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RESEARCH ARTICLE

BitMEX bitcoin derivatives: Price discovery, informational efficiency, and hedging effectiveness

Carol Alexander[1,2] | **Jaehyuk Choi**[3] | **Heungju Park**[4] | **Sungbin Sohn**[3]

[1]University of Sussex Business School, Falmer, Brighton, United Kingdom
[2]Peking University HSBC Business School, Boars Hill, Oxford, United Kingdom
[3]Peking University HSBC Business School, Nanshan, Shenzhen, China
[4]Sungkyunkwan University SKK Business School, Jongno-gu, Seoul, Korea

Correspondence
Sungbin Sohn, Peking University HSBC Business School, University Town, Nanshan District, Shenzhen, 518055, China.
Email: sungbin.sohn@phbs.pku.edu.cn

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, interexchange 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 prioritize the investigation of the legitimacy of BitMEX and its contracts.

KEYWORDS
bitcoin, BitMEX, market efficiency, price discovery, spillover

JEL CLASSIFICATION
G13; 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 10 years ago it has become actively traded through both decentralized and centralized exchanges. Decentralized 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, decentralized exchanges are still in their infancy. In this paper, therefore, we only investigate the microstructure of bitcoin on *centralized* exchanges (CEXs). 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) 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, Krishnamurthy, Kudlyak, and Shultz (2018) argue that the bitcoin price collapse after these futures are launched is not a coincidence—similar patterns

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have been observed in other asset classes. This argument implies that a leader role for those futures contracts in bitcoin spot price discovery. However, using the accumulated price data from both futures exchanges, Corbet, Lucey, Peat, and Vigne (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 (Bohl, Salm, & Schuppli, 2011; Cabrera, Wang, & Yang, 2009; Hauptfleisch, Putniņš, & Lucey, 2016; Rosenberg & Traub, 2009). 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 (Bariviera, 2017; Sensoy, 2019; Tiwari, Jana, Das, & Roubaud, 2018; Urquhart, 2016; Vidal-Tomás & Ibañez, 2018). 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, Nie, & Ruan, 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 & 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 for market manipulation.[2] Our paper aims to inform both traders and regulators about the microstructure of BitMEX, and its crucial role in the cryptoasset 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 prerequisite 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 (AC) and variance ratio (VR) (Comerton-forde & 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; that is, 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, Gulen, & Mayhew, 2004; Chen & 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 interexchange 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 AC and VR, BitMEX is

[1] https://www.bitmex.com.

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

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 (HE) 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 organized as follows. Section 2 discuses 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 1, 2016 to January 3, 2019. We also examine the HE relative to the three main bitcoin spot exchanges. Finally, Section 5 concludes.

2 | EXCHANGE AND CONTRACTS

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

BitMEX is an online cryptocurrency derivative 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 Unites 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 antimoney laundering (AML) procedures during account opening, which is typically enforced by the partner banks for other, fiat-based crypto exchanges. Clients only need an email 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—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

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

[4]We 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.

[5]We further illustrate the difference with an example. Suppose a trader holds 10 bitcoins and hedges the market value by entering into a short future's 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 future 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.

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

	BitMEX		CBOE	CME
Contracts	**Perpetual swap**	**Futures**	**Futures**	**Futures**
Product code	XBTUSD	XBT*mYY*	XBT*mYY*	BTC*mY*
First traded	May 13, 2016	Nov 24, 2014	Dec 10, 2017	Dec 18, 2017
Contract unit	1 USD		1 XBT	5 XBT
Margin requirement	1%		40%	37%
Settlement currency	XBT		USD (cash)	
Profit and 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 and loss', U denotes the contract unit, N denotes the number of contracts, and x_1 and x_2 denote the entry and exit prices in the quoting convention, respectively. The sign $\pm$ denotes long and short positions, respectively.
Abbreviations: CBOE, Chicago Board Options Exchange; CME, Chicago Mercantile Exchange.

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 require 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 1 USD in BitMEX is affordable for retail traders. This is significantly less than the contract units of five bitcoins in CME (or one bitcoin for the CBOE, before the contracts were withdrawn). The tic increment is 0.5 USD on BitMEX compared with 5 USD on CME. And BitMEX trading occurs 24/7, similar to spot exchanges, whereas trading on the CME is from Sunday to Friday, 5 p.m. to 4 p.m. 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 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 summarizes the differences between the BitMEX perpetual swap and the fixed-maturity futures on BitMEX, CME, and CBOE.

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

[7]That 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.

