes that in order to understand herding, one has to consider theories of information. Individuals limit of time and intelligence prevents people to unveil all relevant information. The second model used to explain as to why groups at different places or at times have different information, was developed by Goodwin and Heritage (1990), where they examine how information transfers between groups by using the so called conversation analysis-model.

2.2.2 Concern for Reputation

The concern for reputation as a cause for herding was already investigated by John Maynard Keynes in *The General Theory of Employment, Interest and Money* (1936):

"Worldly wisdom teaches that it is better for reputation to fail conventionally than to succeed unconventionally" (Keynes, 1936, p. 141)

Keynes argues that professional investors does not try to gain money in the long-term by betting against the current market consensus, but rather to foretell what the market will value a security in the short-term under the influence of mass psychology. Because if an investor is unsuccessful in the short run "*... he will not receive much mercy"*. Both Bikchandani & Sharma (2000), and Scharfstein & Stein (1990) examines this theme further, as they present models which explains why investment managers tend to mimic the action of others. They present the rationale that a manager would look like a fool if exiting a position if the stock continues to go up even if the whole market eventually will go down. On the contrary if the market crashes it affects all market participants. They further present some implications for the stock market where they say that excessive volatility in the stock market might be caused by herd behaviour. Trueman (1994) continues further on this notion as he criticizes the widely accepted view that analyst forecasts reflect analyst's private information in an unbiased manner. It is shown that analysts tend to release forecasts closer to previous reports than appropriate and that analysts are affected by other analysts and therefore herd around each other. He shows that the equilibria differ for two different scenarios, one where forecasters release their report simultaneously and one where they release the reports sequentially.

2.2.3 Compensation structures

The third cause for rational herding is compensation structures. If investment managers are evaluated by their performance relative to a benchmark (i.e. broadly diversified market-index) and their compensation depends on their performance it may cause herding (Bikchandani & Sharma 2000; Devanow & Welch 1996). The phenomenon was investigated by Maug & Naik (1995), as they asses how fund managers allocate their assets depending on the fact that their compensation is based on their relative performance to a benchmark. This resulted in investments that deviated from the “return-maximising portfolio” and instead followed their benchmark, which creates uniform decision for stock picking, in this case herding.

2.3 Non-Rational Herding

Irrational herding focuses on the psychology of agents, assuming that they imitate each other without questioning and resulting in an inefficient market outcome. DeLong et al. (1990) investigates the financial implications of investors with no inside information that acts on noise (so called “noise-traders”). The results suggest that they affect prices and are able to earn higher expected returns than rational investors due to the fact that they bear a disproportionate amount of risk that themselves create. Limitations of arbitrage and the mere risk of betting against irrationals, hinders arbitrageurs to take advantage of the inefficiencies occurring in the market. Moreover, as the effectiveness of arbitrage is limited, the prices of assets will be excessively volatile.

Froot et al. (1992) demonstrate that investors who have a short-term horizon can create market inefficiencies due to them herding against other investors. The results show that as more investors study a certain piece of information, more of the same information will get out to market, and thus, the profits from learning that information will initially increase. This means that short-term horizons traders may only focus on one source of information rather than fundamentals, meaning that short horizons may cause herding on specific sources of information.

2.4 Empirical studies on herd behaviour

Furthermore, some empirical studies do not necessarily fall under the definition of rational or non-rational herding, but rather focuses on whether herd behaviour is prevalent and ignores the motives. An example of these types of studies are the one's performed in a market setting.

2.4.1 Empirical studies in a market setting

When analysing a data set based on price changes or asset holdings, the motives of herd behaviour are hard to observe due to the difficulties in identifying the rationale behind a trade that is not driven by fundamentals (Bikchandani & Sharma 2000). Thus, empirical studies have rather focused to study whether the market outcomes are in line with the theory of herding (Gebka & Wohar 2013). Meaning that a large part of the empirical studies investigates whether a certain market has the characteristics of herd behaviour, rather than assessing why that is.

Herd behaviour in equity markets was initially examined by Christie & Huang (1995), who defined herding in a market setting in the following manner:

"*... herds are characterized by individuals who suppress their own beliefs and base their investment decisions solely on the collective actions of the market, even when they disagree with its predictions" (Christie & Huang, 1995, p. 31)*

Herd behaviour in a market-level has branched into two paths (Chiang & Zheng, 2010). First, the studies attributed to analysis of financial contagions. Second, the research attributed to examine herd behaviour observing the cross-sectional correlation dispersion in stock returns.

2.4.2 Financial Contagions

Pericoli & Sbracia (2003) study the different definitions of contagion. Contagion can be seen as the increase in probability for one country to be affected by a crisis, depending on a crisis occurring in other countries. In regards of asset pricing, contagion can be seen as the volatility spill over from a country affected by a crisis spread to the financial markets of other countries. Corsetti et al. (2005) find evidence of contagion for five countries, when examining the international effects of the Hong Kong stock market crisis of October of 1997. Chiang et al. (2007) examines the contagion behaviour on the Asian markets further. By applying a dynamic conditional-correlation model to nine Asian daily stock-return data series between the years 1990-2003 they find evidence of contagion. Moreover, they divide the crisis into two different phases, finding different results for each. In the first phase there is an increase in correlation and in the second phase this behaviour transforms into herd behaviour. In this specific case, herd behaviour describes the simultaneous investor behaviour across the studied markets showing high correlation coefficients in all markets. Celik (2012) chooses to instead examine the contagions effects on the 2007-2008 US subprime crisis inflicted to developed and emerging countries. The findings suggest evidence of contagion of both types, however, emerging countries seems to be more affected than developed countries.

2.4.3 Cross-sectional Correlation Dispersion

Studying financial markets with the use of Cross Sectional Correlation Dispersion has usually been done with the models developed by Christie & Huang (1995) and Chang et al. (2000).

The pioneers within this field of study is Christie & Huang (1995), who assess whether equity returns herd around the market during periods of market stress using the cross-sectional standard deviations of returns. Their goal was to test if herding is present during the times when they are most likely to develop. Individuals are most likely to suppress their belief during market stress (i.e. market crashes). According to rational asset pricing models, dispersions of return should increase as there are large market movements, as stocks sensitivity to the market return differs. However, if dispersion decrease, and is shown to be less than average as an effect of large market movement it means that herd behaviour is present on the studied market.

Chang et al. (2000) introduced a less stringent version of the model developed by Christie & Huang (1995), by instead using the cross-sectional *absolute* deviation as a measurement of dispersion. Assuming that stocks returns are generated from capital asset-pricing models, the dispersion of individual returns is a linear function of market returns. In presence of herding, the non-linearity condition has to be broken. An example of this is when dispersions of return will decrease or increase at a decreasing rate with the market return. Examining herd behaviour using Cross-sectional Correlation Dispersion has usually been performed on either an aggregate market-level or on a sectoral-level.

2.4.3 Cross-sectional Correlation Dispersion on an aggregate market-level

Christie & Huang (1995) examine herd behaviour on the aggregate market-level and at an industry-level. They divide the market into twelve industries, and study if herd behaviour occurs under extreme market movements. The dispersion increased significantly even during the most extreme market conditions, in accordance with rational asset pricing theory. Using daily and monthly data for companies registered on NYSE and AMEX they find no evidence of herd behaviour from neither daily nor monthly returns. Thus, they do not provide any significant evidence that herd behaviour can be an important factor for determining equity returns during periods of large market movements in the US market.

The authors Chang et al. (2000) examines herd behaviour in the US, Hong Kong, Japan, South Korea and Taiwan. In accordance with the study of Christie & Huang (1995) presented above, they find no evidence of herding in the US. However, they find that herding occurs in the emerging markets of South Korea and Taiwan.

The models developed by Christie & Huang (1995) and Chang et al. (2000) are generally accepted in the field and are used by a large number of economists in order to detect herding. By the usage of the models Demirer & Kutan (2006), Tan et al. (2008), Chiang & Zheng (2010) & Balcilar et al. (2013) study herd behaviour on different markets.

Demirer & Kutan (2006) study the presence of herd behaviour on the Chinese stock markets. The authors study herd behaviour at the aggregate market-level and distinguishes the Shanghai and Shenzhen stock exchanges at an industry-level. Their findings are in line with rational asset pricing models, as they find no evidence of herding in the Chinese markets. However, the dispersions seem to be lower at down markets than up markets, indicating that investors invests similarly when return goes down. The results of the aggregate market are similar to those at the sector-level.

Tan et al. (2008) examine the Asian markets further. The Shanghai and Shenzhen markets are divided into A and B-shares. Whereas the A-share market are dominated by domestic investors and B-share markets mainly consists of foreign institutional investors from developed countries. Both the A-share and B-share markets suggest herd behaviour, in both up and down market conditions. This is consistent with the results of Chang et al. (2000), where they are able to detect herding on the emerging markets in Asia. However, the B-share market, mainly consisting of foreign institutional investors is also herding, which is not consistent with earlier research indicating that developed countries act according to rational asset pricing models.

Chiang & Zheng (2010) were the first to examine herd behaviour in the global market, as they measure herd behaviour on 18 different countries, and thus does not limit themselves to one market. They divide the countries into the following categories; advanced markets, Asian market and Latin American markets. Consistent with previous research, they find no evidence of herding in the US market. However, they find evidence of herding in both advanced markets (such as France, Germany and Australia) as well as in emerging markets in both up and down market conditions. Their evidence suggests further that herding activity in a country of crisis may have a contagion effect and spread over to neighbouring countries.

The emphasis of studying herd behaviour has usually been attributed to the Asian and US markets. Balcilar et al. (2013) chooses to study herd behaviour on a more uncharted market - the Gulf Arab stock markets. The results suggest herding in three of the five studies markets.

2.4.4 Cross-sectional Correlation Dispersion at an sectoral-level

As presented above, most empirical research has focused on the herd behaviour at an aggregate market-level (Chang et al. (2000); Tan et al. (2008); Chiang & Zheng (2010); Balcilar et al. (2013)). However, studying herd behaviour on a sectoral-level by using cross-sectional standard deviation models was as early introduced by Christie & Huang (1995). Furthermore, Demirer & Kutan (2006) also chose to study herd behaviour on the market-level as well as a sector-level.

Litimi, Bensaida & Bouraoi (2016) investigate whether excessive market volatility and financial bubbles can be explained by herd behaviour on a sectoral-level. The data consists of all American firms listed on the NYSE, AMEX and NASDAQ. Using the NASDAQ classification, the stocks are divided into twelve sectors. First they assess whether herd behaviour is present on a sectoral-level using the cross sectional standard deviation of return (CSSD) and cross sectional absolute deviation of return (CSAD). According to the results from the CSSD-model, no indication of herding is found for any industries during the studied time period. However, the results from the CSAD-model suggests that herd behaviour is present in two industries - Public Utilities and Transportation. Second, the authors examine whether return, volume turnover and investors sentiment (where the S&P VIX works as a proxy) cause herding. They do this by using a Granger causality tests. According to the results, sector return Granger-causes herding in seven out of the twelve sectors, and that herding Granger-causes the average sector return in all industries. Furthermore, herding can be explained by past volume turnover and vice versa. Also, investor sentiment Granger-cause herding. In sum, the authors asserts that sector return, volume turnover and investor sentiment can, to some extent, explain sectoral-herding.

Zheng et al. (2017) examines herd behaviour across industries in nine Asian markets. Using daily returns they find that herding exists in these markets and is more present on an industry level rather than national or on an international level. Across all markets, herding is more prevalent in Financial and Technology industries than the others. They examine further the characteristics of herding influenced industries, as they discover that herding is also more apparent in both low market value industries, industries with low dividend yield and less concentrated industries.

