A new perspective on how investor sentiment affects herding behavior in the cryptocurrency market

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Abstract

This study examines how investor the economic sentiment impacts herding (anti-herding) behavior in the cryptocurrency market. We categorize the cryptos into two groups, called "clean" and "dirty" based on their energy consumption. The results show that investor sentiment has divergent. Specifically, when economic news positively overwhelms investors, herding becomes more apparent in the "clean" cryptocurrencies, while the "dirty" exhibits more pronounced anti-herding behavior. In the clean group, as the market is downward (upward), herding (anti-herding) is more evident if the investors are more optimistic about economic news. In contrast, there is an increase in anti-herding as participants are overwhelmed positively in the dirty group. The findings are crucial for helping regulators and other market participants to better manage when they invest in the bitcoin market.

Keywords: investor sentiment, herding, cryptocurrency, clean cryptos, dirty cryptos, market return

1. Introduction

The emergence and growth of the cryptocurrency market have been significant since the inception of bitcoin (BTC) in 2009 and ether (ETH) in 2015, with the total number of unique currencies and tokens exceeding 9,000 in 2021. According to data from CoinMarketCap, more than 20,200 cryptocurrencies are in use worldwide currently[1]. The increasing importance of the cryptocurrency market in finance and the environment has led to a growing interest in regulating and investing in this market among various stakeholders, including regulators and investors. Recent attention to this market has been attributed to its unique characteristics, as cryptocurrencies are innovative assets that exhibit high volatility and low correlation with traditional assets such as stocks, gold, oil, and currencies

[1] How Many Cryptocurrencies are There? | Number of Cryptocurrencies (capital.com)

(Guesmi et al. 2019). Bitcoin market attracts less experienced individual investors, facilitating sentiment analysis and potentially fostering herding tendencies driven by sentiment (Foley et al. (2019), Corbet et al. (2019), Baker and Wurgler (2007)). The distinction between "clean" and "dirty" cryptocurrencies based on their energy consumption is an important consideration in understanding the dynamics of the cryptocurrency market. According to Anamika and Subramaniam (2022), each cryptocurrency reacts differently because of the various cryptocurrencies' diversity and heterogeneity. The environmental impact of cryptocurrency mining and transactions has become a significant concern, with many investors and regulators focusing on the energy efficiency of these assets. There has been a lot of criticism about the enormous amount of energy that transactions involving traditional cryptocurrencies (Stoll et al. (2019), Ren and Lucey (2022a)). Gallersdörfer et al. (2020) show that the energy consumption of currencies with ASIC-resistant (Application-specific integrated circuits - resistant) algorithms is excessively disproportionate to their market capitalization, suggesting that it is crucial to distinguish between cryptocurrencies that are built on energy-hungry or energy-efficient algorithms. Following this point of view, Ren and Lucey (2022a) defined "dirty" and "clean" cryptocurrencies based on their energy consumption. The dirty cryptocurrencies are all built on Proof-of-Work algorithms for consensus, which results in massive energy usage regarding mining and transactions, while clean cryptocurrencies are built on different varieties of energy-efficient consensus algorithms, including Proof-of-Stake, Ripple Protocol, Stellar Protocol, and some other alternatives. Ren and Lucey (2022b) discovered strong evidence of asymmetric herd behavior in dirty cryptocurrencies, which is more prominent in bearish than in bullish environments. Investor sentiment is very crucial to investors, regulators, and others from the perspective of market microstructure and policymakers looking for market stability. Forgas (1995) found that a good mood lowers risk aversion whereas a bad mood raises risk aversion. Isen and Labroo (2003) and Isen and Patrick (1983) supported the other concept, showing that positive sentiment can lead to more watchful behavior as investors seek to maintain their positive mood. In finance, herding behavior garners significant attention, denoting investors' tendency to mimic the actions of their peers. Such behavior often leads to market inefficiencies and asset mispricing, as decisions may be influenced more by market sentiment than by fundamental values. King and Koutmos (2021) show that t is crucial to recognize and measure herding behavior because it has the potential to trigger a wide range of phenomena, including excess volatility, momentum, and reversals. From a practical viewpoint, investigating sentiment in herding may have effects on hedging strategies and asset allocation because the likelihood of profiting from asset diversification decreases if herding occurs. These insights can be used by managers of funds and portfolios as well as other market participants to better manage and keep an eye on their risk exposure. The behavioral finance's empirical evidence demonstrates investing decisions are strongly linked to investor sentiment (Nofsinger (2005), Edelen et al. (2010), Ahmed (2020), Lakonishok et al. (1992), Filiz et al. (2019), Aharon (2021), Sibande et al. (2021)). However, while there has been increasing interest in the relationship between investor sentiment and herding behavior in traditional financial markets, research on the behavioral aspects of demand for cryptocurrencies has not yet been fully explored (Gurdgiev and O'Loughlin (2020)). Ballis and Drakos (2020) showed that literature investigating the impact of sentiment on herding in the cryptocurrency market is limited with a few studies explored this issue.

