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Herding Behavior in Security Market and Portfolio Management

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Abstract

This study will examine the herding behavior in security market and its impact on the security pricing and overall market return as well as individual returns. In behavioral finance, herding is known as an excessive irrational tendency of investors ignoring the fundamental information presented to them that act together in the markets (Gębka & Wohar 2013). Herding can directly lead to the security market distress and to the increase in trading volatility. In this study, we have conducted an empirical study, focusing on the Dow Jones Industrial Average over a twenty-year period (2000-2020), to examine the herding behavior in the security market. We have adopted the modeling framework used by Christie & Huang (1995), Cheng et al. (2000), and Dang & Lin (2016) to measure the herding index of the DJIA. We have used the Cross-Sectional Absolute Deviation (CSAD) to measure the absolute return dispersion of each individual market security that makes up the DJIA, and the Cross-Sectional Standard Deviation (CSSD). Based on the findings in this study, it is reasonable to conclude that the market behaves in a rationale sense, ignoring the signals of the market and its' largest influencers. In other words, the Efficient Market Hypothesis stands, and individual investors are able to look past their natural human biases and heuristics. This is not to say that spurious herding does not still occur in today's markets, but there is no evidence that intentional herding is a consistent phenomenon that occurs in the market.

Keywords: Behavioral Finance, Herding behavior, Portfolio Management, Cross-Sectional Standard Deviation (CSSD), Cross-sectional absolute deviation (CSAD).

I Introduction

The term "herd behavior" is referred to a phenomenon where people join the crowd and follow their actions, assuming that other individuals have already done their research. They are largely influenced by emotion and instinct, rather than by their own independent analysis. For example, one may imagine a fire in a building that would often cause herd behavior, with people often suspending their individual reasoning and fleeing together in a pack. In Economics, herding can be defined as the phenomenon when individuals decide to follow others and imitate group behaviors rather than deciding independently and critically on the basis of their own, private information. In behavioral finance, particularly, the herd mentality refers to investors' tendency who follow what they perceive other investors are doing, rather than relying on their own analysis.

Herding behavior has received much attention in finance and security market, where a group of investors tends to trade in the same direction over a period, leading to observed behavior patterns that are correlated across individuals (Bikhchandani et al., 1992). In financial market, particularly, herding behaviors happen when investors face uncertain information, and therefore, they tend to follow the stock-investing decisions and actions of others or depend too much on

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public information without paying sufficient attention to their own private information. In behavioral finance, herd mentality bias refers to investors' tendency to follow and copy what other investors are doing. In this study, we will examine the financial phenomenon of herding and its impact on the security pricing and overall market return as well as individual returns.

In the literature, herding is generally known as an excessive irrational tendency of investors ignoring the fundamental information presented to them that would act together in the markets (Gębka & Wohar 2013). According to Erdenetsogt and Kallinterakis (2016), the practice of herding assumes that individuals follow others' behavior disregarding their own private signals or prevailing market fundamentals. Herding can directly lead to market distress and led to the increase in trading volatility. There is a distinction between two different types of herding: (1) spurious, or unintentional, herding which is commonly a result of publicly known news being interpreted similarly and assumed causing efficient price corrections; but this is not usually a cause of excess volatility in the markets. (2) Intentional herding, when investors possess knowledge of other investors' decisions and knowledge and this in turn affects their investment decisions. The securities market is a very large and complex market that is traded nearly every day on a domestic and international level. There is a constant flow of information to each and every investor that comes from different sources, ideologies, and credibility. The two dimensions of financial decisions, cognitive psychology (how people think) and the limits to arbitrage (when markets will be inefficient) affect the herd behavior. It is our human nature to take what we are given and interpret it in our own light. This very nature is what led to Behavioral Finance and the study of its effects on the market.

Christie and Roger D. Huang (1995), argue that in a market setting, herds are characterized by individuals who suppress their own beliefs and base their investment decisions solely on the collective actions of the market, even when they disagree with its predictions. Accordingly, they believe that traditional herd exist when investors are drawn to the consensus of the market, implying that individual returns would move in harmony with the market return. According to Igual and Santamaria (2017) one of the main theories that dominate the Behavioral Finance field is the irrational phenomena of herding. It is the intention of this study to examine how the market under this irrational tendency would directly affect the prices of securities, and returns on individual's portfolios. More specifically, in this study, we plan to analyze and answer the following questions: (1) Is the return dispersion of individual assets from the market return a significant indicator of herding in financial markets? And (2) What affects does herding have on security pricing and overall market return as well as individual returns?