Gebka & Wohar (2013) investigates whether herding is prevalent in the global equity market by looking at nationwide indices and at a sector-level. Herding cannot be detected on the national markets. However, the results suggest irrationalities on a sectoral-level, namely; basic materials, consumer services and oil & gas. By applying the CSAD-model, and examining if dispersions are linear to the market return they find some interesting results. Dispersion was not linear to market return, and dispersion did not decrease or increase less than proportional, it rather - *increased*. The dispersion increased more than what the linear function suggests, meaning that the dispersion did not act consistently to rational asset pricing models. In contrast to previous research, Gebka & Wohar (2013) chooses to account the excessive dispersion as an irrationality and claims that herding may be a possible explanation for the behaviour.

2.5.2 Herding as an explanation to increased dispersion

Prior studies have addressed the fact that some results yield higher dispersion than what rational asset pricing models would suggest. However, the existing literature often ignores this phenomenon and focuses on the traditional definition of herding which is a decreasing dispersion or increase at a less than proportional rate than theories suggests (Gleason et al. (2004); Chiang & Zheng (2010); Economou et al. (2011); Litimi, Bensaida & Bouraoi (2016). However, others suggest that the increase in dispersion may be caused by behavioural irrationalities.

Gebka & Wohar (2013) claims that increasing dispersion may depend on other factors. The factors are distinguished into three categories; Localised Herding, Excessive flight-to-quality and Overconfidence. Localised herding is an indication of herds or groups of investors who suppresses their own information and beliefs and instead follow each other in and out of positions. The prices of assets of which the investors move in to will increase and the prices of the assets of which they move out from will decrease. Consequently, causing excessive dispersion in return. This means that herding does not only need to drive down dispersion, it can also in some cases increase the dispersion. This is in contrast to previous literature that suggests that only a decrease or an increase that is less-than-proportional to the market return is an indication of herd behaviour (Christie and Huang (1995); Chang et al. (2000); Demirer & Kutan (2006); Tan et al. (2008), Chiang and Zheng (2010); Balcilar et al. (2013); Litimi, Bensaida and Bouraoui (2016). Excessive flight-to-quality is when investors move from their risky portfolio to more safe assets, rebalancing their holdings. Consequently, opposite price movements will occur for the assets or markets involved, resulting in higher dispersion than implied by rational asset pricing models. Overconfidence is the irrational behaviour of investors when they overestimate their ability to generate high returns. Investors overemphasize their own beliefs and chooses to ignore the information stemming from market conditions. Ultimately, this may increase the dispersion on individual returns to such an extent that is higher than the rational level. Overconfidence is also examined by Goodfellow et al. (2009), which suggests that the increasing dispersions can be a sign that investors rely on their own analysis rather than the information that is mirrored by other investors' behaviour or public news.

2.6 Specification of research focus & research objective

The research objective with this study is to examine if herd behaviour can be detected on a sectoral-level in the US and to further investigate the effects of excessive heterogeneous dispersion and excessive homogenous dispersion. Previous studies have generally focused on examining herd behaviour in developed countries on an aggregated market-level (Chang et al. 2000); Chiang & Zheng 2010) without studying the implications of the behaviours at a sectoral-level. The results are usually consistent - herd behaviour, on an aggregate market-level, is seldom present in developed countries. More explicitly - herd behaviour has never been prevalent in the US market on an aggregated level. According to the CSAD-model, this implicates that the US market is in line with rational asset pricing models, meaning market participants are fully rational.

Furthermore, we continue on the notion of Gebka & Wohar (2013), claiming that dispersion which increases more than what rational asset models predicts may also be an indication of herd behaviour, just towards a different consensus. In their view investors instead move away from the overall view of the market or sector and instead focus on views dominant among a subset of actors. Given this looser definition of herd behaviour, we investigate the effectiveness of the market-wide approach developed by Chang et al. (2000) when evaluating the rationality of markets. The market-wide approach tries to show if there is either a negative relationship between market return and dispersion in times of extreme market stress or a non-linear relationship which would indicate that herding is present. This approach makes room for situations where aggregate markets are deemed as rational, whilst sectors within the same market suffers from excessive heterogeneous dispersion and others from excessive homogeneous dispersion. When the model is measures at an aggregate market-level, we test if these opposing effects, prevalent at a sectoral-level, cancel each other out. Since, as findings of Zheng et al. (2017) suggest - herding is more prevalent on an industry-level compared with the domestic or international market-levels. Therefore, testing it on a developed market where market-wide herding seems to be non-present is highly relevant. Thus, this study aims to add further understanding to the market behaviour and criticizes some of the earlier drawn conclusions based on the market-wide measures. Previous results can be an explanation to why research on the topic of herd behaviour in a market setting has shifted towards focusing mainly on emerging markets even though the exact degree or shape of herd behaviour as an irrationality have not been fully addressed. This leads us to the following enunciation of the research question:

"Is herd behaviour prevalent on a sectoral-level in the US, and is it possible that the polarising effects of excessive homogenous dispersion and excessive heterogeneous dispersion cancel each other out while testing for herding on an aggregate market-level?"

3. Method

3.1 The setting of the study

In order to find sector-wide herding in the US, where herding has not showed to be persistent on a market-wide level (Christie and Huang 1995; Chang et al. 2000); Chiang & Zheng (2010); Litimi, Bensaida and Bouraoi 2016), the conventional market-wide detection methods have instead been applied at a sectoral-level. The two widely accepted models used to measure market-wide herding in a market setting are developed by Christie & Huang (1995) and Chang et al. (2000).

3.2 Models to detect market-wide herding

In the following section both market-wide models are presented. Although, only the latter is chosen for this empirical study.

3.2.1 Cross-Sectional Standard Deviation

The conventional ways of detecting and proving existence of herd behaviour in a market setting has consistently been using cross-sectional data on stock returns. Christie and Huang (1995) proposes a method where the cross sectional standard deviations (CSSD) is used in order to measure dispersion. They argue that dispersion is the intuitive measure for the impact of herd behaviour on the aggregate market, as dispersion expresses the average proximity of all individual stock returns to the mean. The dispersion will thus decrease if individual returns converge towards the market return. The method based on CSSD is therefore testing if the dispersion, under the most extreme market movements, is below average. If the dispersion is proven to be below average, one can claim that during large movements herd behaviour exists in the market triggered by the abnormal returns.

The measure of dispersion at a given time *t* is constructed with individual returns from all the stocks in a given market or portfolio. The cross-sectional standard deviation is denoted as:

$$\mathrm{CSSD_t} = \sqrt{\frac{\sum_{i=1}^{N}(R_{i,t}-R_{m,t})^2}{(N-1)}} \tag{1a}$$

Where N is the number of firms in the market or portfolio. $R_{i,t}$ is the return of a given stock and $R_{m,t}$ is the equally weighted returns of the market or portfolio at time t.

$$CSSD_t = \alpha + \gamma_1 D_t^{up} + \gamma_2 D_t^{down} + \varepsilon_t \quad (1b)$$

To detect if herd behaviour is present, the above regression is usually used. The method uses dummy variables for the upper and lower end of daily returns, where D_t^U denotes the days with daily returns in the upper end and D_t^L for the lower end. Although arbitrary, the boundaries are commonly set to a 1 or 5 percent criterion (Chang et al. 2000). If herding is present, the coefficients should be negative indicating that dispersions during extreme market movements are below average and therefore clustered around market consensus.

3.2.2 Cross-Sectional Absolute Deviation

Recent studies have been using the cross-sectional absolute deviation (CSAD) proposed by Chang et al. (2000) instead of the cross-sectional standard deviation (CSSD) presented above, as the latter only can test whether herd behaviour is present during large market movements. Thus, making the model useless if the objective is to test for herd behaviour during a time period. In contrast, the CSAD-model uses the relationship between return and dispersion to test if herd behaviour is present and it can also be used throughout the whole data set. This enables tests for consistent herding regardless of return or the time frame. The model measures the dispersion as the cross-sectional absolute return denoted as:

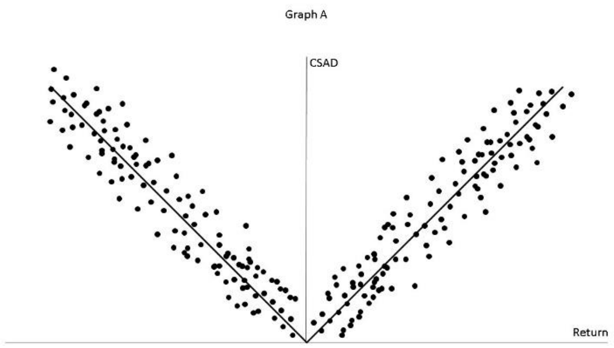
$$CSAD_{m,t} = \frac{1}{N}\sum_{i=1}^{N}\left|R_{i,t} - R_{m,t}\right| \quad (2a)$$

Where *N* is the number of firms in the market, portfolio or sector. $R_{i,t}$ is the return of a given stock and $R_{m,t}$ is the equally weighted returns of the market, portfolio or sector at time *t*.

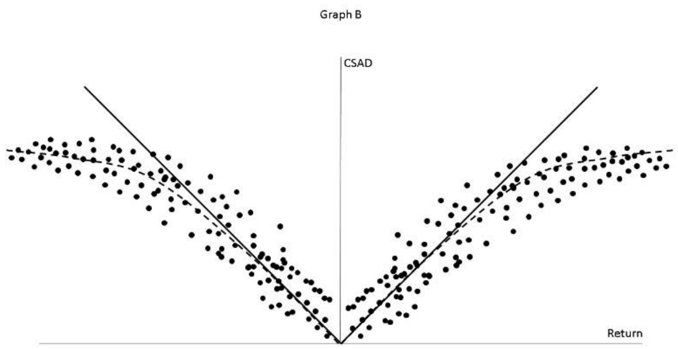
Since rational capital asset-pricing models predicts that the dispersion in cross-sectional returns should increase along with the absolute value linearly, if non-linearity can be proven it would indicate herd behaviour on the market or sectoral level. In other words, if dispersion decrease or increase at a decreasing rate with market return, herd behaviour is present. In contrast to the CSSD-model, an increase in dispersion may still indicate the presence of herding, making the

CSAD-model somewhat less stringent. Furthermore, the model can also detect dispersions larger than what rational asset pricing models predict, which may be evidence of market irrationalities such as localised herding, excessive flight to quality or overconfidence amongst investors (Gebka & Wohar 2013).

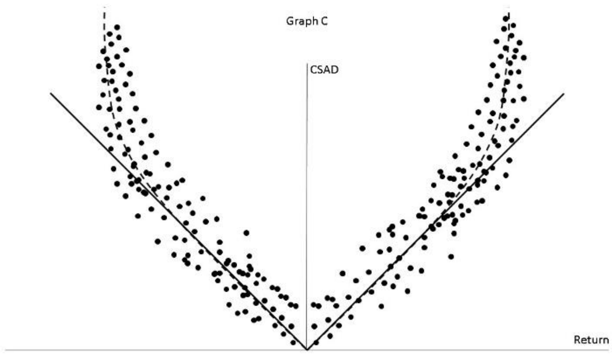
The graphs below shows the relationship between absolute return dispersion (CSAD) and the market return ($R_{m,t}$).



Note: **Graph A** shows when CSAD is a linear function of the market return, which is in accordance to rational asset pricing models.



