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Price dispersion in bitcoin exchanges☆

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ABSTRACT

Bitcoin is traded in a number of exchanges, and there is a large and time-varying price dispersion among them. We identify the sources of price dispersion using a standard time-varying vector autoregression model with stochastic volatility, and we find that shocks to transaction fees and bitcoin price growth explain on average 20%, and sometimes more than 60%, of the variation of price dispersion.

1. Introduction

Many studies on bitcoin have been focused on the price discovery process and market efficiency in the bitcoin market. For example, Giudici and Abu-Hashish (2018) find that large bitcoin exchanges provide more information in the price discovery process. Urquhart (2016) and Cheah et al. (2018) find that the bitcoin market is not efficient, while Nadarajah and Chu (2017) and Tiwari et al. (2018) reach an opposite conclusion.

There are multiple bitcoin exchanges, and price dispersion among them is large and changing over time. In this paper, we use the closing prices in eight bitcoin exchanges (Bitfinex, Bitstamp, Cex.io, Coinbase, Exmo, Gemini, Kraken and Poloniex) that have the longest available data to calculate the price dispersion. Basic descriptions of bitcoin exchanges are presented in Table 1 and summary statistics of price dispersion among these exchanges are presented in Table 2. We find that the price dispersion among these exchanges can range from 0.10% to 5.27% of the current indexed price. Fig. 1 gives us a sense of how the price dispersion changes over time.

To find out what drives price dispersion, we estimate a time-varying vector autoregression model with stochastic volatility (TV-VAR-SV) model and from the variance decomposition and impulse responses, we will argue that transaction fees and bitcoin price growth rate are the major factors that drive price dispersion across the eight exchanges.

2. Data and methodology

The priors of the TV-VAR-SV model are set as in Primiceri (2005). As our model contains five variables, the degrees of freedom are set to 56 for Q, 6 for W, and [2 3 4 5] for the four blocks of S. The priors are:

$$B_0 \sim N(\hat{B}_{OLS}, 4 \cdot V(\hat{B}_{OLS})), \qquad S_1 \sim IW(k_S^2 \cdot 2 \cdot V(\hat{A}_{1,OLS}), 2),$$
$$A_0 \sim N(\hat{A}_{OLS}, 4 \cdot V(\hat{A}_{OLS})), \qquad S_2 \sim IW(k_S^2 \cdot 3 \cdot V(\hat{A}_{2,OLS}), 3),$$
$$log\sigma_0 \sim N(log\hat{\sigma}_{OLS}, I_n), \qquad S_3 \sim IW(k_S^2 \cdot 4 \cdot V(\hat{A}_{3,OLS}), 4),$$
$$Q \sim IW(k_Q^2 \cdot 56 \cdot V(\hat{B}_{OLS}), 56), \qquad S_4 \sim IW(k_S^2 \cdot 5 \cdot V(\hat{A}_{4,OLS}), 5),$$
$$W \sim IW(k_W^2 \cdot 6 \cdot I_n, 6).$$

Following Primiceri (2005) and time-invariant VAR results, we pick $lag = 2$, $k_Q = 0.1$, $k_S = 0.1$ and $k_W = 0.01$. As mentioned in Primiceri (2005), and following Diebold and Yilmaz (2009) and Klößner and Wagner (2014), we are agnostic about the identification and instead present average results obtained from all 120 possible orderings of the variables.

Due to missing data in some exchanges and computational difficulty, we use weekly instead of daily data.[1] Besides average

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[1] With daily data, the information criterion usually suggests to pick 7 to 15 lags. Its means we need to calculate at least 180 posterior values in the B matrix of the TV-VAR-SV model, which we find to be infeasible.

