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Assessing the influence of celebrity and government endorsements on bitcoin's price volatility

Subhan Ullah[a,*], Rexford Attah-Boakye[a], Kweku Adams[b], Ghasem Zaefarian[c]

[a] *Department of Accounting, Nottingham University Business School, University of Nottingham, United Kingdom*
[b] *Department of Management, Huddersfield Business School, University of Huddersfield, United Kingdom*
[c] *Leeds University Business School, University of Leeds, United Kingdom*

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ABSTRACT

The global market capitalisation of bitcoin has exponentially increased in recent years and there are concerns that the current prices of bitcoin do not reflect the true and fair underlying value of this particular type of digital asset. Applying *Cue utilisation theory* and *signalling theory,* and using a panel data on bitcoin prices from Bloomberg between 1st November 2019 and 31st May 2021, we examine the association between celebrity and government endorsements and volatility in bitcoin prices. We find that positive celebrity tweets and positive government sentiments towards bitcoin are significantly positively associated with positive changes in its prices. Our findings imply that although celebrity endorsements may cause a temporary 'exponential rise' in bitcoin prices, investors need to carefully diversify their portfolio to maximise their risk–return relationship.

1. Introduction

From one generation to the next, the simple yet profound microeconomic concept of *price elasticity of demand,* originally introduced by Babbage and somewhat perfected by Marshall in his work *Principles of Economics* (1923), presents interminable research gaps. The implications for refinement and understanding of the core factors that influence consumer attitudes and behaviour towards price (Dodds et al., 1991) and how it stimulates corporate decision-making has been the subject of much debate within business management circles for decades (Kotler & Singh, 1981; Schindler & Schindler, 2011). Despite many years of research, there is still no one-size-fits-all formula that is consistent in measuring the degree to which demand responds to price changes (and vice versa) and the rationalisations for consumer decision choices based on different sectors and markets (Dolan & Jeuland, 1981; Forman & Hunt, 2005; Nair, 2019). The nature of business strategy unceasingly revolves around changes in consumer preferences. And with the emergence of digital technologies such as blockchain and Fintech (for a review on how Blockchain technologuy works, refer to Kimani et al., 2020), it has become obsolete for businesses to set a price simply based on cost, especially in a technology-driven globalised world of constant and complex change caused by customisation, utilisation, and do-it-yourself expetations (see Stott et al., 2016; Natter et al., 2007).

Consequently, cue utilisation theory and signalling theory have been famously used to understand why consumers buy more or less of a good/service, irrespective of it being an inferior, normal or luxury good (Tellis & Wernerfelt, 1987; Helm & Mark, 2007). Thus, announcing a price reduction could even cause a reduction in demand and vice versa, unless the signals and cues presented to consumers align with their expectations. However, sending a coherently symmetric signal that is consistent with consumer expectation requires the producer's credibility and reputation to underscore its validity. As the quality of information depends on the source, changing consumer perceptions to gain confidence in products that are at the introductory stage of their life cycle such as Fintech[1] (digital lending and credit, mobile banking, cryptocurrency and blockchain, bitcoin, among others) requires credible trusted mediums and channels (Kristoufek, 2015; Kimani et al., 2020; Marthinsen & Gordon, 2020). Hence, stakeholders with insider information such as celebrity endorsements, announcements by government agencies, crisis events and increased investments by institutional investors seem to

* Corresponding author.
E-mail addresses: Subhan.ullah@nottingham.ac.uk (S. Ullah), rexford.attah-boakye@nottingham.ac.uk (R. Attah-Boakye), K.Adams@hud.ac.uk (K. Adams), G.Zaefarian@leeds.ac.uk (G. Zaefarian).

[1] According to *Forbes Magazine*'s recent article on *'What Is Fintech and How Does It Affect How I Bank?'* Fintech is a portmanteau for "financial technology" and is a 'catch-all term for any sort of technology that's used to augment, streamline, digitise or disrupt traditional financial services'. https://www.forbes.com/advisor/banking/what-is-fintech/.

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create cues for bitcoin price fluctuations for which further investigation is quite timely. Examined the accountability aspect of celebrity misconduct, resulting into losses for their fans. They find that fans are likely to boycott celebrities when the fan-celebrity relationship is stronger, however they could not find about any evidence whether consumer take any concrete actions because of celebrity misconduct. This also suggest that the impact of any such actions and events related to celebrities are likely to be temporary as the fans are more likely to forgive the celebrity in the longer term.

Wang et al. (2020) examined how informed trading affected bitcoin volatility and returns using augmented AR-GJR-GARCH. They found that positive asymmetric volatility affected market actors for a sustained period. They also confirmed that the presence of 'fear of missing out' presented a significant psychological impact on bitcoin market participants. In a related study, Li et al. (2021) used a Markov regime-switching model to test the forecasting ability of market speculation. They found that the main determinants of bitcoin market volatility consisted of market speculation, investor attention, market interoperability and the interaction between the three. In addition to these, there are a host of studies such as Baur and Hoang (2021), Liu et al. (2021), Xie et al. (2021), Le et al. (2021), Huynh et al. (2021) and Burggraf et al. (2020) that all seem to agree that the COVID-19 pandemic had a significant impact on bitcoin price volatility. Despite the significant contributions presented by these studies, none of them examined how regulatory announcements made by central banks or by a political figurehead could serve as a signal to market participants. In contrast to the above literature, the present work further clarifies and provides the actual decision-making processes and the pathways they follow, firstly to respond to unintended crises, and secondly to examine how major news items and controversial news, as well as celebrity endorsements, cause bitcoin price fluctuations.

Therefore, this paper fills an important research gap and contributes to signalling theory and cue utilisation theory by combining the decision process diagram, both to illustrate and explicate the actual processes investors, regulators, price setters, and directors of firms follow to arrive at pricing and investment decisions respectively. Given that market actors are influenced by factors other than the traditional sources of effect, the six throughput decision-making pathways presented in this study offer unique benefits to policy makers, directors, and investors in minimising bitcoin investment risks. Moreover, whilst the work of Törn (2012) and Fleck et al. (2012) use the match-up hypothesis to examine and explicate the effects of endorsements when there is a fit between the endorser and the brand, this study provides the novel cognitive-throughput decision-making framework both to unpack and enhance our understanding of how market participants make informed investment decisions during bitcoin price fluctuations, by being realistic when interpreting cues and signals from celebrities and high profile entities.

Our study makes a theoretical contribution to this emerging field of digital currencies within the larger fields of accounting, finance, and economics. Historically, agency theory has been predominantly used in finance literature to uncover issues relating to information asymmetries in contractual relationships at firm-level. Our multiple theoretical perspective combines insights from cue utilisation theory, signaling theory, and Rodgers and Gago's Throughput Model (2001). We argue that the complexity and potential risks associated with digital currencies require the application of multiple theoretical lenses to uncover the determinants and dynamics of investors' behaviour when complex and fragile digital transactions are involved. A single theory is unlikely to predict the uncertainties and volatilities associated with digital currencies.

The rest of the paper proceeds as follows: Section 2 reviews the existing literature. Section 3 describes the data and the research design utilised in this study. Section 4 discusses the results and findings, while Section 5, 6 and 7 presents the conclusions and implications and avenues for future research

2. Literature review and hypotheses

2.1. Cue utilisation theory

Cue utilisation theory transcended from the cognitive psychology traditions, which suggest that in dynamic complex and rapid reactive environments, market actors use *anticipation* to circumvent fundamental information-processing constraints (Cox, 1967; Olson, 1972; Helm & Mark, 2007). This implies that market actors judge the quality of a product or service (e.g. the earning potential of a stock) primarily based on the validity of the cues historical market information provides during purchase decisions. Fundamentally, the theory suggests that the extent to which a specific cue is utilised in assessing information validity or product/service quality depends on its *diagnosticity* and the availability of other related cues to affirm decision choices (see Purohit & Srivastava, 2001; Wang et al., 2016). In this paper, the diagnosticity aspect presented in this theory refers to the type of cues that decision-makers find reliable to support quality judgements when investing in bitcoin-backed securities.

