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Is it possible to establish the link between drug busts and the cryptocurrency market? Yes, we can

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ABSTRACT

Following the rampant increase in Bitcoin prices, there has been a proliferation of cryptocurrencies, which have become a major way of doing business across national boundaries. This paper investigates the link between cryptocurrency markets and drug trafficking activities. More specifically, we explore the impact of the announcement of 24 major drug busts on the systematic risk and return of the world cryptocurrency market. We deploy an event study methodology to estimate the abnormal returns associated with drug trafficking activities in the cryptocurrency market. We find that the relationship between the two is quite strong in the case of some cryptocurrencies, albeit weaker in others. However, we show that drug bust news tends to create uncertainty, and accordingly impart risk into cryptocurrency markets. This study confirms the predictions of convenience theories of crime as to the relative attractiveness of cryptocurrencies to criminals, and the extent to which not only general, but also their own future interests, sacrificed readily on the altar of accessibility. We highlight how when social and regulatory foundations are weak, criminal behaviour may overwhelm virtual spaces, marginalizing more orthodox businesses, no matter how altruistic the intentions of their founders.

1. Introduction

Since the creation of Bitcoin in 2009, cryptocurrencies initially captured the attention of investors then subsequently by businesses and government. At present, central banks around the world are trying to launch their own cryptocurrencies as part of the digitization of the financial sector and cyber security is one of their major concerns. The global objective is to create a digital infrastructure that is free of illegal activities. The main purpose of our paper is to contribute to the current debate on the adoption of cryptocurrencies by the governments and more specifically around the illegal activities associated with money laundering of drug related activities.

The impact of 'new age technologies' on business (Chalmers, Matthews, & Hyslop, 2021; Kumar, Ramachandran, & Kumar, 2021), specifically focussing on cryptocurrencies (Fisch, Masiak, Vismara, & Block, 2021), and their impact in an emerging deregulated trans-national market space is an important facet of an emerging technological paradigm (Branzei & Abdelnour, 2010; Coviello, Kano, & Liesch, 2017). The burgeoning size of the cryptocurrency market notwithstanding, cryptocurrencies, and the blockchain technology that underpins their operation, are becoming increasingly appealing to retail investors, corporations and governments. Twitter users, for instance, are attracted to blockchain technology due to its privacy, security and transparency, amongst others (Grover, Kar, Janssen, & Ilavarasan, 2019), while corporations and governments globally are using cryptocurrencies for a range of internal aspects such as control of information in treasury spending and external engagement to secure capital (Deloitte, 2021). In part, the popularity is due to all players in this arena becoming more familiar with cryptocurrencies; however, the pseudonymity provided by cryptocurrencies is firstly and foremost the major source of their popularity. The pseudonymity inferred by cryptocurrencies, while an admirable characteristic, is also the first point of exploitation for criminal activity. Intersecting with cryptocurrencies is the ability of criminals to use cryptocurrencies for nefarious activities that effect the wider

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business ecosystem (e.g. Fernandes, Mason, & Chakrabarti, 2019; Lacerda, 2016; Guzmán, Mehrotra, Morck, & Trujillo, 2020). This paper, at the nexus of cryptocurrencies and criminal activities, contributes to the evolving literature in both these areas by highlighting the impact of drug bust news on the risk and return of cryptocurrencies.

Cryptocurrencies, representing a decentralized digital payment system, are widely used to transfer money globally at low transaction costs and, relative to other methods such as bank transfers, with a higher level of user anonymity (Fisch et al., 2021). Due to these basic characteristics, the cryptocurrency market has seen remarkable growth: its current market value is approximately US$2.3 trillion (CoinMarketCap, 2021), becoming a major medium of exchange across national boundaries. This remarkable growth has led to the belief that the cryptocurrency market is speculative and, indeed, at least part of this ecosystem has assumed the classic characteristics of a bubble market (Corbet, Larkin, Lucey, & Yarovaya, 2020). Nevertheless, there have also been growing reports in the media as to the role this innovative instrument plays in facilitating criminal behaviour, and this is confirmed in an emerging body of scholarly research (Barratt, Lenton, Maddox, & Allen, 2016; Nolasco Braaten & Vaughn, 2021).

