

J.Rakhmatov,
MBA student of Banking and Finance Academy
of the Republic of Uzbekistan

HERDING BEHAVIOR IN STOCK AND CRYPTOCURRENCY MARKETS: EMPIRICAL AND COMPARATIVE ANALYSIS

Abstract: This study investigates the presence of the herding behavior in the US stock market and crypto market by employing daily closing prices of the selected US stocks and cryptocurrencies. Cross Sectional Absolute Deviation (CSAD) method which was developed by Chang, Cheng, and Khorana (2000), has been employed in order to evaluate dispersion of the individual stock's and crypto currency's return from market portfolio. We estimated the results based on OLS and a Markow regime switching model. The presence of the herding behavior was witnessed on both markets under OLS regression tool while adjusted R-square and R-square invalidated the fitting of the model to the data. The US stock market was free of herding mentality during the period October, 2017 – October, 2021 while the existence of herding has been noticed in the regime 3 of the Markow regime switching regression estimation among crypto currency traders. This non-existence of herding in the US stock market and the existence of herding in the crypto currency market can be explained with proper government regulations.

Key words: behavioral finance, herding behavior, stock market, crypto currency market, CSAD, OLS, Markow switching model

Аннотация: В этом исследовании изучается наличие стадного поведения на фондовом рынке США и рынке крипто валют с использованием ежедневных цен закрытия выбранных акций и крипто валют США. Метод поперечного абсолютного отклонения (CSAD), разработанный Chang, Cheng и Khorana (2000), использовался для оценки разброса доходности индивидуальный акций и крипто валюты от рыночного портфеля. Мы оценили результаты на основе OLS и модели переключения режимов Маркова. Наличие стадного поведения было засвидетельствовано на обоих рынках с помощью инструмента регрессии OLS, в то время как скорректированные R-квадрат и R-квадрат сделали недействительным соответствие модели данным. В период с октября 2017 года по октябрь 2021 года фондовый рынок США был свободен от стадного мышления, в то время как наличие стадности было замечено в режиме 3 оценки регрессии переключения режима Маркова среди трейдеров крипто валюты. Это отсутствие стадности на фондовом рынке США и существование стад на рынке крипто валют можно объяснить надлежащими правительственными постановлениями.

Annotatsiya: Maqola Amerika Qo'shma Shtatlari birjasi va kriptovalyuta bozorida investorlarning oldingi investorlar fikriga ergshishlikka bolgan moyillikni tadqiq etadi. Maqolada aksiya va kriptovalyutalarning kunlik yopiladigan narxlari va Chang, Cheng, and Khorana (2000) ning CSAD metodi qo'llanilib, u orqali individual

aksiyalar va kriptovalyutalar daromadlarining investitsiya portfelidan qanchalik darajada oʻgʻish darajasi aniqlangan. Biz OLS va Markow switching econometric modeli orqali regressiya natijalariga erishdik. R-kvadrat qiymati modelning maʼlumotlar toʻplamimizga mos emasligini koʻrsatdi. Natijalar, 2017-yil oktabrdan 2021-yil oktabrgacha boʻlgan davrda AQSh fond bozori bir biriga taqlid qilish mentalitetidan xoli ekanligini hamda ushbu davrda kripto valyuta invetorlari oʻrtasida taqlidiy savdolar Markow Swithing modelining 3 – rejimida amalga oshirilganini koʻrsatadi. AQSH fond birjasida taqlidiy amaliyotlarning mavjud emasligi va kriptovalyuta bozorida ushbi hatti harakatlarning mavjudligi AQSH hukumatining tegishli nazorat qiluvchi qarorlari bilan izohlanadi.

Introduction

Financial derivatives markets that includes stocks, equities, commodities, foreign exchange, cryptocurrency, options, futures and many more, have becoming widely popular and available for every individual. Take for example a stock market, a global stock market value increased from 298 billion to 61 trillion US dollar, during 1975-2020 years¹. According to the Stock Market Statistics, 55 percent of the USA adults' population has money in the stock market². The research, which is conducted by Aite Group, illustrates that more than 54 million adults of the USA population alone have been involved in self-directed trading while professional traders who manages their own retail fund as well as individuals' account constitute only 6 percent of that figure³. In addition, the average age of the US traders is 47-year-old who trades stocks and forex, according to the report by Broker Notes. Until recently, the access to the brokerage firm for trading has been very difficult due to high investment limit set by brokerage firms.