Thus, in uncertain market environments where actors find it difficult to understand and define risk, the primary rationale for *diagnosing* the source of information to be used as a cue is to avoid uncertainty. Given that the cryptocurrency-backed securities' demand-and-supply volatility dynamics are found to be responsive to major news items (see Katsiampa, 2019), users and investors actively seek cues consisting of fundamental and technical analysis to improve decisions and avoid risk. Consequently, the understanding of the interdependencies between the price fluctuations of bitcoin-backed securities and the events that affect the volatility dynamics present critical implications for regulators, investors, users, and the overall evolution of Fintech. In a related study, Bruguier et al. (2010) used the theory of mind (ToM) to postulate that speculative and fully uninformed investors utilise cues and signals from trading processes when the fundamental and technical ability of insiders to predict price changes in markets strongly correlates with future valuation prices. This shows that both speculative and value investors depend on insider information, celebrity endorsements, government endorsements and/or disapprovals when making judgements about investment instruments that derive their value from an underlying asset such as those backed by bitcoin.

Gidron et al. (1993) dissected the cue utilisation theory by reclassifying cues to have high and low scope, depending on the degree of diagnosticity. On the one hand, cues that are established over a period of time and are considered by market actors to be consistent, credible, reliable and have higher *predictive and confidence value* are deemed to be high in scope. On this basis, Hu et al. (2010) argue that when investors are faced with complex and high-risk situations, investors overcome moral hazards and adverse selection by relying on reputation as a basis for isolating high-scope cues for long-term investment decisions. This implies that the interaction effects between (a) security assurance and (b) transaction-integrity guarantee the future value of bitcoin-backed firms, irrespective of the fluctuations in price.

Miyazaki et al. (2005) on the other hand, demonstrated that low-scope cues are easily manipulated and are perceived to be ambiguous in providing the basis for making investment decisions during price fluctuations. Therefore, *cue usage* has been the main resource used by both firms that initiate bitcoin-backed stocks and those who trade in them (see Wang et al., 2016; Pant et al., 2018; Chen et al., 2020). In an attempt to understand the relationship between cues and bitcoin-backed security share prices, it is essential to deduce that reputational signals are designed to invoke confidence and predict certainty. Consequently, juxtaposing the cues with signals could expose the main gap in these theories that have remained unexplored for years. The gaps consist of the processes investors follow to utilise the cues and signals to formulate judgements and decision choices.

2.2. Cues and signals

Signalling theory argues that one party (e.g. a firm with bitcoin-backed securities) conveys credible information to another party (traders). Signals are key influencers in firm interactions and networks (Spence, 1978) and the theory is useful to describe behaviour when two parties have access to different information. This foundational theoretical paradigm presented by Spence inspired sustained research to examine, unpack and understand the factors which affect information sharing amongst market participants, popularly referred to as 'information asymmetry' or 'the agency problem' (Jensen and Meckling, 1976; Stiglitz, 2002). Signalling theory argues that firms send out signals to convey their underlying quality and firm value. Therefore, it seems consistent for us to argue that the combination of cues and signals converge on the information source and the dependability of the signaller. For example, for Fintech investors – who are, by and large, high-risk-takers due to the novelty of bitcoin – investor perception is shaped by high-scope cues and the quality of the signal.

Thus, quality signals depend on "the underlying, unobservable ability of the signallers" to present consistent cues to outside receivers (Connelly et al., 2011, p 43). This implies that firms that use bitcoin-backed security invariably seek opportunities to transmit positive signals to various market actors such as ordinary and institutional investors, customers, and government agencies, among others. Regarding investors who value firms from outside using market-driven signals, Cziraki et al. (2014) and Cioroianu et al. (2021) argue that corporate insiders, including the top management team, executives and sometimes non-executive directors, are most likely to possess superior information about the true value of firms whose stocks are backed by bitcoin. Moreover, as asymmetric information results in moral hazards and adverse selection, having access to superior signals based on insider information could minimise risks, especially if the transmitter is deemed to have privileged access. Whilst our data is robust to confirm such a phenomenon, it seems consistent to hypothesis that celebrity endorsements and social media activity of high-profile individuals and insiders have a strong association with percentage change/s in bitcoin-backed security share prices over a period of time.

Whilst this is presented as our first hypothesis, we take particular interest in the work of Hillier et al. (2015), who found that personal attributes such as insiders' year of birth, education, and gender are key drivers of the trading performance of stocks. Moreover, Cioroianu et al. (2021) also confirm that celebrity Twitter endorsements and positive news from credit-rating agencies significantly influence investor sentiments and social media engagement. They use sentimental analysis to synthesise how market euphoria and the hysterical behaviour of high-profile rating agencies and traders affect percentage changes in bitcoin price. Consequently, we present the following two hypotheses:

H1a: There is a significantly positive association between celebrity endorsement/positive tweets and bitcoin-backed share prices.
H1b: There is a significantly positive association between country/government endorsement and bitcoin-backed share prices.

2.3. Embedding cues and signals into the throughput models

Despite the opportunities offered by cue utilisation theory and signalling theory, the biggest challenge and research gap comes from conceptualising the actual process investors follow in analysing and translating the cues and signals into investment decisions. Whilst a cue represents categorical features that market actors can use as a guide when undertaking a series of investment decisions, there is no present study that provides the clearest approach as to the process of decision making. Moreover, whilst signals provide sustained, perceivable, and traceable behaviours and features that have evolved and acquired specific characteristics that convey information about the signaller or the regulatory environment within which such signals are sent, both theories fail to provide the required steps needed to either invest or not invest in any financial instrument. The decision-making processes of market participants who invest in bitcoin-backed stocks are, to a large extent, influenced by how their personalised construal of the cues deduced from prevailing signals is used. Therefore, a model that embeds these processes is long overdue.

In order to trace and explicate the processes investors follow in arriving at a specific decision choice, Rodgers and Gago (2001) developed conceptual model to explain the various decision pathways investors follow to avoid risk and uncertainty. The throughput model captures the philosophical perspectives and reasoning processes that determine how cues and signals are interpreted to arrive at investment decisions (see Trevino, 1986; Rodgers et al., 2020a; Rodgers et al., 2020b). In this study, it is used to depict how the various stages of the decision-making process of bitcoin investors are influenced by unique underlying reasoning. These stages consist of four main concepts including perception, information, judgement, and decision. The four stages interact with each other and show the simultaneous pathways that lead to an investment decision. Fig. 1 presents the decision process diagram and illustrates how investors, regulators, and directors of firms arrive at key decisions.

First, perception is reflected in the antecedents that frame our environment, the way we view information and the cues we draw from the signals (see Hiaeshutter-Rice et al., 2021). Perception is a higher-level mental activity involving categorisation and reclassification (Vliegenthart et al., 2021). Hence, as a higher-level mental activity, perception is influenced by an individual's past experiences, present circumstances, and future expectations. It is also shaped by the perceived risks associated with the decision to invest, which could be marred by a negative regulatory announcement made by a government institution. In relation to the model, **I → P** represents cues from information that could shape and reshape investors' perceptions. Good quality and consistent information could easily be used to re-modify a commonly held opinion. Second, **I → J** removes a person from the judgement (i.e. existing information is normally used in making judgements). In other words, both positive and negative news would be automatically encoded in the judgement stage and the rule followed in making the final decision. Third, the connection between **I → J** does not suggest that cues and signals could be wrongly applied. In fact, **P → I → J** or even **I → P → J** could actually lead to a bias judgement. This, of course, depends on time pressures, crisis situations, uncertain information, unstable environments, smokescreen situations, how influential the cues are, and of course, the level of fundamental and technical expertise of the investor. These factors could determine whether the decision would be a good or a bad one.