II Literature Review

According to the literature, the average investors have difficult time removing their emotions from their investing activity (Qawi 2010). This issue has been studied extensively in the literature and received much attention. In this study, we plan to analyze a number of deeper implications that would bring light to the direct effects of the individual, as well as the broader market performance. To this end, we examine the relationship between the market return and the individual stock returns in the context of herding, and highlight the degree, if any, of herding that has taken place over the past twenty-year period of stock returns.

The phenomena of social herding in the markets has been extensively studied in the literature from different perspectives. In Finance, particularly, herding has been viewed as a concern to market participants, as it contributes to the market inefficiency (Fama, 1970; Christie & Huang, 1995), and to the financial market volatility and instability (Bikhchandani & Sharma, 2001). Qawi

(2010) has studied herding in finance and argues that everybody comes with this sort of 'bagage'. That implies that we all have our own "inherent biases and heuristics", and consequently "attach emotion to our judgment and actions".

There are two main avenues of thought in finance: (1) The Neo-classical theory of the rational investor who only makes decisions based on available data and proven mathematical theories. (2) However, Qawi (2010) states that this method consists of incomplete information and abbreviated assumptions of reality that do not consider human behavior element. This leads to the newer theory of psychological finance. It involves understanding the market anomalies and accounting for these inherent biases. Qawi (2010) refers to a study by Pretcher (2001) on human behavior and its' reaction to market performance, that argues that herding behavior is rooted in the limbic system and it is impulsive, uncontrollable and immutable, and thus it is a response to the actions of others that stems from impulsive mental activity.

Qawi (2010) highlights another theoretical framework in regards to herding, called the 'Affect Pricing Model'. This model works with the concept that individuals have perceptions of objects being valued as 'good' or 'bad', and that this mindset can be applied to individual stocks. He refers to a study by Kahneman (2002) that highlights another heuristic called the 'affect heuristic'. Gebka and Wohar (2013) argue that on an international level, there is not much herding to be found in the broader sense of the market. However, there are some herding tendencies found when you dig deeper into the returns of individual sectors and get rid of the broad index returns. They conclude that Fama's Efficient Market Hypothesis (EMH) holds true and is one main reason behind social herding tendencies within the market. The reason, they argue, is that the EMH states that the market is immediately receptive to the development of new information. So, the new information of the market is being accounted for immediately at the same time. As humans, it is in our nature to have the tendency to follow the majority, and that is what is occurring through the EMH.

Chang et al. (2000) have studied herding tendencies across multiple international markets. They conducted the study in the U.S., Japanese, Hong Kong, South Korean, and Taiwanese markets. They have used a variant of the empirical model from Christie and Huang (1995) and examined the investment behavior of market participants within different international markets (i.e., US, Hong Kong, Japan, South Korea, and Taiwan), with regard to their tendency to exhibit herd behavior. Their results for the US were consistent with those results reported by Christie and Huang (1995). They found no evidence of herding on the part of market participants in the US and Hong Kong and partial evidence of herding in Japan. However, they found significant evidence of herding for South Korea and Taiwan, the two emerging markets.

Maquieira, C. and C. Espinosa-Méndez (2022), have analyzed the herding behavior in the Chinese stock markets in the context of the COVID-19 pandemic, using the cross-sectional absolute deviation (CSAD) model proposed by Chang et al. (2000), to detect herding behavior in the time period between January 30, 2001, and June 12, 2020. They split the sample according to the market return level (to identify bull and bear markets) and showed that there is asymmetric behavior, revealing stronger herding behavior in an up market. Their results showed more pronounced herding behavior occurs in bull markets and in low volatility regimes (before and after the COVID-19 event date). They argue that more pronounced herding activity in a low volatility market might be associated with a higher level of agreement in the market regarding the quality of stocks; and thus, in this scenario, it is more likely that investors will coincide in their appraisals of investment decisions. They maintain that in situations with extreme perception of systemic gravity, it is likely that investors may have a greater degree of trust in their own decisions, as opposed to the collective beliefs of market participants.

In their empirical analysis, Christie and Huang (1995) have focused on the price implications of herding by using cross-sectional standard deviation of returns. Therefore, in their study, herding behavior will be measured by decreasing dispersion of returns when individual returns changes are in harmony with market return. Because, there is herd behavior when individual returns follow the lead of the portfolio returns. They have also examined the herding behavior during the periods of abnormally large average price movements, or so-called market stress and conclude that, in contrast, the herding of individual returns around the market translates into a reduced level of dispersion. Therefore, during the market stress, their conclusion supports the predictions of rational asset pricing models and suggests that herding is not an important factor in determining equity returns during periods of market stress. Thus, they had found that it was more common for prices to deviate from the market price in these times of crisis rather than follow it.