To further explore the dynamics of the relationship between news sentiment and herding behavior in the two crypto groups, we carry out step-by-step as follows. We first begin the empirical analysis by investigating herding behavior in 6 dirty cryptocurrencies and 10 clean cryptocurrencies by performing a static model with the model following Chang et al. (2000). We utilize the Daily News Sentiment Index as a proxy for investor sentiment about economic news, which is described by Buckman et al. (2020) and based on the methodology developed by Shapiro et al. (2020) to investigate the impact of sentiment on herding in the cryptocurrency market. Using the static model, we demonstrate the presence of herding in the dirty and clean cryptocurrency group. We then examine the relationship between the news sentiment and herding behavior by using the Ordinary Least Squares (OLS) regression and Quantile regression (QR) as a robustness check. The results show that news sentiment strongly links to herding in the data sample. A very interesting result is revealed about the difference impact between the two cryptos groups. The results are also only asymmetric and different in the clean group when the market goes up and down.

The rest of the study is structured as follows. The data and methodology are presented in Section 2. The empirical results are covered in Sections 3. Section 4 concludes the study.

2. Data and methodology

2.1. Data Description

The dataset includes 6 dirty cryptocurrencies (Bitcoin, Ethereum, Bitcoin Cash, Ethereum Classic, Litecoin, and Quant) from CoinMarketCap, spanning from September 9, 2018 to September 18, 2022, and 10 clean cryptocurrencies (Cardano, Algorand, EOS, Hedera, Polygon, TRON, VetChain, Stellar, XRP, and Tezos) from CoinMarketCap, spanning from September 18, 2019 to September 18, 2022.[2] Similar to Ren and Lucey (2022a), the dirty cryptocurrencies are so termed based on their reliance on Proof-of-Work algorithms, while clean cryptocurrencies are built on different kinds of energy-efficient consensus algorithms, including Proof-of-Stake, Proof-of-Authority, Ripple Protocol, and some other alternatives. In this study, we focus on the equal-weighted return due to Bitcoin's significantly larger market capitalization compared to other cryptocurrencies. We employ the daily news sentiment index described by Buckman et al. (2020) and the methodology developed by Shapiro et al. (2020).[3]

[2] We selected the dirty and clean cryptocurrencies based on their energy consumption and energy-efficient consensus algorithms and the link How Green Is Your Cryptocurrency? List of Top 100+ Cryptos (2022) | Cryptowisser, The 28 Most Sustainable Cryptocurrencies for 2023 - LeafScore, and 15 Environmentally Sustainable Cryptocurrencies To Invest In Right Now (yahoo.com). We excluded cryptos that were not in top 50 or the cryptos did not have a full two-year data when we conducted the analysis.

[3] Daily News Sentiment Index – Economic Research (frbsf.org)

Based on lexical analysis of economics-related news articles, sentiment scores are created from economics-related news articles from 24 major U.S. newspapers collated by the news aggregator service Factiva. The higher values indicate more positive sentiment, and lower values indicate more negative sentiment.

