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Herding Behavior in the S&P 500: A Comprehensive Analysis from 2019 to 2022

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ABSTRACT

This paper analyzes the existence of herding behavior in the Standard and Poor's 500 (S&P 500) index. We utilize the Cross-Sectional Absolute Deviation (CSAD) model and linear regressions to identify herding on a monthly and yearly basis as well as during the entire time frame of January 1, 2019 to December 30, 2022, the time period of our study. This timeframe holds particular significance as it includes the COVID-19 pandemic, the following bull market, and the rapid rise in inflation and interest rates towards the end of the study period. By analyzing these significant events, we aim to understand if and how these events triggered herding behavior in the U.S. stock market. Our findings indicate that on a monthly basis, herding existed in 5 of the 48 months, on a yearly basis, herding existed in 2020 only, and for the entire time frame, herding was not significant enough to be detected.

Introduction

Investment behavior refers to the nature of the actions and choices individuals make when investing. It is influenced by a variety of factors including trading strategies, market volatility, changes in corporate value, and fluctuations in the economy. Cognitive biases, such as human error, also impact investment behavior. Sometimes investors fail to act on their own judgements, instead relying on the decisions made by the crowd on whether to buy or sell. This is called herding behavior, broadly defined as the behavior in which individuals in a group act collectively.

In financial markets, herding behavior occurs when investors make decisions dependent on the crowd instead of relying on their own judgment and analysis. This behavior has a history of creating chaos in markets. For example, herding was responsible for the speculative dot com bubble formed in the 90s and the mass selloffs during the 2008 financial crisis (Choi & Yoon, 2020). Devenow and Welch (1996) argue that herding behavior requires some sort of significant event or signal to trigger a coordinated market reaction. Some examples of triggers include significant price movements, observing the investment decisions of others, large financial crises, etc.

Herding behavior can either be rational or irrational. Rational herding behavior occurs when investors follow the decisions of others because they believe that the crowd possesses better information and insights. Under rational herding, investors make the assumption that the information and analysis that the group has is accurate. As a result, rational herding can be seen as a form of information aggregation where investors have the belief that by following the crowd, they are reducing their information asymmetry and can therefore make better decisions (Choi & Yoon, 2020). An example of rational herding is when a group of investors follow the decisions made by a well-respected stock analyst. However, it should be noted that a rational herder's analysis of the crowd is just one factor in their decision making.

This form of herding closely aligns with the Bayesian hypothesis, which states that other people's actions are used in adjusting expectations and probabilities. What this means is that investors following Bayes's rule will adjust their investment decisions in order to take into account the decisions made by others, which, in turn, generates herding (Baddeley, 2010).

On the other hand, irrational herding occurs when investors follow the decisions of others without considering the validity or accuracy of the information behind those decisions. They also do not assess the securities' underlying value (Choi & Yoon, 2020). Certain studies suggest that this behavior is purposeful and is caused by investor sentiment, the prevailing attitude of investors towards price changes in the market. According to these studies, herding is often driven by psychological factors including overconfidence, wishful thinking, and pressure to conform. For example, when prices rise, investors may be prompted to buy due to their fear of missing out on potentially large gains in the market (Bikhchandani & Sharma, 2000).

Irrational herding behavior aligns with the theories of renowned economist John Keynes. He found herding to be a more instinctive response by individuals towards uncertainty and the belief that the crowd is more informed. Keynes observed that, as a reason for herding, people would rather be conventionally wrong than unconventionally right, and therefore, following the decisions made by the crowd protects their reputation (Baddeley, 2010).

These economic conceptions of behavior can be categorized into either Simon's (1979) "substantive rationality" or Baddeley's (2006) "procedural rationality." Under substantive rationality, herding is a result of rational algorithmic processes. This closely aligns with the Bayesian approach in which investors intentionally factor into their decisions the actions of others. Under procedural rationality, herding is a result of instinctive and intuitive behavior rather than intentional calculations. This closely corresponds to Keynes's beliefs in which herding is an instinctive response by individuals. Thus, the idea of substantive rationality follows both Baye's rule as well as the rational theory of herding, whereas the idea of procedural rationality is similar to Keynes's beliefs as well as the irrational theory of herding.

