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The information content of delayed block trades in cryptocurrency markets

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ABSTRACT

This paper examines the price impact of large block trades in cryptocurrency markets by using a natural experiment in Bitcoin provided by the Gemini exchange. The exchange introduced a block trading facility in 2018, but in December 2019, it changed the minimum size threshold that allows market participants to trade a block and report it with a delay. Consistent with theoretical predictions and earlier empirical findings, we largely confirm that the information content of large trades is significantly lower in the upstairs market than in the downstairs. In contrast with prior research in traditional markets, we find that delaying the reporting of a block traded away from the continuous book discourages informed trading and potentially decreases the informativeness of trading and, therefore, information efficiency. Further, we find that the newly implemented size requirement for upstairs trades increases the total market impact, thereby not working as the intended introduction of a block trading facility.

1. Introduction

In the rapidly evolving landscape of financial markets, the price-effect puzzle of block trades has garnered significant attention from both academics and regulators. Traditional equity and derivatives markets have long leveraged block trades as a mechanism to source liquidity when executing large transactions, typically through private negotiations between two counterparties outside the continuous market. Upstairs markets or block trading platforms have proliferated to facilitate those large trades (Frino, 2021). Although a large body of literature has examined this issue in centralised (and regulated) markets (Bessembinder & Venkataraman, 2004; Białkowski et al., 2022; Booth et al., 2002; Comerton-Forde & Putniņš, 2015; Frino, 2021; Frino et al., 2022; Gemmill, 1996; Keim & Madhavan, 1996; Madhavan & Cheng, 1997; Rose, 2014; Smith et al., 2001; Westerholm, 2009), very little is known about how block-trade information flows in decentralised (and less-regulated) markets.[1] The objective of this study is to fill the gap in the literature by examining the effects of large transactions in cryptocurrency markets and answer key open questions. These include: (i) what is the price impact of block trades in cryptocurrency markets? (ii) Does a block trade convey more or less information than a downstairs large trade in cryptocurrency markets? (iii) To what extent do reporting delays affect the information content of cryptocurrency block trades?

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[1] The relevance of studying decentralised markets is in line with the growing trend in the finance literature (see, e.g., Bhambhwani & Huang, 2024; Conlon et al., 2023; Jahanshahloo et al., 2023, among others).

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The evolution of blockchain technology and the emergence of decentralised cryptocurrency markets[2] have introduced new ways of trading blocks. Unlike traditional markets, where block trades are private transactions between informed parties, in cryptocurrency markets, these trades involve an informed taker[3] submitting orders to be filled by uniformed market makers. This distinction is critical, as it potentially raises concerns about information inefficiency in these markets. Indeed, in cryptocurrency exchanges such as Gemini, the process involves a taker sending an Indication of Interest (IOI) with specific details[4] to the exchange and a maker who receives relatively limited information.[5] The maker has to bet to take a position and match the IOI. This structure introduces a unique dynamic where the market makers, often uninformed about the specifics of the block trade, engage in a relatively speculative endeavours to fill these orders.

To the best of our knowledge, Gemini was the first cryptocurrency exchange to introduce an electronic block trading facility for digital assets (i.e., 108 cryptocurrency spot trading pairs) in April 2018.[6] However, on December 6, 2019, Gemini made a change pertaining specifically to Bitcoin spot pairs. The exchange modified its trading rules relating to the minimum order size threshold at which market participants can trade large quantities outside of Gemini's continuous order book. Prior to December 6, 2019, any Gemini trader could have opted to trade an off-market block for orders larger than 10 bitcoins. Starting on December 6, 2019, the minimum order size decreased from 10 to 5 bitcoins, thereby allowing more market participants to use block trades. This potentially affected the liquidity and information efficiency of cryptocurrencies priced on the exchange. As such, trades of between 5 and 10 lots could be executed in the upstairs market and then reported with a 10-minute delay on the continuous order book. This was in contrast to the previous regime in which such trades needed to be reported immediately. This rule change provides an ideal natural experiment to examine the market impact and trading costs associated with large block trades in cryptocurrency markets. In this study, we use the market structure change in the minimum block size threshold on the Gemini exchange to examine the extent to which block trades affect the price information content in cryptocurrency markets.

The uniqueness of this study lies in its novel features: the structure of the Gemini rule change, the proprietary microstructure data that we have access to, and the cryptocurrency market environment. First, the Gemini exchange modified an order size threshold for trading Bitcoin off-market (or better on an upstairs market), permitting an analysis of the impact using a natural experiment design and a difference-in-differences approach. Second, unlike prior studies on equities (e.g., Madhavan & Cheng, 1997), the tick-by-tick data identifies whether a trade is executed as a block, allowing us to distinguish between large transactions executed upstairs (away from the central exchange) or downstairs (on the continuous order book). Last, the absence of the intermediation of search brokerage or block trade houses usually present in traditional financial markets provides a cleaner setting, which enables an accurate assessment of the impact of block trades on crypto prices in cryptocurrency markets.

To answer the question of whether block trades affect the information impounded in prices in cryptocurrency markets, we examine a sample of trades executed as blocks after the change in the minimum order size but not qualified to be executed as blocks before the change (i.e., trades with a lot size between 5 and 10) and compare them with trades classified as blocks during the entire sample period (i.e., trades with a lot size greater than 10 classified as block trades). The market structure change in the threshold can then be used to explain any shift seen in the treatment sample compared to the control, which has not undergone changes. Importantly, we are able to examine whether there is a change in the information content of block trades after the introduction of delayed reporting for smaller-sized trades. In addition, we are also able to test for any difference between large transactions in upstairs and downstairs markets by comparing block trades executed outside the continuous order book and reported to the market with a 10-minute delay with same-size trades not classified as blocks executed immediately on the limit order book of the exchange.

Building on previous literature (i.e., Holthausen et al., 1987; Keim & Madhavan, 1996; Kraus & Stoll, 1972; Scholes, 1972), we hypothesise that block trades have significant permanent price impacts and therefore are informed trades. Despite the abundance of empirical research on the price effects linked to large-block trades, testing hypotheses about how prices are formed in various trading mechanisms remains a challenging task (Madhavan & Cheng, 1997). Numerous studies show that trades executed in upstairs markets have a lesser lasting impact on prices compared to those in downstairs markets (Bessembinder & Venkataraman, 2004; Białkowski et al., 2022; Booth et al., 2002; Madhavan & Cheng, 1997; Rose, 2014; Smith et al., 2001; Westerholm, 2009). This observation aligns with the theory proposed by Seppi (1990) and Grossman (1992), suggesting that upstairs trades are predominantly carried out by traders capable of convincingly signalling their motivation for liquidity rather than information. Therefore, we hypothesise that block trades executed away from the central market have a smaller impact than same-size large trades executed on the continuous order book.

However, all the studies mentioned above examine the price behaviour of securities surrounding upstairs trades that are both executed and reported to the market concurrently. Gemmill (1996) is the first to study the effects of block transactions conducted off-market and subsequently reported to the market at a later stage. While Gemmill (1996) finds that these trades exert a minimal permanent impact on prices at the time of their execution, he is unable to study the price impact of block trades at the time they are later reported to the market. Frino (2021) fills this gap by examining the impact of off-market block trades subject to delayed reporting at the time that they are reported. He finds that an additional price impact occurs at the time off-market trades are

[2] In this paper, decentralised is referred to the type of asset traded rather than the market itself. For further information regarding decentralised markets, the SWIFT report by Aspris et al. (2022) provides a good overview of the various types of centralised and decentralised markets, with Foley, O'Neill, and Putnins (2023) providing an in-depth analysis of truly decentralised exchanges.

[3] We hypothesise the block trader is informed consistent with the literature (e.g., Easley & O'Hara, 1987) and empirically test this hypothesis in our study.

[4] i.e., symbol, limit price, side of the trade, quantity, and an optional minimum fill quantity.

[5] i.e., only the midpoint of the order book at that time and the minimum quantity of the block trade.

[6] See the announcement on Gemini's website at https://www.gemini.com/it-it/blog/introducing-gemini-block-trading (Accessed 31 August, 2022).

reported. This suggests that the delay in reporting these trades introduces an element of informational inefficiency. Frino et al. (2022) extends both Gemmill (1996) and Frino (2021) by investigating whether the inability to delay trade reporting results in informed traders being squeezed out of the upstairs market. They find that block trades are more likely to be informed in a regime with delayed reporting and less likely to be informed when there is an immediate reporting regime for large trades.

Frino et al. (2022) argue that the practice of delaying the reporting of off-market block trades provides traders possessing private information with the time necessary to capitalise on their price knowledge. As a result, these traders are more inclined to engage in off-market block trades. However, when off-market trades are subject to immediate reporting, the capacity of an informed trader to utilise their information effectively diminishes. Consequently, they are less inclined to participate in off-market trades and might resort to alternative, potentially more expensive methods to conceal their information or might even opt to exit the market altogether. Similar to this case, traders on Gemini can choose to face or not face immediate trade reporting by selecting a size to trade. This distinction also allows us to assess whether informed traders are more likely to choose a block trade and, therefore, avoid immediate trade reporting in same-size trades executed on the downstairs market. To evaluate this hypothesis, we employ methodologies from previously cited literature and focus on determining whether the lasting impact of large trades increases as they transition into a regime with delayed reporting.

