The COVID-19 Outbreak and Investor Herding: An Empirical Study of the VWRL All-World Exchange-Traded Fund

Author: Tim Reitsma

University of Twente

P.O. Box 217, 7500AE Enschede

The Netherlands

ABSTRACT

Volatility in financial markets increased when the World Health Organization declared Covid-19 a global pandemic in March 2020. When financial markets become more volatile, investors tend to exhibit herding behavior, particularly when it comes to decision-making under uncertainty and market stress. This means that investors are not using their own judgement but instead are following the crowd. There are several strong indications that herding behavior was exhibited among investors during the COVID-19 period. Therefore, the aim of this study is to examine how the Covid-19 pandemic has influenced investor herding behavior in the globally diversified VWRL All-World Exchange-Traded Fund in the time period between the 1st of January, 2018, and the 31st of December, 2022. More specifically, the two static herding models Cross Sectional Standard Deviation (CSSD) and Cross-Sectional Absolute Deviation (CSAD) were used respectively to identify herding behavior. Contrary to expectations, the results suggested that investors' decisions were based on rational considerations, indicating that they made independent judgments rather than simply following the crowd. Using a static approach, such as CSSD and CSAD, can lead to uncertain results due to the fundamentally dynamic nature of herding behavior. Therefore, a dynamic regression analysis is applied which is capable of capturing a dynamic effect, making the output more visual and informative. By using this dynamic analysis, we can gain a deeper understanding of the dynamics of the underlying process. Based on the results of the dynamic analysis, there are five signs of herding behavior throughout the full sample period that can be linked to global macroeconomic events. However, the outcomes were not statistically significant, which is what we expected beforehand. This study contributes to the literature by studying a globally diversified exchange-traded fund and using both static and dynamic regression analysis methods, which allows us to examine whether herding varies over time in a more visual, dynamic, and informative way.

Graduation Committee members: prof. dr. L. Spierdijk

ir. E.J. Sempel

Keywords

Global ETF; COVID-19; Herding Behavior; Pandemic; CSSD; CSAD; Rolling Window Regression

1. INTRODUCTION

An increasing number of investors are allocating their capital to Exchange-Traded Funds (ETFs) to diversify their portfolios and lower volatility. In 2020, a record-breaking[1] $507.4 billion flowed into U.S.-listed ETFs, which was 55% higher than the previous year's $326.3 billion.

In addition, since March 2020, US stock trading volumes have increased by approximately 60%, partly due to the increased interest from individual investors. Trading volumes of individual investors doubled when the Covid-19 pandemic first hit, and have remained elevated since then. Individual investors became larger net buyers during the pandemic, with average purchases in 2021 increasing to over $2 billion each week (Jankiewicz, 2022).

An ETF can be characterized as an investment fund that tracks the performance of a particular index, basket of assets, or commodity. ETFs are traded on a stock exchange and can be bought or sold throughout the day like traditional stocks. ETFs provide investors with an easier and more cost-efficient way to gain exposure to a variety of asset classes, such as stocks, bonds, commodities, and currencies, without the need to purchase individual securities (Gleason et al., 2004, pp. 682-683).

The principle of Mean-Variance Spanning, introduced by Huberman and Kandel (1987), describes two potential benefits of portfolio diversification:

1) A higher return with the same volatility: in this scenario, investors who incorporate an additional asset into their portfolio may observe an expected return increase without an accompanying risk increase. This implies that for the same level of risk, the portfolio's return potential improves, offering a more favorable investment opportunity (Huberman & Kandel, 1987).

2) Lower volatility with the same return: conversely, the addition of a new asset to the portfolio may result in lower risk for the same level of expected return. This is advantageous as it represents a decrease in the portfolio's volatility while maintaining expected returns. This enhances the portfolio's stability, offering a more secure investment while not compromising on potential returns (Huberman & Kandel, 1987).

Overall, diversification helps to protect investors from losses that may be incurred by a single security, as the gains of some securities may offset the losses of others (Miralles-Quirós et al., 2019c, p. 245). ETF investors who employ a buy-and-hold strategy are taking advantage of the low fees and ease of access to the markets to build their long-term portfolios. However, during the Covid-19 pandemic, there were concerns that ETFs may have disrupted the markets. Currently, about 30% of U.S. equity trading volume is due to ETFs themselves (Glosten et al., 2021, pp. 22-24).

The literature on the impact of ETFs on the market is still developing, but early evidence suggests that ETFs could potentially lead to continued distortion of the fundamental value of assets. There are concerns that ETF activity could result in non-fundamental shocks to the market, leading to a breakdown of the link between the intrinsic value of companies and stock returns. In this case, subjective factors can drive the price of an asset far beyond its intrinsic value, which can result in a bubble or market crash when the prices eventually correct themselves (Glosten et al., 2021, pp. 22-24; Bhattacharya & O'Hara, 2017, pp. 2-4).

1.1 Herding Behavior and Financial Market Fluctuations

In the academic literature, the occurrence of herding behavior in relation to price changes of

[1] https://www.nasdaq.com/articles/inside-the-growing-popularity-of-etfs-2021-06-22

financial assets has become a common theme. Despite this, economists have begun to consider this concept in the literature a few decades ago. Several theoretical studies have proposed that herd behavior could account for the high levels of volatility observed in financial markets (Orléan, 1995, p. 268; Shiller, 1989, p. 49; Topol, 1991, p. 788).

In its most general form, herding can be characterized as behavioral patterns that are shared across individuals. When many investors purchase the same 'hot' stocks, it may simply be because they have received correlated information. The phenomenon of herding that is of interest here, may lead to systematic sub-optimal decision-making across a population. This type of herding has close ties to phenomena such as imperfect expectations, changes in opinion without much new information, bubbles, and fads (Devenow & Welch, 1996, p. 604).

The phenomenon of herding behavior has been observed in both developed and emerging markets, indicating that herding behavior is a pervasive feature of stock market dynamics (Chang et al., 1999, p. 1651; Bogdan et al., 2022). Several studies have also found that herding behavior can increase market volatility and reduce the accuracy of stock market forecasts (Blasco et al., 2012, p. 312; Bekiros et al., 2017, p. 109). As such, understanding and managing herding behavior remains an important area of research for academics and practitioners alike.

In recent years, herding behavior in financial markets has been extensively researched. However, relatively little research has examined the role of the Covid-19 pandemic as a driver of herding behavior among market participants in ETF markets. To the best of my knowledge, no existing studies examine the impact of Covid-19 on herd behavior in globally diversified ETFs like the FTSE All-World UCITS ETF (VWRL).

It's crucial to understand if investors can diversify themselves against such herding behavior. Proper diversification is a fundamental principle in investing to mitigate risks. If herding behavior is pervasive, even in diversified portfolios, it may limit the traditional benefits of diversification, potentially exposing investors to unanticipated risks. This knowledge is important for investors aiming to create portfolios resilient to market anomalies.

Furthermore, if herding tendencies are identified in a comprehensive diversified ETF, it might indicate market inefficiencies. Informed investors could leverage these inefficiencies as opportunities to generate returns above the market average. Thus, understanding herding not only provides risk insights but also potential avenues for superior performance.

1.2 Global Pandemic: Covid-19, Economic Impacts, and IPO Market Surge

On March 11, 2020, The World Health Organization (WHO) declared the COVID-19 outbreak a global pandemic. From this moment, the number of confirmed cases continues to rise, with over 170 countries affected (Zhang et al., 2020, p. 1).

Research has shown that the Covid-19 pandemic had several implications. Firstly, the pandemic has led to limitations on economic activities due to strict quarantine policies, and industries such as tourism and aviation are facing serious setbacks. The global financial markets have responded with dramatic movements, with stock markets in the US, Europe, and Asia plunging in March 2020. Central banks and authorities have responded with policy instruments such as lowering interest rates to zero percent and quantitative easing programs, but uncertainty remains as the pandemic continues (Zhang et al., 2020, p. 1).

Secondly, despite the unknown economic impact of the pandemic, the initial public offerings (IPOs) market saw an exponential increase, with more than $150 billion raised by new firms in 2020, making it one of the best years for IPOs since the dot-com bubble in the late 1990s (Baig & Chen, 2022, p. 1). Investors were very eager to invest in new firms, even in the midst of a pandemic suggesting that investors were (overly) optimistic and potentially ignored risks and uncertainties. This behavior could have led to irrational investment decisions or herding behavior.

Thirdly, research from Baig & Chen (2022, p. 2) shows that IPOs were generally more under-priced and more volatile compared to those that occurred before the pandemic. After taking into account factors such as firm characteristics and industry effects, it was found that pandemic-related factors such as lockdowns and stay-at-home requirements significantly contributed to IPO under-pricing and volatility.

Overall, the picture is mixed. On the one hand, we see a rise in the number of IPOs. On the other hand, studies document a high degree of uncertainty and significant global economic impact.

Nevertheless, over the same period, there was an increase in individual investors who used online brokers to open investment accounts and started trading in the markets (Lush et al., 2021, pp. 1-2).

In the article from Lush et al. (2021, p. 11), it is noted that new investors may have limited knowledge of investing and may not fully understand the risks and costs associated with their trading behavior. As a result, they may be more likely to execute more transactions, which can lead to increased trading costs and reduced investment returns.

Additionally, the authors of this research suggest that these new investors may be more susceptible to behavioral biases, such as overconfidence or herding behavior, which can influence their investment decisions (Lush et al., 2021, p. 11).

For example, we saw strong levels of herding behavior in the rise of meme stocks. When people were stuck at home due to quarantine measures, they turned to stock trading as a form of entertainment and potential income. This trend was fueled by the accessibility of trading platforms and the rise of social media communities sharing investment tips and advice (Costola et al., 2021, pp. 1-2).

The rise of meme stocks, such as GameStop and AMC, was largely driven by individual investors on forums like Reddit, who coordinated to drive up the stock prices. This phenomenon led to discussions about market manipulation, the role of social media, and the democratization of investing. While some new individual investors experienced significant gains, others suffered losses and learned tough lessons about the risks of trading. The impact of the meme stock trend and the influx of new individual investors on the stock market is yet to be fully understood (Costola et al., 2021, pp. 1-2).

1.3 Herding behavior in the VWRL All-World ETF During Covid-19

Based on the foregoing, we suspect that during the Covid-19 pandemic, there was a notable instance of herding behavior in the financial markets.

When the World Health Organization declared Covid-19 a global pandemic in March 2020, there was a significant negative reaction across the globe's financial markets.

The market downturn was likely a result of fear and uncertainty, with investors collectively deciding to sell their shares. This mass action can possibly be seen as an example of herd behavior.

However, as the pandemic continued, this initial reaction decreased, and the markets started to recover relatively quickly. This change suggests a shift in herding behavior over time, with the group’s mood moving away from fear and panic towards a more optimistic outlook.

The strict quarantine measures implemented in response to the pandemic caused severe disruptions to economic activities. Industries like tourism and aviation were particularly affected. Despite this, central banks and financial authorities worldwide responded with policy measures such as reducing interest rates to zero percent and implementing quantitative easing programs to help mitigate the economic impact.

Still, the uncertainty remained as the Covid-19 crisis continued to unfold, with confirmed cases rising and affecting over 170 countries. Despite these challenges, the financial markets showed resilience over time, indicating a decrease in the initial herding behavior.