Herding behavior, or investment behavior in general, is also closely connected with emotion. However, emotion is scarcely considered in economic and financial practice. Most economic theory assumes people are rational and hence, make logical decisions. Introducing the impact of emotion on investment behavior tends to break the well-established standards of economic theory. For instance, a small earnings miss by a company may cause the stock price to experience an exaggerated drop in value as investors become overly fearful of the company's prospects despite the company being fundamentally robust and stable. In this situation, fear causes investors to oversell a stock and therefore, go against the rationally assumed outcome. The few studies (Baddeley, 2010) that do discuss the impact of emotion on investment behavior show that greed, hope, anxiety, and fear are the four most relevant emotions in financial decision making. For instance, bull markets often reflect a surge of greed and hope whereas bear markets often reflect a surge of fear and anxiety. While emotion is constantly present, it is widespread emotion that generally leads to speculative behavior in markets. For example, if the state of confidence is strong and people are generally hopeful, the economy is vulnerable to greed and overconfidence, which may induce irrational herding and other speculative behavior (Baddeley, 2010).

The theories of procedural vs. substantive rationality and the influences of emotion and investor sentiment all provide a great deal of insight on herding in financial markets, assisting us on our goal of analyzing herding during the study period. Within this analysis, we aim to make inferences on why herding occurred in addition to when it occurred. For instance, our results may provide inferences on whether the U.S. economic decline following the COVID-19 pandemic in 2020 led to herding. With the assistance of Dr. Haoran Zhang at Manhattan College's Department of Finance and Economics, we focus on the Standard and Poor's 500 (S&P 500) index to identify herding on a monthly and yearly basis as well as during the entire time period of January 1, 2019 to December 30, 2022. We utilize the Cross-Sectional Absolute Deviation (CSAD) method and linear regressions to obtain data allowing us to identify herding. Recognizing when herding exists is important towards allowing investors to avoid or navigate herding, providing further insight towards predicting herding, as well as towards the furthering of herding behavior research in academia.

Methods

This study analyzes the S&P 500 index using the 1,043 daily gross returns of each company in the S&P 500 from January 1, 2019 to December 30, 2022 to confirm the existence of herding behavior between that period. The S&P 500 is a widely recognized stock market index that measures the performance of 500 of the largest publicly traded companies in the United States and is a key indicator of the overall health of the U.S. stock market. The index is market-capitalization-weighted, meaning that companies with a greater market capitalization have a greater impact on its value. While the index contains a broad range of industries, the technology industry has the greatest weighting due to large tech stocks such as Apple, Microsoft, and Amazon. Health care and financials are respectively the second and third most prominent sectors of the S&P 500. As the S&P is a proxy for the health of the U.S. economy, identifying herding in the index will provide further insight on herding throughout the entire market.

The raw data utilized in this study are the daily returns of each of the stocks in the index. The daily returns are gross returns which include dividends. Lastly, the companies that were not in the S&P 500 for the entire period of January 1, 2019 to December 30, 2022 were excluded so that only 481 companies were analyzed rather than the complete 500.

To identify herding, the Cross-Sectional Absolute Deviation (CSAD) method was used. Other empirical measurement methods exist such as the Lakonishock, Shleifer, and Vishny (LSV) model, the Portfolio Change Measure (PCM), and the Cross-Sectional Standard Deviation (CSSD) model. CSAD is used because unlike the other models it does not rely on information regarding the holdings of individual investors (Choi & Yoon, 2020).