Note: **Graph B** shows that the dispersion decrease or increase at a less-than-proportional rate than what rational pricing behaviour suggests. This is an indication of herd behaviour.



Note: **Graph C** suggests that the dispersion increases more than what rational asset pricing models suggests. This may be an indication of localised herding, excessive flight- to-quality or overconfidence.

3.3 Model development

To detect sector-wide herding, the market-wide approach is used and applied at the sectoral-level. Since the US has not shown any indication of market-wide herd behaviour, the less strict method (CSAD) is chosen. If the sector return can be proven to have a non-linear relationship to the cross sectional absolute deviation in the sector, it could indicate a herd behaviour either towards the market view of that sector or away from it. To test the hypothesis that herding can be present within industries during time periods where herding is not present on the market-level, different measures for dispersion are constructed.

The cross-sectional absolute deviation for the market or the sector at a given day is:

$$\mathrm{CSAD}_{m,t} = \frac{1}{N}\sum_{i=1}^{N}\left|R_{i,t} - R_{m,t}\right| \tag{2a}$$

$$\mathrm{CSAD}_{ind,t} = \frac{1}{N}\sum_{i=1}^{N}\left|R_{i,t} - R_{sector,t}\right| \tag{2b}$$

Where $R_{m,t}$ is the equally weighted returns of the market and $R_{i,t}$ is the daily return for an individual stock *i* at time *t* (2a). $R_{sector,t}$ is the sector index return at date t and $R_{i,t}$ is the daily return for an individual stock *i* at time *t* (2b).

In order to construct the measure for dispersion the daily returns from all individual stocks have to be determined. The daily returns are based on daily closing prices where all stock returns and market index and sector index returns are calculated as:

$$R_t = 100 \times (\mathrm{Log}(P_t) - \mathrm{Log}(P_{t-1})) \quad (3a)$$

Where Log denotes the natural logarithm, P_t denotes either the individual stock price, the market index, or the sector index. In accordance with Demirer & Kutan (2006), Tan et al. (2008), Chiang & Zheng (2010), we use the logarithmic return.

3.3.1 CSAD-regressions

The following OLS-regressions are used to determine the presence of herd behaviour, the regressions use Newey-West standard errors that corrects issues with heteroscedasticity and autocorrelation among the error terms:

$$CSAD_{m,t} = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R^2_{m,t} + \varepsilon_t \quad (4a)$$

$$CSAD_{sector,t} = \alpha + \gamma_1 |R_{sector,t}| + \gamma_2 R^2_{sector,t} + \varepsilon_t \quad (4b)$$

where $|R_{m,t}|$ denotes the absolute value of the daily market return for a given day t and $R^2_{m,t}$ is the squared value of the market return for a given day t (4a). $|R_{sector,t}|$ denotes the absolute value of the daily sector return for a given day t and $R^2_{sector,t}$ is the squared value of the market retur for a given day t (4b). ε_t is the error-term.

The model applies return as main explanatory and γ_1 capture the majority of change in dispersion. This relationship shows how much of the dispersion that can be explained by returns. The coefficient should be significant and positive according to rational asset pricing theory. The non-linear term $R^2_{m,\,t}$ is introduced in the model to capture the possible herding effects. If the coefficient - γ_2, sometimes referred to the herding coefficient, is negative with significance it would indicate that herd behaviour is present (Chang et al. 2000).

If the γ_2 - coefficient instead is positive with significance it would indicate that the dispersion is higher than what rational asset pricing models would predict. In accordance with previous research, this can be an indication of localised herding, excessive flight to quality or overconfidence amongst investors.

3.3.2 Up & Down markets

According to the theories of Christie & Huang (1995) and Chang et al. (2000), herding should be more prominent in extreme market movements. Furthermore, earlier studies test if the herding is asymmetric in up and down markets (Demirer & Kutan, 2006, Tan et al. 2008, Chiang & Zheng 2010). Thus, evaluating the investment behaviour during different market conditions may provide further insights. Firstly, a regression for both market conditions, tests the consistency in the herding coefficient (γ_2 in equation 4a and 4b), and thus may act as a robustness test for the full-time period. Secondly, it also tests if the opposing effects in up and down markets might cancel each other out and result in no significant effect for the full time period. Lastly, if industries show positive coefficients in both up and down markets this might be an indication of differences in underlying causes.

$$CSAD_{m,t} = (\alpha_1 + \gamma_{up,1}|\mathrm{R}_{\mathrm{m,t}}| + \gamma_{\mathrm{up,2}}\mathrm{R}^2_{\mathrm{m,t}})D^{up}_{m,t} + (\alpha_1 + \gamma_{down,1}|\mathrm{R}_{\mathrm{m,t}}| + \gamma_{\mathrm{down,2}}\mathrm{R}^2_{\mathrm{m,t}})D^{down}_{m,t} + \varepsilon_{\mathrm{t}} \tag{5a}$$

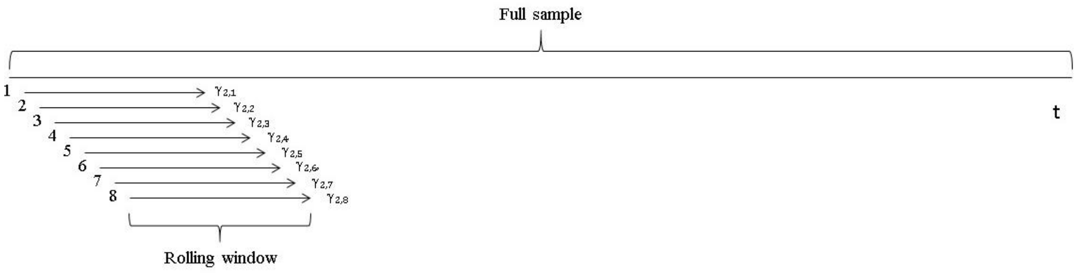
$$CSAD_{ind,t} = (\alpha_1 + \gamma_{up,1}|\mathrm{R}_{\mathrm{sector,t}}| + \gamma_{\mathrm{up,2}}\mathrm{R}^2_{\mathrm{sector,t}})D^{up}_{ind,t} + (\alpha_1 + \gamma_{down,1}|\mathrm{R}_{\mathrm{sector,t}}| + \gamma_{\mathrm{down,2}}\mathrm{R}^2_{\mathrm{sector,t}})D^{down}_{ind,t} + \varepsilon_{\mathrm{t}} \tag{5b}$$

Where $D^{up}_{m,t} = 1$ if $\mathrm{R}_{\mathrm{m,t}} > 0$ or 0 if $\mathrm{R}_{\mathrm{m,t}} < 0$ and where $D^{down}_{m,t} = 0$ if $\mathrm{R}_{\mathrm{m,t}} > 0$and 1 if $\mathrm{R}_{\mathrm{m,t}} < 0$. $|\mathrm{R}_{\mathrm{m,t}}|$ is the absolute value of the market return at a given day t and $\mathrm{R}^2_{\mathrm{m,t}}$ is the squared term while ε_{t} is the error term (5a). $D^{up}_{ind,t} = 1$ if $\mathrm{R}_{\mathrm{sector,t}} > 0$ or 0 if Rsector,t < 0 and where $D^{down}_{ind,t} = 0$ if Rsector,t > 0and 1 if Rsector,t < 0. $|\mathrm{R}_{ind,\mathrm{t}}|$ is the absolute value of the market return at a given day t and $\mathrm{R}^2_{\mathrm{sector,t}}$ is the squared term while ε_{t} is the error term (5b).

3.3.3 Rolling window regression

A rolling window regression is used to investigate whether sector-wide herding and excessive dispersion could cancel out on the aggregated market. A common assumption when estimating a model for time-series data is that the true coefficients are constant. This method enables an analysis on how the coefficients changes over time and also tests the stability of the estimations.

Figure 1: Rolling Window Regression



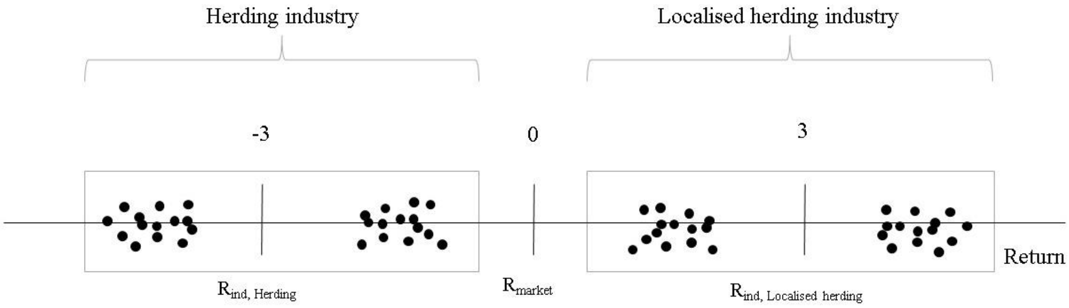
As shown in figure 1 the regression is run for window 1 and the coefficients are estimated for the sub-sample. The first observation is then discarded and the window moves one calendar day. This means that the regression, using equation 4a and 4b, is run for each calendar day throughout the whole sample where all available data points within the window is used (i.e. trading days) and the herding coefficient (γ_2) and standard error for each day are stored. The significance is then calculated for each coefficient estimate in order to see if there are time periods when several industries are showing non-linearity but with opposite signs when the market coefficient equals zero.

The rolling window regression is run with a window size of 365 calendar days. In order to detect both persistent effects and short-term fluctuations in the non-linear relationship between returns and dispersion.

3.4 Implications of method

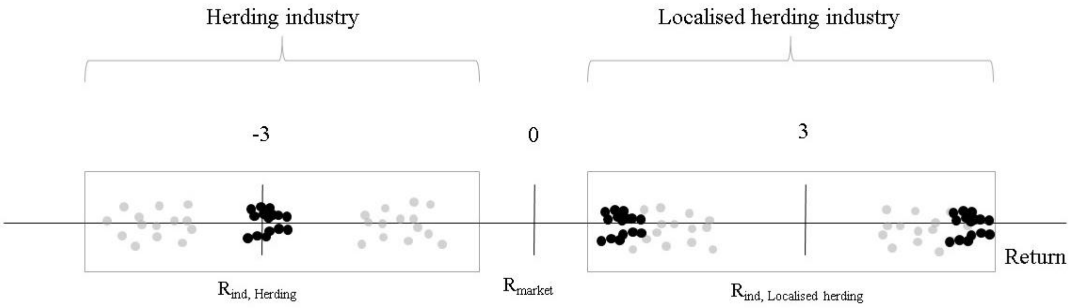
The method presented above (CSAD) uses continuous time-series data and tries to capture the non-linear changes in dispersion caused by high absolute returns. However, there are several implications with the method that demands a further analysis of the underlying characteristics of the market in order to draw the right conclusions from the results. This section shows why two parallel - but opposing irrational behaviours can be present in the market during time periods where the market-wide model fails to detect any irrational behaviours.

Figure 2: Example market



Consider a scenario where individual stock returns are distributed evenly throughout the spectrum, further described in figure 2. The whole market is made up of four different market segments which is grouped into two sectors: Herding sector (left) and Localised Herding sector (right). The market return for the equal weighted index is static around zero while both sectors have an absolute return of three, positive for localised herding sector and negative for herding sector.

Figure 3: Example market with herd movement



In figure 3, these two sectors behave in a herd-like manner. The herding sector herd around its consensus, decreasing the sector dispersion significantly as a result of the irrational behaviour. Meanwhile the localised herding sector is herding around a local consensus within the sector, where investors herd from one part of the sector towards the other, causing sectoral dispersion to increase significantly as a result of the behaviour. However, the individual sector returns do not affect nor drive this change in dispersion given that movements are caused by investor behaviour.