The Covid-19 pandemic is expected to illustrate the potential variability of herding behavior over time. The initial intensely negative reaction, followed by a more moderate response and the eventual extremely optimistic market recovery, is likely to be indicative of the changing group dynamics during this period.

Therefore, the primary objective of this research is to examine the existence of herding behavior in de periods before- and during Covid-19 in a well-diversified VWRL All-World ETF.

In this study, we will analyze the VWRL All-World ETF, which is made up of approximately 3,700 individual listed companies from all over the world. This ETF was chosen because it is one of the largest index funds globally that consists entirely of stocks. By investing in an All-World ETF, investors can gain exposure to a wide range of industries, sectors, and regions from all over the world. The main goal of an All-World ETF is to provide investors with a convenient and efficient way to participate in the growth of global markets. Moreover, considering the widespread impact of Covid-19, it is interesting to examine a globally diversified fund in this context.

The outcome of this research adds to the existing literature by testing for investor herding in an All-World ETF market in the periods before and during the Covid-19 pandemic (Bogdan et al., 2022; Sibande et al., 2021; Papadamou et al. 2021; Batmunkh et al. 2020; Luu and Luong 2020; Arjoon and Bhatnagar 2017; Chen 2013).

In most existing studies, the literature is rarely focused on whether herding changes over time in their models. Some of the older methods used in important studies did not consider the dynamic nature of the patterns they observed, and this has been criticized. However, in this study, we are trying to make a unique academic contribution. By using a different approach using both static and dynamic analysis approaches, which allows us to examine whether herding varies over time in a more visual, dynamic, and informative way. This dynamic approach considers changing patterns and gives a better understanding of herding behavior.

In addition, the practical relevance of the findings of this study is important for investors who invest in ETF markets. It is useful both for individual and institutional investors when forming investment portfolios in terms of efficient risk diversification since herd behavior can significantly distort the equilibrium value of prices in the market, and increases volatility.

Understanding herding behavior can provide valuable insights and implications for individual investors in several ways.

Firstly, studying herding behavior helps individual investors become aware of the potential influence of collective behavior on investment decisions. By recognizing the tendency of investors to follow the crowd, individual investors can better understand the market dynamics and avoid making impulsive or irrational investment choices driven solely by herding behavior. This awareness can help them make more informed and independent investment decisions, considering their own financial goals and risk tolerance.

Secondly, examining herding behavior can shed light on the potential risks associated with following the herd. Understanding this phenomenon can help investors identify potential market bubbles and exercise caution, preventing them from being caught up in speculative investment trends that may lead to substantial losses.

Furthermore, this study of herding behavior can highlight the relevance of diversification for individual investors. When investors exhibit herding behavior, it often leads to increased correlation among investment assets, reducing the benefits of diversification. By recognizing the impact of herding behavior on market dynamics, individual investors can place greater emphasis on constructing well-diversified portfolios that spread risk across different asset classes and geographic regions. This approach can potentially help them mitigate the negative effects of herding behavior and enhance their long-term investment outcomes.

However, the question is whether herding behavior is a general market risk (systematic risk) or a specific risk for individual assets (unsystematic risk). General market risk affects the whole market and can't be reduced by increasing portfolio diversification. Specific risk, however, can be reduced by diversifying or spreading out the number of investments in a portfolio (Xiaohong, 2019).

The findings of this study are also relevant for policymakers and regulators who are in charge of stimulating the development of regulations and efficiency of ETF markets, in particular the VWRL All-World ETF which serves as a well-diversified investment product that can help mitigate risk for investors.

Regulators have been working to enhance investor protection and market transparency for ETFs through several regulatory initiatives. Going forward, they should continue to focus on improving disclosure requirements for ETFs, especially related to portfolio transparency and specific risks related to individual investors. Additionally, regulators could consider implementing measures or disclosures to address potential risks related to herd behavior and volatility in ETF markets (Thomadakis, 2018, pp. 3-4).

To summarise the foregoing , the main objective is to provide insight into whether herding behavior can be detected in the periods before and during Covid-19 in a well-diversified VWRL All-World ETF. This leads to the following research question:

"Is there a difference in herding behavior in the periods before and during Covid-19 in the VWRL All-World Exchange-Traded Fund?"

To answer this research question, we will build upon the study of Bogdan et al. (2022), using static and dynamic regression analysis to determine herding behavior during the Covid-19 period in an All-World ETF. It is important to note that in the context of static regression analysis, it does not capture the dynamics or changes in herding behavior over time. The outcome of the static regression merely indicates the presence or absence of herding behavior during a specific period.

Additionally, by using a dynamic analysis, it is possible to identify potential turning points in herding behavior. This approach allows for the detection of shifts in the degree of herding over time, providing valuable insights into the dynamics of investor behavior. By examining the results of the dynamic regression analysis, we can gain a deeper understanding of how herding behavior may have evolved before and during the Covid -19 period.

This study is structured into several key sections. We will start with the 'Literature Review', where we will explore relevant studies and theories about the efficient and inefficient market hypotheses, Covid-19, social mood and investor behavior. This will be followed by the 'Methodology' section, where the details about the static and dynamic analysis will be further explained. Subsequently, the 'Data' section will provide a comprehensive look at the information we intend to gather. This will lead to the 'Empirical Results', where we will present and analyze these findings. This study will end with the 'Discussion and Conclusion' section, where we will offer interpretations of the results and the broader implications of our study."

2. LITERATURE REVIEW

In this chapter, all the relevant literature, academic articles, and evidence related to financial market theories, Covid-19, and investor behavior will be reviewed. The chapter starts with a brief description of efficient and inefficient market theories. The chapter continues with the characteristics of social mood and their direct and indirect effects on financial markets. Subsequently, the existing literature about the impact of Covid-19 on financial markets and herding in stock markets will be discussed, and how the market theories and social mood are related to this. Finally, the hypotheses that will be tested in this study will be presented.

2.1 Efficient Market Theory

According to Fama (1970, pp. 383-384), capital markets are generally efficient, meaning that stock prices reflect all available information, and investors act rationally. This means that the market is up-to-date, and share prices reflect their fair value.

The efficient market theory is later classified into three distinct categories: weak efficiency, semi-strong efficiency, and strong efficiency (Brealey, Myers, & Allen 2020, pp. 342-348). In weak efficient markets, share prices are based only on past prices, whereas in semi-strong efficient markets, share prices reflect all publicly available information, including information from the media and press. Finally, in strong efficient markets, share prices reflect all information, both public and private, meaning that no investors can benefit from having access to private information or engage in arbitrage trading (Jula & Jula, 2017, pp. 878-879).

In research from Vasileiou et al. (2021, p. 214), the authors divided the Covid-19 timeline into five distinct periods and examined whether the stock market behaved efficiently during this time. They found that during the first two periods (01.01.2020 – 21.02.2020), share prices had a normal return, indicating that the market did not immediately reflect all available information, possibly because investors underestimated the health risks of the virus.

However, during the third and fourth periods (22.02.2020 – 18.03.2020), the market experienced a rapid decline and began to reflect available information, although with a delay. During the fifth period (19.03.2020–31.07.2020), the stock market began to grow again, despite the ongoing health risks of the virus, suggesting that investors may have only considered the latest positive information available. Based on these findings, Vasileiou et al. (2021, p. 214) reject the efficient market hypothesis during Covid-19, as share prices did not immediately reflect all available information.

2.2 Inefficient Market Theory

Contrary to the assumption of rational decision-making in economic theory, speculative bubbles and manias are often driven by crowd behavior characterized by irrational exuberance. This term is used to describe a state of excessive optimism and enthusiasm in financial markets that is not justified by underlying fundamentals. It refers to a situation where market participants exhibit irrational behavior, driving up asset prices to levels that are not supported by economic realities. This behavior, as described by LeBon (1922, p. 85), eventually leads to panic and crashes, as explained by Kindleberger & Aliber (2005).

In addition, the theory from Kahneman (2003) contradicts Fama's theory of Efficient Capital Markets, in which is proposed that asset prices reflect all available information to the market (Fama, 1970).

Kahneman (2003, p. 1449) explores the concept of bounded rationality and its implications for market inefficiencies. Bounded rationality refers to the limitations of human rationality, particularly in terms of cognitive capacity and information processing. For example, he suggests that investors may exhibit overconfidence in their abilities to predict market trends and make investment decisions. This overconfidence can lead to irrational enthusiasm or pessimism, which can create bubbles or crashes in the market.

Additionally, Kahneman (2003, pp. 1459-1460) points out that investors often suffer from framing effects, which refer to how information is presented or framed. People tend to make different decisions depending on how information is presented to them, even when the information is essentially the same.

Kahneman (2003, p. 1449) also discusses the concept of loss aversion, which refers to the tendency for people to weigh losses more heavily than gains. This can lead investors to hold onto losing investments for too long in the hopes of recovering their losses, even when it is clear that the investment is unlikely to recover.

Overall, his work suggests that market inefficiencies can arise due to the limitations of human rationality, particularly when it comes to decision-making under uncertainty. By taking into account these factors, behavioral economists can better understand and predict market behavior.

2.3 Social Mood

The concept of social mood suggests that an individual's attitude is not solely based on independent analysis, but is rather influenced by the emotions and beliefs shared among a group of people. Social mood is the collective opinion or belief that shapes individual decisions and aggregates into social trends (Nofsinger, 2005, p. 147).

Shiller and Pound (1989, pp. 48-49) model the diffusion of opinion, or mood, through a population using a general epidemic model, where the spread of a mood is similar to the spread of a disease. The speed at which people's attitudes are influenced and altered is called the "infection rate." This rate varies among different social movements, causing some to be long-lasting while others are short-lived.

Olson (2011, pp. 193-194) argues that changes in social mood cause people to make different decisions. A change in mood may begin with some people undergoing a substantial change or with most people undergoing a small change. These people make decisions and act on this change in mood. Their interaction and communication with others cause further mood swings in others. The collective decisions take time to appear in various ways. These emotions can cause investors to follow each other's actions and engage in unconscious herding behavior.

During periods of low social mood, these attitudes lead to more government intervention in business. Governments may become more active in antitrust activities and enact more regulations when social mood is declining. However, during optimistic times like the recent Covid-19 pandemic (starting from the second half of 2020), the government may allow more mergers and deregulate industries (Nofsinger, 2005, p. 147-148).

Despite the uncertainty surrounding the impact of the global pandemic, companies exuded confidence and sought to raise funds to facilitate business growth. This was evident in the remarkable increase in IPOs during the Covid-19 pandemic. For example, in 2021, we saw records of Initial Public offerings (IPOs). According to Phil Mackintosh, Chief Economist and a Senior Vice President at Nasdaq[2], there was a significant rise in the popularity of special purpose acquisition companies (SPACs) in 2021 due to the global lockdown. SPACs offered a way for private companies to go public and made some well-known private equity managers available to the public. In 2021, there were 613 SPAC listings, which raised a total of $145 billion, a 91% increase from the amount raised in 2020. This means that, despite the uncertainty surrounding the impact of the global

[2] https://www.nasdaq.com/articles/a-record-year-for-ipos-in-2021

Covid-19 pandemic, companies exuded confidence and sought to raise funds in the financial markets to facilitate their business growth.

In addition, the U.S. market broke IPO records in 2021, with over 1,000 IPO listings, exceeding the estimated 180 needed to offset de-listings and mergers. SPACs accounted for over 59% of total new listings, up from approximately 53% in 2020. While other IPOs increased by 88% from 2020 levels, SPAC listings saw a 150% increase.

