

BitMEX Bitcoin Derivatives: Price Discovery, Informational Efficiency and Hedging Effectiveness

Carol Alexander^{a,b}, Jaehyuk Choi^c, Heungju Park^d, Sungbin Sohn^{c,*}

^a*University of Sussex Business School, Falmer, Brighton, United Kingdom*

^b*Peking University HSBC Business School, Boars Hill, Oxford, United Kingdom*

^c*Peking University HSBC Business School, Nanshan, Shenzhen, China*

^d*Sungkyunkwan University SKK Business School, Jongno-gu, Seoul, Korea*

Abstract

BitMEX is the largest unregulated bitcoin derivatives exchange, listing contracts suitable for leverage trading and hedging. Using minute-by-minute data, we examine its price discovery and hedging effectiveness. We find that BitMEX derivatives lead prices on major bitcoin spot exchanges. Bid-ask spreads, inter-exchange spreads and relative trading volumes are important determinants of price discovery. Further analysis shows that BitMEX derivatives have positive net spillover effects, are informationally more efficient than bitcoin spot prices, and serve as effective hedges against spot price volatility. Our evidence suggests that regulators prioritise investigation of the legitimacy of BitMEX and its contracts.

Keywords: bitcoin, BitMEX, market efficiency, price discovery, spillover

JEL: G14

1. Introduction

Bitcoin was the first digital currency to operate through a peer-to-peer network without a central authority (Nakamoto, 2008). Since inception over ten years ago it has become actively traded through both decentralised and centralised exchanges. Decentralised exchanges are, in effect, smart contract-based limit order books run without central authority, where the change of ownership is made directly between the counterparties' wallets and is recorded on a publicly available blockchain. Although they may be an intriguing research subject in the future, decentralised exchanges are still in their infancy. In this paper, therefore, we only investigate the microstructure of bitcoin on *centralised* exchanges (CEX). Trading activity is still highly anonymous and difficult to trace on a CEX because only cryptoasset transfers to and from the exchange's hot wallet are recorded on the blockchain, unless the exchange is regulated otherwise. A very large number of CEXs have started operating during the last few years and several of them trade bitcoin derivatives contracts such as swaps, futures and options. Since they provide an application programming interface (API)

*Corresponding author *Tel:* +86-755-2603-5324, *Address:* 748 PHBS University Town, Nanshan, Shenzhen 518055, China
Email address: sungbin.sohn@phbs.pku.edu.cn (Sungbin Sohn)

in the hope of attracting automated high-frequency traders, trade-level data may be freely collected using this API. Hence there is a plethora of data on CEX markets and academic research on the microstructure of bitcoin markets has become prolific.

Price discovery is one of the most important research questions. As [Baur and Dimpfl \(2019\)](#) point out, two properties of bitcoin – the absence of a commonly-accepted valuation model and the trading of the same asset in numerous venues – not only make this question particularly challenging but also make empirical evidence more important. The launch of bitcoin futures on the Chicago Mercantile Exchange (CME) and the Chicago Board Options Exchange (CBOE) in December 2017 triggered much academic discussion on the role of futures in bitcoin price discovery. [Hale et al. \(2018\)](#) argues that the bitcoin price collapse after these futures launched is not a coincidence – similar patterns have been observed in other asset classes. This argument implies a leader role for those futures contracts in bitcoin spot price discovery. However, using the accumulated price data from both futures exchanges, [Corbet et al. \(2018\)](#) and [Baur and Dimpfl \(2019\)](#) independently report that the futures markets neither exercise a price leadership nor serve as an effective hedge against spot market, possibly due to low trading volume in futures contracts compared with the spot. Yet, this is contrary to general findings in mature futures markets of other asset classes, where futures markets play a dominant role in price discovery ([Cabrerera et al., 2009](#); [Rosenberg and Traub, 2009](#); [Bohl et al., 2011](#); [Hauptfleisch et al., 2016](#)). Moreover, using much higher frequency data and a longer time span than previous studies, a recent paper by [Alexander and Heck \(2019\)](#) has demonstrated a relatively high role of both CBOE and CME futures. In fact, after the CBOE contract was withdrawn, the CME futures started to play a particularly strong price discovery role, particularly on expiry dates or around price jumps.

Market efficiency is another active area of research. Some conclude that, although not efficient at first, the bitcoin market is now highly efficient ([Urquhart, 2016](#); [Bariviera, 2017](#); [Vidal-Tomás and Ibañez, 2018](#); [Tiwari et al., 2018](#); [Sensoy, 2019](#)). However, this conclusion is not unanimous as the methods, data source, and observation periods vary considerably. For example, a recent study that uses different efficiency indices argues that the bitcoin market was inefficient even until 2018 ([Jiang et al., 2018](#)). For a comprehensive review of the bitcoin efficiency literature to date, see [Bundi and Wildi \(2019\)](#). Note that some research on efficiency has been extended to cryptocurrencies beyond bitcoin ([Brauneis and Mestel, 2018](#); [Wei, 2018](#)).

We make a novel contribution to both strands of the bitcoin literature by examining the bitcoin derivatives traded on BitMEX.¹ This is one of the largest bitcoin exchanges by trading volume, as of April 2019, and counting all bitcoin products its volume is an order of magnitude above CME, CBOE and major spot exchanges. Therefore, BitMEX data should provide a comprehensive view about bitcoin market microstructure and, in particular, a study on the price leadership between spot and derivative trades. BitMEX launched their derivatives contracts before the CME and CBOE but they have many different features which aim to attract small but crypto-focused traders than mainstream financial institutions: 1 USD contract size, no regulation, bitcoin-based contract design, minimal margins, and much lower trading costs. Following [Admati and Pfleiderer \(1988\)](#) we know that all these features should attract the participation of informed traders. While the exchange had been known among cryptocurrency insiders since its launch in 2014, the importance of BitMEX has only recently attracted the attention of regulators, who are concerned about the potential

¹<https://www.bitmex.com>. BitMEX stands for Bitcoin Mercantile Exchange.

for market manipulation.² Our paper aims to inform both traders and regulators about the microstructure of BitMEX, and its crucial role in the crypto asset ecosystem.

To learn more about bitcoin market microstructure we (trivially) confirm the cointegration between prices on the BitMEX perpetual swap, a synthetic spot similar to futures, and three major spot exchanges (Bitstamp, Coinbase and Kraken) as a pre-requisite for estimating a four-dimensional vector error correction model (VECM) which provides the foundation of our price discovery measures. We examine the extent to which each exchange contributes to the common efficient price, measured by the modified information shares (MIS) of [Lien and Shrestha \(2009\)](#) and the component shares (CS) of [Gonzalo and Granger \(1995\)](#). We also measure the extent to which innovations in one exchange are transmitted to the others, using the gross and net spillover effects of [Pesaran and Shin \(1998\)](#) and [Diebold and Yilmaz \(2012\)](#). Moreover, we investigate the extent to which the current return is associated with the past information as measured by the returns autocorrelation and variance ratio ([Comerton-Forde and Putniņš, 2015](#)).

We find that, among the four markets studied, the BitMEX perpetual swap takes almost half of both the MIS and the CS. This very dominant price discovery role is stable and robust throughout the sample period. This finding indicates that the speed with which new information is incorporated into the bitcoin price is more rapid in BitMEX than in these other exchanges, i.e. the BitMEX perpetual swap plays the price leadership role. In addition, we document that the strength of price discovery in BitMEX is positively (negatively) associated with the relative bid-ask spread (trading volume) of the spot markets, consistent with findings in equity derivatives markets ([Chakravarty et al., 2004](#); [Chen and Chung, 2012](#)). We also find that the magnitude of price spreads between exchanges also affects the role of BitMEX in price discovery. Moreover, the effect of inter-exchange spreads depends on whether the market is bull or bear mode. Further analysis shows that BitMEX has significantly positive net spillover effects, meaning that innovations in BitMEX have a disproportionately larger influence on the other three markets.

These strong price discovery and spillover effects from BitMEX derivatives suggest higher informational efficiency and hedge effectiveness. We indeed find much supporting evidence for this. When measured by autocorrelation and variance ratio, BitMEX is informationally more efficient than all three spot exchanges – even more efficient than Coinbase, the most efficient one among the three. Finally, we show that BitMEX derivatives serve as an effective hedge against spot market with the out-of-sample hedging effectiveness between 0.9642 (for the naive hedge of the Kraken price) and 0.9939 (for the minimum variance hedge of Coinbase). These findings are in complete contrast to the conclusions of [Corbet et al. \(2018\)](#) and [Baur and Dimpfl \(2019\)](#), who use the CME and CBOE bitcoin futures as the hedging contract.

The remainder of this paper is organised as follows. Section 2 discusses the characteristics of BitMEX products. Section 3 describes the data and confirms that, of all derivatives contracts traded in BitMEX, the perpetual swap is the most representative. In Section 4, we investigate several market microstructure properties of BitMEX and compare them with those in major spot exchanges, using high frequency data from July 01, 2016 to January 03, 2019. We also examine the hedging effectiveness relative to the three main bitcoin spot exchanges. Finally, Section 5 concludes.

²See [Twomey and Mann \(2019\)](#) and <https://www.bloomberg.com/news/articles/2019-07-19/u-s-regulator-probing-crypto-exchange-bitmex-over-client-trades>.

2. Exchange and Contracts

Here we describe BitMEX and its products, focussing on its flagship contract – the perpetual swap – and compare its characteristics with the bitcoin futures traded on the CME.

BitMEX is an online cryptocurrency derivatives exchange founded in 2014. It is an unregulated exchange with no fiat currency involvement. Although it operates in Hong Kong, BitMEX is wholly owned by an entity incorporated in the Republic of Seychelles, a well-known tax shelter. Therefore, BitMEX is not subject to any futures regulatory bodies such as the Commodity Futures Trading Commission (CFTC) in the United States or the Securities and Futures Commission (SFC) in Hong Kong. In addition, fiat currency is not involved in BitMEX: the margin and settlement are paid only in bitcoin. As a consequence, there are no know-your-client (KYC) or anti-money laundering (AML) procedures during account opening, which is typically enforced by the partner banks for other, fiat-based crypto exchanges. Clients only need an e-mail account and bitcoins to trade on BitMEX. This lack of regulation is an obstacle for some clients such as large financial institutions with strong compliance and those in certain jurisdictions.³ Nevertheless, these features attract a wide retail client base to BitMEX. It is the alternative trading venue of choice for those without access to well-functioning spot exchanges, or indeed those wishing to avoid KYC or other checks on identity. It is possible that many Chinese became BitMEX clients after the Chinese authorities closed local cryptocurrency exchanges in September 2017.

Although the CME (and the – now defunct – CBOE) bitcoin futures have a contract size denominated in bitcoin (XBT), the contracts are managed entirely in USD.⁴ By contrast, BitMEX uses XBT as its base currency. As a result, the profit and loss of BitMEX products (i.e. fixed-maturity futures and the perpetual swap) depends on the *inverse* of XBT/USD. That is, a short (long) position on bitcoin is effectively a long (short) position on USD/XBT. Consequently, the contract size is measured in USD not XBT.⁵ This feature may or may not attract clients, depending on which currency is preferred. For traditional financial institutions trading various asset classes, the bitcoin-based system of BitMEX is perhaps another deterrent

³In January 2019, BitMEX reportedly started refusing and closing client accounts based in US and Quebec, Canada, as requested by regulators in these regions. However, the determination of client jurisdiction based on an IP address can be extremely difficult. See <https://www.scmp.com/business/money/wealth/article/2182043/hong-kong-based-digital-currency-exchange-bitmex-ditches>.

⁴We use XBT for bitcoin's currency code, following the CBOE and BitMEX. This abbreviation comes from the International Standards Organization that maintains a list of internationally recognized currencies. In time, it may replace the abbreviation BTC entirely.

