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Does the cryptocurrency market exhibits feedback trading?

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Abstract

Research has shown that behavioral anomalies affect investors' choices and decisions in the financial markets. One such behavioral anomaly is feedback trading, a phenomenon wherein the investor uses past data to make future decisions. Using Sentana and Wadhwani's (1992) methodology, the 50 most liquid digital currencies (with the most extensive daily data reporting) were analyzed during the period 2013–2018. Results analysis suggests negative feedback trading in Tether Dollar and positive feedback trading in Bitcoin, Ethereum, CassinoCoin and ECC.

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1. Introduction

In the field of behavioral finance, it has long been suggested that human psychology can affect market behavior (e.g., Wood et al., 1985; Karpoff, 1987; Chen and Zhou, 2001; Lee and Rui, 2002; Arnold, 2009). Kramer (2001), for example, points out that optimism and pessimism play an essential role in the pattern of returns and the generation of future returns, volatility, and volume of assets in the market. Another critical factor is the availability of automated online trading for uninformed investors, which resulted in two significant outcomes: increased market participation and increased *feedback trading* (Barber and Odean, 2001).

De Long et al. (1990) assert that investors who generate the effect of *feedback trading,* also known as *feedback traders,* attempt to identify past stock price trends and make their investment decisions based on the expectation that these trends will persist. Consequently, the presence of a large number of *feedback traders* in the market reflects the potential predictability of stock returns, volatility, and volume. This phenomenon aids to explain unusual events in the market, such as excessive volatility, momentum, and reversals in asset prices.

Understanding the behavior of *feedback trading* in the digital market becomes important as trend-tracking amplifies asset price fluctuations in this market in any direction. Such trend-tracking can distort models with boundedly rational traders and short horizons, as can be observed in Abreu and Brunnermeier (2003) and Brunnermeier and Pedersen (2005) for the stock market. Additionally, positive feedback trading induces net selling pressures, increasing liquidity in volatile periods.

The methodology used in this work encompasses Sentana and Wadhwani's (1992) seminal *feedback trading* model, which incorporates the results derived from Bollerslev (1986) using the GARCH model, added to a robustness test to evaluate the GARCH model proposed here (the sign bias test proposed by Engle and Ng, 1993). The database comprised the 50 most liquid digital currencies with the most extensive daily data sets (minimum of 1,000 daily data points). The maximum period of data recording was from April 2013 to April 2018.

2. Literature Review

2.1 The Cryptocurrencies' Market

This market has grown exponentially since 2009 with the launch of the first digital currency, Bitcoin. As noted in Negurita (2014), Bitcoin is the first implementation of a concept called cryptocurrency, which was first described in 1998 by Wei Dai on the cypherpunks mailing list, suggesting the idea of a new form of money that uses cryptography to control its creation and transactions, dispensing a central authority. Officially implemented in 2009 by a programmer or group of programmers with the pseudonym Satoshi Nakamoto.

Currently, there are more than 1,000 digital coins or tokens in the cryptocurrency market, as observed in the Cryptocompare database. The increasing trend in the number of digital coins can be attributed to the introduction of the disruptive blockchain technology by Bitcoin in 2009, which paved the way for shaping the new dynamics that make up the digital universe. In May 2018, the leading digital currencies were Bitcoin (BTC), Ethereum (ETH), Bitcoin Cash (BCH or BCC), Litecoin (LTC), Ripple (XRP), Dashcoin (DASH), NEM (XEM), Monero (XMR), IOTA (MIOTA), and NEO.

Not only does the growth in investments or market cap value impress (despite the devaluation of this market since the end of 2017), but so does the new ecosystem created with this new technology that moves billions of dollars globally. Some of the key examples of new players entering the digital ecosystem are:

- Exchanges: are brokerage firms that trade cryptocurrencies, in other words, where users register to sell and buy Bitcoins or other digital currencies. Some examples are Braziliex and Poloniex, among others;
- Brokerage companies: Brokers are similar to Exchanges, but with the authorization of the regulatory agency for operation (such as SEC in the USA, for example), which can only trade assets registered for sale by the regulatory agency. Some examples are Bitfinex, Noble Markets, BTCC, among others;
- Wallets (soft and hard): these are digital wallets for secure storage of cryptocurrencies. There are more complex modalities that guarantee greater safety (e.g., Trezor) and moderate safety (e.g., Coinkite);
- Investment Companies in Cryptos: developed to operate with loans or investments in funds of Cryptocurrencies, such as Bitbond;
- Banks: the creation of digital (non-physically) banks that operate with cryptocurrencies, and many do not charge fees for sending or receiving remittances, but have their cards (e.g., Moni Bank);
- Digital Payment Platforms: Online payment processors which facilitate payments in cryptocurrencies for online business formats, including integrations with online processors (e.g., GoCoin);
- Database Companies: Companies specializing in generating financial databases for the digital market, as well as historical data (e.g., coinmarketcap);
- Crypto ATMs: operators of ATMs (Automated Teller Machine) for cash withdrawals from cryptocurrencies and purchase cryptocurrencies with fiat currencies (e.g., Lamassu).

It is essential to add that thanks to ICOs (Initial Coin Offer) or ITOs (Initial Token Offer), it has been possible to develop this market, boosting new technologies that have emerged initially in startups and currently are valuable (with growth prospecting). In 2017, in particular, it was the best year for the ICOs, some coins raised the initial value of more than $ 200 million (such as Filecoin, Trezos, and EOS) and others between $ 200 million and $ 100 million (Paragon, DAO, Bancor, Polkadot, QASH and Status). With billions of dollars invested in new projects, investors and speculators are eagerly waiting to see which currency will be the next Bitcoin or Ethereum.

2.2 Investor Behavior and Feedback Models

A growing number of empirical studies have found evidence of a relationship between investor sentiment and market returns. This has motivated many researchers to explore the explanatory power of sentiment for several well-documented anomalies, including size effect (Baker & Wurgler, 2006), the value effect (Frazzini & Lamont, 2008), and momentum effect (Antoniou et al., 2010). The general conclusion of this literature is that sentiment findings are at least a partial explanation for these asset pricing anomalies.

In general, the literature has focused mainly on the positive feedback trading strategy, in which investors buy assets when prices rise and sell when prices fall, the opposite case being negative feedback trading. There is evidence for this feedback trading by individual as well as institutional investors (Nofsinger & Sias, 1999). Furthermore, this phenomenon has been studied and evidenced in a wide variety of markets. Examples include Sentana and Wadhwani (1992) for the North American stock market, Antoniou et al. (2005) for the G-7 stock markets, Laopodis (2005) for foreign exchange markets, Salm and Schuppli (2010) for future index markets, and Chau et al. (2011) for exchange-traded fund (ETF) markets.

The traditional perspective (Friedman, 1953, Fama, 1965) argues that rational speculators with more profitable strategies buy when prices are low and sell when they are high, eliminating market shocks and cushioning excessive price fluctuations. However, proponents of Positive Feedback Trading models (PFT) believe that this view may be incomplete when some market participants adopt strategies based on feedback trading. In the case of this specific destabilizing form called “noise trading” (practice in which decisions to buy, sell or keep assets are irrational and erratic), the negotiation may increase the volatility of returns about the variability of fundamental values. The consequence is a reduction in the autocorrelations of asset returns.

Investors with reactions based on feedback trading strategies buy assets after prices rise and sell after prices fall. There are many common forms of behavior in financial markets, which can be described as PFT. One of the most critical investment trends documented at practical (Shiller, 1990) and academic level (Frankel & Froot, 1986) is the tendency to extrapolate or follow the trend. It may also be a consequence of the stop-loss orders (Osler, 2005), which sell in response to a decline in prices. Another type of PFT is the liquidation of positions held by investors who fail to meet their margin commitments (Hirose et al. 2009) - an investment strategy that was popular until the 1987 crash, prompting institutional investors to increase exposure to equity securities as prices rose and declining exposure to equity securities as prices fell.

The most common methodology for empirically evaluating high-frequency information trading flows in feedback trading is Hasbrouck's (1991) autoregressive vector model (VAR). His model was initially applied to high-frequency data per second, where the direction of causality is explicitly from the flow of orders to the returns of asset prices. Hasbrouck (1991) introduces a shock in the negotiation process, representing private information, and calculates the cumulative effect on the return of the asset. The higher the cumulative effect, or impulse response, the more information transactions are identified. These VAR models have become standard in the literature for high-frequency data - some examples include Dufour and Engle (2000), Evans (2002) and Payne (2003) for currencies and Cohen and Shin (2003) and Green (2003) for treasury bonds and Engle and Patton (2004) for stocks.

