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Can volume predict Bitcoin returns and volatility? A quantiles-based approach[☆]

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ABSTRACT

Prior studies on the price formation in the Bitcoin market consider the role of Bitcoin transactions at the conditional mean of the returns distribution. This study employs in contrast a non-parametric causality-in-quantiles test to analyse the causal relation between trading volume and Bitcoin returns and volatility, over the whole of their respective conditional distributions. The nonparametric characteristics of our test control for misspecification due to nonlinearity and structural breaks, two features of our data that cover 19th December 2011 to 25th April 2016. The causality-in-quantiles test reveals that volume can predict returns – except in Bitcoin bear and bull market regimes. This result highlights the importance of modelling nonlinearity and accounting for the tail behaviour when analysing causal relationships between Bitcoin returns and trading volume. We show, however, that volume cannot help predict the volatility of Bitcoin returns at any point of the conditional distribution.

1. Introduction

Studying the relationship between volume and returns is important in generating a better understanding of how market information is transmitted and then embedded in asset prices. It also helps increase the utility of forecasting asset returns and volatility. In times of stress, in particular, it is critical to examine the return-volume relationship to better understand market booms and crashes (Marsh and Wagner, 2000).

While the volume–return relationship has been extensively covered for equities (Karpoff, 1987; Li et al., 2016; Todorova and Souček, 2014), bonds (Balduzzi et al., 2001), commodities (Chiarella et al., 2016), interest rates and currency futures (Puri and Philippatos, 2008), and real estate (Tsai, 2014), it remains unexplored for the Bitcoin market. The latter has recently attracted the attention of the media and scholars, given the rising importance of Bitcoins not only as an electronic payment system but also as financial and speculative assets (Kristoufek, 2014).

In a speculative market, such as that of Bitcoin, understanding the volume–return paradigm is essential to shedding light on potential implications for trading strategies. Practically, if the transaction volume in the Bitcoin market has a predictive power for its returns, this suggests that practitioners will be able to construct volume-based strategies to increase profits (Chen et al., 2001). This is particularly important given that many traders and practitioners have relied on technical analysis as an alternative tool to study Bitcoin prices, as no reliable, fundamental valuation technique is available to quantify the intrinsic value of Bitcoin. The fact that market technicians employ models and trading rules based on the relation between return and volume further underscores the need for a better understanding of the Bitcoin volume–return relationship.

Since its inception in 2009, Bitcoin has been characterized by sharp upward and downward price movement associated with high transaction volumes. On 19 November 2013, the price of Bitcoin on Bitstamp, the largest European Bitcoin exchange, plunged almost 20% (19.88%) on the highest volume ever recorded (71,560 Bitcoins). Furthermore, on 7 December 2013, the Bitcoin price plunged almost 15% (14.92%) and recorded a new all-time trading volume high of 79,852 Bitcoins. Again, on 18 December 2013, Bitcoin price plunged almost 23% (22.80%) and hit a new daily volume record high of 137,070 Bitcoins.[1] These trends suggest a strong relationship between the magnitudes of price movement and transaction volume. However, no

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[1] For a detailed explanation on the negative and positive bubbles in the Bitcoin market, please refer to Fry and Cheah (2016).

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study thus far to explores this relationship in depth for Bitcoin. To address this research gap, we use the novel, nonparametric causality-in-quantiles test from Balcilar et al. (2016a) to examine the predictability of Bitcoin returns and volatility based on trading volume. For our purpose, we use daily data covering the period of 19 December 2011 to 25 April 2016. The nonparametric causality-in-quantiles approach has three main novelties: First, our approach is robust to misspecification errors as it detects the underlying dependence structure across the variables under study. This novelty arises from the view that stock returns are inherently non-linear (see Bekiros et al., 2016, for a detailed discussion in this regard) – a fact we confirm in our data. Second, our methodology allows for the detection of not only the causality-in-mean but also for any potential causality in the tails of the joint distribution of the variables. This novelty is crucial if the dependent variable has proven to have fat-tails – a fact that has been shown to exist for Bitcoin returns (and volume). Third, our nonparametric causality-in-quantiles approach allows us to examine causality-in-variance and, thus, study higher-order dependency. Such an investigation is important because during some periods, causality in the conditional-mean may not exist, while, at the same time, higher-order interdependencies may turn out to be significant.

