Is herding behaviour present on the financial markets? Evidence from the US and European markets.

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IS HERDING BEHAVIOUR PRESENT ON THE FINANCIAL MARKETS? EVIDENCE FROM THE US AND EUROPEAN MARKETS

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Executive Summary

Herd behaviour is a cognitive bias that has many alternative definitions, we have chosen the following as the most relevant and broadest in our opinion: the tendency to imitate the actions of others. This behaviour can be seen as rational or irrational. We use two methods to analyse the potential herding behaviour on the financial market. We have chosen the US market and the European market and the result of our analysis is that there is no evidence of herd behaviour using the methods we have selected over the period 1 January 2006 to 31 December 2020. The results are in line with previous work done on this subject. We decided to analyse this behaviour because if there is evidence of herding it is challenging the rationality of agents on the financial market. Therefore it could question the relevance of modern financial theories by for example impacting the benefits of portfolio diversification. It can also be a cause for bubbles and crisis. According to our work both the European and the US market seems to be efficient, at least in terms of the herding behaviour. Nevertheless we also pointed out that the methods used were possibly not the best suited to detect this kind of psychological behaviour and where focusing on the local herding behaviour and do not have an international perspective. From our result we also noticed that as the empirical evidence suggested, the metric used to detect herding are more important during the down market and less present for larger companies. We conclude that if there is herding on the market, it has a limited impact on the European and US markets and do not affect the rationality of the agents who are acting on these markets.

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1 Introduction

The financial market is the market that should be the most efficient. As Thaler (2016) explained, the reasons are that it has the following features: low transaction costs, high stakes, lots of competition and the ability to sell short[1]. Therefore it should be harder to find evidence of misbehaving on this market. We decided to test the relevance of this statement by analysing the potential existence of herd behaviour on the financial markets.

The following work is presented as follows: first we will developed some important theories from modern finance. We will focus on the efficient market hypothesis, modern portfolio theory, the capital asset pricing model and the Fama-French three-factor model and we will review them briefly. Then we will have a short section about the economic and financial crisis that the world has faced. Then we will introduce behavioural economics, behavioural finance and two biases, namely overconfidence and loss aversion. After that we will examine the main subject of this work, herding behaviour. In this section we will describe this bias using the literature around this phenomenon and the main research and findings done in the field. Next, we will conduct an analysis using two methods from the literature we have chosen, with our work focusing on European and US financial markets from 1st January 2006 to 31st December 2020. We will end this work with a robustness test, a discussion and a conclusion.

The preliminary work we have done before choosing herding behaviour as our bias of interest can be summarise in table 17 in the appendix. We found that it was one of the most important biases in terms of the literature. Then, in term of type of data needed to make an analysis, they are easier to access and more numerous than the one for others biases that might need access to personal data from banks or make surveys to professionals in the financial field.

2 Theoretical framework

We will begin the theoretical framework by looking at modern finance theories, first the Efficient market theory (EMH). Then, we will look at Modern Portfolio Theory (MPT). After that, we will treat the Capital-asset pricing model (CAPM) to finally end with the Fama-French Three-Factor model. To continue with the theoretical framework, we will discuss the financial and economic crises. Finally, the last topic we will address will be behavioural economics with a focus on behavioural finance. We will first review the founding papers of this "new" field of economic science, then we will review three types of behavioural biases, namely overconfidence, loss aversion and the bias we are most interested in, herding behaviour.

2.1 The main theories of modern theory

Given that the following theories are not the main subject of this work we will only treat them in a relatively simple way, we will not analyse these theories in depth. In spite of this, it is important to treat them and to understand the basis of modern theory of finance. We will see in the following review that they are based on assumption of the rationality of agents. This assumption will be challenged in the part about behavioural economics and finance. Scharfstein and Stein (1990) describe the rationality of the agents as follows *"decisions that are made using all available information in an efficient manner"* (David S. Scharfstein and Jeremy C. Stein, 1990, p. 465), saying it is a tenet of the classical economic theory. This is the same as to say that investors are perfectly rational. In the following paragraphs, we will review some scientific papers dealing with the Efficient market hypothesis, Modern portfolio theory, capital-asset pricing model and the Fama-French three-factor model.

[1]Short selling allows that even if most investors are "fools", the activities of "smart money" arbitrageurs can assure that markets behave "as if" everyone were smart (Thaler, 2016, p.1587)

2.1.1 Efficient market hypothesis

We start with the theory that is seen by many as the foundation of modern finance. It was first developed by Eugene Fama in 1970 in his work *Efficient Capital Markets: A Review of Theory and Empirical Work*. The main point of the theory is that all available information are fully reflected in the prices on the market (at least in the strong form). Another important assumption, is that the equilibrium on the market *"can be stated in terms of expected returns"* (Fama, 1970, p.384). That means in short that the equilibrium price of a security on the market is linked to the risk of this particular security. One of the effect of these assumptions is that it implies that it is impossible for someone on the market to receive profits exceeding the equilibrium expected profit. It is therefore impossible, according to the efficient market theory to get above average returns on the market using private or public information. To be efficient, a market need three sufficient conditions, which are the followings (Fama, 1970, p.387):

- No transaction costs,
- Information that are available and cost-less,
- Everyone on the market agree on the implications of current information for current price and distribution of future prices of each security.

These conditions are of course not a representation of the reality. Fortunately, for this theory, they are sufficient but not necessary conditions for market efficiency. There is one important statement from Eugene Fama in this particular work, he wrote the following sentence : "The results of tests based on this assumption[2] depend to some extent on its validity as well as on the efficiency of the market"(Fama, 1970, p.384). He also stressed that there are other possible measures for the distribution of returns and that the expected returns are only one of them. Eugene Fama also developed in his work three levels for the Efficient Market Hypothesis :

- The weak form, where only historical prices are reflected in the price.
- The semi-strong form, where all the publicly available information are reflected in the price.
- The strong form, where all information public and private are reflected in the price.

This theory can be summarise by two components first there is non "free lunch" meaning that it is not possible to beat the market without taking additional risks and second, price on the market reflect fully all information. This point is the one that behavioural economists found the most difficult to agree with, as in Graham (1965) or Thaler (2016), by taking the example of closed-end-fund that were not always well priced. There is a lot of work that was done that match the findings of this theory, despite all there is also some evidence against the theory. We can think of investor that consistently get returns above the market average such as Warren Buffet, this is against the EMH because an investor should not be able to earn above average returns using fundamental or technical analysis. We can also points out the bubbles and others extreme events on the market, which are not consistent with the EMH. One of the reasons behind the fact that the EMH might not always be in line with the reality of the financial market might come from the fact that the market is not efficient at any point in time. That is one point brought forward by behavioural economists.

2.1.2 Modern Portfolio Theory

The second theory we will analyse is Modern portfolio theory (MPT) from Harry Markowitz[3]. He started to develop it in 1952 in his work *Portfolio Selection* (Markowitz, 1952). The theory states that diversification is key to decrease the risk and maximise the returns, having different assets and assets type that are as less correlated as possible is the best way to decrease the exposure to the unsystematic risk, which is the risk specific to particular securities. There is in this theory two main concepts :

1. Investors are rational and their goal is to maximise return.
2. Risk can be reduced by diversifying using assets that are not too much correlated.

[2] He means the expected returns assumption.
[3] He received the Nobel Price of economics for his work in 1990.

Risk is divided in two types, systematic risk which can be seen as the risk that can not be diversified (i.e. The market risk) and unsystematic risk which is related to each individual securities (e.g. Business risk, Financial risk, Operational risk,..). Markovitz proved with the Modern Portfolio Theory that a diversified portfolio is less volatile than the sum of its individual securities volatility (See figure 21). An additional development linked to Modern Portfolio Theory, is the efficient frontier, which is *"representing the boundary of the set of feasible portfolios that have the maximum return for a given level of risk*[4]*"* and is often represented by the following graph :

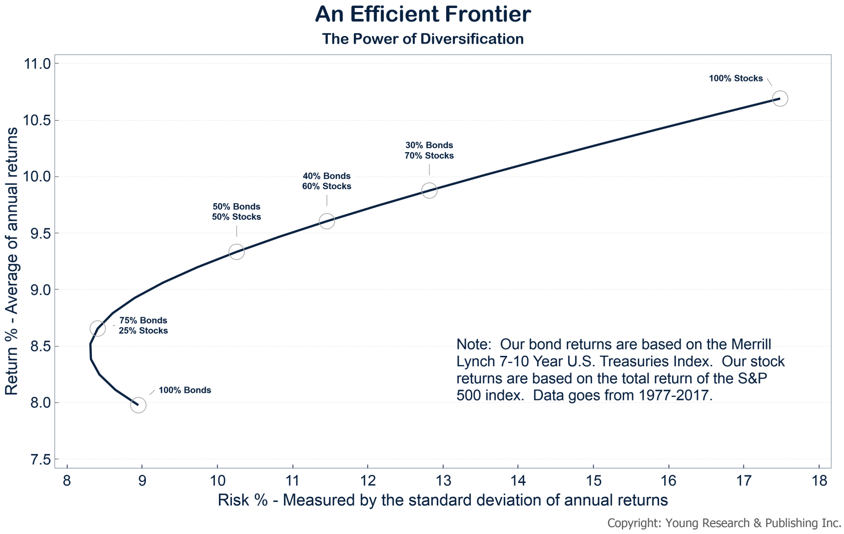

Figure 1: Efficient frontier (Source : E.J. SMITH (2019))

We might want to know the number of stocks that is needed to attain the "best" level of diversification. This question was answered by Evans and Archer in 1968 and they found that according to their research a portfolio of more than ten stocks does not have have an economic justification. In 1987 a behavioural economist, Meir Statman challenged the findings of Evans and Archer. He explained that diversification is used as a risk reduction and therefore we should continue to add stocks as long as the marginal benefits exceed the marginal costs. And according to his findings, the number of stocks needed to achieve the greatest level of diversification should be between 30 to 40 depending on the position of the investors (i.e. if he is borrowing or lending). Jacob (1974) explained that some improvement could be made to the MPT if the selection of stocks was done by choosing stocks wisely, because as Jacob said *"Existing evidence on the benefits of diversification as a function of the number of securities held has been based on random selection"* (Jacob, 1974, p.847) and therefore that investors could reduce unsystematic risk by investing in a few securities if the they chose their stocks wisely. Moreover as explained in Statman (1987) : *there is no evidence that investors follow the suggested rules on optimal diversification with few securities*(Statman, 1987, p.361). It was even shown by Blume and Friend that individual investors often have lower diversification than they should. The summary of their research is as follow : *"The empirical results show, however, that many investors, particularly those of limited means, do not hold well-diversified portfolios. The analysis of the returns realized by them confirms that these investors have exposed themselves to far greater risks than necessary"* (Blume and Friend, 1978, p.58). In addition to the research from Blume and Friend about the diversification by individual investors, King and Leape also have done a empirical review of the diversification of individual investors with their whole portfolio of assets (e.g. Bonds, real estate, stocks, funds) and found that even when taking into account all their assets the individual investors did not diversify as implied by the theory from Markowitz. This can be seen as an evidence that investors are in the real world not totally rational.

[4]From the website NASDAQ.

To summarise, according to this theory, a rational investor who wants to maximise his returns should diversify her portfolio since the volatility of the portfolio will be less than than the sum of the volatility of each of the components of this portfolio. Empirical analysis was also made to find the best number of assets to achieve the best level of diversification. This number, for which it seems their is no more interest to increase the number of stocks, is still argued but we can say it is commonly agreed to be between ten and thirty different stocks.

2.1.3 Capital-asset pricing model

We have seen with the work of Markowitz on Modern Portfolio Theory that it is preferable for an investor to diversify his portfolio, because the volatility, which can be seen as the proxy for the risk, of a portfolio of multiple assets will be lower than the sum of the volatility of each individual component. The theory that will be analysing in this section, the Capital-asset pricing model (CAPM), is for its part focusing on the returns an investor should receive based on the risk they are taking for individual assets. It was mainly developed by four economists, namely Jack L. Treynor (1961, 1962), William F. Sharpe (1964), John Lintner (1965) et Jan Mossin (1966). The CAPM is seen as an extension of the work of Markowitz. We will focus on the work of John Lintner and William F. Sharpe[5]. The CAPM can be summarised by the following equation :

$$ER_i = R_f + \beta_i(ER_m - R_f)$$

Where we have ER_i as the expected returns for the equity i, R_f the risk free rate, β_i the Beta of the equity i, ER_m the expected returns of the market. The beta is a measure of the volatility of an individual security compared to the market, it is therefore measuring the systematic risk. It is described by the equation below :

$$\beta = \frac{Cov(R_i, R_m)}{Var(R_m)}$$

What the equation tells us is that the returns for a single security will be equal to the return of the risk free asset plus the market risk premium, which is the difference between the expected returns of the market and the return for the risk free asset, multiplied by the Beta of the security *i*. The beta being a measure of the volatility of the security compared to the market portfolio. All of this gives us an estimate of the expected returns of an individual asset. In this framework, the only way for an investor to get more returns is to increase the risk.

