On the effects of information asymmetry in digital currency trading

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Abstract

We report on two studies that examine how social sentiment influences information asymmetry in digital currency markets. We also assess whether cryptocurrency can be an investment vehicle, as opposed to only an instrument for asset speculation. Using a dataset on transactions from an exchange in South Korea and sentiment from Korean social media in 2018, we conducted a study of different trading behavior under two cryptocurrency trading market microstructures: a bid-ask spread dealer's market and a continuous trading buy-sell, immediate trade execution market. Our results highlight the impacts of positive and negative trader social sentiment valences on the effects of information asymmetry on observed trading patterns. This includes the spillover effect of volatile social sentiment, and the leverage effect when a cryptocurrency's value falls or rises in response to changing sentiment. Our results highlight how volatility arises in parallel with investors' reactions to public information and trade transaction volume. If the price falls beyond participants' expectations, a negative shock from new information may lead to more volatile social sentiment than a positive shock of the same size does. Our work supports the roles of investment and speculation for cryptocurrency by identifying an immediate impulse and a longer-term effect of economic variables in the presence of sentiment-led information asymmetry. We contribute new knowledge to the interdisciplinary literature on the financial economics of digital currency for a technological innovation that has matured earlier than many observers may realize.

Keywords: Asymmetric information, Cryptocurrency, Data analytics, Digital currency, Fintech, Informedness theory, Public information, Social sentiment, Speculation, Trading, Volatility

1. Introduction

Whoever is attuned to the prevailing mood around a digital asset would likely have an informational advantage. Monitoring social media could be one way to do this."

— Mike Brusov, CEO, CIndicator Capital (a quantitative digital currency fund) and Financial Council Member, Forbes, March 5, 2020

"It is better to debate a question without settling it than to settle a question without debating it."

— Joseph Joubert, French moralist and essayist, 1754–1826

The evolution of digital currencies with blockchain technology is one of the most exciting phenomena in the digital economy. Many blockchain networks for Bitcoin (BTC) and other altcoins have emerged with the goal of connecting traders.[1] Practitioners have recognized that they can help create value in different settings. Yet how such value is created and where it comes from are unclear. These issues are clouded by shared social sentiment, a form of public information, when unexpected effects arise in the market.

BTC transactions are influenced by the prevailing social sentiment in the market. This gives rise to information asymmetry, which exerts an impact on transactions in the ecosystem. The interplay of these factors

[1] Hereafter, we will replace cryptocurrency with BTC for brevity, as the focus of our work, without intended loss of generality.

affect and shape the economic landscape of the market, and its complexity also prompts us to closely examine the intersection of BTC and social sentiment. This requires exploration of public information and its influence on trading. This prompts investigation of transaction costs and information asymmetry. We must also explain investment and speculative behavior, by studying traders who have different information.

This research is positioned to contribute to fintech research.[2] We examine effects of *information asymmetry* related to public information in social sentiment posts by investors, traders and speculators, involving their observations and reactions to BTC and their subsequent trading activities (Lennart, 2020).[3] Trading participants may be *informed* or *uninformed* (Easley et al., 2008), based on whether they can acquire information that makes them more knowledgeable and effective in their BTC trading, investing and speculation activities in different market mechanisms (see Fig. 1, Appendix Table A1 offers a glossary).

We will report on trading in *dealer markets* with *quoted bid-ask spreads*, and in *continuous buy-and-sell order markets*, where traders' instructions to buy or sell are executed immediately (see Fig. 2). The topics we touch on include asset pricing, private and public information, informedness theory, decision-making in trading, and contrasting cognitive processes and trading styles. Past research on digital currencies has involved economic exchange, market reactions to different social issues, evolving market conditions, changing interest rates, and other issues that affect value (Singer, 2022). We investigate if and how sentiment linked with trading creates value in the market, based on participants' improved ability to make more rational and value-aware trades, to support their effort as investors or speculators. As a result, this article is more about technology, information, digital business, and digital currencies than it is about financial economics, trading strategies, or market operations.

Through the Finance, Economics, and Market Microstructure literature, we have examined how BTC-related social sentiment is formed on social platforms that support market trading. Information asymmetry occurs in situations in which only some traders have information access to important and trading-relevant content, while others have insufficient or no access because full information is intentionally not provided or unavailable. This is known to aggravate market risk for any asset, where there is perceived uncertainty about the goods' quality, value, or functionality.

Cryptocurrencies, unimpeded by intrinsic value tied to physical commodities or tangible underlying corporate assets, are affected by uncertainty. This occurs due to the unclear basis for their value, high price volatility over time, and often-dramatic price responses to news of the day. Asymmetric information has existed in financial markets for many years, and many participants tend to think of information as not being evenly distributed across participating traders, investors, and speculators (Spencer, 2000). There has not been much research on social sentiment's role in information asymmetry under different digital currency market microstructures. Nor has there been much effort focused on researching how investing and speculation have been affected in our market setting (Singer, 2022). Our research addresses knowledge gaps for this emerging technology and market setting.[4,5]

We will report on two studies with individual empirical analyses. Each focuses on information asymmetry effects related to our overarching research topic of BTC trading[6]:

- **Study A (Information Asymmetry & Trading).** We seek to understand observable behavioral patterns of digital currency trading with social media information and sentiment sharing. We gather evidence about how information asymmetry may influence more-informed versus less-informed traders. We focus on more granular research questions (RQs) on social sentiment to identify *patterns of BTC trading* and social sentiment—as *asymmetric information*, which is tied to bid-ask price dealer-intermediated trade and buy-sell continuous market trading.
- **Study B (Investment vs. Speculation).** We shift to BTC trading with different levels of public information and transaction costs, and how decision-making may differ for investors versus speculators. We seek evidence to understand trading patterns based on the variables useful to explain the volatility of public information-based information asymmetry.

We use daily BTC trading data over four months in July-October 2018 in South Korea. During that year, BTC rose to a capitalization value of US$133 billion, representing 46% of the global cryptomarket (Suberg, 2018). By 2023, it was about ten times higher at more than US $1 trillion.

We apply social sentiment valence variables that reflect the perceptions of participants for a digital marketplace that supports BTC trading.[7] We study two *market microstructures*[8] that offer different mechanisms for trading: exchange based on bid-and-ask quotes in a dealer's market and a continuous BTC market with immediately executed buy-sell orders from its participants.[9] Our research emphasizes social sentiment influences. We seek evidence to support the impact of social sentiment for observed information asymmetry variance and sentiment valence variance.

In a typical time-series, the *structural dependencies* are explained by

[2] The issues have been explored, along with other financial services technologies, their impacts, and assessments of the emerging research and trends in several special issues of this journal and other fintech-focused articles. The latter address relevant topics, literature surveys and research directions on fintech foundations (Milian et al., 2019) and blockchain in banking. Other articles are on payments (Henningsson and Hedman, 2015), blockchain innovation (Treiblmaier and Sillaber, 2021), digital money and investments (Au and Kauffman 2008; Ng et al., 2021)—to chronicle the emerging technologies.

[3] In a "Fintech Foundations" special issue, cryptocurrency issues related to the present research were studied by Chen (2019). They focused on *initial coin offerings* (ICOs) and applied *multi-channel communication theory* to assess the relationship between information signals, human cognition, and examined trade-related information asymmetry.

[4] Useful references to understand issues on information in financial markets are: Agudelo et al. (2015) on how market information is gauged, which is useful for this study of social sentiment, information asymmetry, and observable trading behavior; and Apergis et al. (2021) on how market mechanisms affect BTC prices and influence participant behavior.

[5] A context that motivates this is the informal, public communication channel, Twitter (now X). It has become increasingly popular with business leaders, politicians, and the public, as well as for study by university researchers. The other context is digital currency exchanges, where investors and speculators can buy or sell blockchain-based digital money. They also can trade digital monetary units, fiat currencies, and other assets that governments declare to be legal tender, too.

[6] We appreciated advice from Maurizio Naldi and Jose Parra-Moyeno to create a single integrated article that covers information asymmetry in BTC trading in two separate studies with RQ variations.

[7] For the sake of simplicity of exposition, we will not distinguish between *measures* and *independent variables* in the various models we estimate and the results we report and explain. They both vary over a range of values and are used in models that we lever to obtain a reading on what factors drive different aspects of BTC trading.

[8] Kissell (2014, p. 47) defines *market microstructure* as the "*structure of exchanges and trading venues (e.g., displayed and dark), the price discovery process, determinants of spreads and quotes, intraday trading behavior, and transaction costs.*".

[9] The average bid-ask spread for BTC is relevant here. Aleti and Mizrach (2021, p. 194) reported that "*spot-market median trade sizes are under US$1,300 but exceed US$18,000 on the Chicago Mercantile Exchange. Bid-ask spreads average 0.0298%. Trade sizes of over US$1 million move the market by less than 1%.* [*Also*], *2.5% of trades and 15.5% of cancellations on Coinbase take place within 50 ms. Bid-ask spreads exceed 0.8% for only 226 seconds.*"

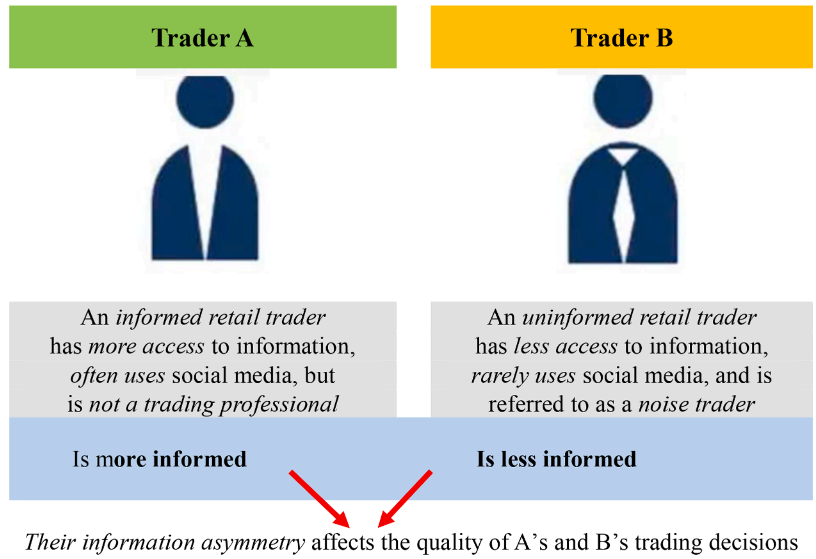

Fig. 1. Trader Informedness and Asymmetric Information in Market Trading. Note. Adapted from Dharma and Vaidya (2023) with our own construction.

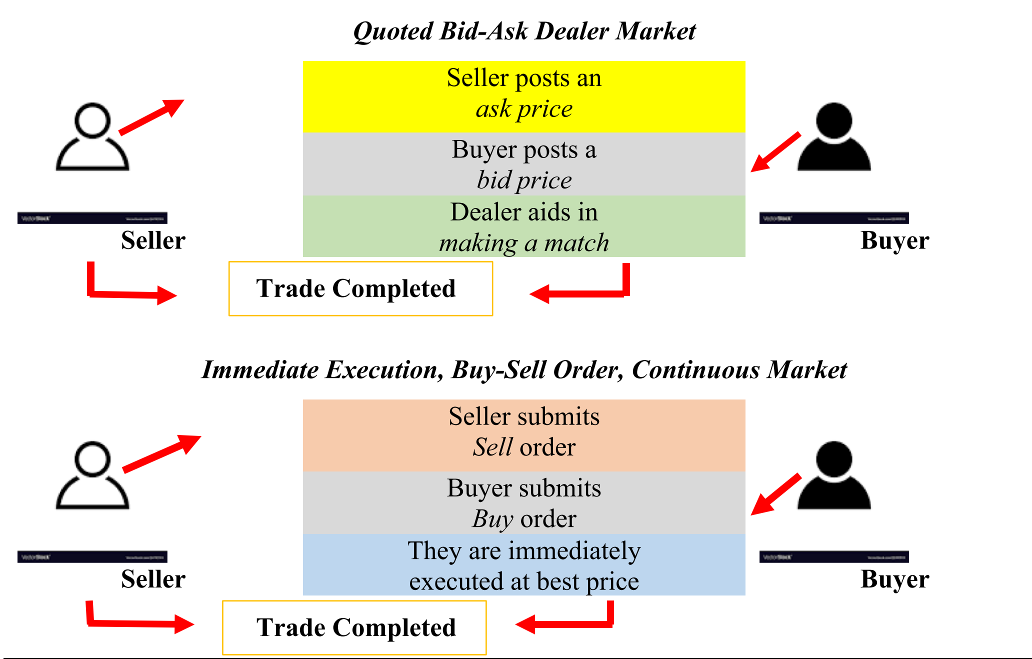

Fig. 2. Quoted Bid-Ask Dealer Market vs. Continuous Market Buy-Sell Orders. Note. In a quoted bid-ask price market, a dealer must match bid-and-ask prices by simultaneously buying from and selling the asset to complete trades. With continuous trading though, the market-maker is required to immediately execute the buyer's order by selling them the asset. We thank Jonas Hedman for his suggestion to clarify the market microstructures to enhance reader understanding.

the *conditional expected values* of the model's variables as averages over time. Dependency structures, such as the *volatility of asymmetric information*, are explained only when the subordinate states between the variances are fully described over time.[10] We present the RQs and our modeling set-up and empirical data analytics for each study separately:

- **RQ1 (Assessing Asymmetric Information Effects)**: *Does sentiment-driven social news impact asymmetric information volatility and BTC market outcomes? Do positive and negative news effects on asymmetric information-bearing sentiment lead to transient or lasting effects?*
- **RQ2 (Understanding Transaction Patterns)**: *For value volatility, what exerts a greater influence: public information and social sentiment or transaction patterns? How do information asymmetry, transaction costs, and public information interact to affect trading value volatility?*
- **RQ3 (Gauging Sentiment-Driven Price Momentum Influence)**: *How do public information and social sentiment influence the upward and downward movements in BTC market prices during periods of positive or negative price momentum?*

We collected data on BTC transactions in two contexts: for quoted

[10] *Volatility* is the degree of variance observed in market trading contexts when the price of an asset becomes less predictable, resulting in sharp price movements. We treat it as the rate at which information asymmetry increases or decreases for new public information in social sentiment that may affect BTC prices and market-trading behavior. It also suggests the range of impacts of social sentiment across which traders' perceptions of information asymmetry tend to increase or decrease.

bid-ask trade volume in a dealer market, and immediate-execution buy-sell volume in a continuous BTC market. Our inquiry centers on the impact of public information, including social sentiment, observable trade transaction patterns, and other accessible measures and variables on BTC market value volatility.