In the example outlined above the equal weighted returns for the market and each sector is unchanged. The cross-sectional absolute deviation for the market using the market return as the midpoint is also unchanged. Using the method on the whole market can therefore detect cases where the entire market is behaving in one direction. However, a drawback with the method is that these two opposite irrational behaviours can be present and therefore the effects are cancelled out when trying to detect any irrational behaviours on the aggregated market-level.

3.4.1 Simulating the opposing effects

A simulation is run on a fictive market to test the hypothesis that sector herding can be present in a market with opposing effects derived from different industries and whether these effects might cancel each other out when tested on aggregate level (Appendix A). We simulate the market by creating 80 different variables representing individual daily stock returns, dividing them into four equal sub sectors with 20 daily returns in each. By randomising an absolute market movement for each day, we trigger a change in the mean and standard deviation in the parameters for each stock. When letting the parameters change in a uniform manner, we can test for herd behaviour on the market and for each individual sector. When the market movement affect all industries in the same way the regressions show no evidence of significant herding coefficients neither for the market nor any of the industries.

In another simulation we instead let the parameters of the different sectors change in a diverse manner. If market stress affect sectors in a diverse way, some sectors might show significant herding while some sectors might show localised herding. Results from the second simulation supports the notion (Appendix B) that strong sector herding might be present while the market seems rational on the aggregate level.

We hypothesise that empirical data showing no evidence of herd behaviour might be caused by the following cases (Appendix C):

1. The market is rational with no significant effects neither on the market-level nor at the sectoral-level.

2. Irrational changes in dispersion is not connected to changes in returns.

3. Herd behaviour is significant on the sectoral level but at opposite directions (Consolidation of sectoral coefficients).

4. The herding coefficients are unstable and switches signs over time either for the market or in the subset (Time aspect of detecting herding).

4. Data

4.1 Data Selection

The data used in the empirical study is collected through Thomson Reuters Datastream, where daily returns and dispersions have been constructed from all the top sectors including: *Consumer Discretionary* (CD), *Consumer Staples* (CS), *Energy* (EN), *Health Care* (HC), *Information Technology* (IT), *Industrials* (IN), *Materials* (MA) *Financials* (FI), *Health Care Utilities* (UT), for the S&P 500 which covers the top 500 stocks in market capitalization in the US.

4.1.1 Time period

The data period ranges from 1/1/1990 through 3/22/2018 for all sectors except for Real Estate, where data ranges from 1/1/2015 through 3/22/2018. Daily data is used for all sectors and time periods. When analysed on a yearly basis all available data points are used, varying slightly depending on number of trading days for that specific year. Reasons for choosing the whole time period is partly due to the available time periods for the indices and their respective launch date. It is also chosen in order to be able to investigate the individual sectors both in the long-run, i.e. over the whole time period, and on an annual level to detect patterns and differences between industries and sub-periods.

4.1.2 Indices

In accordance with Chang et al. (2000), equally weighted indices are used in order to detect herding. The S&P 500 index covers approximately 80% of total market capitalization[1] making it the best available proxy for the market return for the US market. The S&P equally-weighted index are adjusted for extraordinary events such as stock splits, equity carve outs and dividends. The S&P equally-weighted sector indices are used for all the eleven top sectors. Furthermore, previous studies on an sectoral-level in the US (Christie & Huang 1995; Litimi, Bensaida and Bouraoui 2016) chooses other indices than the S&P, meaning that a study performed on the S&P can act as a robustness test to previous results.

[1] S&P Dow Jones Indices LLC, “S&P 500”, https://us.spindices.com/indices/equity/sp-500 (accessed April 29 2018)

4.1.3 Sector classification

The S&P 500 sector indices divides the market into sectors using the Global Industry Classification Standard (GICS) which classifies the companies on qualitative and quantitative factors. Companies are assigned a GICS classification based on their principal business activity, determined by revenues and quantitative measures as key factors but is also reviewed yearly on current earnings and qualitatively factors such as market perception. In accordance to Christie and Huang (1995) only the sectors with at least 25 securities in any particular month were studied, therefore the regression results from the Telecom-sector with only three existing companies, is not significant.

4.2 Descriptive Data

Table 1

Descriptive data – Cross-sectional Absolute Deviations

	Obs	Mean	S.D.	Skewness	Kurtosis	Min	0.25	Mdn	0.75	Max
IT	7,102	1.67	0.83	1.13	4.75	0,33	1,02	1,52	2,13	7,00
HC	7,102	1.48	0.67	1.10	4.74	0,36	0,95	1,37	1,85	5,29
CD	7,102	1.38	0.55	1.54	7.6	0,36	1,00	1,28	1,64	6,08
Market	7,102	1.33	0.53	1.72	8.12	0,38	0,95	1,23	1,52	5,66
IN	7,102	1.23	0.55	2.29	13.99	0,3	0,87	1,12	1,44	7,58
FI	7,102	1.20	0.77	4.03	29.64	0,23	0,77	1,03	1,38	9,88
MA	7,102	1.20	0.56	2.86	20.53	0,24	0,85	1,07	1,39	8,35
EN	7,102	1.19	0.48	1.47	7.05	0,33	0,85	1,09	1,42	5,32
CS	7,102	1.01	0.44	1.15	5.34	0,19	0,67	0,94	1,26	4,07
TC	7,102	0.93	0.72	2.98	20.3	0,02	0,46	0,74	1,16	9,97
UT	7,102	0.72	0.39	3.49	28.31	0,14	0,49	0,64	0,82	6,96
RE	700	0.66	0.24	1.73	8.26	0,23	0,50	0,62	0,77	2,11

Note: The table lists the descriptive statistics of daily, equally-weighted cross-sectional absolute deviations for eleven sectors (Information Technology, Healthcare, Industrials, Financials, Materials, Energy, Consumer Staples, Telecom, Utilities and Real Estate) in the US. The data period ranges from 1/1/1990 through 3/22/2018, except for Real Estate where data ranges from 1/1/2015 through 3/22/2018. The sector-wide stock dispersion is defined as $CSAD_{ind,t} = \frac{1}{N}\sum_{i=1}^{N}\left|R_{i,t} - R_{sector,t}\right|$. The market index or sector index is calculated as $CSAD_{m,t} = \frac{1}{N}\sum_{i=1}^{N}\left|R_{i,t} - R_{m,t}\right|$.

The descriptive statistics for the cross sectional absolute deviation for the sectors gives us some insight on the general dispersion among different sectors in the US market. Data show that the highest average dispersion is present in Information Technology, as previous research for the

Chinese market (Demirer & Kutan 2006); (Zheng et al. 2017) also suggests. Information Technology also has the highest standard deviation in dispersion, which can indicate that the sector had unusual cross-sectional variations due to unanticipated news or shocks (Chiang & Zheng 2010). However, since the cross sectional absolute deviation should increase with returns these numbers are difficult to compare without weighing in the differences in the historical sector returns for each sector.

5. Results

5.1 CSAD-Results

The following section presents the results generated from the CSAD-model.

Table 2

Regression results – Full time period

	α	γ_1	γ_2	Observations	R-squared
Market	1.119***	0.243***	0.015***	7,112	0.248
Consumer Discretionary	1.209***	0.175***	0.014***	7,112	0.175
Consumer Staples	0.879***	0.175***	0.022***	7,112	0.125
Energy	1.004***	0.152***	0.000	7,112	0.162
Financials	0.744***	0.413***	0.009***	7,112	0.685
Health Care	1.267***	0.260***	0.002	7,112	0.098
Information Technology	1.267***	0.326***	0.001	7,112	0.253
Industrials	0.948***	0.281***	0.034***	7,112	0.472
Materials	0.926***	0.226***	0.032***	7,112	0.464
Real Estate	0.581***	0.123***	-0.007	700	0.079
Telecommunications	0.651***	0.260***	0.010	7,112	0.202
Utilities	0.565***	0.181***	0.017**	7,112	0.273

*** p<0.01, ** p<0.05, * p<0.1

Note: The table lists the CSAD regressions results for the overall market and the studied sectors with the following regression for market: $\mathrm{CSAD}_{m,t} = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon_t$ and for the industries: $\mathrm{CSAD}_{sector,t} = \alpha + \gamma_1 |R_{sector,t}| + \gamma_2 R_{sector,t}^2 + \varepsilon_t$.

The data period ranges from 1/1/1990 through 3/22/2018, except for Real Estate where data ranges from 1/1/2015 through 3/22/2018. The regression was made with Newey-West robust standard errors, correcting for heteroscedasticity and autocorrelation.

5.1.2 Aggregate market-level

The results from the regression in table 2 show a significant positive γ_2 - coefficient on the market-level. The result differs from earlier studies that provided insignificant herding coefficients for the aggregated US market (Christie and Huang (1995); Chang et al. (2000); Chiang & Zheng (2010); Litimi, Bensaida and Bouraoi (2016)). The discrepancy may be due to that our study analyses the market behaviour over a different time period than previous research or due to the use of different indices as a proxy for market return.

As a robustness test for the result on the market-level, the regression is tested for a similar period as Chiang & Zheng (2010), who collects their data from the same database, namely DataStreamInternational. The robustness test (Appendix D) which still show a positive coefficient suggests that the chosen time period may be a cause of the differing results.

However, as the herding coefficient (γ_2) is less significant when the time period is adjusted to the one used by Chiang & Zheng (2010) this only explains the deviation in results partly. Furthermore, the discrepancy may also be due to the fact that our study uses the 500 stocks included in the S&P, in contrast to Chiang and Zheng (2010) who uses 155 industry indices as a proxy for the aggregate market.

Since the result is significant for the full time period this still indicate a persistent irrational level of dispersion in the S&P 500. This result cast light on the importance to investigate this topic with an analysis on the sector-level even in a seemingly rational and developed market.

5.1.3 Sector wide-level

Results for herd behaviour within sectors show positive significant values in six out of eleven top sectors in the US. This result would indicate that some sort of irrational behaviour is present whether or not it is caused by localised herding, excessive flight to quality or overconfidence. Obtaining significant positive coefficients in a sectoral-level in the US was also the result of Litimi, Bensaida and Bouraoi (2016), who find it in 5 sectors, however without commenting on the results.

5.2 Sector herding by year

The following table presents the regression results for the overall market and ten studied sectors on a yearly basis. Where the sectors with negative γ_2 – coefficients are highlighted.