Our findings suggest that large trades executed as blocks away from the central market have a smaller price impact and therefore are less informed than same-size trades executed on the continuous book, consistent with the model of Seppi (1990) and Grossman (1992), and the abundance of prior empirical research findings in equity markets (Bessembinder & Venkataraman, 2004; Białkowski et al., 2022; Booth et al., 2002; Madhavan & Cheng, 1997; Rose, 2014; Smith et al., 2001; Westerholm, 2009). This potentially raises questions about the primary functions of the block trading facility in cryptocurrency markets. However, Madhavan and Cheng (1997) argue that the main advantage of having an upstairs market might not be for the trade initiator but rather for the transaction's counterparties. Liquidity providers, particularly institutional traders, often hesitate to place large limit orders to avoid inadvertently giving away free options to the market (Dyhrberg et al., 2023). Consequently, the primary function of the upstairs market is to facilitate transactions that might not take place in the more transparent downstairs market.

Additionally, as opposed to the results in futures market studies (Frino, 2021; Frino et al., 2022), we find that block trades have little or insignificant permanent price effect at the time of their reporting and are certainly smaller compared to their execution time, *prima facie* suggesting that Gemini's introduction of a block trading facility served its purpose. However, the newly implemented size requirement for block trades increased the total market impact, running directly counter to the intent behind the exchange's introduction of a block trading facility. We further find that while block trading in cryptocurrency markets reduces the immediate price impact, thereby ostensibly enhancing information efficiency, it simultaneously discourages informed trading. This is in sharp contrast to the findings of prior research on reporting delays in off-market trades (e.g., Frino et al., 2022), and also calls into question the overall information efficiency of such a mechanism. A possible explanation relates to the way in which blocks are traded in these markets.[7] Block trades in cryptocurrency markets are more similar to dark auctions for market makers than out-of-the-floor private agreements between two counterparties. Also, informed traders might not demand immediacy and thus prefer limit orders instead as they possess relatively long-lived information (Collin-Dufresne & Fos, 2015).

We know of no empirical studies that tackle the issue of the market impact cost of trading large blocks in cryptocurrency markets. This is despite an abundance of studies focusing on equities (Chan & Lakonishok, 1993, 1995, 1997; Holthausen et al., 1987, 1990; Keim & Madhavan, 1996; Kraus & Stoll, 1972; Scholes, 1972). Block trading facilities in cryptocurrency markets are open to any individual (i.e., even retail and less sophisticated types of traders), while in regulated, traditional markets only a subset of market participants can access this trading mechanism — usually more professional types of investors.[8] It is, therefore, important to shed light on this issue and advance our understanding of how different types of investors respond to information impounded in large transactions. Our study is also the first to compare and contrast the information revelation process of large trades in the upstairs and downstairs cryptocurrency markets, extending the work of Madhavan and Cheng (1997), Smith et al. (2001), Booth et al. (2002), and Bessembinder and Venkataraman (2004).

Prior research examines the price impact of delayed off-market trades at the time they are executed (Gemmill, 1996), later reported (Frino, 2021), and also examines whether the inability to report a block with a delay squeezes informed trades out of the upstairs market (Frino et al., 2022). However, it does not examine the impact of a change from immediate to delayed trade reporting. As such, our study also extends this small but rich body of literature on reporting delays in off-market trades by examining a new research question: namely, the extent to which the publication regime of block trades encourages informed trading in upstairs markets. Lastly, this study adds to the theoretical framework of Collin-Dufresne et al. (2021) and Collin-Dufresne and Fos (2015). They show that informed traders select the timing and type of trades (limit orders) to receive the spread when the market is liquid rather than pay it. We contribute by demonstrating that informed traders do not select the size of trades to delay the information revelation process through the order flow and exploit their long-lasting price knowledge.

The paper is organised as follows. Section 2 provides background by detailing the institutional setting. Section 3 describes the data and the statistical method adopted. Section 4 discusses the empirical findings, while Section 5 concludes.

[7] This differs significantly from the settings of previous studies in equity and futures markets (e.g., Frino, 2021; Keim & Madhavan, 1996).

[8] For example, in US equity markets, each party to a block trade must be an Eligible Contract Participant (ECP), which is a defined term under Section 1a of the US Commodity Exchange Act.

2. Institutional setting

Gemini Trust Company, LLC, also known as Gemini, is a well-known US cryptocurrency exchange and custodian bank that began operating in 2014. In recent years, Gemini introduced a new feature called Gemini Block TradingTM (GBTTM), a fully electronic block trading facility that aims to address the challenges associated with large-scale transactions. To ensure best possible trade execution, block orders are electronically and simultaneously routed to participating market makers on the platform. Trade information is published on the continuous order book via market data feeds ten minutes after execution.

The launch date for GBTTM was set for 9:30 a.m. ET on Thursday, April 12th 2018. GBTTM allows customers to place block orders by specifying their buy/sell preference, quantity, minimum required fill quantity, and a price limit, collectively known as the 'Indication of Interest' (IOI). Market makers receive limited information to ensure a fair balance between transparency and market integrity. If the market maker responds to the IOI in the right direction and offers a price within the limit imposed by the taker, the block order is executed. It is important to note that block orders do not interact with continuous or auction order books. The introduction of GBTTM means that Gemini's platform has become more accessible: any Gemini customer can place a block trade. However, only market makers authorised by the exchange can fill a block order. To strike a balance between democratising access and safeguarding platform integrity, Gemini imposes a minimum quantity requirement of 10-coin lots (for Bitcoin spot trading pairs), which changed to 5-coin lots on the 6th of December 2019. This permits an assessment of the change in the information flows in delayed block transactions compared to on-market trades.

GBTTM aims to address concerns about the impact of large orders on cryptocurrency prices by facilitating trades outside of the continuously updated order book, reducing the potential for market disruptions. Specifically, a 10-minute delay in publishing transactions ensures that market participants have access to pricing and liquidity information without triggering abrupt market movements. This move allows investors to execute large orders outside the exchange's order book, a strategy also commonly employed in equities and futures markets.

Here we present an example of how the block trading facility works (and in Fig. 1)[9]:

1. The taker has placed an IOI to buy 15 BTC at a limit price of 1000.10 USD with a minimum fill quantity of 10 BTC.[10]
2. The market makers receive an IOI that has no side, and the *price* stipulation shows a collar price of 1000.00 USD, the midpoint of the continuous book at the time the order was placed.
3. Maker one-side responses to the IOI can happen in the following ways:
    - *Titius* responds with a buy order of 10 BTC at 1000.50 USD;
    - *Gaius* responds with a sell order of 10 BTC at 999.25 USD;
    - *Sempronius* responds with a sell order of 10 BTC at 999.50 USD.
4. At the end of 1 min, the block trading engine will auto-match the IOI against all of the market makers' orders.
    - *Titius*'s buy order is cancelled;
    - *Gaius*'s sell order is executed;
    - *Sempronius*'s sell order is cancelled.[11]

3. Data & method

3.1. Data and sample

This study uses proprietary trade prices data for Bitcoin against the US Dollar (BTCUSD) traded on the Gemini exchange. The data were sourced through the use of an API that directly accessed Gemini's platform.[12] The sample spans over a 2-year period extending from December 6, 2018, to December 5, 2020. It covers symmetrical 1-year pre- and post-periods surrounding the market structure rule change amended by Gemini on December 6, 2019. The dataset consists of trade prices, volumes, turnovers (the US dollar amounts of each transaction), trade side indicators (if it is a buyer- or seller-initiated transaction), the date and time stamp to the nearest hundred of a second, and the flag of block trade indicator.

This study is explicitly concerned with large trades. In doing so, we exclude all small on-market trades with a lot size of lower than 5 bitcoins from our analysis. Second, we distinguish between block trades and non-block trades. In securities markets, there is no general definition of a block trade.[13] However, we do not need to resort to assumptions when determining whether a trade is

9 For more details, please see Gemini's website at https://docs.gemini.com/block-trading/#block-trading (Accessed 31 August, 2022).

10 The block order's limit price must be within 5% of the midpoint of the related continuous order book at the time of order submission.

11 Block trade occur at the best maker price. All remaining quantities and unfilled orders are cancelled and closed.

12 CDD Media & Analytics, LLC, a data provider known for its reliability, helped in the retrieval process, allowing us to avoid the issue analysed in Alexander and Dakos (2020) and Foley, Krekel, et al. (2023).

13 Previous literature has thus been forced to empirically investigate the largest 1% of trades on the assumption that those could be defined as blocks because of their large size compared to the rest of the distribution. Studies in equity markets have been based on the general convention that a transaction of more than 10,000 shares on the NYSE or NASDAQ can be classified as a block trade.