2. Information asymmetry and digital currency

2.1. Empirical research preliminaries for Study A

We draw on the following streams of literature for this research: cryptocurrency linked with social media; information asymmetry in the BTC market; and the nature of social media information. Digital currency-related coverage is still limited in IS and e-commerce research journals.

BTC's links with social media. Cryptocurrency built upon blockchain technology, such as BTC, Ripple, Ether, Binance Coin, and others, have had enormous impacts in e-commerce. The emergence of BTC has influenced the fintech sector's growth and development, along with digital wealth management services (Gomber et al., 2018), and *central bank digital currency development* (CBDC) (Di Giammaria et al., 2023). In terms of market microstructure, the factors that affect the value of digital currencies, especially BTC, have also been studied (Mai et al., 2018). BTC markets have acted like stock markets, only with greater price volatility. The link between BTC and Google search have been essential to its capitalization (Kristoufek, 2015). The connections among web visits, popularity, and firm equity value have similar bases.

BTC prices are predictable using sentiment data posted on news sites reported by experts (Karalevičius et al., 2018). As the BTC market matures, news increasingly can predict the value of BTC in the short term. Reddit sentiment posts in social media are also known to explain its value volatility (Bukovina and Marticek, 2016). But there is difference between the marginal effects between negative and positive sentiment. Positive sentiment may lead to increasing BTC value. Similar work on price prediction and returns to altcoins based on social sentiment has been done (Steinert and Christian, 2018), and a lot of evidence has become available.

Information asymmetry in the BTC market. Think of information asymmetry as unevenly-distributed information across market participants, which may lead to adverse selection and moral hazard in their decision-making processes. It can also bring about the demise of an entire market when it operates without an effective signaling and reputation mechanism. In BTC markets, information asymmetry is viewed as a problematic issue, as a result, as in the stock market (Singer, 2022).

Information asymmetry for BTC has been stronger than for stocks (Park and Chai, 2020). Informed traders tend to transact based on economic policy uncertainty and what is believed to be privileged information about digital currency prices. The reason is that: "*in an information-efficient market, investors cannot obtain abnormal returns using privileged information*" (p. 4049). In recent research though empirical evidence has shown that BTC markets tend to be only weakly efficient (Yi et al., 2023).

BTC is prone to information asymmetry because the related information has not had enough time to accumulate into a consistent single-source, large-scale data corpus so it can be fully studied (Lindman et al., 2017). Thus, traders have difficulty obtaining data they think they need. Second, information disclosure systems to mitigate information asymmetry among traders also have not been effectively established. Third, the market has properties of imperfect market microstructure. So, information is not always distributed equitably (Easley et al., 2010) and information asymmetry is unavoidable. The market microstructures may further intensify asymmetric information among traders, too (Park and Chai, 2020).

2.2. Study A: Data, variables, modeling, and methods details

Study A examines social sentiment impacts on information asymmetry that arise in BTC trading via bid-ask dealer and continuous-execution, buy-sell order market daily trade volume.

Research approach. The stages of our research process to produce both studies' results are laid out in Appendix Fig. A1, which consists of:

(1) **RQs & goals.** This stage defines our approach, which addresses a research problem and management science-focused RQs to explore hypotheses via theory, models and data, and data analytics. We also set the overall goals of this inquiry.
(2) **Data prep & sentiment analytics.** We did data capture, cleaning, and dataset preparation work. We explored sentiment analytics, tools, models and stat tests to support and track data, and produce convincing findings.
(3) **Modeling & estimation.** We use sentiment analysis to estimate the independent variables' effects to explain daily trade volumes for two market microstructures. We focused on time-series stationarity and non-stationarity issues to build revised models and appropriate tests.
(4) **Research issues and findings.** The final step is to explain our findings on: the spillover and leverage effects of social sentiment and impacts on BTC trade volume outcomes for the microstructures; and the asymmetric volatility of social sentiment when the sentiment valence is negative.

During 2018, there was no officially licensed market for cryptocurrency trading in South Korea, though the country was open to such trading and regulation. Investors used private, 24-hour exchanges to trade. We acquired transaction data from Bithumb (https://www.bithumb.com), with its textual content in Korean. We did data collection for closing BTC prices and daily trading volumes.[11] We obtained BTC social sentiment from Twitter posts. Our web crawler used Selenium and Python's Beautiful-Soup library to parse HTML and XML in sentiment text. We did sentiment analysis for post-processed data to record variables for the *Tweet* counts, and *Pos*, *Neg*, and *Neu* sentiment. The notation and definitions of variables we collected daily from July-October 2018 are included in our analysis (see Appendix Table A2).

News, price changes, *PIN*, and trade volume. When new information becomes available, there is a BTC supply increase or decrease in the related dealer market, via *QBid* and *QAsk* price-driven trade volumes; this occurs in the continuous market *CMBuy* / *CMSell* buy-sell trade volumes, too. We also present the *probability of informed trading* (*PIN*), and dealer market *QBid* / *QAsk* (bid-ask) trade volumes and continuous market *CMBuy* / *CMSell* (buy-sell) trade volumes (see Fig. 3).

The *probability of informed trading (PIN)* in a market is based on the ratio of informed trade transactions to total trading volume during a day. This offers a useful estimate of information asymmetry for our market setting. We employed different methods to estimate information asymmetry of social sentiment, such as *maximum likelihood estimation* (MLE) to obtain the *PIN* parameters.[12]The market does not capture who were the informed traders, but *PIN* is known to be a high-quality empirical measure. So, we used *PIN* to estimate uninformed and informed traders' participation (see Appendix B, Remark B2).

Twitter has garnered attention from researchers across disciplines, including for disseminating information and fostering collaboration

[11] The largest exchanges by trading volume in Q1 2023 were: Binance at US $9.32 billion, Coinbase at US$1.32 billion, and Kraken at US$569.40 million (CoinMarketCap.com, 2023). By trade volume in Korea in March 2023, the leaders were: Upbit at US$2.07 billion, Bithumb at US$208.71 million, and CoinOne at US$62.09 million (Statista, 2023).

[12] Tools to implement this and related proxies for information asymmetry in trading are available in R Statistics.

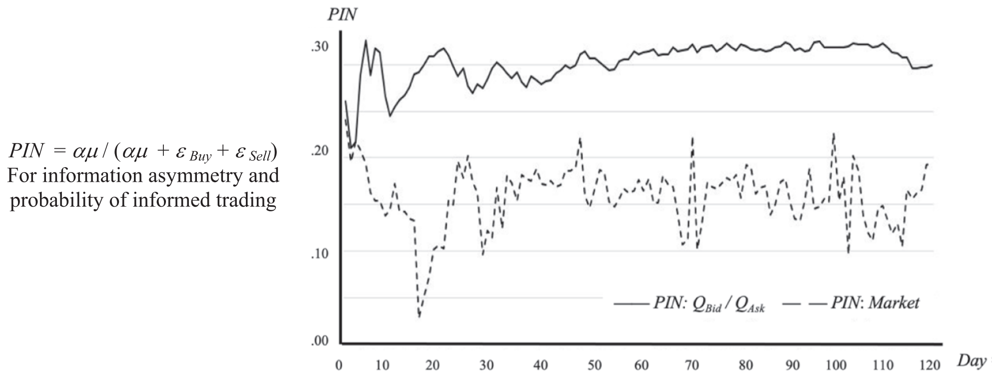

Fig. 3. ***PIN* for Bid-Ask and Buy-Sell for Daily Trade Volumes.** With *PIN*, BTC traders estimate market value with trading information, based on good and bad news that arrives. We, in contrast, estimate investment information based on participant trading volume: we can't know their estimation processes.

(Honey and Herring, 2009). Social media emerged as a tool for distributing information during natural disasters or social crises (Oh et al., 2013). The swiftness with which information spreads plays a crucial role in determining whether it affects stock prices or requires a longer duration, possibly spanning several days to achieve full dissemination (Hong and Stein, 1999). Empirical investigations into networks have revealed that the distribution of connections is not random. Instead, networks feature hubs and individuals with more connections than the average. They often function as opinion leaders, expediting the rapid propagation of information throughout the network (Barabási 2002). Twitter created an ideal environment for studying social sentiment and trading behavior correlation as a result.

BTC-related sentiment posts. We carried out the following series of processes: Social-sentiment data are related to Bitcoin (with a Korean *selector query* 비트코인) gathered from Twitter. Its API has limitations, including restricted access to historical data. So, first, we developed a custom web crawler using Python's Selenium library to collect data. 154,783 tweets were collected. Noisy data (ads, wallpapers) were unsuitable. Filtering was implemented, resulting in a refined dataset of 100,120 tweets. It then underwent additional noise and consistency preprocessing. Second, we restructured the tweet contents for CSV format. In Excel, tweets containing newline characters are a single data unit since CSV treats each line as separate data. We standardized words with similar meanings but varying forms into a consistent format. Some were converted to their original forms and others with diverse representations were unified into their original term. Last, we cut URLs, special characters, and numeric data, retaining the essentials for analysis. We categorized the data into neutral, positive, and negative sentiment with various tools.

Defining social news based on our data manipulation. Social news is:

> "*News which is published, reported or shared by an ordinary user through a social media platform is considered as social media news. This includes … video, photo, or audio formats"* (Beheshti-Kashi and Makki 2015, p. 8).

Social posts can be considered as media news in financial markets. For example, Ranco et al. (2015, p. 1) did causal inference analytics for the sentiment-price relationship, and found that the:

> "*Sentiment polarity of Twitter peaks implies the direction of cumulative abnormal returns*," and "*the amount of cumulative abnormal returns is relatively low (~1–2%), but the dependence is statistically significant for several days after the events*."

Smith and O'Hare (2022) reported a different opinion though:

> "*There is very limited correlation between Twitter sentiment and price movements, and this does not change much when returns are taken relative to the market or when the market is calm or turbulent. There is almost no correlation under any circumstances between non-financial news sources and price movements, however, there is some correlation between financial news sentiment and stock price movements.*"

To ensure we had good data, we identified Bitcoin social media news from posts on BTC and cryptocurrency trading and assessed social sentiment content. The procedure we used is common in social media news studies of financial market trading, and price and volatility analytics. Our sentiment analysis used a three-way classification with positive (*Pos*), negative (*Neg*) and neutral (*Neu*) valence.[13] Classification is based on the polarity of vocabulary units in each post. To classify sentiment, a *sentiment lexicon* with polarities was used. We constructed a dictionary for the BTC market for the sentiment valences.[14]

We describe the *PIN* derivation and how we obtained the informed BTC trading volume, while addressing information asymmetry (see Appendix B, Remark B2). Our definition of *PIN* may seem circular in its logic due its use of informed trade transactions, but this is not the case. Each *PIN* is based on BTC data with fluctuating prices. Estimation is found via the probability of receiving private information (α) and receiving positive or negative news information (δ). When the likelihood of negative news rises, a decline in BTC price should occur. The α and δ relationship thus reflects a buy-sell trade imbalance, and changes in BTC prices can be assessed this way. Price changes are due to other factors as well though.

2.3. Study A: Estimation results and empirical observations

We now present this study's results based on our methods sequence for the impacts of social sentiment on BTC trading, with informed and uninformed traders, and findings for the explanatory variables.

Modeling social sentiment with autoregression models. The *generalized autoregressive conditional heteroskedasticity* (GARCH) model is a candidate for assessing information asymmetry and social sentiment

[13] For sentiment analysis, we did *morpheme analysis* for relevant bases and add-ons (*e.g.*, "`tradability`" = the base "`trade`" + the add-on "`ability`"). We used Twitter data, where spelling, etc. are inconsistent. We isolated nouns as keywords, and applied *RHINO*, a Korean language tool to separate them and then do morphological analysis for 100,000+ entries.

[14] We first determined the vocabulary to include. Failure to include a term may result in its exclusion during sentiment analysis, even if it appeared in posts. To mitigate this, we analyzed Twitter data and constructed a sentiment dictionary for the nouns we identified. We established valences via panel participants for 282 positive, 794 negative, and 21,549 neutral words.

Table 1
Results for *Tweets* (Social Sentiment) and δ (Low Signal from *PIN*).