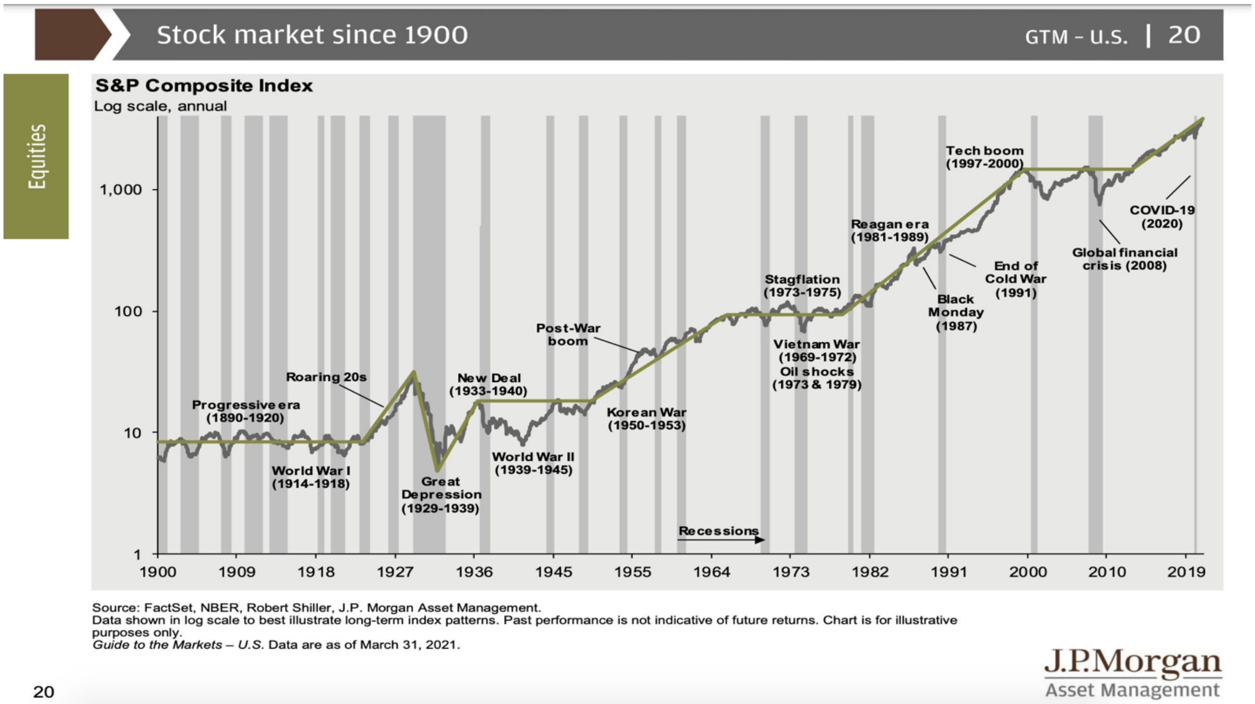
In order to analyze the herding phenomenon in security market, in this study, we will follow the model from Dang and Lin (2016) which had been recreated from another empirical study of herding from Christie and Huang (1995), as well as Cheng et al. (2000). However, in this study, we will focus on the Dow Jones Industrial Average over a twenty-year period from 2000 until 2020. First, we will review the theoretical approaches of herding in the literature, as well as, the empirical studies involving the cross-sectional return dispersion of assets. Next, we will define our analytical framework and the data to develop our model. Finally, we will summarize the empirical findings, and conclusions about herding in the market.

III Modeling Framework

In this section, we formulate herding behavior to capture the magnitude of the dispersion and apply it to long-term portfolio investing, and answer the question of whether or not herding will affect the long-term investment decisions. The model will be used to describe the market volatility for the long-term investor. We use data from early 2000 when the financial tech bubble collapsed, and this gave the market a fresh valuation of asset pricing. The new age of technology has also given investors more access to information and more insight to investment decisions made by the institutional investors. The data set would include the data from the Global Financial Crisis struck and scorned investors' returns and their market behavior.

We have used the daily price activity of the securities comprising the Dow Jones Industrial average from Yahoo!Finance, over a twenty year period spanning from 2000 until 2020. The daily price returns have been calculated by dividing the current stock price of the day by the lagged-one day price. The DJIA also captures the 30 largest stocks on the New York Stock Exchange (NYSE). This study considers price as being the determinant of return dispersion, and the DJIA's criteria for inclusion in the index is the 30 largest stocks, measured by price. There are skeptics on the rationale behind this, for the S&P 500 is comprised of the 500 largest stocks based on market capitalization and weighted on this criterion. However, the measurement of price will be sufficient for this study due to the main focus of this study revolving around price itself. There is one caveat in this data set, and that is that two companies from the DJIA had to be excluded from the individual securities list in order to maintain the consistency and continuity within the data set. The securities that have been removed from the data set are Visa (V) and Salesforce (CRM).