After the introduction of Bitcoin by Nakamoto (2008) and massive cryptocurrency realizations made access to the trading, easy. The number of centralized and decentralized exchanges has been skyrocketed by 2021. The average age of the UK traders is 27-year-old who trades cryptocurrencies according to the report by Broker Notes. Due to no limits in deposit and KYC (know your customer) requirements, the age and the number of traders have increased dramatically. As a result of large-scale improvements in FinTech area, stocks, forex and derivatives brokerage firms have also made mobile apps like WeBull, Robinhood and eToro that enable every individual to have an access to trading via the phone. Interestingly, at the moment, all cryptocurrency and stocks trading web platforms and mobile applications have a copy trading feature which enables every unconfident trader to copy the trading strategies from listed professional licensed traders. Features like copy trading on both stock and crypto currency market, has an imminent impact on herding behavior in the market overall.

¹ The World Bank. Stocks traded, total value (current US\$) <https://data.worldbank.org/indicator/CM.MKT.TRAD.CD>

² Spendmenot. Amazing Stock Market Statistics to Know in 2021 <https://spendmenot.com/blog/stock-market-statistics/>

³ Aite Novarica. Online trading penetration in the United States and retail traders' trading device preferences are rapidly changing <https://aitegroup.com/online-trading-penetration-united-states-and-retail-traders-trading-device-preferences-are-rapidly>

Decision-making is a key factor in successful operations of individual trading accounts or investment portfolios. However, individual decision-making process on investment in stock, commodity, currency, cryptocurrency and derivatives market might be effected by professional gurus or well-know people, i.e., engage in herd behavior. Therefore, more and more researchers have been studying the existence of herding behavior in financial markets, for several years. Banerjee (1992) proposes the foundation to the theory of “A simple model of herd behavior”, where individuals make a decision on choices, by mimicking the decision of others. By utilizing a sequential decision model, Banerjee (1992) founded out that there are two types of decision makers: those who have a signal and those who do not have a signal. People who do not have a signal tended to obtain it from others and imitated as if they have a signal, which creates herding behavior among the selected group of people.

After 1995, scholars have started to include market data of asset’s return on their empirical literatures. Christie and Huang (1995) conducted a research on existence of herd behavior in equity returns. They observed the daily data from 1962 to 1988 for NYSE and Amex firms and the monthly data from 1925 to 1988 for NYSE firms. “The dispersion of equity return, S , is calculated by the following equation:

$$S = \sqrt{\frac{\sum_{i=1}^n (r_i - \bar{r})^2}{n - 1}},$$

where r_i is a return on firm i , $\bar{r}$ is the cross-sectional average of the n returns. In addition, the authors performed regression analysis for the daily and monthly data through the following equation:

$$S_t = \alpha + \beta_1 D_t^L + \beta_2 D_t^U + \epsilon_t,$$

where $D_t^L = 1$ if the market return on day t lies in the extreme lower tail of the return distribution, $D_t^L = 0$ otherwise, and $D_t^U = 1$ if the market return on day t lies in the extreme upper tail of the return distribution, $D_t^U = 0$ otherwise”. Christie and Huang (1995) found out that dispersions increased dramatically only during large average price change and individual equity returns dispersion did not populate close to the market return at the market stress condition. Moreover, Christie and Huang (1995) concluded, “Because dispersion quantifies the average proximity of individual returns to the mean, it reveals the presence of the herd behavior when individual asset returns follow the lead of the portfolio returns. Herd behavior was absent in the US financial market for the taken period”.