2.2. Methodology

2.2.1. Herding measurement

The majority of empirical studies detect the presence of herding by using two alternative measures of dispersion: Christie and Huang (1995) cross-sectional standard deviation (CSSD), and Chang et al. (2000) cross-sectional absolute deviation (CSAD) in (Eq.1) and (Eq.2):

$$\text{CSSD} = \frac{1}{\sqrt{N-1}}\sqrt{\sum_{i=1}^{N}(R_{i,t} - R_{m,t})^2} \quad \text{(Eq. 1)}$$

$$\text{CSAD} = \frac{1}{N}\sum_{i=1}^{N}|R_{i,t} - R_{m,t}| \quad \text{(Eq. 2)}$$

$R_{i,t}$ is the logarithmic return of individual clean or dirty cryptocurrency i at time t, $R_{m,t}$ is the corresponding cross-section average market return, and N is the number of commodities in the total sample. However, using CSSD as a measure for herding may result in a bias toward outliers (Aharon (2021)), we use the CSAD proxy - the most commonly employed measure of dispersion of returns - in this paper.

Most studies employ the OLS regression described in Eq.3 to capture the herding effect:

$$\text{CSAD}_\text{t} = \alpha_0 + \alpha_1|R_{m,t}| + \alpha_2 {R_{m,t}}^2 + \varepsilon_t \quad \text{(Eq. 3)}$$

According to (Eq.3), the relationship between the CSAD and market returns should be linear without herding. The rational pricing is based on the Capital Asset Pricing Model, showing a positive linear relationship between the stock returns' dispersion and the average market returns. However, if herding occurs, investors will act and move following the market, leading to the divergence of individual assets given by the dispersion term should be much lower to market fluctuations. Consequently, the coefficient α_2 of the squared market return is expected to be negative (positive) if herding (anti-herding) exists. However, according to Yao et al. (2014), the CSAD model has a solid theoretical foundation and offers a number of advantages, but there are two potential flaws: a high degree of multicollinearity between variables $R_{m,t}$and $R_{m,t}{}^2$ and the tendency to be auto-correlated of time series data. Therefore, we augmented (Eq.3) as the following Equations:

$$\mathrm{CSAD_t} = \alpha_0 + \alpha_1|\mathrm{R_{m,t}}| + \alpha_2(\mathrm{R_{m,t}} - \overline{\mathrm{R_{m,t}}})^2 + \alpha_3\mathrm{CSAD}_{t-1} + \varepsilon_t \qquad \text{(Eq. 4)}$$

where $\overline{\mathrm{R_{m,t}}}$ is the arithmetic mean of $\mathrm{R_{m,t}}$.

2.2.2. Herding and news sentiment

We examine the role of news sentiment on herding as the following Equation:

$$\mathrm{CSAD_t} = \alpha_0 + \alpha_1|\mathrm{R_{m,t}}| + \alpha_2(\mathrm{R_{m,t}} - \overline{\mathrm{R_{m,t}}})^2 + \alpha_3\mathrm{Sent_t} + \alpha_4\mathrm{CSAD}_{t-1} + \varepsilon_t \qquad \text{(Eq. 5)}$$

where $Sent_t$ is a proxy for news sentiment in time t. The coefficient α_3 of news sentiment is statistically significant and the coefficient α_2 is statistically significantly negative, implying that news sentiment has a strong influence on herding behavior.

To examine whether herding is more pronounced when investors are overwhelmed by news sentiment, we include an interaction term as given below:

$$\mathrm{CSAD_t} = \alpha_0 + \alpha_1|\mathrm{R_{m,t}}| + \alpha_2(\mathrm{R_{m,t}} - \overline{\mathrm{R_{m,t}}})^2 + \alpha_3\mathrm{Sent_t} + \alpha_4(\mathrm{R_{m,t}} - \overline{\mathrm{R_{m,t}}})^2\mathrm{Sent_t} + \alpha_5\mathrm{CSAD}_{t-1} + \varepsilon_t \qquad \text{(Eq. 6)}$$