Our purpose in this study is to examine the magnitude of the effect between the daily returns of the overall market index and the dispersion of returns of the individual securities that comprise the index in comparison to the markets' daily returns. Furthermore, we aim to look into the effect herding will have on portfolio returns based off the calculation of securities dispersions on a daily level. The question to be answered in this context is whether or not an individual investor with a buy and hold, long-term investment strategy will need to calculate the risk of current market volatility inherited from herding to better allocate their portfolio.



We assume that herding is viewed as a behavioral aspect of finance, will occurs when security return data mirrors the overall market or index returns. Investors will begin to ignore the information they have and stay away from their beliefs in making the investment decisions they think are best for them, and instead mimicking the investment decisions of other institutional investors. In this modeling, we follow Christie & Huang (1995), Cheng et al. (2000), and Dang & Lin (2016) to measure the herding index of the DJIA. More specifically, we use the Cross-sectional absolute deviation (CSAD) to measure the absolute return dispersion of each individual market security that makes up the DJIA and the Cross-Sectional Standard Deviation (CSSD). The formulas are as follows:

$$CSAD = \frac{1}{N}\sum_1^N |R_{it} - R_{mt}| \qquad (1)$$

$$CSSD = \sqrt{\frac{1}{N-1}\sum_1^N (R_{it} - R_{mt})^2} \qquad (2)$$

Where $R_{i,t}$ is the stock return of a specific firm (i) at time t, and $R_{m,t}$ is the cross-sectional average of all N stock returns that comprise the market portfolio at time t. Each of these calculations measure the average deviation of the individual stock returns from the market return ($R_{i,t}$ - $R_{m,t}$). In order to prevent any positive and negative values from canceling each other out, CSAD in (1) takes the absolute value of the deviation values while in equation (2), the CSSD squares the deviation values (Dang & Lin 2016). When looking at the values of deviation, any increasing values of CSAD or CSSD would imply that individual stock returns deviate from the market return, and this would imply that there is no evidence of herding between the individual returns and the market return. On the other hand, smaller values of deviation would imply the potential for herding, however, that may be spurious or intentional, yet to be known.

Furthermore, as Dang and Lin (2016) stated, different stocks may react differently to the market changes with different degrees of sensitivity, and would cause the dispersion to increase as the market return increases in absolute term. However, the presence of herd mentality during the extreme market movements will draw individual stock returns closer to the market return, and reducing dispersion.

In order to capture the herd mentality during extreme market movements, following Christie and Huang (1995), we have used dummy variable regression to test for herd behavior:

$$CSSD = \alpha + \beta_L {D_t}^L + \beta_U {D_t}^U + \varepsilon_t \quad (3)$$

Where the two dummy variables D^L_t and D^U_t, assume binary values: 0 when the market return on day t is outside of the upper or lower tails of the distribution, and a value of 1 if it does fall within the extreme upper and lower tails of the distribution. The criteria for the two dummy variables are the lower 5%, and the upper 5%, of the distribution. Any negative values of β_L or β_U that are statistically significant will indicate that there is a potential for herd behavior in the market (Dang & Lin 2016). We can recalculate this equation similarly for CSAD, by replacing CSSD by CSAD in equation (3).

Furthermore, according to Cheng et. Al (2000), in order for herding to exist, during larger market movements, there would need to be a non-linear relationship between $CSAD_t$ and $R_{m,t}$. They propose the following quadratic regression:

$$CSAD_t = y_0 + y_1 |R_{mt}| + y_2 {R_{mt}}^2 + \varepsilon_t \quad (4)$$

Where $|R_{m,t}|$ is the absolute value of the market return at time t, and $R^2_{m,t}$ is the quadratic function of the market return at time t. The market would be exhibiting herd behavior if and when the dispersions increases at a less-than proportional rate or, decreases with the market return. This would result in a negative value and statistically significant value for the quadratic term (y_2) (Dang & Lin 2016).

Cheng et al. (2000) have proposed a slight change in equation (4): $CSAD_t = y_0 + y_1 R_{mt} + y_2 {R_{mt}}^2 + \varepsilon_t$, in order to capture the herd behavior in an up market. The importance of this regression model is that the market return does not need to be in the upper or lower tail of extreme market movements to pick up on herd behavior within the market.

