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The Influence Between the Decay Speed of Information and Future Asset Price—A New Herd Behavior Model with the Decay Factor

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Abstract

Herding behavior measurement models should consider the time dimension since herding behavior studies support that investors enter the market in sequence. Generally, the more recent information and sentiment should be given greater weight because of a greater impact on prices. This research aims to improve the previous herding sentiment model to explain and predict investors' behavior and market by adding a time dimension better accurately. This study finds that herd sentiment could be more volatile when the decay speed of information is faster. Moreover, this study utilizes daily tick data from JoinQuant to conduct a simple test of the HS model. The findings suggest that a decrease in the decay parameter of a specific stock or portfolio may signify reduced volatility of herding sentiment and increased volatility of future prices. During a period of volatile prices, the increase of bullish market sentiment created by herd behavior could lead to an asset price increase in the future.

Keywords

Information decay, herding behavior, investors' sentiment

1. Introduction

Behavioral finance has started to be known as a new research field since the 1990s. Psychological and sociological studies are more and more combined in the emerging theory of behavioral finance field, which contributes to putting forward several theories to further explain reality. Essentially, behavioral finance attempts to dig into the reasoning patterns of investors. In other words, behavioral finance studies try to answer the what, why, and how of finance and investing, from a human perspective [1, 2]. Tuckett (2009) mentioned that besides the information on target assets and macro-environment, investment decisions are also influenced by many other dimensions, such as emotion, habit, and psychology of investors [3]. To predict and understand financial instability better, psychology studies are suggested to be incorporated into economic models more successfully [4]. Behavioral finance should ultimately not only explain the anomalies of the financial market but also comprehensively explain the financial market, society, the behavior of investors and consumers, and a series of economic activities.

Herd behavior has an impact on the social environment and the subject of behavior, might not only drive the asset price to deviate far from the fundamentals, but also aggravate the volatility of the financial market, and even cause financial crises [5, 6]. The herding effect, a hot topic of research in the behavioral finance field, is widely considered to be one of the key causes of financial market turmoil and often be cited by some press and economic agents (e.g. European Union Economic and Monetary Affairs Commissioner) as the main factor that causes extreme economic fluctuation and market instability [7]. On the contrary, some scholars argue that herd behavior does not necessarily lead to mispricing [8] and even can stabilize the futures prices to some extent, such as the hedge fund herding study of Boyd et al. [9]. This study aims to answer the research question of whether price trends or market sentiment can be predicted by measuring and monitoring the herding sentiment models.

It is necessary to consider about time dimension in herding models' studies since they support that investors enter the market in sequence. This research aims to improve the previous herding sentiment model to better accurately explain and predict the market by adding a time dimension (decay over time).

This research proposal is structured as follows: I separate Chapter 2, the literature review, into three parts. Firstly, I will explain some key concepts; Secondly, I will explain why my study wants to use investors' sentiment as an indicator to predict the market trend. Then, I will analyze the necessity of introducing the decay factor of the information into the herd behavior study; Finally, I will briefly review the previous theoretical models and empirical research and summarize the causes of herd behavior. Chapter 3 is the main body of this article, which is divided into two parts. First, combine the previous herd behavior model (LSV model) and the decay factor from the market sentiment model (the CSI model) and come up with a method to monitor the trend of asset price; Finally, describe the Monte Carlo Simulation Procedure. Chapter 4 shows the empirical analysis of the new herd sentiment model. Finally, Chapter 5 presents the main conclusions and limitations of this study.

2. Literature Review

2.1 Interpretation of core concept

The definition of herding can be summarized as two actions: Copy or Change. The first type of herding is described as copying the investment behavior of other investors [10-12]. This kind of herding investor does not necessarily have private signals. Another type of herding is described as changing the original investment decision [28]. These types of investors give up their original decisions after observing other investors' investment decisions. Moreover, Bikhchandani and Sharma (2000) define herding as "spurious herding" or "intentional herding" based on the causes of herding [12]. "Intentional herding" is defined as a copy that is the same as the first type of herding above. "Spurious herding" exists not because investors are influenced by each other's decisions, but because most of them get similar private signals or commonly known information. Typically, "spurious herding" is a consistent response by investors to fundamental information, thus, it will not drive prices far away from fundamentals. However, it remains a challenge to distinguish whether the herd behavior we observed is "spurious herding" or "intentional herding" since the fundamental reasons that lead to the final decisions of institutional investors are hard to observe.