In his work, *Capital asset prices : A theory of market equilibrium under conditions of risk* (Sharpe, 1964) started with a sentence that is interesting. He said *"in equilibrium, capital asset prices have adjusted so that the investor, if he follows rational procedures (primarily diversification), is able to attain any desired point along a capital market line[6]"*(Sharpe, 1964, p.425) The implication of this sentence is that the CAPM assumes that investors are rational.

2.1.4 The Fama-French Three-Factor model

In the continuity of the Capital-Asset pricing model, Eugene F. Fama and Kenneth French developed a model called the Fama-French Three-Factor model. It is an extension of the Arbitrage Pricing Theory developed by Stephen Ross in 1976. The APT allows to build multi-factor model. In this model, they included three factors, the first one is the market risk, which was analysed in the CAPM, they also added the size and the value risks (Fama and French, 1992). The factor on size effect was mainly motivated by the research done by Banz (1981). In this papers he highlights the size effect after having done an empirical study in which he finds that: *"smaller firms have had higher risk adjusted returns, on average, than larger firms"* (Banz, 1981, p.3). In addition to this risk, Fama and French added a factor to take the value risk into consideration. It was found by

[5] He received a nobel price for the development of his "Sharpe Ratio" which is used to measure the return of an investment compared to its risk.

[6] The capital market line (CML) represents portfolios that optimally combine risk and return.

Rosenberg et al. and Stattman that the returns of US stock was positively related to their book to market value. The equation is therefore the following :

$$R_{it} - R_{ft} = \alpha_{it} + \beta_1 (R_{Mt} - R_{ft}) + \beta_2 SMB_t + \beta_3 HML_t + e_{it}$$

The left side of the equation is the premium investors received in exchange for the risk they are taking by buying risky assets. On the right side we have first $R_{Mt} - R_{ft}$ that is representing the excess returns from the market portfolio, then SMB_t (Small minus Big) which is representing the size risk, the premium small companies received on the market compare to bigger companies. Finally HML_t (High minus Low) represents the premium that value stocks are receiving compared to growth stock on the market.

Fama-French also worked on a 5 factors model in *A five-factor asset pricing model* (Fama and French, 2015) where they added two additional factors to their three factor model, namely investment factor and profitability. The investment factor, is taking into account that stocks of companies with a high total asset growth have lower average returns and the profitability is taking into account that companies with high profitability perform better in the market in general.

2.1.5 Conclusion for the section on modern financial theories

The first point we have to highlight is that the theories we treated in the previous pages are all based on the assumption that investors on the market are rational and that the market is efficient. These assumptions are of course too restrictive to describe the reality we are confronted to on the market but are a good foundation to understand the financial market. All this modern finance theory is still the most important in the literature, nevertheless there is some increase in interest by academics about the psychological, cognitive importance that can impact the efficiency on the market and rationality of the agents. There is an increase in papers that tried to take into account that market agents are subject to cognitive, emotional and imitation errors that will affect the efficiency of the market that is used as the basis of most on modern theories. Therefore in the following section we will look at the birth and the main findings made by behavioural economists.

2.2 Financial and Economical crisis

Now that we have reviewed modern financial theories we will take a look at crisis. There were an important number of crisis throughout the history. Moreover, crisis on the financial market is seen by many economists as a result of herding behaviour. Due to the fact that, in time of crisis on the market, investors tend to put aside their own belief and follow the herd. Financial crisis are sometime preceded by bubbles, which can be described as : *"A situation in which news of price increases spurs investor enthusiasm which spreads by psychological contagion from person to person, in the process amplifying stories that might justify the price increases and bringing in a larger and larger class of investors, who, despite doubts about the real value of an investment, are drawn to it partly through envy of others' successes and partly through a gambler's excitement."* (Shiller, 2014, p.1487). Here is some of the three examples of important financial crisis : the Tulip Mania in 1637, Stock Crash of 1929 and the 2007-2008 Global financial crisis. The Tulip Mania is seen as the first bubble on the financial market and took place in the Dutch Republic. During this crisis, the price, as its name suggests, the Tulip bulbs price increased to derisory levels, as the figure 2.

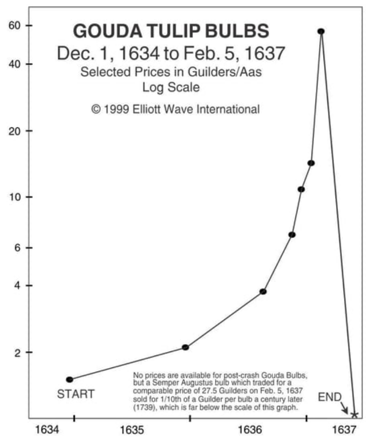

Figure 2: Price of Gouda Tulip Bulbs from Elliott Wave International

In the following lines we will have a look at two crisis that are the most interesting for out work, the 2007-2008 Global financial crisis and the more recent economic crisis linked to the Covid-19 pandemic known as the "The Covid-19 recession". The reason of this interest is that they are both included in the time frame of the analysis that will follow. The financial crisis of 2008 found its foundation in the subprime crisis in the US and became an international financial crisis later. We will focus on the financial impact of both crisis and do not analyse the economical effects. Just below we have a graphic on figure 3, with the effect on the financial market for the 2008 crisis.[7]

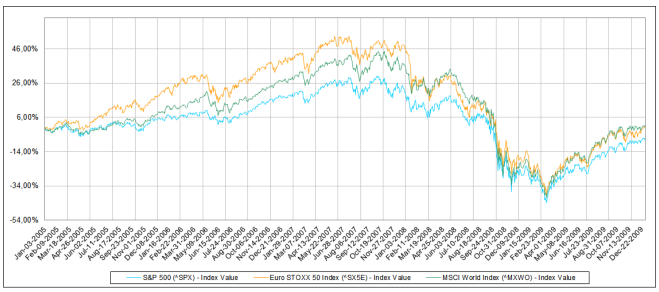

Figure 3: Index value for the S&P500, Eurostoxx 50 and the MSCI World from January 2005 to December 2009; retrieved from CapitalIQ

[7] A graph from 2005 to 2021 can be found in the appendix on figure 18.

We can see that the crisis spans on a quite long period of time and took time to recover. It took about 4 years to recover from this crisis. Now if we compare it with the graph for the Covid-19 related crisis we have the following graph:

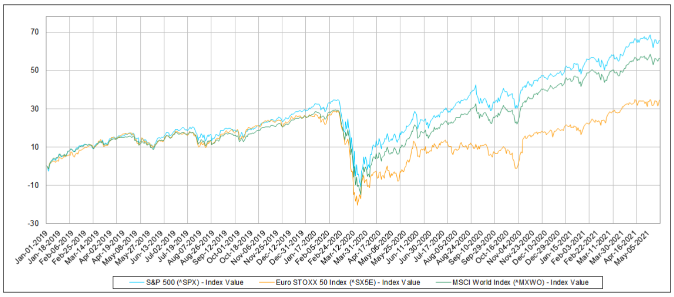

Figure 4: Index value for the S&P500, Eurostoxx 50 and the MSCI World from January 2019 to Mai 2021; retrieved from CapitalIQ

What we can see is that the 2020 stock crash[8] was more brutal, the decrease lasted for about two months and was relatively strong. The recovery for itself took approximately 6 months to recover from this stock crash. Both crisis seems to be irrational in terms of changes in price of equities. We might wonder if there were some rational new information on the market leading to the drop in prices or if there is some phenomenon that might have affect the financial markets. We will try to answer to this question partially. We will try to find if there is evidence of herding behaviour during this two periods of extreme volatility.

2.3 Behavioural Economics

To begin this section here is a citation of Meir Statman from the book *A random walk down Wall Street* (Malkiel, 1999, p.225) :

"Behavioral finance is not a branch of standard finance: it is its replacement with a better model of humanity - Meir Statman"

This statement might be a bit exaggerated but behavioural economics (finance) is a field of economics that is adding a psychological aspect to traditional economics. Richard H. Thaler[9] described behavioural economics by what he called a mixture of economics and psychology, and added the following sentence : *"utilizing a psychologically realistic depiction of the representative agent"* (Thaler, 2016, p.1577). In classical economics we are facing three main assumptions about the agents. They are the following (Thaler, 2016, p.1578):

1. Agents have well-defined preferences and unbiased beliefs and expectations.
2. They make optimal choices based on these beliefs and preferences.
3. Their primary motivation is self-interest.

These assumptions are what defined the *Homo Economicus*. On the other hand, behavioural economics introduced (or at least tried) *Humans* in their models. Unlike what we could expect, because of the recent development of behavioural economics, we could go back in time and find traces of behavioural concepts in the work of for example Adam Smith. He treated, even shortly, some crucial concept as overconfidence, loss aversion or self control. For loss aversion for example we have this phrase from Smith: *"Pain is, in almost all cases, a more pungent sensation than the opposite and correspondent pleasure"* (Smith, 1759, III, ii, 176 –177). There is other examples of economist that had some behavioural point of view. We can cite again Keynes[10], Fisher or Pigou. As Thaler explained many economists from the past were already thinking that psychology

[8] Linked to the Covid-19 recession.
[9] He was awarded the Nobel Memorial Prize in Economic Sciences for his contributions to behavioral economics.
[10] Some examples will be given in the following pages.

should have an impact on economics. He cited an example from another economist, John Maurice Clark which is the following: *"The economist may attempt to ignore psychology, but it is sheer impossibility for him to ignore human nature. If the economist borrows his conception of man from the psychologist, his constructive work may have some chance of remaining purely economic in character. But if he does not, he will not thereby avoid psychology. Rather, he will force himself to make his own, and it will be bad psychology"* (Clark, 1918, p.4). That can be a summary of what behavioural economists are trying to do, include psychology in economics. We could ask ourselves the question, why behavioral economics is not more used by economists. One of the reasons is that the economic field after World War II was more focused on mathematical explanation and therefore using Econs instead of Humans in mathematical models was more convenient. The models based on rational thinking were therefore a good cornerstone for the field of economics to grow on a strong base. As Richard H.Thaler, said as an example in *Behavioral Economics: Past, Present, and Future "One begins learning physics by studying the behavior of objects in a vacuum; atmosphere can be added later. But physicists never denied the existence or importance of air; instead they worked harder and built more complicated models"* (Thaler, 2016, p.1579). What he means is that traditional economics theory considered that everyone is able to solve problem whether it is a simple problems or an absolutely difficult one. Then we have Milton Friedman[11] who had an another position on the fact that humans are not perfectly competent in resolving problem. He came in his essays *Essays in positive economics* with the example of professional billiard player : *"excellent predictions would be yielded by the hypothesis that the billiard player made his shots as if he knew the complicated mathematical formulas that would give the optimum directions of travel, could estimate by eye the angles, etc., describing the location of the balls, could make lightening calculations from the formulas, and could then make the balls travel in the direction indicated by the formulas. Our confidence in this hypothesis is not based on the belief that billiard players, even expert ones, can or do go through the process described; it derives rather from the belief that, unless in some way or other they were capable of reaching essentially the same result, they would not in fact be expert billiard players."* (Friedman and Friedman, 1953, p.21). We can see that even within economists, their is no common agreement on the relevance of the cornerstone assumption that we are facing *Humans* or *Econs* in the theory. Richard Thaler made two comments about the example given by Friedman, first he said that he is speaking of an expert and in economy the theory is used to solve problems for "normal" peoples and second, even experts have difficulties to solve really difficult problems.

The birth of behavioural economics is seen by many to have started by papers written by two psychologists, Daniel Kahneman and Amos Tversky. There is mainly two works that had an important influence on the increase interest on the field. First in terms of publication date we have *Judgement under Uncertainty: Heuristics and Biases* (Tversky and Kahneman, 1974), in this paper, they proved using experiments that when humans make judgements they are systematically biased. They spoke about judgemental heuristics, which are mental processes used to form judgement quickly. Heuristics can be seen as explanations of the cognitive biases humans are subject to. In the first papers by Kahneman and Tversky, they talked about three heuristics, adjustment and anchoring, availability and representativeness. Adjustement and anchoring is a phenomenon when *"People make estimates by starting from an initial value that is adjusted to yield the final answer"* (Tversky and Kahneman, 1974, p.1128), and that this starting point affects the estimation of the agents.[12] Then availability, this heuristic can be represented by the graph 5 below. As we can see, when humans need to form an opinion about something they tend to overweight recent, negative, frequent information and that lead to a biases judgement. Finally, representativeness is when people overweight the outcome of an event because of the similarity with an other event or object. There are other heuristics or rules of thumbs that humans are subject to. What we wanted to show is the founding of the cognitive biases that are in the centre of behavioural economics.

[11] He received the 1976 Nobel Memorial Prize in Economic Sciences for his research on consumption analysis, monetary history and theory and the complexity of stabilization policy.

[12] An example of an experiment done by Kahneman and Tversky about anchoring can be found in figure 20.

