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More heat than light

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More heat than light: investor attention and bitcoin price discovery

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Abstract We investigate how increased attention affects bitcoin's price discovery process. We first decompose bitcoin price into efficient and noise components and then show that the noise element of bitcoin pricing is driven by high levels of attention. This implies that high levels of attention is linked with an increase in uninformed trading activity in the market for bitcoin, while informed trading activity is driven by arbitrage rather than attention.

1. Introduction

Theory identifies two ways in which attention affects pricing. The first is an important path through which the market learns, i.e. informed traders (Hirshleifer and Teoh, 2003; Huang and Liu, 2007; Peng and Xiong, 2006). The second is when attention attracts noise traders (see Barber and Odean, 2008; Shleifer and Summers, 1990). According to Barber and Odean (2008), retail investors are net buyers of attention-grabbing instruments. This is linked to the average investor having to evaluate the investment-worthiness of thousands of instruments when making a purchase decision, but only needing to consider a much smaller sub-set of instruments when making sell decisions. Given that attention is a scarce cognitive resource (see Kahneman, 1973) and making buy decisions can be resource-intensive, investors are prone to buying instruments with extensive media coverage. Shleifer and Summers (1990) argue that such investors *"are not fully rational and their demand for risky asset is affected by their beliefs or sentiments that are not fully justified by fundamental news."* Furthermore, arbitrage, defined as trading by informed (fully rational) investors who are not sentiment-driven, is risky and thus rare. This implies that increased coverage of an instrument will probably lead to increased trading by noise traders rather than by fully rational informed traders.

Bitcoin, which has been the subject of intense global investment media coverage over the past decade (see Urquhart, 2018), fits this mould and is therefore susceptible to attracting noise traders. Such attraction can distort the price discovery process, leading to inefficiencies – as reported by Tiwari et al. (2018) and Urquhart (2016). These inefficiencies in pricing hold far reaching consequences for many retail traders looking to jump on the cryptocurrency 'gravy train'. Consequently, an understanding of the implications of the level of attention cryptocurrencies attract for price discovery is critical from an investment perspective. It is also important from a regulatory perspective as regulators scramble to outline regulatory processes that protect participants in the market for cryptocurrencies. However, while there is a rich

literature investigating the relationship between media and investor attention on the one hand and various bitcoin markets' variables on the other, to our knowledge, the impact of investor attention on noise in the price discovery has not been investigated. Our aim in this paper is to address this gap. Specifically, we investigate the effects of investor attention on price discovery efficiency in bitcoin by following Urquhart (2018) in using *Google Trends* data as a proxy for investor attention. We find that while trading volume enhances bitcoin price efficiency, during periods of high investor attention, these trading volume increases diminish bitcoin price efficiency. This implies that trading volume associated with increased investor attention arises from noise trading.

2. Literature review

Increasingly, and rightfully so, cryptocurrencies, especially bitcoin, are becoming a significant subject of interest of academics, investors and indeed regulators. From an academic viewpoint, there are several open questions regarding the trading of bitcoin.

The first question is linked to one of the fundamental functions of markets, i.e. the informational efficiency of the prices generated during the bitcoin trading process. Urquhart (2016) is the first to investigate the efficiency of bitcoin prices. By employing six different tests, the study finds that bitcoin prices are inefficient. They argue that the driver of the inefficiency in bitcoin pricing is its infancy. Other recent studies, such as Nadarajah and Chu (2017), also conclude that the markets for trading bitcoin are efficient (see also Bariviera, 2017).