Table 3

Regression results – Yearly Herding Coefficients (γ_2)

	Market	CD	CS	EN	FI	HC	IT	IN	MA	RE	UT
1990	0.048*	0.001	0.001	0.016	0.033**	0.037	0.034	0.101***	0.095**	-	0.021
1991	0.050***	0.014	0.040**	0.025	0.013*	0.094**	0.021	0.057**	0.146***	-	0.079
1992	0.088*	-0.023	0.057	0.046**	0.052	0.096***	0.030	0.216***	-0.003	-	0.412**
1993	0.080***	0.063**	0.155***	0.048	0.039	0.013	0.055*	0.113**	0.121***	-	0.037**
1994	0.055*	0.046	0.191*	0.080*	0.081**	0.037	0.056	0.122**	-0.006	-	0.091**
1995	0.016	0.074	0.123	0.063*	0.094***	0.085	0.046	0.024	0.110***	-	-0.003
1996	-0.013	-0.025	0.024	0.010	0.025**	0.007	0.068***	0.038	-0.056*	-	0.004
1997	0.025***	0.015	0.036	0.022***	0.046***	0.010	0.000	0.029***	0.024***	-	0.078**
1998	0.034**	0.014	0.087***	0.029	0.052***	0.012	0.000	0.065**	-0.010	-	0.032
1999	0.025	0.099	0.095	0.024	0.051***	0.090**	0.026	0.182***	0.073***	-	-0.012
2000	0.009	0.004	0.015	0.030***	0.047***	0.029*	0.025***	0.030	0.059***	-	0.071*
2001	0.095***	0.034***	0.012	0.023*	0.107***	0.056*	0.009***	0.067***	0.047***	-	0.031
2002	0.021	0.004	0.030	0.066**	0.036***	0.001	0.017	0.045***	0.040**	-	0.015
2003	0.037*	0.008	0.013	0.027*	0.076***	0.025	0.020	0.080***	0.054***	-	0.024
2004	0.025	-0.007	0.269***	0.018	0.163***	0.112**	0.028	0.060*	0.030	-	0.025
2005	0.084***	0.038	-0.014	0.021*	0.109***	0.006	0.037	0.065**	0.084**	-	0.014
2006	0.200**	0.055*	-0.117	0.015	0.137***	0.004	0.017	0.120***	0.063**	-	0.064**
2007	0.048	0.037	0.008	0.030**	0.032*	0.068	-0.026	0.064***	0.076***	-	0.035
2008	-0.001	0.009	0.004	-0.003	0.005	-0.003	-0.001	0.012*	0.018*	-	-0.009**
2009	0.016	0.009	0.006	0.005	0.009*	0.033**	-0.002	0.031***	0.017*	-	0.033***
2010	-0.004	-0.002	-0.003	0.027	0.025***	-0.008	-0.018**	0.038***	0.035***	-	0.008
2011	0.014**	0.016*	0.030***	-0.002	0.023***	0.003	0.014**	0.029***	0.034***	-	0.011
2012	0.060***	0.026	0.134***	0.047**	0.086***	0.054	0.028	0.057***	0.106***	-	0.001
2013	0.011	0.027	0.002	0.012	0.095***	-0.078**	-0.026	0.081***	0.069***	-	-0.009
2014	0.016	0.000	-0.014	0.028***	0.121***	0.011	0.075	0.058***	0.110***	-	0.050
2015	0.004	0.011	-0.004	0.021**	0.050**	-0.001	0.010	0.068***	0.084***	-0.007	0.026
2016	0.043*	0.064***	0.055	0.031	0.086***	0.031	0.011	0.051***	0.086***	0.006	0.026
2017	0.128	-0.022	0.278***	0.061**	0.133***	-0.206**	0.082	0.068**	0.092***	-0.061	0.130
2018	0.000	0.003	0.008	-0.024	0.040***	-0.046**	-0.016	0.079***	0.081***	-0.014	0.109
1990-2018	0.015***	0.014***	0.022***	0.000	0.010***	0.002	0.001	0.034***	0.032***	-0.007	0.0174**

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Note: The table lists the γ_2-coefficients of the aggregate market and the eleven studied sectors on a yearly basis from 1990-2018. The sectors with a negative herding coefficient are highlighted. A significant positive coefficient would indicate the possible presence of localised herding, excessive flight-to-quality and overconfidence amongst investors. A significant negative coefficient would indicate the presence of herding. A non-significant coefficient provides evidence of non-herding, or rational market behaviour.

Table 3 shows the herding tendencies of the ten studied sectors (*Telecommunications* excluded) and the overall market on a yearly basis. *Healthcare*, *Information Technology* and *Utilities* show significant evidence of herd behaviour during different time periods. Positive $\gamma_2 -$ coefficients are present in all sectors except for Real Estate which might be due to the short time period. These results confirm that sector herding should be more prevalent than herding on the aggregate market-level as suggested by Zheng et al. (2017). None of the years with negative sector γ_2 - coefficients show any significant coefficient on the market-level, which would infer a rational market, considering the results.

The findings from the annual regression does not show any consistent patterns between the sectors other than that *Financials*, *Industrials* and *Materials* provides evidence of excessive dispersion in over 89% of the cases. These results act as a robustness-check for the full-time period. In contrast, sectors such as Healthcare, Information Technology and Utilities appears to consistently have rational tendencies. The contrasting results with the above mentioned sectors provides insights in the inherent differences between the sectors.

The results on the market-level show positive coefficient both prior and post the dot-com and (1999-2000) the global financial crisis (2007-2010) while the market looks rational during these periods. During 2008 only three sectors show non-linearity, whereas *Utilities* were the only one at the 5% significance-level. Since the assumption is that herd behaviour is most prevalent during market stress (Christie and Huang 1995) this is pointing towards contradicting results.

5.3 CSAD-Results in Up & Down markets

The following section presents the results generated from the CSAD-model in up and down markets.

Table 4

Regression results – Up and Down Markets

		α	γ_1	γ_2	Observations	R-squared
Market	Up	1.098***	0.274***	0.015***	3,827	0.256
	Down	1.140***	0.208***	0.017***	3,275	0.243
CD	Up	1.196***	0.211***	0.011***	3,771	0.182
	Down	1.221***	0.138***	0.017***	3,336	0.171
CS	Up	0.864***	0.207***	0.020**	3,786	0.137
	Down	0.895***	0.139***	0.026**	3,321	0.113
EN	Up	0.993***	0.165***	-0.001	3,595	0.159
	Down	1.013***	0.139***	0.001	3,510	0.166
FI	Up	0.734***	0.411***	0.011***	3,748	0.679
	Down	0.758***	0.409***	0.009***	3,363	0.691
HC	Up	1.250***	0.283***	0.003	3,860	0.104
	Down	1.284***	0.236***	0.002	3,251	0.092
IT	Up	1.245***	0.361***	-0.001	3,848	0.266
	Down	1.289***	0.290***	0.005	3,260	0.24
IN	Up	0.942***	0.293***	0.032***	3,784	0.436
	Down	0.953***	0.269***	0.036***	3,323	0.509
MA	Up	0.919***	0.228***	0.035***	3,700	0.444
	Down	0.936***	0.220***	0.031***	3,408	0.485
RE	Up	0.605***	-0.0156	0.039	379	0.040
	Down	0.574***	0.219***	-0.032**	321	0.123
UT	Up	0.552***	0.206***	0.006	3,741	0.213
	Down	0.586***	0.140***	0.032***	3,361	0.340

*** p<0.01, ** p<0.05, * p<0.1

Note: The table lists the regressions results of the CSAD with the following regression for the market (5a): $\mathrm{CSAD_{m,t}} = (\alpha_1 + \gamma_{up,1}|R_{m,t}| + \gamma_{up,2}R^2_{m,t})D^{up}_{m,t} + (\alpha_1 + \gamma_{down,1}|R_{m,t}| + \gamma_{down,2}R^2_{m,t})D^{down}_{m,t} + \varepsilon_t$ and for the ten studied industries (5b): $\mathrm{CSAD_{ind,t}} = (\alpha_1 + \gamma_{up,1}|R_{sector,t}| + \gamma_{up,2}R^2_{sector,t})D^{up}_{ind,t} + (\alpha_1 + \gamma_{down,1}|R_{sector,t}| + \gamma_{down,2}R^2_{sector,t})D^{down}_{ind,t} + \varepsilon_t$. Where $R_{ind,m,down,t}$ is $R_{ind,m,t} * D^D$ and $D^D = 1$ if $R_{ind,m,t} < 0$ and $D^D = 0$ if $R_{ind,mt} > 0$ and where $R_{ind,m,up,t}$ is $R_{ind,m,t} * D^U$ and $D^U = 1$ if $R_{ind,m,t} > 0$ and $D^U = 0$ if $R_{ind,m,t} < 0$. The regression is run for the aggregate market-level and for the ten studied sectors. The data period ranges from 1/1/1990 through 3/22/2018, except for Real Estate where data ranges from 1/1/2015 through 3/22/2018. The regression was made with Newey-West robust standard errors, correcting for heteroscedasticity and autocorrelation.

When the sectors are analysed in up and down market conditions, the results are overall consistent. However, some differences in magnitude of the effect between market conditions can be identified. These findings point toward robust results for the sectors for the full time period, since the coefficients are significant in both market conditions. However, in the Information Technology and Energy sectors, that does not show any significant effect for the full time period, the above results show that there are opposing coefficients depending on market conditions, although these results are non-significant.

Chiang & Zheng (2010) and Gebka & Wohar (2013) suggests non-herding for some markets on the aggregate level but find significant effects when separated for up and down movements. Similarly, we find significant herding for the real estate sector only in the down market. In up-markets the coefficient for absolute returns (γ_1) is not significant, meaning that dispersions does not increase with an increase in return. This is non-consistent with rational asset pricing theory but might be non-robust, considering the short time horizon. This highlights the notion that there are several other factors that might cause herd behaviour or other factors explaining dispersion among individual assets.

In accordance with what Christie and Huang (1995) suggest, all results except for *Real Estate* confirms that dispersions tend to increase more drastically in up markets than down markets. Furthermore, in accordance to the findings of Gebka & Wohar (2013), our results suggests that the behaviours of investors during these extreme market conditions are more in line with rational asset pricing models, as it seems that herding is less prevalent in these conditions. This is in contrast to the general suggestion that herd behaviour is more prevalent in down markets (e.g. Chang et al. 2000). Furthermore, studies on overconfidence show that overconfidence tend to be more prevalent in up markets (Cooper et al. 2004), possibly explaining the tendency of excessive dispersion in up markets. Since most sectors have significant positive coefficients in both up and down markets one cannot eliminate that it might also be caused by localised herding rather than overconfidence.

5.3 Rolling window regression

The results from the sector-herding per year (section 5.2) show that either excessive homogenous dispersion, excessive heterogeneous dispersion, or both are present in the US market at the sector-level during periods where the market does not show any significant irrationality. In order to understand the relationship between the sector herding coefficients and market herding, the findings from the rolling window regressions for the herding coefficients (γ_2) on the sector-level are presented below.

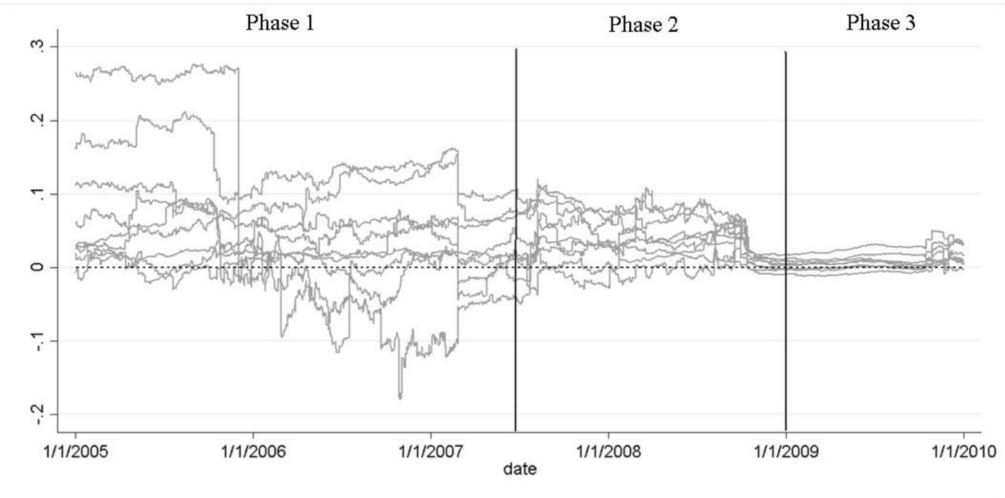
The time-varying herding coefficients estimated through the rolling window regression indicate that empirical data shows consistency with the hypothesized cases, presented in the implications of the method (section 3.4.1). We distinguish the effects into two different problems with assessing market rationality using herding measures at the aggregate market-level: *Consolidation of sector coefficients* and *The time-aspect of detecting herding.*

5.3.1 Consolidation of sector coefficients

The rolling window regression with 365 days window space, uses equation 4a and 4b to test the market and the individual sector herding coefficients over time. The results show evidence (Appendix E) of both positive and negative coefficients. Almost all time-varying sector coefficients are cross-correlated with significance (Appendix F), indicating that sectors deviate from rational behaviour collectively. Positive correlations indicate homogenous behaviour among the sectors and negative correlations indicate heterogeneous behaviour among the sectors. This confirms that sectors tend to show irrational behaviours during the same time period.