[8]For 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

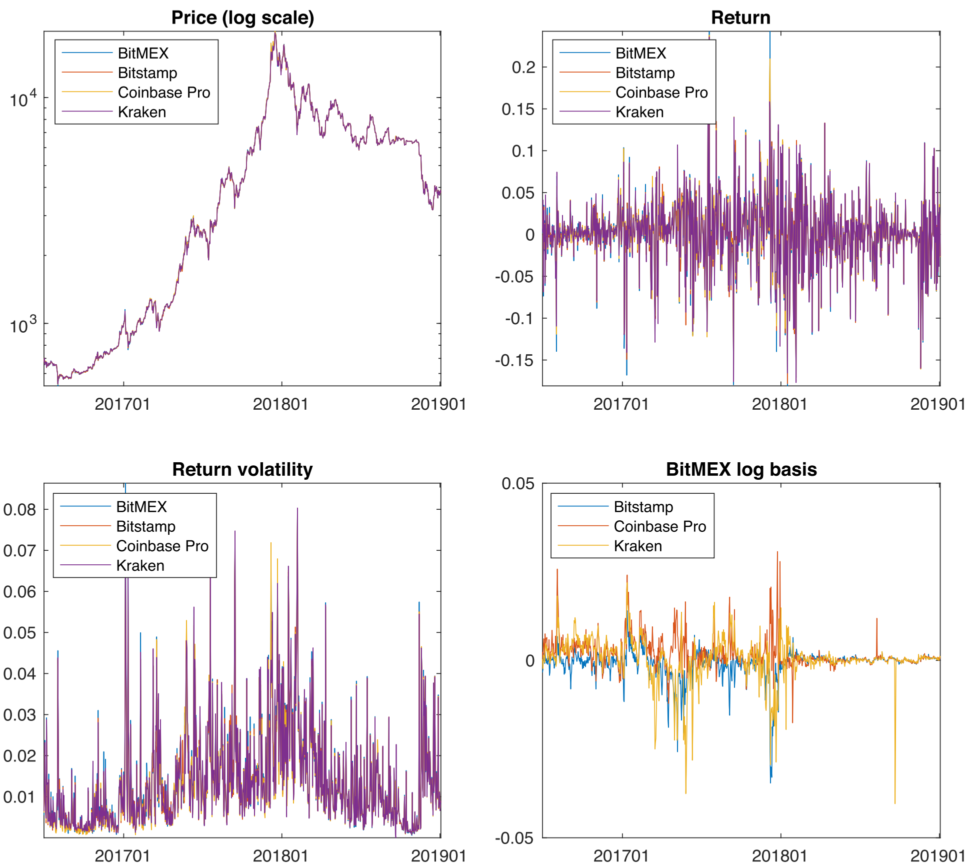

FIGURE 1 Market characteristics of BitMEX and bitcoin spot markets. *Note:* Figure 1 plots the daily market characteristics of the bitcoin spot exchanges (Bitstamp, Coinbase, and Kraken) and the perpetual swap exchange (BitMEX). Return volatility is computed by the standard deviation of 1-min returns. 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 [Color figure can be viewed at wileyonlinelibrary.com]

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. On the basis of this theoretical implication, we hypothesize that conditions on BitMEX lead to fast price discovery and informationally efficient prices, and we test these hypotheses formally in Section 4.

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 6-month periods. For convenience, the 3 days in January 2019 are included in '2018 (Jul–Dec)' and the CBOE data in December 2017 are included in '2018 (Jan–Jun)'. Saturday, Sunday, and other trading holidays were not counted in averaging for CBOE and CBOE.

Abbreviations: CBOE, Chicago Board Options Exchange; CME, Chicago Mercantile Exchange.