In addition, informational cascade and herding are used interchangeably in lots of literature [15]. However, they are slightly different, that is, an information cascade is defined as ignoring private information and simply following the previous investors' decision, whereas herd behavior occurs when a group of individuals moves in the same direction, not necessarily giving up their signal [14, 15]. Once the information cascade occurs, social learning ceases and there would be no new information added to the market. Thus, it is stable. In contrast, herding is fragile because it allows the release of new information, which may lead to more severe herding. For instance, when a bubble is rising, a new signal to the contrary could be the trigger that causes a greater bubble to burst [16]. The decay parameter in the new HS model, as a sensitive indicator, can monitor whether social learning ceases or not.

2.2 Investors' sentiment

The market price might be highly correlated with investor sentiment. Based on one of the main-stream analyzing financial market approaches, Dow, S. C. (2011) mentions that the processes and outcomes of the market are reflections of economic behavior and psychological factors [4]. A report from the Barclays Bank agrees that the volatility surface for stocks has been significantly impacted by Speculative option trading activity [30]. Back, Bandopadhyaya, and Du (2005, cited by Feldman, T, 2010) suggest that investor sentiment might be the best indicator to explain the short-term movements of the asset price [19]. Viv P and Ravi K (n.d.) agree that asset price can be predicted by market sentiment as well. They indicate that there are three classes of market sentiment signals that can influence asset prices, such as Social media sentiment, News sentiment, and Pseudo sentiment. Social media sentiment depends on the positive and negative social comments of the stock; News sentiment is measured by the attribution and classification engine, such as the financial "oriented" sentence of financial news, articles, and blogs of the stock; Pseudo sentiment which derived from financial statistics, such as the volume and the price of the asset transaction [20]. Feldman, T (2010) states that investor sentiment might be a determinant of asset prices and he found that the perceived loss index can be used to detect financial crises and bubbles [19]. Similarly, Tuckett (2009) argues that real economic activities are based on valuation, the asset prices usually fluctuate in accordance with the expectations of price movement which is closely related to market sentiment [3]. Moreover, Blasco et al. indicate that in the strict traditional sense, the efficient market might not hold, and the market sentiment and the investors' herd behavior can influence the market either directly or indirectly [21]. Furthermore, López-Salido et al. found that market sentiment might be the main driver of the economy in credit markets [22]. StockSnips generated news sentiment data for Apple and found that the stock price is highly correlated with the stock sentiment, which is a useful index to predict the stock price trend. In addition, the relationship between stock sentiment and stock price is more significant in cases of larger companies with more news articles [23].

The study by Lemmon, M. and Portniaguina, E. (2006) shed light on that consumer confidence cannot be a good sentiment index to forecast stock returns and momentum premiums in the period before 1977, however, consumer confidence appears to have become a better barometer to predict the economic activities in recent years [24]. The analysis of Brown, G. W., and Cliff, M. T. (2005) shows that the market return over the next 1-3 years can be predicted by investor sentiment viewed by the bull-bear spread [25]. Baker, M. and Wurgler, J (2007) suggest that trading volume can be an investor sentiment index [26]. However, how to measure investor sentiment and quantify the effects is still a question.

Lakonishok et al. (1992) built the LSV model to measure the tendency of fund managers to copy each other in investment decisions [28]. The LSV model uses the difference in the percentage of the number of selling fund managers and buying fund managers to measure the herding degree. The empirical study of Daniel et al. (1997) uses the LSV model with data of portfolio changes of 274 mutual funds between end-1974 and end-I984 to measure herding behavior. They find little evidence of (economically significant) herding in their sample [29]. However, the accuracy of the LSV model is low since it does not consider the volume of transactions. To improve the LSV model, Wermers, R. (1999) came up with the PCM (Portfolio-Change Measure) model based on the LSV model, which introduces both the strength and direction of trading [30]. However, the PCM model does not consider that the more recent difference between the selling and buying stock volumes has more influence on current herding sentiment.