Accordingly, embedding the throughput model in this study helps us to clarify and re-evaluate decision-makers' responses to the unintended crises, controversial issues, major news items and celebrity endorsements and how these all matter to the individuals' philosophical views. These aforementioned factors utilise cues and signals during decision making. Thus, we follow the work of Rodgers et al. (2020a), Rodgers et al. (2020b), and Rodgers et al. (2021) in presenting the throughput model in an organised manner consisting of six dominant pathways, based on Fig. 1. The purpose is to highlight how each pathway properly contributes to individual behaviours and decision processes. Previous studies such as Wołk (2020) argue that the fluctuation of bitcoin price is contingent on people's perceptions and opinions, not institutional money regulation. Perception (**P**) represents how we use our senses to frame our world view and interpret our environment. Since information (**I**) is usually subjectively processed by our perception (Ishaque et al., 2021), it is the interdependencies between information and perception that provide the basis for the six throughput decision-making pathways.

In this study, we identify the main pathways that influence bitcoin-backed security investors' decisions as follows: **P → D** (*expertise pathway*) represents the expertise pathways where market/financial experts rely only on their perception about bitcoin price trends in

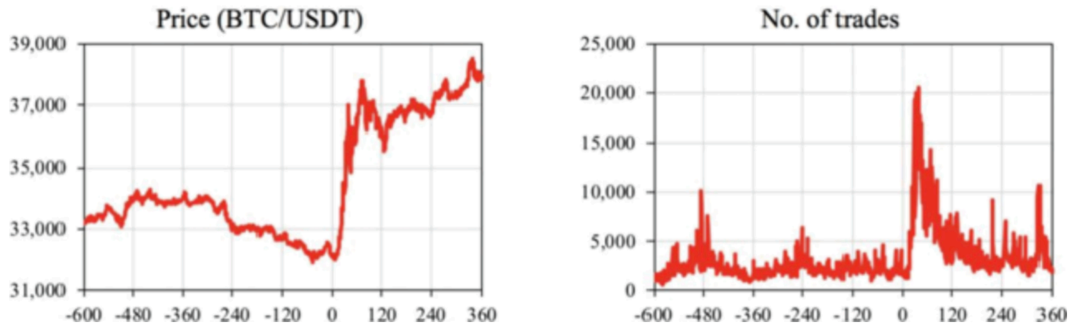


Fig. 1. The effect of Elon Musk changing his Twitter bio to #bitcoin.

making decisions. **P → J → D** *(rule-based trust pathway)* illustrates how existing market/financial rules, guidelines, restrictions, and regulations may influence buyers'/sellers' perceptions and judgements about bitcoin. Although there is no current legislation about bitcoin trading, future bitcoin legislations will directly/indirectly influence bitcoin prices. **I → P → D** *(category-based decision pathway)* assumes that the bitcoin market can be divided into different categories of buyer, who are more responsive to certain types/forms of information. Thus, the perceptions of different categories of market actors are shaped by certain types/forms of information, which influence their bitcoin buying/selling decisions.

In **I → J → D** *(third-party trust pathway)*, market actors use information from trusted third parties such as market/financial experts and trusted celebrities in their bitcoin buying/selling decisions. **P → I → J → D** *(experienced-based decision pathway)* explains how market actors use prior experience and how past/historical market information has shaped their perception about bitcoin trading. In this instance, market actors will accept or refuse to accept particular market information based on their perception, which is mainly based on their market experience. In **I → P → J → D** (*knowledge-based decision pathway)*, unlike the experienced-based decision pathway, decision-makers' perception about bitcoin is influenced by relevant and smart market and financial information rather than their past experience. In some instances, bitcoin decision-makers will use machine learning, neural networks, artificial intelligence, and algorithms in making their investment decisions.

In a nutshell, since information is firstly processed subjectively by decision-makers, the situational information coupled with prior expectation or beliefs about the prevailing cues and signals could determine perceptual covariations (see Brady et al., 2005; Cardon et al., 2017; Breidbach & Tana, 2021). Thus, the interdependency of perceptual concordance or dissonance caused by negative or positive news from a credible source could cause price fluctuation depending on how the market interprets and reacts to such cues and signals. In addition, the re-evaluation of investors' decisions based on emergency or crisis situations could present critical implications for different kinds of judgement and decision choices and the corresponding strategies to be employed by bitcoin-backed security investors.

This model is crucial to this study in two ways: first, the intensity of the cues and signals in a given environment presents a critical impact on judgement and decision choice. Second, it combines the throughput model with the work of Giddens (1990:38), who re-defined perception in the realm of reflexivity by arguing that both concepts consist of *social practices that are constantly examined and reformed in the light of incoming information.* Also, previous studies imply that investors' decision-making on digital assets is influenced by periods of crisis. For example, the empirical studies of Corbet et al. (2020) and Wang et al. (2021b) argue that most people find cryptocurrencies such as bitcoin to be safe-haven assets in times of extreme financial panic caused by events such as the COVID-19 pandemic. They contend that cryptocurrencies such as bitcoin-backed securities' returns were significantly influenced by negative sentiments relating to COVID-19, and that these digital assets act as a safe haven similar to that of precious metals during previous financial crises. Whilst Baur and Hoang (2021) confirm that 'stablecoins' provide stability and a safe haven for bitcoin investors, Li et al. (2021) examined heterogenous features that determine bitcoin volatility. Their interesting conclusion confirms that 'investors' attention' remains the primary source of market volatility.

Scores of recent studies have also examined the impact of crisis on stock market risk. Liu et al. (2021) examined the impact of the COVID-19 pandemic on stock crash risk and how the predictive power of fear could change investor sentiment from the Chinese perspective. Xie et al. (2021) also explored how 44 stock market indices were impacted by the reaction of market participants following the COVID-19 lockdown announcement. In a related study, Le et al. (2021) measured the disproportionate impact of the COVID-19 pandemic and how firms responded differently using machine learning technologies in Vietnamese. In addition, Huynh et al. (2021) found investor sentiments influenced by six main behavioural indicators: media coverage, fake news, panic, media hype, and infodemic and investor sentiment significantly affected the global financial markets during the COVID-19 pandemic. Interestingly, Burggraf et al. (2020) confirmed the connection between investor sentiment and the return on bitcoin.

Consequently, we hypothesise that pessimistic comments from regulators and any crisis which is beyond the control of the decision-makers (market actors) would cause a percentage change in the price of bitcoin-backed stocks.

H2a: There is a significantly positive association between COVID-19 lockdown periods and bitcoin-backed security price changes.
H2b: There is a significantly negative association between pessimistic comments from governments' and bitcoin-backed security prices.

3. Methodology

3.1. Data

The daily firm-level and market datasets used in our study are obtained from the Bloomberg cryptocurrency database. The sample period for our data runs from 1st November 2019 till 31st May 2021. We used the Bloomberg cryptocurrency database because it provides more robust and reliable world-class leading data on bitcoin and many other cryptocurrencies. The database includes data on daily prices and price changes, market capitalisation, shares traded, stock returns and several records on daily transactions of bitcoin and other cryptocurrencies. We concentrated on larger bitcoin-backed security equities due to availability of data. To be able to examine the determinants of bitcoin mispricing (albeit answering the question of why prices of bitcoin are overrated), we decided to include the top performing bitcoin firms in our analysis. First, we searched the Bloomberg database for the top 10 performing bitcoin stocks. However, due to missing data in some of these stocks we settled on seven leading bitcoin-backed listed security companies (please refer to Table 1). Second, since our main dependent

Table 1
Variables definitions.