A third regression model introduced by Chiang and Zheng (2010) has included $R_{m,t}$ as a regressor. This regression specifically will test for asymmetry between the two variables, the market return and dispersion values. Furthermore, by adding these additional regressors we are able to strengthen the explanatory power of the regression model. They propose two separate ways to test or herding behavior, and suggest splitting the data into two categories; the market behavior on up days and the market behavior on down days. The original equation has been formulated as follows:

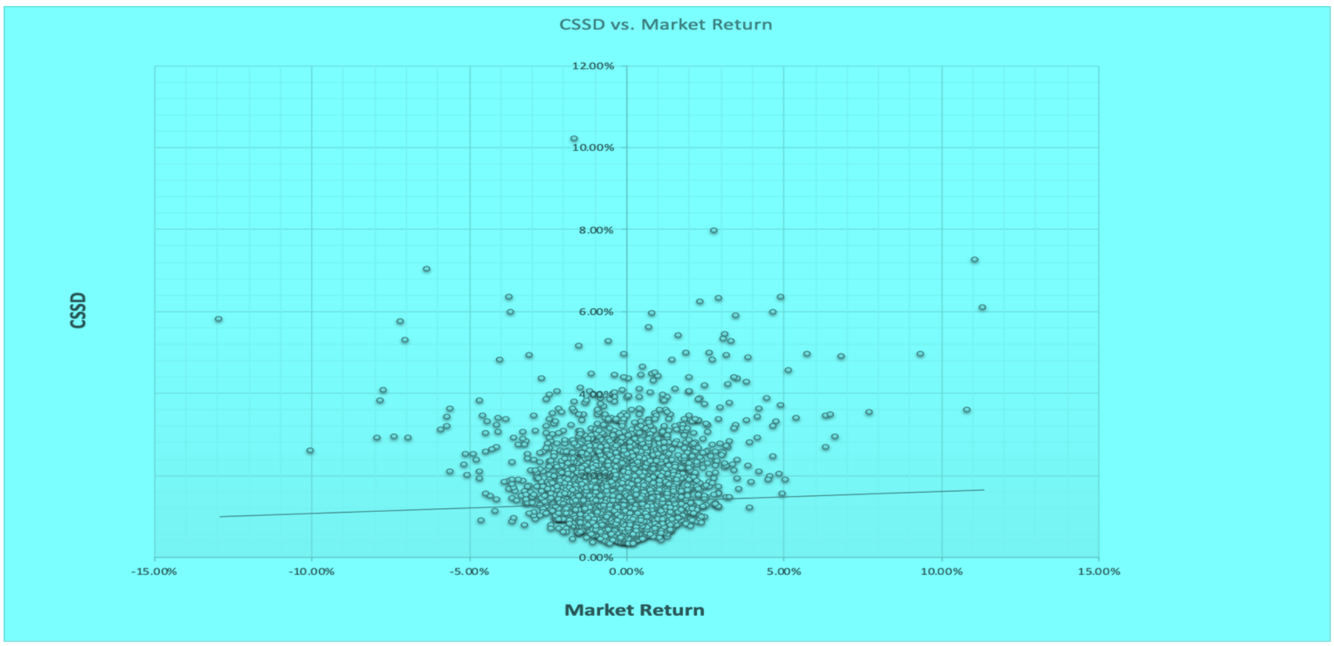
$$CSAD_t = y_0 + y_1 R_{mt} + y_2 |R_{mt}| + y_3 {R_{mt}}^2 + \varepsilon_t \quad (5)$$

They have proposed these changes in order to capture the market on down-days and-up days and thus replace $R_{m,t}$ with (1-D).$R_{m,t}$ and D.$R_{m,t}$ and to replace $R^2{}_{m,t}$ with (1-D) $R^2{}_{m,t}$ and D $R^2{}_{m,t.,}$ where the dummy variable, D, has a value of 1 when $R_{m,t} < 0$, and a value of 0 otherwise.