⁵We further illustrate the difference with an example. Suppose a trader holds ten bitcoins and hedges the market value by entering into a short futures position. Assume that the bitcoin price changes from 5,000 USD to 4,000 USD during the period of hedge. If she uses CME, she would enter into a short futures of 10 XBT, and the profit from the position is

$$(5,000 - 4,000) \times 10 = 10,000 \text{ USD.}$$

The resulting portfolio, consisting of 10 bitcoins and 10,000 USD, has the unchanged value of 50,000 USD. If she uses BitMEX instead, she would create a short position worth of 50,000 USD, and the profit from the position is

$$\left(\frac{1}{4,000} - \frac{1}{5,000} \right) \times 50,000 = 2.5 \text{ XBT}$$

The resulting position, 12.5 bitcoins, also has 50,000 USD value.

– they prefer fiat currency for accounting purposes and fungibility. Hence, the CME contracts are better suited to them. But the XBT base-currency feature of BitMEX is ideal for crypto-based traders who need bitcoins for their daily business operations. Such traders include, for example, miners who have amassed a large XBT balance, blockchain-related start-ups who have raised capital by initial coin offerings (ICO), and hedge funds trading cryptocurrencies. These players might be considered as more informed about bitcoin markets than the mainstream financial institutions who prefer trading on the CME, although their size may be smaller.

The BitMEX margin requirement is just 1%, allowing a leverage ratio of 100, whereas the CME requires 37% and the requirement can be even higher depending on brokerage. For example, TD Ameritrade requires a margin 1.5 times higher than the exchange margin. Interactive Brokers requires a fixed 40,000 USD for the short position on one bitcoin.

Moreover, trading costs on BitMEX are low. The market takers pay a 7.5 basis point fee, but market makers receive a 2.5 basis point rebate when a trade is executed. Along with the availability of an API, the rebate scheme is a strong incentive for crypto-based high-frequency hedge funds for automated market making or statistical arbitrage. To the best of our knowledge, no other major bitcoin derivatives exchange, CME and CBOE included, offers such a rebate scheme.

There are several further properties which make BitMEX contracts more accessible to investors than the CME bitcoin futures. The contract unit of one USD in BitMEX is affordable for retail traders. This is significantly less than the contract units of 5 bitcoins in CME (or 1 bitcoin for the CBOE, before the contracts were withdrawn). The tic increment is 0.5 USD on BitMEX compared to 5 USD on CME. And BitMEX trading occurs 24/7, similar to spot exchanges, whereas trading on the CME is from Sunday to Friday, 5pm to 4pm Chicago time.

Last, but most importantly, BitMEX's unique contract type called the *perpetual swap* has made key contributions to the popularity of BitMEX. Since its founding in 2014, BitMEX offered various products such as traditional fixed-maturity futures on XBT/USD (the XBT series).⁶ However, it was not until the introduction of the XBT/USD perpetual swap in May 2016 that BitMEX gained meaningful trade volume. The perpetual swap has now become by far the most traded product on BitMEX. It can be understood as a cross-currency (i.e. fixed for floating) swap between XBT and USD, where the XBT notional amount is rebalanced against a fixed USD notional amount (i.e. the contract size) according as the market changes.⁷ During the swap, both sides pay interest on the principal in the currency they receive. As in a currency swap, only the interest difference, or *funding* in BitMEX terms, is exchanged between the long and short position holders. Given there is no interest rate in bitcoin, the funding rate is computed using a formula which is designed to prevent divergence between the swap rate and the reference bitcoin spot price index in

⁶BitMEX used to also offer traditional fixed-maturity futures on BTC/JPY (the XBJ series) and BTC/USD quanto futures (the XBU series), but these series are no longer offered.

⁷That is, the up-front principal exchange is x_1 per dollar, where x_1 is the XBT/USD rate at the start of the swap. If the notional is 10,000 USD then party A pays 10,000 USD to party B and receives $10,000/x_1$ bitcoin from party B. On exiting the contract party B returns 10,000 USD to party A and receives $10,000/x_2$ bitcoin from party A where x_2 is the XBT/USD rate when the contract is closed. This makes the product, effectively, a synthetic spot bitcoin featured with long and short positions.

BitMEX (.BXBT).⁸ Unlike a standard currency swap, however, there is no fixed maturity. The perpetual swap may be preferred because there is no need for a roll-over trade – which can be risky due to bitcoin’s high volatility. Following the success of the BitMEX perpetual swap the contract design has been adopted by several followers, such as the OKEx exchange.⁹ Table 1 summarises the differences between the BitMEX perpetual swap and the fixed maturity futures on BitMEX, CME, and CBOE.

Taken together, all these characteristics contribute to large trading volumes and a broad investor base. [Admati and Pfleiderer \(1988\)](#) show, theoretically and under reasonable assumptions, that the introduction of more informed traders generally increases the concentration of trading by liquidity traders, further attracting more informed traders. One implication of this theory is that, in a market with higher trading volume, more information creation occurs and prices are more efficient. Based on this theoretical implication, we hypothesise that conditions on BitMEX lead to fast price discovery and informationally efficient prices, and we test these hypotheses formally in Section 4.

(Insert Table 1 here)

3. Data

In this section, we describe the data and justify several choices we have made for the analysis to come. We obtained trade-level XBT/USD data from two sources: the BitMEX archive ([\[dataset\] BitMEX, 2019](#)) for the trades and the best bid-ask prices for perpetual swaps and traditional futures; and [bitcoincharts.com](#) ([\[dataset\] Bitcoincharts, 2019](#)) for the trades on three spot exchanges, Bitstamp, Coinbase, and Kraken.¹⁰ The data include time-stamp, price, and traded bitcoin amount for each trade. We use the trade-level data to create a price time series and trade volume is aggregated minute-by-minute, or at other required frequencies. Additionally, we use the averaged bid-ask spread of the three spot exchanges from [bitcointy.org](#) ([\[dataset\] Bitcointy, 2019](#)).

We select the sample period from July 1, 2016 to January 3, 2019. The start date is chosen so to exclude the period immediately after the launch of the BitMEX perpetual swap in May 2016. In several analysis, we divide the period into two sub-periods: before and after December 17, 2017 when the bitcoin price reached its peak near USD 20,000. This partition of the sample is intended to detect any structural break between bull and bear markets. The break point also coincides with the launch of the bitcoin futures on CBOE and CME.

The three spot exchanges (Bitstamp, Coinbase, and Kraken) represent the bitcoin spot markets well because they are consistently ranked within top five by XBT/USD trading volume. We exclude Bitfinex although its trading volume is higher than the three exchanges. A significant portion of bitcoin trade in Bitfinex is reportedly made against Tether (USDT), a cryptocurrency whose value is supposed to be in

⁸For the detailed contract specification we refer to the BitMEX website: <https://www.bitmex.com/app/contract/XBTUSD>.

⁹<https://medium.com/okex-blog/okex-launched-perpetual-swap-227eec2c9f29>

¹⁰[\[dataset\] Bitcoincharts \(2019\)](#) has been widely used in previous studies; see [Eross et al. \(2019\)](#) and [Gandal et al. \(2018\)](#) for example. We verify the data integrity by comparing the aggregated daily trade volume to that available from another on-line source, [\[dataset\] Bitcointy \(2019\)](#).

parity with USD because it is issued on USD collateral. Moreover, Bitfinex is closely tied with the issuer of Tether and various legal and accounting issues has been raised recently (Griffin and Shams, 2018). Therefore, Bitfinex is difficult to be considered as a genuine spot exchange. With Bitfinex excluded, Bitstamp, Coinbase, and Kraken account for 21.0%, 25.2%, and 9.7% of the total XBT/USD spot trading volume, respectively, during the sample period ([dataset] Bitcoinity, 2019). The three exchanges are particularly suitable for the analysis of spot-derivative relationship because they constitute the reference spot price index in BitMEX with equal weight.

Figure 1 plots the daily characteristics of the bitcoin spot and perpetual swap prices. The top-left panel shows that prices on the four exchanges clearly share a common stochastic trend, implying a cointegration relationship. The returns and volatilities of the four markets also coincide. The bottom-right panel depicts the log basis of the three spot exchanges, i.e. the log of the BitMEX price minus the log of the spot exchange price.

(Insert Figure 1 here)

Table 2 reports the average trading volume by exchanges and trade types in the six month sub-periods as well as the whole sample. In addition to the four exchanges we report the trading volume on CBOE and CME obtained from their websites, for reference. For BitMEX, the volume from the perpetual swap and the fixed maturity futures are reported separately. Overall the trading volume grows rapidly in all trading venues until the second half of 2018. It is noticeable that the volumes on BitMEX and CME still grow in the last sub-period whereas the volume decrease in the rest of exchanges. To capture the changes in relative volume share over the sample period better, in Figure 2 we plot the ratio of BitMEX's perpetual swap volume to the sum of volumes over the three spot exchanges (Bitstamp, Coinbase, and Kraken). The volume ratio exceeds one by early 2017 and reaches 24 by August 2018.

(Insert Table 2 here)

(Insert Figure 2 here)

While both the perpetual swap and the the traditional futures are traded on BitMEX, we acknowledge the perpetual swap as the legitimate representative of the exchange – a decision based on much larger volume and superior price discovery.¹¹ In the previous section, we also argued that the perpetual swap is more attractive than the fixed maturity futures because it does not require roll-over trades.

Since the following analyses are mostly based on the assumption of cointegration, we formally test whether the cointegration relationship exists over the full-sample and sub-sample periods. Table 3 reports the test

¹¹Indeed, we see that the trading volume of the perpetual swap is larger than that of traditional bitcoin futures, by an order of magnitude. We also examine the price discovery shares between the two BitMEX products –this will be detailed in Section 4.1 and the Appendix. For the analysis of the futures, we form a single time series of minute-by-minute futures prices, using the price of the most nearby contract until there are three trading days left to maturity. After that, the next nearby contract replaces the expiring one. We construct the time series in this way because the prompt contract generally has the largest trading volume and supposedly contains the most information. This method has been adopted in the literature (Booth et al., 1999; Sohn and Zhang, 2017), and our results are robust to the specific timing of the contract replacement. Since the trading volume of the bitcoin futures had been negligible until the end of October 2016, we start considering its price time series from November 2016.

results. The Engle-Granger test assesses the null hypothesis of no cointegration among the log prices of the four exchanges. The Johansen test assesses the null hypothesis of a particular cointegration rank against the alternative of higher ranks. Regardless of the sample periods, the test statistics and their associated p -values confirm that there exists a cointegration relationship and that the rank of the cointegrating matrix is at least three, implying a single stochastic trend. The last row in each panel reports the proportion of days in which the associated null hypothesis is rejected at the 1% significance level when the cointegration tests are conducted on a daily basis. Panel A shows that in the full-sample period, the null of no cointegration is rejected in 912 trading days (99.45%) out of the total 917 trading days according to the Engle-Granger test. The Johansen test shows that the null hypothesis of the cointegration rank being equal to three cannot be rejected for more than 83.64% of the total trading days. These results do not qualitatively change in the two sub-samples, indicating the robustness of the cointegration relationship. Based on these test results, this paper assumes the existence of a cointegration relationship with the cointegration rank of three.

(Insert Table 3 here)

4. Empirical Analyses

This section investigates several market microstructure properties of BitMEX using a four-dimensional VECM with the prices in BitMEX, Bitstamp, Coinbase and Kraken as the state variables. A bivariate VECM is more common in the spot-derivative price discovery literature and we could also have applied such, using the reference spot price index in BitMEX, the equally-weighted average of the three spot exchange prices. However, we decided to use the raw price data from the spot exchanges because the price index may not be the optimal representative of the spot bitcoin price. As will be described in following sub-sections, the price discovery shares of the three spot exchanges are not evenly distributed. Therefore, it may over-represent the exchange with smaller price discovery. Moreover, this four-dimensional setting enables us to learn the influences not only between spot and derivatives markets but also among spot markets.