The direction of the market return may affect investors' behavior. The literature has recognized asymmetry in herding (e.g.,Chang et al. (2000), Tan et al. (2008)), Vo and Phan (2019)) with respect to up and down markets. Therefore, we modified (Eq.6) as below equation:

$$CSAD_t = \alpha_0 + \alpha_{11}D_{UP}|R_{m,t}| + \alpha_{12}D_{DOWN}|R_{m,t}| + \alpha_{21}D_{UP}(R_{m,t} - \overline{R_{m,t}})^2 + \alpha_{22}D_{DOWN}(R_{m,t} - \overline{R_{m,t}})^2 + \alpha_3 Sent_t + \alpha_{41}D_{UP}(R_{m,t} - \overline{R_{m,t}})^2 Sent_t + \alpha_{42}D_{DOWN}(R_{m,t} - \overline{R_{m,t}})^2 Sent_t + \alpha_5 CSAD_{t-1} + \varepsilon_t$$

(Eq. 7)

where D_{UP} and D_{DOWN} are positive and negative market returns, respectively.

An OLS regression based on the linear model focuses on estimating the conditional mean of the dependent variable given one or more explanatory variables. In contrast, a Quantile regression provides a technique to estimate conditional quantiles of the dependent variable given the explanatory variable(s). With outliers exist and when the distribution of the dependent variable has a strongly non-normal pattern, quantile regression is more reliable than the OLS method (Okada and Samreth (2012)). The τth conditional quantile regression introduced by Koenker and Bassett Jr (1978) as follows:

$$Q_y(\tau x) = x'_t\beta(\tau) \quad \text{(Eq. 8)}$$

where y is the dependent variable and x is a vector of the explanatory variables, $\beta(\tau)$ is the quantile regression coefficient determining the dependence relationship between vector x and the τth conditional quantile of y. The values of $\beta(\tau)$ for $\tau \in [0, 1]$ determine the complete dependence structure of y. To obtain an estimation of the conditional quantile functions, we need to minimize the weighted absolute deviations between y and x as described in the following equation:

$$\hat{\beta}_\tau = \min_{\beta \in R^k} [\tau \sum_{y_t \geq x_t\beta} |y_t - x_t\beta| + (1-\tau) \sum_{y_t \leq x_t\beta} |y_t - x_t\beta|] \quad \text{(Eq. 9)}$$

where x_t β is the approximation to the τth conditional quantile of y.

2.2.3 Rolling window estimation

The rolling window regression estimation is significantly more reliable than utilizing static models over the sample years (Stavroyiannis and Babalos (2017). There is no golden rule in determining the size of the rolling window. Su and Hwang (2009) discover that a long window often leads to a smooth estimate and omit the characteristics of the variation of an asset over time, whereas a short window frequently results in substantial variations of estimates. In this study, static analysis is enhanced by employing one-day rolling regression with 250-day.

3. Empirical results and discussion

Table 1 presents the descriptive statistics of observations, showing small fluctuations. The distributions of all variables are highly skewed and peaked, with values distributed far from the mean.

Table 1

Descriptive statistics for the key variables.

Panel A: Descriptive statistics of the variables for the clean cryptos

Variable	Obs	Mean	Median	S.D.	Min	Max	Skew	Kurtosis
CSAD	1097	0.024	0.020	0.016	0.004	0.128	2.263	10.537
Sent	1097	-0.130	-0.087	0.207	-0.675	0.196	-1.052	3.440
$R_{m,t}$	1097	0	0.001	0.053	-0.552	0.216	-1.695	17.593
$\lvert R_{m,t} \rvert$	1097	0.364	0.027	0.039	0	0.552	4.160	40.413
${R_{m,t}}^2$	1097	0.003	0.001	0.115	0	0.304	19.318	469.606
$(R_{m,t} - \overline{R_{m,t}})^2$	1097	0.003	0.001	0.115	0	0.305	19.319	469.510

