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Price discovery in Bitcoin: The impact of unregulated markets

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ABSTRACT

We analyse minute-level multi-dimensional information flows within and between bitcoin spot and derivatives. We show that perpetual swaps and futures traded on the unregulated exchanges Huobi, OKEx and BitMEX are much the strongest instruments for bitcoin price discovery and we examine potential determinants of their leadership strength. Prices on the regulated CME bitcoin futures and the US-based spot exchanges react to, rather than lead, price movements on the unregulated exchanges and they may do so relatively slowly. In a multi-dimensional setting including the main price leaders within futures, perpetuals and spot markets, the CME futures have a very minor effect on price discovery, even less than the spot exchanges Bitfinex, Bitstamp and Coinbase. Our findings highlight the persistent problems stemming from inconsistent regulation in bitcoin spot and derivatives markets, including insufficient price stability and lack of resistance to manipulative trading. We conclude that the SEC are correct to maintain such issues as their main concern for bitcoin ETF applications.

1. Introduction

At the peak of the last bitcoin bubble in December 2017 both the Chicago Board Options Exchange (CBOE) and the Chicago Mercantile Exchange (CME) introduced financially-settled futures contracts on the cryptocurrency bitcoin. The CBOE announced their withdrawal in March 2019, yet the regulated market of bitcoin derivatives has been growing continuously since inception. Over the last year CME futures contracts hit several record highs, both in terms of trading volume and in the number of large open interest holders.[1] The exchange claims this signals advancing market adoption from institutional investors. Moreover, the spectrum of regulated bitcoin derivatives has been extended by the physically-settled futures traded on Bakkt, a subsidiary of the Intercontinental Exchange (ICE), and most recently also with bitcoin options offered by both CME and Bakkt.

Besides regulated bitcoin derivatives there are numerous online centralised crypto exchanges that allow traders to operate in totally unregulated markets, some with a leverage of 100. The venues with the greatest trading volumes (including BitMEX, Huobi, OKEx and Deribit) all offer similar derivatives products, including futures, options and perpetual contracts, mostly on bitcoin but also on several other crypto-asset underlyings. Perpetual swaps are a particularly popular product and they are unique to crypto, not being traded in any of the more traditional asset classes.[2] All these exchanges have very little regulation, some none at all. To trade millions of dollars worth of bitcoin BitMEX, one of the largest exchanges, apparently requires no form of identity verification at all.

This absence of regulation is related to a lack of consensus between supervisory authorities of different jurisdictions – or even

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[1] Large open interest holders are those holding positions worth at least 25 bitcoin, i.e. at least 5 futures contracts.

[2] These operate as a perpetual currency swap without any exchange of notional, just cash flows between fixed and floating leg being exchanged at fixed points in time, usually one to three times a day.

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within the same jurisdiction – with the decentralized, globally-transferable nature of cryptocurrencies exacerbating such issues. Highlighting the lack of control of governmental authorities, Corbet et al. (2020) find protocol-based digital assets such as bitcoin largely immune to US Federal Fund interest rate and quantitative easing announcements. However, even if the authorities of major jurisdictions such as the US and UK agreed on some sort of legislation, its enforcement would still be difficult, because most exchanges are officially headquartered in jurisdictions with historically lax financial laws such as Malta or the Seychelles.

There have been many applications to the US Securities and Exchange Commission (SEC) which attempt to obtain approval for the launch of a bitcoin exchange-traded fund (ETF). However, they have all been rejected, the most recent one of Wilshire Phoenix being due to insufficient resistance to market manipulation.[3] Now, despite continuous growth, trading on regulated bitcoin exchanges remains tiny compared with that on the venues with no supervisory authority preventing illegal manipulative behaviour. For instance, the daily trading volume on BitMEX, Huobi and OKEx derivatives combined currently exceeds \$7.5 billion which is almost 33 times the volume on regulated CME and Bakkt futures.[4] The ongoing attempts at successful filings for bitcoin ETFs in the face of this huge volume discrepancy raises the question of how relevant the regulated bitcoin market is, especially with respect to price discovery and speed of information processing.

To answer this question, we use minute-level data to analyse price discovery both within and across different groups of instruments, including spot exchanges, perpetual contracts, and both regulated and unregulated futures. We focus our analysis exclusively on bitcoin since it accounts for more than 60% of the total cryptocurrency market capitalization and unlike most other cryptocurrencies, it serves as underlying for a wide range of very actively traded derivatives. In addition, bitcoin is the only cryptocurrency for which there are attempts to launch a SEC-approved ETF. Results from several econometric models reveal a strong dominance of the unregulated derivatives products over all spot exchanges and over the regulated CME and Bakkt futures. On average, these products combined account for more than 60% of total price discovery within the bitcoin market. Although CME futures consistently lead the Bakkt contracts, they play a less important role than the three major spot exchanges, which is in line with the results of Baur and Dimpfl (2019). Moreover, we find signs that speculative traders are responsible for the informational leadership of the unregulated futures. During volatile periods the leading role of Huobi futures decreases and that of the BitMEX perpetual increases, probably due to aggressive speculation. We also find a faster speed of adjustment and information absorption on the unregulated spot and derivatives exchanges than on CME bitcoin futures.

Our findings are important in that they highlight the problems arising from inconsistent regulation of bitcoin markets. While well-established spot exchanges such as Coinbase or Gemini are headquartered in the US and apparently undertake considerable efforts to ensure market integrity, the major derivatives exchanges operate without any regulatory requirements at all; indeed some even fail to perform standard know-your-customer procedures. Our results highlight how easy it is for investors to circumvent malpractice-preventing measures and successfully manipulate the bitcoin price by applying high-frequency trading strategies to unregulated derivatives exchanges. A welcome side effect of this would be maximized profits due to high-leverage trading. Therefore, we not only urge investors to be cautious, but also encourage regulators and supervisory authorities to tackle the (admittedly difficult) task of enforcing a consistent regulatory legislation to crypto derivatives. If these financial instruments are to fulfil their potential as a diversified and alternative asset class it is important to ensure sufficient stability and resistance of crypto markets against manipulation and fraud.

Cryptocurrencies began as niche products traded by a limited community, mainly in Asia. However, over the last few years an increasing acceptance of bitcoin among mainstream investors has been a catalyst for cryptocurrency to be designated an investable asset class in its own right. On the other hand there remains considerable concern about the destabilising effects of trading cryptocurrencies and the need to protection of consumer assets. In 2017 the Chinese government banned all trading on crypto assets and soon afterwards both the Bank of England and the Office of the New York State Attorney General issued highly cautionary reports.[5]

Despite the cautionary attitudes of senior regulators, CME bitcoin futures and options and Bakkt futures now allow highly-leveraged positions on bitcoin to be traded by any large financial institution. The total assets under management of crypto hedge funds exceed \$2 billion in 2019 and this figure continues to rise rapidly.[6] Although most hedge fund assets come from family offices and high-net worth individuals, for smaller investors there are several bitcoin ETFs available on the Toronto stock exchange and many other venues such as Germany's Xetra digital stock exchange. This growing acceptance and participation of both financial institutions and retail investors goes hand-in-hand with an increased potential to cause financial distress because, as we show in this paper, bitcoin prices are largely determined by totally unregulated venues where price manipulation is the order of the day (Twomey and Mann, 2020).

With this rapidly increasing demand there is now considerable pressure on the SEC to accept filings for bitcoin products that are listed on the New York Stock Exchange by well-established ETF providers.[7] However, the academic research cited in the SEC reports so far has been inconclusive and contradictory. Also the research they have cited so far is not up to date, given the extremely rapid recent developments of unregulated bitcoin derivatives. Therefore, the SEC and other regulators should take serious consideration of the implications of our findings as they consider applications for bitcoin derivative products and ETFs.

Our study makes two major contributions above the most relevant papers in the existing literature: First, we conduct our analyses in multiple dimensions, of between two and eight instruments at a time. This way, we capture multi-dimensional information flows between exchanges rather than just bilateral dynamics. Our work supports and extends the findings by Alexander et al. (2020) of the BitMEX perpetual leading three major spot markets. However, omitting substantial information flows from other markets can produce misleading results. Indeed, all the other published studies on price discovery in bitcoin markets are limited to the spot market (Brandvold et al., 2015) or rely on just two-dimensional models including only one regulated futures and one spot exchange (Baur and Dimpfl, 2019; Corbet et al., 2018; Entrop et al., 2020) – but in a two-dimensional model one or other of the instruments must necessarily be identified as price leader; Secondly, to the best of

[3] See Coindesk on 26 February 2020.

[4] Although it is difficult to ascertain how much of this is caused by wash trading or other methods of artificial volume inflation, this type of activity is more typical of new exchanges that are vying for custom from coin-ranking sites. See Bitwise Asset Management ETF filing to the SEC.

[5] See the Guardian article of 2 March 2018 Bitcoin faces regulatory crackdown, Bank of England warns and the Office of the New York State Attorney General Report on Virtual Markets.

[6] See the PwC 2020 Crypto Hedge Fund Report.

[7] See CNBC news on 7 March 2020 and see Bloomberg on 26 February and 17 June 2020.

our knowledge, this study is the first to analyse information flows between unregulated bitcoin derivatives and the CME and Bakkt futures, as well as the major spot exchanges. By analysing the heavily-traded futures and perpetual contracts offered by major unregulated exchanges, we show that these products make enormous contributions to price discovery and strongly lead both the regulated bitcoin derivatives and all the spot exchanges. We conclude that excluding them from the analysis, as in all previous work on CME futures, leads to erroneous conclusions about price discovery within the bitcoin market.

The remainder of this paper is organized as follows: Section 2 sets our study within a brief review of the extant literature and exemplifies the contribution of our work; Section 3 describes the exchanges and instruments included in our analyses and their minute-level price and volume data; Section 4 presents our results on price discovery both within and across different instrument groups; Section 5 explores the factors that may influence the discovery roles of the four main price-leading bitcoin products; Section 6 examines the speed of information processing between these leading products and the CME futures; and Section 7 summarises and concludes.

2. Contribution to the literature

Price discovery has been studied across a wide range of assets and products, with most research focussing on information flows between futures and its underlying spot markets. There are several reasons why futures should lead price discovery in established asset classes, such as lower transaction costs, absence of short-sale restrictions, built-in leverage and greater transparency (Garbade and Silber, 1983; Fleming et al., 1996). Most recent empirical studies corroborate this theory, but not all. For instance: Adaemmer and Bohl (2018) explore European agricultural markets during periods of financial turmoil and find a dominance of the futures over the spot market; Shrestha (2014) concludes the same for heating oil and natural gas (but not for crude oil); similar findings in (precious) metal markets are documented by Figuerola-Ferretti and Gonzalo (2010), Hauptfleisch et al. (2016) and Jin et al. (2018), while Chen and Tsai (2017) and Bollen et al. (2017) come to the same result in the VIX market; Mizrach and Neely (2008) also reveal a leading role of futures in the US Treasury market. In contrast, Dimpfl et al. (2017) find a strong leading role for the spot market for agricultural commodities and Cabrera et al. (2009) find the Euro and Japanese Yen spot market consistently leading price discovery for US dollar exchange rates. It is also possible to investigate price discovery between spot and several derivatives jointly, which is of particular interest for the highly-liquid stock index markets (Booth et al., 1999; Chen et al., 2016; Ahn et al., 2019). Other research explores the information flows for assets traded in multiple markets, or for derivative products with the same underlying (Gau and Wu, 2017; Fernandes and Scherrer, 2018; Frino and Garcia, 2018). Benos and Sagade (2016) examine the role of high-frequency traders (HFTs) in price discovery, showing that the most informed traders are those who pursue speculative trading strategies. However, information shares decline with the amount of aggressive HFT volume.

Several papers have studied price discovery with respect to bitcoin, both within the spot market as well as between spot and futures exchanges. Analysing daily spot-market data from several years ago, Brandvold et al. (2015) identify the (now-inoperative) exchanges Mt.Gox and BTC-e as leaders of bitcoin spot prices. Dimpfl and Peter (2019) use the two-dimensional measure of Putninš (2013) to account for microstructure noise and find a leading role for Bitfinex spot prices over those from Kraken, and from Poloniex. Accounting for a potential impact from exchange rates, Pagnottoni and Dimpfl (2019) find that Chinese spot exchanges are the main informational leaders. Not price discovery analysis, but closely related, is the work of Urquhart (2016) who applies a battery of efficiency tests and makes the prediction that the bitcoin market may become more efficient over time.

Results for spot-futures price discovery are mixed. During the first three months after the inception of the (now-defunct) CBOE bitcoin futures, Corbet et al. (2018) find clear dominance of spot over CBOE futures prices, which they explain by the presence of unsophisticated individual investors. Baur and Dimpfl (2019) also identify spot prices to be the main driver of price discovery, this time for CME futures, which they attribute to the higher trading volume and the longer trading hours on spot markets. But contradicting this, Kapar and Olmo (2019) and Fassas et al. (2020) find that CME futures lead the spot market, but their analysis is based on daily and hourly data, respectively, which may not be able to capture real-time information flows adequately. Similarly, Aleti and Mizrach (2019) and Entrop et al. (2020) analyse quotes instead of transaction data, again documenting a leading role of CME futures. Entrop et al. (2020) identify relative trading costs and volume as main drivers of price discovery. Most recently, Akyildirim et al. (2020) find CME and CBOE futures leading over the spot market during the first two months after their introduction. All the studies just cited only analyse bivariate information flows; yet bitcoin spot and derivatives are traded on dozens of different exchanges. Alexander et al. (2020) use a four-dimensional setting to explore information flows and spillovers between the BitMEX perpetual and the three major spot exchanges that determine its settlement price. They find a clear dominant role of the BitMEX instrument which is strongest when trading volume and the basis are both relatively large. In particular, during down markets when the perpetual's price deviates significantly from the spot prices, the discovery role of the BitMEX contract is enhanced. By contrast, during exuberant periods with large positive returns, its discovery role diminishes. They attribute this finding to the perpetual becoming more actively used to explore possible arbitrage opportunities. They also demonstrate a very high effectiveness for naïve hedges of spot positions on Bitfinex and Coinbase, which is only very slightly improved with minimum-variance hedging. The BitMEX perpetual is an ideal hedging tool because it has much lower basis risk than futures.