CSAD is found by taking the average of the absolute value of the differences between market returns and individual returns. It essentially measures the spread or deviation between individual company returns and total market returns. A high CSAD indicates a higher deviation, implying investors are making independent decisions for different stocks, resulting in a wider spread between individual returns and market returns. On the other hand, a low CSAD indicates a lower deviation, implying investors are following the crowd and buying/selling similar stocks, resulting in a narrower spread between individual returns and market returns. Therefore, if herding behavior exists, the CSAD will be very small indicating that individual returns are converging on market returns.

Equation 1. CSAD model

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

In Equation 1, n is the total number of securities on a day t, $R_{i,t}$ is the return of a company on day t, and $R_{m,t}$ is the average market return of all the companies on day t and is also referred to as the equal-weighted market return.

Utilizing the daily returns of each stock in the index, the average market return of each day ($R_{m,t}$) was found by finding the average of each of the 481 returns on that day. This step was repeated every single day. The absolute value of the difference between $R_{i,t}$ and $R_{m,t}$ was calculated by finding the positive difference between a stock's return on a day and the average market return of that day. This was repeated for every single stock for every single day. Lastly, the CSAD was found by averaging the absolute values of the difference between $R_{i,t}$ and $R_{m,t}$ for each day.

With the CSAD value for each day, we can now run a linear regression to identify herding during the entire time span and on a monthly and yearly basis.

Equation 2. Linear regression model

$$CSAD_t = \alpha + \beta_1 \left| R_{m,t} \right| + \beta_2 R_{m,t}^2 + \varepsilon_t$$

In Equation 2, $R_{m,t}$ is the equal-weighted market return on day t, ε_t is an error term used to estimate β_2, α is a coefficient representing the intercept of the graph, and β_1 and β_2 are coefficients of the independent variables $|R_{m,t}|$ and $R_{m,t}^2$.

Having calculated CSAD and $R_{m,t}$, we used the above equation to regress CSAD against the absolute value of market return, $|R_{m,t}|$, and market return squared, $R_{m,t}^2$. We took the absolute value of market return in order to account for both positive and negative market movement and we used $R_{m,t}^2$ because this squared term captures the nuanced non-linear relationship between CSAD and market returns, as opposed to just using $|R_{m,t}|$ which implies a simplified linear relationship. This allowed us to see how CSAD reacts to larger market deviations. The reasoning behind this entire linear regression is to determine the relationship between changing market returns and CSAD. In a herding market, as the market changes, CSAD will decrease, indicating that individual returns are converging on total market returns, which implies investors are abandoning their independent analysis and instead following the market trend.

The output metrics of this linear regression included β_1, β_2, α, t-value, and the p-value but only β_2, the t-value, and the p-value were used to analyze herding. Herding existed if β_2 was negative and statistically significant (had a p-value < 10%). We want β_2 to be negative because it means that as market returns change, CSAD decreases. If β_2 is negative and significant, the t-value will also be negative and statistically significant (below 90% critical value). Therefore, it is only necessary to look at the t-value to determine if herding existed or not.

We then wanted to identify herding on a yearly basis. As in the last segment, we regressed CSAD against the absolute value of market return and market return squared. However, we conducted 4 different linear regressions with each regression representing one of the 4 years from the entire time period. In doing so, we only regressed the CSAD, absolute value of market return, and market return squared values for that corresponding year, which we then repeated for each of the 4 years. We then analyzed the same 3 output metrics: β_2, t-value, and p-value. As in the last segment, herding existed if the t-value was negative and statistically significant.

We repeated these steps but on a monthly basis as well, which allowed us to identify herding per month in addition to per year and during the entire time period. We conducted 48 different regressions with each representing one month within the time frame. As in the first segment, we only regressed the CSAD, absolute value of market return, and market return squared values for each of their corresponding months. Again, to identify herding in this segment, we wanted the t-value to be negative and statistically significant.

Thus, for each of the three time intervals, we utilized the CSAD, absolute value of market return, and market return squared to conduct a linear regression that produced a β_2, t-value, and p-value metric which we used to identify herding on the corresponding time intervals.