Chang et al., (2000), had made another essential research, in terms of presence of herding in financial markets of the countries. Chang et al., (2000) further developed the work, which is carried out by Christie and Huang (1995). Chang et al., (2000) used non-linear regression analysis to find out the relation between the level of the certain equity return dispersions and market return, while Christie and Huang (1995) employed linear regression specifications to detect herding in the equity market. In addition,

Chang et al., (2000) investigated the equity market of both developed and developing countries such as USA, Hong Kong, Japan, South Korea and Taiwan. The authors tested the impact of the quality of the information disclosure and maturity of derivatives market, on investment decision making of both individual and institutional investors. Finally, the authors analyzed the relationship between liberalization of Asian financial markets and shifts in herd behavior.

Chang et al., (2000) used the daily stock price of NYSE and AMEX firms from January 1963 to December 1997. The daily stock price data and data for equally weighted market return index had been obtained from Center for Research in Securities Prices (CRSP) for the USA equity market. The similar data for Hong Kong, Japan, South Korean and Taiwan was obtained from the Pacific-Basin Capital Markets Research Center (PACAP) at the University of Rhode Island. Moreover, “Chang et al., (2000) tended to use conditional version of the Black (1972) CAPM:

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

where γ_0 is the return on the zero-beta portfolio, β_i is the time-invariant systematic risk measure of the security, $i = 1, \dots, N$ and $t = 1, \dots, T$. Also, let β_m be the systematic risk of an equally-weighted market portfolio”. The authors defined the expected cross-sectional absolute deviation of stock returns (ECSAD) as follows:

$$ECSAD_t = \frac{1}{N} \sum_{i=1}^N AVD_{i,t} = \frac{1}{N} \sum_{i=1}^N |\beta_i - \beta_m| E_t(R_m - \gamma_0)$$

As compared to Christie and Huang (1995) who used the linear relations, Chang et al., (2000) come up with the quadratic relationship between dispersions and market return:

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

Chang et al., (2000) concluded that for the USA and Hong Kong equity market, the empirical results were almost the same with Christie and Huang (1995) showing no presence of herding in these markets. However, for emerging markets like South Korea and Taiwan, there was a non-linear relation between certain equity return dispersions and market price movement. The results were in favor of existence of herd behavior in these two emerging markets where there was a lack of a good quality firm specific information.

Data and Methodology

Selected stocks of the companies are Tesla, Amazon, Apple, Microsoft, NVidia corporations, GameStop Corporation and AMC Entertainment Holdings Inc. While Bitcoin, Ethereum, Cardano, Binance, XRP and Dogecoin crypto currencies and tokens were selected from crypto market in order to test existence of herd behavior. As a proxy to the market, S&P 100 index and CCI30 Index are selected. Dataset for stocks covers the period between October 2016 and October 2021 while dataset for cryptocurrencies

covers the period from October 2017 to October 2021. The daily closing prices of the stocks and cryptocurrencies are obtained from finance.yahoo.com. S&P 100 Index daily closing price data are obtained from finance.yahoo.com while CCI30 Index daily closing price data are obtained from <https://cci30.com/#statistics>. Daily return of each crypto tokens or stocks is calculated using the following equation:

$$R_c = (P_{c,t} - P_{c,t-1}) / P_{c,t-1}$$

R_c stands for return on crypto currency or stock c on day t . P_c stands for closing price of crypto currency or stock c on day t and $t-1$.

We can see from the table 1 below that GME (Gamestop Corp) stock had the highest daily average return on investment amid stocks in the portfolio, which is equal to 0.0046 % and the lowest average daily return belongs to MSFT (Microsoft Corp), 0.0014% and AAPL (Apple Inc), 0.0015%. Standard deviation of CSAD is equal to 0.0245%. The data for the stocks shows that the distribution series have more positive values and peaked-curve. The data of GME (Gamestop Corp), CSAD, absolute market return and squared market return have right-skewed data while all other stocks have normal skewness tending to be around 0 with a little bit less or more values deviating from it. The conclusions for crypto dataset can be drawn with the help of table 1.