Variable	Description	Source
Changes in current market price	Last traded price – closing price one day divided by closing price one day ago × 100.	Bloomberg
Changes in current market capitalisation	Last traded total market value – closing total market value one day divided by closing total market value one day ago × 100.	Bloomberg
Changes returns	Measure of changes in corporate profitability, thus how much profit the bitcoin-backed equity generates daily.	Bloomberg
Positive celebrity tweets/ endorsement	We used dummy variable 1 for the periods during which celebrity provided a positive tweets/ endorsement of bitcoin from different news sources, otherwise 0.	Twitter /Google searches
Negative celebrity tweet	We used dummy variable 1 for periods when there were negative celebrity tweets about bitcoin from different news sources, otherwise 0.	Twitter /Google searches
Government pessimism	We used dummy variable 1 for the periods during which government treasury officials from any G7 country provided pessimistic comments about bitcoin from different news sources, otherwise 0.	Twitter /Google searches
COVID-19 during lockdown	We used dummy variable 1 for the COVID-19 lockdown periods, otherwise 0.	Twitter /Google searches
COVID-19 lockdown relaxation	We used dummy variable 1 for the periods during which the lockdown rules were relaxed/lifted (we included periods of negative tweets on bitcoin mining as 1), or otherwise 0.	Twitter /Google searches
Country endorsement	We used dummy variable 1 for the periods during which a country (particularly a G7 country including other countries) endorsed the use of Bitcoin, otherwise 0.	Twitter /Google searches
High-volume purchase by MNC	We used dummy variable 1 for periods during which well-known MNCs/firms endorsed bitcoin and/or make a bulk-purchase of bitcoin, otherwise 0.	Twitter /Google searches

**Note: Celebrity endorsement implies positive celebrity tweets.

variable measures changes in bitcoin prices and returns, we decided to use a time-series approach to capture the daily price changes and changes in revenue of these stocks rather than their monthly, quarterly or yearly price and revenue changes. Third, we used panel data to capture the daily time series at firm level and market data across the seven leading bitcoin firms in our dataset covering the period from 1st November 2019 till 31st May 2021. Also, using https://twitter.com/explore and Google searches, we were able to extract the dates and number of bitcoin-related tweets published during the study period (positive and negative) made by celebrities (for the sake of this study, our definition of celebrities focuses only on well-known/global business leaders – CEOs, founders/owners of multinational corporations etc. Examples of celebrities in our study include the likes of Elon Musk, the founder of Tesla, Jeff Bezos, the founder of Amazon, and Michael Saylor, the CEO and founder of MicroStrategy). Our definition of government officials include Head of Treasury or governors of central banks of a country (we focused on Heads of Treasury because of their unique experience and knowledge about the global financial and monetary systems, such as Andrew Bailey, the governor of the Bank of England, and Janet Yellen, US Treasury Secretary before her appointment). In summary, a total of 1741 unbalanced daily panel data observations were used in our regression analysis after removing outliers and inconsistent data from our dataset.

3.2. Variables

Our study cast novel insights into four fundamental problems regarding bitcoin price changes. First, we examined what happened to bitcoin prices after positive celebrity endorsement. Second, we examined the association between government/country endorsement of bitcoin and changes in the prices of bitcoin. Third, we found out whether the COVID-19 lockdowns or post lockdown situations had any effect on bitcoin price changes. Last but not least, we explored the effects on bitcoin prices as a result of high-volume purchases of bitcoin by well-known multinational corporations. Against the backdrop of the above conundrums, we developed our main variables of interest, which included: changes in market price of the bitcoin-backed security (*CMPx*); celebrity endorsement *(CLBEND)*; negative celebrity tweet *(NCRBtw)*; government pessimism *(GVTPsm)*; COVID-19 lockdown period *(CVDLP)*; COVID-19 lockdown relaxation *(CVDLR)*; country endorsement *(CTREND)* and high-volume purchase of bitcoin by multinational company *(HPBMNC)*. We also included other control variables such as changes in market capitalisation *(CMKTC)* and changes in market returns *(CMKTR)*. Our dependent variable for our regression analysis was changes to market price of bitcoins *(CMPx)*. Previous empirical studies argue that variables such as celebrity tweets (negative/positive), changes in market returns (Corbet et al., 2020), high volumes of bitcoin purchasing by companies and individuals (Gandal et al., 2018), and the COVID-19 pandemic (Choi, 2021) may have had direct/indirect influence in determining bitcoin security prices. For example Choi (2021) found that a 1% increase in tweets lead to about 7% of liquidity improvement of market price in the following five to 10 minutes. He argued that investors' trust and attention to invest in digital assets such as bitcoin are influenced by tweets from reliable people (celebrities/government officials). Thus positive/negative tweets from high-profile celebrities such as Elon Musk about bitcoin signals some level of confidence in the bitcoin security-backed market. Nevertheless, no study has so far examined the effects of these celebrities' tweets (negative/positive) together with tweets from government officials (negative/positive) on the prices of bitcoin-backed security. Our study therefore extends the findings of previous empirical studies and contributes to the literature by contemporaneously examining how each of the above identified variables may influence bitcoin-backed security prices. Our econometric model below is therefore justified by Corbet et al. (2020) and Gandal et al. (2018), who contend that utilising a linear model that takes inputs such as celebrity tweets (celebrity tweets/government officials' tweets, negative/positive tweets, volume of trade etc., can provide some level of prediction or insight into the factors that drive the changes in the price of bitcoin-backed securities.

$$\begin{aligned} CMPx_{1,t} =& \alpha + \beta_1 CMKTC_{i,t} + \beta_2 CMKTR_{i,t} + \beta_3 GVTPsm_{i,t} + \beta_4 CLBEND_{i,t} \\ &+ \beta_5 NCRBtw_{i,t} + \beta_6 CVDLP_{i,t} + \beta_7 CVDLR_{i,t} + \beta_8 CTREND_{i,t} \\ &+ \beta_9 HPBMNC_{i,t} + \varepsilon_{i,t} \end{aligned}$$

3.3. Model validity

We tested for the robustness of our regression models by first examining if any of our models suffered from multicollinearity problems using the variance inflation factor (VIF) measure. All our regression models passed the VIF test, implying that none of our models suffered from any multicollinearity problem. Second, we used Ordinary least squares (OLS) in estimating our regression models, though we are aware that this estimation approach may fail to address some underlying OLS assumptions, such as unobserved firm-level heterogeneity. In dealing with these measurement anomalies we adopted a panel fixed-effect estimation approach.

We explored a suitable estimation approach that could handle endogeneity issues effectively. Fixed-effects estimation can partially control for aspect sources of unobserved heterogeneities (Ullah et al., 2018b, 2020b). Although other superior estimations, such as two-step system GMM, can better control simultaneity bias, while the use of lagged values can overcome the dynamic nature of endogeneity, the nature of our dataset meant that it only spanned a period of less than two years. Also, owing to the nature of our panel dataset, our diagnostic tests (Haussmann test) suggested that a fixed-effects model was an appropriate estimation approach for our dataset (Ullah et al., 2021; Ullah & Nasim, 2021; Wang et al., 2021a). Strict exogeneity is a fundamental assumption of fixed estimation (Ullah et al., 2018a, 2020a). According to this assumption, most of the variables used in our analysis are influenced by exogenous market factors rather than endogenous firm-level factors. For example the effects of the COVID-19 pandemic, celebrity tweets (negative and positive), high volume of purchases, market prices etc. are not within the internal control of management.

3.4. Descriptive statistics and correlation

Tables 2 and 3 represent the pairwise correlation and our summary statistics respectively. From our correlation matrix we noted a negative correlation between bitcoin-backed equity share prices following negative celebrity tweets, government pessimism, and relaxation of COVID-19 lockdown restrictions. On the contrary, our correlation matrix shows a positive correlation between bitcoin-backed equity share prices and positive celebrity tweet/endorsement, and positive tweets from government/country endorsement, COVID-19 lockdown periods and high-volume (bulk) purchasing from multinational corporations. The average value of bitcoin-backed equity price changes was 0.543 (54.3%) and the 25th and 75th percentiles of these equities registering price changes of 1.671 (167%) and 2.858 (approximately 286%) price changes, respectively. These figures underscore the reasons for the high volatility of the changes in the bitcoin-backed security prices.