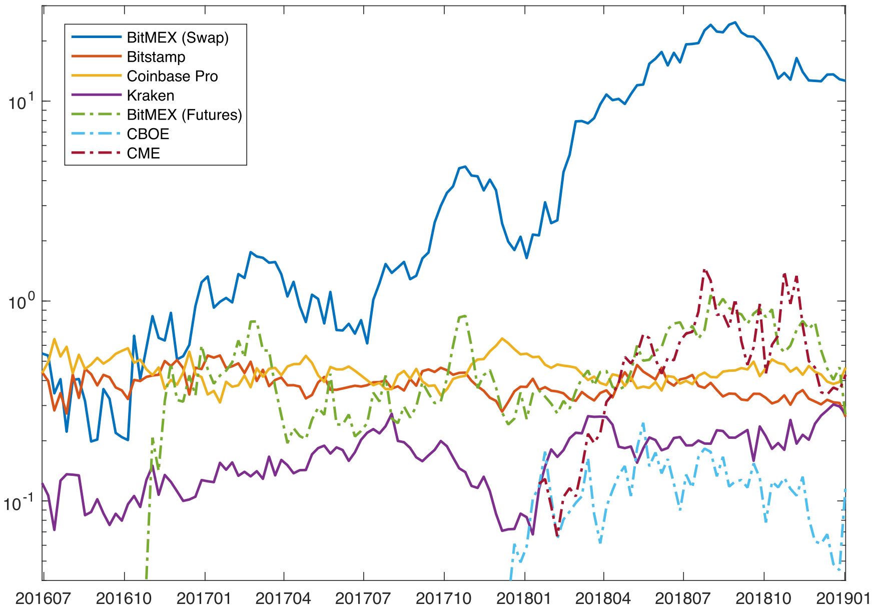

FIGURE 2 The exchange volume share over the sample period. *Note:* Figure 2 plots the ratio of the exchange volume to the total spot trading volume in log scale. For the total spot trading volume, we use the combined volume of Bitstamp, Coinbase, and Kraken. BitMEX, CBOE, Chicago Board Options Exchange; CME, Chicago Mercantile Exchange [Color figure can be viewed at wileyonlinelibrary.com]

TABLE 3 Cointegration tests

	Engle–Granger test	Johansen test			
Null hypothesis	**No cointegration**	$r = 0$ **vs.** $r \geqslant 1$	$r = 1$ **vs.** $r \geqslant 2$	$r = 2$ **vs.** $r \geqslant 3$	$r = 3$ **vs.** $r \geqslant 4$
Panel A. Full-sample period					
Test statistic	−170.43	83,327.02	47,328.19	12,303.39	2.02
p value	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(.1556)
% of rejecting H_0	99.45	100.00	100.00	95.64	16.36
Panel B. Bull period					
Test statistic	−118.32	45,948.37	24,324.38	6,785.31	6.26
p value	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(.0126)
% of rejecting H_0	99.07	100.00	100.00	93.64	14.77
Panel C. Bear period					
Test statistic	−204.58	75,409.72	25,689.56	7,327.58	4.66
p value	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(.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), whereas Panel B (C) presents the period before (after) the historical price peak on December 17, 2017.

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 (BitMEX, 2019) for the trades and the best bid–ask prices for perpetual swaps and traditional futures; and bitcoincharts.com (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,

[10][data set] Bitcoincharts (2019) has been widely used in previous studies; see, for example, Eross, McGroarty, Urquhart, and Wolfe (2019) and Gandal, Hamrick, Moore, and Oberman (2018). We verify the data integrity by comparing the aggregated daily trade volume to that available from another online source, Bitcoinity (2019).