4.1. Modified information shares and component shares

In this sub-section, we examine the contribution to the price discovery by BitMEX and the other three bitcoin spot exchanges (Bitstamp, Coinbase, and Kraken). Price discovery is the process by which new information is incorporated into asset prices. Given a single product traded in several markets (alternatively, given closely related products traded in a market), the market (or product) whose price reflects new information faster would be expected to play the dominant role in price discovery. Assuming a cointegration relationship among the prices in consideration, Hasbrouck (1995) and Gonzalo and Granger (1995) respectively propose the measures of price discovery: information shares (IS) and component shares (CS). Lien and Shrestha (2009) suggest the modified information share (MIS) that overcomes some shortcomings of IS. The MIS of a market captures the extent to which its innovation contributes to the variation in the common factor of the cointegrated time series. The CS reflects each market's relative contribution to the common factor. These two measures are derived from a common cointegration relationship and have similarity, but they differ in that the MIS incorporates the correlation between price innovations of the considered markets (products)

while the CS does not. Therefore, the two measures provide complementary views of price discovery among the markets.¹²

(Insert Table 4 here)

For a given sample period, e.g. the entire sample or on a daily basis, we use minute-by-minute log prices to estimate a vector error correction model (VECM) and compute the MIS and the CS. Panel A of Table 4 reports the price discovery shares of the four markets for the full-sample period. We find that BitMEX plays the dominant price discovery role. Specifically, the average of daily MIS (CS) of BitMEX is 51.53% (57.50%). In contrast, those of Bitstamp, Coinbase, and Kraken are limited to 18.46% (15.61%), 23.18% (21.24%) and 6.81% (5.64%), respectively.

(Insert Figure 3 here)

To examine how the price discovery shares evolve over time, the same analysis is performed for the two sub-periods, before (Panel B) and after (Panel C) December 2017. We also plot the daily time series of MIS and CS for the four exchanges in Figure 3 using day-by-day VECM models. The results are smoothed to remove noise. The table and the figure confirm that the contribution of BitMEX to price discovery has been stable and high, despite some ups and downs. The shares of BitMEX either increased after the structural break (CS: 50.09% to 67.89%) or are almost unchanged (MIS: 52.25% to 50.33%) depending on the measures. In contrast to the stable role of BitMEX, the price discovery shares of Coinbase tends to decrease over time, while the price discovery role of Bitstamp has steadily increased.

Interestingly, the MIS and CS are almost identical, particularly in the earlier sub-sample, implying that the contemporaneous correlation among innovations in the four exchanges is sufficiently small (Baillie et al., 2002). In the later sub-sample, however, the differences between MIS and CS is sizeable, indicating that the exchanges become more inter-connected and their innovations are consequently more correlated.

4.2. Speed of error correction

Since the MIS and CS from the four exchanges should sum to one by construction, they only capture the *relative* strength of price discovery. Hence, when the speed of information incorporation into the price increases or decreases concurrently in the four exchanges, these measures cannot effectively reflect this change. To understand the changes in strength of price discovery comprehensively, we consider whether and to what extent an exchange reacts to short-run deviations from a long-run equilibrium by investigating the error correction coefficients in the VECM. Table 5 reports the average of estimated error correction coefficients obtained from the daily estimation of the VECM and the associated Newey-West standard errors. The error correction coefficients indicate the response speed of each exchange with respect to the deviation of its price from the price in another exchange. For example, the row of BitMEX in Panel A shows the response of the price on BitMEX when the price difference between BitMEX and Bitstamp (Coinbase or Kraken) increases by 1%.

¹²See Appendix for the detailed calculation procedure.

(Insert Table 5 here)

Note that the signs of the error correction coefficients are supposed to be non-positive, under this specification. As expected, all coefficients are either negative or insignificant for all exchanges and sample periods, but their magnitudes vary across the four markets and over time. In the full-sample period, it turns out that the error correction occurs most strongly in Kraken, while the error correction speed is the slowest in BitMEX. When the price difference between Kraken and BitMEX (Bitstamp or Coinbase) widens by 1%, the price in Kraken falls by 0.1804% (0.2487% or 0.2250%) in the following minute. In contrast, when the price difference between BitMEX and Bitstamp (Coinbase or Kraken) increases by 1%, the price in BitMEX reacts very little – it subsequently drops by only 0.0357% (0.0038% or 0.0049%). This result is consistent with the findings from the MIS and CS that BitMEX plays the dominant price discovery role. Intuitively, if the price of one exchange responds strongly to the past cointegration error (i.e. the short-run deviation from a long-run equilibrium) rather than evolving autonomously, it is likely that the exchange incorporates information at a lower speed than others and plays a less important role in price discovery.

The sub-sample estimations indicate that the *absolute* strength of each market's price discovery exhibits dramatic changes over time; the response of the spot exchanges to the cointegration errors became stronger but BitMEX does not significantly respond to price deviation from Coinbase and Kraken in the recent bearish sub-sample. This finding is consistent with the stronger price leadership of BitMEX as well as closer interconnectedness among spot exchanges in the recent period.

4.3. Spillover effects

The findings above suggest that BitMEX and the spot exchanges have become more closely inter-connected over time. To examine the extent to which shocks in one market account for variation in other markets we conduct the forecast error variance decomposition suggested by Pesaran and Shin (1998) and Diebold and Yilmaz (2012) to calculate the gross and net spillover effects from a given market.¹³ While the MIS and CS indicate how each market reacts to the deviation from the long-run common trend, the spillover effects show how each market reacts to shocks in other markets.

(Insert Table 6 here)

(Insert Figure 4 here)

Table 6 presents the gross spillover effects from one market to another, and the net spillover effects from a given market. The (i, j) entry in the gross spillover represents the estimated contribution to the forecast error variance of market i coming from innovations of market j , while the entry in the net spillover is the difference between the spillover from market i to all other markets and the spillover from all other markets to market i . The spillovers are estimated for each day and the values in the table are the average of the daily estimates.

Unsurprisingly, the majority of the forecast error variance in a market originates from its own shocks. In the full-sample period the gross spillover from a market to itself ranges from 64.28% (Coinbase) to

¹³See Appendix for the detailed calculation procedure.

73.16% (Kraken). The total spillover, defined as the average forecast error variance attributed to other markets rather than its own, is 32.85%. One noticeable finding is that BitMEX *gives substantially more than receives*: the spillover from BitMEX to the other exchanges is 44.25%, while that to BitMEX from the others is 36.00%. In other words, innovations in BitMEX influence the other exchanges more than it is influenced by innovations in the others, and this is reflected by the sizeable positive net spillover (8.25%). In contrast, Kraken has a considerable negative net spillover (-8.58%) meaning that the influence of Kraken on the others is disproportionate to that of others on itself. The other two exchanges are well balanced in that the net spillovers are close to zero.

The sub-sample analyses contrast the inter-market influences during earlier and later periods. First, the total spillover increases from 17.02% before the price peak in December 2017 to 55.05% afterwards. This means that an increased fraction of the forecast error variance in one market is attributed to the shocks in the other markets, again implying a greater connectedness between the markets. The gross spillover from each exchange also increases significantly. For example, the shocks in BitMEX account for only 28.79% of the forecast error variances of the other exchanges in the earlier sub-sample, but this fraction increases to 65.91% in the later sub-sample. This trend of intensified interdependence is consistent with the evidence found in Sections 4.1 and 4.2 in that each exchange is more actively incorporating information arising from other exchanges and their innovations are more correlated.

(Insert Figure 5 here)

The averaged values in the table provide a useful and handy snapshot of the overall influence of each market, but cannot show how it has evolved over time. For better understanding of its time-varying features, Figure 4 depicts the daily net spillover from each market. In the earlier sample period the net spillovers are close to zero for all four exchanges, which indicates that there had been little inter-market influences until early 2017. This fact is consistent with the overall trend of the total spillover depicted in Figure 5. However, as the total spillover effects substantially increase after mid 2017, the net spillover from BitMEX has become significantly positive, while that from Kraken has become significantly negative. The net spillovers from the other two markets remain close to zero. If shocks in one market affect the prices in other markets more than the other way around, then the market supposedly plays more important roles in price discovery. In light of this, the positive net spillover in BitMEX is generally consistent with its large price discovery shares.

4.4. Determinants of price discovery

In Section 4.1 we showed that the strength of the price discovery of BitMEX fluctuates over time. To formally examine the determinants of time-varying price discovery shares, we run a regression of the price discovery share (MIS and CS) of BitMEX on several market characteristics. Specifically, we control the relative spread (*RSpread*; average bid-ask spread in spot exchanges divided by BitMEX spread), the relative trading volume (*RTV*; total trading volume of the spot exchanges divided by BitMEX trading volume), the bitcoin log return (*Ret*; the change of log bitcoin prices in BitMEX), the absolute basis (*Abs.Basis*; absolute value of average difference of log prices between BitMEX and the three spot exchanges). We also include a dummy variable that indicates a day with a negative return ($D_{Ret < 0}$) and its interaction with *Abs.Basis*. The spot exchanges are represented by Bitstamp, Coinbase, and Kraken. All control variables except for

the dummy are standardized to have zero-mean and unit-variance for clearer economic interpretation: the coefficients represent the change in the dependent variable – i.e the price discovery share of the futures – per unit standard deviation change in the control variable.

These control variables are motivated by the previous literature and plausible conjectures. First, it has been widely documented that price discovery tend to occur primarily in the market with smaller trading costs (Booth et al., 1999; de Jong and Donders, 1998; Hsieh et al., 2008). To test this trading cost hypothesis, we control for the relative bid-ask spread and the relative trading volume. Secondly, a larger absolute basis indicates wider deviation of prices from a long-run efficient price and this price decoupling may well result from the influx of uninformed investors into spot exchanges, due to exuberance and/or irrationality, which could potentially open a short window of arbitrage opportunity. Therefore, we conjecture that BitMEX traders, who are supposedly more informed, could actively exploit this potential arbitrage opportunity and affect the price discovery strength. Thirdly, when the market is down BitMEX may play a differential price discovery role, because short-selling is possible directly on BitMEX but not on our spot exchanges. To test the second and third conjectures we include the absolute basis, the market return, and the negative return indicator.

Table 7 reports the regression results. BitMEX is stronger when the spot exchanges have relatively greater bid-ask spreads and smaller trading volume, consistent with previous empirical findings that less costly transactions and more trading are conducive to faster information incorporation (Chakravarty et al., 2004; Chen and Chung, 2012; Ahn et al., 2019). Specifically, column (1) shows that when the relative bid-ask spread (trading volume) of spot exchanges increases by 1 standard deviation, the MIS of BitMEX rises by 5.37% (falls by 1.87%). We also find that the absolute value of the basis is negatively associated with the price discovery of BitMEX, meaning that the larger price gap between BitMEX and other spot exchanges lowers the price discovery role of BitMEX. To understand this finding, recall that the market whose price tends to narrow the absolute basis has a low price discovery share because this market follows, rather than leads, the other markets. In light of this fact, our finding is consistent with the conjecture that BitMEX traders more actively exploit potential arbitrage opportunities when prices deviate further from a long-run efficient level. Interestingly, this negative relation between the price decoupling and the price discovery in BitMEX depends on the market situation. During a market downturn this negative association significantly weakens. For example, column (2) shows that when the absolute basis increases by 1 standard deviation, the MIS of BitMEX falls by 3.86% when the market is up, while it falls only by 0.29% ($-3.86\% + 3.57\%$). Given that the average basis is more negative (i.e. the BitMEX price is less other spot prices) during the market downturn, the decoupling of prices when the return is negative is, presumably, due to short selling from BitMEX. We conclude that trades on BitMEX lead the spot prices when the market is down and it is the spot markets that correct the price decoupling.

In summary, our analysis shows that the price discovery role of BitMEX improves when transaction costs are less and trading volume is greater than that on spot exchanges; and that short trades on BitMEX in particular, which are not directly possible on the spot exchanges, contribute much to its price discovery role.

(Insert Table 7 here)

4.5. Informational efficiency

Large price discovery shares of BitMEX and its positive net spillover effects suggest that BitMEX is informationally efficient within the bitcoin ecosystem. To test this conjecture, we now compare the informational efficiency in BitMEX with that of other bitcoin spot markets. An efficient market implies no predictability of future returns and it is therefore standard to measure market inefficiency by the extent to which the current return is correlated with past returns, and/or the return data generation process differs from a random walk (Lo and MacKinlay, 1988; Hendershott and Jones, 2005; Comerton-Forde and Putniņš, 2015). Following the literature, we use the absolute value of return autocorrelation (AC) and the deviation from one of the return variance ratio (VR) as the measures of informational inefficiency.