Table 1: Descriptive statistics of sample data for stocks

	Apple	Tesla	Nvidia	Microsoft	Amazon	Gamestop	AMC	S&P 100	CSAD	Market Return	Absolute Market Return	Squared Market Return
Mean	0,0015	0,0030	0,0024	0,0014	0,0013	0,0046	0,0036	0,0007	0,0197	0,0007	0,0071	0,0001
Median	0,0011	0,0014	0,0026	0,0011	0,0014	-0,0006	-0,0026	0,0008	0,0150	0,0008	0,0042	0,0000
Minimum	-0,1286	-0,2106	-0,1876	-0,1474	-0,0792	-0,6000	-0,5663	-0,1157	0,0024	-0,1157	0,0000	0,0000
Maximum	0,1198	0,1989	0,2981	0,1422	0,1322	1,3484	3,0121	0,1013	0,6392	0,1013	0,1157	0,0134
Standard deviation	0,0190	0,0373	0,0303	0,0172	0,0185	0,0869	0,1092	0,0121	0,0245	0,0121	0,0097	0,0007
Skewness	-0,0841	0,3034	0,4273	-0,0015	0,2390	5,8808	17,3805	-0,5854	14,5209	-0,5854	4,5733	12,6364
Excess kurtosis	6,9355	5,4983	11,7100	11,2336	4,7769	80,6838	465,400	19,6638	334,466	19,6638	32,9772	196,9786
Observations	1257	1257	1257	1257	1257	1257	1257	1257	1257	1257	1257	1257
Jarque-Bera	2520,8016	1602,6576	7220,1771	6609,4076	1207,1032	348199,8865	11407591,2516	20323,2736	5903264,0270	20323,2736	61339,3505	2065632,4319
p-value	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%

Table 2: Descriptive statistics of sample data for crypto currencies

	BTC	ETH	ADA	BNB	XRP	DOGE	CCi30Index	CSAD	Absolute Market Return	Squared Market Return
Mean	0,0025	0,0030	0,0060	0,0060	0,0035	0,0076	0,0023	0,0242	0,0322	0,0022
Median	0,0019	0,0016	0,0013	0,0012	-0,0010	-0,0008	0,0038	0,0166	0,0221	0,0005
Minimum	-0,3717	-0,4235	-0,3957	-0,4190	-0,4233	-0,4026	-0,3840	0,0023	0,0000	0,0000
Maximum	0,2525	0,2646	1,3668	0,6976	0,8347	2,7564	0,2161	0,4729	0,3840	0,1474
Standard deviation	0,0417	0,0522	0,0821	0,0668	0,0722	0,1087	0,0464	0,0275	0,0334	0,0061
Skewness	-0,1507	-0,2606	4,9457	1,8412	2,6118	12,5458	-0,7291	6,3465	2,6580	12,7063
Excess kurtosis	7,2295	5,6092	67,5836	18,7826	24,4975	289,7892	6,1974	70,1255	13,9432	253,0563
Observations	1461	1461	1461	1461	1461	1461	1461	1461	1461	1461
Jarque-Bera	3187,2288	1931,8513	284004,8080	22301,3929	38193,7540	5150474,9255	2467,5371	309165,8375	13555,0677	3937595,2122
p-value	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%

Table 3: Correlation matrix for stock data

	CSAD	_RM_T_	R_2M_T	CSADT_1	CSADT_2	CSADT_3
CSAD	1.000000	0.485338	0.222066	0.663342	0.636593	0.578341
_RM_T_	0.485338	1.000000	0.795266	0.461228	0.472352	0.464887
R_2M_T	0.222066	0.795266	1.000000	0.196294	0.200408	0.203900
CSADT_1	0.663342	0.461228	0.196294	1.000000	0.663293	0.636502
CSADT_2	0.636593	0.472352	0.200408	0.663293	1.000000	0.663245
CSADT_3	0.578341	0.464887	0.203900	0.636502	0.663245	1.000000

Table 4: Correlation matrix for crypto currency data⁴

	CSAD	_RM_T_	R_2M_T	CSADT_1	CSADT_2	CSADT_3
CSAD	1.000000	0.597289	0.337607	0.738614	0.684041	0.635047
_RM_T_	0.597289	1.000000	0.800638	0.519311	0.529276	0.517846
R_2M_T	0.337607	0.800638	1.000000	0.256674	0.263853	0.257657
CSADT_1	0.738614	0.519311	0.256674	1.000000	0.738582	0.684001
CSADT_2	0.684041	0.529276	0.263853	0.738582	1.000000	0.738529
CSADT_3	0.635047	0.517846	0.257657	0.684001	0.738529	1.000000

It is clearly seen from the table 3 and table 4 that almost all variables are highly correlated with each other for both stock and crypto dataset. The highest correlation can be seen on CSAD value with its previous states' values. There is a lower correlation between CSAD and squared market return for both datasets.