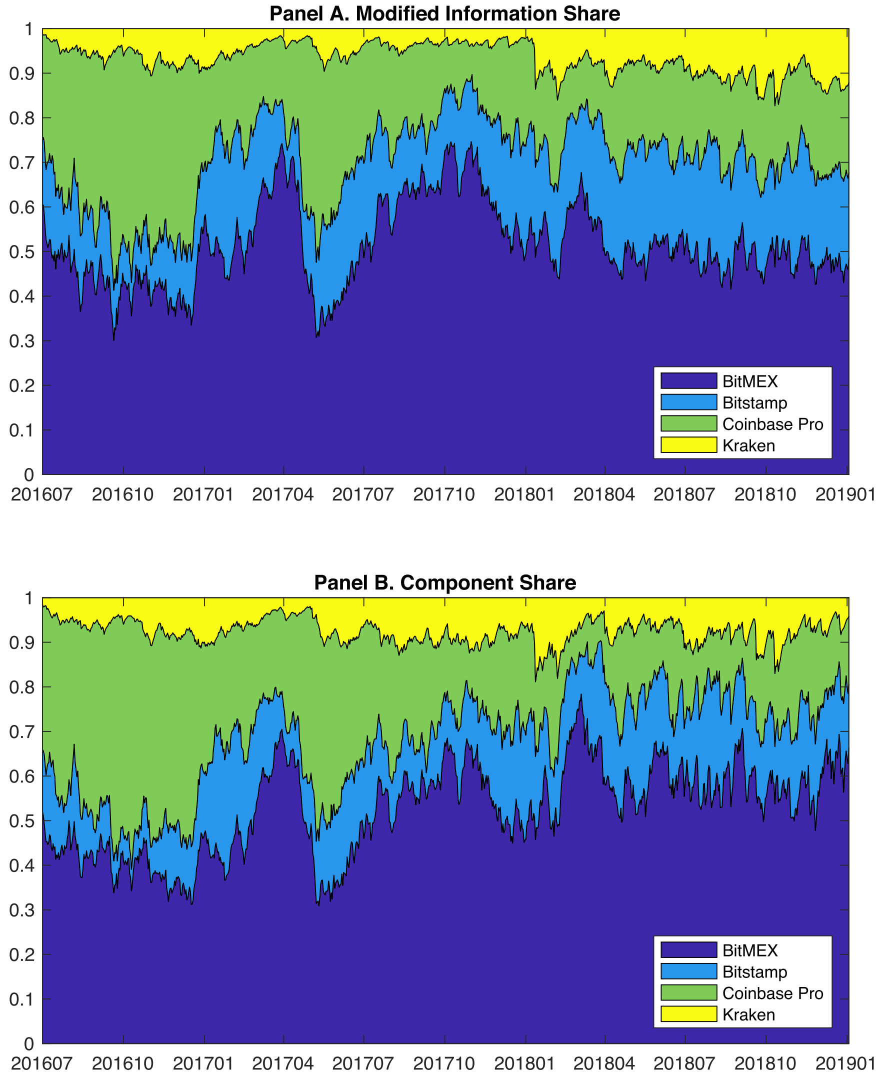

FIGURE 3 (Panel A) Modified information shares (MIS) and (Panel B) component shares (CS). *Note:* Figure 3 plots the daily MIS and CS in the four markets: BitMEX, Bitstamp, Coinbase, and Kraken. The price of bitcoin perpetual swaps represents BitMEX, whereas the price of bitcoin spot represents the other markets. MIS and CS 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: $\mathrm{MA}_t(a) = 0.1a_t + 0.9\mathrm{MA}_{t-1}(a)$, where a is either MIS or common factor weight. VECM, vector error-correction model [Color figure can be viewed at wileyonlinelibrary.com]

or at other required frequencies. Additionally, we use the averaged bid–ask spread of the three spot exchanges from bitcoinity.org (Bitcoinity, 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 analyses, we divide the period into two subperiods: Before and after December 17, 2017 when the bitcoin price reached its peak near 20,000 USD. 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 that of 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 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 have been raised recently (Griffin & 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 (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, that is, the log of the BitMEX price minus the log of the spot exchange price.

TABLE 4 Modified information shares (MIS) and component shares (CS)

	MIS			CS		
	Mean (%)	**Median (%)**	**Overall (%)**	**Mean (%)**	**Median (%)**	**Overall (%)**
Panel A. Full-sample period						
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
Panel B. Bull period						
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
Panel C. Bear period						
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), whereas Panel B (C) presents the period before (after) the historical price peak on December 17, 2017.
Abbreviations: VECM, vector error-correction model.

Table 2 reports the average trading volume by exchanges and trade types in the 6-month subperiods 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 subperiod, whereas the volume decreases 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.

Although both the perpetual swap and 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 Section 2, 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 subsample periods. Table 3 reports the test 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

[11]Indeed, 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, So, & Tse, 1999; Sohn & 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.

TABLE 5 Error-correction coefficients

	With respect to deviation from			
Response of	**BitMEX**	**Bitstamp**	**Coinbase**	**Kraken**
Panel A. Full-sample period				
BitMEX		−0.0357***	−0.0038**	−0.0049***
		(−15.617)	(−2.312)	(−3.359)
Bitstamp	−0.1952***		−0.2497***	−0.2267***
	(−21.835)		(−20.330)	(−21.531)
Coinbase	−0.1047***	−0.1491***		−0.1157***
	(−14.141)	(−13.512)		(−13.874)
Kraken	−0.1804***	−0.2487***	−0.2250***	
	(−23.815)	(−22.491)	(−24.283)	
Panel B. Bull period				
BitMEX		−0.0213***	−0.0081***	−0.0100***
		(−14.935)	(−6.555)	(−10.901)
Bitstamp	−0.1405***		−0.1750***	−0.1604***
	(−19.371)		(−18.725)	(−20.415)
Coinbase	−0.0497***	−0.0659***		−0.0559***
	(−14.870)	(−13.981)		(−15.025)
Kraken	−0.1368***	−0.1785***	−0.1812***	
	(−27.325)	(−25.598)	(−27.164)	
Panel C. Bear period				
BitMEX		−0.0560***	0.0021	0.0023
		(−24.012)	(0.977)	(1.207)
Bitstamp	−0.2718***		−0.3544***	−0.3195***
	(−35.025)		(−31.708)	(−34.081)
Coinbase	−0.1817***	−0.2657***		−0.1993***
	(−29.039)	(−28.871)		(−26.508)
Kraken	−0.2416***	−0.3471***	−0.2864***	
	(−31.454)	(−33.088)	(−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), whereas Panel B (C) presents the period before (after) the historical price peak on December 17, 2017. ***, **, and * indicate the 1%, 5%, and 10% significance levels, respectively.
Abbreviations: VECM, vector error-correction model.

subsamples, indicating the robustness of the cointegration relationship. On the basis of these test results, this paper assumes the existence of a cointegration relationship with the cointegration rank of three.