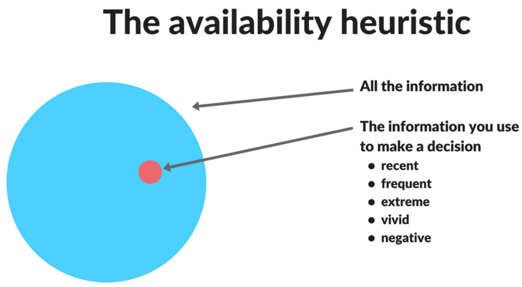

Figure 5: Representation of the availability heuristic from the web site : kenthendricks.com

In the second paper published in 1974, and called *Prospect theory : An analysis of decision under risk* (Kahneman and Tversky, 1979) they developed an alternative model from the one used in Economics to describe utility, they called their model *Prospect theory*. This model is an alternative model of decision making under uncertainty. The expected utility theory is a standard in modeling in economics and is used to characterize how a rational agent should react under uncertainty. Frank Ramsey and Leonard Jimmie Savage were the first to work on this theory and the model was afterwards improved by Morgenstern and Von Neumann (1953). They created axioms that are assumed to be used by people when they are taking decisions under risk. In Prospect theory, Kahneman and Tversky were able to find choices between prospects (i.e. gambles, choice between two problems) that were not in accordance with expected utility theory and that violated the rationality of the agents[13]. They used laboratory experiments to prove their point. For example, traditional theory assumed that for agents a loss of a certain amount would have the same inverse impact on their utility as for a gain. During their research, Daniel Kahneman and Amos Tversky showed that it was not the case for most people, based on their findings a bias was developed, namely Loss aversion that we will talk about later. The fact that investors are not rational is one of the main principle developed in the behavioural theory. In this field of economy, they recognised the fact that in the real world the agents are not what we call in economics “Econs” but “Humans” and that they can be subject to psychological biases. These cognitive differences between “Humans” and “Econs” make the “Humans” less efficient and less rational in their decision than “Econs”, who are always doing the right choice. That leads us to go to a sub-field of behavioural economics, behavioural finance where the rationality of agents is a main assumption as we have seen with the EMH, MPT or the CAPM.

2.3.1 Behavioural finance

In his paper called *Behavioral Economics: Past, Present, and Future* (Thaler, 2016) has a section dedicated to behavioral finance. Behavioural finance is a part of finance that is adding the psychological and sentimental impact in the field. Traditional theory often forgot or did not have the capacity to use psychological aspects in the mathematical and theoretical theories. The behaviour of the agents on the market is often difficult to prove by mathematical formula, and it is the way academics find the most trustworthy. We will in the following pages review three main categories of biases, in this paper we will have a focus on only a few of them. As we have seen with (Fama and French, 1992), they explain the difference in returns between value and growth stocks by a difference in risk while De Bondt and Thaler (1985) for their part argue that it is coming from mispricing. That is an example of the conflict of explanation between the traditional and behavioural finance.

2.3.2 Main behavioural biases

We will discuss three important biases that humans are subject to. We will first talk about overconfidence, and loss aversion. These two biases will be treated quickly, because they are not the main subject of this work. Either way, we believe it is interesting to have a basic understanding of these biases before going to the main

[13] An example from these prospects could be seen inf figure 19.

bias we will analyse : herding behaviour. There are of course other behavioral biases which we will not deal with here, for example framing, anchoring bias, confirmation bias and others.

2.3.2.1 Overconfidence

We first start with overconfidence as our first bias analysed. This cognitive bias can be explained as said in the books *Thinking Fast and Slow* by the tendency human have to place too much faith in there intuition and is due *"to the tendency humans have to construct and believe coherent narratives of the past makes it difficult for them [us] to accept the limits of our forecasting ability"* (Kahneman, 2012). For De Bondt and Thaler (1995) overconfidence is the bias that have the more robust finding in psychology. The example often used for this bias using real life example is the one presented by Svenson (1981) which is about a survey in Sweden about the feeling of drivers about their capacity compared to others and the results were that 90% of drivers thought they were above average drivers, which is mathematically impossible and a good example of overconfidence. On the financial market, which is the subject we are most interested in, overconfidence was found to push investors to trade more aggressively therefore reducing the welfare (Odean, 1998). It also has an impact on diversification because it is pushing investor to "bet" on individual stocks, reducing the amount of assets in their portfolio. However as Hirshleifer (2015) explained overconfidence can also have a positive impact by reducing home bias[14].

2.3.2.2 Loss aversion

Loss aversion is a bias that was also part of the work done by Kahneman and Tversky in "Prospect Theory". They explained it using the following words : *losses loom larger than gain* and means that according to their experiments the pain of losing is psychologically twice as powerful as the pleasure of winning. It can be represented by the function we have below : We see that the function for losses is steeper and convex compared

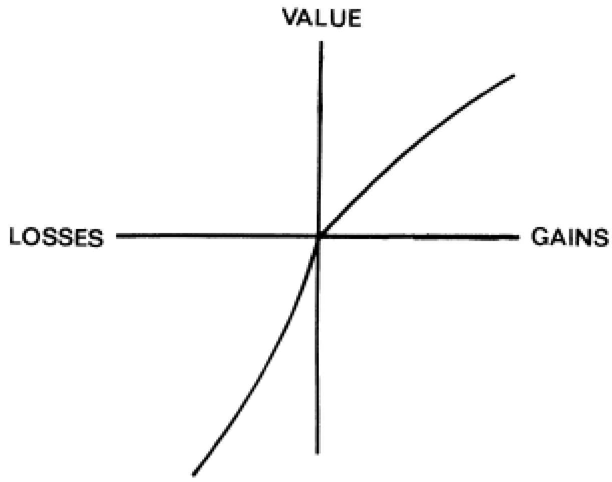

FIGURE 3.—A hypothetical value function.

Figure 6: Figure representing a hypothetical value function from Kahneman and Tversky (1979)

to a flatter and concave function for gains. The implication of such a behaviour could result in a change of the attitude of investors in relation to risk. The loss aversion can induce disposition effects which are the tendency to sell stocks that have performed better and keeping the less performing in hope they will recover and could also explain why some individuals do not want to invest in the stock market.

[14]It is a bias that induced investors to mainly invest in the domestic market leaving other foreign markets aside.

3 Literature review

Now that we have dealt with the two previous biases, we still need to treat the bias we are the more interested in, herding behaviour. In the following section we will treat the most interesting papers, in our opinion, about herding behaviour. Papers that describe herding, explain some particularity, and effects of this behaviour. We will also look at empirical analysis done on this subject and describe the methods used to detect herding behaviour and the results they found and in addition compare them. Then in the next section we will do our own analysis for the European and the US market, during a period of 14 years starting the 1st January 2006 and ending the 31st December 2020, using methods developed by two papers we will describe shortly.

3.1 Herding behaviour

3.1.1 Introduction

We begin this section with an introductory example from (Caparrelli et al., 2004, p.222) :

"One evening we decided to go to Restaurant A, which had been recommended by a very reliable guidebook. When we arrived, we noticed that Restaurant B nearby was very busy, while Restaurant A had only a few customers. So we changed our minds and ate at Restaurant B".

This illustration can summarise what is a herding behaviour with a real life example. The fact that we tend to imitate others is not a new development in psychology, it is a basic human instinct. Despite this we might think that the discovery of this bias should be something new that comes with the development of behavioural economics, yet we can already read about herding behaviour in the writings of John Maynard Keynes in 1936. In his book *The general theory of employment, interest and money* he spoke about the irrationality of the market links to herding which was fairly well summarised by the following sentence : "*the stock market was mostly a beauty contest in which judges picked who they thought other judges would pick, rather than who they considered to be the most beautiful*" or as another example more focused on the behaviour of financial professionals, *"it is better for reputation to fail conventionally than to succeed unconventionally"* (Keynes, 1936). Keynes was also sceptical about the ability of investors to go against the trends of the market (i.e. Herding behaviour). Herding can be commonly described as "*the tendency to mimic the actions of others*" (Chang et al., 2000, p.1652). Devenow and Welch (1996), p.604, described herding as *"a notion that leads to systematic erroneous decision making by entire populations"*. In a more broader way herding can also be defined as a *"behaviour patterns that are correlated across individuals"* (Devenow and Welch, 1996, p.604) but this definition could also be linked to correlated information. Which could lead for example investors to buy the same stock because of positive information. Finally Hwang and Salmon (2004) said herding on the financial market is *"when investors imitate the investment decisions of others without reference to fundamentals"*.

An additional important remark is that herding need a coordination mechanism which can be either a widely spread rule based on a signal (e.g. a price movement) or this mechanism can be the ability to observe the decision of others (Devenow and Welch, 1996).

In the academic literature we have two distinctive types of empirical investigations, as said by Chiang and Zheng (2010) the first one is focusing on co-movement behaviour based on the measure of dynamic correlation. The second one is the type of empirical analysis we will test later in our analysis and is focusing on cross-sectional correlation dispersion in stock returns in response to changes in market conditions.

3.1.2 Rational and irrational herding

The herding behaviour is commonly separated in two forms in the literature, rational and irrational. The irrational view is the herding that happened when *"investors with insufficient information and inadequate risk evaluation disregard their prior beliefs and blindly follow other investors' actions"* (Lin et al., 2013, p.756) putting aside rational analysis and following blindly others. On the other hand, rational herding is *"center on externalities, optimal decisions-making being distorted by information difficulties or incentive issues"*. (Devenow and Welch, 1996, p.604).

The rational herding analysis done in the literature leads to three main models explaining them (Devenow and Welch, 1996):[15]

1. Payoff externalities model
2. Principal-agent model
3. Informational cascade model

Concerning the payoff model, in this herding behaviour theory it was shown that the payoffs increase with the number of people adopting the same behaviour. We can see examples of this theory on bank runs as developed by Diamond and Dybvig (1983). Devenow and Welch (1996) divided the payoff externalities model in three separated categories, bank runs, liquidity in markets and information acquisition. The basis of the model on bank runs is that agents are able to first, have the information on when others are running to the bank. Then, secondly, the bank could potentially have a shortage of funds. This means that the last person who might want their money back could end up empty-handed. In this context, herding behaviour might leads to bank runs. For the liquidity in markets category, work was done that found out that due to economies of scale or when inform trading could imposes an externality on uniformed trading that would leads investors[16] to benefit from the markets that are most liquid and might leads investors to be subject to home bias and trade only on one market. Finally, the information acquisition part for the payoff externalities model, in this model they found that under certain circumstances there is herding on information for certain stock. Therefore increasing the number of investors gathering on the same information and as a consequence lacking on others.

The principal-agent model, or also called reputation model, is a model that takes into account the fact that professional investors are compared based on relative not absolute performance (Morck et al., 1989) which means a manager might prefer to follow his fellow managers rather than take an "unconventional" decision. The reason behind this is as already cited *"it is better for reputation to fail conventionally than to succeed unconventionally"* (Keynes, 1936, p.138). Because the manager prefers to cover his back in case of bad/non satisfying returns on his investments and he might reject private information he has on some specific investments and therefore chooses to mimic other managers (David S. Scharfstein and Jeremy C. Stein, 1990). Trueman (1994) has done research on the effect of herding on empirical research using security analysts earnings forecast. Trueman found that analyst have a tendency to report forecasts that are similar to the ones already released by other analysts, therefore herding. This has the effect of impacting the calculation of a consensus and makes it inappropriate.

Informational externalities or informational cascades is seen by many as the main explanation of herding. Two similar models were developed by Banerjee (1992) and Bikhchandani et al. (1992). We will describe the essence of the models by an example from Banerjee in 1992. Banerjee sets up the model to study the rational behind this behaviour and the potential effect. They found that the reduction of informativeness could impact negatively the welfare under this kind of behaviour. They also used an example of restaurant as we have done in the introduction but more elaborated. Here is the example : we are facing a population of 100 people and two restaurants (A and B). The probabilities for restaurant A to be the best is 51% and 49% for B. The people arrive in sequence and they observe the choice of prior participants before making their own choice and each person received a signal (before they make their choice) saying which restaurant is the best.[17] As said in the example given by Banerjee (1992), we suppose that 99 people received a signal that B is better but one person that A is best and this person is the first to choose. Under these conditions, the first person will go to A, the second having a signal for B but seeing that the first person is going to A and because their signal is both the

[15] Some model are a combination of two or the three types.
[16] Informed and uninformed.
[17] The signal could be wrong and the signals received from each person is the same quality.

same quality they will cancel each other and therefore the rational choice for the second person is to go to A. The situation is the same for all the following participants and every one of the 100 person ends up in restaurant A despite the fact if we look at the aggregate information we are practically certain that B is the best choice of the 2. From (Shilller, 1995, p.181) with that setting *"a bad equilibrium arises from a "herd externality," of imitating others and thereby concealing one's own information"*. After that Banerjee explained that if the second person was someone that was always following its own signal it would have provided information to all the others and therefore avoid negative externality.

The non-rational or irrational herding, also called non-informational based herding[18], is the part of the herding bias that could result in market inefficiencies, make the prices of asset diverge from fundamental values and therefore lead to a mispricing of assets. As Hwang and Salmon (2004) explained herding leads to bias view of expected returns and risks.

There is also an intermediate view which can be seen as a mix between the two preceding types of herding. In this framework agents are near rational and are using heuristics on information processing to gain time. And these heuristics cannot be eliminated. (Devenow and Welch, 1996)

3.1.3 Main methods

In this section, we will take an in-depth look at the scientific papers related to herding on the financial market and the analysis of its presence as well as the possible repercussions of this behaviour. When we look at the literature about the detection of herding behaviour we can bring to light two important contributions that developed models to detect such behaviour. First, *Following the pied piper: Do individual returns herd around the market?* (Christie and Huang, 1995) and second, *An examination of herd behaviour in equity markets: An international perspective.* (Chang et al., 2000).