4. Findings and discussion

Previous studies such as Pant et al. (2018) revealed that both negative and positive tweets about bitcoin have direct or indirect effects on the market value of the bitcoin. However, this study used the recurrent neural-network-based price prediction approach in examining the association between these comments and bitcoin prices. Besides, other studies have used different empirical methods such as the ARIMA method (Poongodi et al., 2020), deep-learning models (Ji et al., 2019), and machine learning models (Chen et al., 2020) in examining bitcoin price determinants. To the best of our knowledge, none of these approaches has used a panel dataset comprising the combinations of firm-level data, market data and handpicked market sentiment data such as celebrities' comments/tweets, government comments/tweets, and COVID-19 pandemic events in examining the market prices of bitcoin.

4.1. Celebrity endorsement and bitcoin price changes

To test our hypothesis 1a, we used celebrity endorsements (please refer to Table 1, variable definition table) in our regression model. Our result revealed a significant positive association between positive celebrity endorsement of bitcoin and the bitcoin-backed equity share prices. Our results are consistent with the cue utilisation theory and signalling theory that imply that investors' attention to invest in risky digital assets such as bitcoin are influenced by tweets from reliable people (Choi, 2021). Empirical studies such as Czaja and Röder (2021) argue that the promotion of digital currency by efficacious celebrities on social media platforms can trigger/increase consumer confidence in the digital assets/bitcoin. Also, our results corroborate the findings in Choi (2021), who revealed that a 1% increase in tweets lead to about 7% of liquidity improvement in bitcoin prices in the five to 10 min following the tweets. There are approximately 47 million Twitter followers, and celebrities such as Elon Musk attract significant attention when they tweet. For example, when Elon Musk changed his Twitter bio to #bitcoin on January 29, 2021, the price of bitcoin skyrocketed from approximately $32,000 to nearly $38,000 within a period of one hour, while trading for bitcoin-backed equity surged, averaging 5000 trades in the hours leading up to Musk's bio change. Please refer to Fig. 1 below.

The situation in Fig. 1 corroborates our throughput decision-making framework that argues that consumer perception about unfamiliar brands can be influenced by information from a reliable third party, including experts or trusted individuals such as celebrities (Heller, Baird and Parasnis, 2011; Naylor et al., 2012).

Examples of positive and negative celebrity tweets

JK Rowling (a British author and writer) in May 2020 tweeted that

Table 3
Summary statistics.

Variable	Minimum	Maximum	Standard dev	Mean	Median
(1) Changes in current market price	−25.325	24.410	5.125	0.543	0.448
(2) Changes in current market cap	−8.183	8.187	4.814	0.164	1.903
(3) Changes returns	−0.001	2.790	0.690	0.0185	0.009
(4) Positive celebrity tweet	0.000	1.000	0.284	0.089	0.000
(5) Negative celebrity tweet	0.000	1.000	0.255	0.070	0.000
(6) Government pessimism	0.000	1.000	0.243	0.063	0.000
(7) COVID-19 lockdown period	0.000	1.000	0.423	0.233	0.000
(8) COVID-19 lockdown relaxation	0.000	1.000	0.359	0.151	0.000
(9) Country endorsement	0.000	1.000	0.377	0.171	0.000
(10) High-volume purchase by MNC	0.000	1.000	0.394	0.191	0.000

Note: HPMNC represents high-volume purchase of bitcoin by multinational corporations. (Please refer to Table 1 for variable definitions)

Table 2
Pairwise correlations.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Changes in current market price	1.000									
(2) Changes in current market cap	0.105*	1.000								
(3) Changes returns	0.008	0.000	1.000							
(4) Positive celebrity tweet	0.071*	0.006	−0.008	1.000						
(5) Negative celebrity tweet	−0.147*	−0.035	0.083*	−0.086*	1.000					
(6) Government pessimism	−0.150*	−0.036	0.088*	−0.081*	0.942*	1.000				
(7) COVID-19 lockdown period	0.130*	0.022	−0.015	0.566*	−0.151*	−0.142*	1.000			
(8) COVID-19 lockdown relaxation	−0.136*	−0.033	0.053*	−0.132*	0.650*	0.613*	−0.233*	1.000		
(9) Country endorsement	0.069*	0.023	−0.012	0.021	−0.125*	−0.117*	0.347*	−0.168*	1.000	
(10) High-volume purchase by MNC	0.095*	0.009	−0.013	0.042	−0.134*	−0.126*	0.262*	−0.206*	−0.221*	1.000

Note: *Show significance level at 0.05

"People are now explaining Bitcoin to me, and honestly, it's blah blah blah collectibles (My Little Pony?) blah blah blah computers (got one of those) blah blah blah crypto (sounds creepy) blah blah blah understand the risk (I don't, though.)"

Elon Musk responded to her thread, stating, "Pretty much, although massive currency issuance by govt central banks is making Bitcoin Internet money look solid by comparison."

In December 2020, Elon Musk posted a negative tweet about the temptations of bitcoin while trying to live a normal life.

Michael Saylor, the CEO and founder of MicroStrategy, responded by stating that Tesla would be doing shareholders a favour if it converted some of its balance sheet to bitcoin.

"If you want to do your shareholders a $100 billion favor, convert the $TSLA balance sheet from USD to #BTC. Other firms on the S&P 500 would follow your lead & in time it would grow to become a $1 trillion favor."

In response, Musk asked, "Are such large transactions even possible?"

The crypto community was quick to inform Musk that this was entirely possible. Musk then made his Twitter bio #bitcoin and said, "In retrospect, it was inevitable."

Later, in a Clubhouse room, Musk posted a very positive tweet commenting about bitcoin as follows:

"I do at this point think Bitcoin is a good thing. I am a supporter of Bitcoin. I was a little slow on the uptake. I think Bitcoin is on the verge of getting broad acceptance by conventional finance people."

Andrew Bailey (Governor of Bank of England) Remains Sceptical About Cryptos

'Crypto-assets', as the central bank's official labels bitcoin and the rest, present a danger to the public, Bailey told the British Parliament's Treasury Committee. The Governor's statement on Monday reiterates his long-standing concern about decentralized digital currencies, Reuters noted in a report. Addressing the committee members, the head of the Bank of England said:

"I'm sceptical about crypto-assets, frankly, because they're dangerous and there's a huge enthusiasm out there."

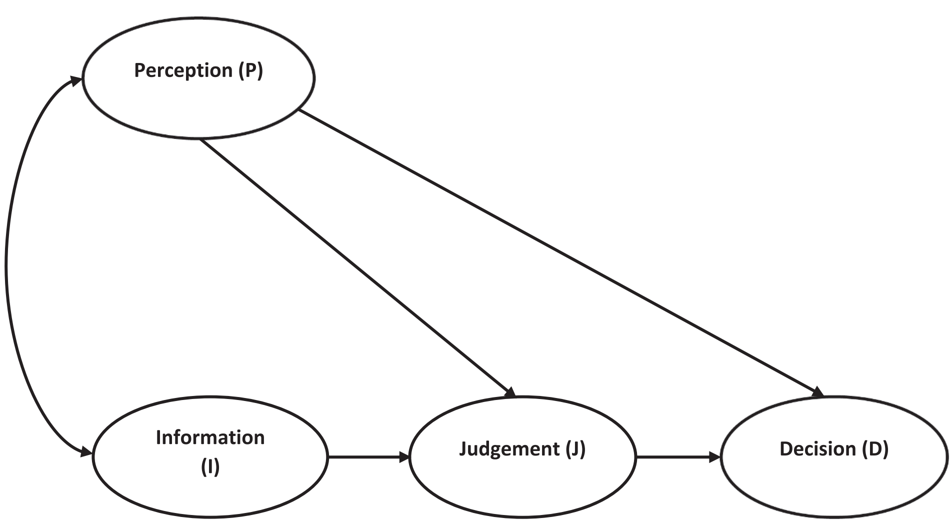
In this instance, consumers rely on the third-party trust using the Throughput decision-making pathway (presented in Fig. 2) when making their purchasing decision, which is contingent on the information from celebrities/experts changing their perception and judgement about unfamiliar/risky digital brands such as bitcoin. The above analysis and results confirm our hypothesis 1a. Also, it is worth mentioning that the bitcoin trades in the hours leading up to Musk's bio change were averaging below 5000 trades per hour. In the 60 min following the bio change, trading jumped to more than 20,000 trades before coming back down closer to their normal trading range.