Methodology

The original method of herding behavior estimations was developed by Christie and Huang (1995) which was based on rational asset pricing model CAPM. The Cross Sectional Standard Deviation method of Christie and Huang (1995) can be expressed as follow:

$$CSSD = \sqrt{\frac{\sum_{i=1}^n (R_{i,t} - \bar{R})^2}{n-1}}$$

where R_i is a return on an asset at the time t while $CSSD_t$ is the cross sectional average of returns on the selected portfolio of any investor at the time t . Christie and Huang (1995) proposed the CSSD method in order to show the deviation of investors' or traders' return to the mean. CSSD might prove the existence of herding if the return is within the range of the mean returns and vice versa.

$$CSSD_t = \alpha + \beta_L D_{Lt} + \beta_U D_{Ut} + \varepsilon_t$$

Moreover, the authors developed the model only for capturing the behavior of herding during *up* and *down* markets while the method might omit the testing during normal distribution periods.

The research was further developed by Chang, Cheng, and Khorana (2000). The authors worked on the drawbacks of Christie and Huang (1995) and developed the Cross Sectional Absolute Deviation (CSAD) method of estimating herding.

⁴ CSAD – cross sectional absolute deviation, _RM_T_ - absolute market return, R_2M_T - squared market return, CSADT_1 - is the value of CSAD's previous state (CSAD t-1) and CSADT_2 - is the value of CSAD's previous state (CSAD t-2) and CSADT_3 is the value of CSAD's previous state (CSAD t-3).

$$CSAD_t = \frac{1}{N} \sum_{i=1}^n [R_{i,t} - R_{m,t}], CSAD_t = \alpha + \alpha_1[R_{m,t}] + \alpha_2 R_{m,t}^2 + \varepsilon_t$$

The CSAD model of Chang, Cheng, and Khorana (2000) focused on the linearity problem of the previous work and solved it by giving alternative non-linear estimation of herding for the financial markets. They assumed that the return of investment of individuals and the market return should make non-linear co-movement. Importantly, the CSAD method has been employed by most of the researchers in this field compared to other methods and those researchers concluded that the CSAD method can depict correct results comparing with the CSSD method. Therefore, we tended to employ the CSAD method of estimating herding in this paper.

Empirical findings

The study regression analysis was carried out under linear herding model (OLS) and non-linear Markow regime switching model. OLS estimations was based on the following equation:

$$CSAD_t = \alpha + \alpha_1[R_{m,t}] + \alpha_2 R_{m,t}^2 + \varepsilon_t$$

While the Markow regime switching model regressions were based on the following equation:

$$CSAD_{t,1} = \alpha + \alpha_1[R_{m,t}] + \alpha_2 R_{m,t}^2 + \alpha_{3+k,1} CSAD_{t-k} + \varepsilon_{t,1}; S = 1$$

$$CSAD_{t,1} = \alpha + \alpha_1[R_{m,t}] + \alpha_2 R_{m,t}^2 + \alpha_{3+k,2} CSAD_{t-k} + \varepsilon_{t,2}; S = 1$$

$$CSAD_{t,1} = \alpha + \alpha_1[R_{m,t}] + \alpha_2 R_{m,t}^2 + \alpha_{3+k,s} CSAD_{t-k} + \varepsilon_{t,s}; S = s$$