Another model that has become widely used was Sentana and Wadhwani (1992), who developed a model of investor behavior that produces a testable implication to evaluate the presence of feedback trading - being a seminal empirical model and the most used since then. Using daily data from the US stock market indexes (1885 to 1988), they found positive evidence of feedback trading, more pronounced in pessimistic markets than in optimistic markets.

Sentana and Wadhwani (1992) developed a theoretical model consisting of two groups of investors: (i) rational investors whose demand for assets depends on the expected return adjusted for risk; and (ii) feedback traders whose demand depends on the previous asset values. This model implies that the real returns are generated as a simple autoregressive process, in which the parameter in lagged returns is a function of the conditional variance, in other words, the existence of a relation between autocorrelation and volatility.

This study uses Sentana and Wadhwani’s (1992) model, which incorporates the results derived from Bollerslev (1986) using the GARCH model. Furthermore, Koutmos (2014) performed an extensive review of the existing literature on positive feedback trading models and their applications to bond markets, foreign exchange, index futures, and individual stocks, pointing to the need to generalize the models for use in behavioral research pertaining to investors in individual asset markets, in addition to the aggregate market.

3. Data and Methodology

Data were collected for 50 currencies with the largest market capitalization, liquidity, and data availability. The daily database was obtained from the CoinMarketCap website. The total period of data recording was from April 2013 to November 2018 (the coin ranking was made on November 13, 2018).

In order to address the issue that the observed autocorrelation may stem from both *feedback trading* and frictions in the market, Sentana and Wadhwani (1992) proposed a model that accounts for two types of investors: rational investors and feedback traders. The rational investor seeks to maximize their expected mean-variance utility according to the following demand function:

$$Q_t = \frac{E_{t-1}(r_t) - \alpha}{\theta \sigma_t^2} \tag{1}$$

where Q_t is the fraction of shares demanded, $E_{t-1}(r_t)$ measures the expected return of shares for the period t based on information from period $t-1$, α is the risk-free return, θ is the risk aversion coefficient and σ_t^2 is the conditional variance in t. The demand for feedback trader shares is a function of past return, given by:

$$Y_t = \gamma r_{t-1} \tag{2}$$

where Y_t is the quantity of shares demanded by the feedback trader and r_{t-1} is the share's return in the previous period (Sentana and Wadhwani, 1992). For positive feedback trading, γ is greater than zero, and for negative it ,is less than zero.

In an equilibrium market, all shares are demanded, and the general market equation is:

$$Q_t + Y_t = 1 \tag{3}$$

Substituting equations (1) and (2) into (3), we have:

$$E_{t-1}(r_t) = \alpha - \gamma r_{t-1} \theta \sigma_t^2 + \theta \sigma_t^2 \tag{4}$$

Assuming the realized returns are equal to the expected returns added to the stochastic error $r_t = E_{t-1}(r_t) + \varepsilon t$, we have:

$$r_t = \alpha - \gamma r_{t-1} \theta \sigma_t^2 + \theta \sigma_t^2 + \varepsilon_t \tag{5}$$

Equation (5) shows that the first-order autocorrelation of returns varies according to market risk σ_t^2, as shown by the term $\gamma r_{t-1} \theta \sigma_t^2$, while its signal will depend on the signal of the feedback trading term γ, wherein positive feedback trading will have a negative autocorrelation, and vice versa.

In order to address the issue that the observed autocorrelation may stem from both feedback trading and market frictions, we propose the following model:

$$r_t = \alpha + \theta \sigma_t^2 + (\phi_0 + \phi_1 \sigma_t^2) r_{t-1} + \varepsilon_t \tag{6}$$

Equation (6) captures the effect of the frictions in the market through the coefficient ϕ_0, while ϕ_1 captures the presence of *feedback trading*.

As ϕ_1= -θγ, this suggests that, if $\phi_1 < 0$ and is statistically significant, positive *feedback traders* are dominant in the market, and vice versa.