Variables	ln(*Tweets*)	Prob (δ) *LowSignal*
• **Mean equation**		
Constant	**4.45*****	**−0.07****
ln (*Tweets* (-1))	**0.28*****	**0.01*****
δ (-)	—	**0.97*****
• **Volatility equation (based on variance)**		
φ (Constant)	**−2.66****	**−0.84*****
η (*ARCH*)	**0.53****	−0.02
θ (*GARCH*)	0.20	**0.99*****
λ (*Leverage*)	−0.08	**−0.02*****
ρ (*Spillover*)	—	**−0.26*****
R^2	0.10	0.39
DW	1.79	2.34
LL	−4.61	288.29
AIC	0.18	−4.71

Note. Signif. as earlier; '(-)' means a variable is lagged, and '(-1)' means the δ variable is lagged 1 period.

Table 2
Spillover effects of social sentiment on asymmetric information.

Variables	Information Asymmetry	
	Dealer Market Trade Volume	*Continuous Market Trade Volume*
• **Mean equation**		
Constant	**0.05*****	**0.08*****
Pos (-1)	0.00	0.00
Diff (*Neg* (-1))	0.00	0.00
InfoAsym (-1)	**0.83*****	**0.53*****
• **Variance equation**		
φ (AR(1)	**−4.45*****	−4.31
η (*ARCH*)	−0.05	**0.48****
θ (*GARCH*)	**0.99*****	0.25
λ (*Leverage*)	**0.29*****	−0.10
ρ_1 (*Spillover*)	**0.45*****	0.15
ρ_2 (*Spillover*)	**0.23*****	**−0.37****
R^2	0.61	0.23
DW	1.39	2.26
LL	427.92	264.88
AIC	−7.08	−4.32

Note. Diff = first diff.; (-1) = 1 lag; DW = Durbin-Watson stat; LL = log likelihood; similar signif. levels.

variance, and *autoregressive conditional heteroskedasticity* (ARCH) model is of similar relevance for studying how news and public information may affect BTC prices.[15]

The GARCH model imposes constraints on the parameters for conditional variance to be positive. This may limit the conditional variance process more than needed though. When BTC's value goes beyond trader expectations due to a negative shock, this may cause more volatility than a positive shock of the same size—a *leverage effect*. We employed the *exponential general auto-regressive conditional heteroscedastic* (EGARCH) *model* and its conditional variance, EGARCH (p, q) (Kawakatsu, 2006). We applied this with (p,q) set to (1,1) to analyze sentiment spillovers on social channels for BTC trading and price.[16]

Lagged sentiment, spillovers, leverage, and asymmetric information effects. We investigated the relationship involving spillover and leverage effects between information asymmetry via *PIN* and positive and negative social sentiment related to BTC trade volume using slightly different modeling specifications for the market microstructures. We estimated a model with the *Pos* and *Neg* sentiment variables separately and together but only report the joint results. The estimation results show that *Tweets* for social sentiment were associated with the low *PIN* signal δ in the market. Also, the spillover effect of *Tweets* (0.01***) for a low probability of information asymmetry was significant at 1%. So, if *Tweets* rose by 1%, δ also increased by 0.01% (see Table 1). We observed no marginal effects for either valence on information asymmetry though, but there is evidence that spillover and leverage effects on sentiment volatility were present, as we discuss show below (see Table 2). Its sentiment estimate (0.29***) has a significant marginal effect.

For BTC, social sentiment does not have a significant impact on information asymmetry by itself. Its volatility has a notable impact on the volatility of information asymmetry though. The estimation results for information asymmetry in the BTC market indicate that the λ value for the bid-ask spread had a positive value. This demonstrates the presence of non-leverage effect at a significance level of 1%. The asymmetric effect of social sentiment volatility is identified by observing that unexpected positive social sentiment has a greater impact on increasing information asymmetry volatility than negative social sentiment of the same magnitude. Also, the *persistence parameter* values, $\eta + \theta$, are close to 1, indicating that the influence of volatility lasts a longer time. If the persistence parameter has a value greater than 1 though, then the estimated conditional variance equation is not stable (see Appendix Fig. B3).

3. Study B: Investment VS. Speculation in BTC trading

The more active that trading activities are, the shorter the time information takes to affect market prices and perceived value. But what factors have greater impact on price volatility? We seek to understand the role of information asymmetry in this respect. It occurs when different trading agents in a financial market are not able to obtain the same public information, irrespective of its source. Instead, some will be able to obtain essentially private information since no other traders will be privy to it. This leads to a market of more or less well-informed traders, which increases the likelihood that some will not know information that others have access to that guides their decisions.

This also enables us to assess the impacts of variables that market participants can observe but do not know the extent to which information asymmetry is affected by. So, the market may devolve such that many participants become uninformed noise traders. We will study supply and demand factor evidence that creates positive and negative market price momentum effects, too. These make the present study's research inquiry sharply different from that of Study A.

3.1. Study B: Empirical research preliminaries

Other research streams support our research inquiry, based on theoretical issues for investment vs. speculation; the reflective and reflexive cognition perspectives on approaches for decision-making and BTC value assessment; and price momentum/volatility, public information, and demand-and-supply issues.

[15] The *Jarque-Bera statistic* (JB) indicates if asymmetric information and social sentiment are not normally-distributed based on their variance at 5% significance. We also performed an *augmented Dickey-Fuller* (ADF) *unit root test* to identify if the variables were stationary or had changing relationships over time in the dataset. One must do this to judge the stability of time-series data to see if there may be a *false regression* that does not have economic significance. The unit root test results showed that some variables have unit roots. We used the first differences, and then the time-series data became stable at 5% significance for the t value.

[16] When modeling volatility involving lagged autocorrelation, one must consider the characteristics of the estimation models in the ARCH family of econometric methods. In particular, as Brownlee (2019) claims, a "*lag parameter must be specified to define the number of prior residual errors to include* …" Thus, we selected an EGARCH(p,q) model with (p,q) = (1,1). This denotes the number of lagged variances and the lags of squared-residual errors to include, and how to seed the estimation process.

Investment vs. speculation. With digital currency, there has been heated debate. The issues are complex and hard to resolve through discussion, as we noted at the outset of this article (de Chateaubriand, 1838). "*Is trading cryptocurrencies an investment or speculation*?" is a good example. This has merit for study and explanation, but not superficial opinions. One side may argue that technology investments will lead to the 4th Industrial Revolution and transform the financial ecosystem. The other may counter that digital trading is just pieces of data with nothing to do with the underlying technology or asset—other than the trade volume, time stamp, and posting advice though represent underlying gambles (Baur et al., 2018).

Speculation is known to be associated with asset bubbles in asset markets. Excess volatility in market prices contradicts the efficient markets hypothesis. The determinants of market efficiency using past trading information have also been examined (Li and Wang, 2017). Efficient pricing reflected improvements in asset supply but did not reduce its speculative elements. Digital currency functions more as a speculative asset due to its high volatility (Blau, 2017). BTC is mainly used as a speculative asset, and most traders perceive it to be useful that way (Baek and Elbeck, 2015). For low adoption for payments, BTC may function less as a currency than expected. Its use as an investment has been overlooked also, as others view it as a currency with limited uses, an exchange medium, and a vehicle for speculation.[17] Thus, the relationship between speculative trading behavior and market value volatility remains a worthwhile topic to study.[18]

Reflective and reflexive cognition. Previous findings imply that trading occurs with different cognitive approaches and impacts, with shorter-term and immediate impulses, and with longer-term and more systemic impacts. This is aligned with human thinking, which occurs with *intuitive* or *reflexive cognition* and *rational* or *reflective cognition* (Tversky and Kahneman, 1981). Decisions can be made through nearly effortless information processing as if reflexes are at work, as opposed to via laborious, systematic information processing limited by resources for thought. BTC trades apparently can act as investments or as speculation—depending on their intended purpose.

Reflexive cognition generates an impulse to engage in some behavior. Reflective cognition, in contrast, leads to reflection on subsequent impulses and later behavior. It determines if they match a decision-maker's objectives and enables them to decide if to make some action. These forms of cognition don't operate separately though; they interact in decision-makers' minds to set up their choices.[19] If the approaches conflict, a tug-of-war between them may influence a trader's decisions and their resulting actions.

BTC price volatility. The volatility of market value and the systematic feedback that market participants receive may be useful indicators of asset value. One can come up with optimistic or pessimistic vales though. Price volatility can be estimated and assets allocated based on short and long perspectives. One also can verify if an asset's price is trending up or down, and if one's judgment will be right or wrong, based on price moves. So, if someone trades as a forecast predicts, then the trader probably is pursuing a strategy with longer-term value in mind. Else, they may be making a more speculative transaction.

Evaluating asset exchange this way mat yield debatable answers – even for stock, though knowledgeable Finance professionals aver that absolute and relative value approaches are reliable.[20] Yet a limited amount of fundamental investment information is available for market participants to use *valuation theory* (Damodaran, 2012). Others have suggested *uncertainty reduction theory* (Berger and Calabrese, 1975), which forces market participants to seek information on specific dimensions of value instead and the environmental forces that affect them to reduce uncertainty.[21] When buyers and sellers are willing to transact though, the result is their valuations will match up. This way, an economic transaction can be completed, resulting in an immediate reading of market value via price. Investors are always looking for prices lower than their owners' absolute or relative valuations. This may cause them to make investment actions, by buying what they perceive to be undervalued or selling what may be overvalued—or both.

BTC prices change dynamically. They are affected by economic news, diffusing social sentiment about the asset category, and opportunities for future value appreciation. So, observers recognize that BTC is volatile but may not serve the same purpose for different participants. Madhavan (1996) examined volatility due to public information, including news, social sentiment, abnormal trends, the trading behavior of market participants, and other transaction costs. Market value also subtracts transaction cost and adds a premium for the information asymmetry present.[22] This way, one can assess the market flow, and trader investments = and speculative actions for how information asymmetry, transaction cost, and public information from sentiment and other sources interact. This applies to both BTC and other financial transactions, too.[23] Fundamental economic variables for demand and supply also affect the process and interact with one another, influencing price and volatility in the short and long term. More research is needed to discover evidence to demystify the transaction processes for investors and speculators.

3.2. Study B: Data, Variables, Modeling, and methods

We assess the impacts of public information, transaction costs, and information asymmetry in BTC trading, while considering its demand and supply, and the extent to which it serves as an instrument for longer-term versus shorter-term speculation. We continue to use the bid-ask dealer and the continuous buy-sell order market daily trade volumes.

Research approach and variables for Study B. Our research approach and methods sequence are depicted (see Appendix Figure b1). We again apply sentiment analysis to pre-processed data to classify them for the analysis of dealer market bid-ask and continuous market related to buy-sell trade volume variables. The dataset we used covers the same market in South Korea and the same period as in Study A (see Appendix Table A2 again).

[17] Speculation may not dominate all behavior though. BTC may represent an alternate investment in an emerging market. So, inefficiency is expected, but should improve over time. Blau (2017) did not find evidence that speculation drove the rise and drop in BTC market value though. Aalborg et al. (2019) reported that higher trading volatility improves sentiment volatility forecasting.

[18] The returns, volatility, trading and transaction volume of BTC, the changing number of addresses, and the Chicago Board Options Exchange Volatility Index for S&P 500 index options did not improve it. Only the number of Google 'bitcoin' searches did.

[19] For example, chess players seem to intuitively judge the quality of their possible next positions and quickly choose the best among them, while others may rationally assess their positions with specific metrics in mind.

[20] The *absolute value* of a stock is based on the intrinsic value of its underlying assets, while *relative value* is based on comparing a stock to others in its class and assessing the value implications of the differences between them.

[21] Human behavior, meanwhile, is largely aimed at satisfying a person's needs, though digital currency seems more utilitarian.

[22] If someone buys BTC via a market order, they must buy at a higher price than current market value. And if they sell it, they will receive less. Information asymmetry adds a transaction benefit beyond the spread for traders who have it.

[23] Informed traders minimize their information exposure and determine their optimal trade quantities by observing uninformed traders. If trade activities of such traders increase, the information exposed will be less, so informed traders will increase their trades. But if price volatility reflecting the transaction cost increases, informed traders may not increase their trades due to risk. Uninformed traders, meanwhile, may act as if they are trading random quantities, even if there is observable information asymmetry.

3.3. Study B: Estimation results and empirical observations

We now discuss our data analytics and statistical tests. We begin by assessing transaction continuity for market efficiency. We then estimate the mechanism for BTC value. We apply a *unit root test* for the modeling variables' stability over time in our dataset. We also will use a *vector error correction model* (VCEM) when it is necessary to correct the time-series data if a unit root is present. We then shift to the decomposition of observed variance in BTC market value. We apply disequilibrium adjustments to normality under conditions indicated by the cointegration coefficient of our models, and the effects of short and long-term trading. We offer new results for public information on BTC prices.

Transaction flows and continuity. When examining transaction flows of traders in terms of BTC value, *transaction continuity* will occur. These are *successive increases or decreases in traded transaction volume* that appear. This reveals a trend that characterizes the orders of informed traders who are transacting a large amount of BTC. The transaction *Continuity* probabilities were 65%, 82%, and 70% for traders who made informed and uninformed *Buy* and *Sell* transactions (see Table 3, top half). These three percentages are probabilities of an increase or decrease in the market value of transactions, for informed transactions (2nd column), and for uninformed buy (3rd) and sell (4th) transactions.

In bid-ask trade volume terms, in contrast, the transaction continuity probabilities were 54%, 53%, and 52%—lower for informed transactions overall, followed by uninformed buy-sell transactions (see Table 3, bottom half). So, the trade transactions were not efficient, with traders apparently trading random quantities. They bought or sold steadily though. The dealer market bid-ask price transactions did not indicate continuity in ordering since the autocorrelation coefficients were low (0.08, 0.07, 0.03). In the continuous market, in contrast, there is evidence that traders followed value-related trends. But for the split orders of informed traders, there was no similar phenomenon in dealer market price-driven trading volume.