4.2. Effects of country/government bitcoin endorsement and bitcoin-backed security share prices

To test our hypothesis 1b, we included country/government endorsement as a dummy variable in our regression analysis. Our result in Table 4 Model 7 showed a significant positive association between country/government endorsement and bitcoin-backed security prices. Our results confirm hypothesis 1b and the cue utilisation theory that contends that usually market actors seek expert knowledge and information from a reliable source when taking risky investment decisions such as cryptocurrency bitcoin investment (Hu et al., 2010). Also, previous studies argue that negative/positive tweets or statements from state governments about bitcoin have direct or indirect influence on the value of bitcoin (Wang et al., 2016; Pant et al., 2018; Chen et al., 2020). This result corroborates our **I** → **J** → **D** *(third-party trust)* throughput decision-making pathways and the signalling theory that both posit that since bitcoin investors lack expertise in the market, they are likely to follow an information source that is more reliable. For example, a positive tweet from a state/country official such as the Governor of the Bank of England or the US Treasury Secretary can provide crucial signals about the true state of affairs of the market situation of bitcoin, since the state and government agencies have access to credible and more reliable cryptocurrency databases. On the contrary, an adversarial position on bitcoin expressed by the government of China, which has significant control over its national Internet infrastructure, can have a significant effect on bitcoin trade and prices (Kaiser et al., 2018).

4.3. Effects of COVID-19 lockdown on bitcoin-backed security share prices

The unprecedented global spread of COVID-19 resulted in several countries enforcing strict quarantine policies and complete lockdowns. The burgeoning studies have also revealed that the COVID-19 pandemic



Whereby, P = perception, I = information, J = judgement, and D = decision

Source: Rodgers et al. (2020a and b)

Fig. 2. The Throughput Model.

Table 4
Determinants of bitcoin-backed security price changes.

VARIABLE	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Changes in market cap	0.00445***	0.00421***	0.00443***	0.00422***	0.00433***	0.00425***	0.00438***	0.00441***
	(0.00100)	(0.00099)	(0.00100)	(0.00099)	(0.00099)	(0.00099)	(0.00100)	(0.00100)
Changes in market returns	0.002	0.003	0.002	0.002	0.003	0.003	0.001	0.002
	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00002)	(0.00003)
Government pessimism		−3.16308***						
		(0.49327)						
Positive celebrity tweet			1.27033***					
			(0.42287)					
Negative celebrity tweet				−2.96042***				
				(0.46879)				
COVID-19 lockdown period					1.58493***			
					(0.28563)			
COVID-19 lockdown relaxation						−1.99674***		
						(0.33813)		
Country endorsement							0.91746***	
							(0.32458)	
High-volume purchase by MNC								1.23947***
								(0.32043)
Constant	0.53995***	0.71012***	0.39446***	0.71720***	0.11807	0.79368***	0.37271**	0.26745*
	(0.12517)	(0.14126)	(0.14518)	(0.14165)	(0.15602)	(0.14597)	(0.14845)	(0.15334)
Observations	1741	1741	1741	1741	1741	1741	1741	1741
R-squared	0.01125	0.03420	0.01644	0.03353	0.02856	0.03080	0.01586	0.01978

Note: Our dependent variable is change in share price. In model (1) we found significantly positive linkages between market capitalisation and changes in share price. Models (2) – (8) examine the relationships between each of the main variables of interest and changes in the share price of the 100% backed bitcoin equities. Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ 100%. (Source: Our analysis is based on 100% bitcoin-backed equity firms datasets collected from Bloomberg).

resulted in an astronomic rise of the use of the Internet, with the concomitant effect of altering consumers' buying/purchasing behaviours, particularly with digital commodities such as bitcoin (Koch et al., 2020). However, studies that examine the effects of the pandemic on cryptocurrencies are scant and scattered. Our study therefore draws from the signalling and cue utilisation theoretical lenses to provide new insights about the effects the COVID-19 pandemic had on bitcoin-backed security prices.

Our results from Model 5 in Table 4 revealed significant positive linkages between COVID-19 lockdowns and bitcoin-backed security price changes. Our findings are consistent with previous empirical studies that revealed that, on average, there was a daily increase in market price of Ethereum, Bitcoin, Litecoin, and Bitcoin Cash by 0.58%, 0.44%, 0.36%, and 0.15% respectively during the COVID-19 lockdown period, particularly when COVID-19-confirmed death cases increased by 3.77%, and 3.65% daily (Sarkodie et al., 2021). Liu and Lee (2020) also used the ARMA and GARCH models to capture bitcoin returns and price-condition volatility, and found a significant positive relationship between the daily trading volume of bitcoin and condition volatility. They argue that the COVID-19 lockdown-period signals resulted in an increase in bitcoin price due to the declining public trust in our traditional currency as a result of the market uncertainties. Also, the upward gains may be partly the negative perception of the financial market investors who saw bitcoin as a potential digital hedge fund that could be used to hedge against global economic financial instabilities and possible inflation that caused by the COVID-19 pandemic (Sarkodie et al., 2021).

On the contrary, our study revealed a significantly negative association between bitcoin-backed security prices and the COVID-19 lockdown relaxation period, especially during the month of May, when both government and celebrities highlighted via negative tweets the increasing CO_2 emissions caused by bitcoin miners. The above empirical findings and our results confirm hypothesis 2a, which argues for a significant positive relationship between the COVID-19 lockdown period and bitcoin-backed security share prices. The above findings imply that, in crisis periods with low levels of economic activity and loss of confidence/trust in our traditional banking and financial ecosystems, investors may seek investment-based refuge in blockchain transactions and cryptocurrencies that offer them more control, less cost and more transparency (Kimani et al., 2020; Sarkodie et al., 2021). Our findings provide important practical lessons that can guide directors, investors and policy makers regarding their preparations for a possible future pandemic.

4.4. Effects of negative/pessimistic comments from governments on bitcoin-backed security share prices

To test our hypothesis 2b, we included a dummy variable that captured negative or pessimistic comments from governments about bitcoin in our corpus of variables (please refer to Table 1, variable description). It is worth mentioning that our dummy variable in this instance covered our sample period when negative or pessimistic comments about bitcoin were made by government officials. These included negative or pessimistic comments from governments that highlighted the risk and dangers associated with the unregulated bitcoin market, as well as negative tweets and statements from government and state officials that elucidated the environmental consequences of bitcoin mining. Our results from Model 2 in Table 4 revealed a significant negative association between negative or pessimistic comments from governments and bitcoin-backed security share prices. These findings corroborate with the cue utilisation and signalling theories and confirm our hypothesis 2b, which contends that relevant information from credible sources such as governments provides important cues and signals to market actors who engage in risky and unregulated financial transactions.

Our finding corroborate our **I** → **P** → **J** → **D** (*knowledge-based throughput decision making pathways*, see Fig. 2) as well as previous studies (Bruguier et al., 2010; Katsiampa, 2019) that contend that investors/buyers who are less informed about the riskiness of a financial product or equity usually seek cues from expert information sources, government information, and regulators to guide their judgement and investment decisions. Our above results offer a practical guide to prospective bitcoin investors. For example, drawing from our *knowledge-based throughput decision-making pathway* **(I → P → J → D),** we noted that buyers' risk perception **(P)** about bitcoin investment can be influenced by drawing from the embedded knowledge and cues inherent in government information **(I)** (albeit tweets, statements etc.) about bitcoin.