The first papers from Christie and Huang, can be seen as the cornerstone of the herding detection. They developed their model, as we will see, around extreme market event. They belief that it is the period of time where we have the better chances to face this behaviour. They motivate their model by the fact that, according to rational asset pricing that dispersion will increase with the absolute value of the market returns due to the fact investors should be trading using their own private information[19]. Then in case of extreme market events, they motivated that investors will herd and therefore the returns for individual stocks would be closer to the one of the overall market. In their paper they used the cross-sectional standard deviation (CSSD) of returns as the metrics in their model to describe the return dispersion. The CSSD is described by figure 7.

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

Figure 7: CSSD formula from Christie and Huang (1995)

Where R_{it} is the returns at time t for stock i, R_{mt} the returns of the market at time t. N the number of stocks in the sample. They then use this metrics in a model of linear regression to have the following form :

$$CSSD_t = \alpha + \beta_L D_t^L + \beta_U D_t^U + e_t \tag{1}$$

Where D_t^L is the dummy variable equal to 1 when the returns of the market lies on the lower tail of the dispersion and 0 otherwise and D_t^U is also a dummy variable equal to 1 when the returns of the market lies on the upper tail of the market return dispersion[20]. α can be translated as the average dispersion of the sample

[18]Where the fact that investors put aside their own belief is not linked to fundamentals movements.
[19]Which are all different.
[20]They use a 1% and a 5% criterion in their work.

that are not covered by the two dummy variables. They explained their thinking as that when investors are herding, the dispersion, here calculated by the CSSD, should be low. They motivate their point by the fact that investors that are herding would put aside their owns beliefs about the market and choose to follow the market sentiment and therefore they would be close to the market returns. CSSD of returns is *"an intuitive measure of dispersion"* (Christie and Huang, 1995). They also added that they were willing to focus on periods when it was more likely to find presence of herding, which is during periods of market stress (they used one and five percent of the observations in the upper and lower tail as extreme market period). Therefore according to the work of Christie and Huang, p.32 we would face herding when *"dispersion are significantly lower than average during periods of extreme market movements"*. This means that, according to the model in equation 1, we would have presence of herding when the betas of the equation are negative and significant. They also made a link with the Capital Asset Pricing model. In the CAPM theory we would see the opposite, there would be an increase in the dispersion due to the fact that assets have different sensitivities to the market return. As a result, if there is evidence of herding on the market the CAPM predictions would be challenged but if there is no evidence of herding on the market, we would have predictions that are in line with the Capital Asset Pricing Model. Their model allows for an analysis of both the bear and the bull market, β_L for the bear market and β_U for the bull market. The rules can be described as follows, if the beta is significant and negative we face evidence of herding, if it is positive and significant we are in line with the CAPM.

The findings from their analysis can be summarised as follows, they found no evidence of herding on the market they analysed, the US market, from 1962 to 1988. Their analysis was split in two, first an analysis in the market as a whole and the other part with an analysis by industry. They found dispersion that was higher than average during extreme periods which is the opposite of what herding would predict. An additional comment about this paper, as we have seen the model is developed to analyse herding in case of extreme events therefore it could be possible that herding happened during periods of normal time which would not be detected here.

The second important papers is called *An examination of herd behaviour in equity markets: An international perspective* (Chang et al., 2000). In this paper, they used an alternative model to the one from Christie and Huang, designed to detect herding in all market conditions. One of the reasons to use an alternative model is that both methods do not always have the same results. They used the cross-sectional absolute deviation (CSAD) of returns as their metrics and not the CSSD. The authors saw their work as an improvement of the

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

Figure 8: CSAD formula from Chang et al. (2000)

method used by Christie and Huang because they found using the Black CAPM[21], that the CAPM predicts a relation between dispersion and the market returns should be increasing but also linear, which was not present in the method of Christie and Huang. In their model they used a linear terms to detect this relationship. As a consequence if investors ignore their own belief and herd during periods of market stress there would not be such a linear and increasing relationship between dispersion and market return and could become non-linearly increasing or decreasing. This is the reason why they added in their model the non-linear term, $R_{m,t}^2$ (see figure below). The model they developed is used to describe the relation between the CSAD and the market return and therefore detect herding and is the following :

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

[21] See figure 22.

They also decided to split the model in two to take into account the possible asymmetry of herding between up and down markets. The models are the following :

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

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

The $|R_{m,t}^{UP}|$ is used to be able to compare both equations. For these equations we would be facing evidence of non-linearity if γ_2 in significant and negative. We have with this model two factors to analyse the first one is γ_1 which is there to give us the linear relation between CSAD and the market returns. An γ_2 that is here to analyse the non-linearity. To be facing herding behaviour we need the non-linear relation between CSAD and the market returns to be negative and significant which means a negative and significant γ_2. We can also face herding if the model is non linear, meaning that γ_1 is non significant. In addition to the analysis based on their model they also used the model developed by Christie and Huang by adapting it by substituting the CSSD by CSAD.

The findings of Chang et al. are that, for the five markets[22] they analysed between 1963 to 1997, they found evidence of herding on the South Korean and Taiwanese markets, partial evidence of herding for Japan and no herding on the US and the Hong-Kong markets. They made a comment about the fact that the scarcity of rapid and accurate information specific to firms in emerging markets[23] could be a reason to find herding, investors might in this context focus more on macroeconomic information and consequently herd with the market.

3.1.4 Additional work

Chiang and Zheng (2010) made a study in 2010 on 18[24] different markets that they split in three groups, advanced, Asian and Latin American and found evidence of herding on the advanced markets (except the US) and in Asian market. The method they used is in some ways different from the ones used in the two others papers we have treated previously. They have done their analysis using a wider set of data compared to others studies. Furthermore the way they have done their work, leads them to add additional variables to take into account absolute domestic stock returns, excess domestic market conditions, and foreign market influences. We can also see that they analysed more countries than the other papers. An additional finding they made is that most of the markets they analysed tend to herd around the US market and found evidence that herding tend to be more important during crisis time. If we compare their results to the ones of other study, we can see that their results are in contrast with the ones we reviewed in Chang et al. (2000) where they found no evidence of herding in advanced markets contrary from the evidence Chiang and Zheng (2010) found. It seems that the difference mainly comes from the fact that in their work Chiang and Zheng used a model that is investigating for herding in the global market and not only on the domestic market.[25]

Demirer and Kutan (2006) have done an analysis on the Chinese market and found no significant evidence of herding on this market between January 1999 and December 2002. Despite their result they nevertheless found that stocks seem to behave more similarly during periods of down market than compare to the up market. They used in their analysis both firm and sector level data from the Shanghai and Shenzhen Stock Exchanges to capture the potential herding on the Chinese market. In Demirer et al. (2010) they worked on the Taiwanese market and found evidence of herding using the methods from Chang et al. (2000). Another analysis was done for the Chinese market by Yao et al. (2014), they found evidence of herding for both the Shanghai and Shenzhen B-share market and no evidence for the two A-share market.

[22] US, Hong Kong, Japan, South Korea, and Taiwan.

[23] Which are South Korea and Taiwan in their analysis.

[24] Australia, France, Germany, Hong Kong, Japan, the United Kingdom, the United States, Argentina, Brazil, Chile, Mexico, China, Indonesia, Malaysia, Singapore, South Korea, Taiwan, Thailand.

[25] One of the model they used can be seen in figure 33.

Caparrelli et al. (2004) made an analysis on the Italian market and found evidence of herding on this market during the period of September 1988 to January 2001. According to their work, the results done on the market, using the model of Christie and Huang, is that herding is present on the Italian market during periods of extreme market event. They also have done an analysis using a metrics developed by Hwang and Salmon (2001) that is supposed to evaluate the degree of herding (see figure 35). Using this metrics they discovered that in the Italian market the H, used to find the degree of herding, is smaller for small-caps than for large-caps meaning that herding is more present for these kind of stocks. Economou et al. (2011) conduct a test on four European markets, Portugal, Italy, Greece and Spain for the period of January 1998 to December 2008, and they found evidence of herding on Greek and Italian markets,[26] mixed evidence in Portugal and no evidence in Spain. They also found asymmetric findings between rising and falling markets. They found an important degree of co-movement in the cross-sectional dispersion of returns on these markets, impacting the potential benefit of diversification within these markets. Lastly they noticed that the degree of herding has not increased during the global financial crisis.

We also think that it is interesting to check papers treating the herding behaviour in other markets than the stock market. We summarise the work on the crypto-currency market from Bouri et al. (2019) and the two papers from Gleason et al. analysing the market of ETFs[27] and the market of futures. An interesting research was done recently on the crypto-currency market by Bouri, Gupta and Roubaud in 2019, they found that there is some evidence of herding on this specific market. They add that herding *"appears to be time-varying and mostly driven by economic policy uncertainty"* (Bouri et al., 2019, p.217). They used cross-sectional absolute standard deviation (CSAD) as their testing method and were inspired by the work of Chang et al.. Finally, in their works Gleason et al. (2003) and Gleason et al. (2004) they treated, in the first papers the used the method from Christie and Huang (1995) to analyse the futures market on three European exchanges. The results from their work is that there is no evidence of herding for these three markets. The second papers is about the ETFs market. One of the specificity of this work is that they used intraday data which might allow them to detect herding that are short-lived. They found no evidence of herding, but they found asymmetric reaction to news.

We made a table summarising the papers we have discussed (See figure 9), and as we can see the results can be divergent, even though we can find some consistency. First the US market seems to be the one that is confronted the less with local herding, second the emerging or less developed markets[28] are subject to more herding probably due to the fact that information is less efficiently transmitted. Finally small-caps seem to face more herding than large-caps. Nevertheless, we can question whether the way in which the analysis is done, which model it used, affect the results. Chiang and Zheng (2010) found results that are not in line with others due to their different way of doing their analysis.

We also want to make an additional remark, a parenthesis, regarding recent event in the market. A phenomena that can be assimilate to herding. Starting from a post on the web site Reddit relative to a short position taken by a hedgefund on a stock of a video-game's store company, people wanted to produce a short squeeze on the stock. This has lead to an important increase on long position on the stock leading to an impressive increase in the price as we can see on figure 34. Similar actions have be done for different stocks in the line of the one on Gamestop. These movements have all the characteristics from a herding behaviour, people are pushing aside their own belief to follow the crowd leading to a mispricing of assets. We have with this case an example of herding behaviour on the financial market even though they are isolated events that affected only a small number of stocks.

[26] Which is in line with the work of Caparrelli et al. (2004).
[27] Exchange traded funds.
[28] At least in terms of financial market.

Authors	Paper's name	Date	Period	Markets	Result
Bouri, E., Gupta, R., and Roubaud, D.	Herding behaviour in cryptocurrencies	2019	2013-2018	Crypto-Currencies	**Evidence**
Yao, Juan and Ma, Chuanchan and He, William Peng	Investor herding behaviour of Chinese stock market	2014	1999-2008	Chinese market	**Evidence** (Shanghai and Shenzhen B-share markets) **No evidence** (Shanghai and Shenzhen A-share markets)
Economou, F., Kostakis, A., and Philippas, N.	Cross-country effects in herding behaviour:Evidence from four south european markets	2011	1998-2008	Greece, Italy, Portugal and Spain	**No evidence** (Spain) **Partial Evidence** (Portugal) **Evidence** (Greece and Italy)
Chiang, T. C. and Zheng, D.	An empirical analysis of herd behavior in global stock markets.	2010	1989-2009	18 countries	**No evidence** (US & Latin America) **Evidence** (All market except US and Latin America)
Demirer, Riza and Kutan, Ali M and Chen, Chun-Da	Do investors herd in emerging stock markets?: Evidence from the Taiwanese market	2010	1995-2006	Taiwan	**Evidence**
Demirer, R. and Kutan, A. M.	Does herding behavior exist in Chinese stock markets?	2006	1999-2002	China	**No evidence**
Caparrelli, F., D'Arcangelis, A. M., and Cassuto, A.	Herding in the italian stock market: A caseof behavioral finance.	2004	1988-2001	Italy	**Evidence** (in extreme market condition)
Chang, E. C., Cheng, J. W., and Khorana, A.	An examination of herd behavior in equity markets: An international perspective.	2000	1963-1997	US, Honk-Kong, Japan, South Korea and Taiwan	**No evidence** (US and Hong Kong) **Partial evidence** (Japan) **Evidence** (South Korea & Taiwan)
Christie, W. G. and Huang, R. D.	Following the pied piper: Do individual returns herd aroundthe market?	1995	1962-1988	US	**No evidence**

Figure 9: Table with the summarised results of the work on herd behaviour that we have analysed.