Other issues. Price volatility in the market value of BTC can be understood based on two causes: public information and transaction activity continuity. But which will have a greater impact on volatility? We analyzed *Tweet* activity for BTC by day of the week to assess this. *Tweet* activity was lower on Saturday-Sunday (see Table 4, top gray highlights). But there was more *Tweet* posting on Thursday-Friday (626.31, 604.50). So, we compared the volatility of *Returns* (in SD terms) calculated from Saturday-Monday's closing values (0.02) with the volatility of returns calculated from Thursday-Friday's closing market values (also 0.02) (see Table 4, bottom half). The results show that volatility was not influenced by trading levels more than public information.

We next offer details about our econometric estimation and related econometrics and time-series issues that we considered in producing additional results for this research (see Appendix B, Remark B3).

Decomposition of variance in BTC market value. The volatility of BTC market value can be attributed to public information (*e.g.*, from social sentiment and market trends) and market participants' observable behavior. Positive or negative public information has an impact on market value leading to price fluctuation. Strategic trading representing market participants' behavior can also affect market price—without any signals—due to the tension between supply and demand. Public information includes sentiment and news on regulatory changes, technology advances, and market trends. This can cause investors to revise their expectations about BTC's prospects, resulting in price changes. For example, positive news about the adoption of blockchain technology by major companies can cause the price of a BTC to rise, and vice versa.

When market participants have access to news that others don't, this can lead to asymmetric reactions, resulting in unpredictable price movements. For example, if a group of investors has information about a potential regulatory change that will affect the value of BTC, they may use it to front-run the market, leading to sudden price movements and reactions. Transaction costs can contribute to such price volatility as well. But high transaction fees discourage trading and limit market liquidity, which can make it difficult for traders to buy or sell large volumes. This still can result in price movement though, since a few large trades can have a significant impact on price volatility.

Table 3
Continuity of BTC transactions.

Measures	Informed trades	Uninform trades (Buy)	Uninformed trades (Sell)
• **Continuous market**			
Continuity	78 / 120	98 / 120	84 / 120
Continuity coef	**0.65**	**0.82**	**0.70**
Autocorrelation coef	0.30	0.63	0.40
• **Dealer market**			
Continuity	65 / 120	64 /120	62 /120
Continuity coef	**0.54**	**0.53**	**0.52**
Autocorrelation coef	0.08	0.07	0.03

Note. Consecutive transactions increase or decrease from t to $t + 1$ and are 0 or 1 during the 120 trading days in our four-month observation period.

- Continuity in investment refers to the practice of an investor engaging in the buying and selling of stocks across successive time periods. To illustrate, this entails an investor acquiring a stock on a specific day and consistently making additional purchases in subsequent days. Conversely, discontinuity implies the cessation of such sequential transactions.
- Autocorrelation, a phenomenon arising from numerous unidentified factors within the error term, denotes the existence of correlations between the current error and its preceding counterpart. This implies specific relationships among these factors, which remain unidentified and are encompassed within the error terms during each time period.

3.4. Reflective-Reflexive trading decisions and transaction cost issues

This research assesses how traders participate in BTC exchanges. This highlights the differences the between reasoned and intuitive decisions of investors and speculators. It also suggests the importance of the informal texting and communication channels that traders use to exchange information, make decisions, and transact in market settings. The impacts of social sentiment, public information, transaction cost, and information asymmetry on value volatility suggest how things operate in informal and formal exchange, and how their interaction affects the observed market outcomes. Thus, volatility is linked to how traders react to public information and to overall trading behavior. Also, the feedback they receive reflects the social, technological, and regulatory environment of trading—the whole market, in other words.

Empirical considerations. A digital currency's expected value is based on transaction activity and related public information. Reflective and reflexive decisions work together in trading. If a conflict occurs, participants' trades may be affected. To determine which decision-making approach has stronger influence, and how it affects investment vs. speculation, we analyzed the volatility of information asymmetry, as well as transaction cost and public information over time.

VECM to assess informed traders' cognitive approaches for investing vs. *speculating.* We examined these relationships using VECM to understand informed traders' behavior. We assessed the correlations between information asymmetry and other proxies to evaluate their associations (see Table 5).

Normalized cointegrating equation and error correction. In the cointegrating equation, our target variable is *InfoAsym.* In the long run for the dealer market, *TransCost* (1.01, 0.99) impacted *InfoAsym* (Thus, increasing *TransCost* caused a decrease in *InfoAsym.* In the dealer market, *PubInfo* (-1.01, −0.98) had a positive effect though, so more *PubInfo* resulted in an increase in *InfoAsym.* see Table 5 again).

For dealer market transactions, the *cointegrating coefficient* estimates the speed at which model equilibrium is restored after a disruption. The coefficient for the error correction term, with *InfoAsym* and *PubInfo* as dependent variables. was positive and significant. This suggests the

Table 4
Tweets and BTC *Returns* by weekday.

Stats	Mon	Tue	Wed	Thu	Fri	Sat	Sun
• ***Tweets***							
Mean	574.75	592.43	562.06	626.31	604.50	415.31	367.25
SD	106.48	124.82	91.95	74.64	100.08	80.57	87.51
JB	7.61	1.02	1.55	2.32	0.14	4.56	0.61
Prob	0.02	0.60	0.46	0.31	0.93	0.10	0.74
• ***Returns***							
Mean	0.00	0.00	0.00	0.01	0.00	0.00	0.01
SD	0.02	0.04	0.04	0.03	0.02	0.03	0.01
JB	1.66	0.08	1.86	3.42	3.05	0.52	0.61
Prob	0.44	0.96	0.39	0.18	0.22	0.72	0.74

Note. *Tweets* by day of the week are normally-distributed.

Table 5
VECM Results for Transactions by Informed Traders.

	Informed Trader Transactions					
	Dealer Market Trading Volume			*Continuous Market Trading Volume*		
	InfoAsym	*TransCost*	*PubInfo*	*InfoAsym*	*TransCost*	*PubInfo*
Constant	**0.00****	**0.00****	**0.00*****	0.00	0.00	0.00
	(0.00)	**(0.00)**	**(3.00)**	(0.00)	(0.00)	(0.00)
Cointegr	**0.13****	0.01	**1.35*****	0.01	−0.14	0.93*
	(0.07)	(0.34)	**(0.36)**	(0.08)	(0.42)	(0.51)
InfoAsym (-1)	**0.84*****	**1.06*****	**1.73*****	**1.45*****	**2.97*****	**3.96*****
	(0.07)	**(0.38)**	**(4.40)**	**(0.14)**	**(0.72)**	**(0.88)**
TransCost (-1)	0.03	0.18	0.06	**−0.19*****	−0.22	−0.42
	(0.05)	(0.25)	(0.21)	**(0.06)**	(0.32)	(0.39)
PubInfo (-1)	0.00	0.00	0.12	−0.01	0.00	0.08
	(0.05)	(0.24)	(0.47)	(0.06)	(0.30)	(0.37)
• **Normalized Cointegrating Equation**						
InfoAsym	1.00	**0.99*****	**0.99*****	1.00	**1.02****	**−1.02*****
		(0.02)	**(0.01)**		**(0.05)**	**(0.04)**
TransCost	**1.01*****	1.00	**−1.01*****	**0.99*****	1.00	**−0.99*****
	(0.02)		**(0.01)**	**(0.05)**		**(0.01)**
PubInfo	**−1.01*****	**−0.99*****	1.00	**−0.98*****	**−1.01*****	1.00
	(0.01)	**(0.01)**		**(0.03)**	**(0.01)**	
R^2	0.77	0.20	0.48	0.78	0.48	0.55
LL	819.00	625.10	621.00	785.20	595.10	572.00
JB	12.54	9.96	10.47	15.25	14.10	14.44
Prob	0.00	0.01	0.01	0.00	0.00	0.00

Note. The variables are differenced except *Cointegration*; () indicates an SE; JB = Jarque-Bera statistic.

- Normalized Cointegrating Equation: (1) For the Dealer Market, the equation is expressed as *InfoAsym* = 1.01 *TransCost* - 1.01 *PubInfo*; (2) For the Continuous Market, the equation is expressed as *InfoAsym* = 0.99 *TransCost* - 0.98 *PubInfo*. In the normalized cointegrating equation derived from the Johansen model, the coefficient value must be interpreted in reverse.
- This formulation adheres to the conventions of the Johansen model, specifically when examining long-term relationships. In this context, the variable *InfoAsym* is considered the target variable. The coefficient associated with *TransCost* demonstrates a negative and statistically significant impact on *InfoAsym* over the long run. Consequently, an escalation in *TransCost* is anticipated to result in a concomitant reduction in *InfoAsym* within the specified time horizon.
- The coefficient linked to *PubInfo* is positive and has statistical significance. Thus, more *PubInfo* is expected to elevate InfoAsym over the extended period under consideration. This nuanced understanding of the normalized cointegrating equation in the Johansen model reflects the long-term dynamics between *InfoAsym*, *TransCost*, and *PubInfo* in both Dealer and Continuous Markets.

model moves from short-term instability to long-term equilibrium. The adjustment coefficients toward long-term equilibrium in the event of disequilibrium were (0.13, 1.35). For *TransCost* though, the adjustment coefficient (0.01) was not significant. This implies that there was no adjustment toward long-term equilibrium that would occur in any disequilibrium situation for this reason. For the continuous BTC market, the coefficients (0.01, −0.14, 0.93) also were not significant, again suggesting no adjustments.

Long and short-run effects. For the dealer market transactions, the coefficient (0.13) for the long term was positive and significant (see Table 5 again). This implies a long-run relationship between *TransCost* and *PubInfo* with *InfoAsym.* But the estimate ought to be negative to indicate the model's ability to return to equilibrium: a positive sign suggests a shift away from equilibrium—in the other direction. For the continuous BTC market, the long-term coefficient (0.01) was not significant. This indicates that there was no long-term relationship between transaction costs and public information for information asymmetry.

For bid-ask transactions in the BTC dealer market, the coefficient (0.841) for *InfoAsym* in the short term indicated that an increase in *InfoAsym* in the prior period resulted in an increase in *InfoAsym*. For the continuous market, the short-term coefficients (1.451, −0.18) indicated that an increase in the prior period *InfoAsym* only increased in the current period, and a rise in *TransCost* resulted in a reduction of *InfoAsym*. But higher *PubInfo* did not lead to a change because the estimated coefficient was not significant.

For the short and long-term, *InfoAsym* was negatively correlated with *TransCost* (short run: −0.19, long run: 1.01, 0.99). From the results, we conclude that BTC volatility was closely linked to transaction costs, indicating a relationship between volatility and the behavior of traders.

In a competitive market, demand premiums decrease, and volatility is lowered because traders compete to offer liquid supply. In a monopoly market with fewer traders, demand premiums would increase, and volatility would rise. Even if there are many traders, if the informed ones decide to control the amount of supply, this will lead to imperfect competition. When the costs of buying and selling BTC increase and lead to higher levels of price instability, traders with greater market knowledge may choose not to increase the volume of their orders due to the elevated level of risk to which they will be exposed.

This set of empirical results suggests that *PubInfo* had no immediate impact on *InfoAsym*. Long term though, *InfoAsym* was positively related to public information (-1.01, −0.98), which is not distributed normally based on the JB statistics. As a result, the likelihood of good or bad signals occurring is not equal, although the probability of extreme positive or negative signals decreases. The findings suggest for informed traders that information asymmetry-led behavior can be attributed differently to good and bad news from public information over the longer term.

Uniformed traders. Next, we considered differences in the results for uninformed traders (see Table 6).

We present evidence that the model transitions from short-term instability to long-term equilibrium. In particular, the adjustment coefficients toward long-term equilibrium during disequilibrium are (0.07, 0.27, 1.71). For bid-ask trades though, only *PubInfo* has a significant positive adjustment coefficient (0.67***). There are no notable adjustments toward the long-term equilibrium in any disequilibrium situation due to *InfoAsym* and *TransCost*. For the buy-sell continuous market, only *InfoAsym* has significant adjustment effects (0.12, 0.05). This indicates that pressure toward long-term equilibrium may occur if disequilibrium arises. The coefficient (0.58) is significant for *TransCost* for *Buy* transactions, while those for *Buy* and *Sell* transactions (1,77, 1.21) were significant for *PubInfo*. The coefficients should be negative to signify the system can restore itself to equilibrium, but when it is positive, the system moves away from stability.

Regarding dealer market prices, over the long term, the coefficients have opposite signs. So, *TransCost* (1.51, 0.62) contributed negatively to information asymmetry, while public information (-1.36, −0.74) had a positive effect on average when other factors were held constant. In the short term, for buying BTC both *InfoAsym* in the past period (0.48) and *TransCost* (0.17) contributed positively to *InfoAsym*. For selling though, *InfoAsym* in the past period (0.79) had a positive impact, while *TransCost* (-0.08) had a negative impact on *InfoAsym*. In the continuous market over the long run, *TransCost* (0.58, 0.97) contributed negatively to *InfoAsym*, while *PubInfo* (-0.69, −0.98) had a positive impact. And in the short term, for buying and selling, *InfoAsym* in the prior period (0.93, 0.88) had a positive impact on current period *InfoAsym*; but *TransCost* and *PubInfo* had none.

