Bitcoin price discovery

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Abstract

Bitcoin surges in price and popularity, but it is highly controversial. There is no observable fundamental information to estimate its intrinsic value. The literature on bitcoin price discovery is sparse, and there is no clear evidence on how its value is determined. A common belief is that the value of bitcoin is dependent on market sentiment and risk factors that are pertinent to cryptocurrencies (hacking, theft, regulatory constraints). With a rich microstructure dataset from one bitcoin exchange, we hope to shed light on the price formation process of this asset and explore potential determinants of bitcoin volatility and liquidity. We base our empirical analysis on a new theoretical model by Ricco, Rindi, and Seppi (2018) of dynamic limit order markets with asymmetric information and non-Markovian learning where traders condition their trading decision not only on the current liquidity supply in the book but also the trade history.

Data

The data for this project were collected by Jacob Sagi from BTC-e, a digital currency trading platform, founded in July 2011 and was seized by US authorities in July 2017 for international money laundering and laundering funds from the hack of Mt. Gox.[1] The platform allowed trading between several cryptocurrencies (bitcoin, litecoin, namecoin, novacoin, peercoin, dash and ethereum) and three currencies (U.S. dollar, Russian ruble and Euro currencies). We focus specifically on Bitcoin (BTC) against the USD, and Litecoin (LTC) against BTC.

The sample period is from 12/6/2013 to 9/25/2014, enclosing several major events in the cryptocurrency world:

- 2/7/2014: major exchanges were hit with massive DDoS attacks (Mt. Gox, Bitstamp, and BTC-e experienced trading stoppage). Mt. Gox halted withdrawal on 2/6/2014. The DDoS attack was detected on 2/11/2014
- 2/24/2014: Mt. Gox Exchange collapsed (after losing 744000 BTC of its customers)
- 3/26/2014: The IRS declares bitcoin to be taxed as property
- 4/10/2014: Chinese exchanges' bank accounts were closed, making it harder to trade bitcoin in China
- 6/13/2014: Mining pool GHash.io reached 51% of the bitcoin network hashing power, giving it the power to reverse transactions and prevent other transactions from being confirmed

[1] Jacob Sagi collected the data through two computers simultaneously and independently "pinging" the exchange's server and downloading transactions and snapshots of the full limit order book. These pings are less than one second apart, unless when there are issues with the connection or computer shutdowns. The two computers work simultaneously so that if one went down for any reason, the data downloading was still covered by the other. As a result, there are two parallel databases that are highly similar but not identical.

- 6/27/2014: US Marshals Service auctioned nearly 30,000 bitcoins seized during the October 2013 bust of the Silk Road website
- 7/17/2014: NY Department of Financial Services released proposed set of regulations for businesses that interact with Bitcoin and cryptocurrencies
- 7/18/2014: Dell started to accept bitcoin
- 9/8/2014: Paypal subsidiary Braintree started to accept bitcoin

The dataset is around 10 terabytes, and consists of two components: 1) transaction history, and 2) limit order book snapshots. Transaction history data contain the following variables: transaction date-time stamp, transaction price, quantity transacted, the passive side of the transaction (bid/ask, corresponding to a seller-initiated/buyer-initiated trade), the order number. The limit order book snapshot data are at sub-second frequency – the frequency at which the two computers ping the exchange's server for data download – with each observation represents a snapshot of the complete limit order book. Variables include: the date-time stamp when the snapshot is taken, the time between two adjacent snapshots, all ask limit orders and all bid limit orders in the book at the time the snapshot is taken. Each order is identified as a (price, quantity) pair, which provides ID information to track the dynamics of individual orders over time.

Empirical analysis

This project aims at providing a comprehensive picture of the microstructure of this bitcoin exchange. Specifically, we study the following:

- Intraday behavior of price, volume, volatility, and liquidity
- Time series behavior of price, volume, volatility, and liquidity
- Price impacts of trades
- Potential determinants of intraday volatility and liquidity
- Market behavior around the collapse of Mt. Gox (and other events during the sample period listed earlier) to shed light on how such events change market valuation of bitcoin
- Bitcoin market behavior around important announcements to shed light on what can explain return dynamics of sentiment-based assets like bitcoin

Furthermore, we seek to empirically test the implications of Ricco, Rindi, and Seppi (2018)'s model of dynamic limit order markets with asymmetric information and non-Markovian learning.[2] The bitcoin market is a great laboratory to test this model given that the value of bitcoin is highly uncertain and not based on fundamental factors that are easily observable or available. Thus, information asymmetry is expected to be high. In addition, the non-Markovian learning feature of the model appears fitting for the bitcoin market if bitcoin is a sentiment asset. If so, traders are likely base their trading decisions and valuation on how the market has been moving along. Hence, if anything, we expect to see stronger evidence of non-Markovian learning in this market, if this is indeed a closer description of learning in financial markets.

[2] "Information, Liquidity, and Dynamic Limit Order Markets", by Ricco, Rindi, and Seppi (2018).