3.1.5 Impact of herding

There are two main effects that may be derived from herding, either it will affect the profit of diversification or the second is that it will lead the asset price to deviate from the intrinsic value. In Chang et al. (2000) they made the important statement about the implication of herding on the financial market, if *"market participants tend to herd around the aggregate market consensus"*(Chang et al., 2000, p.1653), investors will need more equities in their portfolio to achieve the same level of diversification. For their work it would be the case for the two emerging markets, South Korea and Taiwan, that they analysed. This is an important effect of herding on the financial market, if investors are mainly investing in one market, which can often happen for domestic investors, due to the home bias[29], it might increase the impact on the benefits of diversification. Chiang and Zheng (2010) cited in their papers *An empirical analysis of herd behaviour in global stock markets*, because herding cause correlated behaviour of individual it leads to erroneous decision making by entire populations. Therefore it will reduce the benefits of portfolio diversification, which means a larger amount of assets will be needed to achieve the same level of diversification. As Economou et al. said in their papers *Cross-country effects in herding behaviour: Evidence from four south European markets*, *"For investors, an increase in the degree of co-movement among asset returns reduces the benefits of portfolio diversification"* (Economou et al., 2011, p.444).

The second effect is that it could induce that markets are not efficient, resulting in mispricing in assets. It is also argued by some researchers that herding could be a reason of important crisis and bubbles(Avery and Zemsky, 1998) (e.g. Tulipomania, South Sea Bubbles, or more recently the Sub-Prime crisis). Hwang and Salmon (2004) point out that the mispricing due in part by herding could be one of the reasons of the creation of extreme market events as bubbles and the subsequent crashes. As Hwang and Salmon (2004) explained in their papers in 2004, herding leads to bias view of expected returns and risks and therefore impact the results that we have seen from the Capital Asset Pricing Model. This is due to the fact that if investors herd on the market, they will tend to herd to the market and therefore affect one important component of the CAPM which is the beta that *will be biased from their equilibrium value* (Hwang and Salmon, 2004, p.589). Additionally, as explained in the work of Bouri et al. (2019) on herding in the crypto-currency market, herding could be one of the explanation of the trends and high volatility this market in particular is facing.

[29] Which also have an impact on diversification (French and Poterba, 1991).

4 Analysis

For the analysis we will follow the two methods described in the previous section. The first section is about the data that will be used in the analysis. We will then start with the first model from the work of Christie and Huang (1995), then we will carry on with the model of Chang et al. (2000). The data needed for both models are the following: daily data about the markets, as a proxy for the market we will use two indexes. The second type of data required are about individual stocks. Starting from these data set, we will be able to compute the metrics for the two models. As we are following the methodology of Christie and Huang (1995), an additional information we need is to distinguish between "normal" and the extreme time periods. As stated in their papers, during these periods of extreme market movement, the individuals will use the market consensus as their own belief an herd based on this consensus. The common rule used as a indicator for market stress is when the returns of the markets are in the upper or lower tail of the distribution with a percentage of 1% and 5%. We will therefore also use the same percentage in our analysis.

4.1 Data

The analysis that will be done in the following pages is about the European and US market, we will therefore use two different indexes as proxies for these two markets, these proxies will be used to detect extreme market movements and compute the returns of the market during the period analysed. For the European market our choice is on the Stoxx Europe 600 and for the US we choose the S&P 500. Both of them have the same methods of weighting the assets which are based on the market capitalisation and their respective market representation in percentage of capitalisation is also relatively close (about 90% for the Stoxx 600 and about 80% for the S&P 500). For the Stoxx Europe 600, there are 600 stocks included in the index, 505 for the S&P500. 17 countries are represented[30] in the Stoxx Europe 600 and one, the US for the S&P500. We can see more information about these index on figure 26 and 25, which gives us information about the allocation in term of sectors, countries and also give some information on the historical performances. The two indexes are used to detect extreme periods on the two markets and therefore allow us to create the dummy variables used in the method from Christie and Huang (1995).

We decided to use the daily returns to have more precise estimators. In terms of period analysed, we will start with data from the first of January 2006 to 31 December 2020, which gives us a time period of 14 years to analyse, within which we have two important financial crisis, namely the financial crisis of 2007–2008 and the 2020 stock market crash linked to the Covid-19 pandemic.

Now that we have set the context we will have to detect the extreme market moment as Christie and Huang (1995) have done in their analysis. To find the "extreme market events" we used the Value-at-risk (VAR) approach for two levels (1%, 5%). We use the formula following formula to get our indicators of an extreme market event.

$$Var(x\%) = Mean + / - z - score(x\%)\ confidence\ interval\ * standard\ deviation$$

In the table 10 we have the details for the European index. The first columns show the level of confidence the value are referring to. The two columns under "VAR" refer to the values at which we start to consider the returns as an extreme event for each tail. The two next columns are a count of how many of these extreme market events we face on each of the tail of the distribution during the period analysed. We also have the mean and the standard deviation for the Stoxx Europe 600 over the period analysed. To see the same table for the S&P 500 see figure 28 in the appendix. Using the indicators we were able to get the dummy variables we needed.

[30] Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, Luxembourg, the Netherlands, Norway, Poland, Portugal, Spain, Sweden, Switzerland and the United Kingdom.

Europe				
Confidence level	VAR		Count	
	Lower tail	Upper tail	Lower tail	Upper tail
1%	-3,122%	3,150%	61	32
5%	-2,372%	2,400%	121	94

α	Z-score
1%	2,576
5%	1,960

Mean	0,014%
Standard deviation	0,012174739

Figure 10: Own calculation based on data from Refinitiv Eikon using excel formulas

Next we need a sample of individual stocks, we decided to take all the components (current and former) of two main indexes representing large-cap in both markets. This will allow us to have a focus on large caps and then compare the finding to one sample of small caps for the European market in the Robustness check section. We used the Eurostoxx 50 for Europe and the Dow Jones Industrial average for the US market. The Eurostoxx 50 has components from eleven countries from the Eurozone[31]. We can also look at the percentage of each individual country in the index for the European market. The data of March 31, 2020 tells us that 38,7% of the weight in the index come from French companies and 32,2% from Germany meaning that even if we are using an European index we will have a focus on these two countries. The third biggest country represented in the index are the Netherlands with 12%. Now if we take a look at the “supersectors” in both indexes, they both have as the first sector, technology, the US index has a weighting of 21,3% in this sector, compared to 12,6% for the European index, the second and third components are respectively Personal and household goods (12,4%) and Healthcare (11%) for Europe and Industrial (17,1%) and Healthcare (17%) for the US (See figure 23 and 24). Using an add-in from Refinitiv Eikon, we created a list of all the stocks that are or went through the indexes during the period, which is the list in figure 29. We have 90 stocks in our sample for Europe and 46 for the US. We then needed to retrieve the returns for each stock for each day between the 1st January 2006 and 31st December 2020[32]. With all the data, we have everything needed to compute the two metrics required, the CSSD and the CSAD. As a reminder here are the two formulas :

$$CSSD_t = \sqrt{\frac{\sum_{i=1}^{N}(R_{i,t} - R_{m,t})^2}{N-1}} \qquad CSAD_t = \frac{\sum_{i=1}^{N}\left|R_{i,t} - R_{m,t}\right|}{N}$$

Figure 11: CSSD formula from Christie and Huang (1995) and CSAD formula from Chang et al. (2000)

4.2 The first model

The computation was done on excel and then imported on GRETL to do the regression. The results for a 5% criterion[33] are shown in the following tables. The results for a 1% criterion are in figure 30 for the European market and figure 31. The following results are in the line of the work done by Christie and Huang (1995) for the first part (with the dependant variable being CSSD) and the second part is the alternative method from Chang et al. (2000) using the dependent variable CSAD.[34]

[31] Austria, Belgium, Finland, France, Germany, Ireland, Italy, Luxembourg, the Netherlands, Portugal and Spain.
[32] We also used the add-in from Refinitiv Eikon to retrieved these data.
[33] 5% used to be the proxy of extreme market event.
[34] It should be noted that Christie and Huang (1995) also used the CSAD as a robustness test for their results.

```
Model 1: OLS, using observations 2006-01-02:2020-12-31 (T = 3846)
Dependent variable: CSSD
HAC standard errors, bandwidth 11 (Bartlett kernel)

             coefficient   std. error    t-ratio    p-value
  ---------------------------------------------------------
  const       0.0140185    0.000242771   57.74     0.0000    ***
  Dup5        0.0175994    0.00238332     7.384    1.87e-013 ***
  Ddown5      0.0119773    0.00140033     8.553    1.70e-017 ***
Model 2: OLS, using observations 2006-01-02:2020-12-31 (T = 3846)
Dependent variable: CSAD
HAC standard errors, bandwidth 11 (Bartlett kernel)

             coefficient   std. error    t-ratio    p-value
  ---------------------------------------------------------
  const      0.00972762    0.000155876   62.41     0.0000    ***
  Dup5       0.0131918     0.00152870     8.629    8.89e-018 ***
  Ddown5     0.0101312     0.00110234     9.191    6.24e-020 ***
```

Figure 12: Results from the regression done with a criterion of 5% for the European market (Data retrieved from Eikon)

```
Model 4: OLS, using observations 2006-01-03:2020-12-30 (T = 3775)
Dependent variable: CSSD
HAC standard errors, bandwidth 11 (Bartlett kernel)

             coefficient   std. error    t-ratio    p-value
  ---------------------------------------------------------
  const       0.0121141    0.000241083   50.25     0.0000    ***
  Dup5        0.0214989    0.00250082     8.597    1.18e-017 ***
  Ddown5      0.0137589    0.00187354     7.344    2.53e-013 ***
Model 5: OLS, using observations 2006-01-03:2020-12-30 (T = 3775)
Dependent variable: CSAD
HAC standard errors, bandwidth 11 (Bartlett kernel)

             coefficient   std. error    t-ratio    p-value
  ---------------------------------------------------------
  const      0.00855174    0.000160130   53.40     0.0000    ***
  Dup5       0.0154075     0.00151326    10.18     4.88e-024 ***
  Ddown5     0.0103100     0.00118625     8.691    5.26e-018 ***
```

Figure 13: Results from the regression done with a criterion of 5% for the US market (Data retrieved from Eikon)

To have evidence of herding on the market we are analysing, we need the coefficient for D^L (Ddown) and D^U (Dup) to be negative and significant which is not the case here. The results we got using this first model are therefore comforting the idea that there is no herding behaviour on the developed markets. The coefficient we got from using either the CSSD and the CSAD are giving us the same results. It is consistent with the results of most empirical research done in the past for the US. The fact that we got the same results for the European market is not surprising, given that both markets have the same level of economic development. Moreover because we used the most important stocks in terms of capitalisation it might lead us to miss stocks from less developed markets included in the Eurozone. We will test later with small stocks to verify if with this type of stocks we find different results.

4.3 The second model

For our analysis to be more concrete and interesting, we will also use the model of Chang et al. (2000) as a second analysis. We will use the equation they used to find possible asymmetric results between the up and down markets. To be able to do that, we will first need to split the data set in two, one for the period of up market and the other for the period of down market. Then, as we can see on the figure below, we need to compute for both data sets $|R_{m,t}|$, which is the absolute value of returns of the market portfolio for each day of the period we analysed. The other metrics we need is $R^2_{m,t}$, which is simply the square of the returns of the market for the day t. We used formulas on Excel to do the previous computations and the two formulas to detect herding behaviour are the following:

$$\mathrm{CSAD}_t^{\mathrm{UP}} = \alpha + \gamma_1^{\mathrm{UP}} \left| R_{m,t}^{\mathrm{UP}} \right| + \gamma_2^{\mathrm{UP}} (R_{m,t}^{\mathrm{UP}})^2 + \varepsilon_t,$$

$$\mathrm{CSAD}_t^{\mathrm{DOWN}} = \alpha + \gamma_1^{\mathrm{DOWN}} \left| R_{m,t}^{\mathrm{DOWN}} \right| + \gamma_2^{\mathrm{DOWN}} (R_{m,t}^{\mathrm{DOWN}})^2 + \varepsilon_t,$$

Figure 14: Equation retrieved from Chang et al. (2000)

The two tables below are the results we got from GRETL for the US market. Figure 32 shows the results for the European market.

Model 1: OLS, using observations 1-2069
Dependent variable: CSADup
Heteroskedasticity-robust standard errors, variant HC1

	coefficient	std. error	t-ratio	p-value	
const	0.00628470	0.000135232	46.47	0.0000	***
Rabs	0.374181	0.0256810	14.57	7.52e-046	***
R2	0.543625	0.440943	1.233	0.2178	

Model 1: OLS, using observations 1-1706
Dependent variable: CSADdown
Heteroskedasticity-robust standard errors, variant HC1

	coefficient	std. error	t-ratio	p-value	
const	0.00649714	0.000133670	48.61	0.0000	***
Rabs	0.329073	0.0262821	12.52	1.80e-034	***
R2	0.0428872	0.586230	0.07316	0.9417	

Figure 15: Results from the regression inspired by Chang et al. (2000) for the US market (Data retrieved from Eikon)

In the table we see that γ_1 (coefficient for Rabs in the tables) is positive and significant for both the up and down market. The second metrics γ_2 (coefficient for R2 in the tables) are for the US not significant. For us to have evidence of herding in this analysis, we need to have either a non linear model, which is not the case here. The γ_1 coefficient is positive and statistically significant. Or we need to have a γ_2 coefficient to be negative and significant, which is also not the case in our analysis. These results are consistent with the one from Chang et al. (2000) in the US market with no evidence of herding during the period analysed. The same conclusion can be drawn for the European market.