Specifically, we calculate the AC of a market on a given day as follows. For each market we first compute several autocorrelations from the returns on a given day recorded at different intra-day frequencies: 1-minute, 3-minute, 5-minute and 10-minute, and then calculate the average of their absolute values. Note that in a fully informationally efficient market where prices reflect all public and private information, returns should have zero autocorrelation at every observation frequency. Therefore, a higher value of AC indicates that the price does not instantaneously reflect new information; rather, it might either over- or under-react to news.

The daily VR of a market is obtained similarly. For each market, we first calculate the variances of returns recorded at different intraday frequencies: 1-minute, 5-minute, 10-minute and 20-minute, and then compute the absolute deviation of their ratios from one: $|\sigma_{kl}^2/(k\sigma_l^2) - 1|$, where σ_l^2 is the variance of returns recorded at l -minute frequency. We calculate these ratio deviations using three frequency pairs: (5-minute and 1-minute), (10-minute and 5-minute) and (20-minute and 10-minute). Finally, the VR is obtained as the average of these three values. If a price follows a random walk process, the return variance should be proportional to the measurement frequency. Therefore, as in the AC case, a large value of VR indicates more deviation from a random walk process, implying some degree of return predictability.

(Insert Figure 6 here)

Figures 6 plots the daily AC and VR in the four bitcoin markets: BitMEX, Bitstamp, Coinbase, and Kraken. Again, the time series are smoothed for clear readability. The average AC (VR) in BitMEX is only 0.084 (0.137), while those in Bitstamp, Coinbase, and Kraken are 0.155 (0.22), 0.094 (0.158) and 0.144 (0.208), respectively. We find that the values of AC and VR in BitMEX are almost uniformly and significantly smaller than those in other markets, implying BitMEX's higher degree of informational efficiency.¹⁴ It is also noticeable that AC and VR move closely together within each exchange, serving as robustness check to each other. Interestingly, Coinbase has the second smallest AC and VR. The fact that the net spillover effects from Coinbase are negative on average in the same sample period shows that the informational efficiency within a market and its influence on other markets are not necessarily aligned, confirming the importance of the comprehensive examination in this paper.

4.6. Hedging effectiveness

Finally, we examine the out-of-sample hedging effectiveness of the BitMEX perpetual swap. Let $p_{i,d}$ be the log price in exchange i on day d , where $i \in \{\text{BitMEX, Bitstamp, Coinbase, Kraken}\}$. Then, $\Delta p_{i,d+1} -$

¹⁴In an unreported analysis, we find that the p -value of the mean difference test is smaller than 0.1%.

$b_{id}\Delta p_{\text{BitMEX},d+1}$ is the return on day $d + 1$ of the portfolio that purchases one bitcoin spot in exchange i and short sells b_{id} bitcoins of the perpetual swap in BitMEX.¹⁵ The hedge ratio b_{id} is set to be zero for the unhedged position and one for a naive hedge. A utility maximisation problem with a two-period model implies that the hedge ratio which minimises the portfolio return variance is obtained by the ratio of spot-BitMEX return covariance to BitMEX return variance (Ederington, 1979; Park and Switzer, 1995). Therefore, for the minimum variance hedge, b_{id} is set to be the slope coefficient from the OLS regression of spot returns in exchange i on the BitMEX swap returns using the daily observations up to day d . Following de Jong et al. (1997), we investigate the hedging effectiveness in an out-of-sample setting. Specifically, we use the earlier half of the sample (July 1, 2016 to Oct 1, 2017) for the initial estimation of the minimum variance hedge ratio on Oct 1, 2017, and keep updating the daily hedge ratio using a moving window estimation.

Table 8 compares the standard deviations of daily portfolio returns obtained from several hedging methods. The portfolio returns are examined for the later half of the sample period. The results show that even the naive hedge substantially reduces the exposure to the spot volatility risks. In Bitstamp, the return standard deviation for the unhedged position is reduced from 4.69% to 0.39% by taking a unit short position in BitMEX. The minimum variance hedge further decreases the portfolio return variance. Table 8 also reports the measure for hedging effectiveness (HE) suggested by de Jong et al. (1997). The measure of exchange i is defined as

$$HE_i = 1 - \frac{\sigma_p^2}{\sigma_i^2},$$

where σ_p^2 is the variance of the hedge portfolio returns and σ_i^2 is the variance of the unhedged spot returns in exchange i . The HE measure is at least as large as 0.9642 (naive hedge in Kraken) and even reaches 0.9939 for the minimum variance hedge in Bitstamp. The hedging effectiveness varies across the spot exchanges and hedging methods, but the magnitude is always large.

This finding is opposite to Corbet et al. (2018), who report that a hedge using CBOE futures does not effectively reduce the portfolio return volatility. Their findings show that hedging increases, rather than decreases, the variance of the hedge portfolio returns not only for the naive hedging but also for the minimum variance hedging. Hence, they report the negative HE measures. But that is because the size of those contracts is so large that position risk is high, except when hedging huge notional amounts. Our findings about the price discovery also form a clear contrast to Corbet et al. (2018) and Baur and Dimpfl (2019) who also document that bitcoin spot prices lead the bitcoin futures prices in CME and CBOE. However, their results are likely to have been influenced by low trading volumes on the futures contracts (Adämmer et al., 2016).

(Insert Table 8 here)

¹⁵The actual short selling unit in Bitmex is USD and so the return should be calculated from the inverse price, as explained in Section 2. For comparison with previous studies based on CBOE and CME, we assume the short trade in BitMEX works in the USD-based style of CBOE or CME. Unless the daily return is extremely large, the outcomes are similar, by the Taylor approximation.

5. Conclusion

We investigate several market microstructure properties and analyse the information flows between BitMEX and three major bitcoin spot exchanges (i.e. Bitstamp, Coinbase and Kraken). These exchanges are selected from literally hundreds of possible bitcoin spot exchanges because they have the largest real trading volume and because their prices form the reference spot price index used by BitMEX for settlement of its main contracts. BitMEX is a dedicated crypto-only derivative exchange, which has received little attention from bitcoin researchers until recently despite its popularity and controversy. We first explain BitMEX's unique characteristics that appeal to traders and confirm that the perpetual swap, a margined synthetic spot contract in BitMEX, is the most representative derivative contract in BitMEX. The trading volume on the perpetual swap greatly surpasses the volume traded on CME bitcoin futures, as well as total spot trades on other major exchanges – so much so that we had to use a log scale in the graph!

We find that the BitMEX perpetual swap plays a dominant price discovery role and that the relative bid-ask spreads, relative trading volume and the inter-exchange spreads are important determinants of the fluctuation of its price discovery. We also find that BitMEX has significantly positive net spillover to the other exchanges, and is informationally more efficient too. Finally, we show that when the perpetual swap is used as a hedging instrument, the price volatility risk in the spot exchanges can be reduced up to 99.39%.

Unlike the spot exchanges used in our study, BitMEX is almost entirely unregulated. One only needs bitcoin and an email address to open account. Nevertheless, its unique features – and the design of the perpetual swap contract in particular – are obviously attractive to crypto-based traders who are presumably more informed than those trading on spot exchanges. We conclude BitMEX is an exchange that both investors and regulators should pay attention to. Given that derivatives in BitMEX lead the bitcoin spot prices and serve as an effective hedge against spot volatility, institutional investors should be mindful of BitMEX derivatives before deciding whether to consider bitcoin as a mainstream investment asset. The US Securities and Exchange Commission has adopted a conservative position by rejecting or postponing decisions on applications for bitcoin exchange traded funds (ETF), citing concerns about the lack of transparency and potential market manipulation in bitcoin exchanges. Given the substantial role and influence of the perpetual swap in BitMEX, regulators should prioritise investigation of the legitimacy of trading on this contract and on this exchange.

Data Availability Statement

The raw data that support the findings of this study have been obtained from the following public sources as of April 2019: (a) <https://public.bitmex.com> ([dataset] BitMEX, 2019), (b) <http://api.bitcoincharts.com/v1/csv/> ([dataset] Bitcoincharts, 2019), (c) <http://data.bitcoinity.org> ([dataset] Bitcoinity, 2019), and (d) the CME and CBOE websites. The resampled minute-by-minute time series of price and volume are available from the corresponding author, Sunghin Sohn, upon reasonable request.

Acknowledgments

This paper was presented at the 3rd KAFE–JAFEE International Conference on Financial Engineering in Busan, Korea. The authors thank Robert Webb (editor), Doojin Ryu (conference co-organizer) and other

participants at the conference. The authors are grateful to Dr. Kibeom Seong for sharing proprietary data for the earlier version of this paper.

Appendix

This appendix section first describes the procedure of obtaining the modified information share (MIS) and the component share (CS) of a product in a market, which are respectively proposed by [Lien and Shrestha \(2009\)](#) and [Gonzalo and Granger \(1995\)](#). Then, we explain how to measure the spillover effects from one market to another based on [Diebold and Yilmaz \(2012\)](#).

Consider K closely related products traded in different venues, and let p_t be a $K \times 1$ vector of their log prices. Suppose that p_t has a unit root and there exists a $K \times (K - 1)$ full-rank matrix β that makes $\beta'p_t$ stationary. Then, p_t is said to have a cointegration relationship with one stochastic common trend (permanent component) and $\beta'p_t$ is called the cointegration error (transitory component). The cointegrated time series of p_t can be represented by the VECM:¹⁶

$$\Delta p_t = \alpha \beta' p_{t-1} + \sum_{q=1}^Q A_q \Delta p_{t-q} + \epsilon_t, \quad (1)$$

where α is the $K \times (K - 1)$ error-correction coefficient matrix, indicating how prices react to the deviation from the long-run equilibrium relationship. Its sign and magnitude represent the direction and speed of the error correction. Q is the lag length of the model and is chosen by the Bayesian information criterion. A_q is the $K \times K$ autoregressive coefficient matrix, reflecting the effects of the short-term fluctuation on prices. ϵ_t is the $K \times 1$ zero-mean vector of serially uncorrelated disturbances with covariance matrix Ω .

The CS is derived from the permanent-transitory decomposition ([Gonzalo and Granger, 1995](#)) in which the common permanent component in p_t is obtained by its linear combination. Specifically, $\alpha'_\perp p_t$ is the permanent component in p_t where the $K \times 1$ vector α_\perp is defined such that $\alpha'_\perp \alpha = 0$, and the CS in the i th product (market) is obtained as:

$$CS_i = \frac{\alpha_{\perp,i}}{\sum_{k=1}^K \alpha_{\perp,k}}, \quad \text{for } i = 1, \dots, K,$$

which indicates the contribution of each time series to the long-run equilibrium price. A valid cointegration system theoretically implies that $\alpha_{\perp,k}$ should be positive for all k , but in an empirical analysis, negative values are infrequently obtained. Some papers use the absolute value to avoid this economically nonsensical results ([Bohl et al., 2011](#)). In this paper, we set a negative $\alpha_{\perp,k}$ to zero and adjust other values so that they sum to one. Since the negative values are infrequent and mostly close to zero, these treatments yield almost identical results.