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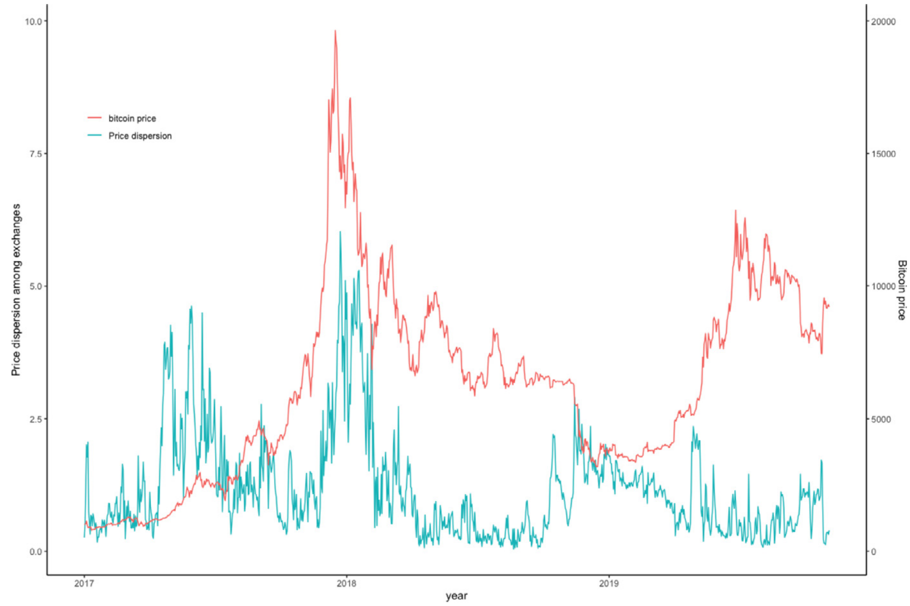

Fig. 1. Price dispersion among exchanges and the average BTC price. This figure shows how the price dispersion ($P_{d,t}$) among different bitcoin exchanges changes along with time.

Table 1
Summary of bitcoin exchanges. While these exchanges are in different time zones, data used in our study are all collected at the UTC+0 time point.

	Bitfinex	Bitstamp	Cex.io	Coinbase
Headquarter	Hong Kong	London	London	San Francisco
Currency	USD, EUR CNH, JPY GBP	USD, EUR	USD, EUR RUB, GBP	USD, EUR GBP
Time zone	UTC+8	UTC+0	UTC+0	UTC-8
	Gemini	Kraken	Poloniex	Exmo
Headquarter	New York	San Francisco	Wilmington	Moscow
Currency	USD	USD, EUR, CAD GBP, CHF, JPY AUD	USD	USD, EUR RUB
Time zone	UTC-5	UTC-8	UTC-5	UTC+3

Table 2
Summary statistics. The data period is from July 2017 to October 2019. See Section 2 for definitions of the variables.

	$P_{d,t}$	F_t	$P_{v,t}$	$P_{g,t}$	V_t
Mean	1.093	0.028	0.171	0.016	3.431
Med	0.755	−0.095	0.146	0.012	3.410
Max	5.274	3.711	1.302	0.356	4.990
Min	0.099	−2.054	0.025	−0.364	2.055
Std.dev	0.985	1.266	0.132	0.112	0.516
Obs.	178	178	178	178	178

transaction fees per transaction (F_t), we also consider other variables that may explain price dispersion ($P_{d,t}$), the inter-exchange price volatility ($P_{v,t}$), the average trade volume dispersion (V_t), and price growth ($P_{g,t}$).

We use Wednesday data from the exchanges to build a weekly dataset.[2] Transaction fees (in USD) and the number of daily transactions recorded in bitcoin blockchain are used to calculate F_t (in log). We define price dispersion as $P_{d,t} = \frac{SD(P_{j,t})}{mean(P_{j,t})}$, where $P_{j,t}$ is the closing price of exchange j at time t. V_t is calculated as the log of the largest trade volume minus the log of the second smallest trade volume (due to the missing data in some exchanges on certain days). $P_{v,t}$ is calculated as the log of the highest price minus the lowest price from last Thursday among these exchanges. $P_{g,t}$ is calculated by using the bitcoin price index data to measure the weekly price growth. All the exchange-level data is obtained from https://www.cryptocompare.com. The bitcoin blockchain-related data and the price index data are available on https://www.blockchain.com. The sample period we are examining is from 2016-06-01 to 2019-11-01, and the summary statistics are in Table 2.[3]

3. Empirical results

We present the variance decomposition results for price dispersion over time in Fig. 2. For the whole sample, transaction fees and price growth on average explain 20% of the forecast error variance, but they account for more than 60% of the forecast error variance in the volatile period. However, the explanation power of all variables goes down after March 2018, around the time when the bitcoin price has dropped more than 50% from the previous peak.[4]

We also plot the impulse responses for price dispersion for a few specific dates. The weeks chosen are the first week of December 2017 (week I), the first week of January 2019 (week II), and the first week of August 2019 (week III).[5] Week I comes from the most volatile period, week II comes from the period with the biggest rebound of transaction fees, and week III comes from the recent period when bitcoin price goes back to above $10,000.