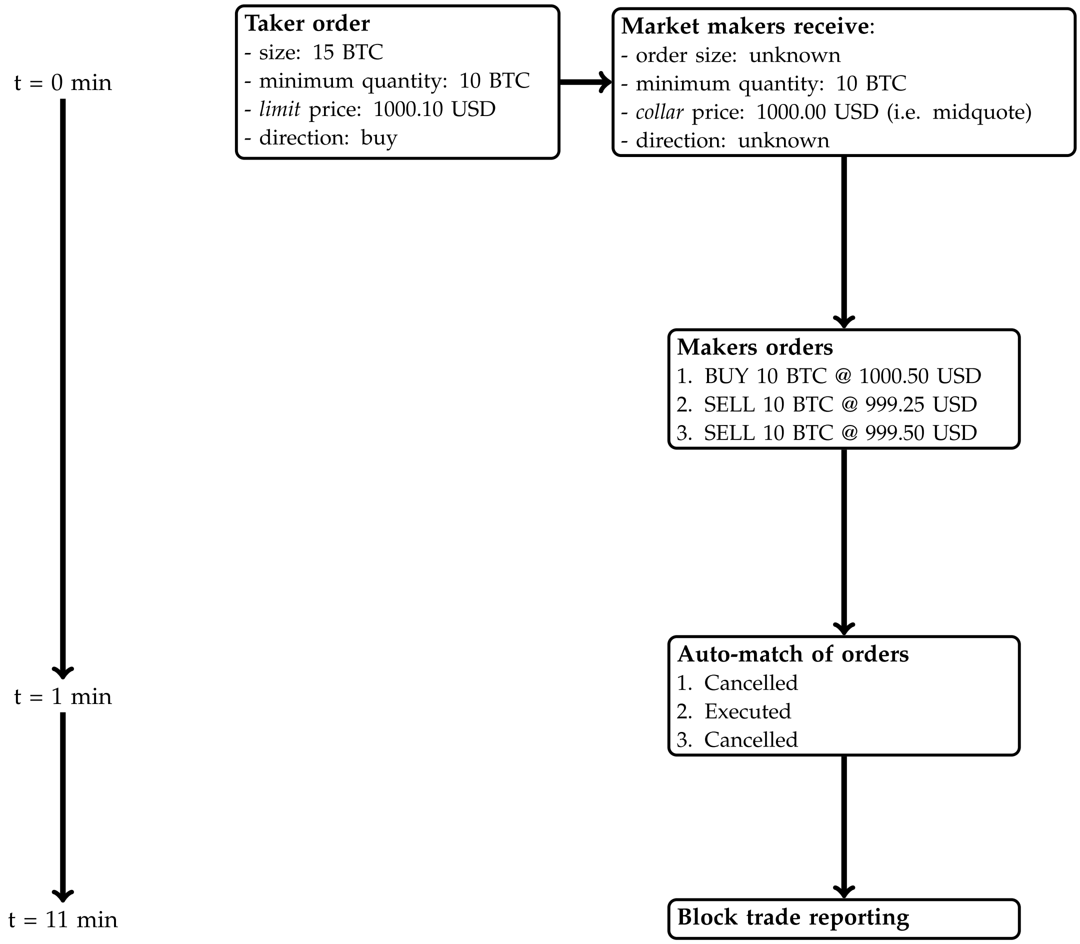


Fig. 1. Example of a block trade execution and reporting.

a block trade. This is because the dataset we use explicitly identifies which trades have been traded as block trades on the Gemini exchange. This permits the distinction of the on-market (or downstairs) trades executed on Gemini's order book from those trades executed in the upstairs market (or off-market).

3.2. Trade direction and market impact measures

Transactions conducted on the continuous order book provide details about whether they are buying or selling orders. Block trades generally lack this information as they are executed outside regular exchanges. That said, our dataset clearly indicates transactional direction for on-market trades — i.e. which party initiated a trade. Instead, we classify block trades as buy or sell transactions using the mainstream approach found in the literature — the 'tick' rule (see Holthausen et al., 1987; Kraus & Stoll, 1972; Lee & Ready, 1991). In doing so, we are consistent with (Frino et al., 2022) in classifying a block as a buy (sell) if its price is higher (lower) than the same-time executed on-market trade.

According to the literature, the total market impact (i.e., imperfect substitution) of large block transactions consists of two main components: the information asymmetry and the short-run liquidity costs (Kraus & Stoll, 1972; Scholes, 1972). The permanent component reflects the shift in the market's assessment of the security's value as a consequence of the block transaction. On the other hand, the temporary component signifies the short-lived price fluctuation required to supply the liquidity needed to accommodate the block trade. Our approach is consistent with the seminal work of Madhavan and Cheng (1997), which takes the 20th trade to measure the price effects. This is also consistent with the other seminal work by Holthausen et al. (1987), who look at the 20th trade as the equilibrium price before and after a block transaction to calculate the measures, although they then focus on a shorter time frame when presenting the results.[14]

[14] For robustness purposes, we also tested for longer (25th, 30th, and 35th trade before and after the block) and shorter (15th, 10th, and 5th trade before and after the block) windows. The results were qualitatively similar.

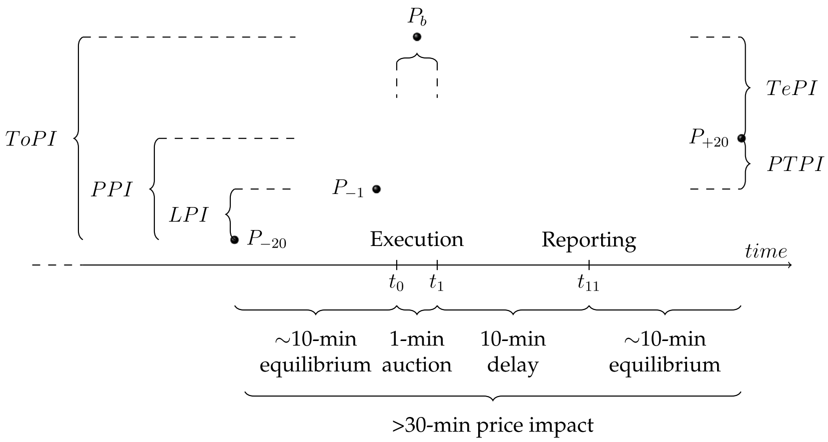


Fig. 2. Price impact measures for block buy transactions.

We first focus on the permanent post-trade price impact measuring the information conveyed by large trades. Consistent with the extant literature, we compute this as $PTPI = ln\left(P_{+20}\right) - ln\left(P_{-1}\right)$, where P_{+20} is the price of the 20th trade after the off-market block trade is reported. P_{-1} is the trade price before the off-market block trade is executed. This measure allows for a delay in the market's speed of adjustment to the block trade (Madhavan & Cheng, 1997). Similarly, we define the temporary price impact as the logarithmic return from the price 20 trades after the block trade is reported to the block, namely $TePI = ln\left(P_b\right) - ln\left(P_{+20}\right)$, where P_b is the price of the block trade.

However, the standard definition of permanent impact might underestimate the actual change in market beliefs following a trade. According to Madhavan and Cheng (1997), this may be due to the potential leakage of information during the negotiation process in the upstairs market. Consistent with the literature (Madhavan & Cheng, 1997), we compute a measure of pre-trade price movement that may reflect this leakage of information as the logarithmic return from the price of the 20th trade before the block is executed to the trade price prior to the off-market block trade: $LPI = ln\left(P_{-1}\right) - ln\left(P_{-20}\right)$, where P_{-20} is the price of the 20th trade before the block is executed. By summing this LPI measure (which is not the focus of this study) to the previously computed $PTPI$, we obtain the overall permanent price impact, which is a more meaningful measure of the information content of a trade that captures the price movements using the prevailing price 20 trades around the block as $PPI = ln\left(P_{+20}\right) - ln\left(P_{-20}\right)$. Our estimate of the overall PPI allows us to encapsulate all the other measures of pre- and post-trade price movements used in Madhavan and Cheng (1997) and accommodates a lag in the market's speed of adjustment in response to the block trade. Finally, we calculate the total price impact, which also captures the above-mentioned temporary effect, as the logarithmic return from the 20th trade before the block is executed to the block: $ToPI = ln\left(P_b\right) - ln\left(P_{-20}\right)$.

Fig. 2 illustrates the price impact measures for block purchases computed above, with the horizontal axis showing the time in minutes and the vertical axis identifying different price levels. The illustration for block sales is symmetrical to Fig. 2. The average time window extends from more than 10 min prior to block trade execution to more than 10 min after the block trade is reported to the market with the aforementioned 10-minute delay. On average, this results in an over-30 min window studied for each block trade. This is also consistent with the literature using minute-based windows (e.g., Bessembinder & Venkataraman, 2004; Frino et al., 2022).

3.3. Statistical tests and DiD regression models

We employ a methodology using natural experiments that is consistent with the mainstream literature on empirical market microstructure (e.g., Galati, 2024). In the first place, we compare the permanent price impact of block trades with similar-size trades executed in the downstairs market. We run t tests on the null of whether the mean price effects (PEs) for both block and non-block trades is equal to 0 and on the null of whether these two means are equal to each other. This allows us to assess whether block trades executed in the upstairs market (i.e., on GBTTM electronic platform) carry more or less information than same-size trades executed on the continuous order book. Consistent with the extant literature, we also run t tests on the difference between the mean of the pre- and post-rule change to see whether there was a change in the information content of block trades throughout our sample period. We then focus on the information efficiency of block trading and use a more sophisticated model to examine the impact of a change in the minimum order size threshold on the information conveyed by block trades in cryptocurrency markets.