As indicated in Equation (1), the volatility of the series of returns is variable over time. The GARCH model, proposed by Bollerslev (1986), is commonly used because it captures not only variance heterogeneity, but also leptokurtic distribution, which most daily financial series follow. The model also incorporates volatility groupings, where large (small) changes in the price of an asset tend to cause large (small) increases in volatility.

Other models documented by Bollerslev (2008), such as TGARCH (Threshold GARCH) and EGARCH (Exponential GARCH), may be more appropriate to capture another common phenomenon in financial series, the leverage effect: negative shocks tend to create more volatility than positive shocks. Sentana and Wadhwani (1992) argue that the choice of less parsimonious models would have little influence on *feedback trading*, the main object of our study. This argument is supported by Shi et al. (2012).

To empirically estimate Equation (2), we incorporate conditional variance by the asymmetric GARCH model (Glosten et al., 1993).

$$\sigma_t^2 = \omega + \beta\varepsilon_{t-1}^2 + \lambda\sigma_{t-1}^2 + \delta S_{t-1}\varepsilon_{t-1}^2 \quad (7)$$

In equation (7), δ captures the volatility asymmetry after positive or negative shocks. S_{t-1} is a binary variable, which takes the value of 1 if the shock at time t-1 is negative, and 0 otherwise. A significantly positive value of δ indicates that a negative shock increases the volatility more intensely than a positive shock.

To evaluate the robustness of the GJR GARCH (1,1), we also made the sign bias test (Engle and Ng, 1993) that examines whether there exist asymmetries following positive versus negative shocks not accounted for by the GARCH-model. According to this test, the squared standardized residuals are regressed against a constant and a dummy that assumes the value of unity in case the residual one period back was negative, and the value of zero otherwise. If the dummy's coefficient is found to be statistically significant, this implies an asymmetric impact on behalf of positive versus negative innovations over volatility (Equation 8).

$$(\varepsilon_t/\sigma_t)^2 = \alpha + \theta s_{t-1} + u_t \quad (8)$$

Other models documented by Bollerslev (2008), such as the TGARCH (Threshold GARCH) and EGARCH (Exponential GARCH) may be more appropriate to capture another very common phenomenon in financial series known as the leverage effect: negative shocks tend to cause more volatility than positive ones. Sentana and Wadhwani (1992), corroborated by Shi, Chiang and Liang (2012), argue that the choice of less parsimonious models would have little influence in detecting feedback trading, the main object of our study.

4. Results and Discussion

Of the 50 cryptocurrencies analyzed, only five showed evidence of *feedback trading*: Bitcoin (BTC), Ethereum (ETH), Tether (USDT), CassinoCoin (CSC) and ECC (ECC). We will focus on these five cryptocurrencies and show an overview of our data by year and by period.

Table 1 presents the SW (Sentana and Wadhwani) test results for the same cryptocurrencies. Concerning conditional variance, δ is positive and statistically significant for all cases, indicating that negative shocks tend to increase volatility at a higher intensity than positive shocks, which is typical for financial assets. The ratio (β+δ) / β was positive and above

1, also indicating that volatility increases in periods when the market shrinks than during market growth.

We observe that the coefficient ϕ_0 is significant and positive for BTC, ETH and CSC and significant and negative for Tether and ECC respectively, indicating positive first-order autocorrelation for BTC, ETH and CSC and negative for the other. The coefficient ϕ_1 of *feedback trading*, the main object of our investigation, proved to be statistically significant, being negative for BTC, ETH, CSC and ECC (positive *feedback traders*) and positive for Tether suggesting the presence of negative *feedback traders* for this coin. This result was expected for Tether, as it has parity with the dollar, which exhibits negative feedback trading in other studies. Regarding feedback trading over time (Table 2) we see that positive (negative) feedback trading was persistent only for BTC (Tether).