Panel B: Descriptive statistics of the variables for the dirty cryptos

Variable	Obs	Mean	Median	S.D.	Min	Max	Skew	Kurtosis
CSAD	1471	0.013	0.010	0.010	0	0.528	2.757	15.772
Sent	1471	-0.105	-0.066	0.193	-0.675	0.228	-1.203	4.127
$R_{m,t}$	1471	0	0.002	0.048	-0.528	0.250	-1.360	16.645
$\lvert R_{m,t} \rvert$	1471	0.013	0.023	0.010	0	0.104	3.911	37.643
${R_{m,t}}^2$	1471	0.002	0.001	0.009	0	0.279	21.737	628.499
$(R_{m,t} - \overline{R_{m,t}})^2$	1471	0.002	0.001	0.009	0	0.280	21.750	629.002

The descriptive statistics reported here are as follows: number of observation (Obs), Mean, Median, Standard Deviation, Maximum (Max), Minimum (Min), Skewness (Skew), and Kurtosis.

Table 2 shows the estimates for the quadratic herding model in (Eq.4), suggesting that herding behavior exists in both clean and dirty crypto groups, but the strength of the herding tendency is weaker in the clean cryptos group.

Table 2

Herding behavior estimation results

	Clean			Dirty		
	α_1	α_2	α_3	α_1	α_2	α_3
all	0.141***	-0.018*	0.394***	0.125***	-0.137***	0.339***
0.2	0.089***	-0.082*	0.213***	0.061***	-0.020	0.130***
0.4	0.071***	0.072	0.327***	0.084***	-0.075**	0.204***
0.5	0.096***	0.020	0.354***	0.086***	-0.087**	0.274***
0.6	0.115***	-0.024	0.414***	0.107***	-0.133***	0.316***
0.8	0.169***	-0.156*	0.610***	0.157***	-0.133	0.464***

"*", "**", and "***" denote significance at the 1%, 5% and 10% levels, respectively.

Table 3 reports (Eq.5) results, showing news sentiment's significant role in herding behavior based on CSAD measures in the two crypto groups. When investors feel optimistic, the dispersion of cryptos returns increases. However, news sentiment has a stronger and more consistent impact on dispersion return in the clean group compared to the dirty group, indicating its greater role in explaining herding behavior in clean cryptocurrencies.

Table 3

Impact of news sentiment on herding behavior

	Clean				Dirty			
	α_1	α_2	α_3	α_4	α_1	α_2	α_3	α_4
all	0.136***	-0.097	0.006***	0.383***	0.123***	-0.132***	0.003***	0.332***
0.2	0.090***	-0.093**	0.004***	0.216***	0.062***	-0.023	0.001	0.126***
0.4	0.069***	0.077	0.002	0.327***	0.084***	-0.075**	0.001	0.203***
0.5	0.091***	0.028	0.002	0.359***	0.088***	-0.089***	0.001	0.270***
0.6	0.119***	-0.028	0.003*	0.385***	0.106***	-0.129***	0.001	0.313***
0.8	0.180***	-0.167*	0.007**	0.565***	0.149***	-0.120	0.004	0.439***

"*", "**", and "***" denote significance at the 1%, 5%, and 10% levels, respectively.

Table 4 shows the results with the interaction terms in (Eq.6). The results imply that the herding (anti-herding) is more pronounced as investors are more optimistic about economic news in the clean cryptos (dirty cryptos). The positive relationship between the news sentiment and herding that are revealed supports the positive effect concept from Isen and Labroo (2003) and Isen and Patrick (1983) regarding the behavior of investors under uncertainty, whereas the positive relationship between the news sentiment and anti-herding supports the concept from Forgas (1995), (Aharon (2021)). **Table 5** shows the estimates asymmetric market performance in (Eq.7). Again, the results reveal the difference in news sentiment's impact in the two groups. The asymmetric effect is only observed in the clean cryptos. This result supports the finding that the performance in the dirty cryptocurrency market does affect investors' behavior in the clean cryptocurrency market from Ren and Lucey (2022b). Moreover, news sentiment correlates positively with herding only in the clean group, suggesting a stronger influence of external factors on these investors compared to those in the dirty cryptos group.