Our study re-examines the results in those papers cited above that relate to the price discovery role of regulated bitcoin futures. Several of these have been cited in hedge fund applications for bitcoin ETFs to the SEC, as evidence for market maturity and resistance to manipulation.[8] However, all such previous studies limit the analysis to only two dimensions, viz. either CME or CBOE futures and some spot exchanges (Corbet et al., 2018; Baur and Dimpfl, 2019; Entrop et al., 2020) or some non-tradeable index over several spot exchanges (Kapar and Olmo, 2019). In fact, we examine 21 different bitcoin spot and derivatives markets with a main focus on the price discovery role played by the heavily-traded derivatives products offered by a large number of unregulated crypto exchanges. Consequently, we provide a much more complete picture about the price discovery role of some highly-speculative instruments and their effect on both regulated bitcoin futures and spot prices. Our work also greatly extends the scope of Alexander et al. (2020). Even though we confirm their results with respect to spot exchanges, we also show that their too-narrow focus misses enormous information flows by restricting analysis to one derivative (the BitMEX perpetual). They do not take into account other very popular bit-

[8] For example, see the Response of Wilshire Phoenix to the SEC Footnote 96, page 21 and the SEC Decision Footnote 180, page 48 and Footnote 239, page 62.

Table 1
Futures specifications.

	Regulated futures		Unregulated futures				
Contracts	CME	Bakkt	BitMEX	Deribit	Huobi	Kraken	OKEx
Contract size	5 XBT	1 XBT	1 USD	10 USD	100 USD	1 USD	100 USD
Frequency	Monthly	Daily, monthly	Quarterly	Quarterly	Weekly, Quarterly	Monthly, Quarterly	Weekly, quarterly
Margin requirement	37%	37%	1%	1%	1%	2%-6%*	10%
Settlement	Cash in USD	Physical	Cash in XBT	Cash in XBT	Cash in XBT	Cash in XBT	Cash in XBT
Trading days	Weekdays	Weekdays	24/7	24/7	24/7	24/7	24/7
Delivery date	Last friday	3rd friday	Last friday	Last friday	Last friday	Last friday	Last friday
Fees (maker/taker)	$1.25	$1.25	−2.5/7.5	−2/5	2/3**	−2/7.5	2/5**

Note: The table shows the main specifications of the quarterly futures contracts included in our analysis. Except for CME and Bakkt, fees are reported in basis points. *Kraken is the only exchange that distinguishes between margins for professional and retail clients. The former face margin requirements of 2–6%, while the latter have to deposit 50% as initial margin. **Huobi and OKEx do not offer maker rebates for ordinary users, but for VIP investors with a 30-day trading volume of at least $500 m or 100,000 XBT, respectively.

coin derivatives such as Huobi or OKEx futures which, as we show, are leading in price discovery.

3. Exchanges, instruments and data

Here we describe the characteristics and trading volumes on all 21 instruments included in our price discovery models. We adopt the ISO 4207 standard ticker XBT for bitcoin.[9] In spot markets we only admit the major well-established bitcoin exchanges (Bitfinex, Bitstamp, Bittrex, Coinbase, Gemini, itBit and Kraken) and a few more interesting minor exchanges (BinanceUS, Exmo and OKCoin).[10] While the seven major exchanges are reported to have real trading-volume figures, and to not participate in wash trades, we cannot rule out the possibility of artificially inflated volume on the three minor exchanges.[11] We further include both regulated and unregulated futures into our price discovery analyses. There are only two regulated contracts – one offered by CME and one by Bakkt, a subsidiary of the ICE. The CME launched their futures during the peak of the last bitcoin bubble in December 2017, while Bakkt introduced their product at the end of September 2019. Finally, crypto derivatives markets have one very popular product that does not occur in other, more traditional asset classes – the perpetual swap (or perpetual for short). These contracts are currency swaps between XBT and USD where the only cash-flows are between perpetual fixed and floating legs and these are usually exchanged one to three times a day. They combine the features of both futures and spot positions in that they do not expire before being closed out (similar to a spot position) and they allow very high-leverage trading (like a futures contract). In contrast to ordinary futures, perpetual contracts are not exposed to any roll-over risk and the basis is very much smaller than it is for futures.

Starting with the futures, Table 1 displays the product specifications for both regulated futures in the two left-hand columns. The most important differences are contract size and settlement: CME futures are for five XBT and cash-settled in USD, whereas Bakkt's contracts are physically-settled with a size of just one XBT. Moreover, Bakkt offers both daily and monthly futures, but we focus on the latter since they usually exhibit a much larger trading volume. The settlement value for CME contracts is the Bitcoin Reference Rate (BRR) which is calculated using data on all trades conducted on major bitcoin exchanges between 3 pm and 4 pm London time. At the time of writing the constituent exchanges are Coinbase, Bitstamp, Kraken, Gemini and itBit. The one-hour observation period is equally partitioned into 5-min intervals and for each interval the volume-weighted median price is calculated from all trades on all four exchanges executed within that interval. The BRR is then a simple un-weighted average of these twelve medians.[12]

For the unregulated bitcoin futures, we include the contracts of all major crypto-derivatives exchanges, i.e. BitMEX, Deribit, Huobi, Kraken and OKEx. The right-hand side of Table 1 displays the specifications of the individual contracts. They are similar, differing only slightly in contract size and settlement price. Unlike the CME and Bakkt futures, the unregulated contracts are so-called inverse futures, i.e. their base currency is XBT so they are futures on USD/XBT instead of XBT/USD. Therefore, their contract size is quoted in USD.[13] Comparing the unregulated contracts to CME and Bakkt futures, it is important to note that the unregulated products have a much smaller contract size and their trading is not interrupted, i.e. they can be traded 24/7. Their small contract size makes the unregulated contracts interesting for retail and smaller institutional investors, whereas the bigger CME and Bakkt futures can only be accessed by large institutions that are allowed to trade on these heavily-regulated exchanges.

Perpetual contracts are offered by a large number of crypto-exchanges and we again focus on the major exchanges (BitMEX, Deribit, Kraken and OKEx). Table 2 shows the product specifications for the different contracts. As the unregulated bitcoin futures, perpetual contracts are of inverse type with XBT being the base currency. It is worth mentioning that Binance offers a perpetual contract between XBT and USDT which was the third most traded crypto derivative product in December 2019.[14] However, since we did not include Binance into our set of spot exchanges, we also leave out the Binance perpetual contract.

A key point to note from Tables 1 and 2 is that the fees on all the unregulated derivatives exchanges follow (at least partly) a

[9] Although BTC is used in some previous literature this is already used in two other ways: as the ISO 4207 ticker for the currency of Bhutan; and as the code for the average-price bitcoin settlement index of some bitcoin derivatives.

[10] As the name suggests, BinanceUS is a subsidiary of the Malta-based Binance exchange – the biggest crypto-exchange in the world. However, Binance only allows crypto-to-crypto trading with bitcoin-tether (i.e. XBT/USDT) being the most liquid pair. Only its US subsidiary allows trading of bitcoin against the US dollar. Therefore, we restrict our analyses to BinanceUS and do not include its parent company. However, note that BinanceUS has not been online before October 2019.

[11] The fee structure on many bitcoin exchanges, which rewards market makers, induces wash-trading order-book activity which artificially inflates reported volumes. See Bitwise Asset Management ETF filing to the SEC. However, volume-inflation strategies such as wash trades are designed not to move prices, so they should not prevent a proper analysis: an exchange or instrument contributes to price discovery if a transaction on it creates a price movement which leads price changes on another exchange or instrument, regardless of the provenance of the transaction.

[12] The CME also performs an automated screening for potentially erroneous data – if the individual median tradeprice of any of the exchanges differs from the total median by more than 25%, all transactions of the respective exchange are omitted in the BRR calculation.

[13] Huobi, Kraken and OKEx offer bi-weekly/weekly as well as quarterly contracts, but the quarterly ones have by far the greatest trading activity and so we limit our analyses to those.

[14] See CryptoCompare's exchange review for December 2019.

Table 2
Perpetuals specifications.

	BitMEX	Deribit	Kraken	OKEx
Contract size	1 USD	10 USD	1 USD	100 USD
Margin requirement	1%	1%	2%-10%*	1%
Settlement currency	XBT	XBT	XBT	XBT
Trading days	24/7	24/7	24/7	24/7
Funding frequency	8 hrs	8 hrs	4 hrs	8 hrs
Fees (maker/taker)	−2.5/7.5	−2.5/5	−2/7.5	2/5**

Note: The table shows the main specifications of the perpetual contracts included in our analysis. All fees reported here are in basis points. *Kraken is the only exchange that distinguishes between professional and retail clients. The former face margin requirements of 2-10%, while the latter have to deposit 50% as initial margin. **OKEx does not offer maker rebates for ordinary users, but for VIP investors with a 30-day trading volume of at least 100,000 XBT.

Table 3
Data statistics.

Type	Instrument	Data start	ADV	Max volume	NTR
Spot	BinanceUS	9 Oct 2019	1.86	6.21	39.01%
	Bitfinex	1 Apr 2019	88.71	712.24	1.71%
	Bitstamp	1 Apr 2019	74.27	484.02	0.84%
	Bittrex	1 Apr 2019	6.39	39.93	32.42%
	Coinbase	1 Apr 2019	124.66	1,062.82	0.22%
	Exmo	1 Apr 2019	2.98	7.83	14.94%
	Gemini	1 Apr 2019	16.04	138.94	17.55%
	itBit	1 Apr 2019	10.45	48.43	46.86%
	Kraken	1 Apr 2019	69.61	411.18	6.72%
	OKCoin	1 Apr 2019	4.72	33.63	34.89%
Reg. Futures	CME	1 Apr 2019	221.40	1,414.78	43.18%
	Bakkt	30 Sep 2019	9.37	38.50	87.62%
Unreg. Futures	BitMEX	1 Apr 2019	66.38	267.66	10.52%
	Deribit	1 Apr 2019	27.48	238.80	24.58%
	Huobi	29 Jul 2019	2,752.00	13,448.69	0.37%
	Kraken	30 Oct 2019	2.02	19.67	77.63%
	OKEx	1 Apr 2019	970.23	4,008.31	1.32%
Perpetuals	BitMEX	1 Apr 2019	3,033.57	13,740.10	0.09%
	Deribit	1 Apr 2019	254.22	1,865.89	5.63%
	Kraken	30 Oct 2019	29.41	150.93	47.09%
	OKEx	17 Jul 2019	482.12	1,634.80	0.66%

Note: The table shows the date from which transaction data are available, the average daily volume (ADV, in million USD), the maximum daily volume (in million USD) and the ratio of minutes where no trade occurred (no-trade-ratio, NTR), during the period from 01 April 2019 to 31 January 2020. For each instrument, the average daily volume is calculated over the interval for which transaction data are available. The no-trade-ratio is calculated based on CME trading times, i.e. for each instrument, we consider the period from 5 pm to 4 pm Chicago time on working days and ignore weekends, starting on the respective data start date of each instrument.

maker-taker model. That is, orders that add liquidity to the book are refunded a small percentage (e.g. 2 or 2.5 basis points) of the order size. BitMEX, Deribit and Kraken give this discount to all users, independent of their trading volume. Huobi and OKEx on the other hand follow a tiered maker-taker model refusing ordinary users maker rebates. Only VIP investors with a 30-day trading volume of at least $500 m or 100,000 XBT, respectively, obtain maker rebates. But even in their respective top tier – trading volume of more than $500 m on Huobi or 300,000 XBT on OKEx – the rebates are at most 1 basis point and thus, significantly smaller than on BitMEX, Deribit and Kraken.

CME and Bakkt are regulated by the CFTC but all other bitcoin derivatives exchanges are still completely unregulated. There is no supervisory authority establishing any rules to prevent malpractice, misconduct and manipulation.[15] Although we cannot rule out the possibility of price or volume manipulation this does not prevent a proper price discovery analysis, as already discussed.

It was a challenge to retrieve and manage data on all 21 instruments, with about 9 million minute-level prices and the same number of corresponding traded volumes. We used two different data sources: Thomson Reuters Eikon for data on the regulated CME and Bakkt bitcoin futures and coinAPI for all remaining spot and derivatives data.[16] The dataset consists of minute-by-minute transaction data and covers the period from 1 April 2019 to 31 January 2020 summing up to 440,640 observations per instrument.[17] Within this period, the XBT/USD price ended its year-long bear market and rose from $4000 to more than $12,000 by June 2019. Subsequently, it dropped to below $7,000 in December 2019 before again increasing to about $9300 by the end of January 2020.