The results we have for both types of analysis and both markets can be summarised by the following sentence: there is no evidence of herding on the European and the US markets even during periods of crisis as the financial crisis of 2008 or the crisis on the stock market due to the Covid-19 crisis in 2020. These results are consistent with the ones of Chang et al. (2000), Christie and Huang (1995) or Demirer and Kutan (2006) in their findings that there is no evidence on herding in advanced markets. An additional point that is worth to be noticed is that the coefficient in up market is wider compare to the down coefficient. It is in line with the work done by McQueen et al. (1996) supporting an asymmetric reaction to bad compare to good macroeconomic news.

5 Robustness checks

5.1 Additional analysis

Chang et al. (2000) explained that in their case their result could be impacted by small caps because they were using equally-weighted measures. In our case, we also have an equally-weighted measure but we made an analysis based on large caps. Therefore our analysis is biased because we do not have small caps in our sample. Therefore our analysis is only detecting herding for a part of the market, even though our sample of individual stocks represents an important part of their respective market. However McQueen et al. (1996) found that smaller stocks take time to respond to news which means that there could be extra dispersion in model using this kind of stocks in their analysis. In spite of everything, Chang et al. argued that only a coefficient supporting no evidence of herding for large stocks would be sufficient to support the results of an analysis of herding on the financial market. Nevertheless, we decided to improve the reliability of our results by doing an additional study on the small caps in the European market. Due to the difficulties to get all the data we needed, using the database and technique we used, we decided to focus on stocks that have the biggest capitalisation in their respective markets. To add more value to our work, we will do the same analysis we have done previously but using small-caps stocks for the European market. We made a random selection using the list of constituents of the index from MSCI the *MSCI Europe Small Caps*[35] and we selected 50 individual stocks considered as small. Then we computed the same metrics as before. For the first model, using the dummies variables to detect herding during extreme market periods, we achieved to get the results we can see in figure 16 (for a criterion of 5%):

```
Model 2: OLS, using observations 2006-01-03:2020-12-31 (T = 3845)
Dependent variable: CSAD
HAC standard errors, bandwidth 11 (Bartlett kernel)

             coefficient   std. error    t-ratio    p-value
  ---------------------------------------------------------
  const       0.0136725    0.000172847   79.10     0.0000     ***
  Dup5        0.0132206    0.00138446     9.549    2.25e-021  ***
  Ddown5      0.0109560    0.00112414     9.746    3.46e-022  ***

Model 1: OLS, using observations 2006-01-03:2020-12-31 (T = 3845)
Dependent variable: CSSD
HAC standard errors, bandwidth 11 (Bartlett kernel)

             coefficient   std. error    t-ratio    p-value
  ---------------------------------------------------------
  const       0.0206949    0.000288878   71.64     0.0000     ***
  Dup5        0.0147053    0.00190139     7.734    1.32e-014  ***
  Ddown5      0.0115131    0.00148779     7.738    1.28e-014  ***
```

Figure 16: Results from our own computation for small caps - top table CSAD and bottom table CSSD (using the 5% criterion)

By comparing these results with the same model and the same market we have done in the analysis section (see figure 12), we can notice first that there is no evidence of herding. In addition the coefficient for both the up and the down markets are lower for this analysis compared to the large cap, which is consistent with the work done previously. The fact that the up coefficient is larger than the down coefficient is consistent with the work of McQueen et al. (1996), where they found asymmetric reactions to the up and down markets for small stocks. This being due to the fact that the small stocks are reacting more slowly to good compared to bad economics news.

[35]There is 972 stocks in the index at the time we retrieved the selection (24/05/2021).

In addition we use the model developed by Chang et al. (2000), using the whole model which is the following :

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

The results we got using this model can be seen in figure 36 in the appendix. The results are still consistent with the ones we got previously. We do not have any evidence of herding behaviour on the European market either with large caps or small caps, which is an additional proof of the relevance of our work.

5.2 Additional comments

The fact that we used two different metrics and two different models that are recognised in the literature in addition to the fact that both models come to the same conclusion is an additional value to our work. In their work, Chang et al. (2000) used the CSSD in addition to their CSAD as an additional robustness check. That is therefore increasing the trustworthiness of our results. The same was done by Christie and Huang (1995). They used the CSAD in addition to the CSSD in their work to check the validity of their work. An additional point linked to the use of both models is that, because the second model checks for the presence of herding for every periods of the period analysed. Using both model allows us to achieve a better analysis compare to an analysis using only one method. We also used an option on the GRETL software to get rid of heteroscedasticity and auto-correlation problems. The software uses the method developed by Newey and West (1987) to get errors of the estimated regressions coefficients that are adjusted for heteroscedasticity and auto-correlation.

6 Discussion

In their work Christie and Huang (1995) assume that herding only (or at least mainly) occurs during periods of market stress, when market participants put aside their own belief and tend to replicate the market. Therefore the model they developed is based on this assumption and does not allow to detect the potential presence of herding in "normal" time. But we arrived to the same conclusions using the model from Chang et al. (2000) therefore this possible problem can be pushed aside.

As Chiang and Zheng (2010) explained in their work, the type of tests we have done[36] is focusing on finding evidence of herding on the market analysed and not in an international context. Therefore they can miss potential information. In their work, Chiang and Zeng have done something different by analysing the market as a whole going from a domestic market analysis to a global market analysis. They found that the methods used could, by excluding foreign markets, produce biased estimates. They found using their technique herding on most markets analysed. And moreover, that most investors herd with the US market in addition to their own. As a consequence, the results we got for the US and the European markets are that there is no evidence of herding in a local scale but we can not exclude that the results would be different with an analysis taking into account the market globally.

We also agree with the comment from the conclusion of Devenow and Welch (1996). They argue that the models used by analysing the dispersion of prices to detect herding, as the one we have used, are maybe insufficient and it could be interesting to develop models that use data which give information on how investors communicate between them. Some additional work on this point could be interesting but we also think that this kind of information can be difficult to get and quantify. Moreover Avery and Zemsky (1998) explained, the fact that the models developed to detect herding are based on price mechanism could affect the results because *"price is a single-dimensional instrument and it only assures that the economy learns about a single dimension of uncertainty at one time"* (Avery and Zemsky, 1998, p.740). This opinion can also apply to our model that is only focusing on the price and as said before not others dimensions of the complexity of the financial market.

[36]From Chang et al. (2000) and Christie and Huang (1995).

7 Conclusion

The fact that people tend to follow each other is a phenomenon that was proven to exist in psychology. We can easily find examples for our day to day life (e.g. Restaurant choice). There is also evidence of herding in political choices or riots, in addition to findings of herding by financial professionals. Nevertheless, finding evidence of this behaviour on the financial market is more complex than it might seem. There have been many analyses in the past, we have review a number of them previously and we have seen that results are not always consistent. A possible reason from that could come from the different models used. In spite of these differences in the results, we can draw a number of conclusions. First, it seems that less developed markets are more subject to herding behaviour as seen in Chang et al. (2000), Economou et al. (2011) or Caparrelli et al. (2004). This implies that the more developed markets on the other hand are less prone to this type of behaviour which is the result we got from our analysis. Another point that needs to be addressed, is that we have done an analysis on the European Union as if it was a single financial market, which is of course not the case. Each and every country from the area has its own stock market. What we found is that there are no traces of herding in the European market as a whole. It is likely that some of the local markets are less efficient and are facing herding and others not. As seen in the work of Caparrelli et al. (2004) they found evidence of herding on the Italian market, which can be seen as less developed compared to other European financial markets. We also have evidence from Economou et al. (2011) for the Italian and the Greek markets. The impact of these weaker markets could be compensated by more developed markets as for example France or Germany and influence our results. The results we managed to get for the United States on the other hand are consistent to most previous analysis done in the literature.

The final conclusion we want to make for this work is that, using two methods, we found no evidence of herding behaviour on these two markets. However, we ask ourselves about the potential weakness of these methods we have used: first about the models themselves and second about the data we used and the sampling we made. For the first point we belief that even if the models are not perfect, they capture an important part of the potential herding behaviour. And for the second point, we decided to make an additional analysis to check whether or not the fact that we have selected only large-caps in our European sample had an effect on the results. Since we did not find evidence of herding using small caps either, this is not the case. Furthermore, our evidence is going against the presence of herding during the 2008 Financial crisis and the stock. The implication of our findings is a supporting evidence in the favour of the rationality of the market in the areas analysed. The consequences is that there is no negative impact on the benefits of diversification or a mispricing of assets coming from the herding behaviour bias. However we can not state that the financial market is efficient and that the agents acting on it are rational. We only analysed the presence on two specific market for herding behaviour and we did not analyse other behavioural biases such as overconfidence, the home bias, or other cognitive biases. These phenomena can lead to irregularities in the financial markets as brought forward by behavioural finance.

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9 Appendix

Important basis paper	Kahneman, Daniel, and Amos Tversky	Prospect Theory: An Analysis of Decision Under Ris
	Kahneman, Daniel, and Amos Tversky	Choices Values and Frames

Bias	Authors	Name	Type of datas
Herding behavior	Arne C. Klein	Time-variations in herding behavior: Evidence from a Markov switching SUR model. Journal of International Financial Markets	End-of-day total returns for all listed stocks from Thomson Reuters Datastream
	Emilios C. Galariotis, Wu Rong, Spyros I. Spyrou	Herding on fundamental information A comparative study	daily price for all S&P100 & FTSE100 + differences between investment style (4 sub samples (B/M & MV)
	Thomas C. Chiang, Dazhi Zheng	An empirical analysis of herd behavior in global stock markets	daily data on industry and market index
	Eric C. Chang, Joseph W. Cheng, Ajay Khorana	An examination of herd behavior in equity markets : An international perspective	daily stock price data for the entire population of US firms
	William G. Christie and Roger D. Huang	Following the Pied Piper: Do Individual Returns Herd around the Market?	daily and monthly returns from CRSP data base
Overconfidence bias	Markus Glaser, Martin Weber	Overconfidence and trading volume	Several data set : 563104 buy and sell transactions from 3079 investors, several demographic and other self reported infos colleted at the opening of the account, online questionnaire
	Richard Deaves, Erik Lüders, Michael Scröber	The dynamics of overconfidence : Evidence from stock market forecasters	ZEW Finanzmarkttest is a monthly survey of about 350 financial market practitioners in Germany
	Bruno Biais, Denis Hilton, Karine Mazurier & Sébastien Pouget	Judgemental Overconfidence, Self-Monitoring, and Trading Performance in an Experimental Financial Market	Experimental market
	Jose´ A. Scheinkman and Wei Xiong	Overconfidence and Speculative Bubbles	Several data set : 563104 buy and sell transactions from 3079 investors, several demographic and other self reported infos colleted at the opening of the account, online questionnaire
Overreaction	Werner F. M. De Bondt and Richard Thaler	Does the Stock Market Overreact?	Monthly return data for New York Stock Exchange (NYSE) common stocks
	Kent Daniel, Davide Hirshleifer & Avanidhar Subrahmanyam	Investor Psychology and Security Market Under- and Overreactions	daily Hirshleifer monthly security from CRSP data base
	Sojung Carol Park	Investor's Overreaction to an Extreme Event: Evidence from the World Trade Center Terrorist Attack	Data of insurance compagnies from Compustat & CRSP ; price
	Allen W. Bathke Jr. Terry W. Mason Richard M. Morton	Investor Overreaction to Earnings Surprises and Post-Earnings-Announcement Reversals	218,168 firm-quarters
Loss aversion	Doron Kligera & Boris Levit	Evaluation periods and asset prices: Myopic loss aversion at the financial marketplace	data on stocks that have been traded daily and weekly
	Shlomo Benartzi & Richard H. Thaler	Myopic Loss Aversion and the Equity Premium Puzzle	Model development
Competence effect	John R. Graham, Campbell R. Harvey, Hai Huang	Investor Competence, Trading Frequency and Home Bias	UBS/Gallup investor survey
Mental accounting	Richard H. Thaler	Mental Accounting and Consumer Choice	Survey and experiment
	Eldar Shafir & Richard H. Thaler	Invest now, drink later, spend never: On the mental accounting of delayed consumption	Survey
Disposition effect	Terrance Odean	Are Investors Reluctant to Realize Their Losses?	Analyzing trading records for 10,000 accounts at a large discount brokerage house
	Andrea Frazzini	The Disposition Effect and Underreaction to News	large class of investors - mutual funds
	Lei Feng Mark S. Seaholes	Do Investor Sophistication and Trading Experience Eliminate Behavioral Biases in Financial Markets?	Data from the national brokerage People's Republic of China (1,511)
Home Bias	Clemens Sialm, Zheng Sun & Lu Zheng	Home Bias and Local Contagion: Evidence from Funds of Hedge Funds	quarterly holdings data from SEC filings for all registered FOFs
	Anders Karlsson, Lars Nordén	Home sweet home: Home bias and international diversification among individual investors	First round of the New Swedish pension system

Covid Related papers	Mohsin Ali, Nafis Alam, Syed Aun R. Rizvi	Coronavirus (COVID-19)— An epidemic or pandemic for financial markets
	Abdullah M. Al-Awadhi, Khaled Alsaifi, Ahmad Al-Awadhi, Salah Alhammadi	Death and contagious infectious diseases: Impact of the COVID-19 virus on stock market returns
	Mohamed Sherif	The impact of Coronavirus (COVID-19) outbreak on faith-based investments: An original analysis