IV Results and Analysis

To begin our analysis, we have chosen to present visual representations of the two return dispersion measures that have been calculated in this study. The first visual graph (figure 1) shows the cross-sectional standard deviation (CSSD as dependent variable plotted on the y-axis. The market return, as independent variable is plotted along the x-axis in this figure 1:

Figure 1. Relationship between (CSSD), and the market return

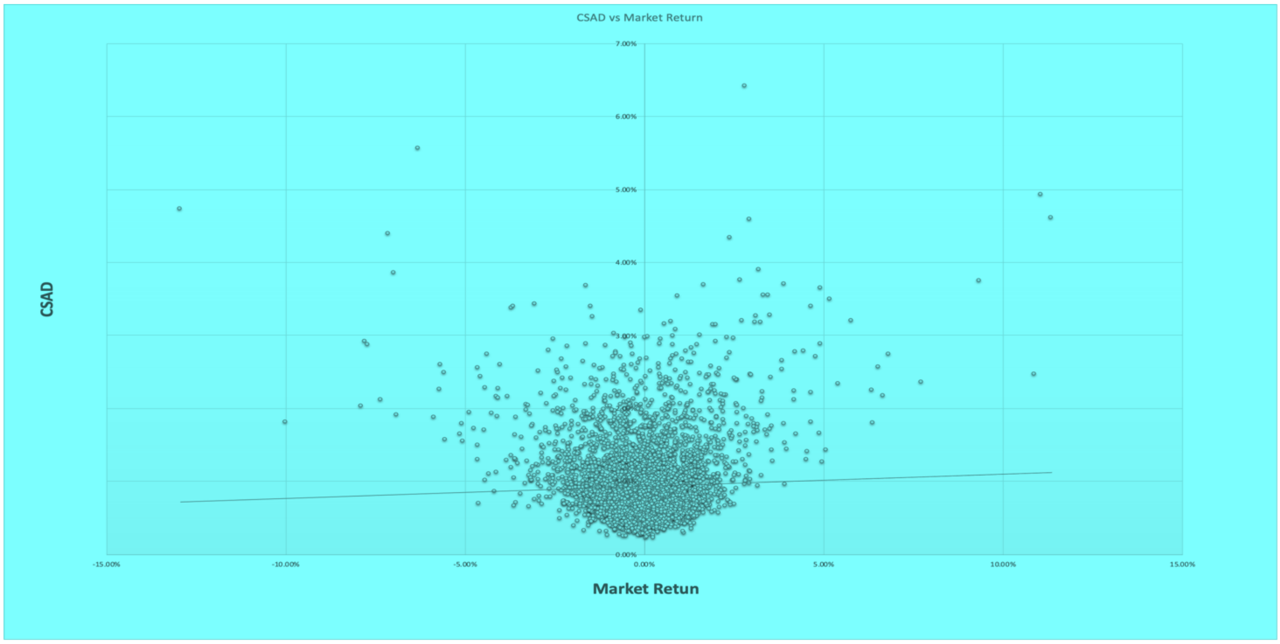


The graph does not show a strong relationship that fits the trend line of the data. Many of the data points exceed 2%, which is a large deviation in terms of financial returns. Another noticeable characteristic of this dataset is the number of outliers. Visually, one can see that there are frequent instances where the individual stock returns deviated upwards of 6% and even deviated as far as 10% away from the market return.

In the second visual representation, the cross-sectional standard deviation (CSSD) has been replaced with the cross-sectional absolute deviation (CSAD), and it is plotted on the same axis as the first graph.

When looking at the graphical representation of the cross-sectional absolute deviation, one can see very similar results. The deviation of individual stock returns continues to show weak signals of herd behavior in the Dow Jones Industrial Average. Each graph does have a cluster of data point around the center of the graph, leading one to believe that there is a slight herding relationship between the two variables — market return and individual stock returns. Later, in the regression analysis sections, it will be shown that the R-squared values do account for some of the data points in this study, but we conclude that they are not statistically significant.

Figure 2. Relationship between (CSAD) , and the market return



Summary Statistics

Table 1 provides summary statistics of the CSSD, CSAD, and the market return over the entire twenty-year time period, with 5282 data points. The mean for the market return over the entire twenty years period is 0.03%. As mentioned earlier, at the start of the dataset period, the market had just come off the tech bubble popping and, shortly later, experienced the Global Financial Crisis. Following the crisis, the market had experienced the longest Bull Run in the history in itself.

One may assume that with having nearly half of the period was in a bull market, the mean would have higher value; however, COVID-19 Pandemic caused a large correction in the DJIA in the final year of the period, which significantly affects the mean over time. Furthermore, by reviewing the basic statistical summary in Table 1, one can see that the mean for both CSSD and CSAD are, 1.34% and 0.93%, respectively. The mean of each of these measurements is significantly larger than the mean of the market return. Each of these values lie within, or extremely close to one standard deviation of the market return mean, however, one standard deviation of the market value is 1.21% which is a significant percentage difference in return value.