Figure 5: OLS regression analysis for stocks

Dependent Variable: CSAD
Method: Least Squares
Date: 12/14/21 Time: 09:48
Sample (adjusted): 10/04/2016 9/30/2021
Included observations: 1257 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.015095	0.000988	15.27331	0.0000
RM T	0.748313	0.132078	5.665690	0.0000
R_2M_T	-4.940084	1.912103	-2.583586	0.0099
R-squared	0.038387	Mean dependent var		0.019710
Adjusted R-squared	0.036853	S.D. dependent var		0.024464
S.E. of regression	0.024009	Akaike info criterion		-4.618433
Sum squared resid	0.722816	Schwarz criterion		-4.606174
Log likelihood	2905.685	Hannan-Quinn criter.		-4.613826
F-statistic	25.02926	Durbin-Watson stat		1.160962
Prob(F-statistic)	0.000000			

As we can see from the OLS regression results coefficients of all independent variables significant at 1%, 5% and 10% level. In spite of the fact that OLS results showed existence of herding in the stock market, R-squared and adjusted R-squared

disproved the fitting of the model to the data. The equation for the regression can be estimated as follows:

$$\text{CSAD} = 0.0150954428522 + 0.748312972453 \cdot \text{RM_T} - 4.94008414279 \cdot \text{R_2M_T};$$

Figure 6: Markow regime switching model analysis for stocks

Dependent Variable: CSAD
 Method: Markov Switching Regression (BFGS / Marquardt steps)
 Date: 12/14/21 Time: 10:45
 Sample (adjusted): 10/04/2016 9/30/2021
 Included observations: 1257 after adjustments
 Number of states: 3
 Initial probabilities obtained from ergodic solution
 Huber-White robust standard errors & covariance
 Random search: 25 starting values with 10 iterations using 1 standard deviation (rng=kn, seed=1559190076)
 Convergence achieved after 68 iterations

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Regime 1				
C	0.042590	0.024619	1.730001	0.0836
_RM_T_	-7.321674	5.431158	-1.348087	0.1776
R_2M_T	880.0604	252.8605	3.480418	0.0005
CSADT_1	1.530589	0.487605	3.138996	0.0017
CSADT_2	-0.079091	0.205372	-0.385110	0.7002
CSADT_3	-0.014302	0.367721	-0.038893	0.9690
LOG(SIGMA)	-3.488985	0.125137	-27.88127	0.0000
Regime 2				
C	0.013773	0.002143	6.427475	0.0000
_RM_T_	0.335304	0.141244	2.373927	0.0176
R_2M_T	-1.423167	1.576828	-0.902551	0.3668
CSADT_1	0.172044	0.011729	14.66860	0.0000
CSADT_2	0.188480	0.021090	8.936945	0.0000
CSADT_3	0.077302	0.040165	1.924635	0.0543
LOG(SIGMA)	-4.462221	0.140751	-31.70297	0.0000
Regime 3				
C	0.009562	0.000491	19.46940	0.0000
_RM_T_	0.089452	0.057863	1.545927	0.1221
R_2M_T	1.657572	0.854946	1.938804	0.0525
CSADT_1	0.096312	0.027063	3.558828	0.0004
CSADT_2	0.062569	0.030999	2.018432	0.0435
CSADT_3	0.037970	0.008272	4.590248	0.0000
LOG(SIGMA)	-5.363952	0.077938	-68.82302	0.0000
Transition Matrix Parameters				
P11-C	-0.997254	0.842797	-1.183268	0.2367
P12-C	0.955411	0.595178	1.605253	0.1084
P21-C	-1.855170	0.717464	-2.585733	0.0097
P22-C	0.744748	0.652191	1.141917	0.2535
P31-C	-3.947227	0.641157	-6.156411	0.0000
P32-C	-2.102787	0.560790	-3.749688	0.0002
Mean dependent var	0.019710	S.D. dependent var	0.024464	
S.E. of regression	0.024455	Sum squared resid	0.739162	
Durbin-Watson stat	1.880835	Log likelihood	4262.056	
Akaike info criterion	-6.738354	Schwarz criterion	-6.628024	
Hannan-Quinn criter.	-6.696889			