The second important question borders on the drivers and the implications of the huge media attention often bestowed on bitcoin. Kristoufek (2013) argues that examining the relationship between bitcoin prices and investor sentiment is very important as, in contrast to "standard" financial assets, bitcoin prices cannot be explained by fundamentals. More

explicitly, Kristoufek (2013) argues and empirically shows that the price dynamics of bitcoin is driven by investor attention (Kristoufek (2013) proxies investor attention with Google Trends and Wikipedia searches), implying that indeed the bitcoin price-investor attention relationship is vital for bitcoin price discovery and is deserving of academic inquiries. Furthermore, the study concludes that the investor attention-bitcoin price discovery relationship is bidirectional. The bidirectional relationship is also tested by Urquhart (2018). Similar to Kristoufek (2013), Urquhart (2018) proxies investor attention using Google Trends. However, by using a vector autoregressive (VAR) model, Urquhart (2018) offers a contrasting view, showing that the relationship is not bidirectional. More specifically, while bitcoin price and volume are significant drivers of investor attention, investor attention offers no significant predictive power in forecasting volatility and volume.

In contrast to Urquhart (2018), Liu and Tsyvinski (2018) show that investor attention strongly forecasts bitcoin returns and thus it is indeed essential to analyse the role of investor attention in the setting of price in the bitcoin market. Liu and Tsyvinski's (2018) results suggest that a one-standard-deviation increase in Google searches (Twitter posts) is linked with a 2.3% (2.5%) increase in bitcoin returns. These estimates are economically significant. Liu and Tsyvinski (2018) further argue that the influence of investor attention on price is one of the most important and unique characteristics of cryptocurrency markets. The bidirectional causal relationship between investor attention (with various variables, such as Google Trends, Twitter posts and Wikipedia searches, used as proxies) and various bitcoin trading variables (e.g. returns, volatility, volume etc.) is also reported by several other studies, examples include Dastgir et al. (2019), Aalborg et al. (2019), Shen et al. (2019) and Figa-Talamanca and Patacca (2019).

This current study ties together the two open questions on cryptocurrencies, i.e. informational efficiency and the effects of investor attention on the price discovery process, by investigating the effects of investor attention on noise in the bitcoin price discovery process.

The effect of media attention on bitcoin trading activity characteristics is linked to the argument by Kahneman (1973) that attention is a scarce cognitive resource and the resource-intensive nature of deciding on what instruments to purchase. Incidentally, this results in the preponderance of trading in bitcoin being conducted by investors that Shleifer and Summers (1990) describe as not being fully rational, i.e. they are noise traders injecting noise into bitcoin price. According to the market microstructure literature, price changes are composed of two components: (1) efficient price discovery, i.e. permanent price impact, and (2) noise, i.e. temporary or liquidity effect (see Menkveld et al., 2007; Rzayev and Ibikunle, 2019), the extent to which prices changes are due to efficient price discovery determines the level of price efficiency. The permanent price impact is viewed as the trading effect on price due to information-driven trading, while temporary price impact results from noise or liquidity-induced trading, thus leading to a price reversal in the following few trades (see for example Chan and Lakonishok, 1995; Easley et al., 2002; Glosten and Harris, 1988). Trades induced, by what investors perceive as information events demand more liquidity than is likely to be available at current quoted prices, since all investors would be crowded on the same side of the order book. For example, if a media release suggests that bitcoin is about to experience a price downturn, many investors will race to short the instrument, thus leading to a scarcity of long positions. This development will inevitably lead to a fall in the bitcoin's stock price. Therefore, in order to ensure the execution of sell orders against the expressed level of liquidity, they will have to 'walk' through the order book, resulting in price impact in the trade direction. Specifically, purchase/buy trades will induce a rise in price and sells will do the opposite. If

the perceived information driving investor reactions/trading turns out to be unsubstantiated, we expect to see a prompt reversal of prices.

Temporary price impact or the noise component of price encapsulates the market's frictional price reaction to the execution of trades induced by unsubstantiated information or market microstructure effects, which should be reversed soon after the trades. The price deviation on account of an un-informed trade execution occurs because counterparties at the best expressed corresponding quote are not readily available, i.e. liquidity constraints. The temporary effect is therefore a compensation to the counterparties providing the liquidity needed for an un-informed order execution. Purchasers (sellers) offer a price premium (discount) as compensation in order to ensure order execution. The permanent impact on the other hand captures the lasting impact of an order execution, that is, the price change that is not reversed within a reasonable timeframe following order execution. The information element of an order execution around an event is therefore captured by the permanent impact. The lack of price reversal in this case suggests a learning event in the market, which ultimately results in the *discovery* of a new price for the traded instrument.