One of the issues with SPACs is that many of the companies they take public have little to no business plan or revenue, which has led to some shareholders filing lawsuits. Nikola is a notable example of this, as the company was accused of fraud just three months after going public through a SPAC merger, leading to a significant drop in their stock price. While there have been some successful SPAC mergers, a recent study shows that most SPACs' post-merger share prices declined (Naumovska, 2021).

Based on this, it is suggested that there was extreme optimism and probably irrational behavior among investors, in the sense that even companies without revenues and a working prototype were able to raise significant amounts of money in the financial markets.

During these periods of optimism, investors become overly confident and enthusiastic about the prospects of a particular asset or market. This can cause them to overlook or downplay risks and ignore fundamental factors that should be considered when making investment decisions, such as the underlying value of the asset or the economic and political conditions affecting the market Shu (2010, pp. 268-269). Based on this, there are signs to expect that there were extraordinary market conditions during Covid-19.

The stock market is a direct representation of social mood due to the efficient and emotional nature of stock transactions. The collective level of optimism or pessimism in society impacts investor decisions (Nofsinger, 2005, p. 147-148). Because of this shared optimism and pessimism among investors during the pandemic, we expect that there was herding behavior exhibited by investors.

In conclusion, social mood plays a significant role in the economy and financial markets. The collective opinions and beliefs shared among a group of people shape individual decisions and aggregate into social trends, which can lead to herding behavior. The stock market is a direct gauge of social mood and can help forecast future financial and economic activity.

2.4 Investor Behavior and Herding

Investors' sentiments tend to grow more negative when the market is heading downward, and they will often hold off investing in the market until a recovery starts (Burns et al., 2011, pp. 659-661; Baker & Wurgler, 2006, p. 1677). Such circumstances cause investors to overreact in the near term. Shu (2010, pp. 279-280), investigated the impact of mood on stock market behavior. The study demonstrates how shifts in investor sentiment have a direct impact on expected returns and pricing for equilibrium assets. Additionally, when investors are feeling more optimistic, they are more likely to follow the herd and invest in the same stocks, resulting in a decrease in the diversity of investments and an increase in price volatility.

According to research from (Engelberg & Parsons, 2011, pp. 70-72), investor behavior is also influenced by media coverage; the more articles about unexpected events there are, the more investors move their money. On top of this, globalization has increased the interdependence of the globe's financial markets by connecting economies all around the world. This increased interconnection across the world's stock markets will affect the decisions made by international investors regarding asset allocation, economies, and economic policies (Mosley & Singer, 2008, pp. 405-408).

In addition, research from Christie and Huang (1995, pp. 35-37) shows that individual investors exhibited herding behavior during periods of market stress. Specifically, they found that individual investors tend to sell during market downturns and buy during market upturns. This is consistent with the herding behavior that has been observed in the past. Additionally, the authors found that individual investors are more likely to herd around the market when market volatility is high, suggesting that individual investors are more likely to base their decisions on market sentiment during periods of market stress.

During market stress, herding behavior in stock markets can occur as investors respond to fear and uncertainty. Investors may be more likely to follow the behavior of other investors and to buy or sell stocks based on the behavior of the market. This can lead to a feedback loop, where investors continue to follow the herd and cause prices to move in the same direction. This type of behavior can lead to large price swings, as investors all react to the same information or news. Herding behavior can also lead to mispricing of stocks and a misallocation of capital, as investors are not using their own judgement but instead are following the crowd (Hwang and Salmon, 2004, pp. 585-586).

2.5 Covid-19 and Stock Market Reactions

During the Covid-19 period, optimism and pessimism in the financial markets varied significantly. The initial phase in March 2020 marked a shift towards pessimism. At this moment in time, the Covid-19 pandemic had a dramatic effect on global financial markets. In a study from Zhang et al. (2020, p. 1), they found that stock markets around the world fell by more than 10% in the ten days following the announcement of the first confirmed case of Covid-19. On March 23, 2020, the S&P 500, one of the world’s largest indexes based on market capitalization has fallen by more than 30% within one month (Zhang et al., 2020, p. 2). This level of stock market volatility has not been seen in relation to any infectious disease before 2020 (Baker et al., 2020, p. 5).

Furthermore, it was observed that stock markets in countries with large numbers of confirmed cases and those that had implemented strict social distancing measures experienced greater drops (Ashraf, 2021, pp. 5-7).

Ashraf (2020, p. 6) conducted a study to investigate the impact of the coronavirus on stock prices and found that the total number of confirmed cases had a significant negative effect on stock prices. According to the study, a daily growth rate of 1% in confirmed Covid-19 cases resulted in a decrease of 0.3% in stock market returns.

The studies discussed above indicate that there is a direct relationship between the number of Covid-19 cases and changes in stock prices. Wagner (2020, p. 440) suggested that during the initial phase of the pandemic, there was a great deal of uncertainty about the severity of the disease and the potential for a vaccine, as well as about the impact of government policies and public response on the market. It is important to note that the number of Covid-19 cases and the severity of government restrictions are closely linked.

In a report published by Deutsche Bank[3], a chart was presented (Figure 1), which demonstrated a strong correlation between the VIX (Volatility Index) and the number of countries experiencing a daily growth rate of COVID-19 infections exceeding 5%. The VIX is a measure of expected market volatility based on options prices of the S&P 500 index. It is calculated by the Chicago Board Options Exchange[4] and reflects the market's expectation of volatility in the S&P 500 index over the next month. The VIX is widely followed by financial market participants and is also considered a reflection of investor sentiment and risk aversion.

[3] https://www.dbresearch.com/PROD/RPS_EN-PROD/HIDDEn_GLOBAL_SEARCH.alias

[4] https://www.cboe.com/tradable_products/vix/vix_options/

The chart, shown in Figure 1, shows that the virus reached its peak in late March to early April. However, it is important to note that at that time, investors were unaware of this fact.

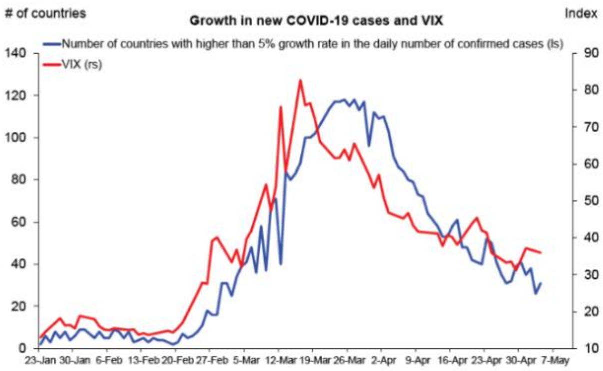

Figure 1: COVID-19, Market Stress and Volatility in 2020

2.6 Hypotheses

In this research, it is suggested that market inefficiencies can arise due to the limitations of human rationality, particularly when it comes to decision-making under uncertainty and market stress (Kahneman, 2003, p. 1449). According to Devenow and Welch (1996, p. 608), investors tend to experience a sense of security when they conform to the behavior of the crowd, particularly in times of increased uncertainty.

In March 2020, financial markets fell significantly while the impact of Covid-19 was not yet known. Relatively shortly after this sharp decline, stock markets began growing again despite the ongoing health risks of the virus, suggesting that investors may have considered only the latest available positive information (Vasileiou et al., 2021, p. 214).

Next to that, during this period a relatively large group of new investors has begun investing in stocks with limited knowledge about financial markets (Lush et al., 2021, p. 11).

Looking at the Covid-19 period, it seems that a lot of irrational behavior was exhibited, which potentially could have led to herding behavior. There were several examples of irrational behavior exhibited due to social mood and investor behavior. (Nofsinger, 2005, p. 147-148; LeBon, 1922, p. 85).

Investors also exhibited signs of potential herd behavior during the pandemic, with many becoming overly confident and enthusiastic about the prospects of a particular asset or market. This caused them to overlook or downplay risks and ignore fundamental factors that should be considered when making investment decisions, such as the underlying value of the asset or the economic and political conditions affecting the market (Aslam et al., 2021, pp. 334-335).

Overall, social mood and investor behavior played a significant role in the irrational behavior exhibited during the Covid-19 pandemic (Aslam et al., 2021, pp. 334-335; Vasileiou et al., 2021, p. 214; Olson, 2011, pp. 193-194; Nofsinger, 2005, p. 147).

Based on the literature, there are indications that herding behavior was present during this period and that the intensity varied over time.

As a result, we want to test if investors used their own judgement instead of following the crowd. This is done by testing if herding behavior is present in periods before- and during notable market volatility and stress. In particular, the period before Covid-19 and the period during Covid-19. Therefore, we propose the following hypotheses:

H_1*: "Between the 1st of January, 2018 and the 30th of January, 2020 there was no herding behavior in the VWRL All-World ETF".*

H_2*: "Between the 31st of January, 2020 and the 31st of December, 2022 there was herding behavior in the VWRL All-World ETF".*

H_3*: "Over the full sample period, we expect that the dynamic analysis approach will detect more pronounced herding behavior in the VWRL All-World ETF than the static analysis."*

In the next chapter, we will explain how these hypotheses will be tested.

3. METHODOLOGY

In this chapter, we offer a preview of methodological procedures that will be used in this thesis to reach empirical results. The chapter starts with a general review of methods widely used in the literature to detect herding behavior. This is followed by a more detailed explanation of how regression is used during different periods related to the Covid-19 pandemic.

3.1 Detecting Herding Behavior

Research from Christie and Huang (1995), have suggested an approach to identify herding behavior in stock markets using data on stock returns. According to Christie and Huang (1995), market conditions play a significant role in the investment decision-making process of market participants. During normal periods, diverse private information of individual investors causes return dispersions to increase with the absolute value of market return, based on rational asset pricing models. However, during periods of extreme market movements, investors tend to follow the collective actions in the market, suppressing their own beliefs, leading to more herding behavior. To identify this behavior, Christie and Huang use a method called the cross-sectional standard deviation (CSSD) which is expressed as follows:

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

where N is the number of firms in the portfolio, $R_{i,t}$ is the observed stock return of firm *i* at time *t*, and $R_{m,t}$ is the average of the cross-sectional return of the market portfolio consisting of N shares at time *t*. This model suggests that if herding occurs, investors will make similar decisions, leading to lower return dispersions.

The CSSD method compares individual stock returns to the cross-sectional average stock returns in the portfolio to determine whether investors are making similar decisions, leading to lower return dispersions. The equation used by their empirical specification is as follows:

$$CSSD_t = \alpha + \beta_1 UP_t + \beta_2 DOWN_t + \varepsilon_t \qquad (2)$$

Where $CSSD_t$ represents the dispersion of returns at a particular time t. The term "alpha" (α) refers to the intercept or constant term in the regression equation. It represents the expected value of the dependent variable when all independent variables are equal to zero. The symbol "ε" (epsilon) represents the error term or residual. The error term captures the variability in the dependent variable that is not explained by the independent variables in the regression model.