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 the following subsections, the price discovery shares of the three spot exchanges are not evenly distributed. Therefore, it may overrepresent 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.

TABLE 6 Gross and net spillovers

	To	From BitMEX (%)	Bitstamp (%)	Coinbase (%)	Kraken (%)	The others (%)
Panel A. Full-sample period						
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	
Panel B. Bull period						
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	
Panel C. Bear period						
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-min) 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, whereas 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), whereas Panel B (C) presents the period before (after) the historical price peak on December 17, 2017.

4.1 | MIS and CS

In this subsection, 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 CS. Lien and Shrestha (2009) suggest the 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), whereas the CS does not. Therefore, the two measures provide complementary views of price discovery among the markets.[12]

For a given sample period, for example, the entire sample or on a daily basis, we use minute-by-minute log prices to estimate a 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.

To examine how the price discovery shares evolve over time, the same analysis is performed for the two subperiods, 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,

[12]See appendix for the detailed calculation procedure.

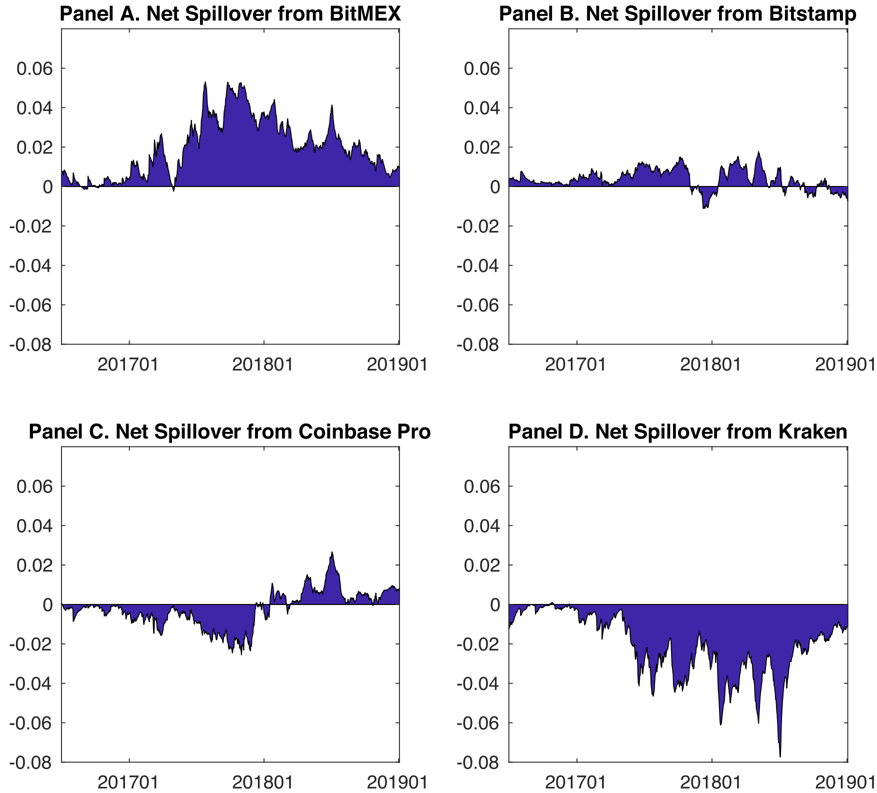

FIGURE 4 Net spillover. *Note:* Figure 4 depicts the daily long-horizon (60-min) net spillovers from the four markets: (Panel A) BitMEX, (Panel B) Bitstamp, (Panel C) Coinbase, and (Panel D) Kraken. The price of bitcoin perpetual swaps represents BitMEX, whereas the price of bitcoin spot represents the 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. VECM, vector error-correction model [Color figure can be viewed at wileyonlinelibrary.com]

despite some ups and downs. The shares of BitMEX either increased after the structural break (CS: 50.09–67.89%) or are almost unchanged (MIS: 52.25–50.33%) depending on the measures. In contrast to the stable role of BitMEX, the price discovery shares of Coinbase tend to decrease over time, whereas the price discovery role of Bitstamp has steadily increased.

Interestingly, the MIS and the CS are almost identical, particularly in the earlier subsample, implying that the contemporaneous correlation among innovations in the four exchanges is sufficiently small (Baillie, Geoffrey Booth, Tse, & Zabotina, 2002). In the later subsample, however, the differences between MIS and CS are sizeable, indicating that the exchanges become more interconnected and their innovations are consequently more correlated.