2 Using other weekdays produce similar results, and they are available upon request.

3 The first 56 observations in our sample are used to calculate the priors of the parameters in the TV-VAR-SV model, so the estimates reported in the following sections begin from the first week of July 2017.

4 Thanks to the suggestion of a referee, we also examined network difficulty as another factor. Using it to replace price volatility or volume dispersion, two variables that we find to be relatively unimportant, we find that network difficulty is also unimportant. As network difficulty changes only every two weeks, we think its lack of variation is why it does not explain much. These results are available upon request.

5 The main conclusion does not change by moving them forward or backward a few weeks.

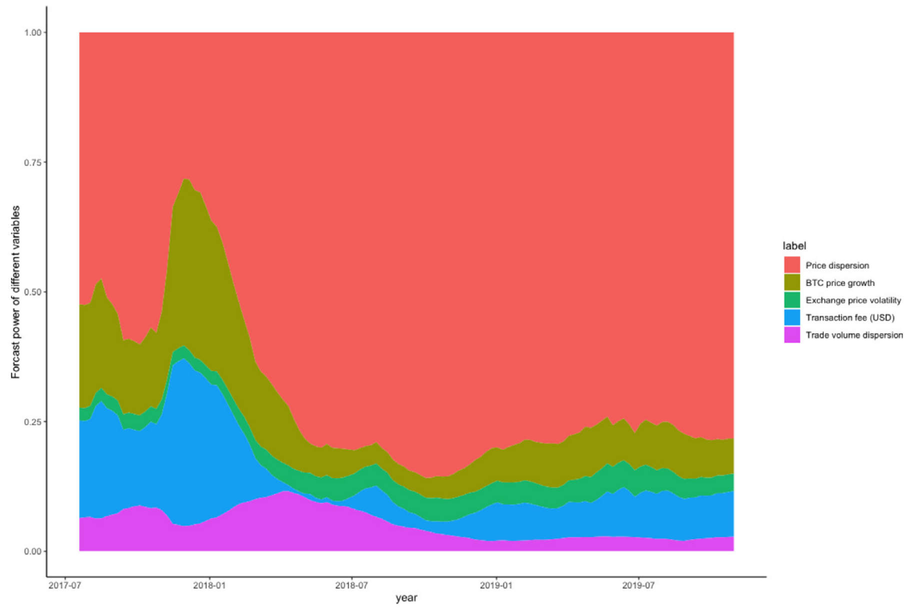

Fig. 2. Power figure of variance decomposition results. This figure shows the average results for the 20-step ahead variance decomposition with rolling windows analysis.

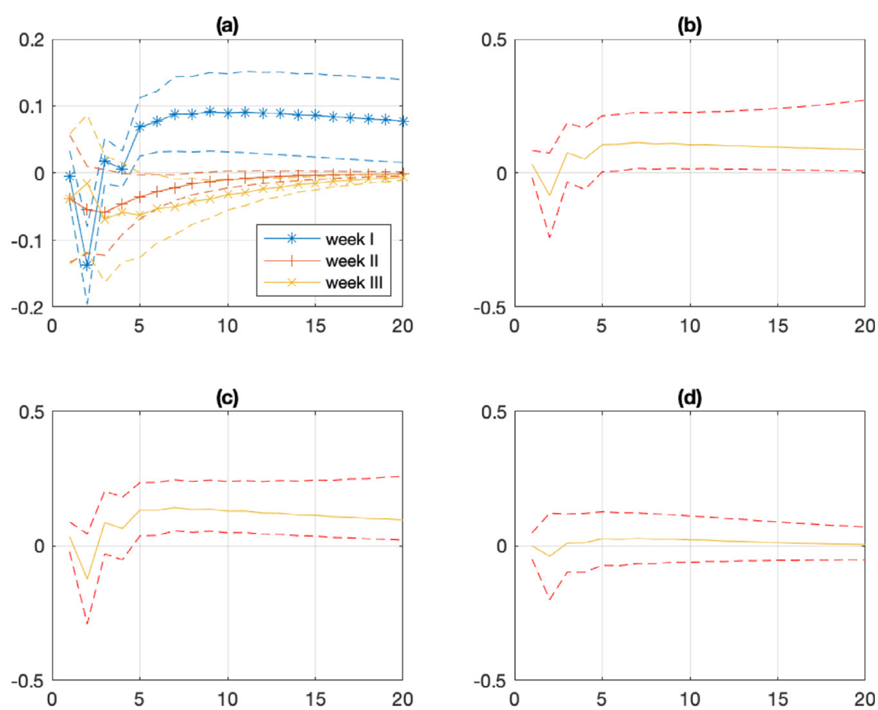

Fig. 3. Impulse response of price dispersion to transaction fees shock. (a) Impulse responses of price dispersion to transaction fee shock in week I, week II, and week III, (b) difference between the responses in week I and week II, (c) difference between the responses in week I and week III, (d) difference between the responses in week II and week III.