Results

Herding behavior exists if β_2 is negative and if the p-value falls under 0.01, i.e. 10%. If this is true, the t-value will automatically be negative and statistically significant.

Table 1. Herding behavior results on the full period (Jan 2019 – Dec 2022)

	β_2	p-value	t-value	Herding
Jan 2019 – Dec 2022	0.005206	0.051539	1.949208	No

Table 1 shows the empirical results for our test for herding in the S&P 500 on the time period of January 1, 2019 to December 30, 2022. The t-value is statistically significant because the p-value falls below 0.1. However, the t-value is not negative indicating that herding behavior does not exist in the S&P 500. It's important to note that herding may have existed but was statistically insignificant to be detected via our CSAD method.

Table 2. Herding behavior results on a yearly basis

	β_2	p-value	t-value	Herding
2019	0.003027581	0.904577247	0.119999026	No
2020	-0.01003323	0.046210006	-2.003123474	Yes
2021	0.003259793	0.936565576	0.079665171	No
2022	0.042916271	0.001873252	3.142337376	No

Table 2 shows the empirical results of our tests for herding for the years 2019, 2020, 2021, and 2022. In 2019, we concluded herding did not exist because the t-value was statistically insignificant (as shown by the p-value) and not negative. In 2020, we concluded that herding did exist because the t-value was both negative and statistically significant. In 2021 and 2022, we concluded that herding did not exist. In 2021, this was because the t-value was both positive and statistically insignificant. In 2022, this was because the t-value was positive despite being statistically significant.

Table 3. Herding behavior results on a monthly basis

	t-value	Herding		t-value	Herding
Jan-19	0.052753488	No	Jan-21	0.67570741	No
Feb-19	-0.023853744	No	Feb-21	0.106658588	No
Mar-19	1.968562344	No	Mar-21	-1.236351114	No
Apr-19	-0.352069555	No	Apr-21	0.308640987	No
May-19	1.636062683	No	May-21	-0.19528144	No
Jun-19	1.999020018	No	Jun-21	-1.113858003	No
Jul-19	-1.054564677	No	Jul-21	0.684760851	No
Aug-19	0.751739248	No	Aug-21	-1.582781214	Yes
Sep-19	0.197256663	No	Sep-21	0.575901724	No
Oct-19	1.590983837	No	Oct-21	-0.219059152	No
Nov-19	0.903838022	No	Nov-21	-1.703344847	Yes
Dec-19	1.353574834	No	Dec-21	-0.246294428	No
Jan-20	0.381720135	No	Jan-22	-0.412920869	No
Feb-20	-1.60608584	Yes	Feb-22	-1.609916164	Yes
Mar-20	0.13696258	No	Mar-22	2.943955008	No
Apr-20	1.447116244	No	Apr-22	-1.822041514	Yes
May-20	1.171148296	No	May-22	1.215657477	No
Jun-20	-1.063440605	No	Jun-22	0.947617169	No

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Jul-20	1.289598926	No	Jul-22	-1.279818916	No
Aug-20	0.388711553	No	Aug-22	0.512724575	No
Sep-20	3.125981653	No	Sep-22	0.794028221	No
Oct-20	-0.519442659	No	Oct-22	0.878801071	No
Nov-20	6.075398468	No	Nov-22	0.744854592	No
Dec-20	0.826486075	No	Dec-22	1.066577592	No

Table 3 shows the empirical results of our tests for herding on a monthly basis from January 2019 to December 2022. Herding did not exist for every month except for February 2020, August 2021, November 2021, February 2022, and April 2022. These 5 months had t-values that were both negative and statistically significant. As a result, the t-values fell below the 90% critical value of -1.32. This value is a fixed value used in herding analysis.