Figure 17: Preliminary work done before the start of the writing of this work

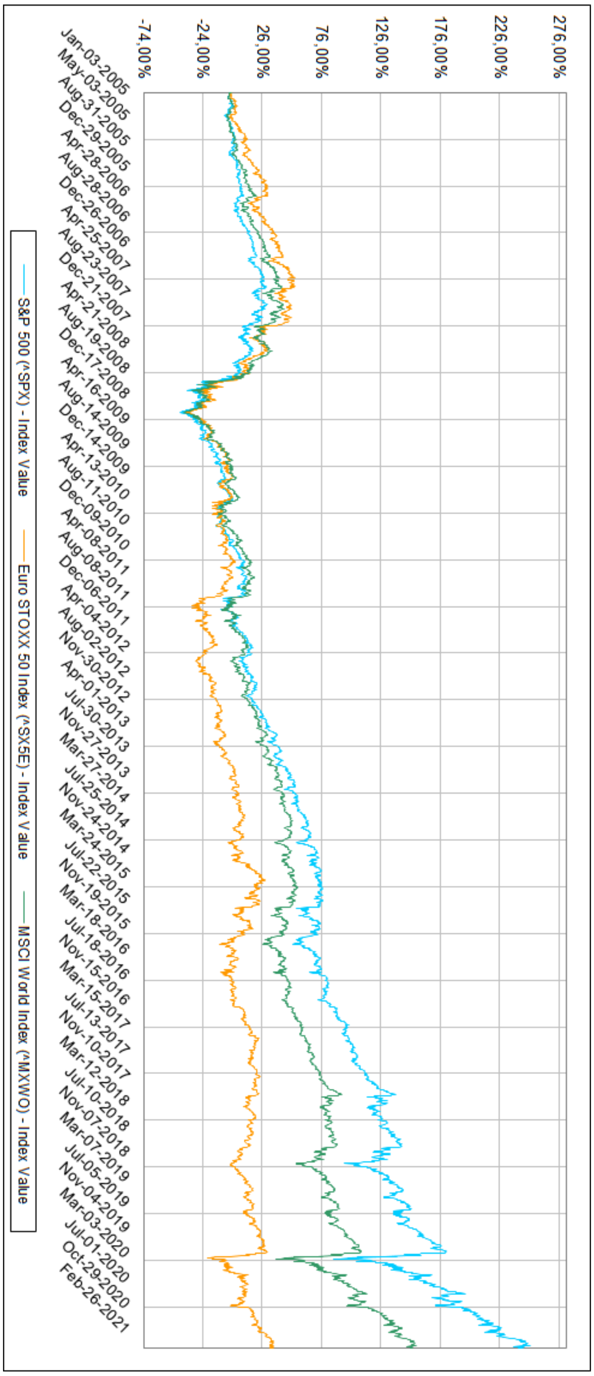

Figure 18: Graph for indexes prices (S&P500, Eurostoxx 50 and MSCI World) from January 2005 to Mai 2021 ; retrieved from CapitalIQ

PROBLEM 1: Choose between

A:	2,500 with probability	.33,	B:	2,400 with certainty.
	2,400 with probability	.66,		
	0 with probability	.01;		
$N = 72$	[18]			[82]*

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PROBLEM 2: Choose between

C:	2,500 with probability	.33,	D:	2,400 with probability	.34,
	0 with probability	.67;		0 with probability	.66.
$N = 72$	[83]*			[17]	

Figure 19: Example of prospects from Kahneman and Tversky (1979)

In one of their first studies, participants were asked to compute, within 5 seconds, the product of the numbers one through to eight, either as 1 × 2 × 3 × 4 × 5 × 6 × 7 × 8 or reversed as 8 × 7 × 6 × 5 × 4 × 3 × 2 × 1. Because participants did not have enough time to calculate the full answer, they had to make an estimate after their first few multiplications. When these first multiplications gave a small answer – because the sequence started with small numbers – the median estimate was 512; when the sequence started with the larger numbers, the median estimate was 2,250. (The correct answer is 40,320.)

Figure 20: Explanation of the experiment done by Tversky and Kahneman (1974)

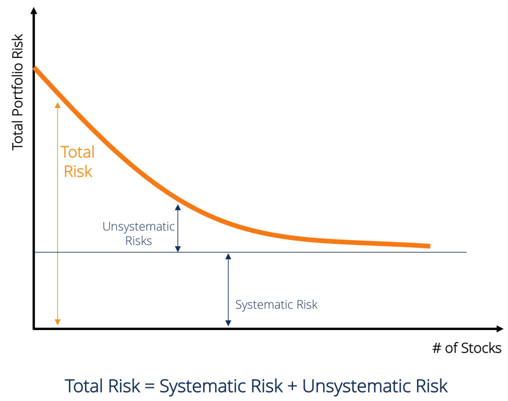
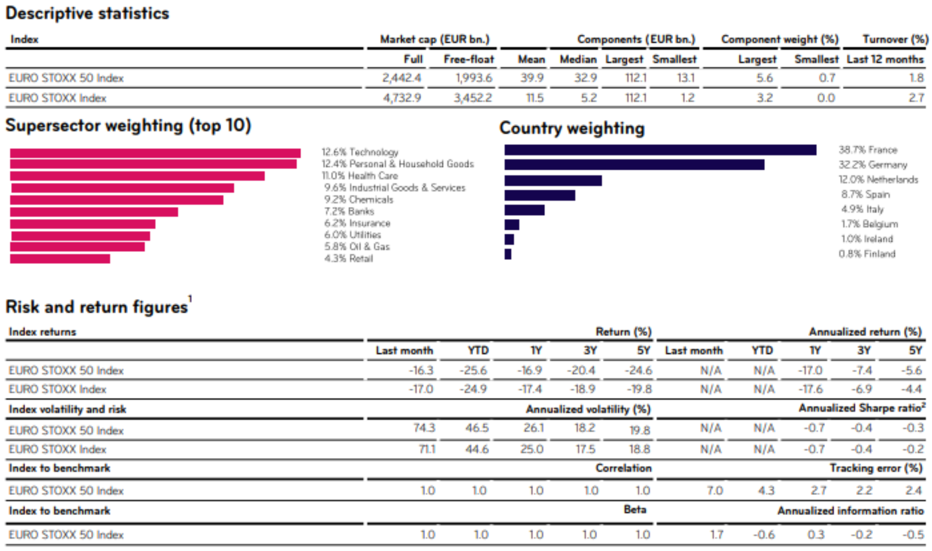


Figure 21: Graphical representation of relation between risk and numbers of stocks in a portfolio (Source : Corporate Finance Institute)

$$E_t(R_i) = \gamma_0 + \beta_i E_t(R_m - \gamma_0),$$

Figure 22: Equation for the CAPM in Chang et al. (2000) from Black (1972)



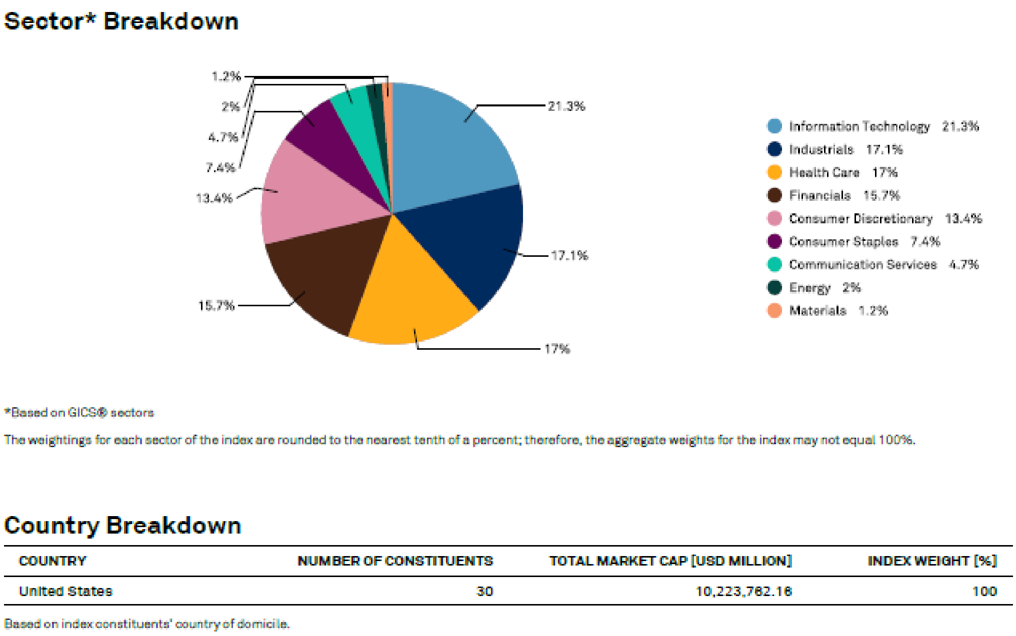
Descriptive statistics

Index	Market cap (EUR bn.)		Components (EUR bn.)				Component weight (%)		Turnover (%)
	Full	Free-float	Mean	Median	Largest	Smallest	Largest	Smallest	Last 12 months
EURO STOXX 50 Index	2,442.4	1,993.6	39.9	32.9	112.1	13.1	5.6	0.7	1.8
EURO STOXX Index	4,732.9	3,452.2	11.5	5.2	112.1	1.2	3.2	0.0	2.7

Risk and return figures[1]

Index returns	Return (%)					Annualized return (%)				
	Last month	YTD	1Y	3Y	5Y	Last month	YTD	1Y	3Y	5Y
EURO STOXX 50 Index	-16.3	-25.6	-16.9	-20.4	-24.6	N/A	N/A	-17.0	-7.4	-5.6
EURO STOXX Index	-17.0	-24.9	-17.4	-18.9	-19.8	N/A	N/A	-17.6	-6.9	-4.4
Index volatility and risk	**Annualized volatility (%)**					**Annualized Sharpe ratio[2]**				
EURO STOXX 50 Index	74.3	46.5	26.1	18.2	19.8	N/A	N/A	-0.7	-0.4	-0.3
EURO STOXX Index	71.1	44.6	25.0	17.5	18.8	N/A	N/A	-0.7	-0.4	-0.2
Index to benchmark	**Correlation**					**Tracking error (%)**				
EURO STOXX 50 Index	1.0	1.0	1.0	1.0	1.0	7.0	4.3	2.7	2.2	2.4
Index to benchmark	**Beta**					**Annualized information ratio**				
EURO STOXX 50 Index	1.0	1.0	1.0	1.0	1.0	1.7	-0.6	0.3	-0.2	-0.5

Figure 23: Fact sheet for the Eurostoxx 50, retrieved from Stoxx website



Sector* Breakdown

*Based on GICS® sectors

The weightings for each sector of the index are rounded to the nearest tenth of a percent; therefore, the aggregate weights for the index may not equal 100%.

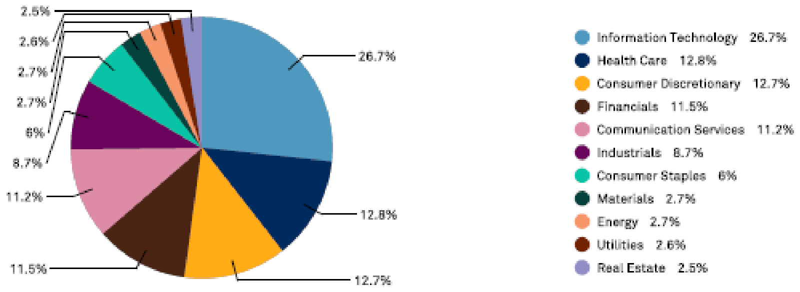
Country Breakdown

COUNTRY	NUMBER OF CONSTITUENTS	TOTAL MARKET CAP [USD MILLION]	INDEX WEIGHT [%]
United States	30	10,223,762.16	100

Based on index constituents' country of domicile.

Figure 24: Fact sheet for the DJI, retrieved from S&P website

Sector* Breakdown



*Based on GICS® sectors

The weightings for each sector of the index are rounded to the nearest tenth of a percent; therefore, the aggregate weights for the index may not equal 100%.

Country Breakdown

COUNTRY	NUMBER OF CONSTITUENTS	TOTAL MARKET CAP [USD MILLION]	INDEX WEIGHT [%]
United States	505	37,267,249.44	100

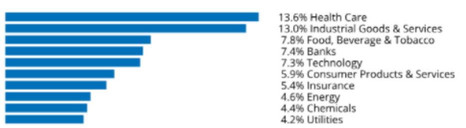
Based on index constituents' country of domicile.