Efficient price discovery and noise as well as their different economic implications have already been extensively investigated for equity markets (see as examples Brogaard et al., 2014; Menkveld et al., 2007). Conversely, the bitcoin literature has mainly focused on efficient price discovery, i.e. permanent price impact issues. However, investigating the evolution of noise within the price discovery process is as important as examining efficient price discovery given that every observed price contains noise (see for example, Biais et al., 1999). Hence, addressing this gap in this paper, by investigating the links between noise in the price discovery process and investor attention in the market for trading bitcoin, is a significant contribution to the cryptocurrency literature.

3. Data and methodology

We use data from two sources. Firstly, Bitcoin data from *Bitstamp*, the most popular and liquid bitcoin exchange in the US. Our dataset contains time, price and volume observations relating to 30.5 million transactions recorded for the period from 13 September 2011 to 10 April 2019. Secondly, we obtain investor attention data from *Google Trends* for the keyword "Bitcoin", which Urquhart (2018) informs us is the most commonly used search term by prospective bitcoin investors.

We derive our trading-related variables from price and volume data. We decompose bitcoin price into its efficient and noise components using the following state space modelling (SSM) approach (see Menkveld et al., 2007):

$$p_{d,\tau} = e_{d,\tau} + n_{d,\tau} \tag{1}$$

and

$$e_{d,\tau} = e_{d,\tau-1} + u_{d,\tau} \tag{2}$$

where

$$p_{d,\tau} = ln\left(Price_{d,\tau}\right), \tag{3}$$

where τ is an intraday event time interval corresponding to when a transaction occurs and d represents a day. $Price_{d,\tau}$ is the price of bitcoin at, $e_{d,\tau}$ is a non-stationary permanent (efficient price) component of bitcoin price, $n_{d,\tau}$ is a stationary transitory (noise) component of bitcoin price, and $u_{d,\tau}$ is an idiosyncratic disturbance error. $n_{d,\tau}$ and $u_{d,\tau}$ are assumed mutually uncorrelated and normally distributed. By using maximum likelihood (likelihood is constructed using the Kalman filter), we estimate σ_d^{2u} and σ_d^{2n}. According to Menkveld et al. (2007), σ_d^{2u} and σ_d^{2n} are the efficient and noise components of price, respectively. From Hendershott and

Menkveld (2014), SSM holds significant economic value over other standard price decomposition methods, such as autoregressive models (see as an example, Hasbrouck, 1991). Firstly, estimating the model by using maximum likelihood is asymptotically unbiased and efficient. Secondly, Kalman filter accounts for level changes across periods with missing observations; thus maximum efficiency in dealing with missing values is achieved. Thirdly, following estimation, the Kalman smoother, which is basically a backward recursion after a forward recursion with the Kalman filter, aids a decomposition of any realised change in the series such that the estimated permanent or transitory component at any interval is estimated using all past, present, and future observations. Therefore, the purpose of filtering is to ensure the estimates are updated following additional new observations.[1]

Bitcoin volume and price are used to compute a measure of illiquidity, the Amihud (2002) illiquidity ratio ($Amihud_d$), which is the absolute return for day d divided by the trading volume on day d. We also employ both variables to compute order imbalance (OIB_d), which is a known information signal (see Chordia et al., 2008). OIB_d is computed as the absolute difference between buyer-initiated[2] and seller-initiated trading volume on day d divided by the sum of buyer-initiated and seller-initiated trading volume on day d.

INSERT TABLE 1 ABOUT HERE

Table 1 shows the descriptive statistics for all our variables. The mean σ_d^{2u} at 1.99bps across our sample period exceeds five times the size of σ_d^{2n} at 0.38bps. This is consistent with the structure of our state space model. The efficient component of the bitcoin price is expected to correlate with informed trading, implying a higher variance for the efficient component.