Diagram 1

Utilities 2008 – 2009



	Phase 1				Phase 2				Phase 3		
	Coeff.	t-stat	p-value		Coeff.	t-stat	p-value		Coeff.	t-stat	p-value
α	0.935	45.31	0.000	α	1.228	25.97	0.000	α	1.279	21.54	0.000
γ_1	0.032	0.41	0.681	γ_1	0.309	7.35	0.000	γ_1	0.259	4.32	0.000
$\boldsymbol{\gamma_2}$	**0.051**	**0.96**	**0.338**	$\boldsymbol{\gamma_2}$	**0.003**	**0.61**	**0.541**	$\boldsymbol{\gamma_2}$	**0.016**	**1.62**	**0.106**
R^2		0.0978		R^2		0.4946		R^2		0.4810	

Note: The graph plots the herding coefficients for the individual sector coefficients of the studied sectors (excluding Real Estate, due to missing data points). The table below the graph presents the regression results using equation 4a for the overall market during each phase. Phase one is between 1/1/2005-6/30/2007, phase two is between 6/30/2007-1/1/2009, phase three is between 1/1/2009-1/1/2010. Neither phase indicates any significant herd coefficient during the studied period.

To illustrate that these co-movements in the sectors does not get reflected by the market coefficient, we plot the individual sector coefficients as well as the overall market during 1/1/2005-1/1/2010 in the graph above. Moreover, the time period is divided into three different phases. According to the results, every phase should be classified as fully rational, as the herding coefficient for the market is insignificant. Although, as the graph suggests, the phases have different characteristics. Phase one has strong indications of irrational behaviour, as the herding coefficients for the individuals sectors either are positive or negative. Worth noting is that the γ_1 – coefficient for phase one is not significant, possibly caused by the fact that sector coefficients diverge from zero. Resulting in an estimation on the market level less accurate, portrayed by the low R^2-value. As time progress, the individual coefficients of the sectors moves towards zero, indicating a more rational behaviour on the market. Although, as the market coefficient is tested, every phase seem to be similar in terms of rationality. This result problematizes the use of the CSAD-model on an aggregate market-level, as the underlying subsets may be characterised with polarizing, non-rational, behaviours without being detected. As a robustness test, the phases are collectively tested and provides evidence of non-significant results for the herding coefficient (Appendix G).

5.3.2 Time aspect of detecting herding

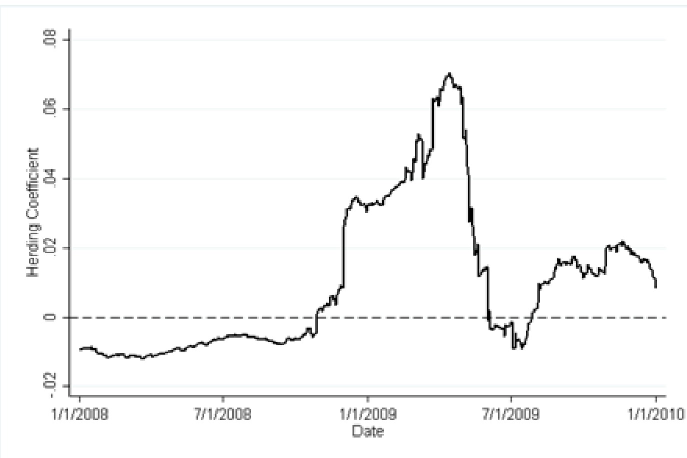
To show the time aspect of detecting herding, the results from the yearly regressions on the sector-levels presented in Table 3 are used where two industries show significant opposing effects during two subsequent years.

Diagram 2

Utilities 2008 – 2009

	Coeff.	t-stat.	P-value
2008			
α	0.617	17.52	0.000
γ_1	0.292	8.00	0.000
γ_2	**-0.009**	**-2.50**	**0.013**
2009			
α	0.681	20.07	0.000
γ_1	0.076	1.65	0.101
γ_2	**0.033**	**3.58**	**0.000**
2008 - 2009			
α	0.617	25.57	0.000
γ_1	0.243	8.99	0.000
γ_2	**-0.004**	**-1.13**	**0.258**

Time-varying Herding Coefficient



Note: Diagram 2 presents a graph where the herding coefficient from the rolling regression is plotted for the Utilities sector between 2008-2009. The table presents the regression results based on equation 4b between 2008-2009.

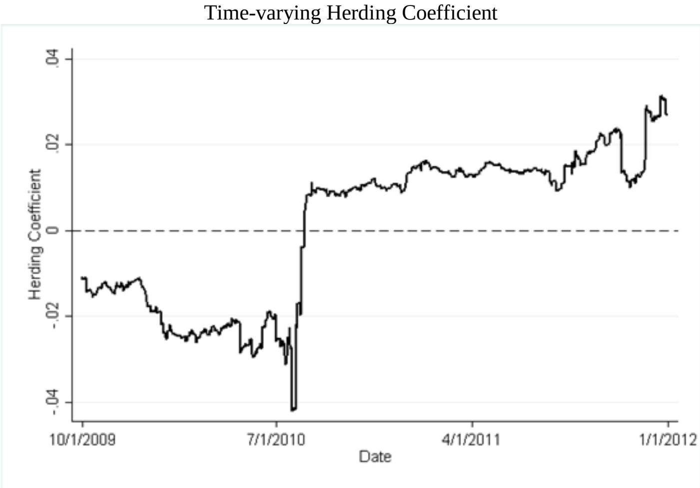
As presented above, during the year 2008 the Utilities sector show significant herding as presented in the regression and in Diagram 2. During 2009 the sector instead shows significant positive herding coefficient which might be caused by herd behaviour (i.e. localised). When these two time periods are tested separately, the model gets two opposing significant effects. However, once tested for the aggregate period the herding coefficient is non-significant, suggesting that the overall market is rational.

Diagram 3

Information Technology 2010 – 2011

	Coeff.	t-stat.	P-value
2010			
α	0.879	38.61	0.000
γ_1	0.176	4.77	0.000
γ_2	**-0.018**	**-2.00**	**0.047**
2011			
α	0.969	33.64	0.000
γ_1	0.056	1.78	0.077
γ_2	**0.014**	**2.28**	**0.023**
2010 - 2011			
α	0.927	52.51	0.000
γ_1	0.098	4.33	0.000
γ_2	**0.005**	**1.08**	**0.282**

Time-varying Herding Coefficient



Note: Diagram 3 presents a graph where the herding coefficient from the rolling regression is plotted for the Information Technology sector between 2008-2009. The table presents the regression results based on equation 4b between 2010-2011.

The same goes for the Information Technology sector, which show evidence of the same cancellation effect during the years 2010 and 2011. As the sector show significant herding in one year and significant positive coefficient in the other. The regression presented above in Diagram 3 for the full time period show no significant evidence of non-linearity in dispersions during the time period as a result for the opposing effects.

These results problematize that previous research where results have not been tested for sub-periods might be misleading, underestimated or false. The regression for the aggregated period confirms that the effects cancel out and the rolling window regression also highlight the importance of testing the stability of the estimated model when using the method for detecting herd behaviour. Long-lived opposing effects might be present within a certain market or sector during different time periods, but detecting them is simply a matter of the chosen time frame.

6. Implication of results

Our empirical results implicate that an excessive increase in dispersion is prevalent in six of the ten studied industries during the period of 1990-2018. There are several interpretations of these results. First, in these six industries investors move away from the overall view of the market of the sector or instead focus on views dominant among a subset of actors. Second, investors in these industries are conducting excessive flight-to-quality, where they rebalance their portfolio holdings. Lastly, the results may suggest that the investors in these industries are overconfident.

Furthermore, examining the herd tendencies on a yearly basis (section 5.2), the results suggests that herd behaviour is present at different times for Healthcare, Information Technology and Utilities, although in the majority of the cases they seem to inhibit rational behaviour. The same results provide evidence of excessive increased dispersion for Financials, Industrials and Materials in over 89% of the cases during the studied time period. Overall, the results stemming from the yearly analysis gives a further understanding of the inherent differences between the industries.

Given the results from the CSAD-regressions, some questions arise: What are the implications of herd behaviour for the concerned sectors? Why is excessive dispersion so prevalent in the sectors of the US? Why do some sectors have tendencies of excessive dispersion and others seems to be more rational?

Firstly, one interpretation is offered by Demirer et al. (2010), who argues that dispersion is associated with idiosyncratic risk. Consequently, investors that are active in the sectors that are consistently influenced by herd behaviour (such as Financials, Materials and Industrials) needs more assets in their portfolio to be able to obtain a reasonable level of diversification. In this case, it would mean that investors within the Financials sectors would need a larger number of assets in comparison to a non-herding sectors in order to have sound level of diversification.

There are several possible answers for the second question. The results were obtained from S&P 500 indices. According to Zhou and Lai (2009), small market capitalization stocks herd to a greater extent. If the opposite is true, that is – large stocks herds in a localised manner to a greater extent than small, it is not surprising that the indices consisting of the largest 500 companies show tendencies of an excessive increase in dispersion. However, as this has not been investigated, it can only be considered a theory. Also, previous research claims that overconfidence is more apparent in developed market rather than emergent ones (Jlassi et al.

2013), which can be interpreted as a possible explanation to the excessive increase in dispersion for the US sectors.

The possible answers to the third question are more speculative, since the field lacks research within the motives of herd behaviour once studied on a sectoral or market-level. However, according to Gebka & Wohar (2013), herd behaviour is most prominent in sectors which are associated with poor information, which they exemplify with the financial sector. Thus, it is possible that the excessive dispersion in the financial sector is partly contributed to localised herding. As to why Materials and Industrials are characterised with excessive dispersion is more surprising and harder to decipher. Furthermore, Zheng et al. (2017) agrees with Gebka & Wohar, as they claim that the Financial industry tends to herd more than others. However, they also claim that the Technology industry herds more than other industries as well, something that is contradicting to our findings. Zheng et al. (2017) also suggests that the herding differences between industries may be due to the differences in market value, dividend yield and concentration of industries.

To summarize, the contrast in results from our study and others highlights the inconclusiveness of the field. As Gebka & Wohar (2013, p. 57-58) states, the most correct conclusion to draw from previous research is that herd behaviour is not universal and may be different depending on the country and exchanges.

The empirical results from the rolling regressions indicates that the opposing effects may cancel each other out when one uses the CSAD-model at an aggregate market-level. It also indicates that the level of significant sector herding varies over time where the market coefficient show no evidence of any such behaviour. The results suggests that one cannot, accurately, draw conclusions from the CSAD-model performed only on an aggregated market-level regarding the behaviour of the market participants. The implications of the method show that a high level of either herding or localised herding, which the model tries to identify, can actually make detection more difficult. With negatively correlated herding coefficients over time, herding in every separate part of a market can make the market appear rational since these effect cancel out rather than magnify the effects. This highlights the risk of misleading results of prior research conducted on a market level. Without taking the underlying behavioural tendencies into consideration, the field will continue to suffer from herd behaviour myopia.