The MIS incorporates additional information about the covariance structure of innovations. By the Granger representation theorem, Equation (1) can be expressed as the VMA(∞):

$$\Delta p_t = \Psi(L) \epsilon_t, \quad (2)$$

where $\Psi(L) = \sum_{q=0}^{\infty} \Psi_q L^q$, Ψ_q is the $K \times K$ moving average coefficient matrix and L is the lag operator. The integrated form of VMA(∞) is expressed as:

$$p_t = \Psi(1) \sum_{q=1}^t \epsilon_q + \Psi^*(L) \epsilon_t, \quad (3)$$

¹⁶A constant term does not affect the analysis and is omitted for notational simplicity throughout this section.

where $\Psi(1)$ is the sum of moving average coefficients and $\Psi^*(L)\epsilon_t$ is a zero-mean stationary process, representing the transient effect. Note that $\beta'\Psi(1)$ should be zero because $\beta'p_t$ is stationary. Hence, assuming that a cointegrating vector for a given pair is $(1, -1)'$, a $K \times K$ matrix $\Psi(1)$ should be a vertical stack of a $1 \times K$ common row ψ . [Hasbrouck \(1995\)](#) interprets $\psi\epsilon_t$ as the common permanent impact of the shock at t into the prices, and calls it the common efficient price. Then, he suggests a measure of the price discovery strength as the weight of the common factor variance. The greater proportion of the variance the innovations in a market constitute, the stronger price discovery capability the market possesses. Formally, the IS in the i th market is obtained as:

$$IS_i = \frac{([\psi M]_i)^2}{\psi\Omega\psi'}, \quad \text{for } i = 1, \dots, K,$$

where M is a lower triangular matrix of the Cholesky factorisation of Ω such that $\Omega = MM'$, and $[\psi M]_i$ is the i th entry in ψM . Note that the IS is closely related to the ordering of state variables because of the nature of the Cholesky factorisation. It maximises (minimises) the IS of the first-ordered (last-ordered) variable in p_t . In a bivariate analysis, the IS is commonly calculated as the midpoint of upper and lower bounds. Since there are $K!$ possible permutations for K state variables, we compute the IS of each market as the average value from the $K!$ permutations, which is the same calculation method as [So and Tse \(2004\)](#) and [Ahn et al. \(2019\)](#).

[Lien and Shrestha \(2009\)](#) suggest an improved version of IS that does not depend on the order of the state variables, and call it the modified information share (MIS). Formally, the MIS in the i th market is obtained as:

$$MIS_i = \frac{([\psi F]_i)^2}{\psi\Omega\psi'}, \quad \text{for } i = 1, \dots, K,$$

where $F = (G\Lambda^{-1/2}G'V^{-1})^{-1}$. G and Λ are derived from the correlation matrix of ϵ_t . Specifically, Λ is a diagonal matrix whose diagonal entries are eigenvalues of the correlation matrix and G is a matrix whose columns are the corresponding eigenvectors. V is a diagonal matrix whose diagonal entries are the standard deviations of ϵ_t . It turns out that $FF' = \Omega$. With this factorisation, the resulting MIS is invariant to the ordering of the state variables.

The spillover effects among markets are also derived from the VECM. Following [Pesaran and Shin \(1998\)](#), we first compute the generalised impulse response, which does not require orthogonalisation of the shocks and is invariant to the variable ordering. Specifically, the h -period ahead generalised impulse response with respect to a unit innovation in variable j is defined as $\phi_j(h) = E[\Delta p_{t+h} | \epsilon_{jt} = 1, \Theta_{t-1}] - E[\Delta p_{t+h} | \Theta_{t-1}]$, where Θ_{t-1} is the known history of the economy up to time $t-1$ and ϵ_{jt} is the j th entry in ϵ_t . [Pesaran and Shin \(1998\)](#) show that it can be calculated as:

$$\phi_j(h) = \omega_{jj}^{-1/2} \Psi_h \Omega e_j, \quad h = 0, 1, 2, \dots, \quad (4)$$

where ω_{jj} is the j th diagonal entry in Ω and e_j is a column vector which takes one for the j th entry and zero for others. Ψ_h is the moving average coefficient matrix from Equation (2). The entry in row i in $\phi_j(h)$ indicates the consequence of the i th-ordered state variable at time $t+h$ with respect to a unit innovation in j th-ordered state variable in time t .

From this generalised impulse response, we obtain the generalised forecast error variance decomposition, which is also invariant to the state variable ordering. Specifically, the generalised h -step ahead forecast error

variance of the i th variable attributed to the innovations in the j th variable, denoted by $\theta_{ij}(h)$, is

$$\theta_{ij}(h) = \frac{\omega_{jj}^{-1} \sum_{k=0}^{h-1} (e_i' \Psi_k \Omega e_j)^2}{\sum_{k=0}^{h-1} e_i' \Psi_k \Omega \Psi_k' e_i}, \quad i, j = 1, \dots, K, \quad h = 0, 1, 2, \dots, \quad (5)$$

For better economic interpretation, we normalise this measure so that the generalised forecast error variances of a variable accounted for by all variables sum to one: $\tilde{\theta}_{ij}(h) = \frac{\theta_{ij}(h)}{\sum_{k=1}^K \theta_{iK}(h)}$. Following [Diebold and Yilmaz \(2012\)](#), $\tilde{\theta}_{ij}(h)$ is interpreted as the gross spillover transmitted from variable j to variable i . The net spillover from variable j to variable i is defined as $\tilde{\theta}_{ij}(h) - \tilde{\theta}_{ji}(h)$. We choose the one-hour horizon ($h = 60$) to capture the long-run spillovers. Finally, the total spillover is defined as $1 - \frac{1}{K} \sum_{i=1}^K \tilde{\theta}_{ii}(h)$.

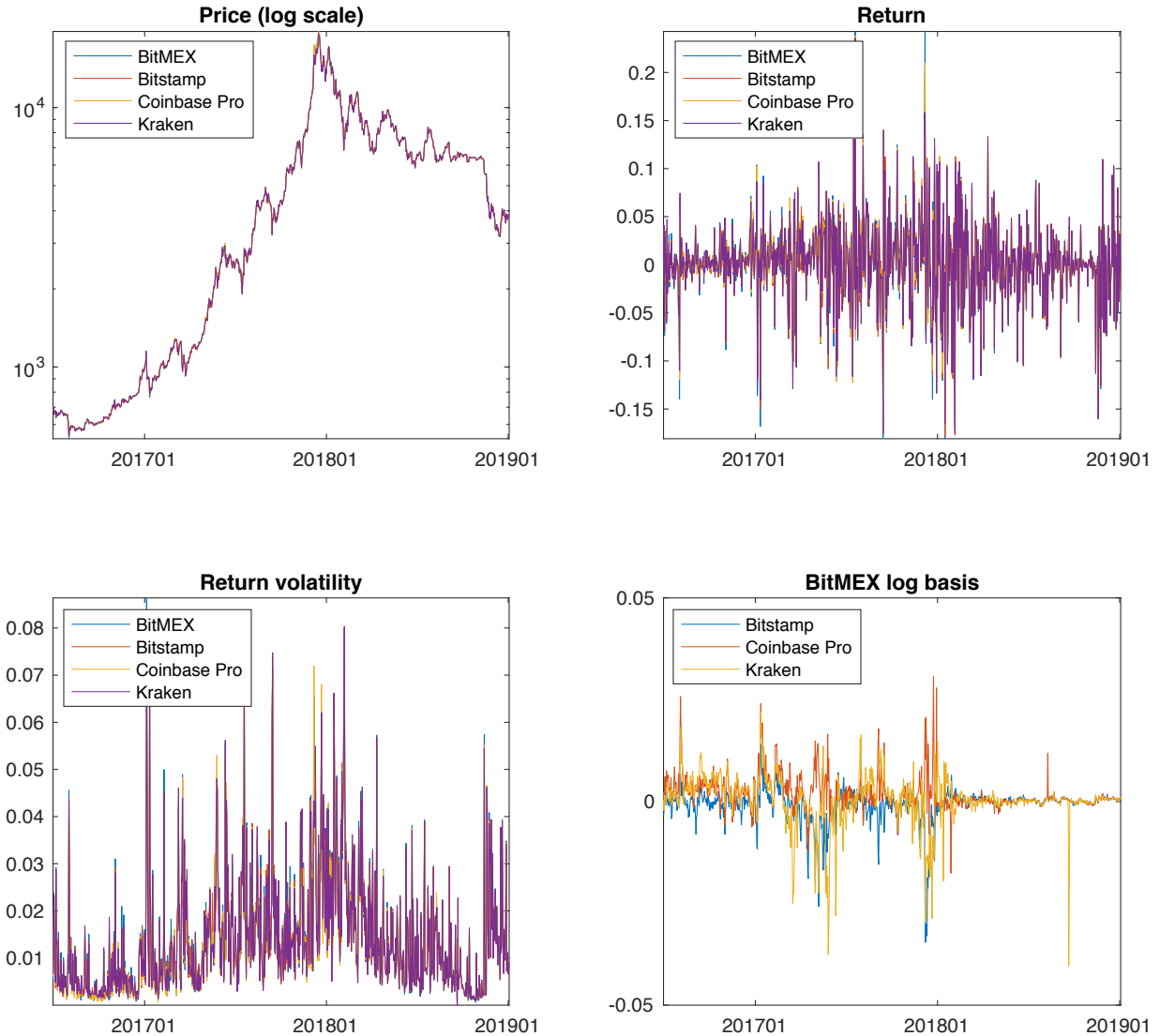
References

- Adämmer, P., Bohl, M.T., Gross, C., 2016. Price Discovery in Thinly Traded Futures Markets: How Thin is Too Thin? *Journal of Futures Markets* 36, 851–869. doi:[10.1002/fut.21760](https://doi.org/10.1002/fut.21760).
- Admati, A.R., Pfleiderer, P., 1988. A Theory of Intraday Patterns: Volume and Price Variability. *The Review of Financial Studies* 1, 3–40. doi:[10.1093/rfs/1.1.3](https://doi.org/10.1093/rfs/1.1.3).
- Ahn, K., Bi, Y., Sohn, S., 2019. Price discovery among SSE 50 Index-based spot, futures, and options markets. *Journal of Futures Markets* 39, 238–259. doi:[10.1002/fut.21970](https://doi.org/10.1002/fut.21970).
- Alexander, C., Heck, D., 2019. Price Discovery, High-Frequency Trading and Jumps in Bitcoin Markets. *SSRN Electronic Journal* doi:[10.2139/ssrn.3383147](https://doi.org/10.2139/ssrn.3383147).
- Baillie, R.T., Geoffrey Booth, G., Tse, Y., Zabolina, T., 2002. Price discovery and common factor models. *Journal of Financial Markets* 5, 309–321. doi:[10.1016/S1386-4181\(02\)00027-7](https://doi.org/10.1016/S1386-4181(02)00027-7).
- Bariviera, A.F., 2017. The inefficiency of Bitcoin revisited: A dynamic approach. *Economics Letters* 161, 1–4. doi:[10.1016/j.econlet.2017.09.013](https://doi.org/10.1016/j.econlet.2017.09.013).
- Baur, D.G., Dimpfl, T., 2019. Price discovery in bitcoin spot or futures? *Journal of Futures Markets* Forthcoming. doi:[10.1002/fut.22004](https://doi.org/10.1002/fut.22004).
- Bohl, M.T., Salm, C.A., Schuppli, M., 2011. Price discovery and investor structure in stock index futures. *Journal of Futures Markets* 31, 282–306. doi:[10.1002/fut.20469](https://doi.org/10.1002/fut.20469).
- Booth, G.G., So, R.W., Tse, Y., 1999. Price discovery in the German equity index derivatives markets. *Journal of Futures Markets* 19, 619–643. doi:[10.1002/\(SICI\)1096-9934\(199909\)19:6<619::AID-FUT1>3.0.CO;2-M](https://doi.org/10.1002/(SICI)1096-9934(199909)19:6<619::AID-FUT1>3.0.CO;2-M).
- Brauneis, A., Mestel, R., 2018. Price discovery of cryptocurrencies: Bitcoin and beyond. *Economics Letters* 165, 58–61. doi:[10.1016/j.econlet.2018.02.001](https://doi.org/10.1016/j.econlet.2018.02.001).
- Bundi, N., Wildi, M., 2019. Bitcoin and market-(in)efficiency: A systematic time series approach. *Digital Finance* doi:[10.1007/s42521-019-00004-z](https://doi.org/10.1007/s42521-019-00004-z).
- Cabrera, J., Wang, T., Yang, J., 2009. Do futures lead price discovery in electronic foreign exchange markets? *Journal of Futures Markets* 29, 137–156. doi:[10.1002/fut.20352](https://doi.org/10.1002/fut.20352).
- Chakravarty, S., Gulen, H., Mayhew, S., 2004. Informed Trading in Stock and Option Markets. *The Journal of Finance* 59, 1235–1257. doi:[10.1111/j.1540-6261.2004.00661.x](https://doi.org/10.1111/j.1540-6261.2004.00661.x).
- Chen, W.P., Chung, H., 2012. Has the introduction of S&P 500 ETF options led to improvements in price discovery of SPDRs? *Journal of Futures Markets* 32, 683–711. doi:[10.1002/fut.20538](https://doi.org/10.1002/fut.20538).
- Comerton-Forde, C., Putniņš, T.J., 2015. Dark trading and price discovery. *Journal of Financial Economics* 118, 70–92. doi:[10.1016/j.jfineco.2015.06.013](https://doi.org/10.1016/j.jfineco.2015.06.013).