BTC price volatility can be attributed to the trading behavior of uninformed traders, which also was affected by transaction costs. When there is healthy competition based on low information asymmetry in the market, the abundance of supply provided by uninformed traders led to reduced volatility and a lower price premium. The opposite was true with only a few market-makers though. Again, since they could control the liquidity supply, there was a premium for demand and volatility increased. Uninformed traders lacked the ability to coordinate their actions related to supply, so competition always was present. This means that every trader made their own transactions based on individual judgment. Thus, traders who lacked knowledge bought an unpredictable amount of BTC, regardless of an information gap among them.

PubInfo did not immediately affect *InfoAsym.* Over a longer time, *PubInfo* and *InfoAsym* were correlated though. This is shown by the values of −1.36, −0.74, −0.69, and −0.98. They do not follow a normal distribution according to the JB statistics. So, the likelihood of good or bad signals was not equal. Still, the chance of extreme positive or negative signals was lower, as indicated by the distribution. This implies that uninformed traders' information asymmetry were influenced differently by positive and negative news as public information in the market over an extended period.

Table 6
VECM Results for Uninformed Traders' BTC Trades.

Variables	Uninformed Trader Transactions											
	Dealer Market Trading Volumes						*Continuous Market* Trading Volumes					
	InfoAsym		*TransCost*		*PubInfo*		*InfoAsym*		*TransCost*		*PubInfo*	
	QBid	*QAskl*	*QBid*	*QSAsk*	*QBid*	*QAsk*	*CMBuy*	*CMSell*	*CMBuy*	*CMSell*	*CMBuy*	*CMSell*
Cointegr	0.00	**0.07****	−0.03	**0.27*****	**0.67*****	**1.71*****	**0.12****	**0.05****	**0.58*****	0.12	**1.77*****	**1.21*****
	(0.00)	**(0.03)**	(0.02)	**(0.09)**	**(0.10)**	**(0.20)**	**(0.05)**	**(0.02)**	**(0.12)**	(0.08)	**(0.22)**	**(0.16)**
InfoAsym (-1)	**0.49*****	**0.79*****	**1.40*****	**1.609*****	**2.19****	1.05	**0.93*****	**0.88*****	**0.89*****	**1.01*****	**1.76*****	0.68
	(0.09)	**(0.10)**	**(0.22)**	**(0.31)**	**(0.96)**	(0.68)	**(0.09)**	**(0.07)**	**(0.21)**	**(0.24)**	**(0.39)**	(0.51)
TransCost (-1)	**0.17*****	**−0.08****	**0.267*****	−0.07	−0.22	−0.21	−0.11*	0.00	0.13	**0.44*****	−0.36	**0.70*****
	(0.04)	**(0.04)**	**(0.10)**	(0.12)	(0.42)	(0.26)	(0.06)	(0.03)	(0.13	**(0.11)**	(0.24)	**(0.22)**
PubInfo (-1)	0.00	0.01	−0.01	0.07	−0.01	**0.20***	0.05	0.02	**0.19*****	0.04	0.20	0.13
	(0.01)	(0.02)	(0.02)	(0.05)	(0.10)	**(0.11)**	(0.03)	(0.02)	**(0.07)**	(0.05)	(0.12)	(0.11)
Constant	0.00	**0.00*****	0.00	0.00	0.00	**0.00**	0.00	0.00	0.00	0.00	0.00	0.00
	(0.00)	**(0.00)**	(0.00)	(0.00)	(0.00)	**(0.00)**	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
• ***Normalized Cointegrating Equation***												
InfoAsym	1.00	1.00	**0.66****	**1.61*****	−0.74	**−1.35*****	1.00	1.00	**1.72*****	**1.03*****	**−1.44*****	**−1.02*****
			(0.32)	**(0.21)**	(0.50)	**(0.12)**			**(0.16)**	**(0.12)**	**(0.10)**	**(0.08)**
TransCost	**1.51*****	**0.62*****	1.00	1.00	**−1.11*****	**−0.84*****	**0.58*****	**0.97*****	1.00	1.00	**−0.84*****	**−0.98*****
	(0.24)	**(0.08)**			**(0.23)**	**(0.06)**	**(0.08)**	**(0.09)**			**(0.04)**	**(0.03)**
PubInfo	**−1.36*****	**−0.74*****	**−0.90*****	**−1.19*****	1.00	1.00	**−0.69*****	**−0.98*****	**−1.19*****	**−1.02*****	1.00	1.00
	(0.17)	**(0.05)**	**(0.10)**	**(0.07)**			**(0.06)**	**(0.07)**	**(0.04)**	**(0.03)**		
Adj. R^2	0.58	0.55	0.67	0.44	0.45	0.55	0.92	0.59	0.93	0.67	0.90	0.81
LL	1,014.00	946.50	913.00	807.90	737.02	714.80	884.70	683.20	784.40	1,013.00	713.90	793.40
JB	15.40	8.53	15.39	8.08	15.30	8.39	12.94	11.92	12.85	15.40	12.93	11.80
Probability	0.00	0.01	0.00	0.02	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00

Note. All right-hand side values were differenced except for *Cointegration;* () indicates an SE, JB = Jarque-Bera statistic, and variable significances are as earlier.

- Normalized Cointegrating Equation: In the regularized cointegration equation of the Johansen model representing the long run, the coefficient values must be interpreted inversely. *InfoAsym* is the target variable. *TransCost* has a negative and significant impact on *InfoAsym* in the long run. An increase in *TransCost* will lead to a decline in *InfoAsym*. In the case of *PubInfo*, *InfoAsym* is positive and significant. So, am increase in *PubInfo* will lead to an increase in InfoAsym.

The impact of public information on BTC market value movement. Informed traders often transact in anticipation of rising or falling BTC value. But what role does public information play in predicting such value changes? We again applied the EGARCH) *model* (Bollerslev, 1986) to estimate the spillover effect of public information on market value volatility.[24,25]

If informed traders bought BTC in anticipation of a future price increase, its value likely would have risen. Information obtained by such traders was exposed to the market through the trades of BTC though. If such information was exposed, others could have used it and price momentum may have occurred. Informed traders tend to use strategies to determine order quantity and timing, to minimize their information exposure.

The related estimation results are presented next (see Table 7). The equation includes constants for ln(*Tweets*), *PubInfo* (δ), and the uptrend of dealer market and continuous market trading volumes, as well as the downtrend of trading volumes for both. These are arrayed across the top headings of the table's columns. The results show that social sentiment was associated with *PubInfo* (δ) in the form of social media *Tweets* related to the BTC market. The spillover effect of *Tweets* (0.01***) to *PubInfo* was significant at 1% also. Thus, if *Tweets* increased by 1%, δ would have increased by 0.01%. More importantly, the coefficient value of (-0.26***) explains the spillover effect of the variance of *Tweets* at 1% significance. The volatility of public social sentiment via δ was also affected by its and the *Tweets* variable's previous variances. Here, there was a tie between social sentiment and public information in the BTC market. The parameter δ (bad signals) and 1 - δ (good signals) factored into estimating Prob(*UpTrend*) and Prob(*DownTrend*) and were factors for sentiment associated with price momentum.

The spillover effect of social sentiment was significant, but its influence also was small in the BTC market. Spillover effects of positive sentiment volatility (0.11***) to the Prob(*UpTrend*) / (0.06***) and to Prob(*DownTrend*) for bid-ask volume were significant at 1% though.. The spillover effects of negative sentiment volatility (−0.50*) to Prob (*UpTrend*) (−0.55**) and to Prob(*DownTrend*) were significant at the 5% and 10% levels in comparison.

EGARCH tests for positive and negative social sentiment volatility and spillover effects. whereas GARCH can only treat symmetric effects. We lever EGARCH's suitability for modeling social sentiment impact on BTC prices and volatility. also reveals the significance of ρ_{Pos} (*Spillover*) for the volatility effect of sentiment. A 1% increase in ρ_{Pos} led to a 0.1% rise in BTC value in the bid-ask dealer market, while a 1% increase in ρ_{Neg} resulted in a 0.5% decrease in the continuous buy-sell market (see Table 7). Thus, positive sentiment positively influenced BTC value, whereas negative sentiment exerted a negative influence. The results indicate that positive sentiment volatility increases price momentum, proxied by Prob(*UpTrend*) and Prob(*DownTrend*) in *QBid / QAsk*, while negative sentiment volatility decreases price momentum, proxied by Prob(*UpTrend*) and Prob (*DownTrend*) (see Fig. 4).

In the variance equation results for EGARCH (1,1) model estimation, the sentiment coefficient, indicating the model's AR(1) structure, was significant at the 1% level, and the conditional variance was stable in the BTC market (see Table 7 again). The sentiment spillover effect was not, though the variance spillover effect was significant at 1%. So, a 1% increase in positive sentiment variance resulted in a 0.11% increase based on upward price momentum via Prob(*UpTrend*) and a 0.06% increase was from the downward price momentum, proxied by Prob (*DownTrend*), in dealer market BTC trade volume. If negative sentiment variance rose by 1%, then a 0.49% price momentum decrease on Prob (*UpTrend*) and a 0.55% price momentum decrease on Prob(*DownTrend*) in the market would follow.

Further, the asymmetry effect of sentiment variance based on new information did not appear in the Prob(*UpTrend*) estimate. But the leverage effect of sentiment variance was −0.04 for bid-ask dealer market volume and −0.37 in continuous BTC market volume. Both were negative and significant with respect to Prob(*DownTrend*). This result confirms that the negative signal was greater than the positive signal for creating price momentum via the Prob(*DownTrend*) for negative social sentiment.

Social sentiment also consistently affected price momentum via Prob (*UpTrend*) and Prob (*DownTrend*) in dealer market exchange since the effects of ARCH and GARCH were less than 1. So, the influence of social sentiment volatility persisted in bid-ask BTC volume for a longer time. In the continuous market though, the persistence parameter value was slightly greater than 1, indicating that the estimated conditional variance was not stable. We conclude that social sentiment volatility predicted Prob(*UpTrend*) or Prob(*DownTrend*)-driven volatility in dealer market volume for time into the future.

4. Discussion

We next will discuss the issues that arose and our assessment of them in the empirical analyses of both Studies A and B. They span observations that merit additional consideration for the issues they raise that deserve discussion. We will discuss Studies A and B first since they raise different issues.

4.1. Summary of empirical findings from studies A and B

We summarize the findings for the research questions for Studies A and B next (see Table 8). There are three main results. Social sentiment does not affect information asymmetry for dealer market trade volume, and likewise in the continuous market. But *social sentiment volatility*—for variance over time—affected information asymmetry. This suggests a sentiment volatility spillover on trading. Other sources of spillover effects have been noted for equities and other traded assets, too (Fasanya et al., 2021).

Social news seems to persistently influence information asymmetry. For information asymmetry coupled with positive news, a rising price shock seems to cause more volatile reactions than a falling price shock because the leverage effect is positive. If it is linked to negative news though, the falling price shock is more volatile than the rising price shock. And the same observation pertains to social sentiment volatility, specifically negative sentiment influences asymmetric information.

4.2. Study A: Discussion issues

As the trading volume of BTC increases worldwide, studies on price prediction based on price volatility and momentum are being more actively conducted. We examined information asymmetry in this context. Our results have suggested that trade-relevant information is not always evenly distributed among traders or available to everyone who trades.

We used the EGARCH model for multiple time-series estimations of information asymmetry and social sentiment. This choice is appropriate due to the influence of social sentiment volatility and asymmetric information—with shocks of greater positivity or negativity in opinions expressed, that have an effect that is felt by the market immediately and in future periods. Also, because of the spillover effect, information

[24] In the GARCH model, for the value of the *conditional partial product* to always be positive, certain constraints must be applied, which may limit the *conditional dispersion process* more than necessary. The *asymmetric information effect*, which has a much greater impact on volatility when it is in a downtrend trend (for a negative shock) than market participants' expectation (also for a negative shock) is synonymous with the *leverage effect*. Considering these points, we used the EGARCH model, and the *conditional variance equation* of EGARCH (1,1) to assess the effect of price momentum.

[25] Volatility observed in public information acts as an exogenous variable representing the effect transferring social sentiment volatility to market value volatility to create price momentum.

Table 7
Spillover effect of social sentiment on BTC market value.

Variables	ln (*Tweets*)	*PubInfo* (δ)	Prob (*UpTrend*)		Prob (*DownTrend*)	
			DealerMarket	*Continuous Market*	*DealerMarket*	*Continuous Market*
• **Mean equation**						
Constant	**4.49*****	**−0.07****	0.02	**0.023****	0.01	**0.06****
ln (*Tweets*) (-1)	**0.28*****	**0.01*****	—	—	—	—
PublInfo, δ (-1)	—	**0.97*****	—	—	—	—
Positive (-1)	—	—	−0.00	0.00	0.00	**−0.00***
Diff (*Negative*) (-1)	—	—	−0.00	**−0.00*****	0.00	**0.00*****
Prob (*UpTrend*) (-1)	—	—	**0.95*****	**0.90*****	—	—
Prob (*DownTrend*) (-1)	—	—	—	—	**0.98*****	**0.93*****
• **Variance equation**						
φ (*Constant*)	**−2.66****	**−0.84*****	−1.20	−0.98	−0.75***	−0.63
η (ARCH)	**0.53****	−0.02	−0.10	**0.88****	−0.07	**0.83****
θ (GARCH)	0.20	**0.99*****	**0.95*****	**0.48****	**0.94*****	**0.45****
λ (*Leverage*)	−0.08	**−0.02*****	0.06	0.31	**−0.04*****	−0.37*
ρ_{Tweets} (*Spillover*)	—	**−0.26*****	—	—	—	—
ρ_{Pos} (*Spillover*)	—	—	**0.11*****	0.08	**0.06*****	0.05
ρ_{Neg} (*Spillover*)	—	—	0.02	−0.50*	−0.01	**−0.55****
R^2	0.10	0.24	0.68	0.65	0.66	0.64
DW	1.79	2.34	2.19	2.72	2.16	2.69
LL	−4.60	288.29	355.37	179.20	355.11	179.14
AIC	0.18	−4.71	−5.89	−3.47	−5.88	−3.47

Note. DW = Durbin-Watson stat; LL = log likelihood; AIC = Akaike information criterion; signif. as earlier.