The researchers also introduce two dummy variables, UP_t and $DOWN_t$, which take a value of 1 when the market return at that particular time is in the extreme upper or lower tail of the distribution, respectively. Otherwise, these variables take a value of 0. This is important because, during periods of market stress or extreme market movements, investors may tend to follow the collective actions in the market, leading to herding behavior. By using these variables and the CSSD method, the researchers aim to detect whether herding behavior is more prevalent during these periods of market stress. Thus, statistically significant negative values β_1 and β_2 in Equation (2) would indicate the presence of herding, which is tested by the following hypothesis:

$H_0 : \beta_1 < 0$ and $\beta_2 < 0$

$H_A : \beta_1 > 0$ or $\beta_2 > 0$

To determine the significance of β_1 and β_2, we perform a Wald test. We estimate the regression model using the CSSD method and obtain the coefficient estimates along with their robust standard errors. The Wald test would then be used to compare the estimated coefficients to the values predicted under the null hypothesis. If the test results indicate a statistically significant ($\alpha = 0.05$) negative value for either β_1 and β_2, we would not reject the null hypothesis, indicating the presence of herding behavior.

An additional crucial element in the Wald test is the inclusion of covariances. Covariances provide insight into the degree to which two variables vary together. When executing a Wald test, it becomes especially important to consider the covariances between the estimated coefficients. This ensures we account for potential interrelationships between our predictor variables, which if disregarded, can potentially distort our results.

Thus, to successfully execute a Wald test, it is essential to include not only the estimated coefficients and the robust standard errors but also the covariances, thereby providing a comprehensive account of the interdependencies within our predictors.

One of the challenges associated with the method proposed by Christie and Huang (1995), is that it requires the definition of extreme returns. However, the definition of extreme returns is subjective and arbitrary. Christie and Huang have used values of one percent and five percent as cut-off points to identify the upper and lower tails of the return distribution. However, investors may have different opinions on what constitutes an extreme return, and the characteristics of the return distribution may change over time. This can make it difficult to identify herding behavior accurately using this method.

Moreover, herding behavior may occur in the return distribution, not just during periods of extreme returns. Although the Christie and Huang method captures herding during extreme returns, it may not be able to identify herding behavior that occurs during normal market conditions. Additionally, herding behavior can become more pronounced during periods of market stress, which means that the method may not capture all instances of herding behavior.

Therefore, the method of Christie and Huang (1995) was further explored by Chang et al. (2000) who examined market upswings and downswings across a range of countries using the average cross-sectional absolute standard deviations (CSAD) of returns. By analyzing daily stock prices from developed and emerging countries over a period of 34 years, they found that weak cases of herding became more pronounced over time. The CSAD method is sensitive to the presence of herding behavior and market conditions and reflects the degree to which individual returns deviate from the market return. This method is explained in more detail in section 3.2.

3.2 The Cross-Sectional Absolute Standard Deviations (CSAD)

An alternative test to detect herding is proposed by Chang et al. (2000). They argue that if investors tend to follow the overall market behavior during periods of extreme market conditions, the traditional linear and increasing relationship between dispersion and market return may no longer hold. Instead, this relationship can become non-linear, either increasing or decreasing.

To capture this potential non-linear relationship, Chang et al. suggest using a non-linear regression model to estimate the association between the CSAD of returns (a measure of dispersion) and the market return. By adopting this approach, we can detect and analyze herding activity in the financial markets, taking into account the potential changes in the relationship between dispersion and market return during periods of large average price movements. The measure of return dispersion, known as the CSAD statistic, is defined as follows:

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N}|R_{i,t} - R_{m,t}| \tag{3}$$

Similar to the CSSD formula mentioned in Equation (2), $R_{i,t}$ refers to the return of firm *i* on period *t*, and $R_{m,t}$ is the average of the cross-sectional return of the market portfolio consisting of N shares during period *t*.

Chang et al. (2000) suggest that during times of high market volatility, individual asset returns will show greater differences due to variations in how each asset reacts to market fluctuations. This leads to higher dispersion in returns across the market. However, if investors engage in herding behavior by mimicking other investors and following market trends, this pattern can be disrupted, resulting in lower dispersion in returns. Bikhchandani and Sharma (2000, p. 283) argue that during periods of market uncertainty and volatility, investors are more likely to ignore their private information and follow market consensus. Based on this argument, Chang et al. (2000) propose a quadratic model in which the relationship between market return and cross-sectional dispersion of returns is negative and nonlinear. To identify herd behavior in the market, the regression equation to be estimated will be as follows:

$$CSAD_t = a + \gamma_1 r_{mt} + \gamma_2 |r_{mt}| + \gamma_3 r_{mt}^2 + \varepsilon_t \quad (4)$$

Chang's suggestion of using the cross-sectional absolute deviation regression for detecting herding on stock markets has some advantages over the traditional cross-sectional standard deviation method. The key differences are that the indicator of the cross-sectional differences in returns is the absolute deviations of standard deviation and that the model specification is non-linear.

To test for non-linearities between the cross-sectional absolute deviation and the market volatility, Chang's model includes the market return (r_{mt}), absolute market return ($|r_{mt}|$), and squared market return (r_{mt}^2) as independent variables. The coefficient γ_3 that relates cross-sectional absolute deviation to squared market return, checks for non-linear dynamics of herding behavior. If herding is present in the market, this coefficient would be negative and significant. This indicates greater directional similarity in asset returns, resulting in lower dispersion when the market moves significantly up or significantly down. If the market is rational, we would expect this coefficient to be significantly positive. Chang et al. argue that this model is much more powerful and allows researchers to detect herding with much greater precision. This will be tested by the following hypothesis:

$H_0 : \gamma_3 < 0$

$H_A : \gamma_3 > 0$

To calculate the cross-sectional absolute deviation for a stock return from the market return, we apply the average of the absolute deviation of returns of the stocks from the market return represented by the VWRL All-World ETF.

By applying the Chang et al. cross-sectional absolute deviation regression to the data, we can estimate the coefficient for the squared market return and use a z-test to determine if it is significant at the 95% quantile. For a one-tailed test, the critical value is approximately 1.645.

In the right-tailed test, we reject the null hypothesis if the calculated z-statistic is greater than 1.645. If the calculated z-statistic is less than or equal to 1.645, we would not reject the null hypothesis.

It should be noted that the z-test offers certain advantages over the t-test in specific contexts. Specifically, the z-test proves to be robust under conditions of non-normality and heteroskedasticity. This robustness, however, is contingent upon the use of robust standard errors and covariances.

Non-normality refers to a condition where the data does not fit the typical bell-shaped curve. Heteroskedasticity, on the other hand, means there are varying levels of variability in the data.

The t-test is sensitive to these conditions and may not provide reliable results. However, the z-test, by using robust standard errors and covariances, is designed to handle these anomalies and still provide trustworthy outcomes.

In addition, we will use the R-squared, which is a statistical measure, to evaluate the goodness of fit of the regression analysis. The R-squared is a value between 0 and 1, with higher values indicating a better model fit of the data. In general, the R-squared measures the proportion of variance in the dependent variable that can be explained by the independent variables in the model.

3.3 Dynamic Analysis

Next to the static analysis, a rolling window regression analysis is used to study herd behavior which can lead to much more meaningful research results. This method is used because herd behavior occurs during several periods of market stress which results in sharply fluctuating stock prices.

The basic idea of rolling regression is to determine the rolling window, which means using samples of consecutive observations. This is a statistical technique that is widely used in time series analysis of financial data to examine the variation of the linear regression output, such as the regression coefficient, over time. This method applies linear regression to each period or window of fixed length, similar to the principle of a rolling average (Lang et al., 2019, pp. 2-3).

When using a rolling window regression analysis, the data is partitioned into subsets of a fixed size, based on a rolling window width, M. Each subset is then shifted one observation ahead of the previous subset, creating a set of rolling windows with length M. The rolling windows are consecutive and offset by one observation from each other (Lang et al., 2019, pp. 2-3).

The determination of the window width for a rolling window regression often involves an iterative process. This process aims to strike a balance between two key considerations: avoiding overly erratic output and ensuring that the output is not excessively flat.

We will experiment with different window widths, adjusting them incrementally, to assess the impact on the regression results. The goal is to find a window width that captures enough data points to estimate a meaningful relationship while also allowing for the detection of changes in dynamics. If the window width is too narrow, the output may exhibit excessive variability, making it challenging to draw reliable conclusions. On the other hand, if the window width is too wide, the output may appear overly smooth and fail to capture nuanced changes in the relationship.

After creating the rolling windows, linear regression is applied to each window. The regression coefficients and intercepts are recorded for each rolling window. This process is repeated for each rolling window in the time series. Rolling window regression enables researchers to examine the evolution of the regression coefficients over time, which can provide insights into the dynamics of the underlying process (Lang et al., 2019, pp. 2-3).

4. DATA

In this chapter, we describe the process of necessary data collection to conduct my data analysis. The chapter starts with a description of the total population that we want to draw conclusions about. This is followed by an explanation of what a proper sample size is. Finally, it is discussed how daily stock returns will be calculated.

4.1 Sample of the VWRL All-World ETF

As stated previously, this study focuses on the VWRL All-World ETF, which is one of the largest exchange-traded funds in the world based on market capitalization[5]. A total amount of 3732 companies from all over the world were represented as of February 2023.

Studying all 3732 companies[6] in the VWRL All-world ETF may not be feasible due to time limitations. Therefore, we will study a smaller set of units to say something about all the units, as was done in previous studies from Ramadan (2015) and Blasco et al. (2011). By using a sample, we can obtain a smaller, manageable subset of data that still provides meaningful information about the population (in this case, all the companies represented in the ETF).

To ensure that the sample is representative of the population, it is important to use random sampling techniques. This means that each company in the VWRL All-World ETF has an equal chance of being selected for the sample.

Using a sample is a common practice in research and analysis when studying large populations. It allows for more efficient use of time and resources while still providing valuable insights into the population of interest.

[5] https://www.statista.com/statistics/1181252/largest-etfs-market-cap-global/

[6] https://www.vanguardinvestor.co.uk/investments/vanguard-ftse-all-world-ucits-etf-usd-distributing/overview

In the case of the VWRL All-world ETF, which contains over 3,700 companies, a sample size of at least 30 is generally considered a proper starting point, but the ideal sample size may depend on the specific research objectives. A larger sample size generally leads to greater precision and a higher level of confidence in the results.

However, a larger sample size also requires more time and resources, so we have to balance the level of precision and confidence required with the available resources.

4.2 Calculating a proper sample size with a finite population

To determine an appropriate sample size, we will use Slovin's formula which is calculated as follows:

$$n = \left[\frac{N}{1+Ne^2}\right] \quad (5)$$

Within this formula, "N" denotes the total population size, while "e" signifies the margin of error. This margin of error represents the acceptable likelihood of making an error when choosing a representative subset of the population (Tejada & Punzalan, 2012).

Applying Slovin's formula entails first deciding on the acceptable margin of error. For example, a 95% confidence level corresponds to a margin of error of 0.05. Once this margin of error is set, the formula can be used to compute the proper sample size "n" (Tejada & Punzalan, 2012).

$$n = \left[\frac{3732}{1+3732*(0.05^2)}\right] = 361$$

Based on Slovin's formula, a sample size of 361 companies should be sufficient. This provides a larger sample size to work with while still being feasible to study within the time constraints.

Additionally, with a sample size of 361 companies, we are still able to achieve a high level of precision and confidence in the estimates of the overall population characteristics of the ETF.

The weighting factor for each country will be taken into account when the sample is created. For example, North America represents about 60% of all companies in the ETF. As a result, the sample will consist of 60% randomly selected American companies.