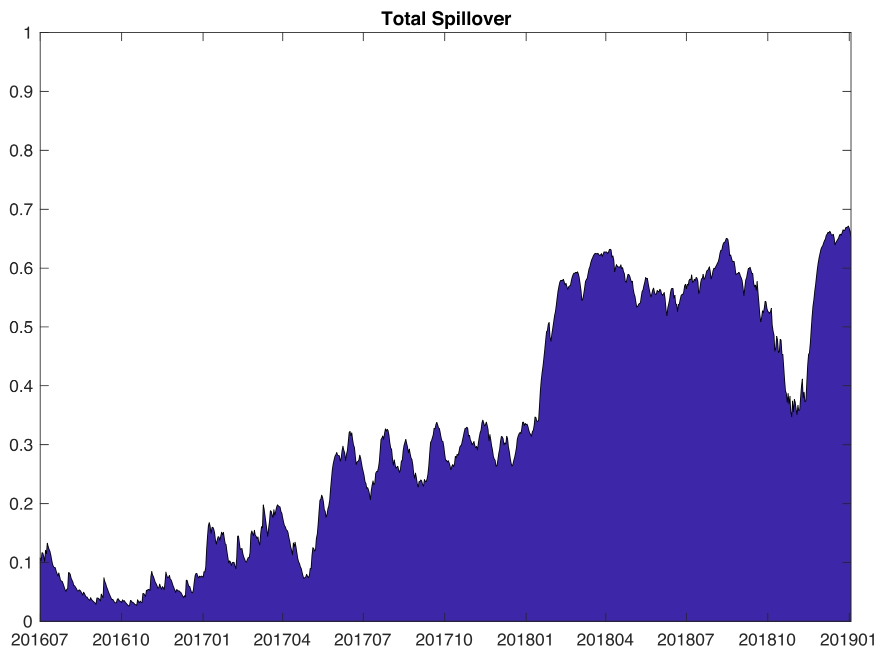

FIGURE 5 Total spillover. *Note:* Figure 5 depicts the daily long-horizon (60-min) total spillovers among the four markets: BitMEX, Bitstamp, Coinbase, and Kraken. The price of bitcoin perpetual swaps represents BitMEX, whereas the price of bitcoin spot represents the other markets. The total spillover is estimated on a daily basis from a VECM using minute-by-minute log prices. VECM, vector error-correction model [Color figure can be viewed at wileyonlinelibrary.com]

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)
RSpread	0.0537*** (8.44)	0.0536*** (8.41)	0.0267*** (3.08)	0.0265*** (3.08)
RTV	−0.0187** (−2.31)	−0.0188** (−2.34)	−0.0560*** (−4.56)	−0.0565*** (−4.64)
Ret	0.0171*** (2.72)	0.0195** (2.35)	0.0128 (1.25)	0.0222* (1.71)
Abs.Basis	−0.0235*** (−3.19)	−0.0386*** (−3.95)	−0.0550*** (−5.62)	−0.0739*** (−6.06)
$D_{\text{Ret}<0}$		0.00220 (0.13)		0.0216 (0.93)
$D_{\text{Ret}<0}$ × 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 (MIS) and component share (CS) 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). $D_{\text{Ret}<0}$ 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 levels, respectively.

4.2 | Speed of error correction

Since the MIS and the 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%.

Note that the signs of the error-correction coefficients are supposed to be nonpositive, 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, whereas 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 the 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.