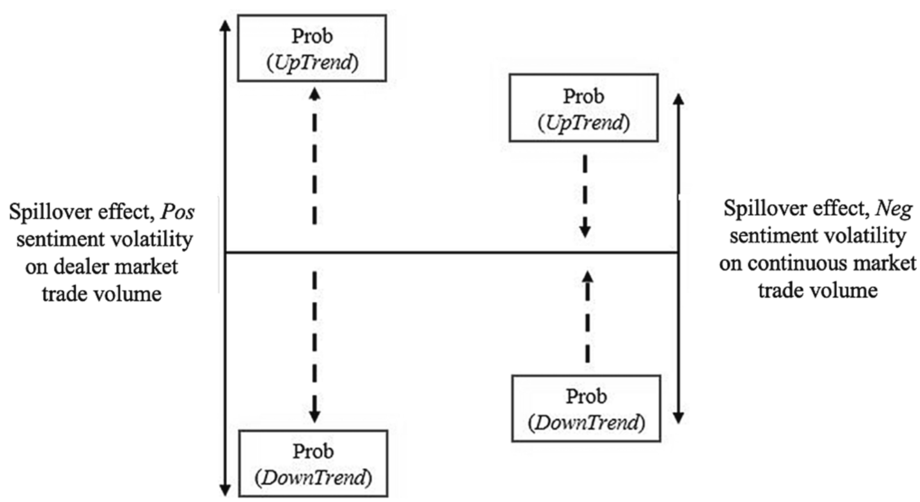

Fig. 4. The Spillover Effect of Social Sentiment Variance and Probabilistic Price Trends.

asymmetry volatility representing the probability of informed trading was affected by price volatility from the day before and is similarly affected by prior-day social sentiment volatility.

We applied the *PIN* model of market microstructure to cryptocurrency transactions to predict the trading intensity of informed traders. We also examined their information utilization related to social sentiment. The model for measuring information asymmetry was based on price data, but we shifted to transaction volume because BTC price volatility in the period we studied was high. In addition, we investigated the association between information asymmetry and social sentiment, an element of public information. This suggested the need to develop and test an information asymmetry model for BTC, representing the perceptions and sentiment of traders who posted their sentiment online.

Information asymmetry should be reduced to promote fairness. We verified the presence of information asymmetry by applying the *PIN* measure from Finance and its connection with social sentiment in the market. Our study suggested the need to analyze the behavior of BTC traders to examine their trading behavior and decisions in the market. This, it turns out, was useful for revealing unique characteristics and similarities of different markets by analyzing the traders and their trading patterns.

Trade exchanges that handle BTC are strengthening their capacity to reduce serious information asymmetry. The U.S. is leading the global markets but is affected by shifting economic policies and development issues. Currently, there is no established regulatory system for market trading and currency-related disclosures, so individual participants have had to rely on information provided by industry researchers and institutional investors for their trading strategies. The digital currency trading sector, meanwhile, is striving to achieve two goals: better trader protection and promotion of participation through the accessibility of relevant research information. Trader protection is the main reason why exchanges share economic and investment information, such as macroeconomic metrics and trading instrument diffusion information, despite their limited workforces. Transactions can only actively occur when the digital divide is bridged. By emphasizing market policy, analytics-focused research exchanges will remain viable as intermediaries.

Information asymmetry comes from many sources. In the late

Table 8
Summary of empirical findings in studies A & B.

Research question	Explanation of findings
RQ1 (Assessing A-symmetric Info Effects) *(a) Does sentiment-driven news impact asymmetric info volatility and crypto market outcomes?* *(b) Do positive and negative news effects on asymmetric info-led sentiment have transient or lasting effects?*	• Positive sentiment variance positively affects info asymmetry, via the positive coefficient for the spillover effect. • Negative sentiment volatility negatively affects info asymmetry, via the estimated negative coefficient for the spillover effect. • Bid-ask dealer and buy-sell continuous market trading volumes negatively affect each other, but their volatility does not affect other variables. • A positive signal affects info asymmetry since the summed ARCH and GARCH effects together are less than 1. For info asymmetry due to positive news, the positive signal is greater than the negative signal because the leverage effect > 0. • Negative sentiment also is associated with info asymmetry because ARCH + GARCH < 1. The negative news signal is stronger than the positive signal with leverage < 0.
RQ2 (Crypto transaction patterns) *(a) For value volatility, what exerts greater influence: public information and social sentiment or transaction patterns?* *(b) How do info asymmetry, transaction costs, and public info interact to affect trading value volatility?*	• Transaction consistency is 65%-81%. Dealer transaction continuity is 52–54%. When probability is ~ 50% →no continuity. Traders find patterns for informed trading. • Informed traders (long run), *TransCost* → '-' effect; *PubInfo*: '+' on *InfoAsym.* • Dealer mkt (short term), prior *InfoAsym* → higher current *InfoAsym* (autocorrelation); continuous market, prior *InfoAsym* → increase in current *InfoAsym.* • Impulsive and thoughtful processes are considered in informed trading, but information-based trading reveals investment than its speculative nature. • Dealer market, uninformed trades, *TransCost* negatively contribute to *InfoAsym but PubInfo* has a positive effect on average. • Buy trades, short term, prior *InfoAsym, TransCost* → positively affect *InfoAsym* now; sell trades, prior *InfoAsym* → positive impact on *InfoAsym*; *TransCost* → negative impact on InfoAsym: so there were opposite impacts. • Continuous market, long run, *TransCost* → negatively affects *InfoAsym,* while *PubInfo* → positive impact; buy-sell trades, short term, prior *InfoAsym* → positively impact on current *InfoAsym; TransCost* and *PubInfo* had no impact though. • Impulse decisions are more common than thoughtful ones; so, less-informed trades have a more speculative nature than investment nature.
RQ3 (Sentiment-driven price momentum influence): *How do public information and social sentiment influence up-down movement in prices?*	• There is a spillover effect of sentiment variance. • When positive variance increases by 1% →0.11% increase in uptrend probability 0.06% increase in downtrend probability in dealer trading volume. • When negative variance rises by 1% → 0.49% decrease in uptrend probability and 0.55% decrease in probability of price downtrend will occur. • Dealer and continuous market → leverage effect of sentiment variance is negative for volume, and significant with probability of downward cryptocurrency price trend. • Results suggest negative social sentiment has a greater impact on the probability of a price downtrend than positive sentiment.

1980s, Ausubel (1991) analyzed how much asymmetric information exists in relation to credit cards in the U.S. market. Its financial services sector has continued to support the vast accumulation of individual credit information and decisions that affect consumers are made with it. So, asymmetric information in this quadrant of the sector is viewed as relatively low. The market segmentation that many banks have used is based on data for consumer credit and lending services, *small and medium enterprises* (SMEs), and corporate lending. But based on client information, transaction histories and data analytics, financial institutions have in-depth knowledge about who they are, what they want, and what they'll pay.

Some customers don't need much credit because their finances are healthy, while others need money because their available funds are limited. So, a typical customer with good financial standing should have no reason to obtain a new credit card, unless it has attractive terms and a lower interest rate. They may wish to diversify lender risk and funds sources. The results suggest that in markets where information asymmetry exists, it is persistent and more widespread than most recognize.

Social media's role in information asymmetry. Mass media, including newspapers, TV and Internet articles, diffuses public opinion. It also has unleashed undesirable fake news, leading to considerable information asymmetry that has impacted the financial markets. In fact, mass media influences many decisions we make in our lives without distinguishing among society, politics, and economy sources. In the past, it was possible for firms to promote their products by taking advantage of information asymmetry and delivering selective information favorable to the firm and its customers' purchase decisions. Now, transparency is a basis for strategy and management, but it hasn't reduced fake news (Clemons et al., 2017).

When someone writes a post on Twitter, it is often immediately seen by thousands of people, and after that, many active users on Twitter will see it within ten minutes. The biggest features of social media are people's conversations, disclosures, and participation, which often act to bring about social change. In social media, all content is from users. It continues to grow based on their interactions and expanding relationships. Social media participants create another world by posting what is happening on interfaces such as Twitter or Facebook and sharing it with others. This shared content has persuasive power because it is based on trust between acquaintances and their relational connections, reducing their information asymmetry somewhat – while others have less or no access to the information.

Explaining price without access to firm fundamentals for BTC. It is difficult to explain the intensity of fluctuations in BTC value—without access to a firm's fundamentals, but only based on a currency's performance in the market and the social sentiment that surrounds its trading. Investors and speculators alike must pay close attention to the mood of traders whom they are psychologically close to for trade flows and market trends. They seem to be more sensitive to negative than positive sentiment though, based on our findings. The influence of sentiment, as we noted, sometimes lasts a long time, and its ripple effects are widespread and may be felt with surprising force. Our study suggests that emotion dominates rational thinking in this context sometimes. By focusing on market efficiency and volatility, our sentiment analysis with time-series econometrics provides information for decisions by traders, policy-makers, and entrepreneurs.

4.3. Study B: Discussion issues

Market efficiency and its sources. If the financial market is rational and efficient, the value of an asset should be determined by factors related to the business activities that occur around it, and the influence of random public sentiment should be limited. Although settings in which such information is reflected quickly in market prices are in line with efficient market theory, the market's reactivity to sentiment has been high, and trading strategies based on it can achieve excess returns. For most traders though, a market with normal returns reflecting risk and growth, not excess returns, is healthier. But a rational market can only be realized when information asymmetry is limited – without controlling access. Market efficiency, uncertainty and information asymmetry are different for cryptocurrency trading compared to instruments that have a basis in physical assets. And when it is high, information asymmetry increases and so will market volatility.

Other salient issues. Globally, there is broad recognition that trading activities related to investment and speculation are different. When information asymmetry is prominent, damage is likely to be caused to the value that most traders can appropriate from market participation, as ours and other authors' results affirm. The damage caused can be substantial, especially for uninformed traders.

It isn't easy for non-professional traders to understand the problems caused by differences in their access to information though, nor do they fully understand digital cryptography and blockchain-based structures. There is always the specter of regulation for *foreign-exchange* (FX) trading, cross-border funds remittances, and *buy-now, pay-later* (BNPL) card services. Nevertheless, to prepare regulatory codes and legislation to protect digital currency traders, it is necessary to balance developmental strategy for market innovation with the establishment of a sound market mechanism when designing new firm and market guidelines. To alleviate information asymmetry, it is also worthwhile to initiate eligibility criteria for market participation and standardized verification methods for virtual currency transactions. This is much like ISO 20022 has done to build global formatting standards for the digitalization of online cross-border payments.

Currently, cryptocurrency issuance based on blockchain technology is being actively promoted, and start-ups that are applying this technology in an effort to make markets have rapidly emerged. But some economists and financial and government institutions still view cryptocurrencies with a degree of skepticism. In this situation, their price has risen sometimes with convincing consistency and at others with volatile downward fluctuation (IMF, 2022). Progress toward an economy with more pervasive diffusion of cryptocurrencies is well underway. But there are knowledgeable observers around the world who are cautious amid the hype because the control of their price volatility is still a distant and unreachable dream.

For example, recently economists at the Bank of England (2019) asked: "*Will cash die out*?' Their answer was a resounding "*No, not in the foreseeable future*," The explanation they offered is:

> *"Over the coming years, it is likely that alternative digital payment methods will become ever more widely accepted and used. In fact, in 2017, debit cards overtook cash as the most frequently used payment method in the UK. … Even so, many people will continue to use cash in their daily lives. Many people say that they like cash because:* [*i*]*t is a fast and convenient way to pay; …* [*i*]*t is very widely accepted; … and* [*i*]*t is helpful for budget management. Some people also like the fact that cash payment is entirely anonymous.* And i*t is easy to access cash, with over 45,000 cash machines in the UK that are free to use."*

Many still do not fully accept cryptocurrencies as though they are cash or stocks. So, we must identify the characteristics that support trading different from other kinds of markets. This study lowers the barriers to entry in cryptocurrency research by identifying perspectives and issues that occur in popular discourse and research inquiry for the area. By presenting research results that help others to understand how cryptocurrency traders make decisions, this study will help them to understand how returns are cointegrated over time with changes in other aspects of cryptocurrency market microstructure and trading volume. Finally, trial and error in user decision-making is useful for learning. But reliance on it is less effective when market participants think in terms of information asymmetry-related variables linked to social sentiment and metrics that characterize the probability of active and informed market traders to address their uncertainty.

5. Final remarks

Despite our emphasis on the uncertainty associated with cryptocurrency trading, its credibility has been increasing in recent years – even with continuing BTC price volatility. In early to mid-2021, senior management at Paypal and Tesla indicated their firms would begin to accept BTC for transactions and automobile purchases, after some "on again, off again" arrangement uncertainty. Mastercard also issued a policy to accept such payments, and the Bank of New York Mellon announced plans to include BTC in its portfolio of investment assets. A qualitative change in BTC investments occurred, such that institutional capital began to drive its demand. As a result, the proportion of digital currency ownership by institutional investors has exceeded 75% in the U.S. market, while individuals also constitute most of the investors in other markets. As liquidity increases, investors will pay greater attention to the market as one that offers alternative investment vehicles. Overheated sentiment is a prevalent risk though.