The effects of the transaction fee shock and the price growth shock on price dispersion are statistically different in week I compared with the other two weeks (see Figs. 3 and 4). In week I, transaction fees shock reduces price dispersion first, but eventually it increases price dispersion among different exchanges. However, transaction fees shock only reduces price dispersion in the other two weeks. On the other hand, price growth shock increases price dispersion in week I but reduces in the other two weeks.[6]

In the bitcoin system, high transaction fees deter users from arbitraging when price dispersion is small, but they also encourage miners to confirm more transactions and reduce price dispersion. In Fig. 5 we plot transaction fees along with the daily

[6] The results for price volatility and trade volume dispersion do not show any significant time variation.

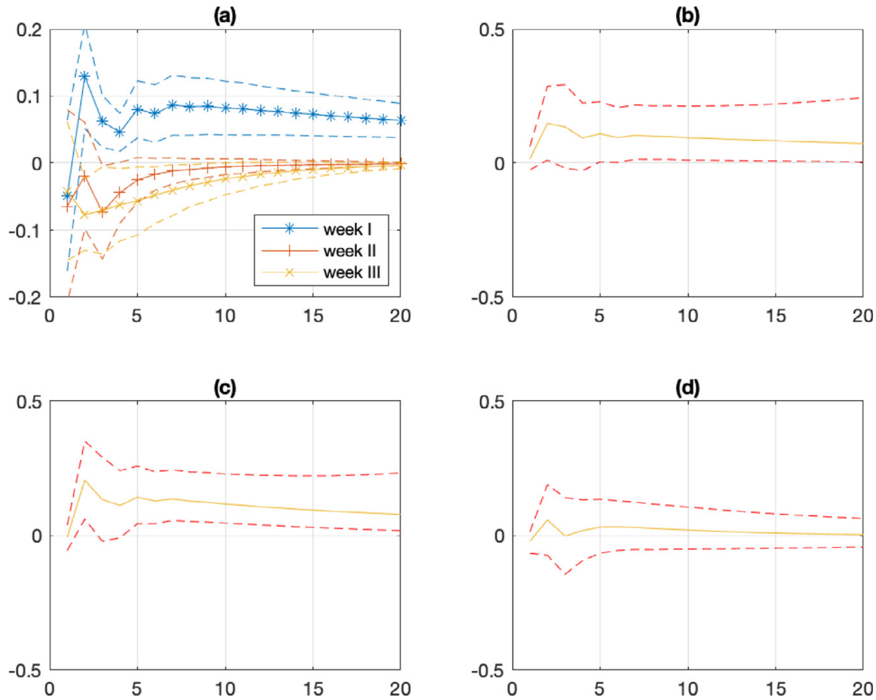

Fig. 4. Impulse response of price dispersion to price growth shock. See note to the previous figure.