Note that we could have also used nonlinear causality tests (for example, Hiemstra and Jones, 1994, and Diks and Panchenko, 2005) and GARCH models to analyse the impact of volume on Bitcoin returns and/or volatility, as used recently by Bampinas and Panagiotidis (2015) while analyzing causality between gold and oil markets. As pointed out by Diks and Panchenko (2005), Himestra-Jones test is generally not compatible with the definition of Granger causality and over-rejects the null of no Granger causality. Diks and Panchenko (2005) rectify the over-rejection problem of the Himestra-Jones test by using the average of local dependence measures. However, these approaches rely on conditional-mean based estimation, and hence, fail to capture the entire conditional distribution of returns and volatility – something we *can* do with our nonparametric causality-in-quantile approach. Indeed, Bampinas and Panagiotidis (2015) find evidence that mean-based test cannot deal with the time dependent causality linkages due to structural breaks. In the process, our nonparametric causality-in-quantiles test is a more general procedure of detecting causality in both returns and volatility simultaneously at each point of their respective conditional distributions. Hence, we are able to capture existence or non-existence of causality at various states of the Bitcoin market: bear (lower quantiles), normal (median), and bull (upper quantiles). As a more general test, our nonparametric causality-in-quantile approach is more likely to pick up causality when conditional mean-based tests might fail to do so. In addition, since we do not need to decide on the number of regimes as in a Markov-switching model, and can test for causality at each point of the conditional distribution characterising specific regimes, our test also does not suffer from any misspecification in terms of specifying and testing for the optimal number of regimes. An important issue however, is that like standard causality tests, existence of causality would imply that it holds at all horizons. As discussed in Bampinas and Panagiotidis (2015), a more informative causality test would be to use the approach of Hill (2007), which allows us to detect causality in tri-variate system and at multiple horizons and in a time-varying fashion using recursive or rolling windows. While the advantages in terms of multiple-horizons are undeniable, the approach of Hill (2007) remains a conditional mean based approach restricted to only the first-moment.

Indeed, certain studies, such as Chuang et al. (2009), Chiang and Li (2012), Gebka and Wohar (2013), Lin (2013), and Chen et al. (2016), have used quantile based methodologies to study the relationship between returns and volatility based on the volume of traditional stock indices of Pacific Basin and Asian countries. However, to the best of our knowledge, this is the first study that analyses the predictability of returns and volatility of Bitcoin based on trading volume using a nonparametric method that covers the entire conditional distribution of returns and volatility, and is free from misspecification due to nonlinearities and structural breaks.

The rest of the paper is organized as follows: Section 2 reviews related literature on the finance and economics of Bitcoin. Section 3 presents our methodology, while Section 4 discusses the data and the results. Finally, Section 5 concludes.

2. Literature review

Bitcoin is an open source software-based online payment system. Its popularity among practitioners and economic actors has soared in response to the perceived failures of governments and central banks during the global financial crisis of 2008 and the European sovereign debt crisis (ESDC) of 2010–2013. While central authorities and central banks guarantee or have control over conventional currencies, Bitcoin is fully decentralized and depends on a sophisticated protocol that uses only cryptography to control transactions, manage its supply, and prevent harmful actions that may endanger the system. All transactions are stored digitally and recorded in a shared ledger data technology known as *blockchain*. While the algorithm behind Bitcoin represents a solid safeguard against counterfeiting, the system has proved to be vulnerable to illicit activities such as the massive theft of 350 million USD worth of Bitcoins from the Mt. Gox exchange in February 2014. The principles of Bitcoin are explained by Dwyer (2015) and at bitcoin.org. Bitcoin is the first cryptocurrency to come into existence. While other cryptocurrencies, such as Feathercoin and Peercoin, now exist, Bitcoin has managed to maintain its leading position in this particular market.[2] At the end of June 2016, Bitcoin market capitalisation exceeded 10 billion USD (coinmarketcap.com), which represents more than 80% of the total market capitalisation of all cryptocurrencies on the market.

In addition to the early, extensive literature on the technical and legal aspects of Bitcoin, the economics and finance debate on Bitcoin have recently intensified. Kristoufek (2014) argues that Bitcoin represents a unique asset, possessing properties of both a standard financial asset and a speculative one. On the other hand, Popper (2015) considers Bitcoin to be digital gold and Bouri et al. (2017a, 2017b) highlight some valuable characteristics of Bitcoin as an investment. Regardless of whether Bitcoin is a financial or a speculative asset, digital gold, or a commodity, some studies have been interested in the 'moneyness' of Bitcoin. Yermack (2013) argues that Bitcoin has no intrinsic value but behaves more like a speculative investment than a currency because its market capitalisation is high compared to the economic transactions it facilitates. The author also concludes that Bitcoin volatility adversely affects its usefulness as a currency. Glaser et al. (2014) find that most of the interest in Bitcoin is due to its 'asset' aspect and not its currency aspect. Hanley (2013) also indicates that Bitcoin has no fundamental value to support its pure market valuation against conventional currencies. In contrast, Woo et al. (2013) argue that Bitcoin has some fair value due to its money-like properties. Garcia et al. (2014) and Hayes (2016) show that the cost of producing a Bitcoin via mining adds some fundamental value to Bitcoins.

Other studies have examined the price formation in the Bitcoin market. Kristoufek (2013) reports a strong bidirectional causality between the prices of Bitcoin and the search queries for Bitcoin on Google Trends and Wikipedia. Bouoiyour and Selmi (2015) illustrate the significant role of a lagged Google search for the word 'Bitcoin' in explaining the Bitcoin price, whereas the velocity of Bitcoin, measured by data transactions, fails to explain the Bitcoin price. Similar results regarding the roles of the two above-mentioned variables (the volume of daily searches for Bitcoin on the Internet and the number of Bitcoin transactions) in explaining the Bitcoin price are reported by Polasik

[2] By the end of June 2016, there were more than 700 cryptocurrencies traded in the market.