On January 31, 2020, the second meeting of the Emergency Committee[7] was held under the International Health Regulations by the WHO Director-General to address the outbreak of Covid-19 in China and its potential global impact. The committee advises the Director-General on declaring a Public Health Emergency of International Concern (PHEIC) and may provide public health advice or Temporary Recommendations as needed.

Therefore, the Pre-Covid-19 subsample ranges from 1 January, 2018 to 30 January, 2020, and the During-Covid-19 subsample from 31 January, 2020 to 31 December, 2022. Table 1 summarizes the sample periods of this study.

Sample	Sample range
Pre-Covid-19	1 January, 2018 to 30 January, 2020
During-Covid-19	31 January, 2020 to 31 December, 2022
Full sample	1 January, 2018 to 31 December, 2022

Table 1: Sample periods to detect herding

4.3 Sample Selection

As mentioned before, 48 countries are represented in the VWRL All-World ETF. In addition, the companies in the ETF are categorized into one of the following eleven sectors[8] (Table 2): technology, financials, consumer discretionary, industrials, healthcare, consumer staples, energy, basic materials, utilities, telecommunications, and real estate.

The sectors will be represented in the sample based on the weighting as shown in Table 2. This means that one sector is represented to a greater extent in the VWRL All-World ETF than another. For example, the technology sector has the highest weighting with 20.5%

[7] https://www.who.int/docs/default-source/coronaviruse/situation-reports/20200131-sitrep-11-ncov.pdf

[8] https://www.vanguardinvestor.co.uk/investments/vanguard-ftse-all-world-ucits-etf-usd-distributing/portfolio-data

while real estate is the least represented with a weighting of only 2.8% of the total ETF.

Sector	Weight in VWRL
Technology	20.50%
Financials	15.30%
Consumer Discretionary	13.90%
Industrials	13.20%
Healthcare	12.00%
Consumer Staples	6.60%
Energy	5.40%
Basic Materials	4.30%
Utilities	3.10%
Telecommunications	2.90%
Real Estate	2.80%
Total	**100%**

Table 2: Sector Weighted Exposure VWRL All-World ETF

4.4 Quantitative Data Collection Method

For this quantitative research, daily returns of individual stocks and the VWRL All-World ETF will be collected by using Eikon Refinitiv[9], which is a financial information platform that provides access to real-time and historical market data. The platform offers comprehensive and up-to-date information on stock prices, trading volumes, and other key indicators, allowing investors to monitor market movements.

The daily closing prices of each of the 361 individual stocks will be aggregated for the proposed time frames, shown in Table 1. The same will be done with the data from the VWRL All-World ETF. The relevant data will then be exported to Excel to calculate two dispersion metrics. That is the cross-sectional standard deviation (CSSD) and the cross-sectional absolute standard deviation (CSAD). Subsequently, statistical software SPSS will be used to conduct a linear multiple regression analysis and additionally, a rolling window regression to approach it more visually.

As herding behavior is usually found to be a short-lived phenomenon in the literature, we will use daily data, which can help identify instances of investor herding even if they are short-lived. We will obtain data on the daily closing prices of each of the companies. The daily returns of the companies will be calculated using their respective daily closing prices (Bogdan et al., 2022, p. 7; Lao & Singh, 2011, p. 500).

To start with, we calculate the daily stock returns for the individual stocks and the total market, which is in this case the VWRL All-World ETF. To calculate this, we will use the formula below for the relative price change:

$$R_{i,t} = \frac{P_t}{P_{t-1}} - 1 \tag{6}$$

Where P_t and P_{t-1} are current and previous closing prices, respectively. Thus, the price today is divided by the price yesterday minus one.

As the number of working days differs between countries and exchanges, the absence of stock prices on non-working days in a particular country will be substituted with the closing price of the last working day.

4.5 Descriptive Statistics CSSD and CSAD

4.5.1 Interpretation Descriptive Statistics CSSD and $R_{m,t}$

Table (3) summarizes the descriptive statistics of the returns on the VWRL All-World ETF market ($R_{m,t}$) and the cross-sectional standard deviation of individual stock returns within the ETF ($CSSD_t$) for two distinct periods: Pre-Covid-19 and During Covid-19.

[9] https://eikon.refinitiv.com/index.html

Statistic	Pre-Covid-19			During-Covid-19			Full Sample		
	$R_{m,t}$	$CSSD_t$	$CSAD_t$	$R_{m,t}$	$CSSD_t$	$CSAD_t$	$R_{m,t}$	$CSSD_t$	$CSAD_t$
Minimum	-3.17%	1.16%	0.74%	-9.00%	1.40%	1.47%	-9.00%	1.16%	0.74%
Maximum	2.96%	7.90%	4.03%	7.22%	16.11%	22.86%	7.22%	16.11%	13.87%
Mean	0.03%	2.27%	1.58%	0.02%	3.06%	3.46%	0.02%	3.06%	1.91%
Std. Deviation	0.86%	0.62%	0.46%	1.23%	1.62%	1.95%	1.23%	1.62%	1.01%
Skewness	-0.488	2.705	2.011	-0.963	4.359	4.086	-0.963	4.359	5.336
Kurtosis	1.595	1.595	1.595	7.84	25.271	25.251	7.84	0.09	42.943

Table 3: Summary of Descriptive Statistics CSSD

In the Pre-Covid-19 period, the daily market returns ($R_{m,t}$) had an average of 0.03%, with a minimum return of -3.17% and a maximum return of 2.96%. The cross-sectional standard deviation of individual stock returns ($CSSD_t$) in the same period had a mean value of 2.27%, a low of 1.16%, and a high of 7.90%.

During the Covid-19 period, the average daily market return ($R_{m,t}$) was slightly lower at 0.02%, with returns ranging from a low of -9.00% to a high of 7.22%. The average dispersion of individual stock returns ($CSSD_t$) during this period was higher at 3.06%, with a range between 1.40% and 16.11%.

The data suggests that the Covid-19 period witnessed more extreme market returns, as demonstrated by the broader range of minimum and maximum values for $R_{m,t}$. These extreme returns indicate heightened market volatility during the pandemic. At the same time, the higher cross-sectional standard deviation ($CSSD_t$) reflects more varied performance among individual stocks within the ETF during Covid-19.

By considering both the minimum and maximum values, we can gain insights into the range and spread of the variables. Additionally, when combined with other descriptive statistics like the mean and standard deviation, the minimum and maximum values can help to assess the overall distribution and identify any potential data quality issues.

In the context of working with returns, we typically do not address outliers in the dataset. This is because returns exhibit a distribution with fat tails. Essentially, extreme values are expected, and treating them as outliers would imply a failure to acknowledge this characteristic of returns (Nirei, 2013, pp. 2-3).

Returns often follow a distribution that is not perfectly normal and exhibits more extreme values than a normal distribution would predict. These extreme values, or "fat tails," are common in financial markets. They indicate the presence of rare but significant events that can have a substantial impact on investment performance (Nirei, 2013, pp. 2-3).

Since these extreme values are an inherent part of returns and can contain valuable information, we generally do not treat them as outliers. Outliers, in the traditional sense, are typically considered data points that are unusual or aberrations from the norm. However, in the case of returns, extreme values are not considered anomalies but rather integral components of the distribution.

4.5.2 Interpretation Descriptive Statistics CSAD

Table (3) provides also a summary of the descriptive statistics for the cross-sectional absolute deviation of individual stock returns ($CSAD_t$) during the Pre-Covid-19 and During-Covid-19 sample periods.

In the Pre-Covid-19 sample period, the average daily cross-sectional absolute deviation of individual stock returns during the pre-Covid-19 sample is 1.58%. This suggests that the individual ETF returns exhibited moderate variability and dispersion during this period.

In contrast, in the During-Covid-19 sample period, the average daily cross-sectional absolute deviation of individual stock returns significantly increased to 3.46% in the During-Covid-19 sample. This indicates a higher level of dispersion and heterogeneity among individual stock returns, suggesting that different stocks experienced varying levels of performance and volatility during this turbulent period.

These findings suggest that the Covid-19 pandemic had a substantial impact on the VWRL All-World ETF market, leading to increased market volatility and greater dispersion in individual stock returns compared to the pre-Covid-19 period.

5. EMPIRICAL RESULTS

This chapter will describe the empirical results, starting with descriptive and statistical analysis. The purpose of this chapter is to present and discuss the findings derived from the collected data.

The data for this study was collected from the financial data platform Eikon Refinitiv and subsequently organized and structured in Microsoft Excel. Finally, the prepared data was imported into SPSS and RStudio to perform the necessary statistical analyses.

5.1 Multiple Linear Regression CSSD

Table 4: Estimated Regression Coefficients for the Pre- and During Covid-19 subsamples

	Cross-Sectional Standard Deviation	
	Pre-Covid-19	**During-Covid-19**
α	2.206 (80.137)	2.905 (48.456)
β1 (right tail)	0.572** (4.755)	1.812** (6.860)
β2 (left tail)	0.655** (5.451)	1.419** (5.371)
R^2	0.087	0.090

Notes: 1. Refer to Equation (2) for the detailed equation.
*2. ** Represent statistical significance at the 5% level.*

5.1.1 Interpretation of the regression results in the Pre-Covid-19 sample CSSD method

The coefficients table (4) shows that both β_1 (0.572) and β_2 (0.655) in the Pre-Covid-19 sample are positive. To determine the significance of β1 and β2, we perform a Wald test. We estimate the regression model using the CSSD method and obtain the coefficient estimates along with their robust standard errors.

In this study, we faced the complexity of conducting a one-sided hypothesis test involving multiple coefficients. To simplify this, we employed a practical approach based on a standard Wald test, which is designed to test the following null and alternative hypotheses:

H0 : β1 < 0 and β2 < 0

HA : β1 > 0 or β2 > 0

As can be seen in table (5), the Wald statistic is 45.7 with 2 degrees of freedom, and the p-value is 1.2E-10. This extremely low p-value and the positive coefficients β1 and β2 indicate that we should reject the null hypothesis of the Wald test ($\alpha = 0.05$).

Wald Chi-squared Test		
Statistic	**df**	**Wald p-value**
45.7	2	1.2E-10

Table 5: Wald Chi-squared test Pre-Covid-19 sample

The positive and significant coefficients observed in this context indicated that investors behaved rationally rather than exhibited herding behavior. This means that we do not reject H_1 :

“Between the 1st of January, 2018 and 30th of January, 2020 there was no herding behavior in the VWRL All-World ETF”.

The positive coefficients implied that an increase in the values of the predictors (Right Tail and Left Tail) was associated with an increase in CSSD. This suggested that investors' decisions were based on rational considerations, indicating that they made independent judgments rather than simply following the actions of others (herding).

Based on the provided model summary, the R^2 value is 0.087. This means that approximately 8.7% of the variance in the dependent variable can be explained by the independent variables included in the model. In this case, the “Left- and Right Tail".

It is important to note that R^2 ranges from 0 to 1, where 0 indicates that none of the variance in the dependent variable is explained by the independent variables, and 1 indicates that all of the variance is explained. In this case, an R^2 value of 0.087 suggests that the included independent variables explain a relatively small proportion of the variance in the dependent variable. In this context, it can be noted that the observed R^2 is consistent with previous research on investor herding behavior, where similarly low R^2 values have been reported (Elshqirat, 2021, pp. 120-122; Maquieira & Espinosa Méndez, 2022, pp. 213-214).