The Fama (1970) efficient market hypothesis (EMH) suggests that prices reflect all available information, and we argue that this includes information relating to drug trafficking. In particular, market participants assess how news of drug trafficking activities affects prices, risk, return and profitability through expected (ex-ante) effects on the costs of drugs. If we extend the work of Fama (1970), we argue that immediately after the news of a drug bust, drug dealers (and possibly addicts) attempt to determine the price of drugs, albeit with a delay while the full effect is reflected in prices. Some studies indicate that the cryptocurrency market is weak form efficient (Bariviera, 2017; Nadarajah & Chu, 2017; Urquhart, 2016). The impact of social media messages, as a measure of news dissemination, has been show to have a degree of predictability on Bitcoin prices, however only over a short horizon (Tandon, Revankar, & Parihar, 2021). Nonetheless, this predictability indicates that news information, albeit in social media form, contributed to price determination. Nonetheless, what information is relevant for cryptocurrency price discovery remains unclear. We argue that the reaction of cryptocurrency markets to drug trafficking news will be realized ex-post as market participants—whether they are dealers or buyers have no advance knowledge of the drug bust. In total, we use 24 recent drug busts to test the underlying hypotheses.

This study explores the scale of drug trafficking capital flows through the medium of cryptocurrencies. Specifically, it explores two main related research questions—namely the impact of news announcements of drug busts on cryptocurrency risk and the impact of those same busts on cryptocurrency return. Note that in this study we measure the systematic risk of the cryptocurrency but use the term “risk” through out the paper. This paper aims to shed light on the dark side of cryptocurrencies as an emerging and unregulated market, and the extent to which wrongdoing can overwhelm activity that is more legitimate. The organization of the rest of the paper is as follows. Section 2 provides a brief literature review and Section 3 is where we formulate relevant hypotheses. Section 4 discusses the methodology used in this paper and Section 5 presents the data and empirical results. Section 6 is our discussion section and finally, Section 7 provides some concluding remarks.

2. Literature review

The literature on the economics and finance of cryptocurrencies is still at its infancy. Much of it is applied, with theory being deployed in terms of the development and deployment of analytical models, rather than the phenomena per se (Gkillas & Katsiampa, 2018). However, there has been recent theorising focusing on the viability of self-governance, and the interplay between the social and the economic. It is held that for a cryptocurrency to be successful, it must have clear objectives, proper incentives, de facto or de jure recognition by regulatory authorities, auditing processes, a basis for collective decision making, and ways of resolving conflict and levying sanctions (Spithoven, 2019). No cryptocurrency perfectly meets all of these criteria (ibid.). Given that cryptocurrencies as an emerging and evolving asset is still relatively under-researched, legislators and economists are currently battling to decide if they primarily represent legitimate currencies or speculative assets. Yermack (2015) and Ciaian, Rajcaniova, & Kancs (2016b) argue that Bitcoin fails to satisfy the three functions of a currency as (i) a medium of exchange, (ii) a unit of account, and (iii) a store of value. Irrespective of whether Bitcoin, classified as a currency or otherwise, Glaser, Zimmermann, Haferkorn, Weber, and Siering (2014) indicate that many Bitcoin users tend to hold Bitcoin for speculative purposes rather than use it as a means of payment. According to Pace (2017), cryptocurrencies have weak social foundations; these shortfalls harbour and encourage illegal behaviour. For example, the self-governance and decentralized nature of these platforms makes the monitoring of unusual activities more difficult (Barratt et al., 2016; Cheah & Fry, 2015) and is in alignment with the convenience theoretical effects identified by Kethenini and Cao (2019) and ; Gottschalk (2017a, 2019b).