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[1] In addition to SSM, for robustness, we also employ the Bandi and Russell (2006) decomposition approach, which is based on the ARIMA model, in decomposing trading volume into efficient and noise components of the price discovery process. The results obtained from the analysis based on the Bandi and Russell (2006) decomposition are consistent with our main results. We also present the additional/robustness analysis results in Appendix A1.
[2] We use the Bulk Volume Classification (BVC) approach proposed by Easley et al. (2012) to classify transactions into sell and buy trades. For robustness, we use the tick rule as well and obtain qualitatively similar results.

To determine whether higher levels of investor attention impairs bitcoin price discovery, we estimate the following predictive model:

$$\sigma_d^{2n} = \alpha + \delta_1 lnVolume_{d-1} + \delta_2 Amihud_{d-1} + \delta_3 OIB_{d-1} + \delta_4 TimeTrend_{d-1} +$$

$$\delta_5 D_{attention,d-1} + \delta_6 lnVolume_{d-1} * D_{attention,d-1} + \varepsilon_d \qquad (4)$$

where σ_d^{2n} is the SSM-estimated measure of noise and inversely captures the efficiency of the pricing process. $lnVolume_{d-1}$ is the natural logarithm of bitcoin volume traded on day $d-1$, $Amihud_{d-1}$ is the Amihud (2002) illiquidity ratio on day $d-1$, OIB_{d-1} is the bitcoin order imbalance on day $d-1$, $TimeTrend_{d-1}$ is a trend variable starting at 0 at the beginning of the sample period and incrementing by one every trading day d and $D_{attention,d-1}$ is a dummy equalling 1 during high investor attention days. A day d is designated as a high attention day if *Google Trends* investor attention ($attention_d$) measure is one standard deviation higher than the mean for surrounding -30, +30 corresponding days. The coefficients' standard errors are Newey and West (1987) heteroscedasticity and autocorrelation consistent standard errors. Table 2 presents a correlation matrix showing no multicollinearity concerns with Equation (4).[3]

INSERT TABLE 2 ABOUT HERE

4. Empirical results

Table 3 presents results for the estimation of Equation (4). δ_1 and δ_6 are the main coefficients of interest. The δ_1 estimate is -0.471×10^{-4} and it is statistically significant at the 0.05 level. This implies that increases in bitcoin trading volume would on average lead to less noise in the price discovery process. This is consistent with the microstructure literature (see as examples Barclay and Hendershott, 2003; Biais et al., 1999). Trading volume is critical to

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[3] We also employ the Augmented Dickey-Fuller and Philips-Perron tests in ascertaining that the time series we include in the regression analysis are stationary. The results obtained show that for all the variables the null hypothesis of the existence in the time series is rejected at <0.001 level of statistical significance.

price discovery efficiency, such that pricing inefficiencies are more likely to be eliminated when markets are liquid (see also Chordia et al., 2008). Although trading volume increases are more likely to be driven by uninformed traders (see Collin-Dufresne and Fos, 2016), the ultimate consequence of increased trading activity is to enhance the prospect of executing orders.

However, excessive uninformed (noise) trading could impair price discovery, by obscuring information signals generated through the activities of informed traders. Thus, drawing away uninformed liquidity from exchanges by using market structures, such as dark pools, positively impact price discovery (see Aquilina et al., 2017; Zhu, 2014). The adverse effects of high levels of noise/uninformed traders (typically the retail traders) is evidenced by the positive and statistically significant (0.05 level) δ_6 estimate (0.382×10^{-4}) in Table 3. The interaction between trading volume and the investor attention dummy, $D_{attention,d}$, increases the noise evident in the price discovery process. This implies that elevated investor attention on bitcoin drives more noise/uninformed trading. The results confirm our conjecture that increases in trading linked to increased investor attention is not due to informed trading, because informed investors trade only when arbitrage opportunity exists, such opportunity is risky and limited. Furthermore, arbitrage is not driven by sentiment (Shleifer and Summers, 1990).