Thus, given that bitcoin prices are extremely volatile, our six throughput decision-making pathways can offer relevant and unique benefits to policy makers, directors and prospective bitcoin investors. Our results from Model 8 in Table 4 also show a significant positive association between huge/high-volume purchases from multinational companies and the price of bitcoin-backed securities. Further, our results in Table 4 consistently show significant positive linkages between changes in market capitalisation and bitcoin-backed security price changes. These finding are consistent with the signalling theory and the previous empirical studies that argue that when bigger organisations or multinational corporations adopt bitcoin, it signals trust and confidence among other buyers of the cryptocurrency (Connolly and Kick, 2015).

Regarding our regression Table 5, we report a summary of results that highlights some of the key findings in our study (a) at the individual firm level and (b) from the perspective of all firms involved in our dataset. We noted consistent significant positive linkages among each company between bitcoin-backed security prices and the following: celebrity endorsements (positive celebrity tweets), changes in market capitalisation, COVID-19 lockdown periods and the high-volume/(huge) purchases by multinational corporations. Regarding the negative relationships, we noted that at individual firm-level, negative celebrity tweets and COVID-19 lockdown relaxation had negative but insignificant associations with bitcoin-backed equity prices. Nonetheless, when all seven companies were combined, the insignificant negative associations between these two variables and bitcoin-backed security prices changed to a significant negative association. These results are consistent with other studies that contend that, on aggregate, the bitcoin market is sentimental to market information (Cioroianu et al., 2021; Pant et al., 2018), and follow the assumptions of the efficient market hypothesis (Jacub 2015). Fig. 3 provides a better insight and understanding about the effects of our main variables on bitcoin price changes.

5. Conclusion

Bitcoin prices have experienced an unprecedented level of volatility in the recent past. Currently the global market value of bitcoin has surpassed $653 billion, and research on bitcoin price volatility is in its infancy. The vast majority of literature in business, marketing, economics, finance, and accounting have explored factors affecting the prices of a product, commodity or an asset. As a financial asset, bitcoin prices are vulnerable to a wider range of micro- and macro-level factors, including celebrity endorsements, government announcements relating to the adoption, governance and regulations of bitcoin. However, a key and fundamental question arises as to whether the current prices of bitcoin are economically justified. Can these prices be explained from cognitive and psychological theories? To what extent does the price of bitcoin change following endorsement by leading celebrities, and subsequent to government decisions regarding the adoption of bitcoin?

Applying *Cue utilisation theory* and *signalling theory,* we collected data on bitcoin prices from Bloomberg between 1st November 2019 till 31st May 2021 to assess how positive and negative endorsements from celebrities and governments affect changes in bitcoin prices. Our time period covers extremely challenging economic times, including the COVID-19-related lockdowns and subsequent relations to assess the degree of volatility in this unique socio-economic and psychological setting. We also applied the Throughput Model, which offers a conceptual framework to examine how various cues, including information, perception and judgement, affect investors' decision-making i.e. price volatility of bitcoin. We found a significantly positive association between the positive celebrity endorsement of bitcoin and the rising of bitcoin-backed equity share prices. We also found a significantly positive association between country/government endorsements and rising bitcoin-backed security prices. Our findings can be explained using insights from signalling theory, and these findings can only be generalised in the context of digital financial assets and securities.

6. Implications for theory, practice, and government policy

The findings from our studies imply that tweets from well-known celebrities on social media platforms, particularly during crisis periods, can offer significant cues and signals that may attract/influence prospective investors to invest in digital assets. Most well-known people have social media accounts that can accumulate significant data, from which both businesses and investors can extract significant benefits to guide their trading activities in digital assets. For example, using big-data analytics, algorithms, and artificial intelligence can support cryptocurrency investors in predicting the prices of digital assets. On the contrary, it is worth mentioning that, unscrupulous celebrities may use these social media platforms to manipulate the price of digital assets for their own self-interest (thus using their tweets, for example, as a profit-making tool). Consequently, we suggest that future cryptocurrency regulatory measures should provide strict regulations that will prevent such occurrences. Also, using insights from traditional finance literature,

Table 5
Determinants of bitcoin-backed security price changes or individual securities.

VARIABLES	ABTC-SW	BTCE-GR	BTCE-GY	BTCW-SW	COINXBE	VBTC-GR	VBTC-GY	AGG-EFT
Changes in market cap	0.12259***	0.12259***	0.12940***	0.46062***	0.29271***	0.75051***	0.22387***	0.32412***
	(0.00703)	(0.00703)	(0.01155)	(0.02339)	(0.00302)	(0.05422)	(0.09214)	(0.00098)
Positive celebrity tweet	0.86593***	0.81507**	0.49918**	0.91996***	0.61286**	0.49307**	0.93291***	0.89567***
	(1.28672)	(1.06134)	(1.41284)	(0.90907)	(0.75030)	(1.27820)	(2.17804)	(0.53087)
Negative celebrity tweet	−0.85486	−0.04639	−0.05915	−0.09730	−0.28607	−0.30915	−0.09619	−0.39464**
	(3.44125)	(2.21024)	(3.68699)	(2.47399)	(2.02731)	(2.76637)	(4.70024)	(1.42153)
Government pessimism	−2.85123	−0.30979	−2.56341	−0.20539	−0.23825	−0.10257	−2.92038	−0.99426**
	(3.48316)	(2.24390)	(3.74281)	(2.50353)	(2.05354)	(2.81092)	(4.77598)	(1.43882)
COVID-19 lockdown period	0.61206**	0.50594**	0.87177***	0.67861**	0.62078**	0.58202**	0.92725***	0.80876***
	(0.94628)	(0.75659)	(1.26078)	(0.67955)	(0.55715)	(1.09982)	(1.86903)	(0.41458)
COVID-19 lockdown relaxation	−0.30295	0.21643	−0.26041	0.39139	0.27485	−0.28409	−0.25816	−0.84708**
	(1.12275)	(1.51903)	(1.18238)	(0.74761)	(0.60975)	(1.96120)	(3.33478)	(0.44612)
Country endorsement	0.98868	−0.33454	−0.55462	−0.65912	−0.10133	−0.96649	−3.83642	0.53148
	(0.92208)	(1.29194)	(1.48283)	(0.59845)	(0.49055)	(1.60811)	(2.73532)	(0.37965)
High-volume purchase by MNC	0.85248***	0.88200***	0.87142***	0.52651**	0.51971**	0.93571***	0.76597***	0.80296***
	(0.81500)	(1.29112)	(0.86375)	(0.51935)	(0.42185)	(1.64292)	(2.79557)	(0.36769)
Constant	0.20402	0.46755	0.57684	0.21328	0.12961	0.90073	4.95767	0.28371
	(0.52317)	(1.37559)	(0.50061)	(0.23006)	(0.17949)	(1.79181)	(3.04724)	(0.18052)
Observations	241	133	240	370	392	129	126	1780
R-squared	0.45075	0.72653	0.55032	0.53400	0.72166	0.63936	0.48303	0.44899

Note: We examined the linkages between each variable of interest and the changes in share price of each individual 100%-bitcoin-backed equity in our dataset. We noted a significant positive association between market capitalisation, celebrity endorsement, COVID-19 lockdown, multinational corporation high-volume purchasing of bitcoin and changes in bitcoin-backed equity share prices. Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