5.1.2 Interpretation of the regression results in the During-Covid-19 subsample CSSD method

The coefficients table (4) shows that both β_1 (1.812) and β_2 (1.419) are positive in the During-Covid-19 sample. In Section 5.2.1, we introduced the Wald test as a method for assessing the significance of the regression coefficients. We apply this test again in this section to specifically evaluate the significance of the coefficients β_1 and β_2 in the During Covid-19 sample. The null and alternative hypotheses for the Wald test are formulated as follows:

H0 : $\beta 1 < 0$ and $\beta 2 < 0$

HA : $\beta 1 > 0$ or $\beta 2 > 0$

As can be seen in Table (6), the Wald statistic is 20.5 with 2 degrees of freedom, and the p-value is 3.6E-10. This extremely low p-value and the positive coefficients $\beta 1$ and $\beta 2$ indicate that we should reject the null hypothesis of the Wald test (a = 0.05).

Wald Chi-squared Test		
Statistic	**df**	**Wald p-value**
20.5	2	3.60E-05

Table 6: Wald Chi-squared test During Covid-19 sample

The findings from the regression analysis provide no evidence of herding behavior among investors in the during Covid-19 subsample. Contrary to the expectations, the coefficients observed in this study are positive and significant. Therefore, based on the results of this regression analysis, it can be concluded that there are no indications of herding behavior among investors in the VWRL All-World ETF. The findings support the notion that investors acted rationally, making independent investment decisions based on their own assessments rather than conforming to the behavior of the herd.

Based on the provided model summary, the R^2 value is 0.090. This means that approximately 9.0% of the variance in the dependent variable can be explained by the independent variables included in the model. In this case, the "Left- and Right Tail".

5.2 Multiple Linear Regression CSAD

Table 7: Estimated Regression Coefficients for the Pre- and During COVID-19 subsamples CSAD Approach

Cross Sectional Absolute Deviation		
Coefficients	**Pre-Covid-19**	**During-Covid-19**
α	6.835E-16 (.000)	6.343E-16 (.000)
γ_1	.052** (-1.354)	-.061 (-1.741)
γ_2	.106** (-1.044)	.339** (5.170)
γ_3	.467** (-4.524)	.069 (1.028)
R^2	.312	.175

Notes: 1. Refer to Equation (4) for the detailed equation.
2. Values in parentheses represent z-statistics.
*3. ** Represent statistical significance at the 5% level.*

This analysis focused on detecting herding behavior in the Pre- and During Covid-19 period using the Cross-Sectional Absolute Deviation. Using this approach, we are looking for a significant negative γ_3 which indicates herding behavior, while a significant positive value of the same indicates the presence of anti-herding behavior.

The Pre-Covid-19 results indicate that herd behavior was not present in the VWRL All-World ETF during this period. The positive and significant value of γ_3 supports the notion that investors behaved rationally, making independent investment decisions based on their own assessments rather than conforming to the behavior of the crowd.

The results presented in the During Covid-19 period show that γ_3 is positive but non-significant, suggesting that there is a tendency towards independent investment decisions among investors, but this relationship lacks statistical robustness. In other words, while there may be some indication of investors making independent decisions, the data does not provide strong evidence to support this claim.

It is worth noting that non-significant results do not necessarily imply that the relationship between γ_3 and independent investment decisions does not exist. It simply means that the available data does not provide sufficient evidence to 'reject' this relationship. Further research or a larger sample size may be required to establish a more definitive conclusion.

5.3 Dynamic Analysis: Rolling Window Regression Analysis

In practice, a static analysis of herd behavior may not be sufficient since herd behavior is fundamentally dynamic (Bischi et al., 2006, p. 504). It commonly occurs during periods of market stress, such as the Covid-19 pandemic, where sharp fluctuations in stock prices are prevalent. Hence, it is more appropriate to employ a rolling window regression analysis to study herd behavior. This approach ensures continuity in analyzing the data and capturing the evolving patterns of herd behavior (Lang et al., 2019, pp. 2-3).

Moreover, the utilization of the rolling window regression enables the identification of potential turning points in herding behavior. This method facilitates the detection of shifts in the degree of herding over time, providing valuable insights into investor behavior dynamics. Through an examination of the results from the rolling window regression, a deeper understanding of the evolution of herding behavior before and during the Covid-19 period can be gained.

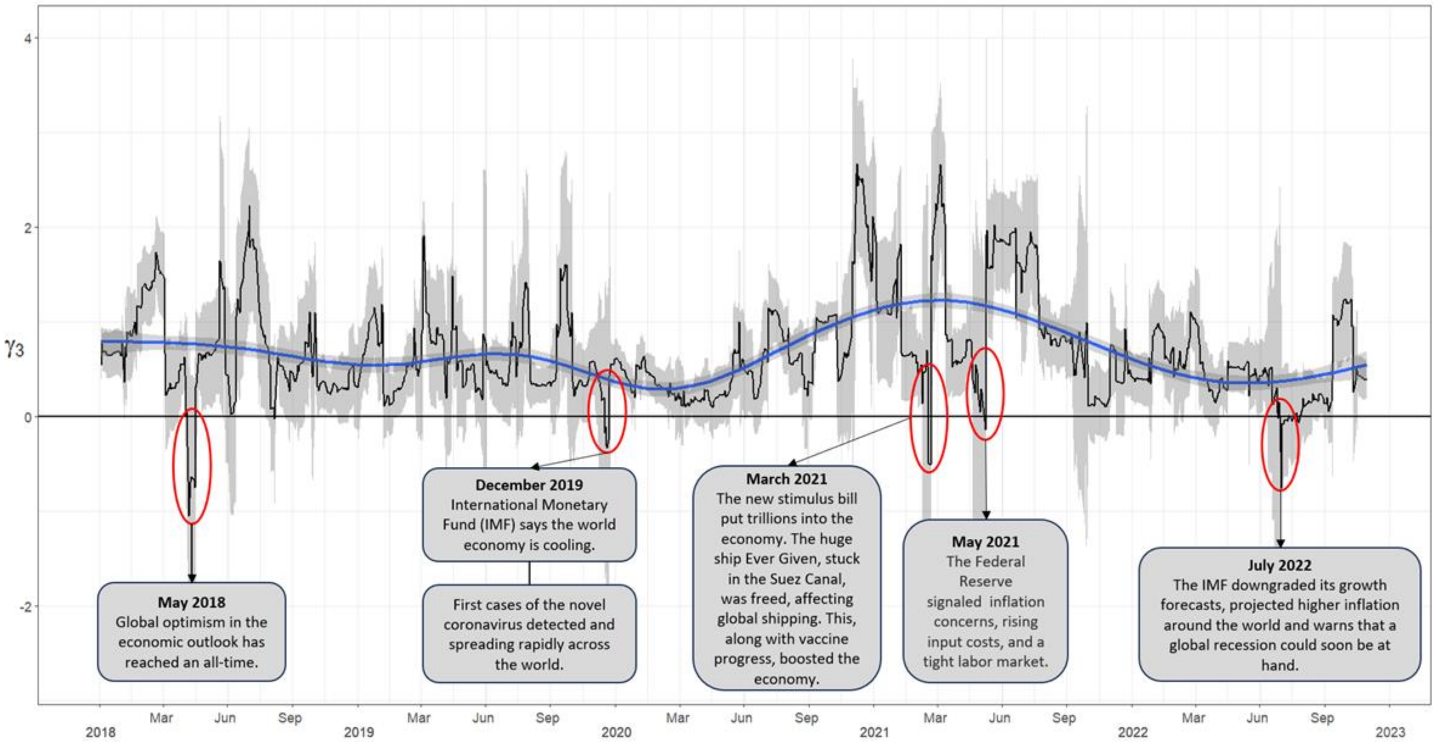

Figure 2: Rolling Window Regression Analysis Herding Coefficients. Note: the shaded region around the trend line represents the 95% confidence interval.

According to the results of the rolling window regression analysis, as seen in Figure 2, we can detect some signs of herding behavior. The rolling window regression analysis shows the evolution of γ_3 for the VWRL All-World ETF during the period between January 01, 2018, and December 31, 2022. We built a window of 20 days to generate a series of the estimated coefficients, particularly looking to analyze γ_3 from Equation (4). Experimenting with a range from 5 to 40 days, we found that window sizes larger than 20 days made the plot too flat, whereas window sizes smaller than 20 days resulted in a plot that was too erratic. Both extremes can compromise the interpretability of the analysis, making it more difficult to draw meaningful conclusions.

Based on the output, we can see that there are five signs of herding behavior in the full sample period of which two in the Pre-Covid-19 subsample and three in the During Covid-19 subsample. If we want to conclude that γ_3 is significantly negative, the entire 95% confidence interval would need to lie below the zero line. If any part of this interval lies above the zero line, we can't claim with 95% confidence that γ_3 is statistically significant negative. Using a window width of just 20 days for a rolling window regression analysis might not provide enough data points to achieve statistically significant results. The limited number of data points within each window can potentially reduce the power of the test. Therefore, even if we observe signs of herding behavior in the data, the results might not be statistically significant due to the relatively small window width.

In essence, while there might be indications of herding behavior in the dataset, the choice of a 20-day window could limit our ability to conclusively demonstrate its significance. It is worth noting that "not significant" in this context doesn't necessarily mean "not present." It simply indicates that, given the chosen window width, we don't have enough evidence to make a robust statistical claim of the detection of herding behavior.

However, in numerous points of the plot (Figure 2), we observe that the coefficient γ_3 and its confidence interval lie above the zero line. This indicates that investors were making decisions independently, diverging from the herd.

The observed patterns in the full sample period support the findings that herding behavior is a short-lived and dynamic effect among investors. This behavior was especially pronounced when during periods of significant macroeconomic events, both positive and negative, was released to the public.

When negative news was spread, such as concerning inflation figures, bleak economic forecasts, or warnings by institutions like the IMF about potential worldwide recessions, there was a sense of panic in the markets. Many investors, driven by fear, sold off their assets massively, even if the underlying fundamentals of those assets remained robust. This reaction could be attributed to herding behavior, as individuals seemed to be largely reacting to the collective sentiment and behavior rather than their own analyses as we saw in December 2019, May 2021, and July 2022 (Figure 2).

Conversely, positive news also triggered notable market responses. Announcements indicating breakthroughs in the development of a coronavirus vaccine or positive reports pointing to the recovery and stabilization of global supply chains led to a surge of optimism. The market witnessed significant buying, again, not purely driven by individual analysis but influenced heavily by the collective sentiment and actions of the broader investment community as we saw in May 2018 and March 2021 (Figure 2).

The market often switches between herding and anti-herding behavior during periods of market stress, where investors tend to experience a sense of security when they conform to the behavior of the crowd, particularly in times of increased uncertainty. In both scenarios, the presence of herding behavior can strengthen market movements, making them more volatile. It is crucial for investors to be aware of these dynamics, recognize the influence of collective sentiment on market trends, and ensure they are making informed decisions based on their own research.

6. DISCUSSION AND CONCLUSION

6.1 Key Findings

This study investigates the presence of investor herd behavior in the VWRL All-World ETF market in the Pre- and During the Covid-19 period. The sample of this study constituents of companies trading in the VWRL All-World ETF and the full sample period of analysis ranges from the 1st of January, 2018 to the 31st of December, 2022.