The obtained estimate for δ_6 is also economically significant, despite the estimates being small in absolute terms. A one unit change in $lnVolume_{d-1} * D_{attention,d-1}$ will increase noise in the price discovery process (σ_d^{2n}) by 0.382 bps. 0.382 bps is non-negligible when compared with the mean value for σ_d^{2n}. As presented in Table 1, the mean estimate for σ_d^{2n} (bps) is 0.38 bps. Thus, the implication is that one unit change in $lnVolume_{d-1} * D_{attention,d-1}$ (or an 11% = 1/8.63 increase in trading volume during higher than average investor attention

periods)[4] will increase noise in price discovery by 100.05% (0.382/0.38). This estimated effect is very large by any standard and underscores the economic significance of our findings. Furthermore, in economic terms the impact of $lnVolume_{d-1} * D_{attention,d-1}$ on noise in the price discovery process is larger than the impact of $lnVolume_{d-1}$ itself. The coefficient estimate and standard deviation of $lnVolume_{d-1}$ are -0.471x10^{-4} and 1.40 which means that one standard deviation increase in $lnVolume_{d-1}$ decreases noise in price discovery by -0.659x10^{-4} (-0.471x10^{-4}*1.40) standard deviations. By comparison, the coefficient estimate and standard deviation of $lnVolume_{d-1} * D_{attention,d-1}$ are 0.382x10^{-4} and 3.92 which means that one standard deviation increase in $lnVolume_{d-1} * D_{attention,d-1}$ increases noise price discovery by 1.497x10^{-4} standard deviations. Comparing the above values suggest that the impact of $lnVolume_{d-1}$ on noise in the price discovery process is less than the impact of $lnVolume_{d-1} * D_{attention,d-1}$ on noise in price discovery in economic terms, specifically, the latter's impact is about 2.27 times larger than the former's in strict economic terms.

5. Conclusion

We examine the effects of attention on noise in the bitcoin price discovery process through the trading activity channel. We postulate that when attention in bitcoin is high, irrational uninformed trades become more likely. By contrast, being fully rational, informed traders only trade to exploit information and are impervious to increased attention. This implies that high levels of attention is related to increased participation by uninformed traders in the bitcoin market, which is unmatched by any increase in informed trading. Therefore, increases in trading activity linked with high levels of attention increases noise in bitcoin's price discovery.

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[4] 8.63 is the mean $lnVolume_d$ value.

For a speculative market with a high level of media coverage, such as bitcoin, understanding the effects of increased investor attention is crucial for investment decision making.

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Table 1. Summary statistics

Table shows the summary statistics for variables represented in Equation (4).

Variables	Mean	Standard Deviation
σ_d^{2u} (bps)	1.99	74.92
σ_d^{2n} (bps)	0.38	4.86
$lnVolume_d$	8.63	1.40
$Amihud_d$ (bps)	0.83	11.02
OIB_d (bps)	57.93	86.81

Table 2. Correlation matrix

Table shows the correlation matrix for variables represented in Equation (4).

	$lnVolume_d$	$Amihud_d$	OIB_d	$lnVolume_d * D_{attention,d}$	$D_{attention,d}$	$Attention_d$	$TimeTrend_d$
$lnVolume_d$	1						
$Amihud_d$	-0.306	1					
OIB_d	0.050	0.170	1				
$lnVolume_d * D_{attention,d}$	0.198	-0.018	0.022	1			
$D_{attention,d}$	0.111	-0.018	0.033	0.426	1		
$Attention_d$	0.226	-0.038	0.166	0.330	0.437	1	
$TimeTrend_d$	0.442	-0.121	0.413	0.054	0.029	0.341	1

Table 3. The effects of attention on noise in the bitcoin price discovery process