Similar to that used in Galati (2024), Eq. (1) specifies the linear regression analysis of our second specification, employing a difference-in-differences approach that thus accounts for market-wide fluctuations:

$$y_t = \beta_0 + \beta_1 Event_t + \beta_2 Treatment_t + \beta_3 Event_t \times Treatment_t + \beta_4 X + \epsilon_t \quad (1)$$

where y_t is the PPI metric of the overall permanent price impact measuring the information content of block trades at time t. $Event_t$ is an indicator variable equal to 1 from December 6, 2019, the post-rule change in minimum order size, and 0 otherwise. $Treatment_t$ is a dummy variable equal to 1 for large trades that have a lot size between 5 and 10 bitcoins and 0 for the control block trades with a lot size greater than 10 bitcoins. The interaction term $Event_t \times Treatment_t$ is our variable of interest and captures the marginal effects of being a treatment large trade in the post-size-change period. Following the literature cited above, we include a set of cryptocurrency-level control variables in the vector X, namely the natural logarithm of the total turnover and the volatility at time t, measured as the squared natural logarithmic return of each trade relative to the preceding trade. In a further specification, we use a dummy variable to control for the COVID-19 pandemic, taking the value of 1 after 11 July 2020 and 0 otherwise,[15] and, consistent with Brauneis et al. (2022), the natural logarithmic Bitcoin returns as further controls.

We divide our sample in treatment and control groups consistent with Frino et al. (2022). The treatment group is composed of large trades with a lot size between 5 and 10 bitcoins, which are simultaneously executed and reported on the downstairs market before falling later into an off-market delay reporting regime. The control group consists of block trades with a lot size greater than 10 bitcoins, which are always executed off-market and reported with a 10-minute delay to the order book in both periods. Further, to avoid biases we use an additional control group. This group consists of trades in the downstairs market between 5–10 bitcoins that are not traded as blocks.[16]

4. Empirical results

4.1. Descriptive statistics

Fig. 3 presents the distribution of the block *vs* non-block trades during pre- and post-regulatory change. Of the 18,084 large trades in the sample, 8.07% are block trades, 46.77% are buys, and 45.16% are sells. Transactions executed in the auction market were excluded from the sample and those executed in the continuous intraday market and upstairs market were considered. Trades executed as blocks in the upstairs market are mainly distributed as lots of 10 coins, while downstairs large trades present smaller sizes. From the figure, we note that upstairs trades are larger than downstairs trades, as suggested by intuition (Madhavan & Cheng, 1997).

4.2. Price movements surrounding execution time of block trades in upstairs markets

We begin by analysing the price movements surrounding (only) block trades at the time they are actually executed. We do this to show whether the decision of the cryptocurrency exchange to introduce a block trading platform aimed at alleviating the price impact of large trades was successful.

Following Gemmill (1996), we measure cumulative abnormal returns around the time block trades are executed[17] on the upstairs markets by taking an average return (from the 29th to the 20th prior to the block trade) as a benchmark return. This is then subtracted from the cumulative returns ranging from the 10th trade prior to the block to the 10th trade after the block: $CARs_{-10,10} = \sum R_{it} - B_{it}$, where R_{it} denotes the return on the ith trade surrounding the block and B_{it} is the benchmark return calculated as $B_{it} = \frac{1}{10}\sum_{t=-29}^{t=20} R_{it}$. These excess returns may be interpreted as the unexpected component of percentage price changes relative to the block (Gemmill, 1996), which is defined as the trade at time 0. Consistent with Aitken and Frino (1996), we excluded a block trade if it was within 10 trades of another block in order to ensure a clean sample of block trades.

Table 1 reports the mean values of excess returns for 21 trades surrounding the block trades at the time they were executed in the pre and post periods, broken down into buys and sells transactions. We run t-tests on the null of whether the abnormal return was equal to 0. As expected, average price changes are positive for buys and negative for sells in both periods. These results are statistically significant at the 1% level after the execution of the block at time 0. This implies that executing such block trades on the continuous order book would have disrupted the market had they themselves not been taken on an upstairs market and processed with a 10-minute lag on the exchange, thereby *prima facie* supporting the effectiveness of the introduction of a block trading facility by the exchange.

As consistently documented in the literature (e.g. Aitken & Frino, 1996), large trades have an 'intriguing' and 'puzzling' asymmetry in price reaction, with sell transactions showing a more pronounced impact. This asymmetry is documented in Table 1 and even more evident in Fig. 4. Consistent with Białkowski et al. (2022), Fig. 4 illustrates the cumulative average excess returns surrounding block trades. These are broken down into buys and sells, and before and after the change in the minimum trade size for block trades introduced by Gemini. Nevertheless, there is documented evidence of an increasing price impact from the period before to the period after the adjustment in the minimum trade size for block trades. This naturally leads to the question of whether the microstructural adjustments made by Gemini have fulfilled their intended purpose. We use these results as a motivation for the following analyses.

[15] The date coincides with the announcement by the World Health Organisation (WHO) declaring COVID-19 a pandemic. Given the period, this variable not only controls for differences in the sample periods due to the pandemic but also for Bitcoin speculative bubbles in 2020.

[16] In untabulated tests, we show that the results are almost identical when not considering this additional control sample and keep two constant samples as control and treatment in the DiD setup.

[17] While the study by Gemmill (1996) uses data reporting only execution time for delayed block trades (i.e., does not have a timestamp of the time at which the block are later reported), we follow Frino et al. (2022) in simulating execution times in our data. This involves adjusting the timestamps of block trades to eleven minutes before their actual records. This adjustment aligns with the hypothetical execution times of these trades in the downstairs market, assuming there were no delays in their reporting.

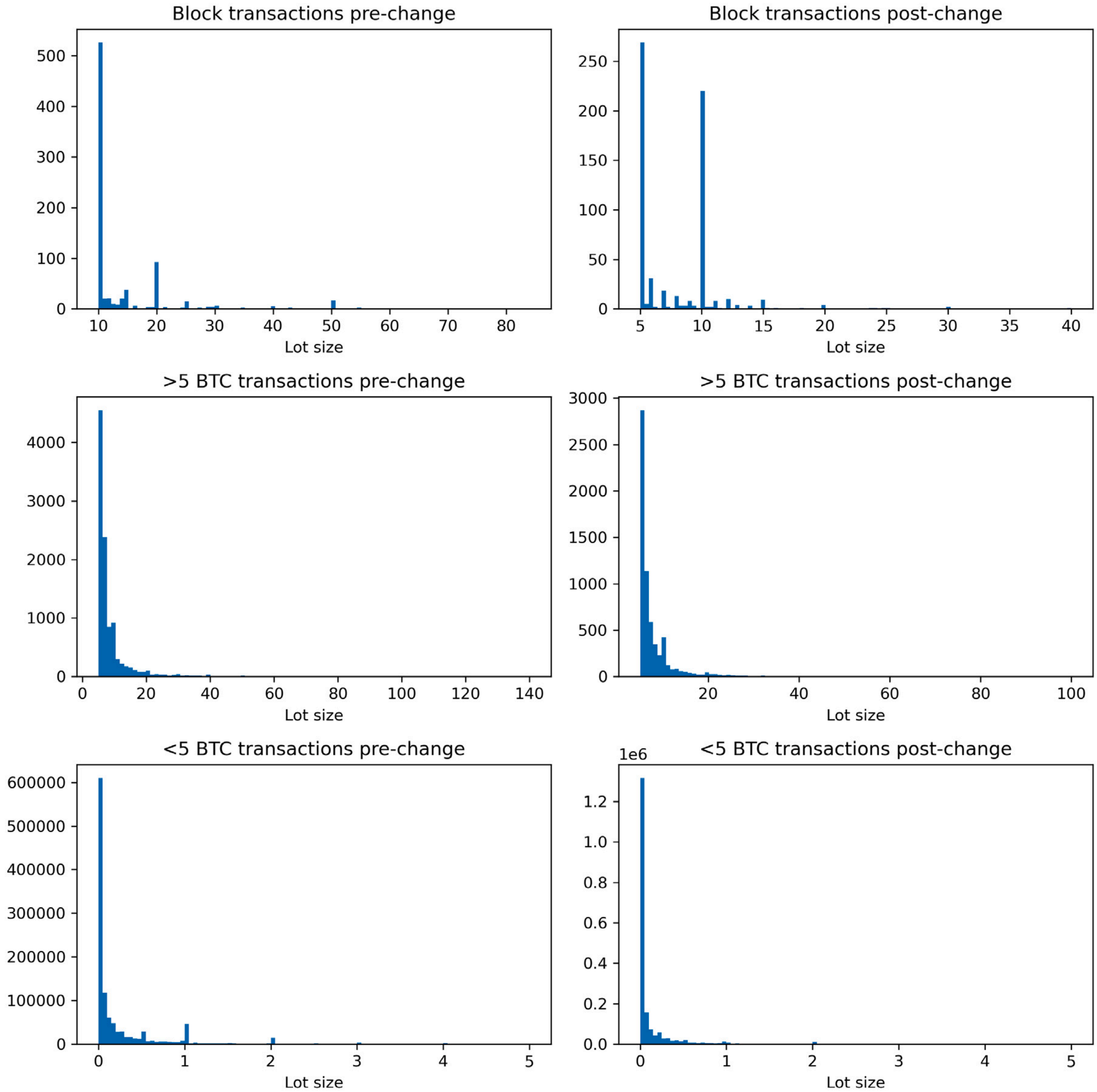


Fig. 3. Frequency of block and non-block trades in the sample. The sample period covers December 6, 2018, to December 5, 2020.