Table 3 provides summary statistics on the different exchanges and instruments included in our analyses. Depending on the exchange, there were between two and five active bitcoin futures contracts during the observation period – for CME, even eleven. In our price discovery analyses, we use continuous time series of futures prices formed by rolling over from the prompt to the next contract at midnight the day before expiration. Therefore, we only report summary statistics on the trading volume of these time series. However, since almost all trading activity usually occurs on the prompt contract until one day before expiration, including all active futures will not lead to significant changes. We can see that the individual spot exchanges are quite small compared to futures and perpetuals. Over our observation period, the largest spot exchange, Coinbase, has an average daily volume (ADV) of $125 m – the CME and Huobi futures have an ADV of $221 m and $2.75 bn, the BitMEX perpetual contract even $3.03 bn. Overall, perpetuals and futures markets are roughly the same size (ADV of $3.8 bn), followed by spot ($400 m) and regulated futures ($230 m). Both Huobi futures and BitMEX perpetual show a maximum daily volume of more than $13 bn, OKEx futures ($4bn) and Deribit perpetual ($1.9 bn) trail far behind.

In Sections 4.3 and 4.4 we are interested in whether trading volumes are mainly due to hedgers or speculators. To this end, we consider the ratio of daily trading volume to open interest (OI) as a measure for speculative trading activity, as proposed by Garcia et al. (1986). The measure distinguishes between speculators and hedgers based on the length of a position's holding period, i.e. it assumes that speculators open and close their positions more rapidly than hedgers.[18] Hence, other things being equal, the shorter the holding period the greater the speculative activity. Holding periods decrease when trading volume V is high while OI is low. Hence, the greater the V/OI ratio, the more speculative the trades.

We obtained daily open interest (OI) data on all bitcoin futures and perpetuals from Skew and Thomson Reuters Eikon.[19] These data cover the period from 6 September 2019 to 31 January 2020, a total of 148 observations per instrument. Table 4 reports average, standard deviation and maximum of daily open interest as well as V/OI, i.e. the average ratio of daily trading volume to open interest for the derivatives. With an average of $780 m, the BitMEX perpetual clearly leads in open interest, followed by the futures contracts of OKEx ($583 m) and Huobi ($378 m), and the CME futures ($160 m) trail quite far behind. Interestingly, the Huobi futures – which are the second most traded instrument – have by far the highest

[15] In fact, some exchanges such as BitMEX or Huobi are even unauthorized and explicitly banned in the US. In practice however, this ban can be circumvented quite easily using a virtual private network (VPN).

[16] Data and software provider coinAPI links with hundreds of crypto spot and derivatives exchanges, offering historical and streaming order-book and trades in tick-by-tick or highest granularity data from all major centralized and decentralized exchanges.

[17] The total of around 9 million is because a few instruments were launched at a later stage or their data are not available before a certain point.

[18] That the extent of speculative activity is proportional to the average length of time that an instrument is held is a reasonable assumption, especially in the highly volatile bitcoin market.

[19] Skew is a provider of real-time data analytics on bitcoin and ether derivatives.

Table 4
Open Interest

Type	Instrument	Average	St Dev	Max	V/OI
Reg. futures	CME	160.36	41.94	240.15	1.53
	Bakkt*	3.91	3.24	11.88	3.35
Unreg. futures	BitMEX	308.02	33.42	426.40	0.17
	Deribit	98.16	17.01	156.60	0.26
	Huobi	377.79	97.00	685.00	7.38
	Kraken	13.25	5.08	24.60	0.17**
	OKEx	583.41	101.46	866.40	1.52
Perpetuals	BitMEX	780.17	104.80	1,003.30	3.07
	Deribit	85.83	7.10	103.90	2.20
	Kraken	26.68	7.66	46.60	1.13**
	OKEx	152.87	36.58	249.30	3.46

Note: The table shows average, standard deviation and maximum of daily open interest (in million USD) as well as the average ratio of daily trading volume to open interest (V/OI) over the period from 06 September 2019 to 31 January 2020. *For Bakkt futures, the data start at 30 September 2019. **Results for Kraken futures and perpetual are distorted, because their transaction data are not available before end of October 2019.

V/OI. This points towards a comparatively large number of intraday speculators who use the Huobi contracts to draw profits from price movements and are market neutral at the end of day. Compared with the perpetuals however, the unregulated futures (with the notable exception of Huobi) have a relatively low ratio of volume to open interest, indicating more active use for hedging than the perpetual contracts.

Fig. 1 compares monthly trading volume of bitcoin spot and derivatives from April 2019 to January 2020. Since most derivatives products are of inverse type and have a contract size denominated in USD, we plot the volumes both in number of bitcoin and in USD. As one can see, the trading volume of the spot market is tiny and on average accounts for only 6% of the total volume. Between April and June 2019, it was comparatively larger (8%–10% of the total volume) whereas from August onwards the relative contribution of the spot market never exceeded 5%. This change is caused not only by an increased trading volume on derivatives (from end of July 2019 we include three more products) but also by a significant decrease in the spot market. At 1.9 m XBT, the average monthly spot volume over the period from April to July is almost double the average between August and January. During the same period, the average derivatives volume increased from 20 bn to 25 bn XBT.

Fig. 2 compares the monthly volume on different exchanges and instruments during the last month of our sample, i.e. in January 2020, starting with the overall market (Panel A) and then considering the different sub-markets individually. From Panel A the Huobi futures have 45% of the overall total volume traded, followed by BitMEX perpetual (30%), OKEx futures (12%) and OKEx perpetual (8%). The three major spot exchanges (Bitfinex, Bitstamp, Coinbase) only account for about 2% of the total trading volume. As in other asset classes such as equity where the volume on derivatives exceeds the spot by far, one may interpret this as a sign of maturity in the bitcoin market. It is remarkable that OKEx has managed to establish both their futures and the perpetual contracts because most exchanges have only one liquidly-traded product. Looking at the spot market alone, in Panel B, with a monthly trading volume of $2.8 b Coinbase has by far the largest share followed by Bitstamp ($1.7 b), Bitfinex ($1.6 b) and Kraken ($1.5 b). The remaining 6 spot exchanges trail far behind and together only account for 10% – or roughly $912 m – of the total spot volume in January 2020. Panel C of Fig. 2 shows that the bitcoin futures market is extremely dominated by the quarterly Huobi contracts, which account for a huge 74% of the futures trading volume, corresponding to $125b. The regulated CME futures exhibit a trading volume of about $9b, making them the third most traded futures product – only exceeded by the OKEx contracts with a volume of $32b. As can be seen in Panel D, the BitMEX contract similarly dominates the perpetuals market. With a monthly volume of $85b, it is responsible for 75% of the perpetuals trading volume, while the remaining 25% mainly originate from the OKEx contract ($21b).

4. Price discovery

Price discovery denotes the process by which new information are incorporated into asset prices. If N homogeneous or closely-linked securities are traded on multiple trading venues, their prices are cointegrated and follow a long-run equilibrium. That is, there exists a N-dimensional vector error correction model (VECM) and we can calculate two different price discovery metrics: the Information Share (IS) proposed by Hasbrouck (1995) and the Component Share (CS) from Gonzalo and Granger (1995). The sum of the N individual information metrics is 1 and the higher the metric for a particular market, the more influential its price discovery role. There are slight differences between the two metrics – the IS takes into account the contemporaneous correlation between price innovations of the different assets, whereas the CS does not. However, this leads to the problem of non-uniqueness of the IS. To overcome this, we use the so-called Generalized Information Share (GIS), a generalization of the IS proposed by Lien and Shrestha (2014). In theory, the CS of individual markets should always be positive. However, in practice, it might happen that the CS of some markets become slightly negative. There are two possibilities to deal with this: We could either use the absolute value (see for example Bohl et al. (2011)) or set the negative shares to 0 and adjust the others so that they still sum up to 1 (Alexander et al., 2020). We apply both approaches, but since their results are not significantly different, we only report those of the second approach.[20]

A recent structural analysis by Yan and Zivot (2010) reveals that both IS and CS account for the relative avoidance of noise, including liquidity shocks and microstructure frictions such as tick size discreteness, and only the IS is able to provide correct information about price discovery. For this reason, Putniņš (2013) proposes the Information Leadership Share (ILS), a combined metric of IS and CS, which under certain conditions, may help to isolate the impacts of permanent shocks from those of transitory shocks. However, the ILS is only applicable in a two-dimensional setting and since we are interested in multi-dimensional informational flows, rather than just bilateral dynamics, we rely only on GIS and CS. In addition, a recent study by Dimpfl and Peter (2019) already applies the ILS measure to price discovery in bitcoin, albeit it includes only three spot exchanges.

Because we have 21 bitcoin instruments in total we employ a staged approach, first applying a within-group price discovery analysis for four different sets of instruments, i.e. spot, regulated futures, unregulated futures and perpetuals. Then we choose the leading instrument(s) of each group and analyse price discovery between those. We conduct the analyses on a day-by-day basis to see how individual contributions to price discovery have changed over time.[21]

In contrast to Aleti and Mizrach (2019) and Entrop et al. (2020), we employ transaction prices, not mid-quotes data. The advantage is that we analyse actual trades, not non-traded prices. However, we may have to deal with infrequent trading on some instrument(s): if it is too thin on any given day this illiquidity can distort results. Therefore, we exclude an instrument on any day when there was no trade for more than 4.5 hours, which is usually the case only when

[20] See the Appendix for a mathematical description of the methodology.

[21] For most instruments the sample period ranges from 1 April 2019 to 31 January 2020 but we have to choose a shorter period for the regulated futures analysis since Bakkt futures were not launched before end of September 2019.

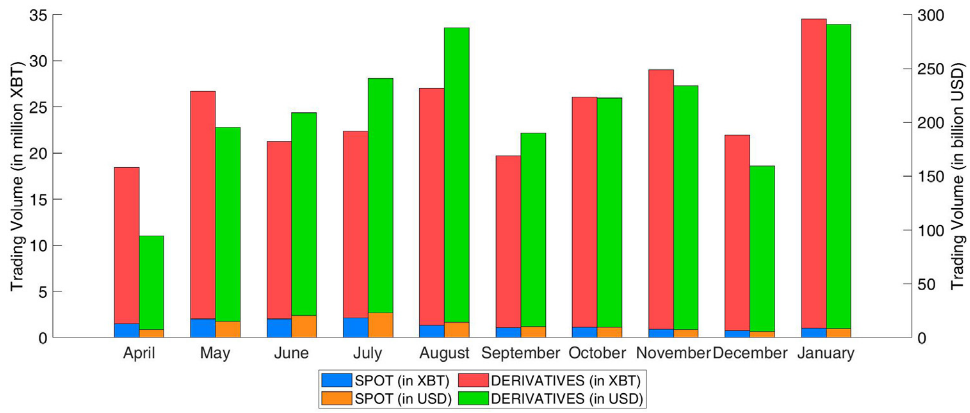

Fig. 1. Volume spot vs derivatives. *Note:* The figure shows the monthly trading volume of bitcoin spot and derivatives, in million XBT on the left-hand axis and in billion USD on the right-hand axis. We use the Coinbase price to convert between XBT and USD.

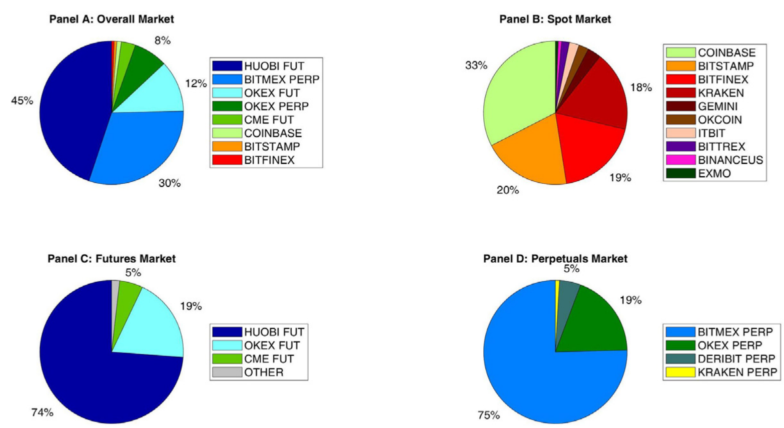

Fig. 2. Relative trading volume. *Note:* The figure shows relative trading volume within each group of instruments during January 2020. Panel A is for the overall market, panel B for the spot market, panel C for (un)regulated futures and panel D compares the trading volume for perpetual contracts.

an exchange was offline for some reason. A relatively large number of intervals in which no trade occurred does not necessarily imply distorted price discovery results, it is rather the length of the time interval between trades that is crucial. For this reason, we place the liquidity threshold on the length of the time interval between two trades, rather than on the trades frequency. Following Adaemmer et al. (2016), we could choose the threshold to be longer than 4.5 hours, but we do not want to risk any liquidity-related distortion in our results and thus we choose this conservative threshold. Even though the average trading volume of bitcoin derivatives is larger than that of the spot exchanges, their liquidity levels (measured as the ratio of minutes in which no trade occurred) are similar, as indicated in Table 3. The three spot exchanges with the largest daily volume (Bitfinex, Bitstamp, Coinbase) exhibit ratios of 1.71%, 0.84%, and 0.22% respectively, which is comparable to the BitMEX perpetual (0.09%), Huobi futures (0.37%) and OKEx perpetual (1.32%). Therefore, we apply the same liquidity threshold of 4.5 hours to both spot and derivatives exchanges.