Table 4

Impact of news sentiment on herding behavior with the interaction terms

	Clean					Dirty				
	α_1	α_2	α_3	α_4	α_5	α_1	α_2	α_3	α_4	α_5
all	0.150***	-0.225***	0.007***	-0.503***	0.384***	0.106***	0.032	0.002*	0.587***	0.330***
0.2	0.069***	-0.005	0.005***	-0.352**	0.220***	0.043***	0.156***	0	0.485***	0.129***
0.4	0.088***	-0.077	0.003	-0.411**	0.329***	0.063***	0.121**	0	0.531***	0.201***
0.5	0.102***	-0.123*	0.003*	-0.455**	0.350***	0.073***	0.104**	0	0.561***	0.268***
0.6	0.127***	-0.196**	0.004*	-0.517**	0.396***	0.084***	0.062	0.001	0.514***	0.310***
0.8	0.195***	-0.402***	0.008**	-0.708**	0.567***	0.134***	0.056	0.002	0.880**	0.449***

"*", "**", and "***" denote significance at the 1%, 5% and 10% levels, respectively.

Table 5

Impact of news sentiment on herding behavior on asymmetric market returns

Clean group:

	α_{11}	α_{12}	α_{21}	α_{22}	α_3	α_{41}	α_{42}	α_5
all	0.232***	0.071***	-0.123	-0.058	0.757	0.006***	-0.494***	0.353***
0.2	0.104***	0.034**	0.328*	0.08	1.032**	0.004***	-0.285*	0.194***
0.4	0.151***	0.053***	0.236	0.01	1.156**	0.002	-0.342*	0.291***
0.5	0.175***	0.049***	0.059	0.006	1.348**	0.002	-0.352*	0.310***
0.6	0.206***	0.071***	-0.073	-0.059	0.702	0.003	-0.410*	0.369***
0.8	0.300***	0.092***	-0.404	-0.154	3.021***	0.006*	-0.515	0.507***

Dirty group:

	α_{11}	α_{12}	α_{21}	α_{22}	α_3	α_{41}	α_{42}	α_5
all	0.161***	0.058***	-0.082	0.163**	0.929*	0.689***	0.002*	0.308***
0.2	0.079***	0.024***	0.099	0.238***	0.444*	0.640***	0	0.119***
0.4	0.113***	0.036***	-0.076	0.215***	0.490	0.672***	0.001	0.182***
0.5	0.132***	0.040***	-0.176	0.193***	0.748**	0.651***	0	0.248***
0.6	0.160***	0.048***	-0.056	0.164**	0.797*	0.615***	0.001	0.284***
0.8	0.230***	0.080***	0.050	0.073	1.983***	0.592*	0.003	0.474***

"*", "**", and "***" denote significance at the 1%, 5% and 10% levels, respectively.

Figure 1 and **Figure 2** show strong evidence of both herding and anti-herding behavior in both groups across the sample period. Moreover, the herding patterns in the two groups appear oppositely, again showing the clearly different tendencies in the two groups. Herding tendency in the clean group exists strongly after Sep 2020, whereas herding in the dirty cryptos is prominent before Sep 2020. This finding also follows our prior results, the impact of sentiment is more noticeable since investors are more upbeat about the state of the economy in the clean cryptos.