In a nutshell, investors' sentiments could be a good indicator to predict and monitor asset prices. This study uses the Herding Sentiment Index of the PCM model.

2.3 Importance of information decay

There is a gap between theoretical herding studies and empirical herding studies. The empirical research is still in the exploratory stage. There is no single standard for measuring herd behavior. Existing empirical herding studies analyze herding through either statistical measures of clustering or estimating structural parameters of a herding model [31, 32]. Recognizing the herding behavior which is defined strictly by theoretical studies is still a challenge. A lot of herding measurement studies still use previous herding measurement models. However, some classical herding measurement models have been questioned [33, 34].

According to the "Rational Expectations" hypothesis theory, the economic system generally does not waste any information since information is scarce [17]. Similarly, as mentioned in the study of Alexander, S. S. (1961), though the two main schools of professional analysts, the "fundamentalists" and the "technicians", have different methods for collecting and analyzing the information, both the two kinds of professional analysts agree that market price usually responds to the information gradually rather than has an instantaneous jump [18]. Investors are more interested in new information rather than old messages, and the market price usually incorporates all the information gradually and tends to develop a particular trend ultimately. Feldman, T. (2010) states that investors usually place greater weight on more recent events [19]. Viv P. and Ravi K. (n.d.) also argue that the decay of news is important to ensuring signal reliability, that is, the old messages and information should be given less weight than the new ones [20]. Their research found that the correlation between investor sentiment and stock price increases after improving the investor sentiment signal indicators by introducing the message weight that decays over time. Similarly, the CSI model of Hafezk, P and Xie, J (2013) uses the number of positive and negative events and news of the company to test the relationship between the sentiment of the company and the stock price [27]. This model includes a decay function that emphasizes more importance of more recent information compared with past information. The decay function to sentiment gives more weight to new events than old events when several events occur in the same look-back window. The CSI model finds that it is necessary to include the decay factor in the sentiment model compared with using the same model and giving the same weight to the information and event at a different time. Furthermore, Bikhchandani and Sharma (2001, cited by Dow, S. C, 2011) emphasize that herd behavior usually gives underweight to past information since herding is not fully rational [4]. In summary, information and sentiment have time value. In other words, they should decay over time, but cluster or decay slower during the herding period or bubble years. However, until now the herding models have been unsatisfactory. One reason is that they failed to include the time value of information, making the prediction and explanation of the real market inaccurate. Particularly, herd behavior models usually suppose that investors enter the market in sequence, thus, it is not possible to ignore the different importance of information at different times.

3. Methodology

3.1 Herding sentiment model

Similarly, to measure the whole market sentiment, our herding sentiment model (hereafter, HS model) uses the volume of fund managers' selling orders and buying orders to substitute the number of fund managers in the LSV model.

Assumption 1

$\theta \sim \beta\,(\alpha, \beta)$ indicates the probability that the investment sentiment of the target asset shows as bullish, following the beta distribution since this model supposes that there exist only two sentiments in the market and only two kinds of events occur, either bullish events (e.g. investors buy the stock) or bearish events (e.g. investors sell the stock). Where parameters α and β represent the bullish events represented by the buying orders and bearish events represented by the selling orders respectively from time a to time b.

Assumption 2

$X|\theta \sim \text{Binominal}\,(n, \theta)$. The investment activities follow the Binominal model where the investors are homogeneous. There exist n times independent trials in each period of trading, where n is the number of investment decisions. The success probability of buying activities is highly correlated with the market's bullish sentiment θ.

Moreover, none of the investors in the same trading period knows the current period number of selling and buying orders since investors will invest at the same time due to homogeneity.