In light of Dimpfl and Peter (2019) other important issues are microstructure noise arising from liquidity, different ranges of order types and trading volume or trading intensity. As the sampling frequency increases so does the amount of noise in the data and this will distort price discovery results. Therefore, we must not choose the data frequency too high. At the same time however, we have to use data of a sufficiently high frequency to capture real-time information flows adequately. Under consideration of the results by Dimpfl and Peter (2019) we choose 1-min data for our analyses, as a suitable trade-off between these two aspects. However, to check the robustness of our results we re-do the analyses on 5- and 15-min frequencies, where noise is unlikely to produce distortions. This analysis of robustness to noise does not produce any unexpected results.[22] Moreover, for illustration purposes, we smooth the resulting series of GIS and CS using an exponentially weighted moving average (EWMA) as in Alexander et al. (2020). The rate of smoothing depends on the number of instruments included in the analysis – the more instruments, the stronger we have to smooth. Finally, to be consistent, we choose the number of lags to be 1 in all models.[23]

4.1. Spot markets

We first analyse price discovery day-by-day within the spot market where we include all ten exchanges at the same time. Since all of them offer continuous trading throughout the day, we do not have to consider any interruptions and we can simply base our analysis on UTC days, i.e. our daily observation periods last from midnight UTC to midnight UTC. If some exchange reports no trades or no data are available for a day, we exclude this exchange from our analysis and set its share to 0 for that day.

Table 5 shows the monthly mean of the (non-smoothed) GIS for the different exchanges. We also plot the ten smoothed time series

[22] The results are not presented here, for lack of space, but they are available from the authors upon request.

[23] For the vast majority of models, the BIC also selects 1 as the optimum number of lags.

Table 5
Monthly GIS for spot exchanges.

	BinanceUS	Bitfinex	Bitstamp	Bittrex	Coinbase	Exmo	Gemini	itBit	Kraken	OKCoin
April	–	17.68%	23.97%	2.03%	27.88%	2.87%	7.21%	4.86%	9.25%	4.25%
May	–	26.42%	20.36%	1.74%	23.27%	6.44%	5.65%	3.41%	9.41%	3.31%
June	–	20.10%	16.66%	2.77%	27.43%	5.36%	6.65%	4.72%	8.95%	7.36%
July	–	21.14%	13.36%	4.92%	24.98%	4.80%	7.91%	4.31%	12.01%	6.57%
August	–	18.27%	13.87%	2.58%	29.57%	8.22%	5.97%	5.85%	10.67%	4.99%
September	–	16.37%	14.14%	2.64%	30.15%	5.11%	6.37%	2.78%	10.00%	12.44%
October	6.38%	14.85%	18.34%	2.99%	22.55%	7.31%	6.19%	3.98%	9.73%	7.68%
November	6.43%	13.58%	11.38%	2.71%	28.80%	5.44%	6.81%	3.40%	12.61%	8.85%
December	5.01%	9.75%	11.24%	2.03%	33.17%	2.51%	9.61%	5.13%	11.98%	9.56%
January	5.34%	12.79%	13.64%	3.05%	30.08%	7.88%	5.09%	4.23%	10.34%	7.56%

Note: The table shows the monthly average GIS of the 10 different spot exchanges for the period from 01 April 2019 to 31 January 2020. If there are not enough data to include an exchange for any month, we insert an hyphen.

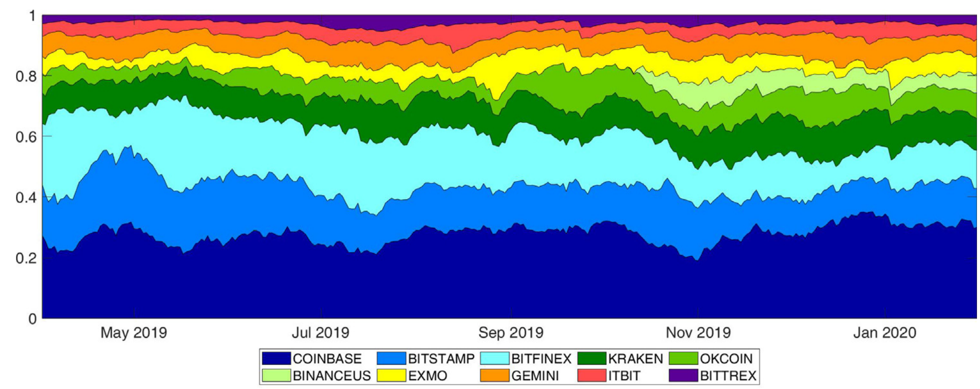

Fig. 3. GIS spot. *Note:* The figure shows the smoothed time series of GIS for the individual spot exchanges. The smoothing uses an EWMA with the parameter equal to 0.9.

of daily GIS in Fig. 3. The large number of variables in the model requires a high degree of smoothing, thus we set the parameter in the EWMA model equal to 0.9. Both the table and the figure show that Coinbase has been leading in price discovery, followed by Bitstamp, Bitfinex and Kraken. Most recently, these four exchanges have accounted for 67% of price discovery in the spot market with Coinbase contributing even 30%. This dominance can be explained by the large trading volumes of the 4 exchanges, especially Coinbase (see Fig. 2). However, the leading role of Coinbase was less pronounced during the beginning of our observation period – in April 2019, Coinbase had a share of 28% and Bitstamp one of 24%, while in May, Bitfinex's contribution to price discovery (26%) even exceeded that of Coinbase (23%). Moreover, Fig. 3 makes clear how much the share of Bitfinex has decreased over time from 26% in May 2019 to 13% in January 2020 – in December, it was even less than 10% and only slightly bigger than the GIS of Gemini and OKCoin.

Both the table and the figure show an unusually high contribution of OKCoin during September 2019. In this month, its average GIS was more than 12% which is almost twice the average over all remaining months. At the same time, OKCoin's average daily volume during September was 670 XBT, compared to 509 XBT over the remaining months. However, looking at the particular daily GIS, there seems to be no correlation between trading volume and price discovery contribution – days with unusually large volumes do not necessarily show large GIS. Thus, the increase in price discovery contribution of OKCoin might be related to a temporary change in the investors structure: in September 2019, OKCoin expanded its service in the US offering trading in 7 new states.[24] This might have attracted more informed investors and as a result, both price discovery share and trading volume of OKCoin increased.

4.2. Regulated futures

There are two regulated bitcoin futures exchanges, CME and Bakkt, a subsidiary of the ICE. While the former launched their contracts during the last bitcoin bubble in December 2017, the Bakkt futures could not be traded before September 2019. Therefore, we analyse price discovery between the two instruments for the period from 1 October 2019 to 31 January 2020. However, contrary to the unregulated bitcoin spot and derivatives market, these two products cannot be traded 24/7. The CME interrupts trading over the weekend and between 4 pm and 5 pm Chicago Time on each working day (corresponding to 9 pm and 10 pm UTC during summer time or 10pm and 11pm during winter time). Bakkt allows trading on working days between 8 pm and 6 pm Eastern Time which is equivalent to 12am and 10 pm UTC (during winter time, 1 am and 11 pm UTC). For our analysis, we choose the longest possible period of overlapping trading hours taking into account the time change, i.e. from midnight to 9pm UTC during summer time and from 1am to 10pm UTC during winter time. We conduct our price discovery analysis based on continuous time series of futures prices constructed by rolling over from the prompt to the next contract at midnight the day before expiration.

Table 6 displays monthly average GIS, CS and trading volume of CME and Bakkt futures. We also plot the smoothed time series of GIS in Fig. 4, together with the trading volume on the respective time series of futures prices. Bakkt futures took some time to capture significant trading volume. In the first three weeks after introduction, the prompt contract had an average daily volume of only 61 XBT or equivalently $505,013 – the CME prompt contract had more than the 200-fold volume (13,157 XBT or $108,309,183). Thus, Bakkt often does not exceed our liquidity threshold of 4.5 h and contributes very little to price discovery during the first three weeks. In November and October 2019, both the average daily volume and the price discovery share of Bakkt sharply increased to $11.48 m and

[24] See Cointelegraph on 6 September 2019.

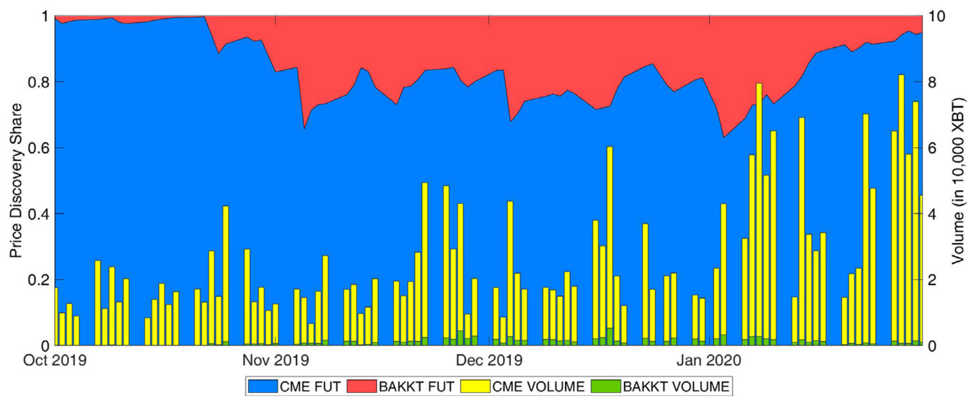

Fig. 4. GIS regulated futures. *Note:* The figure shows the smoothed time series of daily GIS for the CME and Bakkt futures on the left-hand axis during the period from 1 October 2019 to 31 January 2020. The smoothing is done by using an EWMA with the parameter equal to 0.75. In addition, we plot the trading volume of the prompt contracts of CME (yellow) and Bakkt (green) on the right-hand axis (in 10,000 XBT).

Table 6
Monthly shares for regulated futures

	GIS		CS		ADV	
	CME	BAKKT	CME	BAKKT	CME	BAKKT
October	95.11%	4.89%	93.18%	6.82%	128.03	1.83
November	77.58%	22.42%	77.59%	22.41%	147.77	11.48
December	77.47%	22.53%	77.15%	22.85%	132.52	13.44
January	85.91%	14.09%	84.98%	15.02%	331.15	11.72

Note: The table shows the monthly average GIS and CS of CME and Bakkt futures for the period from 1 October 2019 to 31 January 2020. We also include the average daily volume of the respective prompt contract (in million USD) for each month. Note that the average volume for CME is slightly distorted since Sunday is counted as an entire trading day, even though trading is only possible for 2 h.

22%, respectively. However, Bakkt is still responsible for no more than 10% of the total trading volume on regulated bitcoin futures. With shares of more than 85%, the price discovery dominance of CME futures grew during January 2020 probably due to development of trading volumes: compared with December 2019 trading on the prompt CME contract more than tripled, whereas the daily Bakkt volume declined by 13% to less than $12 m.

Interestingly, one day is out of line with our observation of CME dominance in price discovery. On 5 November 2019, the GIS and CS of CME futures were only 9.5% and 6.85%, respectively. Therefore, we take a closer look at the CME data for that day. Fig. 5 depicts the price of the CME November 2019 contract, together with its minute-by-minute trading volume, on the morning of 5 November. To compare the CME futures price to that of other contracts, we also plot the prices of the unregulated Huobi and OKEx futures. We see an usually high trading volume of 289 contracts (corresponding to 1445 XBT) on CME between 7:01 am and 7:02 am UTC, which is accompanied by a decline in price from $9375 to $9105. In the following minute, the price dropped further to $8510, but now on a lower volume of only 330 XBT. Subsequently, the CME futures price recovered to more than $9100 within 2 min, again on higher volumes of 510 XBT.

Neither the Huobi nor the OKEx futures followed with extreme price movements at this time. Their prices fell only a little, from around $9470 to $9380. The shape of the decline and the instantaneous rebound of the CME futures price looks very similar to that of a flash crash.[25] With respect to price discovery, this large but transitory price move implies that the CME futures price deviated far from the long-run equilibrium and this is why both GIS and CS consider Bakkt as the main driver of price discovery on that day.

4.3. Unregulated futures

In contrast to the CME and Bakkt contracts, the unregulated futures offered by BitMEX, Deribit, Huobi, Kraken and OKEx can be traded 24/7. Therefore, we proceed as for the spot market and perform our daily price discovery analysis from midnight UTC to midnight UTC the next day. Our observation period ranges from 1 April 2019 to 31 January 2020, but data on Huobi and Kraken futures are not available before July and October 2019, respectively. Hence, we start with only BitMEX, Deribit and OKEx futures and include the two remaining products once their data are available (and trading exceeds our defined liquidity threshold). Again, we construct continuous time series of futures prices by rolling over from the prompt to the next contract at midnight the day before expiry.

As before we report monthly average GIS and CS in Table 7 and plot the smoothed time series of daily GIS in Fig. 6. Before data on the Huobi contracts were available the OKEx futures strongly dominated price discovery – in April and May 2019, they even accounted for more than 62% of price discovery. BitMEX (GIS between 22% and 27%) and Deribit futures (GIS of 14%–27%) follow far behind. This can be explained by the individual trading volumes between March and July: With $975 m, the ADV of OKEx futures was 12 times that of BitMEX futures ($84 m) and even 30 times that of Deribit futures ($32 m). Note that the drop in the GIS of OKEx futures around the middle of July which can be seen in Figure 6 is caused by a small data gap.[26] From the end of July onwards the Huobi contracts enter our analysis and immediately overtake the BitMEX and Deribit futures, accounting for more than 30% of price discovery in August – only second to OKEx (GIS and CS of 38% and 46%, respectively). By September the contribution of the Huobi futures even exceeded that of OKEx contracts, while BitMEX and Deribit futures dropped to shares of less than 16% and 10%, respectively. By the end of October, data on Kraken futures becomes available. However, including of those leads to no significant changes since their monthly average contribution to price discovery is consistently less than 5% for GIS and 8% for CS.