7. Conclusion

The conclusion of the study is that the opposing effects, characterised by excessive heterogeneous dispersion and excessive homogenous dispersion, being prevalent at a sectoral-level, can cancel out the effects if the CSAD-model is applied at a market-level. If the objective is to measure and to study irrational behaviour, its existence, causes or implications in financial markets a good measure for how market stress is related to irrational behaviour would be measuring these non-linear effects in an additive way rather than a subtractive one (Appendix H).

We contribute to the field of study by, to our knowledge, being the first to study the possible implications of effects of excessive heterogeneous dispersion and excessive homogenous dispersion. Also, by conducting the study with a different time series and other data points (S&P), we extend the literature of sectorial herd research in the US. Furthermore, we contribute by distinguishing two different types of phenomenon that creates the cancellation effects. First, both in our simulation and in our empirical results, the markets provides evidence of opposing effects when evaluating its subsets. These effects can sum up to zero once consolidated, misrepresenting the magnitude of irrationality on the studied markets. Second, in regards to the time aspect the rolling regression show both positive and negative signs for the same sector, which highlights that opposing irrationalities might be present, and conclusions regarding market rationality is just a matter of the selected time period. In conclusion, previous research which base their conclusions of market rationality on the CSAD-measure at an aggregate-market-level might be incorrect.

7.1 Limitations to research

This study simply criticizes the herding measure used to detect market-wide herding but does not present any alternative measure. Instead it applies the market-wide measure in a subset of the market and on a rolling time period in order to give a more nuanced view on herd behaviour in the US stock market compared to earlier studies.

The data used is limited to the S&P 500 which does not represent the entire US market. Thus, the significant results with a majority of positive herding coefficients might be related to the S&P 500 rather than the entire US stock market. These results might therefore be non-robust if the same study would be applied to smaller market capitalization stocks. However, such contradicting results would be relevant on its own, implicating a difference in behaviour among small and large market capitalization stocks.

Another limitation of the study is inability to discern the different effects which are characterised by an excessive heterogeneous dispersion. The inability is mainly contributed to the lack of previous literature and research within the area. If we were able to separate the behaviours of localised herding, excessive flight-to-quality and overconfidence it would provide a more nuanced picture of the irrational tendencies in the studied market.

Furthermore, the analysis is based on the fact that non-linear dispersion would imply irrational behaviour in the market and external exogenous factors are not taken into account. Therefore, no fundamental explanation to neither sector herding nor potential causes for different reactions among sector participants are proposed. The same criticism was stated by Gebka & Wohar (2013):

"… the market model may be too simplistic and omitting relevant factors, hence the finding of excessive return dispersion could be due to model failure rather than irrationality of investors"- Gebka & Wohar (2013, p. 83)

7.2 Directions for future research

Examining the underlying effects associated with excessive dispersion is needed. If someone was to solely examine herd behaviour, and not behavioural irrationalities, one has to distinguish between localised herding, excessive flight-to-quality and overconfidence, since not all effects are characterised by a herd-like behaviour (i.e. excessive flight-to-quality and overconfidence).

Also, to continue with the notion of Zheng et al. (2017) and examine the underlying differences of sectors would cast a light to the potential motives for irrational behaviours and answer the question as to why some sectors herd and others do not. Today, the literature is mainly speculative to the potential reasons of herd behaviour on a sectoral-level.

Our main conclusion is that previous research might have misleading results, highlighting the importance of conducting the same tests again, but at a subset-level. This would give further insight on whether seemingly rational developed markets are actually more rational than emerging markets or if they are affected by the opposing effects presented in this study. Additionally, developing a new, more precise model for herd detection may be of need. Since, based on our findings, one can argue that the opposing effects, characterised by irrational behaviour, should be treated in an additive manner rather than a subtracting one. This would more accurately represent the nature of investment behaviour occurring in the studied market.

8. References

Balcilar, M., Demirer, R., & Hammoudeh, S. (2013). *Investor herds and regime-switching: Evidence from gulf arab stock markets* doi:https://doi.org/10.1016/j.intfin.2012.09.007

Banerjee, A. V. (1992). A simple model of herd behavior. *The Quarterly Journal of Economics, 107*(3), 797-797–817. doi:10.2307/2118364

Barberis, N., & Thaler, R. (2003). *Chapter 18 A survey of behavioral finance* Elsevier. doi:https://doi.org/10.1016/S1574-0102(03)01027-6

Bikhchandani, S., & Sharma, S. (2000). Herd behavior in financial markets. *IMF Staff Papers, 47*(3), 279-310. doi:10.2307/3867650

Celık, S. (2012). *The more contagion effect on emerging markets: The evidence of DCC-GARCH model* doi:https://doi.org/10.1016/j.econmod.2012.06.011

Chang, E. C., Cheng, J. W., & Khorana, A. (2000). *An examination of herd behavior in equity markets: An international perspective* doi:https://doi.org/10.1016/S0378-4266(99)00096-5

Chiang, T. C., Jeon, B. N., & Li, H. (2007). *Dynamic correlation analysis of financial contagion: Evidence from the Asian market* doi:https://doi.org/10.1016/j.jimonfin.2007.06.005

Chiang, T. C., & Zheng, D. (2010). *An empirical analysis of herd behavior in global stock markets* doi:https://doi.org/10.1016/j.jbankfin.2009.12.014

Christie, W. G., & Huang, R. D. (1995). Following the pied piper: Do individual returns herd around the market? *Financial Analysts Journal, 51*(4), 31-37. Retrieved from http://www.jstor.org/stable/4479855

Cooper, M. J., Gutierrez, R. C., & Hameed, A. (2004). Market states and momentum. *The Journal of Finance, 59*(3), 1345-1365. Retrieved from http://www.jstor.org/stable/3694739

Corsetti, G., Pericoli, M., & Sbracia, M. (2005). *'Some contagion, some interdependence': More pitfalls in tests of financial contagion* doi:https://doi.org/10.1016/j.jimonfin.2005.08.012

De Long, J. B., Shleifer, A., Summers, L. H., & Waldmann, R. J. (1990). Noise trader risk in financial markets. *Journal of Political Economy, 98*(4), 703-738. doi:10.1086/261703

Demirer, R., & Kutan, A. M. (2006). *Does herding behavior exist in Chinese stock markets?* doi:https://doi.org/10.1016/j.intfin.2005.01.002

Demirer, R., Kutan, A. M. & Chen, C. D. (2010). *Do investors herd in emerging stock markets? Evidence from the Taiwanese market.* doi: https://doi.org/10.1016/j.jebo.2010.06.013

Devenow, A., & Welch, I. (1996). *Rational herding in financial economics* doi:https://doi.org/10.1016/0014-2921(95)00073-9

Economou, F., Kostakis, A., & Philippas, N. (2011). *Cross-country effects in herding behaviour: Evidence from four south european markets* doi:https://doi.org/10.1016/j.intfin.2011.01.005

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The Journal of Finance, 25*(2), 383-417. doi:10.2307/2325486

Froot, K. A., Scharfstein, D. S., & Stein, J. C. (1992). Herd on the street: Informational inefficiencies in a market with Short-Term speculation. *The Journal of Finance, 47*(4), 1461-1484. doi:10.1111/j.1540-6261.1992.tb04665.x

Gębka, B., & Wohar, M. E. (2013). *International herding: Does it differ across sectors?* doi:https://doi.org/10.1016/j.intfin.2012.09.003

Gleason, K. C., Mathur, I., & Peterson, M. A. (2004). *Analysis of intraday herding behavior among the sector ETFs* doi:https://doi.org/10.1016/j.jempfin.2003.06.003

Goodfellow, C., Bohl, M. T., & Gebka, B. (2009). *Together we invest? Individual and institutional investors' trading behaviour in Poland* doi:https://doi.org/10.1016/j.irfa.2009.03.002

Goodwin, C., & Heritage, J. (1990). Conversation analysis. *Annual Review of Anthropology, 19*(1), 283-307. doi:10.1146/annurev.an.19.100190.001435

Jensen, M. C. (1978). *Some anomalous evidence regarding market efficiency* doi:https://doi.org/10.1016/0304-405X(78)90025-9

Jlassi, M., Naoui, K., & Mansour, W. (2014). *Overconfidence behavior and dynamic market volatility: Evidence from international data* doi:https://doi.org/10.1016/S2212-5671(14)00435-3

Keynes, J. M. (1936). *The General Theory of Employment, Interest and Money,* doi:10.2307/2980590

Litimi, H., BenSaïda, A., & Bouraoui, O. (2016). *Herding and excessive risk in the american stock market: A sectoral analysis* doi:https://doi.org/10.1016/j.ribaf.2016.03.008

Marcello, P., & Massimo, S. (2003). A primer on financial contagion. *Journal of Economic Surveys, 17*(4), 571-608. doi:10.1111/1467-6419.00205

Maug, E. G., & Naik, N. Y. (1995). Herding and delegated portfolio management: The impact of relative performance evaluation on asset al.location. *IFA Working Paper 223-1996,* doi:http://dx.doi.org/10.2139/ssrn.7362

Scharfstein, D. S., & Stein, J. C. (1990). Herd behavior and investment. *The American Economic Review, 80*(3), 465-479. Retrieved from http://www.jstor.org/stable/2006678

Shiller, R. J. (1995). Conversation, information, and herd behavior. *The American Economic Review, 85*(2), 181-185. Retrieved from http://www.jstor.org/stable/2117915

Shiller, R. J. (2003). From efficient markets theory to behavioral finance. *Journal of Economic Perspectives, 17*(1), 83-104. Retrieved from http://www.aeaweb.org/articles?id=10.1257/089533003321164967

Shleifer, A. (2000). *Inefficient markets: An introduction to behavioral finance*. Oxford: Oxford University Press.

Tan, L., Chiang, T. C., Mason, J. R., & Nelling, E. (2008). *Herding behavior in chinese stock markets: An examination of A and B shares* doi:https://doi.org/10.1016/j.pacfin.2007.04.004

Trueman, B. (1994). Analyst forecasts and herding behavior. *The Review of Financial Studies, 7*(1), 97-97–124. doi:http://dx.doi.org/10.1093/rfs/7.1.97

Zheng, D., Li, H., & Chiang, T. C. (2017). *Herding within industries: Evidence from asian stock markets* doi:https://doi.org/10.1016/j.iref.2017.07.005

Zhou, R. T., & Lai, R. N. (2009). *Herding and information based trading* doi:https://doi.org/10.1016/j.jempfin.2009.01.004

9. Appendix

Appendix A

Simulation on opposing sector effects

Simulation 1

	α	γ_1	γ_2
Market	0.227	0.232	0.053
	0.000	0.000	0.303
Sector 1	0.243	0.237	-0,049
	0.000	0.002	0.521
Sector 2	.250	0.222	-0.043
	0.000	0.001	0.482
Sector 3	.241	.269	-0.094
	0.000	0.000	0.207
Sector 4	.263	.175	0.004
	0.000	0.018	0.961

Note: In the first simulation we simulate a market of 80 stocks divided into 4 sectors. First, we randomise an absolute market trigger representing a market shock. The trigger is randomised through a normal distribution with mean 2 and standard deviation 0.5. Then we construct daily returns based on the market shock indicating an absolute movement of the market. This movement effect all stocks in the same way causing the parameters for the randomised numbers change according to the market shock. All stock return are randomised normally distributed with mean (trigger*0.25) and standard deviation 0.25 + 0.1*trigger. This parameters rest on the assumption that dispersion should increase along with an increase in returns. Regression on each sector and on the market level show no evidence for non-linearity as in line with our assumptions.