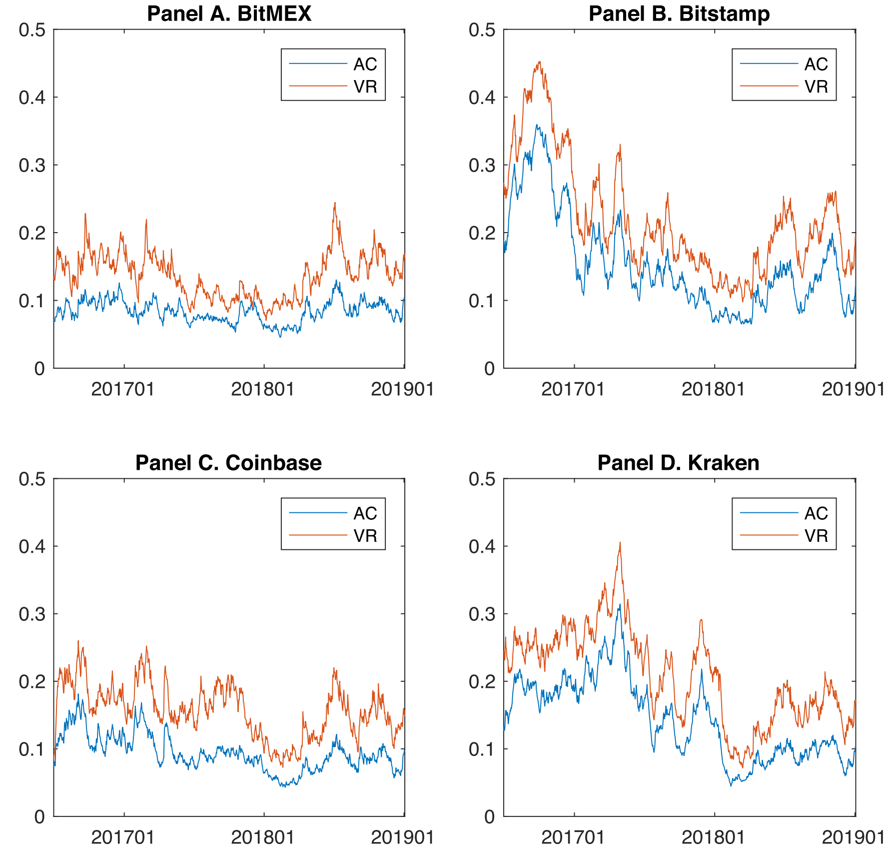

FIGURE 6 Autocorrelations (ACs) and variance ratios (VRs). *Note:* Figure 6 plots the daily absolute ACs and VRs in the four bitcoin markets: (Panel A) BitMEX, (Panel B) Bitstamp, (Panel C) Coinbase, and (Panel D) Kraken. The price of bitcoin perpetual swaps represents BitMEX, whereas the price of bitcoin spot represents the other markets. AC on a given day is obtained as an average of absolute return ACs measured at various intraday frequencies: 1, 3, 5, and 10 min. VR on a given day is obtained as an average of deviation of VR from one measured at different combinations of intraday frequencies: (5 and 1 min), (10 and 5 min), and (20 and 10 min). The time series are smoothed with a trailing exponentially weighted moving average: $\mathrm{MA}_t(a) = 0.1a_t + 0.9\mathrm{MA}_{t-1}(a)$, where a is either AC or VR [Color figure can beviewed at wileyonlinelibrary.com]

The subsample 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 subsample. 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 interconnected 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] Although the MIS and the 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.

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, whereas 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 variances 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 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%, whereas that to BitMEX from the others is 36.00%. In other words, innovations in BitMEX

[13]See appendix for the detailed calculation procedure.

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 subsample analyses contrast the intermarket 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 subsample, but this fraction increases to 65.91% in the later subsample. 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.

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 intermarket 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, whereas 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 ($D_{\mathrm{Ret}<0}$) 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—that is, 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 tends to occur primarily in the market with smaller trading costs (Booth et al., 1999; F. de Jong & Donders, 1998; Hsieh, Lee, & Yuan, 2008). To test this trading cost hypothesis, we control for the relative bid–ask spread and the RTV. Second, 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. Third, 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 (Ahn, Bi, & Sohn, 2019; Chakravarty et al., 2004; Chen & Chung, 2012). 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, whereas 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.

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 (Comerton-forde & Putniņš, 2015; Hendershott & Jones, 2005; Lo & MacKinlay, 1988). Following the literature, we use the absolute value of return AC and the deviation from one of the return VRs 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 ACs from the returns on a given day recorded at different intraday frequencies: 1, 3, 5, and 10 min, 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 AC 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, 5, 10, and 20 min, 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 and 1 min), (10 and 5 min), and (20 and 10 min). 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.

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), whereas 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 HE of the BitMEX perpetual swap. Let $p_{i,d}$ be the log price in exchange i on day d, where $i \in$ {BitMEX, Bitstamp, Coinbase, Kraken}. Then, $\Delta p_{i,d+1} - b_{id}\Delta p_{\text{BitMEX},d+1}$ is the return on day

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

TABLE 8 Out-of-sample hedge effectiveness

	Standard deviation of portfolio return			Hedging effectiveness		
Hedging methods	**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 ($i \in$ {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.
Abbreviations: OLS, ordinary least squares.

$d + 1$ 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 maximization problem with a two-period model implies that the hedge ratio which minimizes the portfolio return variance is obtained by the ratio of spot-BitMEX return covariance to BitMEX return variance (Ederington, 1979; Park & Switzer, 1995). Therefore, for the minimum variance hedge, b_{id} is set to be the slope coefficient from the ordinary least squares (OLS) regression of spot returns in exchange i on the BitMEX swap returns using the daily observations up to day d. Following A. de Jong, de Roon, and Veld (1997), we investigate the HE in an out-of-sample setting. Specifically, we use the earlier half of the sample (July 1, 2016 to October 1, 2017) for the initial estimation of the minimum variance hedge ratio on October 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 HE suggested by A. de Jong et al. (1997). The measure of exchange i is defined as

$$\text{HE}_i = 1 - \frac{\sigma_p^2}{\sigma_i^2},$$

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 HE 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, Bohl, & Gross, 2016).