4.3. *Price effects surrounding the execution and reporting time of large trades in upstairs and downstairs markets*

Following Madhavan and Cheng (1997), we now turn to an analysis of the price effects surrounding large trades in downstairs against upstairs markets. We also examine whether there was a change in these price movements after the change in exchange policy.

Table 2 presents the mean values for the price impact measures computed as in Section 3.2 around both the execution and reporting time.[18] These are broken down by trade direction and event periods, both for the upstairs and downstairs markets. Upstairs block trades are examined at the time they are later reported to the exchange (i.e. following a 10-minute delay), while downstairs large trades are examined at the time they are executed as they are immediately reported to the exchange's continuous book. We run *t* tests on the null of whether the means are equal to 0 and on the null of whether the means of the two distributions (for

[18] For upstairs block trades reported with a 10-minute delay, we consider the trades before the execution time taken 10 min before the timestamp of the block trade, being the trades which lead to the price of the block submitted at that time, and the trades after the reported timestamp of the block trade, being the transactions later influenced by the price of the reported block. This is consistent with Frino et al. (2022). For downstairs large trades, being executed and immediately reported to the market, we consider the trades surrounding the normal timestamp of the trades.

Table 1

Block trade cumulative abnormal returns at execution time. The table presents the mean values of cumulative abnormal returns for block trades, broken down into trade direction and event periods, and calculated as $CARs_{-10,10} = \sum R_{it} - B_{it}$, where R_{it} denotes the return on the ith trade surrounding the block and B_{it} is the benchmark return calculated as $B_{it} = \frac{1}{10}\sum_{t=-29}^{t=20} R_{it}$. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are within parentheses and means are in percentage. The pre-event sample period covers December 6, 2018, to December 5, 2019, while the post-event period covers December 6, 2019, to December 5, 2020.

	Block buys pre	Block sells pre	Block buys post	Block sells post
−10	0.274 (0.899)	−0.102 (−0.411)	0.007 (0.03)	0.164 (0.593)
−9	0.174 (0.438)	−0.343 (−1.009)	0.101 (0.307)	−0.079 (−0.181)
−8	0.343 (0.669)	−0.16 (−0.376)	−0.6 (−1.537)	−0.679 (−1.371)
−7	−0.632 (−0.998)	−0.314 (−0.609)	0.151 (0.314)	−1.089 (−1.961)*
−6	−0.801 (−1.082)	−0.673 (−1.131)	−0.317 (−0.593)	−1.363 (−2.232)**
−5	−0.641 (−0.771)	−0.481 (−0.598)	0.148 (0.214)	−1.417 (−1.965)*
−4	−0.684 (−0.755)	−0.365 (−0.423)	0.34 (0.462)	−1.481 (−1.807)*
−3	−0.643 (−0.626)	−0.112 (−0.123)	0.326 (0.39)	−1.5 (−1.721)*
−2	−0.791 (−0.689)	0.391 (0.394)	−0.08 (−0.09)	−1.75 (−1.892)*
−1	−0.857 (−0.694)	0.495 (0.463)	0.534 (0.516)	−0.875 (−0.852)
0	−1.19 (−0.891)	0.734 (0.637)	−0.984 (−0.89)	−0.567 (−0.489)
1	7.308 (3.175)***	−4.874 (−2.587)**	10.808 (4.322)***	−11.93 (−5.5)***
2	7.508 (3.183)***	−5.308 (−2.779)***	10.193 (3.981)***	−12.378 (−5.769)***
3	7.707 (3.153)***	−6.103 (−3.101)***	10.426 (4.004)***	−12.968 (−5.912)***
4	8.047 (3.178)***	−6.422 (−3.197)***	10.904 (4.132)***	−13.196 (−5.875)***
5	8.614 (3.298)***	−6.684 (−3.289)***	10.938 (4.048)***	−13.815 (−6.056)***
6	8.565 (3.204)***	−7.016 (−3.446)***	10.892 (3.977)***	−14.142 (−6.056)***
7	8.728 (3.208)***	−6.998 (−3.303)***	10.935 (3.911)***	−14.511 (−6.109)***
8	8.155 (2.936)***	−7.39 (−3.406)***	11.004 (3.862)***	−14.821 (−6.109)***
9	8.43 (2.945)***	−7.723 (−3.478)***	10.908 (3.737)***	−15.279 (−6.083)***
10	8.995 (3.056)***	−8.845 (−4.074)***	10.875 (3.671)***	−15.558 (−6.075)***
# Obs	369	328	344	275

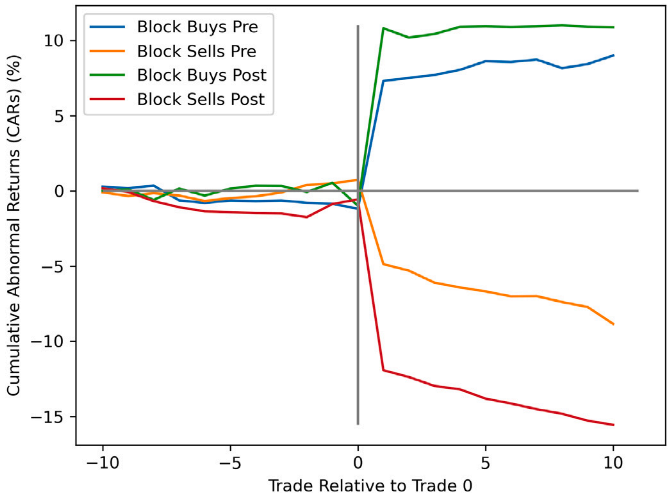


Fig. 4. Block trade cumulative abnormal returns at execution time. The figure presents the mean series of cumulative abnormal returns for block trades, broken down into trade direction and event periods, and calculated as $CARs_{-10,10} = \sum R_{it} - B_{it}$, where R_{it} denotes the return on the ith trade surrounding the block and B_{it} is the benchmark return calculated as $B_{it} = \frac{1}{10}\sum_{t=-29}^{t=20} R_{it}$. The pre-event sample period covers December 6, 2018, to December 5, 2019, while the post-event period covers December 6, 2019, to December 5, 2020.

downstairs and upstairs trades) are different. As one would expect, the average price impacts in both markets are positive for buys and negative for sells, but are relatively small in percentage terms (with the exception of spurious results in the information leakage for block trades).

Panel C of Table 2 reports mean values for the entire sample period from December 6, 2018, to December 5, 2020. As in Madhavan and Cheng (1997), the total price impact for sell trades is roughly similar in both markets. However, for buys there is a statistically significant higher total price impact for block trades executed in the upstairs market (i.e., B) than non-block large trades executed in the downstairs market (i.e., NB). This result is driven by the sample period after the minimum size threshold change shown in Panel B. However, it should be kept in mind that the average trade size in the upstairs market is about a third

Table 2
Means of price impact measures for block trades *vs* non-block trades. The table presents the mean values of the price impact measures computed around both the execution and reporting time, broken down by trade direction, event period, and market. Leakage is computed as $LPI = ln(P_{-1}) - ln(P_{-20})$, temporary as $TePI = ln(P_b) - ln(P_{+20})$, post-trade as $PTPI = ln(P_{+20}) - ln(P_{-1})$, permanent as $PPI = ln(P_{+20}) - ln(P_{-20})$, and total as $ToPI = ln(P_b) - ln(P_{-20})$. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are within parentheses and means are in percentage. The pre-event sample period covers December 6, 2018, to December 5, 2019, while the post-event period covers December 6, 2019, to December 5, 2020.

Price impact	Buys			Sells		
	B	NB	NB − B	B	NB	NB − B
Panel A: pre-change in block trade threshold						
Leakage (LPI)	−0.008	0.133	0.141	0.009	−0.09	−0.098
	(−1.093)	(11.618)***	(7.541)***	(0.89)	(−7.109)***	(−4.685)***
Temporary (TePI)	−0.006	−0.063	−0.057	−0.077	0.051	0.128
	(−0.268)	(−5.823)***	(−2.672)***	(−2.514)**	(4.232)***	(4.709)***
Post-Trade (PTPI)	0.135	0.078	−0.056	−0.017	−0.061	−0.043
	(5.399)***	(7.337)***	(−2.437)**	(−0.545)	(−4.977)***	(−1.571)
Permanent (PPI)	0.126	0.211	0.085	−0.008	−0.15	−0.142
	(4.893)***	(14.108)***	(2.955)***	(−0.254)	(−9.428)***	(−4.372)***
Total (ToPI)	0.121	0.149	0.028	−0.085	−0.099	−0.014
	(8.1)***	(12.872)***	(1.351)	(−6.984)***	(−7.773)***	(−0.66)
Panel B: post-change in block trade threshold						
Leakage (LPI)	0.009	0.067	0.058	0.015	−0.087	−0.102
	(0.932)	(11.211)***	(3.206)***	(1.609)	(−11.685)***	(−4.014)***
Temporary (TePI)	0.044	−0.033	−0.077	−0.007	0.025	0.032
	(2.288)**	(−4.814)***	(−3.606)***	(−0.304)	(3.617)***	(1.304)
Post-Trade (PTPI)	0.105	0.047	−0.058	−0.132	−0.04	0.092
	(4.107)***	(6.807)***	(−2.595)***	(−4.751)***	(−5.597)***	(3.578)***
Permanent (PPI)	0.114	0.114	0.001	−0.117	−0.128	−0.011
	(4.173)***	(12.619)***	(0.023)	(−3.91)***	(−13.41)***	(−0.326)
Total (ToPI)	0.158	0.081	−0.077	−0.123	−0.102	0.021
	(9.263)***	(13.211)***	(−3.998)***	(−6.851)***	(−13.542)***	(0.8)
Panel C: total sample period						
Leakage (LPI)	−0.0	0.084	0.085	0.011	−0.088	−0.099
	(−0.074)	(15.707)***	(6.682)***	(1.63)	(−13.648)***	(−6.073)***
Temporary (TePI)	0.017	−0.041	−0.058	−0.047	0.031	0.079
	(1.179)	(−7.009)***	(−3.894)***	(−2.368)**	(5.188)***	(4.615)***
Post-Trade (PTPI)	0.121	0.055	−0.066	−0.065	−0.045	0.02
	(6.778)***	(9.465)***	(−4.261)***	(−2.977)***	(−7.27)***	(1.122)
Permanent (PPI)	0.121	0.139	0.019	−0.053	−0.133	−0.08
	(6.435)***	(17.905)***	(0.948)	(−2.356)**	(−16.244)***	(−3.553)***
Total (ToPI)	0.138	0.099	−0.039	−0.101	−0.102	−0.001
	(12.23)***	(18.034)***	(−2.867)***	(−9.759)***	(−15.603)***	(−0.046)