The effect of attention on bitcoin price discovery is estimated using the following model:

$$\sigma_d^{2n} = \alpha + \delta_1 lnVolume_{d-1} + \delta_2 Amihud_{d-1} + \delta_3 OIB_{d-1} + \delta_4 TimeTrend_{d-1} + \delta_5 D_{attention,d-1} +$$
$$\delta_6 lnVolume_{d-1} * D_{attention,d-1} + \varepsilon_d$$

where σ_d^{2n} is the state space measure of noise and inversely captures the efficiency of the pricing process. $lnVolume_{d-1}$ is the natural logarithm of bitcoin volume traded on day $d-1$, $Amihud_{d-1}$ is the Amihud (2002) illiquidity ratio on day $d-1$, OIB_{d-1} is the bitcoin order imbalance on day $d-1$, $TimeTrend_{d-1}$ is a trend variable starting at 0 at the beginning of the sample period and incrementing by one every trading day d and $D_{attention,d-1}$ is a dummy equalling 1 during high investor attention days. A day d is designated as a high attention day if *Google Trends* investor attention ($attention_d$) measure is one standard deviation higher than the mean for surrounding -30, +30 corresponding days. The coefficients' standard errors are Newey and West (1987) heteroscedasticity and autocorrelation consistent standard errors.

Dependent variable: σ_d^{2n}	
α	0.474×10^{-3}**
	(2.53)
$lnVolume_{d-1}$	-0.471×10^{-4}**
	(-2.52)
$Amihud_{d-1}$	0.111
	(1.52)
OIB_{d-1}	0.703×10^{-2}*
	(1.93)
$TimeTrend_{d-1}$	0.605×10^{-6}**
	(2.11)
$D_{attention,d-1}$	0.342×10^{-3}*
	(1.66)
$lnVolume_{d-1} * D_{attention,d-1}$	0.382×10^{-4}**
	(2.15)
$\overline{R^2}$	13.64 %

Appendix A1. Effects of attention on bitcoin price discovery

The effect of attention on bitcoin price discovery is estimated using the following model:

$$\sigma_d^{2n} = \alpha + \delta_1 lnVolume_{d-1} + \delta_2 Amihud_{d-1} + \delta_3 OIB_{d-1} + \delta_4 TimeTrend_{d-1} + \delta_5 D_{attention,d-1} + \delta_6 lnVolume_{d-1} * D_{attention,d-1} + \varepsilon_d$$

where σ_d^{2n} is the Bandi and Russell (2006) measure of noise and inversely captures the efficiency of the pricing process. $lnVolume_{d-1}$ is the natural logarithm of bitcoin volume traded on day $d-1$, $Amihud_{d-1}$ is the Amihud (2002) illiquidity ratio on day $d-1$, OIB_{d-1} is the bitcoin order imbalance on day $d-1$, $TimeTrend_{d-1}$ is a trend variable starting at 0 at the beginning of the sample period and incrementing by one every trading day d and $D_{attention,d-1}$ is a dummy equalling 1 during high investor attention days. A day d is designated as a high attention day if *Google Trends* investor attention ($attention_d$) measure is one standard deviation higher than the mean for surrounding -30, +30 corresponding days. The coefficients' standard errors are Newey and West (1987) heteroscedasticity and autocorrelation consistent standard errors.

Dependent variable: σ_d^{2n}	
α	0.259×10^{-3}
	(1.14)
$lnVolume_{d-1}$	$-0.799 \times 10^{-3}**$
	(-2.41)
$Amihud_{d-1}$	1.802
	(1.15)
OIB_{d-1}	0.878×10^{-2}
	(1.28)
$TimeTrend_{d-1}$	$0.274 \times 10^{-5}***$
	(3.70)
$D_{attention,d-1}$	$0.126 \times 10^{-1}*$
	(1.69)
$lnVolume_{d-1} * D_{attention,d-1}$	$0.145 \times 10^{-2}**$
	(2.01)
$\overline{R^2}$	14.75 %