5.1. Implications of our findings for social sentiment and related issues

Our findings have implications for research and practice. It is widely accepted in Economics and Finance that social sentiment can be informative in financial markets, even though its impact has been inconsistent and controversial (Guégan and Renault, 2021). But what role does information play? Earlier recipients do better with investing than later recipients do (Hirshleifer et al.,1994). It clearly has an impact on investors: it prompts them to decide whether to buy or sell a particular asset. The problem is that not everyone thinks the same way. Information may be ubiquitous but not everyone can acquire it. And, depending on a market participant's perceptions and their depth of knowledge, their conclusion may be the opposite from what may be expected due to their experience in the market.

Not all information reaches every investor; so information asymmetry is bound to occur. Not all information is useful also: one interpretation is that it is just the *noise of an active market* (Peng et al., 2020). An analogous interpretation from the 20th century economist, John Maynard Keynes, is that this is not a case of choosing whose faces are the prettiest based on one's judgment – nor even those with average opinions about who is the prettiest. The same goes for financial markets: it is more important to judge what information people think is surprising and new, rather than what information they think is good. The nature of information asymmetry is that it causes traders to make different judgments. Criteria for transacting assets should be objective and not involve subjective judgment that market participants make in isolation.

Our analysis framework is based on *variance decomposition* (Madhavan, 1996). It is useful for interpreting the flow of information in the market and its influence on BTC prices. It helps us understand how news articles and social media posts impact market prices, and to examine how information asymmetry shapes how markets change. Speculation was believed to have been occurring due to price volatility, and fast and large returns that generated an urge for people to impulsively get involved with cryptocurrency trading. Our study embraces the idea that trading decisions can be driven by impulsivity but also by patient and thoughtful cognitive processes. The latter enables analytical and rational thinking to implement an effective investment strategy, so speculation and investment can coexist. Our use of a variance decomposition methodology empirically confirmed this.

Cryptocurrency prices and trading volume data normally are available in time-series form. They are characterized by high price volatility, which causes practical difficulties in market analysis and forecasting. As an alternative, a volatility prediction method that combines a time-series model and machine-based learning method are typically viewed as more suitable for effective data analytics. Through this, results and insights can be derived that enable a deeper understanding of characteristics that cannot be identified with only time-series models but must be extracted from big datasets with new econometric models.

For this, we combined techniques involving big data analytics and a high-tech but low-cost research design, econometrics,and machine learning methods. We also applied a paradigm-shifting research perspective called *computational social science* (Chang et al., 2014). Based on this approach, we can get closer to the root of the problems and suggest insights for business policy and trading and pave the way forward.

5.2. Investment versus speculation

The difference between investment and speculation is based on market participants' purpose for trading. But there is a common thread: investment is aimed at catching the longer-term wave of rising market value, while speculation involves transactions that have asset price volatility risk with the speculator expecting an attractive return in a short time—a faster-breaking wave. We investigated the investment and speculative nature of the BTC market, by decomposing price volatility related to observable trades and public information and assessing their correlations from two cognitive decision approaches. We also identified the role of public information and its connection to the probability of upward and downward-trending BTC prices, as proxies for price momentum that determine value.

Based on our study's results, it seems as though BTC is an investment vehicle, despite the relatively high-risk environment it operates in (BIS, 2021, IMF, 2021). Our work corroborates earlier findings on cryptocurrency trading and the attributable information asymmetry. Through returns analysis on BTC transaction continuity, we showed that the strength of transaction impacts on price volatility—especially due to information asymmetry and transaction cost—is similar or slightly larger than that of other observable activities as a form of public information, consistent with the theory we have discussed.

The results of our research suggest three take-aways. First, the impact of public information on BTC price and value volatility is large compared to that of other variables we tested. Second, as information asymmetry increases, public information tends to increase too, such that informed traders are more beneficially affected than uniformed traders. And last, the more active investment in BTC is, the shorter the time for public information to be reflected in BTC price. We also validated that sentiment volatility has a spillover effect on upward and downward trends in BTC value, suggesting price momentum effects.

5.3. Contributions and future research

From the e-commerce perspective, our findings contribute to understanding the factors on the role of technology in reducing information asymmetry and transaction costs for cryptocurrency trading. For example, blockchain technology is known to facilitate peer-to-peer transactions and reduce the need for intermediaries such as banks and brokers. This can lower transaction costs and increase market liquidity, which can further reduce volatility in the market for asset prices. This appears to work as the past theory predicts it should in the cryptocurrency market. Further, understanding the impact of public information, trader behavior, information asymmetry, and transaction costs on cryptocurrency market volatility is critical for traders and policymakers. Different tactics to reduce the influence of these factors and promote a more stable and efficient market for cryptocurrency trading are worth study.

Since digital currency research is in its infancy, there is little empirical work on factors influencing the volatility of its market prices. A multidimensional study can clarify factors influencing market value and volatility from the perspective of microstructure and behavioral finance in connection with fintech-related theory (Gomber et al., 2018). In addition, future research should explore the use of artificial intelligence (Goodell et al., 2023) and deep learning (Goutte et al., 2023) to analyze public information and identify patterns that can help investors make informed cryptocurrency trading decisions.

Authorship contribution statement

Kwansoo Kim: Conceptualization, Methodology, Writing – original draft. **Robert J. Kauffman:** Conceptualization, Methodology, Writing – review responses and editing.

Declaration of competing interest

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

Data availability

The authors do not have permission to share data.

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Appendix A. Glossary, Modeling Notation, and Research Sequence

Table A1
Glossary of terms and definitions for studies A & B.

Term	Definition
Bid (ask) price	The price at which a dealer is willing to buy (sell) a tradable asset.[(b)]
Bid-ask spread	Difference between highest price a buyer will pay for an asset and lowest price a seller will accept.[(b)]
Blockchain	Encrypted transaction record maintained across computers linked in a peer-to-peer network.[(a)]
Buy, sell orders	Market order to buy or sell an asset immediately at the best prices available.
Cointegration	This occurs "*when two or more variables are each nonstationary, yet there exists a combination of these variables which is stationary. This statistical definition leads to a rich economic interpretation, where the variables can be thought of as sharing a stable relationship*" (Stigler 2020, p. 229).
Continuous market	Trading occurs all day, with execution of buy-sell orders by dealers or an electronic matching mechanism; market-makers must buy from sellers and pay a spread price for best execution for a buyer.[(b)]

(*continued on next page*)

Table A1 (*continued*)

Term	Definition
Cryptocurrency	Digital currency in which transactions are verified and records are maintained by a decentralized system using cryptography rather than a centralized authority.[a]
Dealer market	"*Multiple dealers* [*market-makers*] *post prices at which they will buy or sell* [*an*] *instrument.* [*They provide*] *liquidity and transparency by electronically displaying prices at which it is willing to make a market …, indicating both the price at which it will* [*buy and sell*]" (Kenton, 2022).
Information asymmetry	Relevant information is not evenly distributed to investors and speculators, who can't make informed decisions, and it is costly to search and acquire such information.
Informed, uninformed traders	Informed traders have access to information to assess an asset's value in the current market and trade prior to when its price reflects market knowledge of new information; uniformed traders lack that.
Investment	Assigning financial resources to something that can generate future income or create profit [b]
Leverage effect	Down-trending prices have a greater effect on information asymmetry than gains, and vice versa.
Market micro-structure	Market mechanisms use a price discovery process, for how bid-ask spreads and quotes are created, how intraday trading occurs, and what transaction costs and trade reporting consist of.[b]
PIN	A proxy for informed trading probability; traders estimate market value with information from good and bad news sources to obtain support for their decisions.
Price momentum	Momentum is a difference ratio for a crypto's price now compared to its price at an earlier time.
Public information	Information from online social posts, with views and reactions to trading, that can be used by others to make inferences about asset value to earn excess returns in the market.
Social sentiment	Market participants' and observers' online texted opinions on traded assets are positive, neutral, or negative, with more intense sentiment indicating greater evidence of stronger market reactions.[b]
Speculation	Conducting risky transactions with potential for losing value but also with possible gain.[b]
Spillover effect	Social sentiment affects crypto volatility due to cross-links from social media that transmit uncertainty to the asset and general uncertainty to other asset classes traded in the same markets.
Transaction costs	Expenses incurred when buying or selling a cryptocurrency after a trade is made.[b]
Unit root test	Used in time-series estimation to diagnose a non-stationary, stochastically unpredictable variable.
Variance decomposition	Estimation that "*allows partitioning the total variance in an outcome variable, e.g., firm performance, into several components. …* [*Identifies*] *groups of factors (e.g., firm-, industry-, and country-specific) that explain a significant portion of the variation in firm performance*" (Zaefarian, 2022, p. 315).
Vector autoregression (VAR)	Used to analyze stochastic processes when a univariate autoregression model is generalized for joint estimation of a multivariate model with more than one correlated variable jointly changing over time.
Vector error correction model	Estimates non-stationary time-series data by combining equilibrium and dynamic adjustment into one model; restricted to time-series data with one-lag variable structure though.
Volatility	Rate that traded asset's price changes over time, proxied by price variance. *Social sentiment volatility* captures sentiment's change rate effects on crypto value for positive and negative valences.[b]

Note. We marked *Oxford English Dictionary* definitions with [a] and *Investopedia* with [b], and gave none for our own.

Table A2
Notation and Definitions for Key Trading and Sentiment Variables in Studies A & B.

Variable	Definition
BTC variables for $t = \{1 \text{ or } 3 \ldots 121 \text{ days}\}$	
$TradVol_{Bid,t}$	BTC trade volume for dealer market bid price trades, t
$TradVol_{Ask,t}$	BTC trade volume for dealer market ask trades, t
$TradVol_{Buy,t}$	BTC trade volume for continuous market order buy trades, t
$TradVol_{Sell,t}$	BTC trade volume for continuous market order sell trades, t
Twitter sentiment variables for $t = \{1 \text{ or } 3 \ldots 121 \text{ days}\}$	
$Tweets_t$	# all tweets about BTC, t
Pos_t	# positive sentiment tweets about BTC, t
Neg_t	# negative sentiment tweets about BTC, t
Neu_t	# neutral sentiment tweets about BTC, t
Trades and VECM variables for $t = \{1 \text{ or } 3 \ldots 121 \text{ days}\}$	
InformTrad (μ_t)	Daily BTC trades from informed traders, t
$UninformTrad_{Buy,t}$	Daily BTC buy trades from uninformed traders, t
$UninformTrad_{Sell,t}$	Daily BTC sell traders from uninformed traders, t
P($UpTrend_t$)	Probability of BTC value rise via momentum, t
P($DownTrend_t$)	Probability BTC value fall via momentum, t
TransCost (ϕ_t)	BTC trade transaction cost, t
InfoAsym (χ_t)	Information asymmetry for sentiment & trades, t
PubInfo (σ_t)	Public news as social sentiment, t
***EGARCH* model notation**	
η (*ARCH effect*)	Captures serial correlation for heteroscedasticity.
θ (*GARCH effect*)	Moving avg. component beyond serial corr. for heteroscedasticity
λ (*Leverage effect*)	Down-trending prices affect information asymmetry more
ρ (*Spillover effect*)	Social sentiment may affect trader information asymmetry more
***PIN* model notation for $t = \{1 \text{ or } 3 \ldots 121 \text{ days}\}$**	
φ	*AR* (1) constant
δ_t	Probability of a low signal for market value, t
μ_t	Daily arrival rate of orders from informed traders, t
α_t	Probability an event occurs with private information, t

(*continued on next page*)

Table A2 (*continued*)

Variable	Definition
$\varepsilon_{Buy,t}$	Daily arrival rate of BTC buy orders from uninformed traders, t
$\varepsilon_{Sell,t}$	Daily arrival rate of BTC sell orders from uninformed traders, t
PIN	$\alpha\mu$ / $(\alpha\mu + \varepsilon_{CMBuy} + \varepsilon_{CMSell})$, δ for bad signals, 1 - δ for good signals
	$P(UpTrend_t) = 0.5 + 0.5 \cdot \alpha\ (1\text{-}2\delta)$; $P(DownTrend_t) = 0.5–[0.5 \cdot \alpha\ (1\text{-}2\delta)]$

Note. We applied Easley et al. (1996) *PIN* model and Madhavan (1996) VAR estimation in our study. The price uptrends and downtrends are proxies for price momentum over time.