Figure 25: Factsheet for the S&P 500, retrieved from S&P website

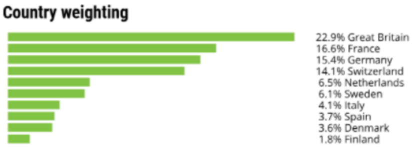
Descriptive statistics

Index	Market cap (EUR bn.)		Components (EUR bn.)				Component weight (%)		Turnover (%)
	Full	Free-float	Mean	Median	Largest	Smallest	Largest	Smallest	Last 12 months
STOXX Europe 600 Index	11,838.9	9,443.3	15.7	7.1	274.4	2.1	2.9	0.0	3.1
STOXX Europe Total Market Index	13,689.1	10,386.5	7.0	1.8	274.4	0.0	2.6	0.0	2.6

Supersector weighting (top 10)



Country weighting



Risk and return figures[1]

Index returns	Return (%)					Annualized return (%)				
	Last month	YTD	1Y	3Y	5Y	Last month	YTD	1Y	3Y	5Y
STOXX Europe 600 Index	6.5	8.3	37.6	27.4	49.7	N/A	N/A	38.1	8.5	8.5
STOXX Europe Total Market Index	6.4	8.5	39.1	27.3	50.5	N/A	N/A	39.6	8.5	8.6
Index volatility and risk	**Annualized volatility (%)**					**Annualized Sharpe ratio[2]**				
STOXX Europe 600 Index	12.9	12.0	19.2	18.9	16.9	N/A	N/A	1.8	0.5	0.5
STOXX Europe Total Market Index	12.9	12.0	19.1	18.9	16.8	N/A	N/A	1.9	0.5	0.5
Index to benchmark	**Correlation**					**Tracking error (%)**				
STOXX Europe 600 Index	1.0	1.0	1.0	1.0	1.0	0.5	0.6	0.6	0.5	0.5
Index to benchmark	**Beta**					**Annualized information ratio**				
STOXX Europe 600 Index	1.0	1.0	1.0	1.0	1.0	2.6	-1.4	-1.9	0.1	-0.2

[1] For information on data calculation, please refer to STOXX calculation reference guide.
[2] Based on EURIBOR1M

(EUR, gross return), all data as of Mar. 31, 2021

Figure 26: Information about the Stoxx 600 index retrieved from Stoxx website

$$CSAD_t = \alpha + \beta_L D_t^L + \beta_U D_t^U + e_t$$

Figure 27: Equation adapted from Christie and Huang (1995) by Chang et al. (2000)

US				
Confidence level	VAR		Count	
	Lower tail	Upper tail	Lower tail	Upper tail
1%	-3,250%	3,324%	56	47
5%	-2,464%	2,538%	115	78

α	Z-score
1%	2,576
5%	1,960

Mean	0,037%
Standard deviation	0,012759655

Figure 28: Own calculation based on data from Eikon using excel formulas

Count	46
DJI	
GS.N	THE GOLDMAN SACHS GROUP ORD
NKE.N	NIKE INC -CL B ORD
CSCO.OQ	CISCO-T ORD
JPM.N	JPMORGAN CHASE ORD
DIS.N	WALT DISNEY ORD
INTC.OQ	INTEL-T ORD
DOW.N	DOW INC ORD
MRK.N	MERCK ORD
CVX.N	CHEVRON TEXACO ORD
AXP.N	AMERICAN EXPRESS ORD
VZ.N	VERIZON COMMUNICATIONS ORD
HD.N	HOME DEPOT ORD
WBA.OQ	WALGREENS BOOTS ALLIANCE INC
MCD.N	MCDONALD'S ORD
UNH.N	UNITEDHEALTH GRP ORD
KO.N	COCA-COLA ORD
JNJ.N	JOHNSON&JOHNSON ORD
MSFT.OQ	MICROSOFT-T ORD
NULL	HONEYWELL INTL ORD
CRM.N	SALESFORCE.COM ORD
PG.N	PROCTERGAMBLE ORD
IBM.N	INTL BUSINESS MACHINES CORP ORD
MMM.N	3M ORD
AAPL.OQ	APPLE ORD
WMT.N	WALMART INC ORD
CAT.N	CATERPILLAR ORD
AMGN.OQ	AMGEN-T ORD
V.N	VISA INCORPORATION ORD
TRV.N	TRAVELERS COS INC/THE ORD
BA.N	BOEING U ORD
MO.N	Altria Group
HON.OQ	Honeywell Intl
AIG.N	AIG
GM.N^F09	Motors GUC Trust
C.N	Citigroup
MDLZ.OQ	Mondelez Intl
HWM.N	Howmet
BAC.N	BofAML
HPQ.N	HP
T.N	AT&T
DD.N^I17	DuPont
GE.N	GE
DD.N	Dupont De
RTX.N	Raytheon Tech
PFE.N	Pfizer
XOM.N	Exxon Mobil

Count	90		
Eurostoxx 50			
DPWGn.DE	DEUTSCHE POST ORD	ITX.MC	INDUSTRIA DISENO TEXTIL ORD
PERP.PA	PERNOD-RICARD ORD	ISP.MI	INTESA SANPAOLO ORD
AIRP.PA	AIR LIQUIDE ORD	ADSGn.DE	ADIDAS ORD
VNAn.DE	VONOVIA SE	ABI.BR	ANHEUSER-BUSCH INBEV SA/NV ORD
IBE.MC	IBERDROLA SA	SPI.MI^A07	Sanpaolo IM
SIEGn.DE	SIEMENS ORD	AIBG.I	AIB Grou
SAN.MC	BANCO SANTANDER SA ORD	LAFP.PA^J15	Lafarge
VOWG_p.DE	VOLKSWAGEN PRF	AD.AS	Ahold Delhaize
SAPG.DE	SAP SE ORD	ELE.MC	Endesa
AD.AS	KONINKLIJKE AHOLD DELHAIZE NV ORD	AAH.AS^D08	RBS Hldg
BNPP.PA	BNP PARIBAS ORD	LYOE.PA^F10	Suez eniivi
DTEGn.DE	DEUTSCHE TELEKOM AG ORD	ALUA.PA^K16	Alcatel Lucent
PHG.AS	KONINKLIJKE PHILIPS NV	RENA.PA	Renault
FLTRF.I	FLUTTER ENTERTAINMENT ORD	AGES.BR	Ageas
ENGIE.PA	ENGIE ORD	VOWG.DE	Volkswagen
SASY.PA	SANOFI-AVENTIS ORD	AEGN.AS	Aegon
ESLX.PA	ESSILORLUXOTTICA ORD	APAM.AS	Aperam
ASML.AS	ASML HOLDING ORD	DIDA.MC	DIA
DB1Gn.DE	DEUTSCHE BOERSE AG ORD	DB1Gn.DE	Deutsche Boerse
ADYEN.AS	ADYEN NV ORD	ALSO.PA	Alstom
IFXGn.DE	INFINEON TECHNOLOGIES ORD	CAGR.PA	Credit Agricole
CRH.I	CRH PLC ORD	TLIT.MI	Telecom IT
ALVG.DE	ALLIANZ SE ORD	NOKIA.HE	Nokia
SAF.PA	SAFRAN ORD	OSRn.DE	Osram Licht
AMA.MC	AMADEUS IT GROUP SA ORD	MT.AS	ArcelorMittal
OREP.PA	L OREAL S.A.	CRH.I	CRH
SGEF.PA	VINCI ORD	RWEG.DE	RWE
BMWG.DE	BMW AG	REP.MC	Repsol
KNEBV.HE	KONE ORD	UN01.DE	Uniper
TOTF.PA	TOTAL ORD	CRDI.MI	Uni Credit
VIV.PA	VIVENDI ORD	GASI.MI	Generali
ENI.MI	ENI ORD	CARR.PA	Carrefour
PRTP.PA	KERING SA	SGOB.PA	Cie Saint Gobain
BAYGn.DE	BAYER AG	DBKGn.DE	Deutsche Bank
BASFn.DE	BASF SE ORD	EONGn.DE	E.ON
ENEI.MI	ENEL GLOBAL TRADING ORD	LIN1.DE^J18	Linde DE
PRX.AS	PROSUS NV ORD	UNc.AS^G19	Unilever
AIR.PA	AIRBUS SE	URW.AS	Unibail Rod West
SCHN.PA	SCHNEIDER ELECTRIC SE	SOGN.PA	Societe Generale
MUVGn.DE	MUNICH RE ORD	FREG.DE	Fresenius
DANO.PA	GROUPE DANONE ORD	TEF.MC	Telefonica
LVMH.PA	LVMH MOET HENNESSY LOUIS VUITT	BBVA.MC	BBVA
DAIGn.DE	DAIMLER ORD	ORAN.PA	Orange
AXAF.PA	AXA ORD	ENR1n.DE	Siemens Energ
LINI.DE	LINDE PLC ORD		
INGA.AS	ING GROEP ORD		

Figure 29: List of index constituents (former and current) between 1st January 2006 to 31st December 2020 - Data from Eikon

```
Model 3: OLS, using observations 2006-01-02:2020-12-31 (T = 3846)
Dependent variable: CSSD
HAC standard errors, bandwidth 11 (Bartlett kernel)

             coefficient   std. error    t-ratio    p-value
  ---------------------------------------------------------
  const       0.0143074    0.000265565   53.88      0.0000    ***
  Dupl        0.0289933    0.00388231     7.468     1.00e-013 ***
  Ddownl      0.0174515    0.00195736     8.916     7.34e-019 ***

Model 4: OLS, using observations 2006-01-02:2020-12-31 (T = 3846)
Dependent variable: CSAD
HAC standard errors, bandwidth 11 (Bartlett kernel)

             coefficient   std. error    t-ratio    p-value
  ---------------------------------------------------------
  const      0.00995631    0.000173366   57.43      0.0000    ***
  Dupl       0.0220467     0.00275770     7.995     1.70e-015 ***
  Ddownl     0.0144405     0.00155432     9.291     2.50e-020 ***
```

Figure 30: Results from the regression done with a criterion of 1% for the European market - Data from Eikon

```
Model 2: OLS, using observations 2006-01-03:2020-12-30 (T = 3775)
Dependent variable: CSSD
HAC standard errors, bandwidth 11 (Bartlett kernel)

             coefficient   std. error    t-ratio    p-value
  ---------------------------------------------------------
  const       0.0123112    0.000253281   48.61      0.0000    ***
  Dupl        0.0283599    0.00331629     8.552     1.74e-017 ***
  Ddownl      0.0211100    0.00264399     7.984     1.86e-015 ***

Model 3: OLS, using observations 2006-01-03:2020-12-30 (T = 3775)
Dependent variable: CSAD
HAC standard errors, bandwidth 11 (Bartlett kernel)

             coefficient   std. error    t-ratio    p-value
  ---------------------------------------------------------
  const      0.00871988    0.000171893   50.73      0.0000    ***
  Dupl       0.0196003     0.00188061    10.42      4.29e-025 ***
  Ddownl     0.0148482     0.00151033     9.831     1.54e-022 ***
```

Figure 31: Results from the regression done with a criterion of 1% for the US market - Data from Eikon

```
Model 1: OLS, using observations 1-2030
Dependent variable: CSADup
Heteroskedasticity-robust standard errors, variant HC1

             coefficient   std. error   t-ratio    p-value
  ---------------------------------------------------------
  const      0.00726109    0.000138430   52.45     0.0000     ***
  Rabs       0.318519      0.0245432     12.98     4.68e-037  ***
  R2         2.71712       0.518177       5.244    1.74e-07   ***
```

```
Model 1: OLS, using observations 1-1817
Dependent variable: CSADdown
Heteroskedasticity-robust standard errors, variant HC1

             coefficient   std. error   t-ratio    p-value
  ---------------------------------------------------------
  const      0.00726533    0.000199877   36.35     8.42e-218  ***
  Rabs       0.340444      0.0383675      8.873    1.66e-018  ***
  R2         0.228627      0.930234       0.2458   0.8059
```

Figure 32: Results for the regression of the European Market with the model inspired by Chang et al. (2000) - Data from Eikon

$$
\begin{aligned}
CSAD_t = \gamma_0 + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R^2_{m,t} + \gamma_4 CSAD_{us,t} + \gamma_5 R^2_{us,m,t} \\
+ \gamma_6 CSAD_{c,,m,t} + \gamma_7 R^2_{c,m,t} + \varepsilon_t
\end{aligned}
$$

Figure 33: One of the model used in Chiang and Zheng (2010)

Figure 34: Gamestop stock price retrieved on Google finance

$$H(m,t) = \mathrm{var}_c\left(\frac{\beta_{imt} - 1}{\sqrt{s_i^2 S^m}}\right)$$

Figure 35: Formula of the metrics developed by Hwang and Salmon (2001) in the work of Caparrelli et al. (2004)

Model 2: OLS, using observations 2006-01-03:2020-12-31 (T = 3845)
Dependent variable: CSAD
HAC standard errors, bandwidth 11 (Bartlett kernel)

	coefficient	std. error	t-ratio	p-value	
const	0.0112767	0.000225805	49.94	0.0000	***
Rabs	0.360337	0.0457027	7.884	4.09e-015	***
R2	0.737316	0.968252	0.7615	0.4464	

Model 1: OLS, using observations 2006-01-02:2020-12-31 (T = 3846)
Dependent variable: CSAD
HAC standard errors, bandwidth 11 (Bartlett kernel)

	coefficient	std. error	t-ratio	p-value	
const	0.00775774	0.000187397	41.40	0.0000	***
Rabs	0.357693	0.0425367	8.409	5.75e-017	***
R2	1.20243	0.870149	1.382	0.1671	

Figure 36: Results from the regression using the complete model from Chang et al. (2000) - Data from Eikon