Figure 1. Rolling regression result in the clean cryptos with a 250-day window

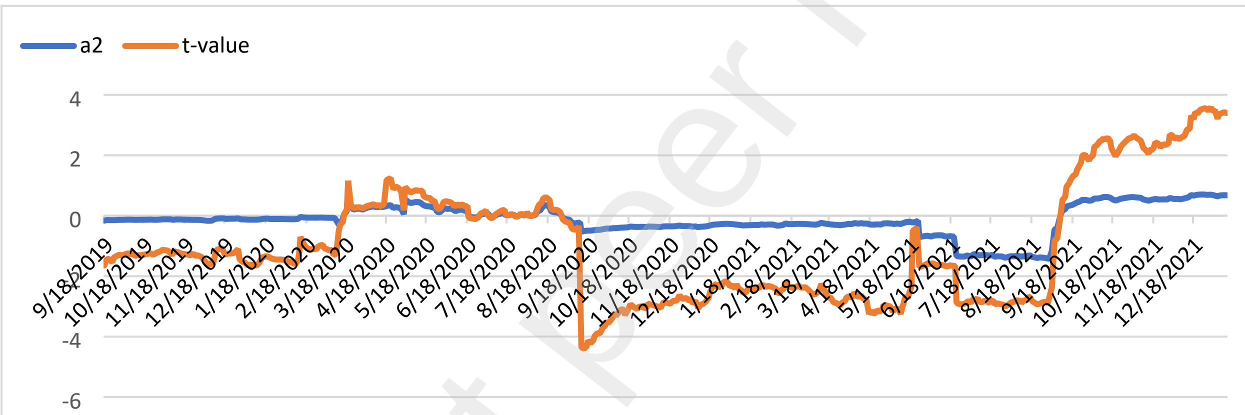
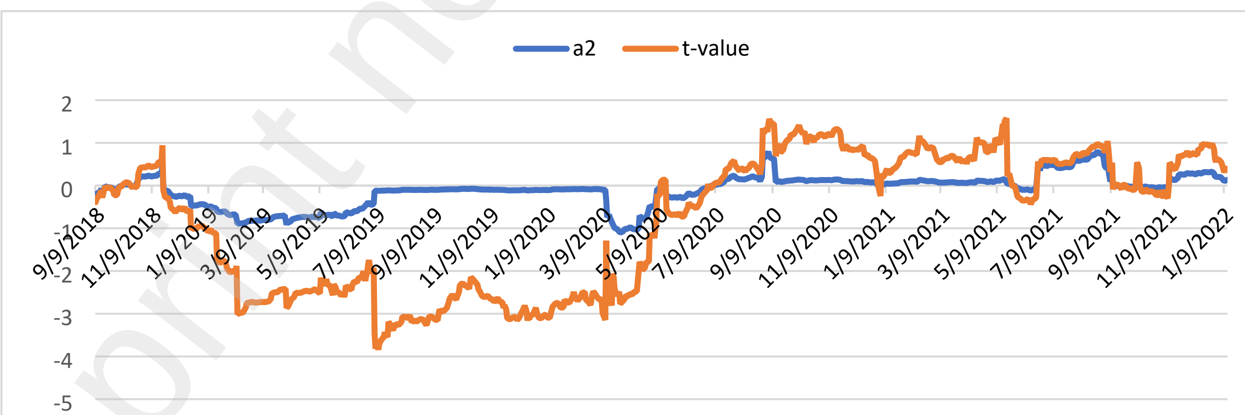


Figure 2. Rolling regression result in the dirty cryptos with a 250-day window



4. Conclusion

This study examines the relationship between news sentiment and herding behavior in the cryptocurrency market, focusing on the differences between the clean and dirty cryptocurrency groups. Our results provide evidence that news sentiment plays a more important role in explaining herding behavior in the clean cryptocurrency group than in the dirty cryptocurrency group. When news sentiment is positive, investors in the clean cryptocurrency group tend to herd more, leading to a higher dispersion of returns. However, in the dirty cryptocurrency group, the impact of news sentiment on herding behavior is less pronounced and less consistent across different quantiles of the distribution. We also found that the relationship between news sentiment and herding behavior is asymmetric in the clean cryptocurrency group. When the market is going up, investors in the clean cryptocurrency group tend to exhibit anti-herding behavior, while when the market is going down, they tend to herd more. Our results suggest that investors in the clean cryptocurrency group may be more influenced by external factors such as news sentiment and market performance, while investors in the dirty cryptocurrency group may be more driven by other factors such as perceived risk and uncertainty. These findings highlight the importance of considering news sentiment as a driver of herding behavior in the cryptocurrency market, and suggest that the effect of news sentiment may depend on the type of cryptocurrencies being considered.

5. Competing interests

The authors declare that they have no competing interests.

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