larger than in the downstairs market, as highlighted by Madhavan and Cheng (1997). Even so, this evidence raises concerns about the effectiveness of the policy change implemented by the exchange.

Consistent with the extant literature, the temporary price effects presented in Table 2 provide evidence of a significant price reversal for large trades executed in the downstairs market across all sample periods. This implies that executing and contemporaneously reporting large trades to the market can temporarily disrupt the latter by the magnitude of the price difference between the large and normal trades, thereby supporting the necessity of an upstairs market. This is also supported by the leakage hypothesis, showing that pre-trade price movements associated with downstairs trades are greater than in upstairs markets. This is consistent with the common position held in previous research that large trades are typically "shopped" in the downstairs market. The puzzle is why there is no such leakage in upstairs markets — a phenomenon documented in prior studies (e.g., Frino, 2021). Possible explanations are that leakage in upstairs markets can occur less systematically (Madhavan & Cheng, 1997). However, it is important to remember the decentralised and centralised markets vastly differ in the way in which these large trades are traded.

A measure of more interest to this study is the permanent price impact. This is because the permanent price impact captures the complete information effect of large trades. Consistent with theoretical models and empirical findings of prior works, Panel A and Panel C of Table 2 document a statistically significant higher effect in the overall permanent price impact (i.e., PPI, which is the sum between $PTPI + LPI$) in non-block large trades executed directly on the continuous order book of the exchange. This suggests that downstairs markets convey more information than upstairs block trades. Nonetheless, the same is not true in the sample period following the change in the minimum trade size implemented by Gemini. The information content of such large trades is similar regardless of the market in which they are traded. Panel B of Table 2 shoes that there is no significant difference between block and non-block trades. Here, the question naturally arises as to whether the implementation of a smaller minimum trade size for block trades allows market participants to preserve their price knowledge and convey more information to the market through block trades and, therefore, influences the efficiency of the market itself.

Table 3
T-test coefficients for price impact measures of block trades (pre *vs* post change in the minimum trade size threshold). The table presents *t*-test coefficients of the difference between the pre and post event periods in terms of the price impact measures computed around both the execution and reporting time, broken down by trade direction. Leakage is computed as $LPI = ln(P_{-1}) - ln(P_{-20})$, temporary as $TePI = ln(P_b) - ln(P_{+20})$, post-trade as $PTPI = ln(P_{+20}) - ln(P_{-1})$, permanent as $PPI = ln(P_{+20}) - ln(P_{-20})$, and total as $ToPI = ln(P_b) - ln(P_{-20})$. The sample period covers December 6, 2018, to December 5, 2020.

Price impact	Buys			Sells		
	t-test	*p*-value	# Obs	*t*-test	*p*-value	# Obs
Leakage (LPI)	1.428	0.154	778	0.420	0.675	677
Temporary (TePI)	1.733	0.083	778	1.721	0.086	677
Post-Trade (PTPI)	−0.838	0.402	778	−2.602	0.009	677
Permanent (PPI)	−0.333	0.739	778	−2.368	0.018	677
Total (ToPI)	1.642	0.101	778	−1.841	0.066	677

Table 4
Means of permanent impact for block trades *vs* non-block trades. The table presents the mean values of the overall price impact measure computed as $PPI = ln(P_{+20}) - ln(P_{-20})$ around both the execution and reporting time taken separately, broken down by trade direction, event period, and market. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are within parentheses and the means are in percentage. The pre-event sample period covers December 6, 2018, to December 5, 2019, while the post-event period covers December 6, 2019, to December 5, 2020.

Event	B_{exec}	B_{report}	NB	NB − B_{exec}	NB − B_{report}
Panel A: Buys					
Pre	0.1 (5.23)***	0.038 (2.88)***	0.211 (14.108)***	0.112 (4.19)***	0.173 (6.876)***
Post	0.136 (5.714)***	0.027 (1.979)**	0.114 (12.619)***	−0.021 (−0.758)	0.087 (3.199)***
Total	0.116 (7.739)***	0.033 (3.48)***	0.139 (17.905)***	0.023 (1.223)	0.106 (5.747)***
Panel B: Sells					
Pre	−0.064 (−3.654)***	0.005 (0.231)	−0.15 (−9.428)***	−0.086 (−3.107)***	−0.155 (−5.487)***
Post	−0.147 (−6.525)***	−0.006 (−0.439)	−0.128 (−13.41)***	0.019 (0.588)	−0.122 (−3.747)***
Total	−0.099 (−7.06)***	0.0 (0.014)	−0.133 (−16.244)***	−0.034 (−1.613)	−0.133 (−6.309)***

Table 3 helps answer this question by presenting *t* tests on the null of whether there was a difference in the price impact measures of block trades in the period before and after the change in Gemini's microstructure policy. While there was no claimed change in the information content conveyed by block buyer-initiated trades, there is evidence of a significantly larger permanent price impact for seller-initiated block trades. Similarly, while no change is seen in the information leakage measured in the pre-trade price movements, it is apparent that the decision to change the minimum size threshold that allows market participants to trade large transactions in the upstairs market resulted in a statistically significant increase in the total price impact those block trades have on the market. This warrants policy revision regarding Gemini's discretional decision on minimum tick sizes for off-market trades.

4.3.1. Permanent price effect around execution and reporting time of large trades in upstairs and downstairs markets

Following Frino et al. (2022), we now narrow the focus on to the information price effects of block trades. We do this to account for both the execution and reporting times taken separately. We then investigate the differences in the information content conveyed by upstairs and downstairs large trades. As in Section 4.2, we examine price dynamics surrounding a simulated execution time for large trades and the trades before and after the actual reporting timestamp.

Table 4 reports the mean values for the overall permanent price impact (information effect) of large trades around both the execution (B_{exec}) and reporting (B_{report}) time for the upstairs and downstairs markets. These measures are broken down by trade direction and event periods. We run *t* tests on the null of whether the means are equal to 0 and on the null of whether the means of the two distributions (for non-block trades in downstairs markets and block trades in upstairs markets at execution and reporting time) are different. Interestingly, for sells, block trades carry no information to the market when they are later reported, showing again an asymmetry with block buys that instead have a statistically significant permanent price impact in all the sample periods analysed. At the execution time, block trades would have a larger and significant price impact on the exchange had they been executed without delay in the upstairs markets, suggesting once again the effectiveness of the introduction of a block trading facility to alleviate the market impact of large transactions.

Table 5
Difference-in-differences linear regression model around reporting time of block trades. The table presents the OLS regression results of the DiD analysis around the reporting time of block trades, with and without control variables, according to the following equation:

$$y_t = \beta_0 + \beta_1 Event_t + \beta_2 Treatment_t + \beta_3 Event_t \times Treatment_t + \beta_4 X + \epsilon_t.$$

The dependent variable is the overall permanent price impact (information effect) of block trades in upstairs markets. $Event_t$ is an indicator variable equal to 1 from December 6, 2019, the post-rule change in minimum order size, and 0 otherwise. $Treatment_t$ is a dummy variable equal to 1 for large trades that have a lot size between 5 and 10 bitcoins and 0 for the control block trades with a lot size greater than 10 bitcoins. The interaction term $Event_t \times Treatment_t$ is our variable of interest and captures the marginal effects of being a treatment large trade in the post-size-change period. The first specification in both panels refers to the baseline case model, while the second specification includes volatility and the natural logarithm of total turnover as control variables. In the third specification, we add the Covid-19 dummy and the logarithmic returns control variables. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are within parentheses and coefficients are in percentage. The sample period covers December 6, 2018, to December 5, 2020.