Table 1: SW test for *feedback trading*

	BTC	**ETH**	**TETHER**	**CSC**	**ECC**
α	0,0007	0,0005	7,06E-05	0,0260	-0,0108
	0,4832	0,7955	0,000	0,5629	0,0756
θ	1,6186	0,2772	-46,420	-0,2566	-0,0018
	0,0911	0,2547	0,000	0,6067	0,9772
φ0	0,1552	0,0712	-2,059	0,0003	-0,2550
	0,0009	0,0406	0,000	0,9972	0,0000
φ1	-50,8226	-1,2016	27,184	-1,7442	-0,2915
	0,0037	0,0374	0,000	0,0144	0,0277
ω	1,24E-05	0,0003	-1,41E-09	0,0291	2,02E-07
	0,0000	0,0000	0,0000	0,0000	0,9979
β	0,1463	0,3207	0,7652	0,0704	0,0087
	0,0000	0,0000	0,0000	0,0001	0,1269
λ	-0,0663	-0,0650	1,8609	-0,0718	0,0892
	0,0000	0,0762	0,0000	0,0001	0,0000
δ	0,8947	0,6940	0,7166	0,6245	0,9540
	0,0000	0,0000	0,0000	0,0000	0,0000
(β + δ)/β	7,1152	3,1644	1,9365	9,8698	110,3789

Table 2: Feedback trading results

			2015 - 2017				
	BTC	TETHER	DGB	UBQ	GAME		
φ1	-37,3827	2,3464	2,8898	0,1399	-2,1000		
Prob.	0,0463	0,0000	0,0814	0,0270	0,0936		
			2015 - 2016				
	BTC	XRP	TETHER	XVG	VTC	BITCNY	NMC
φ1	-117,7479	-14,3547	4199,5600	6,94890	2,8438	0,6047	-10,4690
Prob.	0,0007	0,0211	0,0000	0,00910	0,0000	0,0200	0,0988
			2015				
	RDD	CSC	NMC	FTC			
φ1	-25,1110	-0,7352	-39,9368	-2,6940			
Prob.	0,0023	0,0696	0,0000	0,0005			
			2016				
	BTC	XRP	DOGE	XVG	RDD	UBQ	BITCNY
φ1	-111,6830	11,1693	6,3444	5,1624	8,2050	-20,5521	-0,0350
Prob.	0,0368	0,0194	0,0296	0,0423	0,0124	0,0684	0,0000
	UNO	BITUSD	XCP				
φ1	-44,5485	-1,2712	4,8042				
Prob.	0,0011	0,0172	0,0003				
			2017				
2017	ETH	DGB	XVG	NXS	VTC	CRW	
φ1	-17,5250	4,6219	-1,5725	26,4268	-8,4496	7,9992	
Prob.	0,0068	0,0000	0,0514	0,0960	0,0295	0,0184	
			2018				
	BCN	DGB	MONA	RDD	BURST	CLOAK	GAME
φ1	-0,8145	24,2477	-6,7393	15,3774	38,32184	60,5641	98,7906
Prob.	0,0000	0,0766	0,0035	0,0018	0,00000	0,0880	0,0000

The sign bias test of Engle and Ng (1993)[1] allow us to conclude that the asymmetric GARCH (1,1) framework employed here successfully captures the volatility asymmetries in our sample (for all period 2015 – 2018), since dummies' coefficients θ were found statistically significant (at least at the 10% level) in 46 of 50 cryptocurrencies[2].

5. Conclusions

Using the model proposed by Sentana and Wadhwani (1992), which incorporates the findings derived by Bollerslev (1986) with the GARCH model, it was possible to capture the negative *feedback trading* in TETHER and the positive *feedback trading* in the BTC, ETH, CSC and ECC currencies.

Thus, we noted the presence of investors who use past data to trade in the purchase and sale of these five currencies, which was as expected, since there are no pricing models that

[1] Not reported here. The results can be provided by the authors on request.
[2] Exceptions were BAY, UNO, XDN and Tether.

exist in practice for digital assets. As it is challenging to use fundamental analysis in this market, technical analysis involving graphs and trends prevails in the investors' decision-making.

We observed that stable coins (like Thether), with inflationary control or based in well-known assets, as the US dollar, tend to attract more assertive investors. We noted the opposite in large coins (like Bitcoin), which exhibited a positive feedback trading effect (existence of noise traders) - often the news of highs and success that the media itself brings about cryptocurrencies induces the inexperienced investor to buy in periods of great optimism. Finally, the GJR GACH model used in this study proved to be adequate, as the sign bias test of Engle and Ng (1993) was statistically significant for 46 of 50 coins.

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