- Corbet, S., Lucey, B., Peat, M., Vigne, S., 2018. Bitcoin Futures – What use are they? *Economics Letters* 172, 23–27. doi:[10.1016/j.econlet.2018.07.031](https://doi.org/10.1016/j.econlet.2018.07.031).
- Diebold, F.X., Yilmaz, K., 2012. Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting* 28, 57–66. doi:[10.1016/j.ijforecast.2011.02.006](https://doi.org/10.1016/j.ijforecast.2011.02.006).
- Ederington, L.H., 1979. The Hedging Performance of the New Futures Markets. *The Journal of Finance* 34, 157–170. doi:[10.1111/j.1540-6261.1979.tb02077.x](https://doi.org/10.1111/j.1540-6261.1979.tb02077.x).
- Eross, A., McGroarty, F., Urquhart, A., Wolfe, S., 2019. The intraday dynamics of bitcoin. *Research in International Business and Finance* 49, 71–81. doi:[10.1016/j.ribaf.2019.01.008](https://doi.org/10.1016/j.ribaf.2019.01.008).
- Gandal, N., Hamrick, J., Moore, T., Oberman, T., 2018. Price manipulation in the Bitcoin ecosystem. *Journal of Monetary Economics* 95, 86–96. doi:[10.1016/j.jmoneco.2017.12.004](https://doi.org/10.1016/j.jmoneco.2017.12.004).
- Gonzalo, J., Granger, C., 1995. Estimation of Common Long-Memory Components in Cointegrated Systems. *Journal of Business & Economic Statistics* 13, 27–35. doi:[10.1080/07350015.1995.10524576](https://doi.org/10.1080/07350015.1995.10524576).
- Griffin, J.M., Shams, A., 2018. Is Bitcoin Really Un-Tethered? *SSRN Electronic Journal* doi:[10.2139/ssrn.3195066](https://doi.org/10.2139/ssrn.3195066).
- Hale, G., Krishnamurthy, A., Kudlyak, M., Shultz, P., 2018. How Futures Trading Changed Bitcoin Prices. FRBSF Economic Letter 2018-12. Federal Reserve Bank of San Francisco.
- Hasbrouck, J., 1995. One Security, Many Markets: Determining the Contributions to Price Discovery. *The Journal of Finance* 50, 1175–1199. doi:[10.1111/j.1540-6261.1995.tb04054.x](https://doi.org/10.1111/j.1540-6261.1995.tb04054.x).
- Hauptfleisch, M., Putniņš, T.J., Lucey, B., 2016. Who Sets the Price of Gold? London or New York. *Journal of Futures Markets* 36, 564–586. doi:[10.1002/fut.21775](https://doi.org/10.1002/fut.21775).
- Hendershott, T., Jones, C.M., 2005. Island Goes Dark: Transparency, Fragmentation, and Regulation. *The Review of Financial Studies* 18, 743–793. doi:[10.1093/rfs/hhi013](https://doi.org/10.1093/rfs/hhi013).
- Hsieh, W.L.G., Lee, C.S., Yuan, S.F., 2008. Price discovery in the options markets: An application of put-call parity. *Journal of Futures Markets* 28, 354–375. doi:[10.1002/fut.20302](https://doi.org/10.1002/fut.20302).
- Jiang, Y., Nie, H., Ruan, W., 2018. Time-varying long-term memory in Bitcoin market. *Finance Research Letters* 25, 280–284. doi:[10.1016/j.fr1.2017.12.009](https://doi.org/10.1016/j.fr1.2017.12.009).
- de Jong, A., de Roon, F., Veld, C., 1997. Out-of-sample hedging effectiveness of currency futures for alternative models and hedging strategies. *Journal of Futures Markets* 17, 817–837. doi:[10.1002/\(SICI\)1096-9934\(199710\)17:7<817::AID-FUT5>3.0.CO;2-Q](https://doi.org/10.1002/(SICI)1096-9934(199710)17:7<817::AID-FUT5>3.0.CO;2-Q).
- de Jong, F., Donders, M.W.M., 1998. Intraday Lead-Lag Relationships Between the Futures-, Options and Stock Market. *Review of Finance* 1, 337–359. doi:[10.1023/A:1009765322522](https://doi.org/10.1023/A:1009765322522).

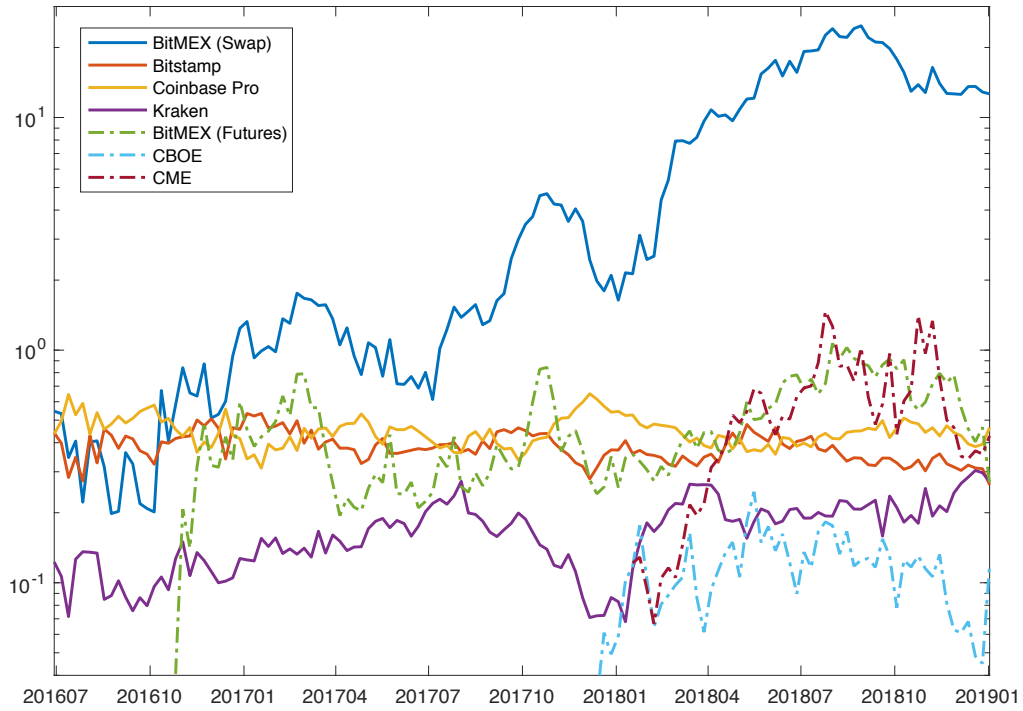
- Lien, D., Shrestha, K., 2009. A new information share measure. *Journal of Futures Markets* 29, 377–395. doi:[10.1002/fut.20356](https://doi.org/10.1002/fut.20356).
- Lo, A.W., MacKinlay, A.C., 1988. Stock Market Prices Do Not Follow Random Walks: Evidence from a Simple Specification Test. *The Review of Financial Studies* 1, 41–66. doi:[10.1093/rfs/1.1.41](https://doi.org/10.1093/rfs/1.1.41).
- Nakamoto, S., 2008. Bitcoin: A Peer-to-Peer Electronic Cash System. Technical Report.
- Park, T.H., Switzer, L.N., 1995. Bivariate GARCH estimation of the optimal hedge ratios for stock index futures: A note. *Journal of Futures Markets* 15, 61–67. doi:[10.1002/fut.3990150106](https://doi.org/10.1002/fut.3990150106).
- Pesaran, H.H., Shin, Y., 1998. Generalized impulse response analysis in linear multivariate models. *Economics Letters* 58, 17–29. doi:[10.1016/S0165-1765\(97\)00214-0](https://doi.org/10.1016/S0165-1765(97)00214-0).
- Rosenberg, J.V., Traub, L.G., 2009. Price Discovery in the Foreign Currency Futures and Spot Market. *The Journal of Derivatives* 17, 7–25. doi:[10.3905/JOD.2009.17.2.007](https://doi.org/10.3905/JOD.2009.17.2.007).
- Sensoy, A., 2019. The inefficiency of Bitcoin revisited: A high-frequency analysis with alternative currencies. *Finance Research Letters* 28, 68–73. doi:[10.1016/j.frl.2018.04.002](https://doi.org/10.1016/j.frl.2018.04.002).
- So, R.W., Tse, Y., 2004. Price discovery in the hang seng index markets: Index, futures, and the tracker fund. *Journal of Futures Markets* 24, 887–907. doi:[10.1002/fut.20112](https://doi.org/10.1002/fut.20112).
- Sohn, S., Zhang, X., 2017. Could the Extended Trading of CSI 300 Index Futures Facilitate Its Role of Price Discovery? *Journal of Futures Markets* 37, 717–740. doi:[10.1002/fut.21804](https://doi.org/10.1002/fut.21804).
- Tiwari, A.K., Jana, R.K., Das, D., Roubaud, D., 2018. Informational efficiency of Bitcoin—An extension. *Economics Letters* 163, 106–109. doi:[10.1016/j.econlet.2017.12.006](https://doi.org/10.1016/j.econlet.2017.12.006).
- Twomey, D., Mann, A., 2019. Fraud and Manipulation within Cryptocurrency Markets, in: Alexander, C., Cumming, D. (Eds.), *Corruption and Fraud in Financial Markets : Malpractice, Misconduct and Manipulation*. S.I.
- Urquhart, A., 2016. The inefficiency of Bitcoin. *Economics Letters* 148, 80–82. doi:[10.1016/j.econlet.2016.09.019](https://doi.org/10.1016/j.econlet.2016.09.019).
- Vidal-Tomás, D., Ibañez, A., 2018. Semi-strong efficiency of Bitcoin. *Finance Research Letters* 27, 259–265. doi:[10.1016/j.frl.2018.03.013](https://doi.org/10.1016/j.frl.2018.03.013).
- Wei, W.C., 2018. Liquidity and market efficiency in cryptocurrencies. *Economics Letters* 168, 21–24. doi:[10.1016/j.econlet.2018.04.003](https://doi.org/10.1016/j.econlet.2018.04.003).
- [dataset] Bitcoincharts, 2019. Bitcoincharts API data repository. URL: <http://api.bitcoincharts.com/v1/csv/>. accessed as of April 2019.
- [dataset] Bitcoinity, 2019. Bitcoinity trading volume and bid/ask spread. URL: <http://data.bitcoinity.org>. accessed as of April 2019.
- [dataset] BitMEX, 2019. Public BitMEX API data repository. <https://public.bitmex.com/>. Accessed as of April 2019.

Figure 1: Market characteristics of BitMEX and bitcoin spot markets



Note: Figure 1 plots the daily market characteristics of the bitcoin spot exchanges (Bitstamp, Coinbase, and Kraken) and the perpetual swap exchange (BitMEX). Return volatility is computed by the standard deviation of 1-minute returns. BitMEX log basis is the difference in log prices between BitMEX and a spot exchange. All variables are measured at a daily frequency. The sample period is from July 1, 2016 to January 3, 2019.

Figure 2: The exchange volume share over the sample period



Note: Figure 2 plots the ratio of the exchange volume to the total spot trading volume in log scale. For the total spot trading volume, we use the combined volume of Bitstamp, Coinbase, and Kraken.