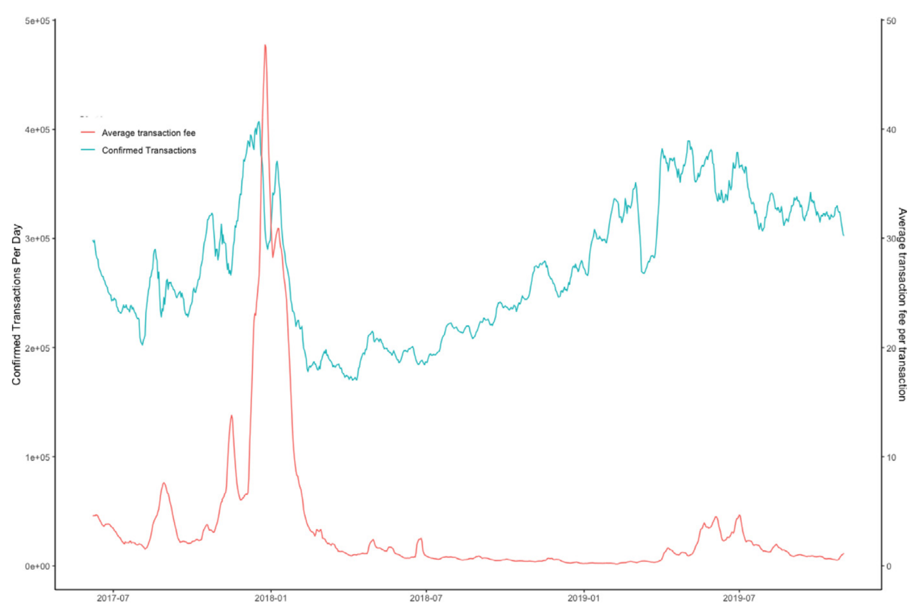

Fig. 5. Average transaction fees and confirmed transactions per day. This figure shows the seven-days moving average change of the average transaction fees and the daily total confirmed transactions.

number of transactions. Around the time of week I, fees go up to 50 USD per transaction, and the number of daily transactions is almost the same as that around the time of weeks II and III when fees are around 2 USD per transaction. The number of transactions in mempool (Fig. 6) serves as another piece of evidence.[7] Consistent with Tsang and Yang (2020), these figures show that high fees around week I are mainly driven by demand (users) and supply (miners) has difficulty catching up. Transaction fees shock with inelastic supply makes users reluctant to arbitrage during this period and drives up price dispersion. As supply is becoming more elastic later in weeks II and III, fees shock actually slightly reduces price dispersion.[8]

[7] The mempool is recorded by snapshots, the absolute number should not be treated as the real demand. However, the relative magnitude of these numbers can tell us how dramatic the demand has changed.

[8] There are two possible reasons for more elastic supply: (1) the demand from users is relatively low and does not hit the miners' processing limit and (2) the introduction of SegWit increases miners' processing capacity.

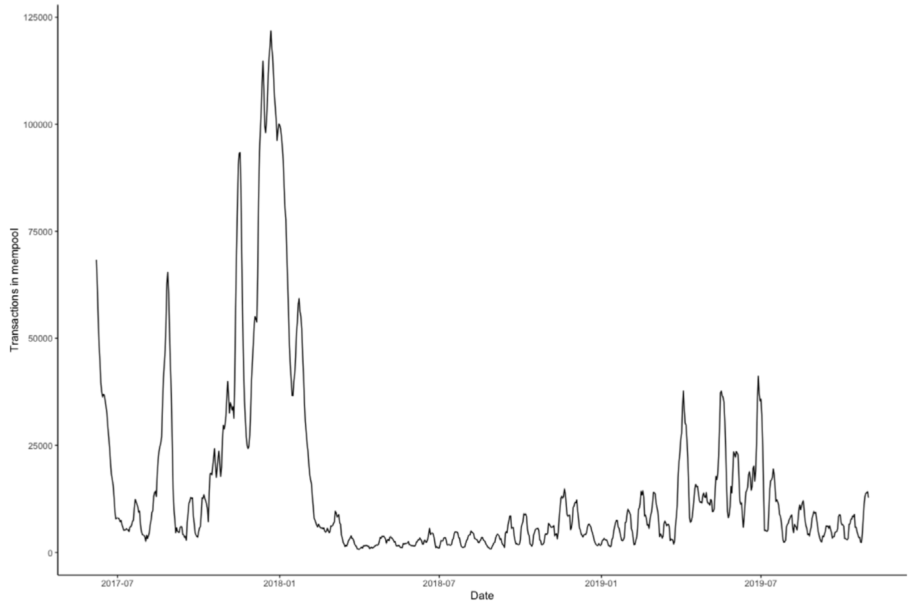

Fig. 6. Number of transactions in mempool. This figure shows the seven-days moving average of the daily number of transactions in mempool.

Since transaction fees are not related to the transaction volume in the bitcoin system, when bitcoin price is increasing transaction becomes cheaper and encourages people to reduce price dispersion. Hence, in weeks II and III we see from the impulse responses that price growth shock eventually having a negative impact on price dispersion. However, in week I when bitcoin price was volatile, users find it too risky to take advantage of the price dispersion.

4. Conclusion

We show that a substantial proportion of price dispersion in the bitcoin markets can be explained by transaction fees and price growth. Still, there is a large proportion of price dispersion that is unaccounted for, and we believe that more micro-level data are needed to pin down the other sources.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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