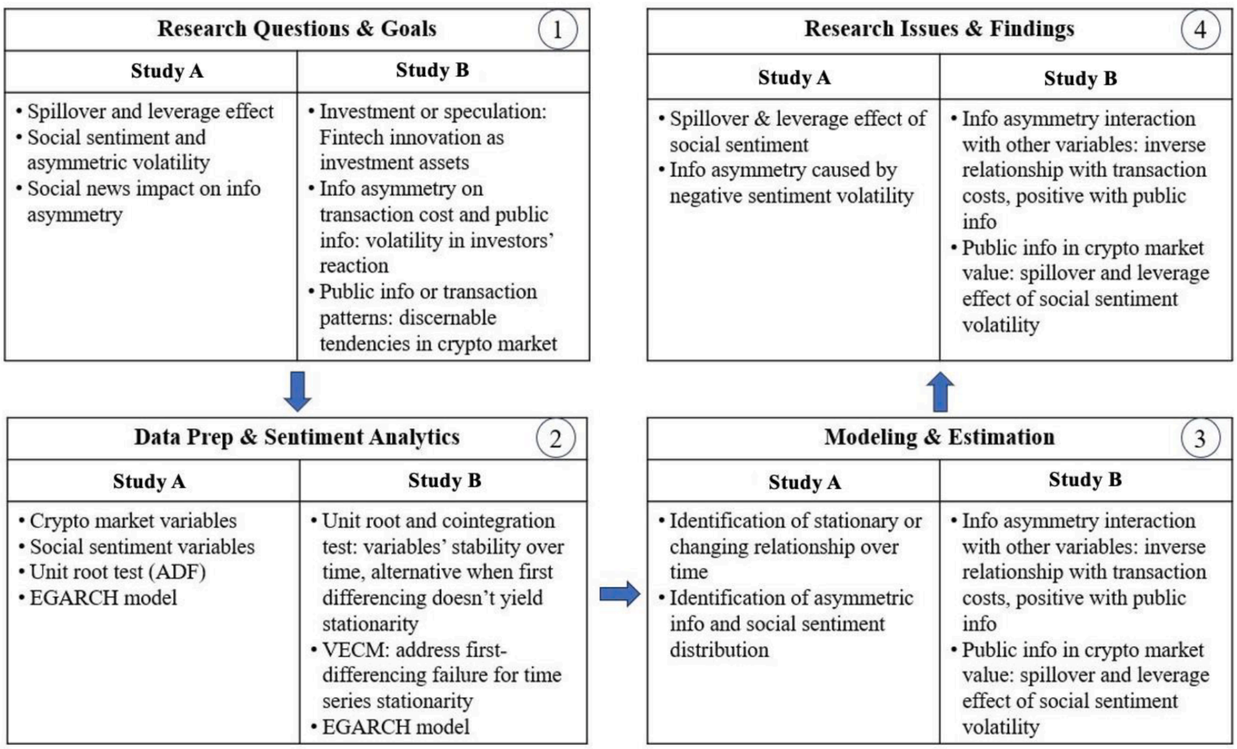

Fig. A1. Four-Stage Research Processes and Methods Sequence for Studies A and B. The logical connections between stages of the research process are described by: (1) the RQs and goals of the inquiry; (2) our dataset preparation work, sentiment analytics, econometric tests, and analysis; (3) the empirical modeling, related theory and hypotheses, and estimation techniques to diagnose issues with time-series stationarity and social sentiment valence distributions to support estimation adjustments; and (4) tests of key relationships to build rigorous empirical findings.

Appendix B. Remarks: Study Data Appropriateness, How PIN Works, and Information Signals from Sentiment

Appendix B, Remark B1. 2018 Twitter Data: Why Is It Appropriate for This Research?

In the review process for the publication of this research, we were asked to justify our use of cryptocurrency trading data from 2018. We offer the following justification in response so the reader will understand our thought process behind this decision. We do so separately here since the main purpose of Section 2 narrative is on Study A's design and findings, rather than get into these issues.

First, if we could have obtained newer data—say, for 2020 before Covid-19 began in 2021—we still would have wished to assess how social sentiment drives observable trading patterns in the cryptocurrency market for "apparently" more vs. less informed traders. Our research inquiry on the general implications of information asymmetry in financial markets suggests that what we have learned about cryptocurrency trading points to there being an *evergreen problem* that is truly worthwhile to study.

Second, whether social sentiment influences trader decision-making and markets is not a matter or "whether or not" anymore. Instead, it is "to what extent," and "what its implications might be." As such, the date and timestamps on our trading data are not of first importance. At the root of the issues we are studying is the emergence in recent decades of social media, the related market-wide sharing of individual opinions on social players, and traders' increased desire to assess the market environment through others before they fire off their own trades. Since cryptocurrency value does not lend itself to assessment of tangible assets or application of the present value of future growth opportunities, value is more about social perceptions in the market than it is about fundamentals. Local media makes it easy to gauge the market's mood or interest in a specific asset based on how available financial asset sentiment is.

Third, our data are from South Korea, a global leader in fintech innovation and a new titan of digital financial market trading (Antsey, 2023). We recognize that market informedness from sentiment may not stand the test of time in market operations (Kim et al., 2023). But Siripurapu and Berman (2023, p. 1) concluded that "*the increasing popularity and high levels of market volatility have raised the stakes of digital asset experimentation.*" Fourth, our studies use BTC trading data from 2018, not as it became available during Covid-19 in 2021 and 2022 though. Trading patterns changed in 2021–2022, while 2023 data will be incomplete until 2Q 2024.

The findings we have obtained from the present exploratory research are crucial to create a baseline for future comparison and longitudinal research. Obtaining fresh data from Bithumb may no longer be viable going into 2024. But harvesting observable digital currency trading data, conducting social-sentiment tracking, and detecting cross-market microstructure trading patterns data will surely persist—as the technical support capabilities make it easier. Indeed, most historical data analytics studies often begin this way. Their authors hope the light they shine on past behavior will nurture new scientific thinking that continues into the present and future—through research innovation.

Appendix B, Remark B2. Informed and Uninformed Traders in the Market—How PIN Works

The focus of market microstructure theory is on traders who base their actions on information, as asset prices are closely linked to it. But is possible to determine the number of informed traders participating by examining market data? For BTC trading, understanding the *PIN* model is necessary.

The *PIN* measure. Easley et al. (1996) introduced the *probability of informed trading* (*PIN*), to gauge the market participation of informed traders. The related model assesses the amount of information entering the market via transaction data, such as BTC buy and sell trade quantities (Easley et al., 2002). This reveals the information they possess in the market. Volume is for BTC transactions and the degree of imbalance between them can be observed. This affects BTC price volatility, which results in traders' reactions. The *PIN* model was designed to account for the possibility of information being present or absent (see Fig. B2).

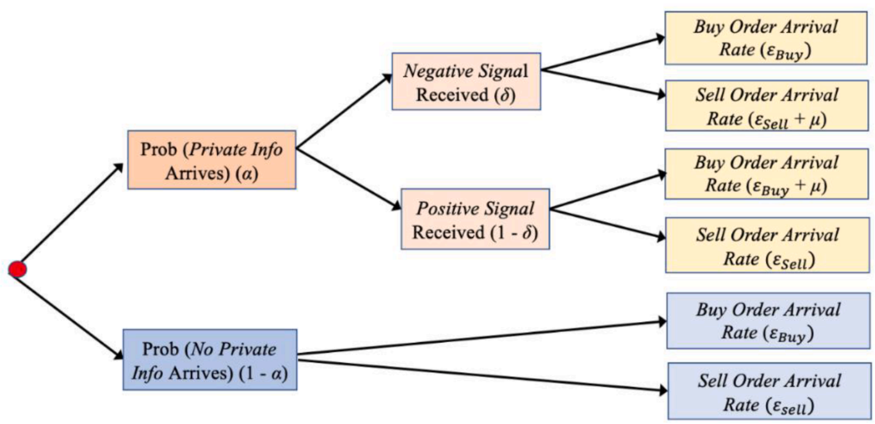

Fig. B2. Probability of Informed Trading. Adapted from Easley et al. (2002, p. 2196); and reconstructed by authors for illustration.

Information refers to what is known to information-based traders, as opposed to all others from public news. The *probability of information being present* is represented by α, while the probability of its *absence* is 1 - α. When there is no information, only uninformed noise traders participate in the market. As such, BTC prices will follow a random walk (like stocks) because there is no information present in the market: only volatility from uninformed traders.

The model we use allows estimation of total BTC buying and selling intensity. It enables estimation of involvement of information-based traders. *Total buying strength* in the market is expressed using the conditional probability in Eq. (B1). The three cases of buying are summed to yield the total buying strength. Similarly, Eq. (B2) expresses *total selling strength*, while Eq. (B3) is *total trading strength* as the sum of the buying and selling strengths:

$$BuyIntensity = \alpha(1-\delta)(\mu+\varepsilon_{Buy}) + \alpha\delta\varepsilon_{Buy} + (1-\alpha)\varepsilon_{Buy} = \alpha(1-\delta)\mu + \varepsilon_{Buy} \tag{B1}$$

$$SellIntensity = \alpha(1-\delta)\varepsilon_{Sell} + \alpha\delta(\mu+\varepsilon_{Sell}) + (1-\alpha)\varepsilon_{Sell} = \alpha\delta\mu + \varepsilon_{Sell} \tag{B2}$$

$$TradStrength = \alpha(1-\delta)\mu + \varepsilon_{Buy} + \alpha\delta\mu + \varepsilon_{Sell} = \alpha\mu + \varepsilon_{Buy} + \varepsilon_{Sell} \tag{B3}$$

Observing the total quantity of BTC bought and sold each day makes it possible to proxy for buying and selling strength in our BTC setting. The right-hand side parameters ($\alpha, \delta, \mu, \varepsilon$) can be estimated though. In the *PIN* model, the behavior of the asset price is determined by the values of α and δ. When $\alpha = 0$, indicating the absence of information, the buy strength and sell strength are equal to ε_{Buy} and ε_{Sell}. If these are normally distributed, the BTC price will follow a random walk. However, if $\alpha = \delta = 1/2$, indicating that all probabilities are equally likely, then the buy and sell strength will be $\mu/4 + \varepsilon_{Buy}$ and $\mu/4 + \varepsilon_{Sell}$. If ε_{Buy} and ε_{Sell} are symmetric, the buy-sell strength will also be symmetric, leading to a random walk again so price prediction won't be possible. And, when $\alpha = 1$ and $\delta = 0$ indicating the presence of information and good news, the buying strength will be $\alpha\mu + \varepsilon_{Buy}$ and selling strength will be ε_{Sell}. The buy-sell strength will be asymmetric, resulting in market imbalance. On this basis, the total strength of informed traders will be $\alpha\mu$ and $PIN = \alpha\mu \,/\, (\alpha\mu + \varepsilon_{Buy} + \varepsilon_{Sell})$.

Appendix B, Remark B3. How PIN identifies information signals from sentiment

A question was raised during the peer review of this research: How to distinguish an information signal that is from news as opposed to from a market price trend? We first measured *PIN*, as discussed in Remark B1. Consider, for instance, starting with 100 buy orders, 80 sell orders, and total volume of 200 BTC. Later, the average volume surpasses 200 and reaches 300 BTC trades. Transactions in each 5-minute period are Poisson-distributed with $f(x) = \frac{e^{-\lambda\omega}\omega^x}{x!} = \frac{e^{-300}300^x}{200!}$, with, ω, the order arrival rate. We include buy-sell orders and total volume. The transaction intensity for a

5-minute period points to the average transactions that occur. If this is 300, the volume over 5 min will be 200, and the news event that generates volume will be independent of earlier news. This is based on market data for informed traders' participation. We used a likelihood function to estimate the parameters for the *PIN* model, based on the available data that we had.

For transaction costs, Madhavan (1996) explained the relevant market attributes and suggested examining asset price and volatility. Two factors are important: dissemination of public information from news and participants' trading behavior. They contribute to price volatility. Positive or negative news triggers BTC price changes. Without it, the BTC price still will vary due to interactions reflecting supply and demand changes. These enable assessment of what each factor contributes to transaction costs. Current BTC price P_t is based on $P_{t\text{-}1}$ adjusted for market-making transaction cost ϕ, the extent of information asymmetry χ, and persisting market orders ρ. These affect the estimated price residuals, which arise from new public information σ, like market news. We will not give the financial econometrics details here; instead the reader should see Easley et al. (2002).

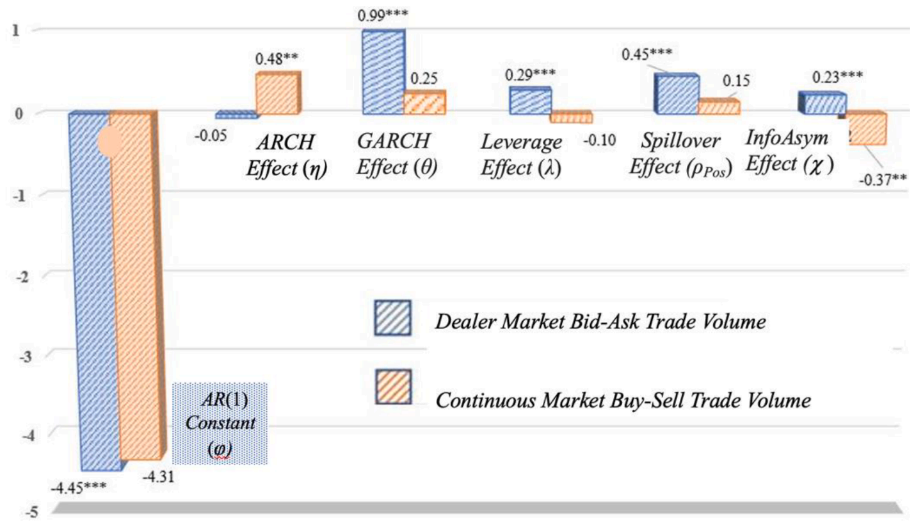

Fig. B3. Spillover Effects for Dealer vs. Continuous Market Trade Volumes. Prior information asymmetry for dealer bid-ask and continuous market buy-sell trades impact information asymmetry more for the former than the latter market microstructure. But volatility for information asymmetry estimates was not significant; so, the past doesn't account for current volatility (no autocorrelation).

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