The HS_t indicates the net market Bullish sentiment from herd behavior at time t. Without introducing the decay factor and weight of information, the single-period market bullish sentiment at period i shows as follow,

$$HS_i = \left|\frac{V_i(B)}{V_i(B)+V_i(S)} - p_i\right| - AF_i \tag{1}$$

$$HS_i = |\theta_i - E(\theta_i)| - E|\theta_i - E(\theta_i)|$$

$V_i(B)$ and $V_i(S)$ are the number of buying and selling orders for the individual stock at period i respectively. The first part of the equation (1). θ_i represents the actual market sentiment at period i, which is measured as $\frac{V_i(B)}{V_i(B)+V_i(S)}$. If θ_i is larger than 0.5, the market sentiment is shown as bullish, otherwise, bearish. p_i is the expected market sentiment, $\mathrm{E}[\theta_i]$, which can be calculated by averaging past market sentiment. The first part of the equation, $|\theta_i - E(\theta_i)|$, indicates the difference between the market actual sentiment and the market expected sentiment. The second part of the equation (1), $AF_t(i)$, is an adjustment factor, which can be measured by $E|\theta_i - E(\theta_i)|$. The adjustment factor shows the difference between the actual market sentiment and the expected market sentiment under the null hypothesis (no herd behavior), that is, the trading behavior is independent of each other. The HS indicator indicates the herd sentiment (the market sentiment created from herd behavior). As same as the PCM model (Wermers, R, 1999), which improves the LSV model by introducing the volume of buying and selling transactions, this model uses the Monte Carlo Simulation to generate AF_i and the detailed process is shown in next section.

Observing all past information on the target stock is inefficient and uneconomical. Information investors typically prefer only to observe the information from a time in the past since the information from a long time ago hardly has an impact on recent asset prices. According to the previous assumption, investors are homogenous, therefore the information they collect is typically from the same period (e.g., the information over the past month or the past quarter). Suppose the length of the information observing window is m, which means that investors at time t collect the information about the target stock from the time $t - m$ to time t. Then the herding sentiment at time t has accumulated since time $t - m$ because any information and sentiment before time $t - m$ have been ignored. Accordingly, the cumulative HS indicator at time t can be measured as follows:

$$HS_t = \left|\theta_t - \frac{\sum_{i=1}^{m} V_i(B)}{\sum_{i=1}^{m} V_i(B) + \sum_{i=1}^{m} V_i(S)}\right| - AF_t \tag{2}$$

$$HS_t = |\theta_t - E(\theta_t)| - E|\theta_t - E(\theta_t)|$$

$\theta_t = \frac{V_i(B)}{V_i(B)+V_i(S)}$. $\sum_{i=1}^{m} V_i(B)$ and $\sum_{i=1}^{m} V_i(S)$ indicate the total number of buying stock orders from the time $t - m$ to time t and the total number of selling stock orders from the time $t - m$ to time t respectively. And $E(\theta_t) = \frac{\sum_{i=1}^{m} V_i(B)}{\sum_{i=1}^{m} V_i(B) + \sum_{i=1}^{m} V_i(S)}$. p_t is the expected market sentiment, which is the average of the actual market sentiment during the information observing window m. The adjustment indicator, AF_t indicates the null hypothesis, which is measured by $E|\theta_t - E(\theta_t)|$.

$$P_{t+1} = \alpha + \beta HS_t + \varepsilon_i;\ t \in N_{++}$$

Future asset price is affected by the accumulated market sentiment over a while. Run the regression above to find the relationship between the herding sentiment and the next period's asset price.

3.2 Introduce the "decay" and "risk aversion" factors

Hafezk, P and Xie, J. present a Company Sentiment Indicator model (hereafter, CSI model) to measure the company-specific sentiment. The CSI model can reflect both breaking news and trailing news sentiment by counting the number of positive and negative news about the company during a single look-back window.

$$CSI_t = \sum_{i=t}^{t-m} \frac{w_{1,i} w_{2,i}(\#pos_i - \#neg_i)}{\#pos_i + \#neg_i} \tag{3}$$

$$w_{1,i} = 2^{\frac{i\delta}{m}};\ w_{2,i} = \frac{2^{\frac{i\rho}{m}} |\#pos_i - \#neg_i|}{\sum_{i=t}^{(t-m)} 2^{\frac{i\rho}{m}} |\#pos_i - \#neg_i|}$$

First, they measure the difference between the number of positive and negative events on each company basis divided by the total number of events, shown as $\frac{(\#pos_i - \#neg_i)}{\#pos_i + \#neg_i}$, where the $\#pos_i$ and $\#neg_i$ are the counts of positive and negative events decided by ESS[1]. Then, they introduce two decay functions which are the focus of this section. The first decay function, $w_{1,i}$, is a sentiment decay function to ensure that the information and events decay over time, where m is the length of the sentiment aggregation window and δ is the decay parameter which is defined by the half-life relative to the look-back window. And the second decay function, $w_{2,i}$, bounds the value of the company sentiment indicator between -1 and 1 where the ρ is the weight parameter[2]. They introduce the exponential decay function into the CSI model since it can easily incorporate the feature of the time value of information and offer an intuitive value range for interpretation. And for indicators of decay, they set m=91, δ=1, ρ=10.