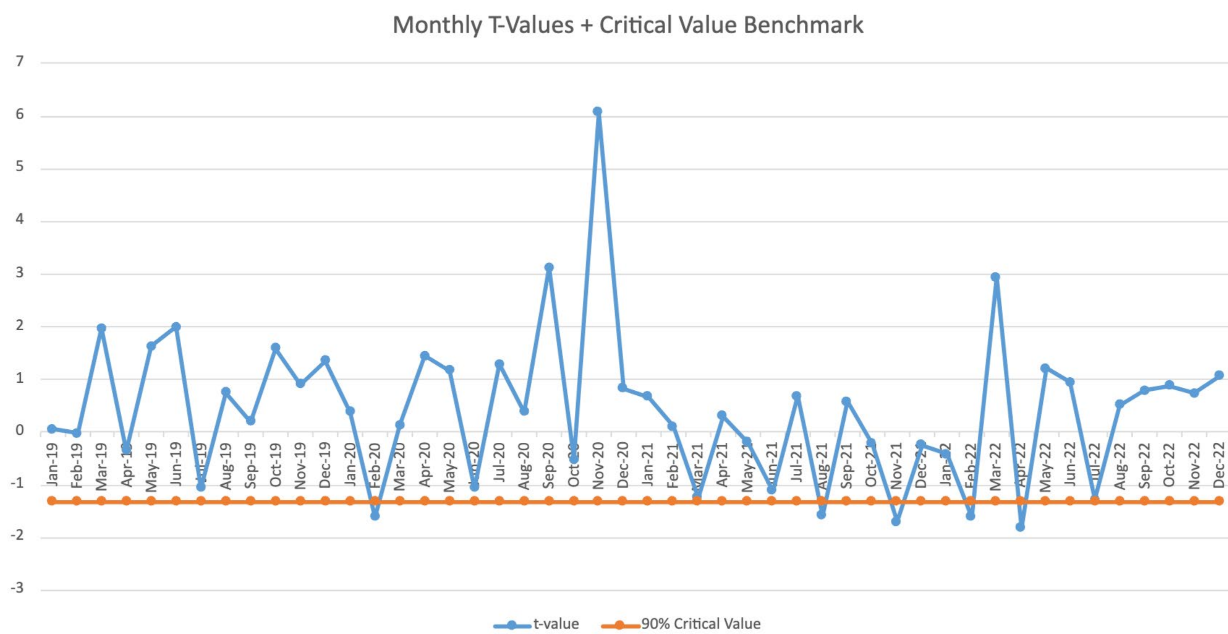

Figure 1. Monthly herding behavior with a graphed 90% critical value benchmark

Figure 1 graphs the results indicated in Table 3 where the x-axis represents each month, and the y-axis represents the t-values. Points falling under the graphed -1.32 critical value benchmark indicate that herding existed for that respective month. Points lying above the graphed -1.32 critical value benchmark indicate that herding did not exist. The greater the t-value is, the less herding there was. Again, herding activities may have existed but were too insignificant to detect.

Discussion

This study analyzed the existence of herding behavior in the S&P 500 stock index during the time period of January 2019 to December 2022. Tests were conducted to identify herding behavior on a monthly basis, a yearly basis, and during the entire time frame. The Cross-Sectional Absolute Deviation (CSAD) method was utilized in which the CSAD was calculated and used in a linear regression against market return and market return squared.

Our analysis on a four year, annual, and monthly basis are as follows: During the entire time frame of January 1, 2019 to December 31, 2022, we found that herding did not exist. On an annual basis, herding existed only in 2020. On a monthly basis, herding existed in February 2020, August 2021, November 2021, February 2022, and April 2022.