[15]The 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 analyze 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, RTV, and the interexchange 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 prioritize 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 (BitMEX, 2019), (b) http://api.bitcoincharts.com/v1/csv/ (Bitcoincharts 2019), (c) http://data.bitcoinity.org (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, Sungbin Sohn, upon reasonable request.

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ORCID

Carol Alexander http://orcid.org/0000-0003-1247-0184
Jaehyuk Choi http://orcid.org/0000-0002-6837-4856
Heungju Park http://orcid.org/0000-0002-5572-3578
Sungbin Sohn http://orcid.org/0000-0002-9160-7291

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APPENDIX

This appendix section first describes the procedure of obtaining the MIS and the 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]

$$\Delta p_t = \alpha\beta' p_{t-1} + \sum_{q=1}^{Q} A_q \Delta p_{t-q} + \varepsilon_t, \tag{A1}$$

where α is the $K \times (K-1)$ error-correction coefficient matrix, indicating how prices react to the deviation from the

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

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 & 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 $\alpha_{\perp}$ is defined such that $\alpha'_{\perp}\alpha = 0$, and the CS in the ith product (market) is obtained as

$$\mathrm{CS}_i = \frac{\alpha_{\perp,i}}{\sum_{k=1}^{K} \alpha_{\perp,k}} \quad \text{for } i = 1, \ldots, K,$$

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 (A1) can be expressed as the vector moving average (VMA; ∞):

$$\Delta p_t = \Psi(L)\varepsilon_t, \tag{A2}$$

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

$$p_t = \Psi(1)\sum_{q=1}^{t} \varepsilon_q + \Psi^*(L)\varepsilon_t, \tag{A3}$$

where $\Psi(1)$ is the sum of moving average coefficients and $\Psi^*(L)\varepsilon_t$ 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 $\psi\varepsilon_t$ 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 ith market is obtained as

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

where M is a lower triangular matrix of the Cholesky factorization of Ω such that $\Omega = MM'$, and $[\psi M]_i$ is the ith entry in ψM. Note that the IS is closely related to the ordering of state variables because of the nature of the Cholesky factorization. It maximizes (minimizes) 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 MIS. Formally, the MIS in the ith market is obtained as

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

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 factorization, 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 generalized impulse response, which does not require orthogonalization of the shocks and is invariant to the variable ordering. Specifically, the h-period ahead generalized impulse response with respect to a unit innovation in variable j is defined as $\varphi_j(h) = E[\Delta p_{t+h}|\varepsilon_{jt}=1,\Theta_{t-1}] - E[\Delta p_{t+h}|\Theta_{t-1}]$, where Θ_{t-1} is the known history of the economy up to time $t-1$ and ε_{jt} is the jth entry in ε_t. Pesaran and Shin (1998) show that it can be calculated as

$$\varphi_j(h) = \omega_{jj}^{-1/2}\Psi_h\Omega e_j, \quad h = 0,1,2,..., \tag{A4}$$

where ω_{jj} is the jth diagonal entry in Ω and e_j is a column vector which takes one for the jth entry and zero for others. Ψ_h is the moving average coefficient matrix from Equation (A2). The entry in row i in $\varphi_j(h)$ indicates the consequence of the ith-ordered state variable at time $t+h$ with respect to a unit innovation in the jth-ordered state variable in time t.

From this generalized impulse response, we obtain the generalized forecast error variance decomposition, which is also invariant to the state variable ordering. Specifically, the generalized h-step ahead forecast error variance of the ith variable attributed to the innovations in the jth variable, denoted by $\theta_{ij}(h)$, is

$$\theta_{ij}(h) = \frac{\omega_{jj}^{-1}\sum_{k=0}^{h-1}(e_i'\Psi_k\Omega e_j)^2}{\sum_{k=0}^{h-1}e_i'\Psi_k\Omega\Psi_k' e_i}, \quad i,j = 1,...,K, \quad h = 0,1,2,..., \tag{A5}$$

For better economic interpretation, we normalize this measure so that the generalized forecast error variances of a variable accounted for by all variables sum to one: $\tilde{\theta}_{ij}(h) = \theta_{ij}(h)/\sum_{k=1}^{K}\theta_{iK}(h)$. 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 1-hr horizon ($h = 60$) to capture the long-run spillovers. Finally, the total spillover is defined as $1 - (1/K)\sum_{i=1}^{K}\tilde{\theta}_{ii}(h)$.