Appendix B

Simulation on opposing sector effects

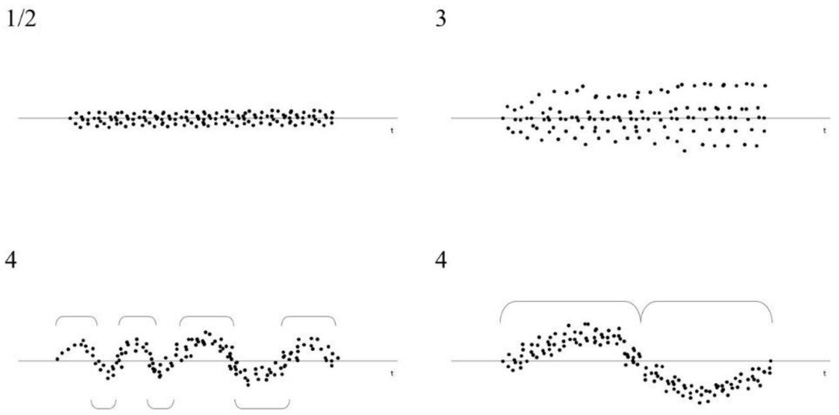
Simulation 2

	α	γ_1	γ_2
Market	0.194	0.299	-0.008
	0.000	0.000	0.000
Sector 1	0.356	0.237	0.039
	0.000	0.007	0.657
Sector 2	0.214	0.133	-0.029
	0.000	0.015	0.533
Sector 3	0.192	0.320	**-0.103**
	0.000	0.000	0.003
Sector 4	0.189	0.167	**-0.035**
	0.000	0.000	0.081

Note 1: In the second simulation we instead let different sectors and different parts of a sector change its parameter (mean, standarddeviation) with different functions of the Trigger which represents different behaviour among the sectors to the same market shock. Now we fins significant herding in two sectors. But due to effects of the other two industries and an additional effects from the dispersion among the four sectors no significant coefficient is seen for the aggregated market.

Note 2: The chosen effects are arbitrary set in order to simulate different reaction to market movements. A simulation based on the similar approach but with refines assumptions and additional stocks would show a perfect cancellation effect.

Appendix C



Note: Above is an illustration of herding coefficients over time. The graphs are numerated based on the cases presented below.

1. The market is rational with no significant effects neither on the market-level nor at the sectoral-level.

2. Irrational changes in dispersion is not connected to changes in returns.

3. Herd behaviour is significant on the sectoral level but with opposite directions (Consolidation of sectoral coefficients).

4. The herding coefficients are unstable and switches signs over time either for the market or in the subset (Time aspect of detecting herding).

Appendix D

Regression results robustness – Chiang & Zheng (2010)

	α	γ_1	γ_2	Observations	R-squared
Market	1.254***	0.297***	0.008*	4.869	0.315
Consumer Discretionary	1.346***	0.214***	0.007*	4,869	0.208
Consumer Staples	1.879***	0.001	0,236***	4,869	0.151
Energy	1.008***	0.161***	-0.001	4,869	0.163
Financials	1.088***	0.401***	0.010***	4,869	0.688
Health Care	0.847***	0.285***	-0.004	4,869	0.124
Information Technology	1.614***	0.273***	0.003	4,869	0.253
Industrials	1.077***	0.286***	0.031***	4,869	0.472
Materials	1.002***	0.232***	0.032***	4,869	0.464
Telecommunications	0.770***	0.236***	0.008	4,869	0.202
Utilities	0.622***	0.246***	0.009	4,869	0.273

*** p<0.01, ** p<0.05, * p<0.1

Note:The table above presents the results from the robustness check of Chiang & Zheng (2010). The studied period ranges from 1/1/1990 – 4/24/2009, in similarity to the studied period of Chiang & Zheng (2010) who studied the US market between 4/25/1989 – 4/24/2009. The difference in time period is due to limitation of data points from the S&P indices.

Appendix E

365 Days

	n	Mean	S.D.	Min	0.25	Mdn	0.75	Max
Market	9943	0.04	0.04	-0.08	0.01	0.04	0.06	0.22
Consumer Discretionary	9943	0.04	0.08	-0.18	0.00	0.03	0.06	0.34
Consumer Staples	9943	0.02	0.03	-0.08	0.00	0.02	0.03	0.18
Energy	9943	0.03	0.03	-0.05	0.01	0.02	0.04	0.17
Financials	9943	0.06	0.04	-0.03	0.03	0.05	0.09	0.21
Health Care	9944	0.03	0.05	-0.24	0.00	0.02	0.05	0.20
Information Technology	9943	0.02	0.03	-0.05	0.00	0.02	0.04	0.12
Industrials	9943	0.07	0.04	-0.01	0.04	0.06	0.08	0.27
Materials	9943	0.06	0.04	-0.07	0.03	0.06	0.08	0.21
Real Estate	813	0.00	0.03	-0.09	-0.01	0.00	0.01	0.06
Utilities	9943	0.03	0.05	-0.09	0.01	0.03	0.05	0.47

Note: The table shows descriptive statistics for the estimated Herding coefficients from the rolling regression described in section 3.3.3. The rolling regression is run from the 1/1/1990 through the 3/22/2018 with a window space of 365 calendar days.

Appendix F

Correlation matrix of time-varying herding coefficients

365 Days Rolling Window Regression											
	CD	CS	EN	FI	HC	IN	IT	MA	Market	RE	UT
CD	-	0.06	**-0.21**	0.19	0.45	**-0.48**	**-0.51**	**-0.21**	0.32	0.55	**-0.66**
	-	0.08	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
CS	**-0.17**	-	0.54	0.74	0.18	0.44	0.10	**-0.03**	0.83	0.17	0.08
	0.00	-	0.00	0.00	0.00	0.00	0.00	0.37	0.00	0.00	0.02
EN	**-0.14**	0.45	-	0.47	0.22	0.81	0.36	0.46	0.31	**-0.02**	0.12
	0.00	0.00	-	0.00	0.00	0.00	0.00	0.00	0.00	0.57	0.00
FI	0.17	0.82	0.60	-	0.25	0.29	0.28	0.16	0.82	0.09	**-0.12**
	0.00	0.00	0.00	-	0.00	0.00	0.00	0.00	0.00	0.01	0.00
HC	0.34	**-0.62**	0.01	**-0.32**	-	0.09	**-0.11**	0.32	0.10	0.77	**-0.55**
	0.00	0.00	0.80	0.00	-	0.01	0.00	0.00	0.01	0.00	0.00
IN	**-0.52**	0.21	0.72	0.21	0.27	-	0.31	0.29	0.18	**-0.26**	0.23
	0.00	0.00	0.00	0.00	0.00	-	0.00	0.00	0.00	0.00	0.00
IT	**-0.48**	0.57	0.40	0.51	**-0.44**	0.39	-	0.49	**-0.05**	**-0.24**	**0.45**
	0.00	0.00	0.00	0.00	0.00	0.00	-	0.00	0.14	0.00	0.00
MA	**-0.35**	0.08	0.53	0.12	0.44	0.84	0.39	-	**-0.14**	0.17	0.19
	0.00	0.02	0.00	0.00	0.00	0.00	0.00	-	0.00	0.00	0.00
Market	0.12	0.87	0.40	0.85	**-0.48**	0.04	0.34	**-0.02**	-	0.14	**-0.08**
	0.00	0.00	0.00	0.00	0.00	0.31	0.00	0.50	-	0.00	0.02
RE	0.42	**-0.39**	0.04	**-0.10**	0.84	0.21	**-0.34**	0.46	**-0.19**	-	**-0.39**
	0.00	0.00	0.26	0.00	0.00	0.00	0.00	0.00	0.00	-	0.00
UT	**-0.51**	0.58	0.16	0.22	**-0.57**	0.25	0.59	0.19	0.30	**-0.50**	-
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-

Note: The table show both the Spearman & Pearson correlation coefficients for all herd coefficients through the full rolling window regression with 365 calendar day's window space. The top right triangle show Pearson's correlation coefficient and the bottom left show Spearman's correlation coefficient. P-values are presented under each coefficient.

Appendix G

Regression

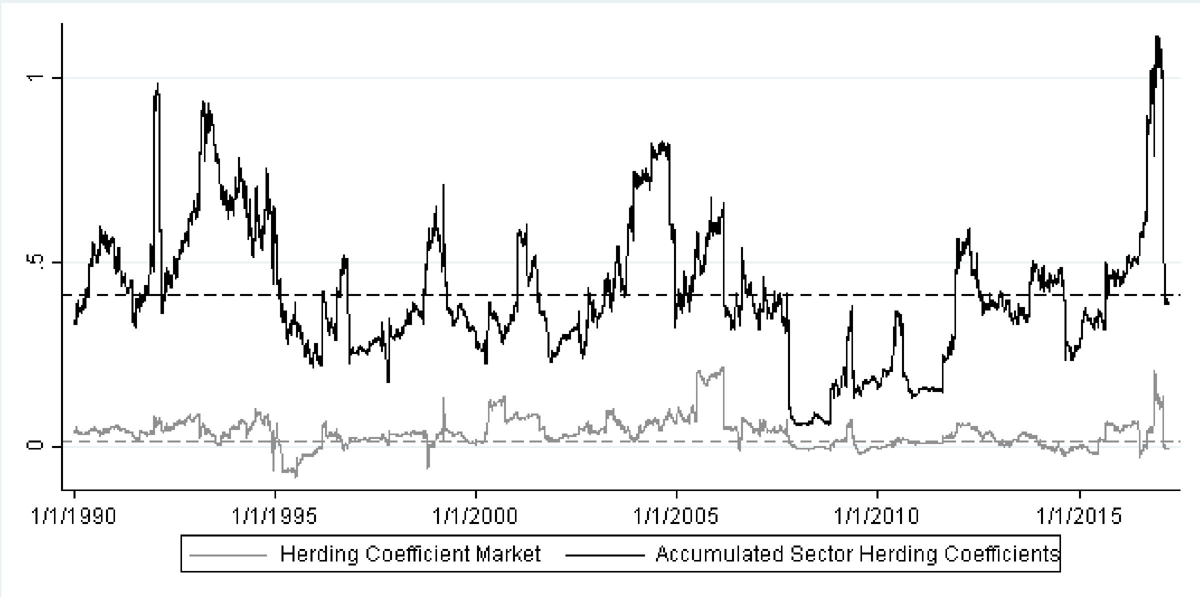
	α	γ_1	γ_2	Observations	R-squared
Market 2005 - 2009	0.948***	0.394***	-0.001	1,259	0.5398

*** p<0.01, ** p<0.05, * p<0.1

Note:Above table presents the regression result of the overall market using equation 4a. The findings suggest no evidence of herd behaviour during 2005-2009.

Appendix H

Accumulated Herding Coefficients (1990 - 2018)



Note: The above diagram plots the accumulated sectors coefficients and for the overall market from the rolling regression with a 365 calendar day window size. The accumulated coefficients is presented as a proxy for total market irrationality. The Diagram indicates a fluctuations over time with time periods with high levels of sector non-linearity, indicating irrational behaviour and time periods with low levels of sector non-linearity.