The HS model introduces the first decay function, $w_{1,i}$, from the CSI model, shown as w_i in the HS model since the information of the HS model has the same decay feature assumption as same as the CSI model. With the decay function w_i, the probability that the market sentiment of the target asset, θ, shows as bullish shown as follows:

$$\theta \sim \beta\ (\alpha, \beta)$$

where

$$\left(\alpha = \sum_{i=1}^{m} V_i(B) w_i\ ;\ \beta = \sum_{i=1}^{m} V_i(S) w_i\right)$$

Either bullish or bearish information should decay over time. Therefore, each period bullish events, $V_i(B)$, and bearish events, $V_i(S)$, should be weighted by the decay factor w_i, where $w_{1,i} = 2^{\frac{i\delta}{m}}$. From the time $t - m$ to time t, the influence of bullish events and the bearish events are indicated by parameters α and β, where $\alpha = \sum_{i=1}^{m} V_i(B) w_i$; $\beta = \sum_{i=1}^{m} V_i(S) w_i$.

In addition, not every market is risk-neutral, such as the venture capital market or pension funds market. The rational investors in different markets might have different risk aversion levels, and the investors might not equally treat the bullish and bearish events. As a result, the average risk aversion of the market should be considered in the HS model. To better distinguish the positive and negative events, the risk aversion parameter ρ is also incorporated in the HS model to adjust the weights placed by investors to positive and negative information, depending on the average risk aversion of the target stock. For example, suppose there already existed 10 pieces of good news and 10 pieces of bad news, each of the news has the same quality and impact force on asset prices. For any risk-neutral investor, the investor should show optimistic sentiment once the good news is more than bad news. However, risk-averse investors might require more good information to support their investment decisions. If a risk-averse investor buys the stock when there are 13 pieces of good news and 10 pieces of bad news, then the risk aversion parameter ρ for this investor is 1.3.

The probability that the bullish sentiment of the target asset with the decay function w_i and the risk aversion parameter ρ is $\theta \sim \beta\ (\alpha, \beta)$, where

$$\left(\alpha = \sum_{i=a}^{b} V_i(B) w_i\ ;\ \beta = \rho \sum_{i=a}^{b} V_i(S) w_i\right)$$

[1]ESS is the RavenPack's Event Sentiment Score, which range is between 0 and 500. The CSI model consider the ESS>50 and ESS<50 as positive sentiment and negative sentiment, respectively.

[2]Hafezk, P & Xie, J. (2013) place more weight on more recent events during a single look-back window.

3.2.1 The HS model with "decay" and "risk aversion"

Introducing the decay function w_i and the risk aversion parameter ρ into the previous HS model. The actual market sentiment of the target asset at time t is $\theta_t = \frac{V_i(B)}{V_i(B)+V_i(S)}$. And the expected market sentiment, $E(\theta_t)$, is the average of the actual market sentiment from the time $t - m$ to time t, which is measured y $\frac{\sum_{i=1}^{m} w_i V_i(B)}{\sum_{i=1}^{m} w_i V_i(B)+\sum_{i=1}^{m} \rho w_i V_i(S)}$. And the market sentiment contributed by herd behavior is measured as follows:

$$HS_t = \left|\theta_t - \frac{\sum_{i=t-m}^{t} w_i V_i(B)}{\sum_{i=t-m}^{t} w_i V_i(B)+\sum_{i=t-m}^{t} \rho w_i V_i(S)}\right| - AF_t \tag{4}$$

$$HS_t = |\theta_t - E(\theta_t)| - E|\theta_t - E(\theta_t)|$$

The relationship between the herding sentiment and the future asset price can be measured by running the regression as follows:

$$P_{t+1} = \alpha + \beta HS_t + \varepsilon_i;\ t \in N_{++} \tag{5}$$

3.3 Description of Monte Carlo Simulation Procedure

This section describes the procedure of generating the simulated distribution of herding sentiment (HS) by Monte Carlo Simulation. The simulated method used in this study to generate AF_t is the same as the method that the PCM model used, where $AF_t = E|\theta_t - E(\theta_t)|$.