Table 1: Comparison of contract types traded on BitMEX, CBOE, and CME

Contracts	BitMEX		CBOE	CME
	Perpetual swap	Futures	Futures	Futures
Product Code	XBTUSD	XB T_{mYY}	XB T_{mYY}	BTC mY
First Traded	5/13/2016	11/24/2014	12/10/2017	12/18/2017
Contract Unit	1 USD		1 XBT	5 XBT
Margin Requirement	1 %		40%	37%
Settlement Currency	XBT		USD (Cash)	
Profit & Loss	$\pm UN (1/x_1 - 1/x_2)$		$\pm UN (x_2 - x_1)$	
Tick increment	0.5 USD		5 USD	
Trading days	Everyday		Monday to Friday	
Quoting Convention	1 XBT = x USD			

Note: In ‘Product Code’, m denotes the code for the expiry month and Y and YY denote the last one and two digits of the expiry year, respectively. In ‘Profit & Loss’, U denote the contract unit, N the number of contracts, x_1 and x_2 denote the entry and exit prices in the quoting convention. The sign \pm denotes long and short positions respectively.

Table 2: Daily average trading volume by exchanges

	BitMEX		Spot Exchanges			Futures Exchanges	
	Swap	Futures	Bitstamp	Coinbase	Kraken	CBOE	CME
2016 (Jul-Dec)	5.60	1.47	4.27	4.96	1.15		
2017 (Jan-Jun)	28.42	9.59	10.73	11.47	4.22		
2017 (Jul-Dec)	96.32	14.67	14.98	18.58	5.86		
2018 (Jan-Jun)	280.86	14.97	13.62	16.27	7.07	5.88	14.33
2018 (Jul-Dec)	398.18	16.90	7.93	10.35	5.49	3.62	22.80
Full-sample period	162.70	11.53	10.29	12.31	4.76	4.79	18.79

Note: Table 2 shows the daily average volume by exchange in thousand bitcoin. The sample period is divided into six month periods. For convenience, the three days in January 2019 are included in ‘2018 (Jul-Dec)’ and the CBOE data in December 2017 is included in ‘2018 (Jan-Jun)’. Saturday, Sunday, and other trading holidays were not counted in averaging for CBOE and CME.

Table 3: Cointegration tests

Null hypothesis	Engle-Granger Test	Johansen Test			
	No cointegration	$r = 0$ vs $r \geq 1$	$r = 1$ vs $r \geq 2$	$r = 2$ vs $r \geq 3$	$r = 3$ vs $r \geq 4$
<i>Panel A. Full-sample period</i>					
Test statistic	-170.43	83,327.02	47,328.19	12,303.39	2.02
p -value	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(0.1556)
% of rejecting H_0	99.45%	100.00%	100.00%	95.64%	16.36%
<i>Panel B. Bull period</i>					
Test statistic	-118.32	45,948.37	24,324.38	6,785.31	6.26
p -value	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(0.0126)
% of rejecting H_0	99.07%	100.00%	100.00%	93.64%	14.77%
<i>Panel C. Bear period</i>					
Test statistic	-204.58	75,409.72	25,689.56	7,327.58	4.66
p -value	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(0.0309)
% of rejecting H_0	100.00%	100.00%	100.00%	98.43%	18.59%

Note: Table 3 presents the results of the cointegration tests for a given sample period. The Engle-Granger test assesses the null hypothesis of no cointegration among the log prices. The Johansen test assesses the null hypothesis of a particular cointegration rank against the alternative of higher ranks. The number of lags in the tests is set to zero. The last row in each panel reports the proportion of days in which H_0 is rejected at the 1% significance level when the cointegration tests are conducted on a daily basis. Panel A presents the results in the full sample (July 1, 2016 to Jan 3, 2019), while Panel B (C) presents the period before (after) the historical price peak on December 17, 2017.

Table 4: Modified information shares and component shares

	MIS			CS		
	Mean	Median	Overall	Mean	Median	Overall
<i>Panel A. Full-sample period</i>						
BitMEX	51.53%	53.35%	59.52%	57.50%	54.91%	59.72%
Bitstamp	18.48%	16.88%	16.78%	15.61%	13.72%	13.79%
Coinbase	23.18%	18.17%	19.29%	21.24%	21.26%	18.17%
Kraken	6.81%	4.12%	4.41%	5.64%	4.79%	8.31%
<i>Panel B. Bull period</i>						
BitMEX	52.25%	54.94%	65.85%	50.09%	49.39%	58.94%
Bitstamp	16.32%	13.77%	14.40%	13.55%	11.27%	13.56%
Coinbase	26.65%	20.63%	17.56%	29.39%	29.35%	20.60%
Kraken	4.79%	2.76%	2.19%	6.97%	6.12%	6.90%
<i>Panel C. Bear period</i>						
BitMEX	50.53%	52.81%	49.60%	67.89%	69.39%	59.10%
Bitstamp	21.50%	21.06%	25.78%	18.50%	17.94%	24.91%
Coinbase	18.32%	16.93%	15.05%	9.83%	9.31%	3.40%
Kraken	9.64%	7.17%	9.57%	3.78%	1.27%	12.59%

Note: Table 4 shows the modified information shares (MIS) and component shares (CS) of the four markets: BitMEX, Bitstamp, Coinbase, and Kraken, for a given sample period. The columns of Mean (Median) report the average (median) of the values obtained from the daily VECM estimation. The column of Overall reports the values obtained from one VECM estimation using the whole observations in the given sample period. Panel A presents the results in the full sample (July 1, 2016 to Jan 3, 2019), while Panel B (C) presents the period before (after) the historical price peak on December 17, 2017.

Table 5: Error correction coefficients

Response of	With respect to deviation from			
	BitMEX	Bitstamp	Coinbase	Kraken
<i>Panel A. Full-sample period</i>				
BitMEX		-0.0357*** (-15.617)	-0.0038** (-2.312)	-0.0049*** (-3.359)
Bitstamp	-0.1952*** (-21.835)		-0.2497*** (-20.330)	-0.2267*** (-21.531)
Coinbase	-0.1047*** (-14.141)	-0.1491*** (-13.512)		-0.1157*** (-13.874)
Kraken	-0.1804*** (-23.815)	-0.2487*** (-22.491)	-0.2250*** (-24.283)	
<i>Panel B. Bull period</i>				
BitMEX		-0.0213*** (-14.935)	-0.0081*** (-6.555)	-0.0100*** (-10.901)
Bitstamp	-0.1405*** (-19.371)		-0.1750*** (-18.725)	-0.1604*** (-20.415)
Coinbase	-0.0497*** (-14.870)	-0.0659*** (-13.981)		-0.0559*** (-15.025)
Kraken	-0.1368*** (-27.325)	-0.1785*** (-25.598)	-0.1812*** (-27.164)	
<i>Panel C. Bear period</i>				
BitMEX		-0.0560*** (-24.012)	0.0021 (0.977)	0.0023 (1.207)
Bitstamp	-0.2718*** (-35.025)		-0.3544*** (-31.708)	-0.3195*** (-34.081)
Coinbase	-0.1817*** (-29.039)	-0.2657*** (-28.871)		-0.1993*** (-26.508)
Kraken	-0.2416*** (-31.454)	-0.3471*** (-33.088)	-0.2864*** (-27.871)	

Note: Table 5 tabulates the average of estimated error correction coefficients obtained from the daily estimation of the VECM and the associated Newey-West t -statistics. The lag length in the VECM is chosen by the Bayesian information criterion. The row of BitMEX shows the response of price in BitMEX when the price difference from the other exchanges (Bitstamp, Coinbase or Kraken) increases by 1%. The other rows can be similarly interpreted. The coefficients for other terms (constant and autoregressive terms) are not reported to save space, but available upon request. Panel A presents the results in the full sample (July 1, 2016 to Jan 3, 2019), while Panel B (C) presents the period before (after) the historical price peak on December 17, 2017. ***, **, * indicates the 1%, 5%, 10% significance level, respectively.

Table 6: Gross and net spillovers

		From				
		BitMEX	Bitstamp	Coinbase	Kraken	The others
<i>Panel A. Full-sample period</i>						
Gross spillover	BitMEX	64.00%	14.94%	14.80%	6.26%	36.00%
	Bitstamp	16.32%	67.15%	11.03%	5.50%	32.85%
	Coinbase	17.69%	11.52%	64.28%	6.51%	35.72%
	Kraken	10.24%	7.75%	8.85%	73.16%	26.84%
	The others	44.25%	34.21%	34.67%	18.26%	32.85%
Net spillover		8.25%	1.36%	-1.04%	-8.58%	
<i>Panel B. Bull period</i>						
Gross spillover	BitMEX	78.99%	10.96%	8.94%	1.10%	21.01%
	Bitstamp	12.10%	81.89%	5.20%	0.81%	18.11%
	Coinbase	12.80%	6.35%	79.83%	1.02%	20.17%
	Kraken	3.89%	2.40%	2.51%	91.20%	8.80%
	The others	28.79%	19.71%	16.65%	2.93%	17.02%
Net spillover		7.78%	1.60%	-3.51%	-5.87%	
<i>Panel C. Bear period</i>						
Gross spillover	BitMEX	43.01%	20.51%	22.99%	13.48%	56.99%
	Bitstamp	22.23%	46.52%	19.19%	12.06%	53.48%
	Coinbase	24.54%	18.77%	42.51%	14.19%	57.49%
	Kraken	19.15%	15.23%	17.73%	47.89%	52.11%
	The others	65.91%	54.51%	59.91%	39.74%	55.02%
Net spillover		8.92%	1.03%	2.42%	-12.37%	

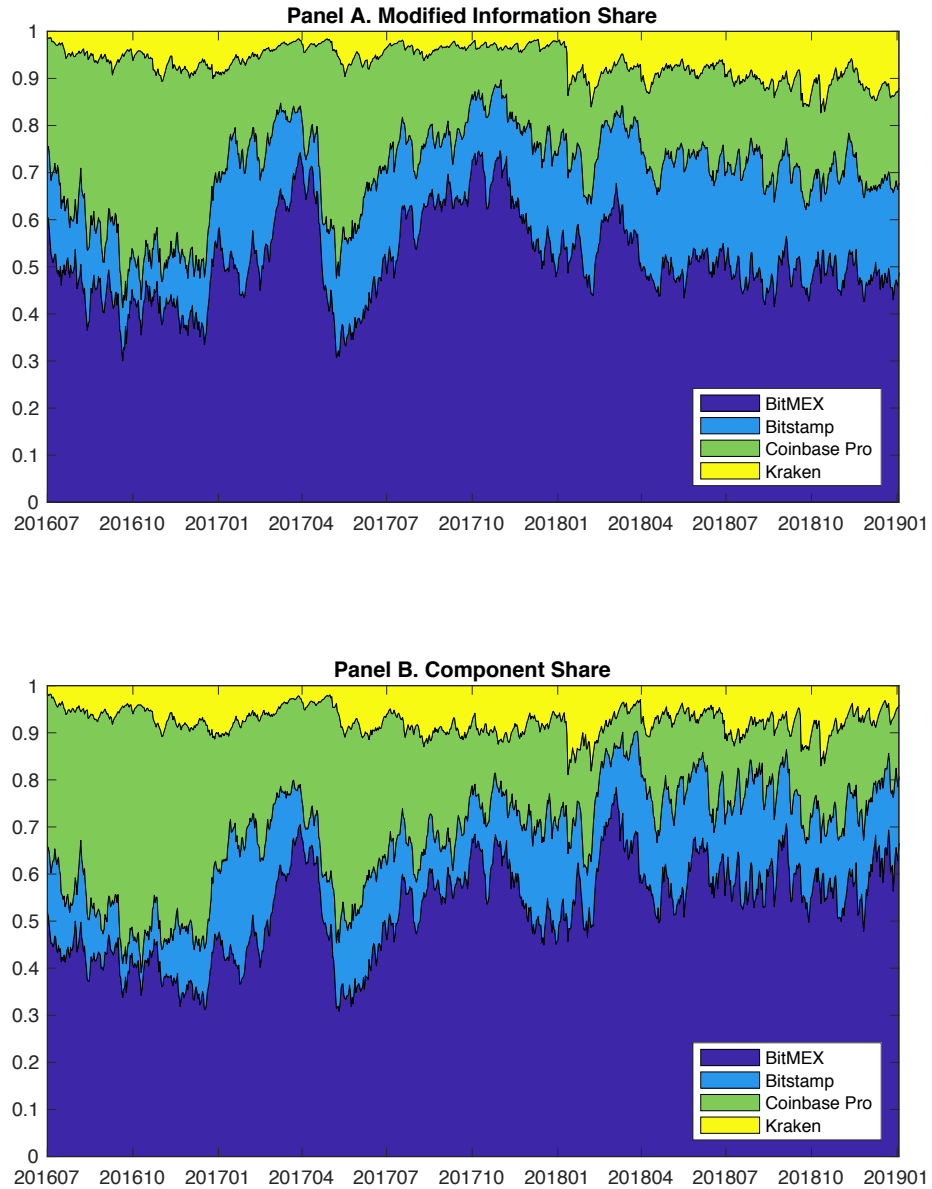
Note: Table 6 shows the long-horizon (60-minute) gross and net spillovers for a given sample period. The (i, j) entry in the gross spillover represents the estimated contribution to the forecast error variance of market i coming from innovations of market j , while the entry in the net spillover is the difference between the gross spillover from market i to the other markets and the gross spillover from the other markets to market i . The total spillover is defined as the gross spillover from *the others* to *the others*. Panel A presents the results in the full sample (July 1, 2016 to Jan 3, 2019), while Panel B (C) presents the period before (after) the historical price peak on December 17, 2017.