	Permanent price impact					
	Buys			Sells		
	(1)	(2)	(3)	(1)	(2)	(3)
Event	0.064***	0.068***	0.046	−0.124***	−0.127***	−0.128***
	(0.025)	(0.025)	(0.031)	(0.026)	(0.026)	(0.032)
Treatment	0.101***	0.107***	0.108***	−0.133***	−0.140***	−0.142***
	(0.024)	(0.026)	(0.026)	(0.025)	(0.027)	(0.027)
Event ×*Treatment*	−0.174***	−0.183***	−0.189***	0.259***	0.268***	0.270***
	(0.042)	(0.043)	(0.043)	(0.047)	(0.048)	(0.048)
Intercept	0.038*	−0.022	−0.033	0.005	0.153	0.169
	(0.023)	(0.140)	(0.140)	(0.024)	(0.147)	(0.147)
Turnover (ln)		0.005	0.006		−0.013	−0.015
		(0.012)	(0.012)		(0.013)	(0.013)
Volatility (ln)		0.024	0.040**		0.004	0.027*
		(0.017)	(0.018)		(0.013)	(0.015)
Covid-19 dummy			0.026			−0.001
			(0.023)			(0.023)
BTC returns (ln)			0.152***			0.122***
			(0.042)			(0.041)
# Obs	7,673	7,673	7,673	7,299	7,299	7,299
R^2	0.36%	0.36%	0.52%	0.47%	0.46%	0.56%

Table 4 provides additional evidence supporting theoretical predictions (Grossman, 1992; Seppi, 1990) and prior empirical findings in equity markets that downstairs large trades are more informed than upstairs block trades at the time they are reported. Smaller evidence exists when we compare non-block downstairs trades with block upstairs trades at execution time. These results partially support Gemini's decision to modify the minimum tick size for trading in the upstairs market.

4.4. The information content of delayed block trades in upstairs markets

In this section, we implement a staggered difference-in-difference analysis. We do this to examine the extent to which the publication regime encourages informed trading in upstairs markets as a consequence of the ability to delay reporting block trades. The analysis accounts for market-wide fluctuations. While the evidence reported above suggests that upstairs trades carry little (although significant) information in cryptocurrency markets, previous research found that the inability to report a block with a delay squeezes informed trades out of the upstairs market, making it important to study the reverse research question.

Table 5 presents the OLS regression results of the DiD analysis around the reporting time of block trades, with and without control variables according to Eq. (1). The dependent variable is the overall permanent price impact (information effect) of block trades in upstairs markets. Table 5 reports coefficients for buy and sell transactions. The first specification in both panels refers to the baseline case of our model, while the second specification includes volatility and the natural logarithm of total turnover as control variables. In the third specification, we add another control variable consistent with the literature, and a dummy variable to account for market fluctuations due to COVID-19 and Bitcoin speculative bubbles in part of the post-sample period. Our variable of interest, the interaction term between the treatment block trade sample and the event of changing the minimum tick size for executing block trades with a 10-minute delay, indicates a statistically significant decrease in the permanent price impact of block trades in cryptocurrency upstairs markets. Stated differently, there is evidence of a decrease in the information content carried by block trades to the market at the 1% significance level for both block buys and sells. This means that the ability to report a large trade potentially containing more information to be conveyed to the market with a delay discourages informed trading and, therefore, potentially decreases the information efficiency of the market by the decrease in the informativeness of those large trades.

This finding contrasts previous studies in traditional futures markets that document a decrease in the information content of off-market block trades due to the inability of market participants to report their private knowledge with a delay to exploit profit

Table 6
Difference-in-differences linear regression model around execution and reporting time of block trades. The table presents the OLS regression results of the DiD analysis around the reporting time of block trades, with and without control variables, according to the following equation:

$$y_t = \beta_0 + \beta_1 Event_t + \beta_2 Treatment_t + \beta_3 Event_t \times Treatment_t + \beta_4 X + \epsilon_t.$$

The dependent variable is the overall permanent price impact (information effect) of block trades in upstairs markets. $Event_t$ is an indicator variable equal to 1 from December 6, 2019, the post-rule change in minimum order size, and 0 otherwise. $Treatment_t$ is a dummy variable equal to 1 for large trades that have a lot size between 5 and 10 bitcoins and 0 for the control block trades with a lot size greater than 10 bitcoins. The interaction term $Event_t \times Treatment_t$ is our variable of interest and captures the marginal effects of being a treatment large trade in the post-size-change period. The first specification in both panels refers to the baseline case model, while the second specification includes volatility and the natural logarithm of total turnover as control variables. In the third specification, we add the Covid-19 dummy and the logarithmic returns control variables. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are within parentheses and coefficients are in percentage. The sample period covers December 6, 2018, to December 5, 2020.

	Permanent price impact					
	Buys			Sells		
	(1)	(2)	(3)	(1)	(2)	(3)
$Event$	−0.020	0.005	−0.016	−0.118***	−0.086***	−0.073**
	(0.026)	(0.026)	(0.032)	(0.027)	(0.027)	(0.033)
$Treatment$	0.013	0.042	0.042	−0.120***	−0.094***	−0.087***
	(0.025)	(0.027)	(0.026)	(0.026)	(0.028)	(0.028)
Event ×Treatment	0.005	−0.047	−0.026	0.171***	0.134***	0.124**
	(0.044)	(0.045)	(0.044)	(0.049)	(0.050)	(0.050)
Intercept	0.126***	−0.008	−0.004	−0.008	0.168	0.106
	(0.024)	(0.145)	(0.145)	(0.025)	(0.152)	(0.151)
Turnover (ln)		0.010	0.010		−0.019	−0.015
		(0.013)	(0.013)		(0.013)	(0.013)
Volatility (ln)		0.193***	0.150***		0.146***	0.055***
		(0.018)	(0.019)		(0.013)	(0.015)
Covid-19 dummy			0.027			−0.005
			(0.023)			(0.024)
BTC returns (ln)			−0.407***			−0.480***
			(0.043)			(0.042)
# Obs	7,673	7,673	7,673	7,299	7,299	7,299
R^2	0.06%	1.5%	2.61%	0.26%	1.96%	3.67%

opportunities. If the reverse is true, then traders should be motivated to hold their information as much as possible and, therefore, choose a size to trade that allows them to report their trade later to the market. Table 6 reports similar findings for the DiD regression models surrounding both the execution and reporting times of block trades taken together. If we expect a positive price impact for buys and a negative price impact for sells, then an inverted sign in the coefficient of the interaction term, our variable of interest, suggests a decrease in the magnitude of our dependent variable, the permanent information effect.

Although there is less evidence for block buys, Table 6 presents a statistically significant decline in the permanent price impact of block trades when these trades enable market participants to hold their private information about future cryptocurrency prices. This reinforces the rejection of our hypothesis that allowing traders to report a large trade with a delay increases the informativeness of trading and, in turn, potentially increases the information efficiency of the market. This also questions the effectiveness of the decision of the cryptocurrency exchange to decrease the minimum tick size threshold for block trades as it allows smaller and perhaps less sophisticated types of market participants to opt for upstairs trading. These results could also potentially be explained by the type of investors choosing to trade in this way. Although this is an interesting departure from prior research on traditional financial markets, these implications on retail and institutional investors remain somewhat speculative due to the lack of data.

In summary, large trades in both upstairs and downstairs cryptocurrency markets convey an important information component as per the evidence of their significant permanent price impact. Consistent with the extant literature, the information conveyed by downstairs large trades is greater than that conveyed by upstairs block trades. But, if this difference between the upstairs and downstairs markets exists on average, then what is the rationale behind the existence of cryptocurrency block trading facilities in the first place? As mentioned above, the literature has predominantly approached the upstairs market from the perspective of the trade initiator. However, every block trade necessitates the participation of agreeable parties on each side of the transaction. This prompts (Madhavan & Cheng, 1997) to argue that, at least in centralised markets, the main advantage of having an upstairs market might be for liquidity providers, and upstairs markets provide a platform for these traders to selectively engage in trades that have been vetted by block brokers. These brokers filter out trades that are likely to be based on insider information. Thus, the upstairs market may facilitate trades that would not otherwise occur on the continuous book.

Nevertheless, a notable departure from prior research is that the setting outlined in Section 2 enables us to account for the market makers' perspective rather than that of the trade initiator. This is due to the different way in which block trades are traded in cryptocurrency markets compared to centralised equities and futures markets. In cryptocurrency markets, market makers face an environment similar to a dark auction. They have little information regarding the trade and the counterpart against whom they are taking positions. Traditional markets, on the other hand, are more similar to out-of-the-floor private agreements between two (potentially informed) counterparties. Therefore, the cryptocurrency market setting examined in this study provides a reasonable explanation for our findings. The exchange's dedication to a transparent market-place permits the simultaneous electronic sharing of block orders with participating market makers.