Most recently, Huobi and OKEx futures have been the main driver of price discovery. During January 2020 both had shares in excess of 32%, followed by BitMEX (15%–17%), Deribit (7%–12%) and Kraken (5%–6%). It is remarkable that from August onwards, the

[25] This was reported in the news at that time as price manipulation (see Cointelegraph on 5 November 2019).

[26] Due to our defined liquidity threshold, this gap leads to a temporary exclusion of OKEx futures and thus, to a GIS of 0 on 3 consecutive days.

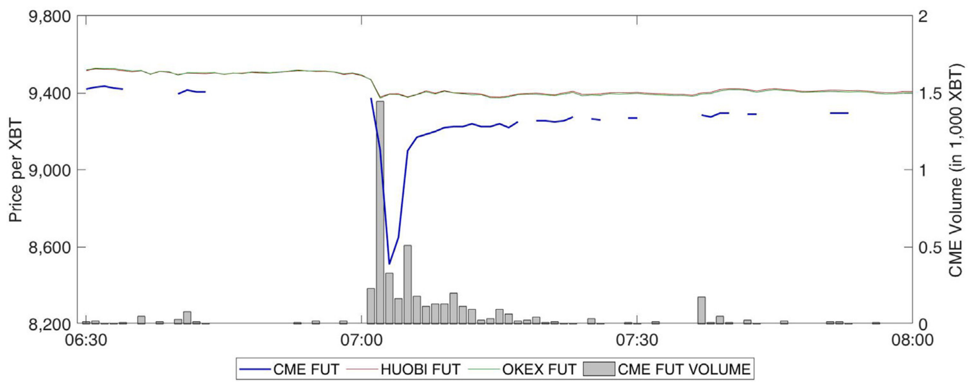

Fig. 5. CME Flash Crash on 5 November 2019. *Note:* The figure shows the prices of the CME November, Huobi December and OKEx December futures (in USD on the left-hand axis) on 5 November 2019 between 6:30 am and 8 am UTC. We also include the trading volume on the CME November contract (in 1000 XBT on the right-hand axis).

Table 7
Monthly shares for unregulated futures

	GIS					CS				
	BitMEX	Deribit	Huobi	Kraken	OKEx	BitMEX	Deribit	Huobi	Kraken	OKEx
April	22.55%	15.11%	–	–	62.34%	22.17%	8.08%	–	–	69.75%
May	23.17%	13.92%	–	–	62.91%	19.65%	4.19%	–	–	76.16%
June	22.23%	18.94%	–	–	58.83%	14.06%	10.89%	–	–	75.05%
July	27.00%	26.74%	3.63%	–	42.63%	21.86%	20.94%	4.97%	–	52.24%
August	17.01%	14.05%	30.94%	–	38.00%	11.94%	7.33%	34.32%	–	46.41%
September	15.97%	9.86%	39.99%	–	34.17%	12.36%	4.31%	44.66%	–	38.67%
October	20.06%	13.59%	34.99%	–	31.37%	21.10%	6.10%	41.87%	–	30.93%
November	14.98%	14.16%	34.41%	1.73%	34.71%	10.00%	9.86%	39.54%	1.61%	38.99%
December	16.08%	10.16%	36.03%	4.71%	33.03%	12.89%	5.20%	41.44%	7.07%	33.40%
January	16.85%	12.35%	33.31%	4.74%	32.75%	15.14%	7.44%	36.99%	5.89%	34.55%

Note: The table shows the monthly average GIS and CS of the five futures contracts for the period from 01 April 2019 to 31 January 2020. Data on Huobi and Kraken futures are not available before 29 July and 30 October 2019, respectively. Thus, the monthly averages before those dates are 0. Note that the Huobi July and the Kraken October averages are distorted since data are not available from the beginning of the respective month. If there are not enough data to include an instrument for any month, we insert an hyphen.

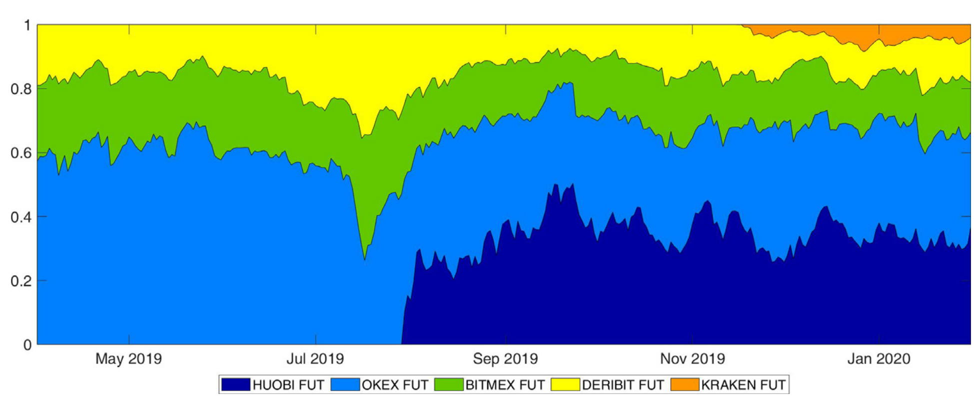

Fig. 6. GIS unregulated futures. *Note:* The figure shows the smoothed time series of daily GIS for the five unregulated futures contracts over the period from 1 April 2019 to 31 January 2020. The smoothing uses an EWMA with the parameter equal to 0.85.

Huobi and OKEx futures combined consistently account for more than 65% of price discovery clearly dominating within the unregulated futures market. These results come as no surprise because the trading volume is so great. As can be seen in Table 3 and Fig. 2, the Huobi and OKEx contracts have by far the largest volumes and together account for 93% of the entire trading on unregulated bitcoin futures.

The fact that Huobi and OKEx contracts make similar contributions to price discovery, although the former have a far greater trading volume, might be explained by better informed investors on the OKEx contracts on the one hand, and by the behaviour of investors on Huobi futures on the other. Speculation is usually beneficial for efficient price discovery (Chen et al., 2016) and we previously found evidence of greater speculation on Huobi. However, Benos and Sagade (2016) provide evidence that information shares decline as aggressive high-frequency trading volume increases. Therefore, under consideration of the extremely high ratio of volume to open interest on Huobi in Table 4, it seems that (aggressive) speculative activity on Huobi futures is both the reason for their large influence on price discovery, but also the obstacle for an even higher information share.

It is striking that Huobi and OKEx have been leading in price discovery while being the only two exchanges that do not offer maker rebates for ordinary users. This finding might seem counterintuitive at first sight, but it can be explained by the size of the individual fees. Huobi and OKEx have very low taker fees for very active users: VIP customers are charged only 2–3bps, compared to 7.5bps on BitMEX, Deribit and Kraken. As Brogaard et al. (2014) show, high-frequency traders trade in the direction of permanent price movements and in the opposite direction of transitory pricing errors by using liquidity-demanding marketable orders, i.e. taker orders. Naturally, they would route such orders to the exchange charging the lowest fees, that is Huobi and OKEx. Consequently, the efficiency of prices on these two exchanges increases and thus, Huobi and OKEx futures lead in price discovery.

4.4. Perpetual contracts

As with both spot and unregulated futures, the perpetual contracts can be traded 24/7, so our daily observation period ranges from midnight UTC to midnight UTC the next day. Data on OKEx and Kraken perpetuals are not available before 17 July and 30 October 2019, respectively, so we start with a two-dimensional analysis between BitMEX and Deribit perpetuals and include the other two products in a four-dimensional model once their data become available.

Table 8 reports the monthly average price discovery shares and Fig. 7 depicts the smoothed time series of daily GIS for the four different perpetuals. Between April and June 2019 the BitMEX perpetual leads the Deribit contract with contributions between 51% and 66%. In July, the shares of BitMEX and Deribit decline significantly and, although data were not available before the second half of the month, the OKEx perpetual still accounts for more than 18% on the monthly average. During August and September, the shares of all three products are fairly constant. The GIS shows roughly equal contributions to price discovery, whereas the CS slightly favours the BitMEX contract over Deribit and OKEx perpetuals. The Kraken perpetual contributes very little to price discovery. Its maximum monthly averages are 10% for GIS and only 2% for CS.

With monthly average GIS and CS of more than 47% and 62% respectively, the OKEx perpetual was dominating price discovery during the last three months of our observation period – in November 2019, its CS was 68% whereas BitMEX had a CS of only 20%. The price discovery share of the BitMEX perpetual has been declining considerably, from more than 58% in April 2019 to around 25% in January 2020. Even if we take into account that we included two new products during our observation period and it is therefore natural that the BitMEX contribution reduces to some extent, this decrease is still impressive. We attribute this to the declining trading volume on this contract, reducing from 17 m XBT or $122 b in May to less than 8 m XBT or $55b USD in December 2019. In January 2020 its ADV rose a little, to $85 b (or equivalently 10m XBT) but its GIS and CS both fell further.

Remarkably, this is the first group of instruments where the product with the highest trading volume is *not* consistently leading in price discovery. According to Table 3 and Fig. 2, the BitMEX perpetual still has by far the highest trading volume out of all perpetual contracts and is responsible for 75% of the trading on perpetuals – in fact, the BitMEX contract has been the most traded product over all different instrument groups during our observation period (see Table 3). Nevertheless, the share of the BitMEX perpetual almost halved from October to November 2019, and since then the OKEx contract has been leading price discovery very strongly.

This shift of price discovery from BitMEX to OKEx might be related to the *change* in trading volumes of the two products, rather than the level. While the average monthly volume of the BitMEX perpetual declined from $2.8 bn between August and October 2019 to $2.3 bn from November 2019 to January 2020, the volume of the OKEx contract significantly increased from $390 m to $597 m. As Chen et al. (2016) show, hedgers reduce the price discovery contribution of an instrument, whereas speculators are beneficial for efficient price discovery. Therefore, we are interested in whether this change in the trading volumes of the two products was mainly caused by hedgers or speculators. To this end, we consider the changes in the ratio of daily trading volume to open interest as a measure for speculative trading activity, breaking down the average V/OI figures reported in Table 4 month by month. We find a higher average importance of speculative activity in the BitMEX perpetual during September and October 2019. But from November onwards it is the OKEx perpetual that shows more speculative activity. This indicates that in November 2019, investors with a mainly speculative intention started to invest in the OKEx perpetual instead of the BitMEX contract. Since speculators usually contribute more to price discovery this explains why the less-traded OKEx contract has been leading the BitMEX perpetual during the last three months of our observation period.

4.5. Main instruments

We now analyse price discovery between the main bitcoin spot and derivatives markets, so from each different set of instruments we select only those that contribute most to price discovery, these being: Bitfinex, Bitstamp and Coinbase spot, CME regulated futures, Huobi and OKEx unregulated futures and the BitMEX and OKEx perpetual contracts. To deal with the trading breaks on CME futures, we exclude weekends and perform our daily price discovery analysis from 10pm to 9pm on the next day. During this period, trading on CME futures is continuously possible. This limitation of daily observation periods in our analysis should, if anything, only overestimate the role of CME futures and is therefore maintainable for our concluding recommendations. As in the two previous analyses, data on Huobi futures and OKEx perpetual are not available before July 2019. Therefore, we again start our analysis with a reduced number of instruments and include those two products once their data are available, in the full eight-dimensional VECM.[27]

Table 9 reports the monthly average GIS for the 8 different instruments. We also plot the smoothed time series of daily GIS in Fig. 8. It can be seen that with shares between 25% and 36%, the OKEx futures clearly led price discovery before data on Huobi futures and OKEx perpetual were available. With a GIS between 17% and 23%, the BitMEX perpetual came in second place, followed by Bitfinex (14%–21%), Coinbase (13%–18%), Bitstamp (14%–21%) and at last CME futures (3%–9%). Between August and October 2019, Huobi and OKEx futures as well as the BitMEX perpetual were the leading instruments, together accounting for more than 50% of price discovery. Here, the Huobi futures exhibited a very pronounced leading role contributing more than 25% in September 2019. During this time, the shares of the 3 spot exchanges were fairly constant and together accounted for less than a third of price discovery. In line with Section 4.4, the share of the OKEx perpetual almost doubled to 24% in November 2019, with the BitMEX perpetual being the main loser of this extreme increase – its GIS halved from 20% to 10%. From this month on, the Huobi futures and the two OKEx products started leading the remaining instruments very strongly and together they now account for around 60% of overall price discovery on the main bitcoin trading venues.[28] Considering the three different instrument groups as a whole, the price discovery results are again in line with trading volumes. According to Fig. 2, the (un)regulated futures are responsible for 60% of the total volume in bitcoin spot and derivatives markets during January 2020 and so it is not surprising that they lead the price discovery pro-

[27] As before, we do not report the day-by-day VECM re-estimation results, but they are available from the authors on request.

[28] Most recently, Huobi was the main driver (23%), closely followed by OKEx perpetual (19%) and OKEx futures (18%). The BitMEX contract trailed quite far behind (10%), followed by Bitfinex (10%), Coinbase (9%), Bitstamp (6%) and at last CME (5%).