Under the null hypothesis of herding only by random chance, each investment decision for each period is made independently of all other investment decisions at the same decision-making period. The number of bullish events (buying orders) is modeled as a binomial distribution, $b(V_t, \beta_t)$, where V_t is the number of the actual total buying and selling orders during period t, and $\beta_t = |\theta_t - E(\theta_t)|$. θ_t is the actual proportion of the bullish market sentiment created by buying orders relative to the whole market sentiment created by all orders at period t. And $E(\theta_t)$ is the expected proportion of the bullish market sentiment relative to the whole market sentiment from the information collecting window m.

For a given period t, the simulation proceeds as follows. First, a random-number generator is used to produce a draw from a U(0,1) distribution (uniformly distributed between zero and one). Then, if the random draw is larger than $|\theta_t - E(\theta_t)|$, the outcome is rounded to one, which indicates a buying order, otherwise, it is rounded to zero. This procedure is repeated V_t times, getting a sample of V_t Bernoulli draws, whose outcomes are summed to give a draw from a binomial distribution, $b \sim (V_t, |\theta_t - E(\theta_t)|)$. This binomial draw represents the number of buying orders randomly occurring among V_t buying orders and selling orders during the period t. Finally, the adjustment factor, AF_t, which is $E|\theta_t - E(\theta_t)|$ can be calculated by $\frac{N}{V_t}$, where N is the outcomes summed from the binominal distribution $b \sim (V_t, |\theta_t - E(\theta_t)|)$.

$$HS_t = |\theta_t - E(\theta_t)| - E|\theta_t - E(\theta_t)| \tag{6}$$

4. Empirical Study

4.1 Data introduction

This dissertation gets support from the JoinQuant, a data interface, which can call market ticks data. The empirical study uses the auction data, which includes the current prices, cumulative trading volume, cumulative turnover, the volume of the first five buying orders, and the volume of the first five selling orders.

4.2 Theoretical Analysis

The HS model improves the LSV model by introducing the decay function w_i from the CSI model. This chapter will analyze the relationship among decay factor, herding sentiment, and asset price.

The decay speed of the decay function w_i rests with the decay parameter δ and sentiment cumulative window m. The graph of the decay function w_i with different decay parameter δ and the information collecting window m. The grape of decay functions as follows:

As shown in Figure 2, when the information collecting window m remains the same, the smaller the decay parameter δ in the decay function w_i, the slower the information decay speed. For example, the difference of the weight placed between the new information and old information with a larger decay parameter (e.g. $\delta = 3$ in Figure 2) is larger than that with a smaller decay parameter (e.g. $\delta = 0.5$ in Figure 2). In addition, the decay speed is also affected by the length of the decay period which is determined by the information collecting window m. The decay function is steeper with the month information collecting window ($m = 20$) than the quarter information collecting window ($m = 58$). In other words, the shorter the information collecting window m is, the faster the decay function will be.

A decline of decay parameter might be a result of herd behavior since the herd behavior usually places undue weight on past information (Bikhchandani & Sharma, 2001, cited by Dow, S. C, 2011). And the slower decay speed indicates a smaller gap of weight that is placed between the old information and the new information, which means that the past information is placed more weight. The decay speed of information suddenly decreases might indicates a higher probability of forming herd behavior and higher volatility of asset price. For instance, if a piece of information suddenly stops decay or decay slower, it means that the investors are activating more on this information, thus, this information could influence more on price changes.