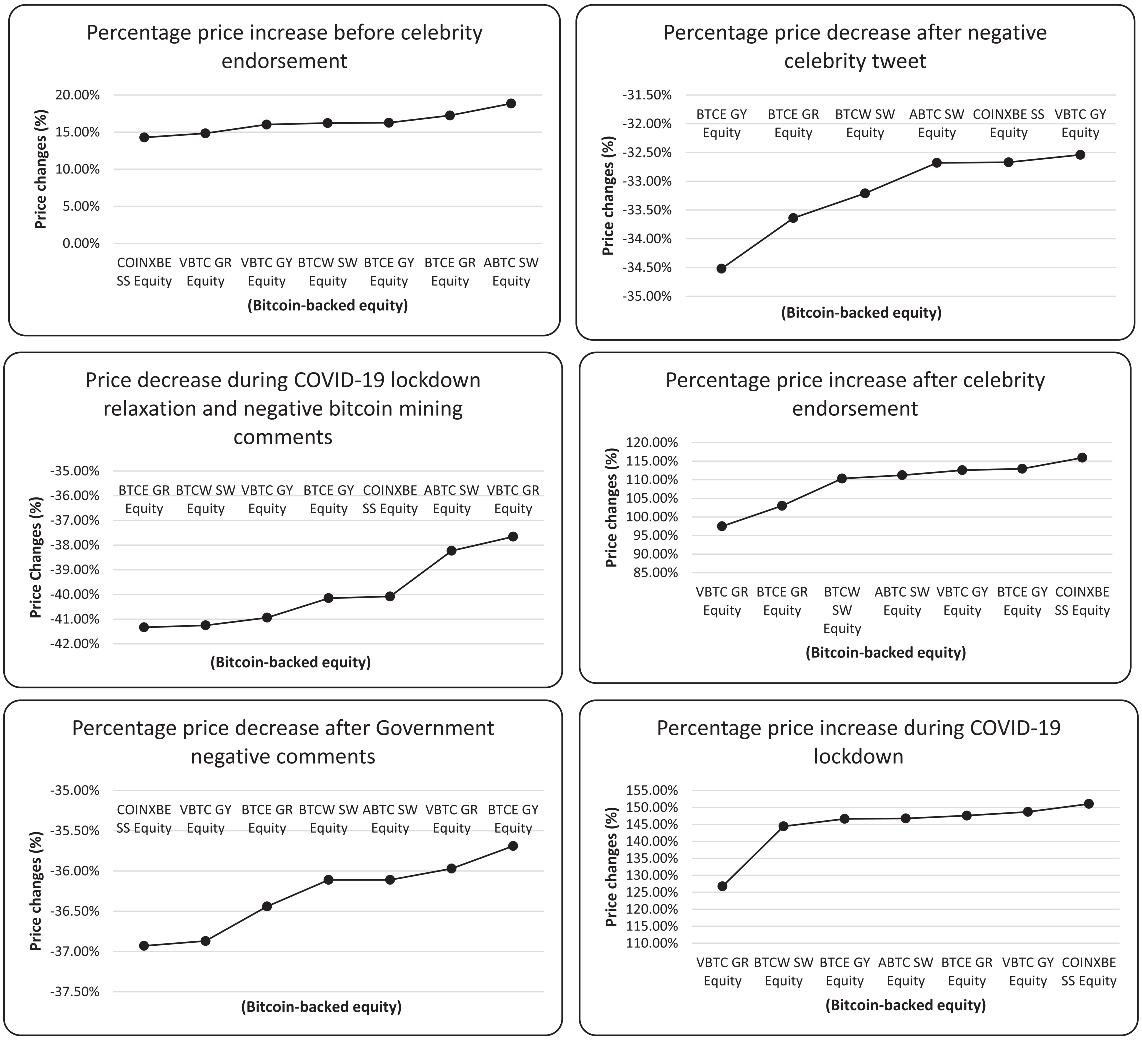


Fig. 3. Price changes following celebrity and government endorsements.

a simple rule of 'not putting all eggs in one basket' also applies to Bitcoin. Investors need to diversify their portfolio by considering other financial and non-financial assets (gold, oil, stocks and commodities), to minimise their risk and enhance their portfolio return. The six throughput decision-making pathways offer unique benefits to policy makers, directors and investors in understanding and assessing the risk exposure in the bitcoin market. We suggest the use of a cognitive-throughput decision-making framework (DMTPF) that will support customers to make informed decisions against bitcoin mispricing and consequently reduce the risk associated with it. Governments and regulatory bodies around the world also need to develop investment guidelines for general awareness about bitcoin investment platforms, so that investors can make informed decisions about their investment choices.

From a traditional finance perspective, investors interested in bitcoins need to apply traditional valuation techniques, including the use of 'technical analysis' and 'fundamental analysis' in determining the intrinsic value of bitcoin-based securities. Investors also need top diversify investment in various bitcoin-based securities, adding alternative and traditional investment options to their baskets, such as stocks, bonds, and gold. Such diversification strategy is likely to enhance investor return in the long run.

7. Avenues for future research

The findings of our existing research should be interpreted with caution, particularly in the context of traditional assets and commodities. Future studies can explore how positive and negative media sentiments (comments on other social media, Instagram, LinkedIn etc.) by different categories of celebrities (albeit celebrities from varied backgrounds such as entertainment, football, athletics, academia, etc.) can influence the volatility of financial assets and other commodities. We also suggest the use of more interpretive qualitative-based research in the context of Fintech research. For example, using an interview-based approach would help researchers in understanding investors' perceptions about bitcoin and the determinants of paying a price premium for such overvalued assets. Perhaps a large-scale, cross-country survey could be very useful to tease out how institutional differences and variations in culture affect investors' sentiments towards bitcoin and other digital assets. Doing so is beyond the scope of our existing study, and hence we leave that for future research.

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

Data will be made available on request.

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Dr Subhan Ullah is an Associate Professor in Accounting and Departmental Research Director at the University of Nottingham, UK. He has extensive experience of teaching in several institutions, including, University of Hull, Nottingham Trent University, University of Buckingham, The Open University, COMSATS University (Pakistan), University of Peshawar (Pakistan) and Allied Bank Limited (Training Academy). Subhan Ullah is a Senior Fellow of HEA and is a member of CPA (Australia). His research in the area of corporate governance appears in leading international journals, namely, *British Journal of Management, Critical Perspectives on Accounting, International Review of Financial Analysis, International Journal of Finance and Economics, Annals of Operations Research, Industrial Marketing Management, Technological Forecasting & Social Change, Journal of Environmental Management,* and others.

Dr Rexford Attah-Boakye is a Assitant Professor of Accounting at the University of Nottingham, UK. Rexford is also a module leader for financial control and information systems in Accounting and finance at university of Hull. As a qualified chartered accountant and a member of four professional bodies including ACICM, CQRM, QTS and FHEA, Dr Attah-Boakye has over ten years' experience as Head of Audit of a major bank in Ghana. His area of speciality is in integrated financial reporting, accounting and accountability, corporate governance, social accounting, environmental accounting, taxation, auditing, merger and acquisition, quantitative risk management, financial analysis. His work has been published in *British Journal of Management, Technological Forecasting and Social Change, Journal of Enviromental Management, and International the Journal of Finance and Economics.*

Dr Kweku Adams is a Senior Lecturer in Management (Strategy) at the Huddersfield Business School, University of Huddersfield, UK. He is a Senior Fellow of the Higher Education Academy and holds a PhD from Swansea University. Dr. Adams has also held academic positions in North America. First, as a Lecturer in Strategy and Global Management at the Haskayne School of Business, University of Calgary and a Visiting Lecturer of Management at the University of Lethbridge School of Management in Calgary, Canada. His research interests centers on business strategy and international business, specifically the management of headquarters-subsidiary relations, investigating the wider governance challenges facing multinational corporations. His work has appeared in quality outlets such as the *Journal of International Management, Technological Forecasting and Social Change, IEEE- Transactions on Engineering Management, Journal of Environmental Management, Critical Perspectives on International Business, Thunderbird International Business Review, The International Journal of Minerals Policy and Economics, Employee Relations,* amongst others.

Dr. Ghasem Zaefarian is an Associate Professor of Marketing at Leeds University Business School, University of Leeds, UK. He has been awarded a PhD in Marketing from Manchester Business School, the University of Manchester, UK. His research has been published in many journals of international repute including *Long Range Planning, Journal of International Marketing, International Journal of Operations & Production Management, Journal of Business Research, and Industrial Marketing Management*. Dr. Zaefarian currently serves as an Associate Editor of the Industrial Marketing Management journal.