2.1. Cryptocurrency risk, return and value

At an applied level, a burgeoning body of work evaluates the fundamental value of cryptocurrencies whereby there has been an emphasis on Bitcoin as the first and most heavily traded cryptocurrency. For instance, Bolt and van Oordt (2016), Li and Wang (2017), and Hayes (2017) estimate the value of cryptocurrencies and determine the factors that affect its exchange rate from both technical and economic perspectives. da Gama Silva, Klotzle, Pinto, and Gomes (2019) indicates that prices are determined through the supply and demand within the cryptocurrency markets, and largely determined by expectations of market participants. Ciaian, Rajcaniova, & Kancs (2016a) investigate the impact of differences between Bitcoin and other cryptocurrencies in terms of their attractiveness for investors to speculate on Bitcoin or other cryptocurrencies. The authors find that market forces and speculation influence the price of Bitcoin. Furthermore, Cheah and Fry (2015) argue that the fundamental value of Bitcoin is zero, and accordingly, its pricing reflects an insubstantial speculative bubble. Stavroyiannis (2018) examines risk measures for Bitcoin, suggesting that Bitcoin investors bear higher levels of risk than investors in other assets do. Urquhart (2017) considers the potential of price clustering in Bitcoin from the perspective of the impact of news and media. Kristoufek (2013), Garcia, Tessone, Mavrodiev, and Perony (2014), Polasik, Piotrowska, Wisniewski, Kotkowski, and Lightfoot (2015), and Karalevicius, Degrande, and De Weerdt (2018) examine the interaction between media sentiment and the price of Bitcoin and explain how Bitcoin users react to news articles and blog posts related to the cryptocurrency market. This literature sets the foundation for our study in that it highlights the importance of risk and return in the digital market.

Commonly in financial markets, measurement of risk is measured as the variability, or more loosely termed ‘volatility’, in returns from one period to another and, as such, studies have focused on pricing volatility on Bitcoin exchanges. Carrick (2016) and Kasper (2017), amongst others, show that the volatility of Bitcoin is extremely high. Dwyer (2015) shows that the average monthly volatility of Bitcoin is higher than the volatility of gold and a set of foreign currencies while Baek and Elbeck (2015) find that Bitcoin is 26 times more volatile than the S&P 500 index. We contend that dramatic price fluctuations in cryptocurrency prices has resulted in skepticism about the use of cryptocurrencies as a medium of exchange.

The extent and speed that information is incorporated into cryptocurrency prices, namely cryptocurrency (in) efficiency, is an important facet that links news, cryptocurrency prices and volatility. Urquhart (2016) was the first to test weak form efficiency in the Bitcoin market. He indicates that cryptocurrency prices exhibit informational inefficiency, though moving towards efficiency. More recently, Tiwari, Jana, Das, and Roubaud (2018) shows that the Bitcoin market is informationally efficient. We use the EMH—the efficiency of the incorporation of drug bust news into prices—to identify the reaction of the market in terms of cryptocurrency risk and return.

2.2. Criminal behaviour in cryptocurrency markets

From the perspective of user behaviour, especially exploitative, within cryptocurrency markets and affiliated areas, Möser, Böhme, and Breuker (2013) discuss the opportunities and limitations of anti-money laundering regulations of Bitcoin as an anonymous transaction system while Moore and Christin (2013) document the problem of frequent outages and security breaches on 40 Bitcoin exchanges. Böhme, Christin, Edelman, and Moore (2015) discuss the risk and regulatory challenges of Bitcoin, as a virtual currency, and its interaction with the conventional financial system and the real economy. Vasek and Moore (2015) investigate different types of frauds targeting cryptocurrencies, how they work, and to what extent they spread. Finally, Gandal, Hamrick, Moore, and Oberman (2018) analyze the impact of suspicious trading activity and price manipulations on the Mt. Gox exchange.

Given this background literature on user behaviour, we turn to the illegal drug market literature. This literature is well documented from both an economic and financial aspect. Drug trafficking as a context of study in business and management journals is still nascent (e.g., Fernandes et al., 2019; Lacerda, 2016; Guzmán et al., 2020; Coviello et al., 2017; Branzei & Abdelnour, 2010). Hence, we aim to extend our contribution to this field. Although we find several networks and platforms that discuss the possibility of drug dealers using cryptocurrencies, the study of Aldridge and Décary-Hétu (2014) was the first to formalize this link through a discussion of online drug cryptomarkets. Furthermore, some studies have investigated the distribution of illegal goods and services, mainly for controlled drugs, using cryptomarkets (Aldridge & Décary-Hétu, 2015, 2016; Dolliver, 2015; Munksgaard & Demant, 2016).[1] Foley, Karlsen, and Putniņš (2018) argue that since cryptocurrencies are not backed by any government agency and have features of intractability and anonymity as a means of payment; they attract illicit activities such as the funding of terrorist attacks, drug dealing, illegal pornography, money laundering, weapons trade and even murder-for-hire. Further, Bancroft and Reid (2016) and van Buskirk et al. (2016) refer to the quality and cost of cryptomarkets products as motivations for purchasing drugs online. However, there has been less attention to exploring the linkages between drug trading activity and cryptocurrency market outcomes. Accordingly, this study attempts to bridge this gap.