Table 7: Determinants of price discovery shares in BitMEX

	MIS		CS	
	(1)	(2)	(3)	(4)
Constant	0.515*** (83.10)	0.515*** (53.35)	0.575*** (61.70)	0.566*** (43.48)
<i>RSpread</i>	0.0537*** (8.44)	0.0536*** (8.41)	0.0267*** (3.08)	0.0265*** (3.08)
<i>RTV</i>	-0.0187** (-2.31)	-0.0188** (-2.34)	-0.0560*** (-4.56)	-0.0565*** (-4.64)
<i>Ret</i>	0.0171*** (2.72)	0.0195** (2.35)	0.0128 (1.25)	0.0222* (1.71)
<i>Abs.Basis</i>	-0.0235*** (-3.19)	-0.0386*** (-3.95)	-0.0550*** (-5.62)	-0.0739*** (-6.06)
$D_{Ret<0}$		0.00220 (0.13)		0.0216 (0.93)
$D_{Ret<0} \times Abs.Basis$		0.0357*** (2.64)		0.0454** (2.33)
Obs.	917	917	917	917
R^2	0.112	0.121	0.102	0.109
Adjusted- R^2	0.106	0.112	0.095	0.100

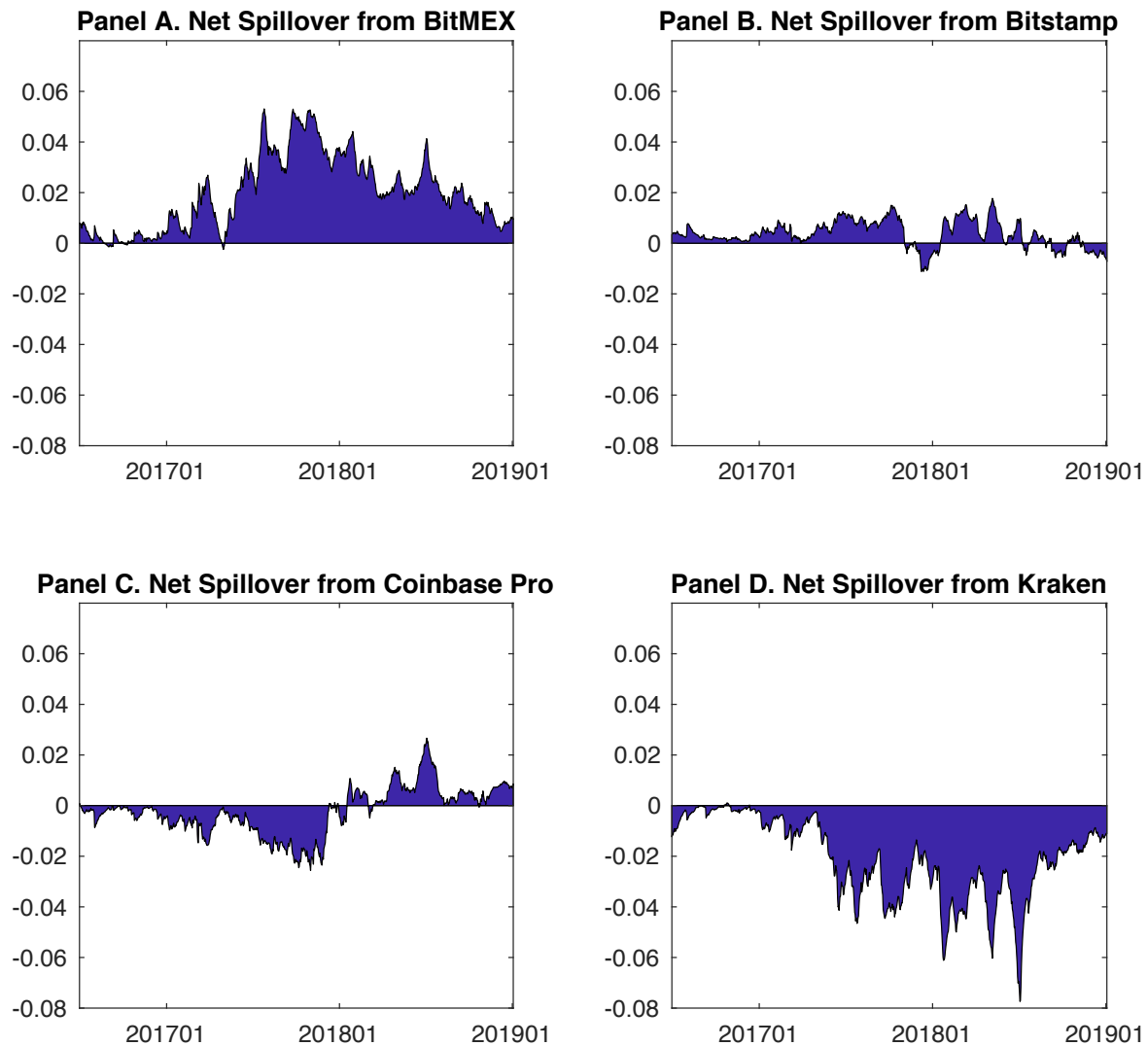
Note: Table 7 tabulates the regression results of the daily modified information share and component share in BitMEX on several market characteristics. *RSpread* is the relative spread of spot markets (average spread of the spot markets divided by BitMEX spread). *RTV* is the relative trading volume of spot markets (total trading volume of the spot markets divided by BitMEX trading volume). *Ret* is the log change of bitcoin prices in BitMEX. *Abs.Basis* is the absolute basis (absolute value of average difference of log prices between BitMEX and the spot markets). $D_{Ret<0}$ is a dummy indicating observations when daily return is negative. The spot markets are represented by Bitstamp, Coinbase, and Kraken. All variables are measured at a daily frequency and standardized to have zero-mean and unit-variance except for the dummy. The values in parenthesis are the corresponding robust *t*-statistics. ***, **, and * indicate the 1%, 5%, and 10% significance level, respectively.

Figure 3: Modified information shares and component shares



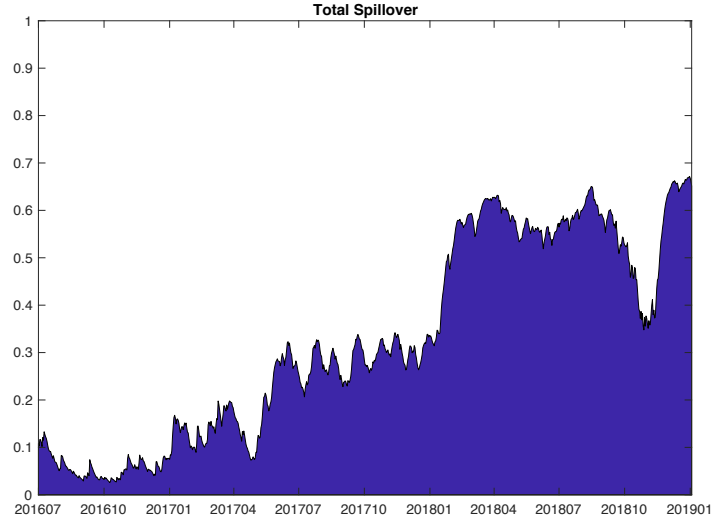
Note: Figure 3 plots the daily modified information shares and component shares in the four markets: BitMEX, Bitstamp, Coinbase, and Kraken. The price of bitcoin perpetual swaps represents BitMEX, while the price of bitcoin spot represents the other markets. Modified information shares and component shares are calculated on a daily basis from a VECM using minute-by-minute log prices in the four markets according to Hasbrouck (1995) and Gonzalo and Granger (1995), respectively. The lag length of the model is chosen by the Bayesian information criterion. The time series are smoothed with a trailing exponentially weighted moving average: $MA_t(a) = 0.1a_t + 0.9MA_{t-1}(a)$, where a is either modified information share or common factor weight.

Figure 4: Net spillover



Note: Figure 4 depicts the daily long-horizon (60-minute) net spillovers from the four markets: BitMEX, Bitstamp, Coinbase, and Kraken. The price of bitcoin perpetual swaps represents BitMEX, while the price of bitcoin spot represents the other markets. Following Diebold and Yilmaz (2012), the net spillover from market i is defined as the gross spillover from market i to the other markets minus that to market i from the other markets. The spillovers are estimated on a daily basis from a VECM using minute-by-minute log prices.

Figure 5: Total spillover



Note: Figure 5 depicts the daily long-horizon (60-minute) total spillovers among the four markets: BitMEX, Bitstamp, Coinbase, and Kraken. The price of bitcoin perpetual swaps represents BitMEX, while the price of bitcoin spot represents the other markets. The total spillover is estimated on a daily basis from a VECM using minute-by-minute log prices.

Table 8: Out-of-sample hedge effectiveness

Hedging methods	Standard Deviation of Portfolio Return			Hedging Effectiveness		
	Bitstamp	Coinbase	Kraken	Bitstamp	Coinbase	Kraken
Unhedged position	4.69%	4.71%	4.66%			
Naive hedge	0.39%	0.50%	0.88%	0.9930	0.9888	0.9642
Minimum variance hedge	0.37%	0.48%	0.86%	0.9939	0.9894	0.9658

Note: Table 8 presents the hedge effectiveness of the BitMEX perpetual swap. The standard deviations are calculated from the daily portfolio returns, $\Delta p_{i,d+1} - b_{id}\Delta p_{\text{BitMEX},d+1}$, for the second half of the sample, where p_{id} is the log price in exchange i on day d ($i \in \{\text{BitMEX, Bitstamp, Coinbase, and Kraken}\}$). The hedge ratio, b_{id} , is zero for the unhedged position and one for a naive hedge. For the minimum variance hedge, b_{id} is obtained as a slope coefficient from the OLS regression of spot returns in exchange i on BitMEX swap returns using a rolling window up to d . The hedging effectiveness is defined as the ratio of the variance reduced by hedging.

Figure 6: Autocorrelations and variance ratios



Note: Figure 6 plots the daily absolute autocorrelations (AC) and variance ratios (VR) in the four bitcoin markets: BitMEX, Bitstamp, Coinbase, and Kraken. The price of bitcoin perpetual swaps represents BitMEX, while the price of bitcoin spot represents the other markets. AC on a given day is obtained as an average of absolute return autocorrelations measured at various intraday frequencies: 1-minute, 3-minute, 5-minute and 10-minute. VR on a given day is obtained as an average of deviation of variance ratio from one measured at different combinations of intraday frequencies: (5-minute, 1-minute), (10-minute, 5-minute) and (20-minute and 10-minute). The time series are smoothed with a trailing exponentially weighted moving average: $MA_t(a) = 0.1a_t + 0.9MA_{t-1}(a)$, where a is either autocorrelation or variance ratio.