Table 8
Monthly shares for perpetual contracts

	GIS				CS			
	BitMEX	Deribit	Kraken	OKEx	BitMEX	Deribit	Kraken	OKEx
April	57.89%	42.11%	–	–	65.62%	34.38%	–	–
May	51.11%	48.89%	–	–	52.55%	47.45%	–	–
June	54.71%	45.29%	–	–	60.40%	39.60%	–	–
July	46.81%	34.28%	–	18.91%	51.38%	23.81%	–	24.81%
August	36.44%	31.58%	–	31.98%	40.03%	31.83%	–	28.14%
September	34.89%	31.27%	–	33.84%	35.05%	30.52%	–	34.44%
October	43.20%	23.21%	–	33.59%	53.04%	15.86%	–	31.10%
November	25.05%	17.35%	5.73%	51.88%	20.15%	9.82%	1.97%	68.07%
December	27.68%	14.53%	6.30%	51.49%	26.14%	8.75%	2.41%	62.70%
January	25.49%	16.95%	10.40%	47.15%	23.46%	11.18%	2.21%	63.15%

Note: The table shows the monthly average GIS and CS of the 4 different perpetual contracts for the period from 01 April 2019 to 31 January 2020. Note that the OKEx July and the Kraken October averages are distorted since the data are not available from the beginning of the respective month. If there are not enough data to include an instrument for any month, we insert an hyphen.

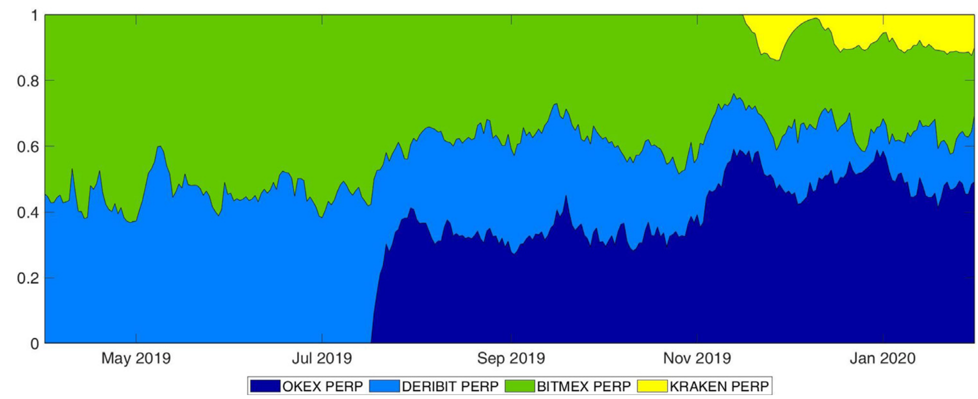

Fig. 7. GIS perpetual contracts. *Note:* The figure shows the smoothed time series of daily GIS for the 4 different perpetual contracts over the period from 1 April 2019 to 31 January 2020. The smoothing uses an EWMA with the parameter equal to 0.80.

Table 9
Monthly GIS for main instruments.

	Futures			Perpetuals		Spot		
	CME	Huobi	OKEx	BitMEX	OKEx	Bitfinex	Bitstamp	Coinbase
April	5.83%	–	35.55%	17.03%	–	15.89%	12.83%	12.88%
May	5.69%	–	26.50%	17.61%	–	21.18%	14.58%	14.44%
June	3.23%	–	24.94%	22.94%	–	17.82%	12.68%	18.39%
July	8.94%	0.98%	26.84%	19.82%	8.77%	14.00%	8.19%	12.46%
August	4.82%	14.16%	21.37%	17.86%	10.55%	7.24%	9.09%	14.92%
September	3.36%	25.46%	20.77%	13.35%	10.53%	9.07%	6.41%	11.05%
October	5.30%	16.20%	18.59%	19.68%	12.13%	8.34%	9.22%	10.55%
November	4.74%	19.67%	14.77%	10.34%	24.08%	8.92%	6.35%	11.13%
December	4.60%	25.30%	16.17%	14.43%	20.13%	6.13%	4.74%	8.50%
January	5.03%	22.75%	17.77%	10.47%	18.70%	10.05%	6.01%	9.21%

Note: The table shows the monthly average GIS of the 8 different main instruments for the period from 01 April 2019 to 31 January 2020. Note that the July averages of Huobi futures and OKEx perpetual are distorted since the data are not available from the beginning of the respective month. If there are not enough data to include an instrument for any month, we insert an hyphen.

cess, followed by perpetuals (38% of trading volume) and spot (2% of trading volume).

Our findings support the results by Alexander et al. (2020) on the BitMEX perpetual contract leading price discovery with respect to three major spot exchanges (Bitstamp, Coinbase, Kraken). We also confirm the results of Baur and Dimpfl (2019) who reveal a leading role of Bitstamp over CME futures. On the other hand, our results contradict the dominance of CME over spot exchanges identified by Kapar and Olmo (2019), but their analysis is based on daily data which may not able to capture real-time information flows adequately. Similarly, we cannot confirm the results of Entrop et al. (2020) who use quotes instead of transaction data and find CME futures leading in nine contract months. As our findings show, these studies are incomplete in that they leave out heavily traded unregulated derivatives instruments and therefore miss extremely important information flows.

In a professional market, derivatives are more attractive for informed investors due to lower transaction costs, absence of short-sale restrictions, built-in leverage as well as more transparency (Garbade and Silber, 1983; Fleming et al., 1996). Most empirical studies for traditional asset classes corroborate this theory (Adaemmer and Bohl, 2018; Chen and Tsai, 2017; Ahn et al., 2019). Even futures with much smaller trading volumes than the underlying spot market can dominate price discovery (Hauptfleisch et al., 2016). This theory also holds in the bitcoin market, as is evident from the results in Table 9. However, to illustrate how the situation

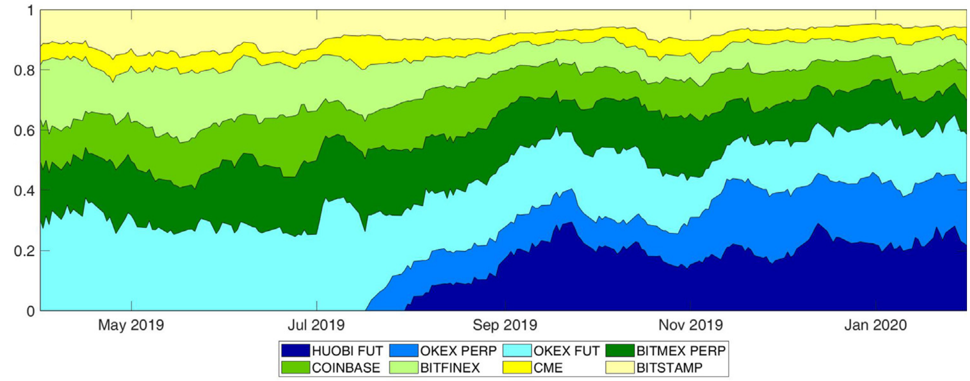

Fig. 8. GIS main instruments. *Note:* The figure shows the smoothed time series of daily GIS for the 8 different main instruments over the period from 1 April 2019 to 31 January 2020. The smoothing uses an EWMA with the parameter equal to 0.90.

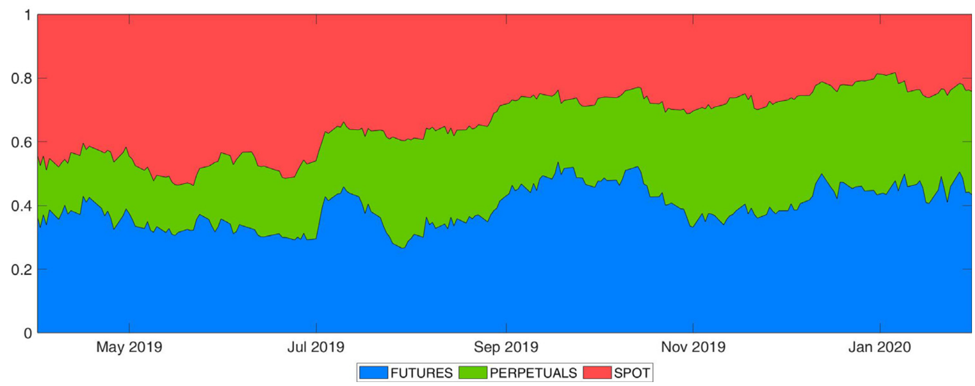

Fig. 9. GIS instrument groups. *Note:* The figure shows the smoothed time series of daily GIS for bitcoin spot and derivatives products over the period from 1 April 2019 to 31 January 2020. The smoothing uses an EWMA with the parameter equal to 0.90.

has changed over time, we plot the total GIS of spot, futures and perpetuals in Fig. 9. We see that the contribution of the spot market started at roughly 50%, while futures and perpetuals accounted for only 35% and 15%, respectively. However, from July onwards, the share of bitcoin derivatives has continuously increased and at the beginning of January 2020, the total GIS of futures and perpetuals reached a record high of 82%. During mid-January, the derivatives lost a small share to the spot market and accounted for only 75% of price discovery. Overall however, we conclude that the influence of derivatives (futures and perpetuals) in the bitcoin market has sharply increased. Theoretically this implies an evolution from an immature marginal market towards an established asset class, such as gold or commodities. With the small but *very* significant difference that the bitcoin market is still almost completely unregulated.

Remarkably, the CME futures have never accounted for more than 9% of price discovery, indeed all the monthly GIS statistics are below 6%, and CME has always contributed least to price discovery, except during July 2019. This indicates that traders on the CME bitcoin futures are *less* informed than those on unregulated spot and derivatives exchanges because most of the time they are just reacting to price movements in other bitcoin products. We attribute this finding to the following three features: (i) The trading volume of each individual unregulated derivatives is much larger than that of CME futures; (ii) In traditional asset classes large institutional investors with access to regulated exchanges like CME are usually most informed and incorporate new information extremely quickly. However, in bitcoin markets there are many other smaller players – such as miners or crypto-specialized hedge funds – that have easy access to unregulated exchanges and ultra-high-frequency trading platforms. These might be considered as more informed bitcoin investors than the CME clients; (iii) The often-suspected manipulation in bitcoin markets could be another explanatory factor. If some investors wanted to manipulate the price of bitcoin – for example by pump and dump strategies or spoofing orders[29] – they may do so much more easily on an unregulated exchange rather than on the CME, which is heavily regulated by the CFTC. This highlights a problem arising from the lack of regulation of bitcoin markets. As long as investors are able to rig the price on the derivatives exchanges that lead in price discovery, with no supervisory authority trying to stop them, the bitcoin market as a whole can never be sufficiently stable for an evolution towards a widely accepted asset class with mainstream products such as ETFs.

5. Determinants of price discovery

In the previous section we identified four unregulated bitcoin derivatives products as main price discovery leaders. Now, we examine which factors are influencing their leadership roles.[30] To this end, we consider the four leading instruments (i.e. Huobi futures, OKEx futures, BitMEX perpetual, OKEx perpetual) and examine the relationship between their daily GIS and several market characteristics using multiple linear regressions.[31] Our analysis

[29] Common manipulative strategies within cryptocurrency markets are explained in Twomey and Mann (2020).
[30] A similar analysis for CME futures has been conducted in Entrop et al. (2020).
[31] We ran the same analysis with CS instead of GIS, but the results were not qualitatively different.

Table 10
Regression results.

	GIS			
	Huobi Fut	OKEx Fut	BitMEX Perp	OKEx Perp
Constant	0.222***	0.188***	0.152***	0.172***
	(0.012)	(0.010)	(0.007)	(0.008)
DRet	0.024**	−0.008	0.007	−0.003
	(0.012)	(0.010)	(0.007)	(0.008)
ATS	−0.001	0.008		0.027***
	(0.012)	(0.010)		(0.009)
ABas			−0.014**	
			(0.007)	
IVol	−0.070***		0.021***	
	(0.012)		(0.007)	
EVR		−0.032***		
		(0.010)		
RTV				0.017*
				(0.009)
Observations	186	186	186	186
R^2	0.174	0.061	0.080	0.104
Adjusted R^2	0.160	0.045	0.065	0.089

Note: The table shows the regression results of the GIS of the 4 leading instruments (Huobi futures, OKEx futures, BitMEX perpetual, OKEx perpetual) on several market characteristics. DRet denotes daily returns, ATS is the daily average trade size (daily trading volume divided by daily number of trades), ABas is the daily average basis (difference between the instrument's price and Coinbase price), IVol is the intra-day volatility (equally weighted average over squared 1-min log returns), EVR is the excess variance ratio (absolute deviation between 1 and the ratio of 5-min log return variance to 5 times the 1-minute log return variance) and RTV is the relative trading volume (instrument's trading volume divided by the trading volume of all 4 instruments). All predictor variables are scaled to have zero-mean and unit-variance. The values in brackets are the corresponding standard errors. ***, **, and * indicate the 1%, 5%, and 10% significance levels, respectively.

covers the period from 30 July 2019 – the day from which on there is enough data to include Huobi futures in the price discovery analysis – to 31 January 2020, summing up to 186 observations per exchange. As predictor variables, we include daily returns (DRet), daily average trade size (ATS; daily trading volume divided by daily number of trades), daily average basis with respect to Coinbase (ABas; difference between the instrument's price and Coinbase price), intra-day volatility (IVol; equally weighted average over squared 1-min log returns), daily relative trading volume (RTV; the individual trading volume divided by the trading volume of all 4 instruments) and average relative bid-ask spread (RSpr; individual average bid-ask spread divided by total average bid-ask spread). Moreover, we also include the excess variance ratio (EVR) which is commonly considered as a measure for market efficiency. Following Alexander et al. (2020) this is calculated each day as the absolute deviation between 1 and the ratio of 5-min log return variance to 5 times the 1-minute log return variance.[32]

We scale all explanatory variables to zero-mean and unit-variance, so that the coefficients resulting from the linear regressions represent the change in GIS for one standard deviation change in the regressor. We start by including all seven regressors but to deal with multicollinearity and insignificance we test down our models to eventually include only three predictor variables each. The results are shown in Table 10. Because we have standardized all explanatory variables the constant in these regressions represents an instrument's price discovery share when all regressors are at their average. Thus, for instance, the Huobi futures (constant = 0.222) contribute significantly more to price discovery than the BitMEX perpetual (constant = 0.152) in an 'average' market state. Combining this with the V/OI results in Table 4 we attribute this to a greater importance of speculative activity on the Huobi futures. Next, we discuss each individual regression in turn.