The herd sentiment is also affected by the decay speed. And the following figure uses the whole data of the Shanghai stock market and Shenzhen stock market to explore the influence of decay speed on the herding sentiment. The graph of the HS indicator with different decay parameters δ is shown as follows:

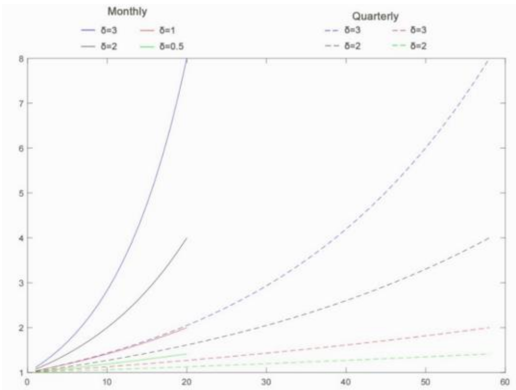


Figure 1. Decay parameter δ.

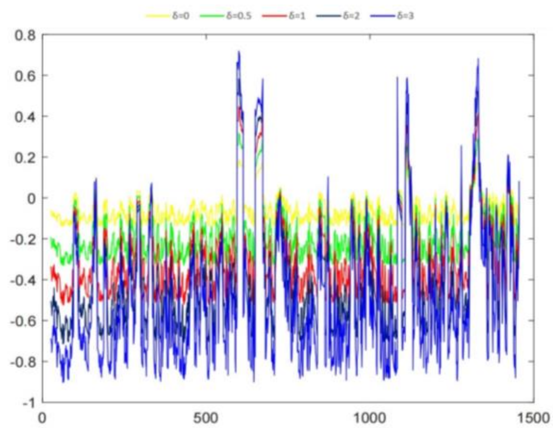


Figure 2. The HS indicator with different decay parameters δ.

Figure 3 illustrates that the larger the decay parameter δ, the higher the absolute value of the HS indicator which means that the higher the herd sentiment. This result is logical. According to Figure 2, the shape of the decay function w_i with a larger decay parameter δ is steeper, which means that the speed of information decay and updating is faster. And the herding sentiment cumulates based on the information over a certain past period. If the information updating in the past is faster the cumulative herding sentiment is more unstable. Herd behavior could be more difficult to form with unstable herding sentiment. In other words, a smaller decay parameter means a slower decay speed and more stable herd sentiment which contributes to developing herd behavior. And herd behavior could cause the price to deviate from fundamentals and increase price volatility. This is consistent with previous analyses that a drop of decay parameter might indicate an increase in herd behavior which could lead to price volatility.

In summary, a smaller decay parameter δ indicates a slower decay speed and lower volatility of the HS indicator, which increases the herd sentiment and contributes to forming the herd behavior.

4.3 Regression Analyzing

The main idea of this theoretical study is training the HS model by machine learning and monitoring the sensitive indicators (e.g. decay parameter δ) which are different between the herding period and general period to predict the future herd behavior. The decay parameter δ should be different during different periods, such as the periods of stable price and volatile prices. The HS model should be trained by continuously monitoring the future market price, and adjusting the parameters (decay parameter δ and sentiment cumulative window m) until the actual price for the future stays around the price forecast of the model to get to the most suitable model parameters. If the suitable parameter of the model (e.g. decay parameter δ) of the model suddenly has a decline in the future, it indicates that the herding sentiment could increase and asset price might fluctuate shortly.

To simplify the empirical analysis, this section does not use machine learning to train the model to get the decay parameter. In order to find the most suitable parameter, this study first sets the different decay parameter δ and the sentiment cumulative window m into the HS model, then compares the root-mean-square error (RMSE[3]) of the model with different parameters, and finally gets the most suitable decay parameter δ and the sentiment cumulative window m for this model at the minimum RMSE (root-mean-square error). To simplify the process, the study here only considers whether to choose the month information collecting window ($m = 20$) or the quarter information collecting window ($m = 58$).

This section randomly chooses six stocks and uses the daily tick data from 2015-07-31 to 2021-07-31 to explore whether monitoring the decay parameter can predict the price trend. The correlation coefficient β between the asset price and herding sentiment and the most suitable decay parameter δ is as follows.