The results show that coefficients for c, absolute market return and previous 2 states CSAD are statistically insignificant at 1%, 5% and 10% level at regime one. The only statistically significant coefficient stands for squared market return. However, the

sign is positive which means there is no herding behavior in the stock market during almost all three regimes. The equations for the regression can be estimated as follows:

$$\begin{aligned} \text{CSAD} &= 0.0425903040743 - 7.32167369721 \cdot \text{_RM_T_} + 880.060356544 \cdot \text{R_2M_T} + 1.53058929715 \cdot \text{CSADT_1} - 0.0790906510997 \cdot \text{CSADT_2} - 0.0143018347591 \cdot \text{CSADT_3}; \\ \text{CSAD} &= 0.0137730786979 + 0.33530375722 \cdot \text{_RM_T_} - 1.4231673924 \cdot \text{R_2M_T} + 0.172044062136 \cdot \text{CSADT_1} + 0.188479927554 \cdot \text{CSADT_2} + 0.0773023587733 \cdot \text{CSADT_3}; \\ \text{CSAD} &= 0.00956235837808 + 0.0894518694059 \cdot \text{_RM_T_} + 1.65757235616 \cdot \text{R_2M_T} + 0.0963124011632 \cdot \text{CSADT_1} + 0.0625693453909 \cdot \text{CSADT_2} + 0.0379703469929 \cdot \text{CSADT_3}; \end{aligned}$$

Figure 7: OLS regression analysis for crypto currencies

Dependent Variable: CSAD

Method: Least Squares

Date: 12/14/21 Time: 10:31

Sample (adjusted): 10/02/2017 10/01/2021

Included observations: 1461 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.015403	0.001125	13.68778	0.0000
_RM_T_	0.323393	0.038153	8.476241	0.0000
R_2M_T	-0.740724	0.209091	-3.542591	0.0004
R-squared	0.073071	Mean dependent var		0.024236
Adjusted R-squared	0.071800	S.D. dependent var		0.027479
S.E. of regression	0.026474	Akaike info criterion		-4.423253
Sum squared resid	1.021875	Schwarz criterion		-4.412397
Log likelihood	3234.186	Hannan-Quinn criter.		-4.419204
F-statistic	57.46833	Durbin-Watson stat		0.977954
Prob(F-statistic)	0.000000			

The same results can be seen in the crypto currency market. The lower figures of R-squared and adjusted R-squared showing no reliability of the model for the selected data. Squared market has negative coefficient but it is statistically significant at all levels. The equation for the regression can be estimated as follows:

$$\text{CSAD} = 0.0154031319066 + 0.323393499567 \cdot \text{_RM_T_} - 0.740724056573 \cdot \text{R_2M_T};$$

Figure 8: Markow regime switching model analysis for crypto currencies

Dependent Variable: CSAD
 Method: Markov Switching Regression (BFGS / Marquardt steps)
 Date: 12/14/21 Time: 10:35
 Sample (adjusted): 10/02/2017 10/01/2021
 Included observations: 1461 after adjustments
 Number of states: 3
 Initial probabilities obtained from ergodic solution
 Huber-White robust standard errors & covariance
 Random search: 25 starting values with 10 iterations using 1 standard deviation (rng=kn, seed=1620665384)
 Convergence achieved after 37 iterations