Huobi: With increasing daily returns, more price discovery originates from Huobi futures. Combining this with the disproportionally low open interest of Huobi futures in Table 4 and the findings by Chen et al. (2016) of speculative activity being beneficial for price discovery, this finding is a clear indication that the Huobi contracts are mainly used by speculators trying to profit during periods of increasing bitcoin prices. On the other hand, we find a strongly significant negative relationship between price discovery shares of Huobi futures and its intra-day volatility. We can think of two possible explanations for this. The first is that an increase in volatility during the day attracts more uninformed speculators who are obstructive for efficient price discovery. Another reason might be the trading structure on Huobi futures. As Benos and Sagade (2016) show, the information shares decline as aggressive high-frequency trading volume increases. Following this, an increase in intra-day volatility might cause high-frequency traders to place more aggressive orders to be ahead of other traders and as a result, price discovery on Huobi futures is inhibited.

BitMEX: Unlike Huobi futures, the BitMEX perpetual exhibits a strongly significant *positive* relationship between its intra-day volatility and GIS. Hence, when intra-day volatility increases traders on BitMEX become relatively more informed and/or place relatively less aggressive orders than on Huobi – and this leads to an increase in BitMEX's price discovery role. Combining this with Table 4, we conclude that traders on the BitMEX perpetual pursue different goals than those on Huobi futures. While the former are more interested in hedging their risks and reducing their market exposure (for example bitcoin miners) the latter mainly aim at making profits from (aggressive) speculation (or even manipulative trading?) rather than hedging.[33] Moreover, the BitMEX perpetual shows a negative influence of the daily average basis on its GIS. That is, when the price difference between the BitMEX perpetual and Coinbase increases, the influence of BitMEX declines.[34] Thus, the BitMEX perpetual tends to narrow a positive basis relative to Coinbase. We conclude that arbitrage traders may be using the BitMEX perpetual to exploit opportunities relative to the spot market during periods when the futures curve is in contango.[35]

OKEx: In OKEx futures there is a strongly significant negative relationship between the GIS and the EVR. This matches our expectations: if the variance ratio's absolute deviation from 1 rises, the instrument's price becomes less efficient and its influence on price discovery declines. Finally, we see that the GIS of the OKEx perpetual is positively connected to average trade size and relative trading volume. These relations are also in line with our expectations: when an instrument's volume or trade size increases, one would expect the instrument's price discovery role to rise, and vice versa.

6. Impulse response

So far we have we shown that almost all price discovery takes place on derivative instruments traded on unregulated crypto exchanges and we have identified the factors that influence the

[32] In the most efficient case that an instrument's price follows a random walk, the ratio is 1 so the EVR is exactly 0. As positive or negative autocorrelation in returns increases, the EVR increases. Thus, higher values of the EVR indicate lower levels of efficiency.

[33] Hedging efficiency is extremely high on the BitMEX perpetual (Alexander et al., 2020) but the Huobi futures are quarterly, and so have more basis risk which makes them less efficient hedges. In this context, also recall our remarks above about the constant in the linear regressions serving as an indicator of the type of trader.

[34] Taking into account the previous results on price discovery, this finding might seem counterintuitive at first sight, but it is in line with Alexander et al. (2020): The instrument that narrows the basis has a smaller influence on price discovery because it follows rather than leads the other instruments.

[35] In contrast to fixed-term futures, the funding of perpetual contracts keeps their price rather close to the spot market. Nevertheless, the basis of the BitMEX perpetual and that of Huobi futures are highly correlated.

Table 11
Price differences.

	CME Fut	Huobi Fut	OKEx Fut	BitMEX Perp	OKEx Perp	Bitfinex	Bitstamp	Coinbase
CME Fut	–	1.70%	1.64%	−0.62%	−0.63%	−0.55%	−0.66%	−0.66%
Huobi Fut	−1.67%	–	−0.06%	−2.23%	−2.24%	−2.15%	−2.27%	−2.26%
OKEx Fut	−1.61%	0.06%	–	−2.17%	−2.18%	−2.10%	−2.21%	−2.20%
BitMEX Perp	0.63%	2.28%	2.22%	–	−0.01%	0.08%	−0.04%	−0.03%
OKEx Perp	0.64%	2.30%	2.24%	0.01%	–	0.09%	−0.03%	−0.02%
Bitfinex	0.56%	2.21%	2.15%	−0.08%	−0.09%	–	−0.12%	−0.11%
Bitstamp	0.67%	2.32%	2.27%	0.04%	0.03%	0.12%	–	0.00%
Coinbase	0.66%	2.32%	2.26%	0.03%	0.02%	0.11%	0.00%	–

Note: The table shows the average spreads between two instruments, based on minute-by-minute data for the CME trading times during January 2020. The spread is defined as the price of the instrument in the column minus the price of the instrument in the row, expressed as percentage of the price of the instrument in the row.

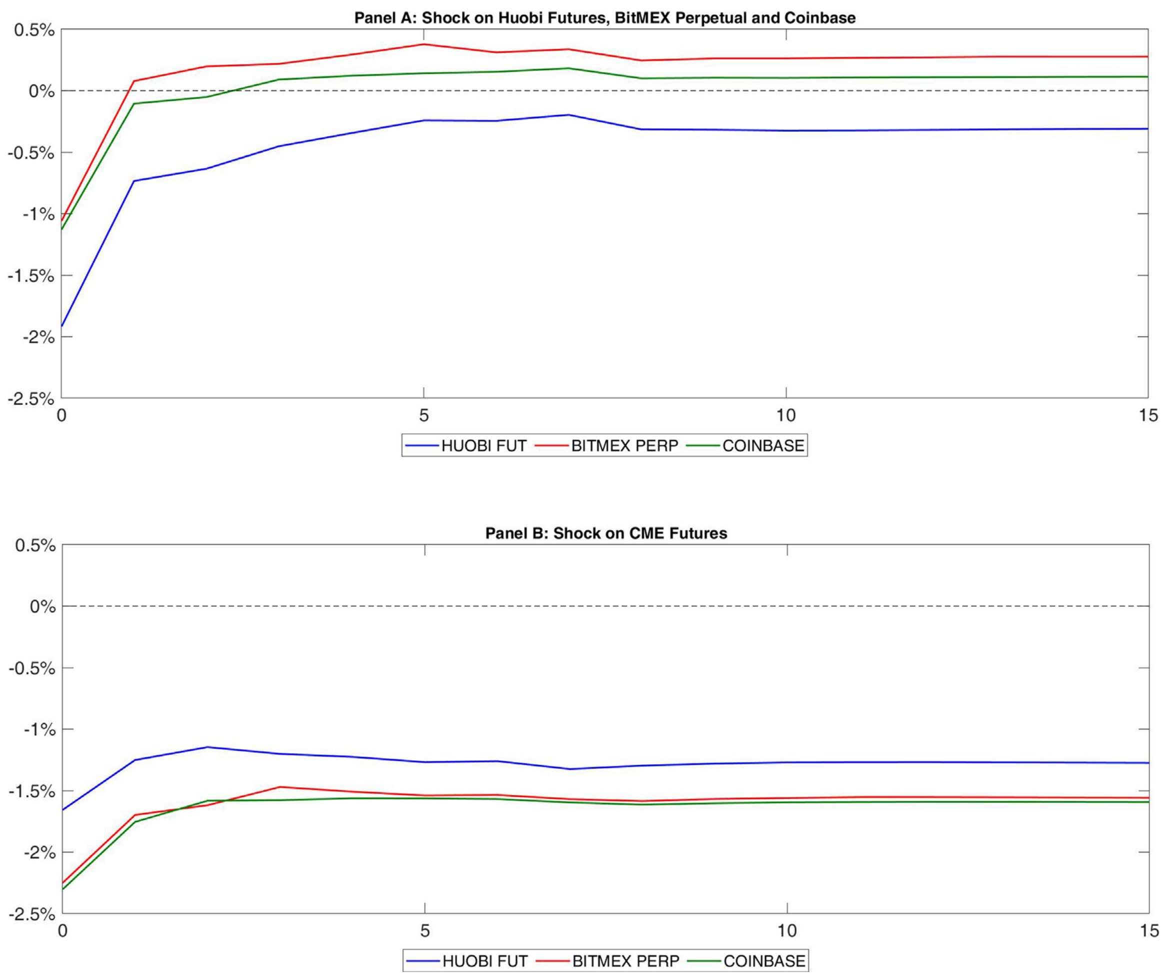

Fig. 10. Impulse responses. *Note:* The figure shows the expected spread between CME futures and 3 unregulated instruments (Huobi futures, BitMEX perpetual, Coinbase), resulting from two-dimensional VECMs and 10% price shocks at time 0. In the upper panel, the price shock happens on the unregulated instruments and we plot the price difference between CME futures and unregulated instruments. In the lower panel, the price shock happens on the CME futures and we plot the price difference between unregulated instruments and CME futures. The *x*-axis is denoted in minutes.

individual price discovery roles of these instruments. Now, we are interested in the speed of adjustment of the regulated CME futures to shocks originating from these unregulated exchanges, and vice versa. In some cases such an analysis may be carried out using orthogonalized impulse responses that rely on a Cholesky decomposition. However, this approach is not independent of the variable ordering in the VECM and therefore, we use the so-called generalized impulse response function proposed by Pesaran and Shin (1998) to overcome this shortfall.[36]

For brevity we limit our goal to analysing the speed of adjustment during the more recent month in our sample, i.e. January 2020. Therefore we consider the entire minute-by-minute transaction data from January (44,640 observations). To cover all different types of products, we include the same instruments as in Section 4.5. However, we now have to deal with trading interruptions on CME futures.[37] To this end, we include two dummy variables as exogenous predictors in the models and remove the respec-

[36] See the Appendix for a detailed derivation.

[37] Trading on CME bitcoin futures is interrupted on weekends and each working day from 4 to 5pm Chicago time.

tive non-trading periods from our dataset reducing the number of observations to 30,121. Moreover, we base our analyses on ordinary (not logarithmic) prices and always assume a price shock of 10%, which occurs quite infrequently even for a highly volatile asset like bitcoin. The most extreme minute return between April 2019 and January 2020 was less than 9%.

We split our analysis into two parts: First, we assume price shocks on the seven unregulated products and examine how the CME futures react to these shocks. Then, we turn it around and assume a price shock on the CME futures to analyse how the unregulated instruments respond. Since we are interested in the speed of adjustment of the individual instruments rather than multi-dimensional information flows between CME and crypto exchanges as before, we run our analyses for only two instruments at a time, i.e. we only fit two-dimensional models. That is, we estimate in total 14 different models.[38]

Before running the impulse response analysis we calculate averages and standard deviations of the spreads (or percentage price differences) between the five derivatives products and the three spot exchanges. This way, we can decide how many minutes it takes the spread between two instruments to return to an ordinary level after the shock.[39] The results are reported in Table 11. We can see that the Huobi and OKEx futures trade on average more than 2% above spot and perpetuals, indicating that the futures curve was in contango and investors expected bitcoin prices to increase during January. Interestingly, the CME futures trade roughly 1.6% lower than the unregulated futures and only about 60bps above spot and perpetuals. This highlights the trend in the price spreads between CME futures and unregulated products caused by the approaching maturity.[40] Moreover, spot and perpetuals trade at a very similar price level. This is caused by the funding of perpetuals, the exchange of periodic payments between buyer and seller which keeps the perpetuals price very close to the underlying spot price. Altogether, the spreads within the three groups of instruments as well as between spot and perpetuals are reasonable and within usual arbitrage limits.

Now we proceed to the analysis of the individual speed of adjustment between CME and unregulated products. For reasons of clarity, we present results for only one instrument to represent each group of unregulated products viz. the Huobi futures, the BitMEX perpetual and the Coinbase spot. However, results are quite similar within each group, so the results would change little if we selected a different product to represent the group. Fig. 10 depicts the individual price spreads between CME futures and Huobi futures, BitMEX perpetual and Coinbase, respectively, during the first 15 min. after 10% price shocks on the unregulated products (Panel A) and CME futures (Panel B). We can see that the spreads do not necessarily converge to 0, which is in line with Table 11.