Previous studies have indicated that during periods of market stress, investors tend to exhibit irrational behavior. This can be attributed to a lack of information, leading them to imitate each other, resulting in what is commonly known as herding behavior. While there is a significant body of literature on the subject of herding behavior, there is a scarcity of research that specifically examines herding behavior in the world's most diversified exchange-traded funds. To the best of my knowledge, there has been no study conducted to identify herding behavior in the VWRL All-World ETF during the Covid-19 outbreak.

In this study, the approaches Cross Sectional Standard Deviation (CSSD) and Cross-Sectional Absolute Deviation (CSAD) of Christie and Huang (1995) and Chang et all., (2000) were used respectively to identify herding behavior in stock markets using data on stock returns.

After conducting the analysis we did not find evidence to support the existence of herd behavior in the VWRL All-World ETF. Surprisingly, we observed the presence of anti-herding behavior in both the Pre- and During Covid-19 samples, indicating that market participants made independent decisions, diverging from the herd. Only in the During-Covid-19 sample, the CSAD approach did not show statistically significant results.

However, recognizing the importance of exploring alternative methods to assess herding behavior, we conducted a dynamic analysis using an OLS Rolling Window Regression analysis based on the CSAD model. Notably, this analysis revealed indications of herding behavior at five distinct points within the full sample period. Nevertheless, these results were not statistically significant. It is also worth noting that due to our small window width, we should not expect significant results.

One of the key findings is the strong indication of herding behavior in the VWRL All-World ETF, which is one of the most diversified exchange-traded funds in the world. This suggests that even the most diversified portfolios are not insulated from the effects of herding behavior, especially during significant global macroeconomic events. Investors, therefore, cannot rely on diversification as a protection against the effects of herding behavior. Instead, awareness of the herding phenomenon becomes critical. During these events, it seems that the intrinsic value of stocks may temporarily decouple from their fundamental values. This means that informed and alert investors can only capitalize on or guard against such behaviors if they recognize and understand this phenomenon. This is potentially an interesting outcome for investors who are striving to 'outperform the market' as they have a better chance of achieving that goal during impactful macroeconomic events.

The findings of this study highlight the utility of a rolling window regression analysis in detecting indications of herding behavior. Such a dynamic approach allows for a more nuanced understanding of the market, capturing the changes in investor sentiment over time. However, it is important to note that this methodology demands a lot of data. The richer the dataset, the more refined the insights will be, shedding light on the temporal patterns and triggers of herding behavior.

While diversification remains a cornerstone of a conservative investment strategy, it can be argued that investors who allocate their capital to globally diversified exchange-traded funds (ETFs) are likely to be exposed to herding behavior. Investors must remain alert, especially during significant macroeconomic events, and be prepared with the knowledge of potential herding behavior and its implications on asset valuation.

To conclude, the OLS rolling window regression analysis shows different outcomes compared to using a static approach, which means using a static approach can lead to uncertain conclusions since herding behavior is fundamentally a dynamic effect. Therefore, it can be concluded that a rolling window analysis is much more reliable and the static approaches like the CSSD and CSAD can lead to a more questionable conclusion.

6.2 Limitations of this research

There are several limitations in this study. Firstly, this research focuses only on the VWRL All-World ETF market, which may limit the generalizability of the findings. ETFs vary in their underlying assets, investment strategies, and investor preferences. Therefore, the conclusions drawn from this study may not apply to other ETF markets, which could have different dynamics and investor behaviors.

Secondly, another limitation of this study is the lack of insight into the underlying causes of herding behavior. While the study successfully determines the presence or absence of herding behavior, it does not delve into the specific factors that might trigger or influence this behavior. Further exploration into key variables such as market transparency, liquidity, stability, and other relevant factors during times of market stress could provide a more comprehensive understanding of the mechanisms driving herding behavior.

Furthermore, the identification of the structural break in this study solely relies on the Covid-19 pandemic outbreak announcement by the World Health Organization. However, it is important to note that the virus spread gradually and did not cause an immediate and distinct structural break in the market. Alternative approaches to identifying a structural break, such as considering significant market fluctuations or governmental interventions, could be explored to strengthen the robustness of the findings.

6.3 Applications for Future Research

As described earlier, several limitations require further research. Firstly, examining the possible influence of crucial factors such as transparency, liquidity, stability and other market-related variables on the emergence of herding behavior during periods of market stress provides an interesting path for future research. Since different sectors may react differently during crises, it is a complex challenge to assess the extent of herding behavior in different sectors within the VWRL All-World ETF.

In addition, from both a financial and legal perspective, it is promising to investigate which measures within financial markets are most effective in limiting herd behavior in different financial markets. This facet of research can provide valuable insights into promoting more resilient and stable financial systems.

Secondly, large institutional investors, like pension funds, are significant players in financial markets, but their presence can probably create challenges in detecting herding behavior.

One of the reasons for this is their regular portfolio rebalancing activities. Institutional investors have specific long-term asset allocation targets determined by their liabilities. As these liabilities change over time, they need to adjust their portfolios to maintain a balance between risk and return. For example, if the maturity of their liabilities increases, they might shift investments from riskier assets like stocks to safer alternatives such as conventional and index-linked bonds. These portfolio adjustments are part of their asset-liability management strategies, ensuring their investment approach aligns with long-term obligations (Blake et al., 2017, pp. 18-20).

To continue this research, it might be interesting to focus on the effect of portfolio rebalancing strategies of institutional investors on the extent to which herding behavior is detectable. However, this long-term rebalancing of the asset mix may give the appearance of herd behavior. When multiple institutional investors make similar portfolio adjustments, it becomes difficult to distinguish between true herd behavior and strategic rebalancing based on liability considerations. Researchers studying herd behavior should therefore be careful not to misinterpret such strategic adjustments as herd behavior. In addition, it would be interesting to study whether the detection of herding behavior is not canceled out by these large investors as they act contrarily based on market movements.

Overall, the portfolio rebalancing activities of large institutional investors can interfere with the accurate identification of herding behavior in financial markets. Researchers must carefully consider the nuances between genuine herding and rational portfolio adjustments driven by long-term asset-liability considerations and short-term market fluctuations. Robust methodologies are essential to differentiate between the two phenomena and provide accurate insights into market dynamics.

7. ACKNOWLEDGEMENTS

As a final remark, I would like to express my profound gratitude to my supervisor prof. dr. Laura Spierdijk. I would also like to thank my second supervisor, ir. Jeroen Sempel, for his valuable insights during this research. Additionally, I want to thank my fellow students who were part of the same master's program for their assistance and support. I would like to extend a special note of gratitude to Mathieu Jamin for his invaluable guidance and insights throughout my research.

8. REFERENCES

Agapova, A. (2011). Conventional mutual index funds versus exchange-traded funds. Journal of Financial Markets, 14(2), 323–343. https://doi.org/10.1016/j.finmar.2010.10.005

Ahmad, M., & Wu, Q. (2022). Does herding behavior matter in investment management and perceived market efficiency? Evidence from an emerging market. Management Decision, 60(8), 2148–2173. https://doi.org/10.1108/md-07-2020-0867

Ali, S., Badshah, I., & Demirer, R. (2022). Anti-Herding by Hedge Funds, Idiosyncratic Volatility and Expected Returns. Social Science Research Network. https://doi.org/10.2139/ssrn.4010287

Arjoon, V., & Bhatnagar, C. S. (2017). Dynamic herding analysis in a frontier market. Research in International Business and Finance, 42, 496–508. https://doi.org/10.1016/j.ribaf.2017.01.006

Ashraf, B. N. (2021). Stock markets' reaction to Covid-19: Moderating role of national culture. Finance Research Letters, 41, 101857. https://doi.org/10.1016/j.frl.2020.101857

Aslam, F. et al. (2021) 'Herding behavior during the COVID-19 pandemic: A comparison between Asian and European stock markets based on Intraday multifractality', Eurasian Economic Review, 12(2), pp. 333–359. https://doi:10.1007/s40822-021-00191-4

Baig, A. S., & Chen, M. (2022). Did the COVID-19 pandemic (really) positively impact the IPO Market? An Analysis of information uncertainty. Finance Research Letters, 46, 102372. https://doi.org/10.1016/j.frl.2021.102372

Baker, M., & Wurgler, J. (2006). Investor Sentiment and the Cross-Section of Stock Returns. *The Journal of Finance*, *61*(4), 1645–1680. https://doi.org/10.1111/j.1540-6261.2006.00885.x

Baker, S. E., Bloom, N., Davis, S. J., Kost, K. J., Sammon, M., & Viratyosin, T. (2020). The Unprecedented Stock Market Impact of COVID-19. National Bureau of Economic Research. https://doi.org/10.3386/w26945

Batmunkh, M., Choijil, E., Vieito, J. P., Espinosa-Méndez, C., & Wong, W. (2020). Does herding behavior exist in the Mongolian stock market? Pacific-basin Finance Journal, 62, 101352. https://doi.org/10.1016/j.pacfin.2020.101352

Bekiros, S., Jlassi, M., Lucey, B., Naoui, K., & Uddin, G. S. (2017). Herding behavior, market sentiment, and volatility: Will the bubble resume? The North American Journal of Economics and Finance, 42, 107–131. https://doi.org/10.1016/j.najef.2017.07.005

Bhattacharya, A., & O'Hara, M. (2017). Can ETFs Increase Market Fragility? Effect of Information Linkages in

ETF Markets. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.2740699

Bikhchandani, S., & Sharma, S. (2000). Herd Behavior in Financial Markets. Imf Staff Papers, 47(3), 279–310. https://doi.org/10.2307/3867650

Bischi, G. I., Gallegati, M., Gardini, L., Leombruni, R., & Palestrini, A. (2006). HERD BEHAVIOR AND NONFUNDAMENTAL ASSET PRICE FLUCTUATIONS IN FINANCIAL MARKETS. Macroeconomic Dynamics, 10(4), 502–528. https://doi.org/10.1017/s136510050605036x

Blake, D., Sarno, L., & Zinna, G. (2017b). The market for lemmings: The herding behavior of pension funds. Journal of Financial Markets, 36, 17–39. https://doi.org/10.1016/j.finmar.2017.03.001

Blasco, N., Corredor, P., & Ferreruela, S. (2012). Does herding affect volatility? Implications for the Spanish stock market. Quantitative Finance, 12(2), 311–327. https://doi.org/10.1080/14697688.2010.516766

Blasco, N., Santamaria, R., & Ferreruela, S. (2011). Detecting intentional herding: what lies beneath intraday data in the Spanish stock market. Journal of the Operational Research Society, 62(6), 1056–1066. https://doi.org/10.1057/jors.2010.34

Bogdan, S., Suštar, N., & Draženović, B. O. (2022). Herding Behavior in Developed, Emerging, and Frontier European Stock Markets during COVID-19 Pandemic. Journal of Risk and Financial Management, 15(9), 400. https://doi.org/10.3390/jrfm15090400

Bonato, M., Gkillas, K., Gupta, R., & Pierdzioch, C. (2021). A note on investor happiness and the predictability of realized volatility of gold. Finance Research Letters, 39, 101614. https://doi.org/10.1016/j.frl.2020.101614

Brealey, R. A., Myers, S. C., & Allen, F. (2020). Principles of Corporate Finance.