4.5. Robustness tests

Following Comerton-Forde and Putniņš (2015), we perform a further analysis to measure the informativeness of block *vs* non-block trades in a different way. To this extent, we employ the vector auto-regression (VAR) model of Hasbrouck (1991) and estimate the cumulative impulse response for a shock in each variable of interest. After resampling our data at 1-minute intervals,[19] for each interval, we compute x_t^B and x_t^{NB} as the signed dollar volumes of block and non-block trades, and r_t as the Bitcoin log-returns in the intervals. Then, we estimate the VAR system as follows:

$$\begin{aligned}
x_t^B &= \mu^B + \sum_{i=1}^{20} \phi_i^B x_{t-i}^B + \sum_{i=1}^{20} \phi_i^{NB} x_{t-i}^{NB} + \sum_{i=1}^{20} \phi_i^r r_{t-i} + \epsilon_t^B \\
x_t^{NB} &= \mu^{NB} + \sum_{i=1}^{20} \theta_i^B x_{t-i}^B + \sum_{i=1}^{20} \theta_i^{NB} x_{t-i}^{NB} + \sum_{i=1}^{20} \theta_i^r r_{t-i} + \epsilon_t^{NB} \\
r_t &= \mu^r + \sum_{i=1}^{20} \lambda_i^B x_{t-i}^B + \sum_{i=1}^{20} \lambda_i^{NB} x_{t-i}^{NB} + \sum_{i=1}^{20} \lambda_i^r r_{t-i} + \epsilon_t^r.
\end{aligned} \tag{2}$$

Finally, we compute the cumulative impulse response ten minutes forward for a shock of 1 million dollars in block and non-block volumes, respectively, while holding the other variables equal to their unconditional means. Fig. 5 illustrates that a shock of roughly 20 Bitcoins (equivalent to 1 million dollars) in non-block volumes is associated with a higher impact on Bitcoin returns compared to a similar shock in block volumes. Therefore, confirming previous results, the permanent price impact of downstairs trades is larger than that of block trades. More specifically, Fig. 6 shows that the effect is reversed to zero after 10 min when considering the shock on block volumes in the pre-event period. However, we observe an impact in the post-event period, albeit small. On the contrary, the shock on non-block volumes impacts the returns with a higher magnitude in the pre-event period. Overall, the robustness tests largely confirm that non-block downstairs trades convey more information to the market compared to upstairs block trades, which is again consistent with the models of Seppi (1990) and Grossman (1992).

5. Conclusion

Our research contributes to the growing literature on market microstructure by providing the first empirical analysis of the market impact cost of trading large blocks in cryptocurrency markets. This study examines the price-impact dynamics of block trades in the realm of decentralised cryptocurrency markets, with particular focus on the information content of these trades under different reporting regimes. Our investigation is grounded in the unique context of Gemini's microstructure rule change and leverages proprietary microstructure data. It offers valuable insights into the market impact and informational efficiency of block trades, especially in a landscape where traditional financial market mechanisms intersect with the innovative sphere of cryptocurrencies. This contribution is significant, considering the increasing prominence of cryptocurrency markets and the unique characteristics they bring to the landscape of financial trading.

Our empirical findings reveal a nuanced picture of block trade price impacts in cryptocurrency markets. Consistent with the models of Seppi (1990) and Grossman (1992), and previous empirical research on traditional equity markets, we observe that block trades executed away from the central market have a smaller permanent price effect. This suggests that they are less informed compared to same-size trades executed on the continuous order book. Therefore, these facilities might not serve informed traders as intended. This outcome stands in direct contrast to conventional ideas underpinning the introduction of block trading facilities into cryptocurrency markets.

Furthermore, our analysis indicates that the transition from immediate to delayed reporting of block trades has a significant impact on the nature of trading. The general position held in the literature is that under the regime of delayed reporting, block trades are more likely to be informed, whereas immediate reporting diminishes the likelihood of informed trading. This shift suggests that the ability to delay trade reporting is a critical factor in the decision-making process of informed traders in cryptocurrency markets. However, a paradox emerges in our findings: while delayed reporting seems to enhance information efficiency by reducing the immediate price impact of block trades (temporary component), our results show that it simultaneously deters informed trading (permanent component). This raises questions about the effectiveness of delayed block trading reporting in ensuring information efficiency in cryptocurrency markets.

It is also noteworthy that our study extends the understanding of the upstairs market beyond the initiator's perspective, incorporating the viewpoint of liquidity providers. This broader perspective reveals that the upstairs market's primary role may

[19] We cannot select intervals with higher frequencies because of the limited availability of blocks at higher frequencies.

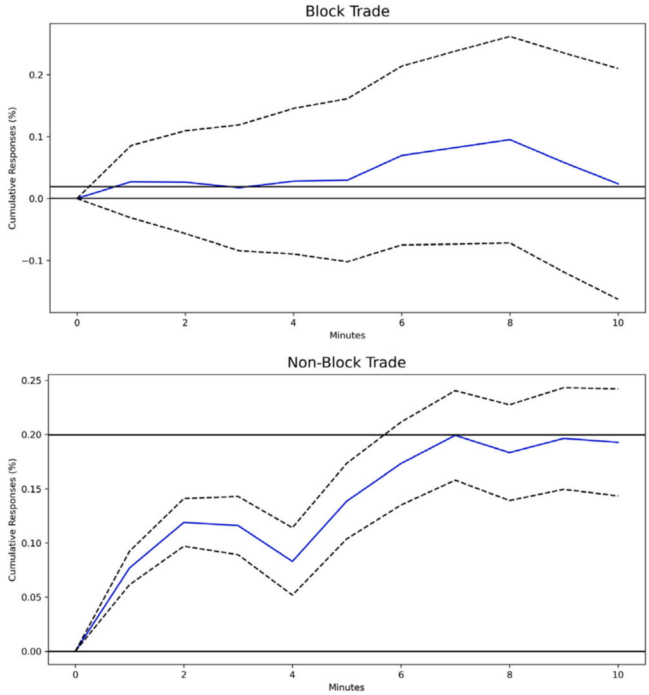
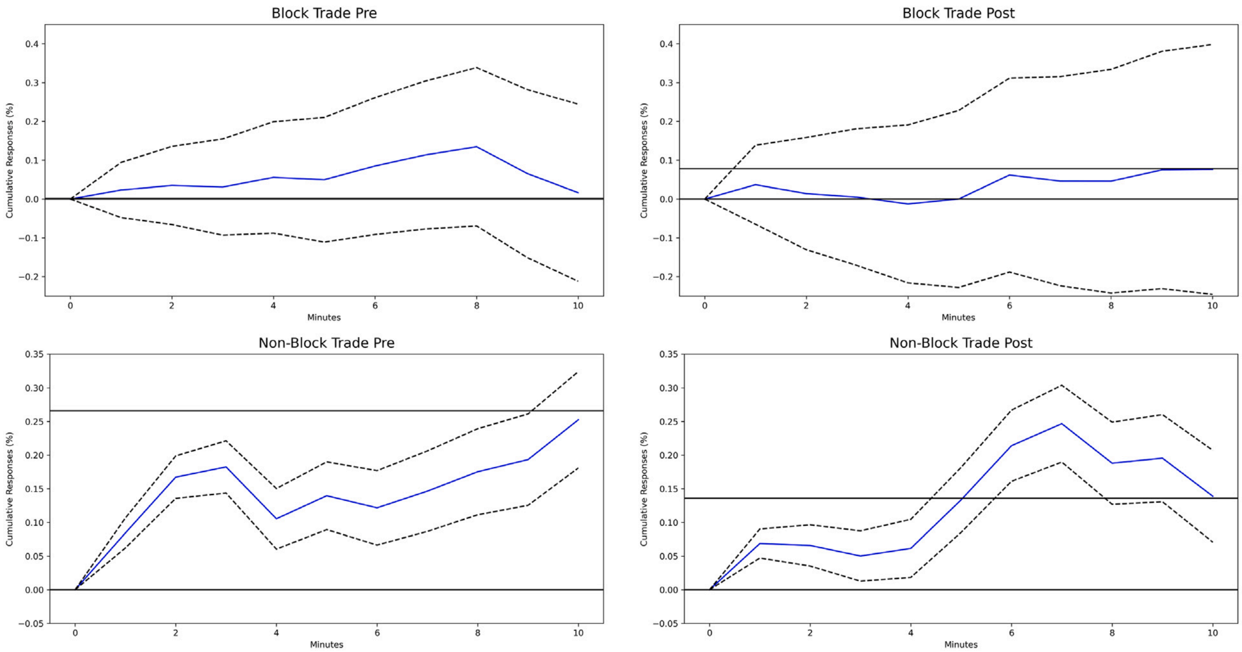


Fig. 5. Permanent price impact computed from cumulative impulse response function (total period).



(a) Pre-period (b) Post-period

Fig. 6. Permanent price impact computed from cumulative impulse response function (pre *vs* post).

not be serving the initiators of trades, but rather facilitating transactions for liquidity providers who might otherwise be hesitant to participate in the more transparent downstairs market. Indeed, as argued by Madhavan and Cheng (1997), upstairs markets provide a platform for market makers to selectively engage in trades that have been vetted by block brokers in traditional markets.

Ultimately, this study underscores the complexity of block trading in cryptocurrency markets and highlights the delicate balance between information efficiency and the mechanisms that govern trade reporting. As the market continues to evolve, further research is needed to fully understand the implications of these mechanisms on market behaviour, particularly in the context of an increasingly digital and decentralised financial world. One avenue for future research might be to examine the price impact of smaller-sized trades in cryptocurrency markets to shed more light on whether the information content of trades is an increasing or decreasing function of tick sizes. This will help us gauge to what extent cryptocurrency markets genuinely function like traditional financial markets — or whether new theory is required to properly model cryptocurrency market structures.

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Data availability

The authors do not have permission to share data.

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