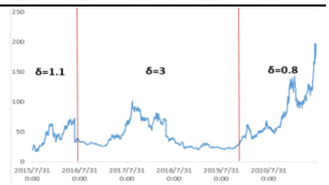
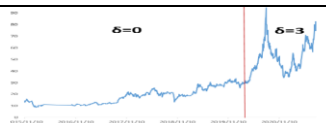
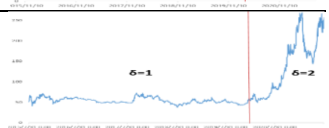
Stock	period	Stable	δ	β	Asset price and δ
000792 (1)	2015.07-2016.01	U	0.5	1026.98*** (-2.404)	
	2016.02-2017.05	S	3	231.127 (1.576)	
	2017.06-2018.07	U	1.5	869.883*** (-2.981)	
	2018.07-2020.03	S	5	14.550 (0.10789)	
002460 (2)	2015.07-2016.06	U	1.1	2559.135* (1.664)	
	2016.07-2019.12	S	3	-873.231*** (-3.208)	
	2020.01-2021.07	U	0.8	2632.132** (2.071)	
300274 (3)	2015.08-2020.05	S	3	1962.653*** (7.416)	
	2020.06-2021.07	U	1.5	5800.377*** (3.475)	
002607 (4)	2015.08-2018.05	S	4.3	-199.090* (-1.685)	
	2018.06-2021.07	U	2.9	1115.690*** (-4.123)	
330142 (5)	2015.11-2020.03	S	0	324.3316 (1.030)	
	2020.04-2021.07	U	3	-412.328 (-0.546)	
002594 (6)	2015.08-2020.01	S	1	-320.136* (-1.813)	
	2020.02-2021.07	U	2	1526.07 (-0.542)	

Figure 3. The asterisks *, ** and * indicate statistical significance at the 10%, 5%, and 1% levels, respectively.**

[3]In this section, $\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{m}(\hat{p}_{t+1}-p_{t+1})^2}{n}}$

First, this test divides the data of each stock into different groups according to price stability. As shown in the third column (Stable) in Table 1, U and S represent unstable periods (the period of volatile price) and stable periods (the period of stable price) respectively. Then, the decay parameters δ are set from 0.0 to 10.0. Finally, the most suitable decay parameter δ for each group can be found at the minimum RMSE, shown in the fourth column δ in Table 1. The fifth column β is the correlation coefficient between P_{t+1} (the asset price at the period t+1) and HS_t (the market sentiment created from herd behavior at the period t).

According to the most suitable decay parameter result in the fourth column δ, the result of the first four stocks shows that the decay parameter δ in the period of stable price is larger than that in the period of volatile price. Although the result of stock (5) and (6) is opposite, the regressions of stock (5) and (6) are not significant. Therefore, the following conclusion can be drawn, when the regression result is significant, the decay parameter δ is smaller in the period of volatile price, which means that the decay speed of information is slower and herd sentiment is more stable which is good for forming herd behavior. This is consistent with the previous hypothesis, Moreover, according to the stock (1,2,3,4,6), the correlation coefficient β between P_{t+1} and HS_t is positive during the period of volatile price, which means that the increasing market bullish sentiment created by herd behavior could lead to stock price increases and vise versa.

5. Conclusion and Limitation

The main contribution of this dissertation is the theoretical model which adds the time dimension to the previous herd behavior models. This HS model improves the LSV model by introducing the decay function w_i from the CSI model. Different from previous studies, the purpose of this dissertation is not to explore the factors that cause or affect herd behavior but to come up with a method to find a sensitive indicator to predict the possible future price trend or herd behavior.

In order to predict the price trend better, it is important to move beyond previous approaches that test the herd behavior which had already occurred based on historical data. The main aim of this model is to predict the short-term trends of asset price through monitoring and following up the HS indicator and the decay parameter δ. If the decay parameter δ suddenly decreases, it means that the herd sentiment and the volatility of futures prices might increase shortly. However, this model can only focus on a certain asset or portfolio, that is, if a new asset is added to the original portfolio, the model has to be retested to get new decay parameters. And if the correlation coefficient between HS_t and P_{t+1} keeps significantly positive for a while, it could suggest the increasing future price. The future study can use machine learning to train this model and monitor the sensitive indicator to make more accurate predictions.

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