In the upper graph of Fig. 10 (i.e. Panel A) the spreads move quite sharply towards 0 within the first minute after the shock. This confirms our previous results and discussion of the role of CME futures in bitcoin price discovery. There is a strong immediate response of the CME futures to price shocks on all these unregulated products. All the spreads become almost constant from 4 to 5 minutes after the shock, implying that it takes the CME futures between 4 and 5 min to absorb and price the information content of price shocks on Huobi futures, BitMEX perpetual or Coinbase.

By contrast, in the lower graph (Panel B), which depicts the evolution of the spreads after a 10% price shock on CME futures, we see that they move hardly at all. Clearly, the unregulated instruments have a weak response to price movements on the regulated CME futures. This model prediction is corroborated by prior events. Indeed, following the November 2019 CME flash-crash depicted in Fig. 5 the prices of bitcoin on other markets moved very little. The unregulated instruments only need roughly 2 min to incorporate most of the (comparatively little) information contained in price shocks on CME futures, but they do not adjust completely because CME is not the price leader. These findings again corroborate our previous results on price discovery. A price shock on CME futures contains less information than price shocks to the other exchanges and thus, the unregulated instruments react only slightly. On the other hand a shock on any of the unregulated instruments carries a larger amount of information to which the CME futures price reacts and adjusts quite heavily. We conclude that the CME futures have a lower speed of adjustment and information absorption than the unregulated derivatives and spot exchanges.

7. Conclusion

We analyse multi-dimensional information flows in the bitcoin market, both within and across the different groups of instruments covering a total of 21 different futures, perpetuals and spot prices. Based on minute-by-minute transaction data, we find a strong consistent dominance of unregulated derivatives products over the regulated futures, CME and Bakkt. For instance, just four derivative contracts traded on Huobi, BitMEX and OKEx those products combined account for more than 60% of total price discovery in the bitcoin market – compared to only 5% from CME futures. We attribute this to three features: First, the trading volume on the individual unregulated derivatives is much larger than on CME futures. Second, unlike in more traditional asset classes, smaller players such as miners or crypto-specialized hedge funds which have no access to large regulated exchanges like CME and instead trade on unregulated crypto-exchanges can be considered as informed traders in crypto asset markets. Finally, the often-suspected manipulation in bitcoin markets could be another explanatory factor. This finding extends the work of Alexander et al. (2020) who identify the very popular BitMEX perpetual as the price discovery leader over the spot market. All remaining papers investigating price discovery between bitcoin spot and derivatives markets restrict their two-dimensional analyses to CME futures and a single spot exchange, consequently identifying one of them as price discovery leader. However, as we show, this ignores extremely important market instruments and information flows. Having said that, we can confirm the results of Baur and Dimpfl (2019) in that the major spot exchanges in general play a more important role in price discovery than CME futures. Moreover, we find a faster speed of adjustment and information absorption on the unregulated spot and derivatives exchanges than on CME bitcoin futures. This confirms and expands the results obtained by Baur and Dimpfl (2019) in their two-dimensional futures-spot analysis.

[38] However, we now find quite weak cointegration between CME and some of the unregulated products, indicating a decoupling of prices. This is related to both the removed trading times and the different expiration times of CME futures and unregulated contracts. For this reason, we refrain from fitting a VECM to the data and estimate a vector autoregression (VAR) model instead. However, since we are interested in the immediate impulse responses rather than the impact on the long-term efficient price, this model change has very little to no influence on our results. The only difference between a VECM and a VAR is the disequilibrium term which keeps the variables tied together. In our case however, the error correction coefficients are very close to 0 and therefore, this additional term has only tiny impact on the variables in the short-term. Moreover, we consider up to ten lags in the VAR and select the optimum number using the BIC.

[39] The two instruments will not necessarily converge to the exact same price level after the shock and there may be small differences between the prices. For example, a futures contract will not trade at the exact same price as the spot market (except at maturity).

[40] CME futures expire monthly but the unregulated futures are quarterly contracts due in March 2020. This causes a saw-tooth pattern in the spread between CME and other instruments – as the monthly maturity approaches the CME futures price moves towards the spot prices and away from the unregulated futures prices.

Our findings highlight the insufficient stability of the bitcoin market and the problems arising from its inconsistent regulation. The major part of price discovery takes place on the still (completely) unregulated bitcoin derivatives market. Consequently, if some investors wanted to manipulate the bitcoin price – for example by pump and dump operations or spoofing orders – they can do this quite easily by applying their strategies on derivatives with no supervisory authority trying to stop them. This insufficient resistance to manipulation inhibits the bitcoin market's evolution towards a more professional asset class with mainstream products such as ETFs. Nevertheless, the bitcoin market has matured in the sense that the leading role of derivatives products in price discovery has further manifested itself exactly as theory predicts for established markets.

Within both ordinary futures and perpetuals, we find large price discovery contributions originating from OKEx. In the futures market, their contracts are only slightly second to those of Huobi, whereas they have on average overtaken the significantly more traded BitMEX product in the perpetuals market. We attribute this to more informed investors and/or a higher importance of speculative activity on OKEx. On top of this, we find opposite relationships between price discovery contribution and volatility for Huobi futures and BitMEX perpetual contract. Given the results of Benos and Sagade (2016), we credit this to different investor types: while the Huobi contracts are mainly used by aggressive speculators to profit from price movements (or even manipulation?), more investors on the BitMEX perpetual are interested in hedging their risk and reducing their exposure to the market.

In terms of future work, we can think of two empirical extensions of this study. First, when using only the most recent data one could include options in the spectrum of bitcoin derivatives. So far, since January 2020 there are five exchanges offering trading of bitcoin options (Bakkt, CME, Deribit, LedgerX, OKEx). With a continuously increasing volume – especially on Deribit and CME – and a very recent all-time high of almost \$2 billion in combined open interest, the options should now be mature enough to include them in a proper price discovery analysis. Second, one could examine price discovery in cryptocurrencies other than bitcoin such as ether, ripple or litecoin. Although they are less popular than bitcoin their derivatives are now becoming actively traded. For example, the ether perpetual swap on Huobi has a daily volume of more than \$500 million. Even a cross-cryptocurrency analysis between bitcoin and/or other currencies that includes both spot and derivatives exchanges would be possible.

Appendix A. Price discovery methodology

In this appendix we present a detailed derivation of the Generalized Information Share (GIS) from Lien and Shrestha (2014) and the Component Share (CS) proposed by Gonzalo and Granger (1995). Afterwards, we also outline the methodology of the generalized impulse response function as proposed by Pesaran and Shin (1998).

Consider N homogeneous or closely related products traded on different venues. Let $\mathbf{p}_t$ be a $N \times 1$ vector representing their (log) prices at time t. Assume that these products are cointegrated with one common stochastic trend (or permanent component), i.e. there exists a $N \times (N-1)$ matrix $\boldsymbol{\beta}$ of full rank so that $z_t = \boldsymbol{\beta}^T \mathbf{p}_t$ is stationary. In this setting, $z_t = \boldsymbol{\beta}^T \mathbf{p}_t$ is called disequilibrium term and there exists a vector error correction model (VECM) of the form

$$\Delta \mathbf{p}_t = \boldsymbol{\alpha} + \sum_{i=1}^{q-1} \boldsymbol{\Gamma}_i \Delta \mathbf{p}_{t-i} + \boldsymbol{\delta} z_{t-1} + \mathbf{e}_t, \tag{1}$$

where $\boldsymbol{\alpha}$ is a constant, $\boldsymbol{\delta}$ represents the $N \times (N-1)$ error correction matrix, $\boldsymbol{\Gamma}_i$ are some $N \times N$ parameter matrices and $\mathbf{e}_t$ is a vector of serially uncorrelated innovations with zero mean and covariance matrix $\boldsymbol{\Omega}$. $\boldsymbol{\delta}$ captures the prices' reactions to transitory deviations from the long-run equilibrium.

The VECM (1) can be transformed to a vector moving average (VMA) of the form

$$\Delta \mathbf{p}_t = \boldsymbol{\Psi}(L) \mathbf{e}_t \tag{2}$$

with $\boldsymbol{\Psi}(L)$ denoting a matrix polynomial in the lag operator L. Integrating this VMA yields

$$\mathbf{p}_t = \mathbf{p}_0 + \boldsymbol{\Psi}(1) \sum_{j=1}^{t} \mathbf{e}_j + \boldsymbol{\Psi}^{\star}(L) \mathbf{e}_t \tag{3}$$

where $\mathbf{p}_0$ is a constant vector, $\boldsymbol{\Psi}(1)$ is the sum of the moving average coefficients and $\boldsymbol{\Psi}^{\star}(L)$ a matrix polynomial in the lag operator. The stationarity of $\boldsymbol{\beta}^T \mathbf{p}_t$ implies $\boldsymbol{\beta}^T \boldsymbol{\Psi}(1) = 0$ and assuming all pairwise cointegration relationships are of the form $(1, -1)^T$, it follows that the rows of $\boldsymbol{\Psi}(1)$ are identical. We denote the common row vector by $\boldsymbol{\psi}$. The scalar $\psi \mathrm{e}_t$ is the common efficient price and can be interpreted as the effect of new information that is permanently incorporated into the prices. Hasbrouck (1995) now defines the information share of each market as its relative contribution to the variance of the common efficient price, i.e.

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

where $\mathbf{M}$ is the lower triangular matrix of the Cholesky decomposition of $\boldsymbol{\Omega}$ and $[\psi \mathrm{M}]_i$ is the ith entry of $\psi \mathrm{M}$. Because of the Cholesky decomposition, the IS depends on the ordering of the variables in the VECM (1) and is thus not unique. To overcome this, Lien and Shrestha (2014) use the spectral decomposition, factorizing the correlation matrix $\mathbf{C}$ of the residuals as $\mathbf{C} = \mathbf{Q}\boldsymbol{\Lambda}\mathbf{Q}^{-1}$, where $\boldsymbol{\Lambda}$ denotes the diagonal matrix of eigenvalues of $\mathbf{C}$ with the corresponding eigenvectors given by $\mathbf{Q}$. By defining $\mathbf{F} = \left(\mathbf{Q}\boldsymbol{\Lambda}^{-\frac{1}{2}}\mathbf{Q}^T\mathbf{V}^{-1}\right)^{-1}$, where $\mathbf{V}$ represents the diagonal matrix of the residuals' standard deviations, Lien and Shrestha (2014) obtain the decomposition $\boldsymbol{\Omega} = \mathbf{F}\mathbf{F}^T$ yielding a unique information share which they call generalized information share. It is given by

$$\mathrm{GIS}_i = \frac{([\boldsymbol{\psi}\mathbf{F}]_i)^2}{\boldsymbol{\psi}\boldsymbol{\Omega}\boldsymbol{\psi}^T} \quad \text{for } i = 1, \ldots, N.$$

Moreover, Lien and Shrestha (2014) show that the generalized information share can be used in situations where the cointegration relationship is not one-to-one.

For the CS, Gonzalo and Granger (1995) decompose $\mathbf{p}_t$ into the permanent component given by $\boldsymbol{\delta}_{\perp}^T \mathbf{p}_t$ with $\boldsymbol{\delta}_{\perp}$ denoting the orthogonal complement of $\boldsymbol{\delta}$ and some transitory component. The CS of product i is then defined as its contribution to the permanent component, i.e.

$$\mathrm{CS}_i = \frac{\delta_{\perp,i}}{\sum_{j=1}^{N} \delta_{\perp,j}} \quad \text{for } i = 1, \ldots, N.$$

The cointegration relationship theoretically implies a positive CS for all products. In practice however, it is possible to obtain a negative share. Some authors deal with this by using absolute values (Bohl et al., 2011), others set a negative share to 0 and rescale the remaining ones so that they still sum up to 1 (Alexander et al., 2020). However, in our case, both methods lead to similar results. The main difference between GIS and CS is that the GIS account for the possible correlation of the markets' innovations $\mathbf{e}_t$, while the CS only measures a product's contribution to the long-run equilibrium price.

The impulse responses of the individual products can also be derived from the VECM (1) (or the equivalent vector autoregression model). We consider the generalized impulse response function introduced by Pesaran and Shin (1998), which is invariant to the ordering of the model variables. The n-step ahead generalized impulse response with respect to a shock of magnitude γ in variable i is defined by $\mathbf{GI}_i(n, \gamma) = E[\mathbf{p}_{t+n} \mid e_{jt} = \gamma, \mathbf{\Theta}_{t-1}] - E[\mathbf{p}_{t+n} \mid \mathbf{\Theta}_{t-1}]$, where $\mathbf{\Theta}_{t-1}$ denotes the known history of the economy up to time $t-1$ and e_{jt} is the j-th entry of $\mathbf{e}_t$. Pesaran and Shin (1998) show that this simplifies to

$$\mathbf{GI}_i(n, \gamma) = \frac{\gamma}{\sigma_{ii}} \mathbf{A}_n \boldsymbol{\Omega} \mathbf{u}_i$$

where σ_{ii} is the ith diagonal entry of $\mathbf{\Omega}$ and $\mathbf{A}_n = \sum_{j=0}^{n} \mathbf{\Psi}_j$ with $\mathbf{\Psi}_j$ denoting the j-th coefficient matrix of the VMA (2). $\mathbf{u}_i$ is the ith N-dimensional standard unit vector. The k-th entry of $\mathbf{GI}_i(n, \gamma)$ is then the value of the k-th model variable at time $t+n$ after a shock of magnitude γ in the ith variable at time t.

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