Table 1. Summary Statistics of CSSD & CSAD

	Mean	Std. Dev.	Minimum	Maximum
$R_{m,t}$	0.03%	1.21%	-12.93%	11.37%
CSSD	1.34%	0.78%	0.31%	10.21%
CSAD	0.93%	0.53%	0.23%	6.42%

Dummy Variable Regression

We have also used CSSD and CSAD in various regression models to further investigate the herding behavior within the market. In the first regression, we have used two dummy variables describing whether the market return fell within the lower tail or the upper tail of the return distribution. This regression has attempted to capture the herding tendencies of investors during extreme market movements. Earlier in the study we defined the upper tail as any return that is 1.7% and higher, and the lower tail as any return that was -1.83% and lower (Dang and Lin 2016). Table 2 shows the results of the regression analysis.

Table 2: Dummy Variable Regression

	Left	Right	Intercept
Coefficient	0.007751083	0.011381754	0.012437045
Standard Error	0.000460344	0.00045952	0.0001056
R-Square	0.139443911	0.007280243	#N/A
F-Stat.	427.7027475	5279	#N/A
	0.045338154	0.279797261	#N/A
T-Stat.	16.83760502	24.76879225	
P-value	0.00%	0.00%	

The coefficient estimates of the left tail and right tail are positive, thus implying that per change in the market return there is not a drastic or extreme response in the asset prices of the securities that comprise the index; and furthermore, they imply that if there is any change. The value of R-squared, 0.1394, indicates that the regression analysis is accounting for around 14% of all the variations in data points. Furthermore, the p-values are extremely low and near zero, indicating the significance of these values. In the context of study by Christie and Huang (1995), the DJIA behaved rationally and there are no signs of herding over this twenty-year period. The dispersion values continually increased in the left tail and the right tail. This implies that the investors do not herd toward the market signals, and ignore the opinions of key influencers.

CSAD Regression Analysis

We have further expanded the regression analysis by utilizing the cross-sectional absolute deviation (CSAD), and added a third regressor. This time, instead of using dummy variables to determine when the market was within extreme market movements, we were able to capture whether or not there is any non-linearity between the two variables. We shifted our focus towards the return measures and regress the absolute market return and squared market return against the cross-sectional absolute deviation return values.

The regression estimates are shown in Table 3. There is a negative coefficient for the return squared component, with a value of -0.0149. The presence of a negative estimate for the quadratic term (y_2) indicates that there is a potential that herding behavior is present in the market. However, the R-squared value is not that significant, as it is only explaining around 25% of variations in CSAD. The p-value is relatively high which indicates the estimated coefficient is not significant. There is a stronger potential of herding in the market when considering the CSAD model due to the non-linear relationship present in the data set. The model specifically tested for a nonlinear relationship, which would indicate that as the market return increased (decreased) the dispersion measurement would not move in comparison with the market. It instead would move in an opposite direction, increasing the dispersion value. Therefore, the presence of a non-linear relationship is a strong indication of herd behavior.

Table 3: CSAD Regression Table

Components:	$(\text{Return})^2$	ABS Rreturn)	Intercept
Coefficient	-0.01497852	0.293223448	0.007041245
Standard Error	0.20011615	0.012207646	9.72089E-05
R-Square	0.253024616	0.00460304	#N/A
F-Stat.	894.0836443	5279	#N/A
	0.037887656	0.111851355	#N/A
T-Stat.	-0.074849134	24.01965595	72.43417061
P-value	94.03%	0.00%	0.00%

Asymmetry Regression

The third regression that has been conducted is the most powerful of the three in regards to explanatory power. There are two versions of this regression. The first version uses both the market return and absolute market return, as well as the quadratic function from the previous regression model. This model has the potential to capture the market behavior during any conditions, both up and down. More specifically, for every change in the market return, CSAD will change by $Y_2 + Y_1$ for any value that $R_{m,t}$ is positive and change by $Y_2 - Y_1$. Moreover, this means that asymmetry can be quantified as the ratio of $\frac{Y_2+Y_1}{Y_2-Y_1}$ (Dang and Lin 2016). The estimates of this regression are presented in table 4.

Table 4: Asymmetry Regression Table

Equation 5	$(\text{Return})^2$	ABS (Return)	Return	Intercept
Coefficient	-0.031451987	0.295111599	0.02442784	0.007022484
Standard Error	0.199756386	0.012190531	0.005244672	9.71025E-05
R-Square	0.256082274	0.004594045	#N/A	#N/A
F-Stat.	605.6235316	5278	#N/A	#N/A
	0.038345506	0.111393505	#N/A	#N/A
T-Stat	-0.157451725	24.20826442		
P-value	87.49%	0.00%		

The coefficient for the quadratic term is negative, which in turn does present a potential for herding behavior to be present in the market. The R-squared value is still not entirely significant with a value of about 25% of the data points in the study. Although the R-squared value is not significant the p-value does indicate there is some significance to the coefficient estimate for the regression.