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Regime 1				
C	0.038698	0.008957	4.320297	0.0000
_RM_T_	0.618347	0.372455	1.660191	0.0969
R_2M_T	-2.889655	2.360628	-1.224104	0.2209
CSADT_1	0.243690	0.061089	3.989114	0.0001
CSADT_2	0.068080	0.106581	0.638760	0.5230
CSADT_3	-0.074492	0.088097	-0.845563	0.3978
LOG(SIGMA)	-2.896188	0.203936	-14.20144	0.0000
Regime 2				
C	0.006300	0.000730	8.631106	0.0000
_RM_T_	0.099253	0.021906	4.530766	0.0000
R_2M_T	-0.155734	0.190816	-0.816148	0.4144
CSADT_1	0.111190	0.058778	1.891705	0.0585
CSADT_2	0.044506	0.026166	1.700923	0.0890
CSADT_3	0.062025	0.020810	2.980572	0.0029
LOG(SIGMA)	-5.564497	0.082455	-67.48517	0.0000
Regime 3				
C	0.010467	0.003804	2.751486	0.0059
_RM_T_	0.175873	0.025226	6.972015	0.0000
R_2M_T	-0.275098	0.075188	-3.658806	0.0003
CSADT_1	0.188537	0.129214	1.459113	0.1445
CSADT_2	0.151253	0.071940	2.102500	0.0355
CSADT_3	0.111990	0.065058	1.721400	0.0852
LOG(SIGMA)	-4.683717	0.105042	-44.58912	0.0000
Transition Matrix Parameters				
P11-C	1.661333	0.627587	2.647174	0.0081
P12-C	-1.782065	2.200329	-0.809908	0.4180
P21-C	-3.598290	0.870818	-4.132083	0.0000
P22-C	0.852729	0.468786	1.819015	0.0689
P31-C	-2.661960	0.445473	-5.975583	0.0000
P32-C	-0.398233	0.439709	-0.905675	0.3651
Mean dependent var	0.024236	S.D. dependent var	0.027479	
S.E. of regression	0.021636	Sum squared resid	0.674109	
Durbin-Watson stat	1.974024	Log likelihood	4627.403	
Akaike info criterion	-6.297608	Schwarz criterion	-6.199904	
Hannan-Quinn criter.	-6.261162			

On the other hand, figure 8 shows the regression results for selected crypto currency data. Unlike stock market, the crypto currencies tended to show prominence towards market herding. In spite of the fact that there is a herding in the regime 1 and regime 2, the results are statistically insignificant at 1%, 5% and 10% level. The coefficient of squared market return is -0.275098 and it is statistically significant at all levels which mean in regime 3 period there is existence of herding in the market. The equation for the regression can be estimated as follows:

$$\text{CSAD} = 0.0386981436732 + 0.618346952759 \cdot \text{_RM_T_} - 2.88965496236 \cdot \text{R_2M_T} + 0.243689653575 \cdot \text{CSADT_1} + 0.0680797208311 \cdot \text{CSADT_2} - 0.0744916015388 \cdot \text{CSADT_3};$$

$$\begin{aligned} \text{CSAD} &= 0.00630016399583 + 0.0992531557218 * \text{RM_T_} - \\ &0.155734444238 * \text{R_2M_T} + 0.111189742971 * \text{CSADT_1} + \\ &0.0445061522724 * \text{CSADT_2} + 0.0620254588599 * \text{CSADT_3}; \\ \text{CSAD} &= 0.0104668209471 + 0.175873358304 * \text{RM_T_} - \\ &0.27509776656 * \text{R_2M_T} + 0.18853720858 * \text{CSADT_1} + \\ &0.151253206211 * \text{CSADT_2} + 0.111990239021 * \text{CSADT_3}; \end{aligned}$$

Conclusion

The social media is playing a key role in the traders' life. The professional and nonprofessional analysts are attempting to grow their audience and followers in the social media which can be a sign to the collaborative work or action as a group within any financial markets. Therefore, more and more researchers are attempting to analysis the herding behavior of individuals in the market in order to make a solid conclusion and recommendation for government and individuals.

The most common methods of estimating existence of herding behavior are CSSD and CSAD methods. The static feature of CSSD made the researchers to choose CSAD model for their analysis. The four-year data for stock market and five-year data for crypto market were derived from finance.yahoo.com. In addition, time varying aspect of the data made us choose a Markow regime switching model to carry econometric analysis. The results of this paper illustrate that the herding behavior is common amid crypt traders and individuals rather that stock market followers.

The limitations of this paper includes not performing tests for autocorrelation. Therefore, the results can be biased. However, the main contribution of this paper is, reviewing the concise theory of herding behavior and literature review for the different market. Furthermore, this paper is making a contribution to the existing literature in terms of inclusion recent hype periods (from March 2021 to May 2021) in the crypto market. The period of hype, tweets of well-know people have been reviewed for certain assumptions of herding. Those people are creating herding in the market by manipulation of the price and the volume which can be seen in the crypto market where there is no regulation while the US stock market exhibits free of herding sentiment that is might be due to proper regulations in the market.

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