Burns, W. J., Peters, E., & Slovic, P. (2011). Risk Perception and the Economic Crisis: A Longitudinal Study of the Trajectory of Perceived Risk. Risk Analysis, 32(4), 659–677. https://doi.org/10.1111/j.1539-6924.2011.01733.x

Chang, E. C., Cheng, J. W., & Khorana, A. (1999). An Examination of Herd Behavior in Equity Markets: An International Perspective. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.181872

Christie, W. G., & Huang, R. D. (1995). Following the Pied Piper: Do Individual Returns Herd around the Market? *Financial Analysts Journal*, *51*(4), 31–37. https://doi.org/10.2469/faj.v51.n4.1918

Cont, R., & Bouchaud, J. P. (1998). Herd Behavior and Aggregate Fluctuations in Financial Markets. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.58468

Costola, M., Iacopini, M., & Santagiustina, C. R. M. A. (2021). On the "momentum" of meme stocks. Economics Letters, 207, 110021. https://doi.org/10.1016/j.econlet.2021.110021

Dang, H. V., & Lin, M. (2016). Herd mentality in the stock market: On the role of idiosyncratic participants with heterogeneous information. International Review of Financial Analysis, 48, 247–260. https://doi.org/10.1016/j.irfa.2016.10.005

Devenow, A., & Welch, I. (1996). Rational herding in financial economics. *European Economic Review*, *40*(3–5), 603–615. https://doi.org/10.1016/0014-2921(95)00073-9

Elshqirat, M. (2021). How COVID-19 affected herding behavior in the Jordanian stock market. Journal of Accounting and Finance, 21(3). https://doi.org/10.33423/jaf.v21i3.4398

Engelberg, J. E., & Parsons, C. A. (2011). The Causal Impact of Media in Financial Markets. The Journal of Finance, 66(1), 67–97. https://doi.org/10.1111/j.1540-6261.2010.01626.x

Espinosa-Méndez, C., & Arias, J. L. (2021). COVID-19 effect on herding behaviour in European capital markets. Finance Research Letters, 38, 101787. https://doi.org/10.1016/j.frl.2020.101787

Euronext. (2023). ETFS ALL MARKETS. Euronext Live Markets. https://live.euronext.com/en/products/etfs/list

Fama, E. F. (1970). EFFICIENT CAPITAL MARKETS: A REVIEW OF THEORY AND EMPIRICAL WORK*. Journal of Finance, 25(2), 383–417. https://doi.org/10.1111/j.1540-6261.1970.tb00518.x

Gleason, K. C., Mathur, I., & Peterson, M. A. (2004). Analysis of intraday herding behavior among the sector ETFs. Journal of Empirical Finance, 11(5), 681–694. https://doi.org/10.1016/j.jempfin.2003.06.003

Glosten, L., Nallareddy, S., & Zou, Y. (2021). ETF Activity and Informational Efficiency of Underlying Securities. Management Science, 67(1), 22–47. https://doi.org/10.1287/mnsc.2019.3427

Huberman, G., & Kandel, S. (1987). Mean-Variance Spanning. The Journal of Finance, 42(4), 873–888. https://doi.org/10.2307/2328296

Jula, N., & Jula, N. (2017). RANDOM WALK HYPOTHESIS IN FINANCIAL MARKETS. Challenges of the Knowledge Society, 7, 878–884. https://doaj.org/article/47dccac6708c4ca5a75fadcb66e2c91e

Kahneman, D. (2003). Maps of Bounded Rationality: Psychology for Behavioral Economics. The American Economic Review, 93(5), 1449–1475. https://doi.org/10.1257/000282803322655392

Kindleberger, C.P. & Aliber, R.Z. (2005). Speculative Manias. In: Manias, Panics and Crashes. Palgrave Macmillan, London. https://doi.org/10.1057/9780230628045_3.

Lang, P. E., Carslaw, D. C., & Moller, S. (2019). A trend analysis approach for air quality network data. Atmospheric Environment: X, 2, 100030. https://doi.org/10.1016/j.aeaoa.2019.100030

Lao, P., & Singh, H. (2011). Herding behaviour in the Chinese and Indian stock markets. Journal of Asian Economics, 22(6), 495–506. https://doi.org/10.1016/j.asieco.2011.08.001

LeBon, G. (1922). The Crowd: a Study of the Popular Mind (London: T. Fischer, Unwin).

Lee, C., Chen, M., & Hsieh, K. (2013). Industry herding and market states: evidence from Chinese stock markets. Quantitative Finance, 13(7), 1091–1113. https://doi.org/10.1080/14697688.2012.740571

Lee, W. Y., Jiang, C. X., & Indro, D. C. (2001). Stock market volatility, excess returns, and the role of investor sentiment. Journal of Banking &Amp; Finance, 26(12), 2277–2299. https://doi.org/10.1016/s0378-4266(01)00202-3

Loang, O. K., & Ahmad, Z. (2020). Social Factors and Herd Behaviour in Developed Markets, Advanced Emerging Markets and Secondary Emerging Markets. Journal of Contemporary Eastern Asia, 19(1), 97–122. https://doi.org/10.17477/jcea.2020.19.1.097

Lush, M., Fontes, A., Zhu, M., Valdes, O., & Mottola, G. (2021, februari). Investing 2020: New Accounts and the People Who Opened Them. Finra.org. https://www.finrafoundation.org/sites/finrafoundation/files/investing-2020-new-accounts-and-the-people-who-opened-them_1_0.pdf

Luu, Q. T., & Luong, H. T. T. (2020). Herding Behavior in Emerging and Frontier Stock Markets During Pandemic Influenza Panics. The Journal of Asian Finance, Economics and Business, 7(9), 147–158. https://doi.org/10.13106/jafeb.2020.vol7.no9.147

Maquieira, Carlos, and Christian Espinosa Méndez. “Herding Behavior in the Chinese Stock Market and the Impact of COVID--19.” Papers.ssrn.com, 4 June 2022, papers.ssrn.com/sol3/papers.cfm?abstract_id=4318148.

Miralles-Quirós, J. L., Del Mar Miralles-Quirós, M., & Nogueira, J. M. (2019c). Diversification benefits of using exchange-traded funds in compliance to the sustainable development goals. Business Strategy and the Environment, 28(1), 244–255. https://doi.org/10.1002/bse.2253

Mosley, L., & Singer, D. A. (2008). Taking Stock Seriously: Equity-Market Performance, Government Policy, and Financial Globalization. International Studies Quarterly, 52(2), 405–425. https://doi.org/10.1111/j.1468-2478.2008.00507.x

Nasdaq's Economic Research Team, & Jankiewicz, R. (2022, February 4). Covid Draws New Investors Into Markets. Nasdaq. https://www.nasdaq.com/articles/covid-draws-new-investors-into-markets

Naumovska, I. (2021, 18 februari). The SPAC Bubble Is About to Burst. Harvard Business Review. https://hbr.org/2021/02/the-spac-bubble-is-about-to-burst

Nirei, M. (2013). Beauty Contests and Fat Tails in Financial Markets. Social Science Research Network. https://doi.org/10.2139/ssrn.2362341

Nofsinger, J. R. (2005). Social Mood and Financial Economics. Journal of Behavioral Finance, 6(3), 144–160. https://doi.org/10.1207/s15427579jpfm0603_4

Nofsinger, J. R., & Sias, R. W. (1999). Herding and Feedback Trading by Institutional and Individual Investors. *The Journal of Finance*, *54*(6), 2263–2295. https://doi.org/10.1111/0022-1082.00188

Nofsinger, John, and Kenneth Kim. Infectious Greed: Restoring Confidence in America's Companies. Upper Saddle River, NJ: Financial Times Prentice-Hall, 2003.

Olson, K. R. (2011). A Literature Review of Social Mood. Social Science Research Network. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1919833

Orléan, A. (1995). Bayesian interactions and collective dynamics of opinion: Herd behavior and mimetic contagion. Journal of Economic Behavior and Organization, 28(2), 257–274. https://doi.org/10.1016/0167-2681(95)00035-6

Papadamou, S., Kyriazis, N., Tzeremes, N. G., & Corbet, S. (2021). Herding behaviour and price convergence clubs in cryptocurrencies during bull and bear markets. Journal of Behavioral and Experimental Finance, 30, 100469. https://doi.org/10.1016/j.jbef.2021.100469

Pessina, C. J., & Whaley, R. E. (2020). Levered and Inverse Exchange-Traded Products: Blessing or Curse? Financial Analysts Journal, 77(1), 10–29. https://doi.org/10.1080/0015198x.2020.1830660

Rakowski, D., & Shirley, S. (2020). What drives the market for exchange-traded notes? Journal of Banking &Amp; Finance, 111, 105702. https://doi.org/10.1016/j.jbankfin.2019.105702

Ramadan, I. Z. (2015). Cross-Sectional Absolute Deviation Approach for Testing the Herd Behavior Theory: The Case of the ASE Index. International Journal of Economics and Finance, 7(3). https://doi.org/10.5539/ijef.v7n3p188

Shiller, R. J. (1989). Market Volatility (First Edition). The MIT Press.

Shiller, R. J., & Pound, J. D. (1989). Survey evidence on diffusion of interest and information among investors. Journal of Economic Behavior and Organization, 12(1), 47–66. https://doi.org/10.1016/0167-2681(89)90076-0

Shu, H. C. (2010). Investor mood and financial markets. *Journal of Economic Behavior &Amp; Organization*, *76*(2), 267–282. https://doi.org/10.1016/j.jebo.2010.06.004

Sibande, X., Gupta, R., Demirer, R., & Bouri, E. (2021). Investor Sentiment and (Anti) Herding in the Currency Market: Evidence from Twitter Feed Data. Journal of Behavioral Finance, 24(1), 56–72. https://doi.org/10.1080/15427560.2021.1917579

Smith, R. D. (2006b). Responding to global infectious disease outbreaks: Lessons from SARS on the role of risk perception, communication and management. *Social Science &Amp; Medicine*, *63*(12), 3113–3123. https://doi.org/10.1016/j.socscimed.2006.08.004

Soosung Hwang, & Mark Salmon. (2004). Market Stress and Herding. *Social Science Research Network*.

Tejada, J. J., & Punzalan, J. R. B. (2012). On the Misuse of Slovin's Formula. The Philippine Statistician, 61. https://www.psai.ph/docs/publications/tps/tps_2012_61_1_9.pdf

Thomadakis, A. (2018, April 24). The European ETF Market: What can be done better? EUROPEAN CAPITAL MARKETS INSTITUTE. https://aei.pitt.edu/93708/1/AT_EuropeanETFMarket_0.pdf

Topcu, M., & Gulal, O. S. (2020). The impact of COVID-19 on emerging stock markets. Finance Research Letters, 36, 101691. https://doi.org/10.1016/j.frl.2020.101691

Topol, R. (1991). Bubbles and Volatility of Stock Prices: Effect of Mimetic Contagion. The Economic Journal, 101(407), 786. https://doi.org/10.2307/2233855

Vasileiou, E., Samitas, A., Karagiannaki, M., & Dandu, J. (2021b). Health risk and the efficient market hypothesis in the time of COVID-19. International Review of Applied Economics, 35(2), 210–223. https://doi.org/10.1080/02692171.2020.1864299

Wagner, A. F. (2020). What the stock market tells us about the post-COVID-19 world. Nature Human Behaviour, 4(5), 440. https://doi.org/10.1038/s41562-020-0869-y

Xiaohong, H. (2019). Business valuation. Pearson Education Limited.

Zhang, D., Hu, M., & Ji, Q. (2020). Financial markets under the global pandemic of COVID-19. Finance Research Letters, 36, 101528. https://doi.org/10.1016/j.frl.2020.101528