The second version of this regression model divides the performance on the market into two separate groups; days when the market is up and days when the market is down. By using dummy variables to create a distinction between the two conditions. The estimates for the regression are presented in table 5. The coefficient estimates for this regression are mainly positive with only one of the regressors having a negative estimate. The dummy term of the regression has the highest p-value levels showing the highest significance, however, the R-squared values range from 2% to 27% of the data points within the dataset. The significance level given by the p-values for the quadratic term and the dummy variable give an indication that there is not a strong significance to these coefficients.

Table 5: Revised Asymmetry Regression (Up & Down)

	D	D.R^2.m,t	(1-D). R^2.m,t	D.Rm,t	(1-D).Rm,t	ABS RET	Intercept
Coefficient	0.2552528	-0.3032706	0	0.1014482	0.24	0.00	0.01
Standard Error	0.2865408	0.2782435	0	0.0243679	0.02	0.00	0.00
R-Square	0.2574049	0.0045908	#N/A	#N/A	#N/A	#N/A	#N/A
F	365.76286	5276	#N/A	#N/A	#N/A	#N/A	#N/A
	0.0385436	0.1111955	#N/A	#N/A	#N/A	#N/A	#N/A
T-Stat	0.8908078	-1.089947		4.1631916	14.139274	3.05915	
P-value	37.31%	27.58%		0.00%	0.00%	#N/A	

V Conclusion

After exploring the scope of the relationship between the market returns and return dispersion, we can conclude that there is not enough evidence to support the statement that herding is prevalent in the Dow Jones Industrial Average during the years of 2000 and 2020. There was not sufficient evidence presented by the Christie and Huang (1995), cross-sectional standard deviation dummy regression calculated in this study, to prove that herding is present in the market during extreme market movements. The only regression that presents a case for herding being present in the market index is the first CSAD regression performed in this study. Although, the R-squared value is not nearly as significant, the coefficient estimate of the quadratic term is still negative and this represents a non-linear relationship between CSAD and the market return. The results of asymmetric regression is quite similar to the non-linear test. The quadratic term does have a negative estimate. However, the R-squared value is not strong enough to indicate that the results present a potential for herd behavior in the market place. The second version of the asymmetric regression does not provide any sufficient evidence that herding occurs on down or up days in any specific pattern.

Based on the findings in this study it is reasonable to conclude that the market behaves in a rationale sense, ignoring the signals of the market and its' largest influencers. In other words, the Efficient Market Hypothesis stands. In opposition to the literature for behavioral finance, based on the empirical evidence, individual investors are able to look past their natural human biases and heuristics. This is not to say that spurious herding does not still occur in today's markets, but there is no evidence that intentional herding is a consistent phenomenon that occurs in the market.

When we examine the meaning of the coefficients throughout each of the regression examples, we noticed that only two of them points towards potential herd behavior in the market. As referenced earlier in this study, the CSAD regression has the strongest indication of herding in the market, due to the negative coefficient. This means that for any move in the market return that is positive, the cross-sectional absolute deviation will move in the opposite direction closing the spread between the market return and the stock returns. The second most indicative regression was the asymmetric regression, which also presents a negative coefficient, leaning towards the presence of potential herd behavior in the market. The p-values do show a strong significance; however, the R-squared values show that the regressions don't represent enough of the dataset to make it significant.

The first regression points to a positive relationship between the market return and the dispersion of stock returns, meaning that as the market return increases, so does the deviation of other stock returns from the market return. For example, during the days of market down, the individual stock returns are likely to move in a positive direction, and on market up days the individual stock returns are likely to move in a negative direction. The CSSD regression has a positive coefficient, which indicates that the market return and the dispersion value move in relation with each other. In other words, as the market price increases so does the dispersion of the individual stock returns. The fact that the R-squared values don't give sufficient backing to the indication of herd behavior in the Dow Jones Industrial Average it leads us to believe the market behaves rationally.

In regards to the earlier questions asked in this study, the return dispersion of individual assets does not present itself as a strong indicator of herding in the market. Instead, it serves as proof that investors do not act on market signals, and instead develop their own investment decision process with the information at hand. As for the second question, there is not sufficient evidence of herding being present in the market; so, it is not reasonable to assume there is or is not an effect on overall asset prices. Instead, the evidence presented in this study lead to the conclusion that the market is overall rational. The investors, individually, use the readily available public knowledge to forge their own investment thesis. The effect of financial information is priced into the market; however, that does not always mean spurious herding cannot occur in this situation. Volatility will always be present in the market, but that does not always mean it is directly correlated to herd behavior.

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