The herding found during the monthly periods can possibly be attributed to the economic and financial crisis triggered by the COVID-19 pandemic and the following bull market that began in March 2020. Initially, the market largely ignored the COVID-19 pandemic until cases began rapidly rising in late February 2020. The escalation of COVID-19 cases had an inverse impact on market returns, resulting in a market decline that lasted until March 2020 (Fan, 2023). At this point, a remarkable turnaround occurred, propelling the markets into a bull market phase that extended well into 2021. This resurgence was fueled by central bank and government intervention, as well as other external factors. A significant catalyst was the passage of the $2 trillion Coronavirus Aid, Relief, and Economic Security Act signed by former President Donald Trump on March 27, 2020 (Fan, 2023). Further contributing to the bullish trend, the Federal Reserve lowered the target federal funds range to 1-1.25% on March 3, 2020. Congress then passed the Coronavirus Preparedness and Response Supplemental Appropriations Act on March 6, 2020, allocating $8.3 billion for the preparation of COVID outbreaks in the U.S.. Persistent near-zero interest rates throughout 2020, along with optimism surrounding the discovery of a vaccine, also played a role in continuing the bull market (Fan, 2023). Lastly, the relaxation of lockdowns in mid-2020 and the subsequent release of pent-up demand potentially further propelled economic activity, reinforcing the bull market.

Research has shown that herding is often found during financial crises and up market periods. Adem and Sarioğlu (2020), using data from 2000 to 2018, found that when the market falls and when market volatility is high, stock prices deviate from their fundamental values as a result of traders herding. During these periods, their findings show that traders act irrationally. On the other hand, Kang and Pyun (2014), using data from the bull market following the stock market crash of 2007, found that herding behavior is concentrated in the extremely upper values of stock prices during a bull market. They also showed that the greater the dispersion of a stock away from its moving average line, the stronger the evidence is of herding behavior. This supports the notion that herding becomes more prevalent as stocks move further from their fundamental values (Kang & Pyun, 2014).

The herding identified in February 2020 could potentially be a result of the COVID-19 triggered market decline that lasted from February 2020 to March 2020. Furthermore, as recorded highs in stock and index prices were seen during the bull run of 2020 and 2021, an inference could be made that the herding identified in August 2021 and November 2021 could be a result of the bull market fueled by central bank and government intervention (among other factors). Furthermore, Khan et al. (2023) found that the COVID-19 pandemic led to widespread financial volatility during the years of 2018 to 2021. Thus, the pandemic-induced volatility may have further fueled the herding behavior identified during this time frame. Lastly, Baddeley (2010), who argues against the dichotomous categorization of behavior as either rational or irrational, states that a state of confidence and optimism can cause the macro-economy to be vulnerable to waves of greed and overconfidence, precipitating herding and speculative bubbles. This may be another factor in the herding we found during this time frame.

However, this does not explain the herding behavior identified in February 2022 and April 2022. A possible explanation for the herding found during this time frame can be attributed to the rapid rise of inflation beginning in 2021 and the subsequent interest rate hikes. Inflation in the U.S. first began rising in 2021 until peaking in June 2022. In response to inflation, the Federal Reserve began a cycle of interest rate hikes beginning on March 17, 2022. Rates, which prior to the cycle were at near-zero levels, have since remained at the 5.00-5.25% level. Gong and Dai (2017), in their study of Chinese stock markets, found that interest rate hikes, along with Chinese currency depreciation, often induce rational or intentional herding behavior. Thus, the herding identified in February 2022 and April 2022 may be in response to growing inflation. In this way herding could be caused by the increased market downturn as a result of inflation or because of the resulting rate hikes.

Therefore, our research suggests that investors should be aware of significant financial events, both positive and negative, because of the high likelihood they might influence herding behavior. Herding can be found during significant financial hurdles such as during the early moments of the pandemic and during the rapid rise of inflation and interest rates and conversely, during upmarket periods such as the bull market beginning in March 2020. As a result, investors should be extra cautious during events like these because herding behavior, either rational or irrational, may be prevalent which can cause the market to become more unpredictable, possibly leading to speculative financial bubbles.

Future research can further analyze specific emotional and cognitive factors that influence collective investment decisions. Research can also be done to determine the impacts of regulatory measures and government and central bank intervention on herding behavior. Doing so may allow policymakers to dodge speculative bubbles and to ensure greater market stability and resilience.

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