2.3. The convenience of cryptocurrencies

Recent efforts at theorizing cryptocurrencies include approaches that explore the relative balance between the social and the economic, and on the viability of self-governance (Pace, 2017). It has been argued that despite utopian intensions, the social foundations of seemingly utopian web-based platforms and mediums are shallow, leading them to be overwhelmed by purely and unregulated economic choices, with criminal wrongdoing in the latter's wake (Pace, 2017). Notably, when studying criminal activity, scholars (e.g., Nolasco Braaten & Vaughn, 2021) have applied convenience theories of white-collar crime to cryptocurrencies to explain their burgeoning usage. Convenience theory suggests that wrongdoers make choices based on ease (given it simplifies complex activities and reduces the space for detection); they focus on immediate benefits, and have little concern for social consequences down the line, even when it comes to what might make their future behavior more difficult (Gottschalk, 2017b). Criminal usage of cryptocurrencies may levy a cost on more conventional users of cryptocurrencies, and, indeed, criminals themselves in adding to the costs incurred through choosing convenience. At a time of increasing cryptocurrency volatility - especially given there are high levels of instability in the global economy - further turbulence induced by criminal behavior may undermine the viability of the medium itself (c.f. Barratt et al., 2016). Hence, we investigate the effects of criminal usage of cryptocurrencies on their volatility, and accordingly evaluate the predictions of convenience theory regarding the discounting of future consequences. As suggested by social foundations approaches, a lack of social and regulatory dampers (Pace, 2017) when combined with convenience choices (Gottschalk, 2017b) may affect input (criminal usage) and output (volatility). This leads to the risk of a self reinforcing cycle of negative feedback loops (as criminals are likely to be less concerned with volatility, as they factor it into convenience choices) further undermining their limited social footprint (as the legitimacy of the currency is eroded), in turn driving out other users, making the future effects of drug busts more pronounced.

While cryptocurrencies offer a wide range of opportunities for business and personal activities, criminals can and are exploiting their innate characteristics to facilitate illegal activities. For instance, Foley et al. (2018) found that around 25% of Bitcoin users and 44% of Bitcoin transactions are associated with illegal activities. Their results suggest that a significant component of the fundamental value of Bitcoin derives from its use as a medium of exchange to settle illegal transactions. All Bitcoin transactions are recorded in a public decentralized ledger (blockchain),[2] and are identified through the link between the IP address and the wallet address of active clients (Corbet et al., 2020). This feature has caused supporters of the anonymous feature in traditional cryptocurrencies to develop new kinds of digital currencies that offer a higher level of encryption and privacy. Examples of these currencies are the *Darksend* technique-based Dash, the *Ring Signature* system used by Monero, while Zcash uses an untraceable billing system. These three cryptocurrencies in addition to Bitcoin, Bitcoin Cash, Ethereum, Litecoin, Dogecoin are more likely to be used by drug traffickers than other traditional cryptocurrencies.[3] This literature motivates us to study whether other cryptocurrencies are being used for illegal purposes.

It is argued that the emergence of cryptocurrencies has significantly influenced the growth of online dark-net marketplaces or cryptomarkets. According to Barratt et al. (2016) cryptomarkets are "digital platforms that use anonymizing software (e.g., Tor) and Cryptocurrencies (e.g., Bitcoin) to facilitate peer-to-peer (P2P) trade of goods and services". Hence, a cryptomarket employs a wide range of strategies to hide participant identities, their transactions, and the physical location of its servers. Additionally, they provide a virtual location for drug dealers—allowing them to sell their products worldwide, with minimal risk posed by law enforcement agencies (e.g. Kethenini and Cao, 2019; Fernandes et al., 2019; Lacerda, 2016; Guzmán et al., 2020; Coviello et al., 2017; Branzei & Abdelnour, 2010).[4] Dark-net websites such as Silk

[1] Some developments suggest that different countries are proposing changes in cryptocurrency markets. For example, the Abu Dhabi Financial Regulator is considering embracive regulations for the cryptocurrency industry (https://www.ccn/bitcoin-regulation-abu-dhabi-financial-regulator-considers-cryptocurrency-framework/framework) and Iceland lawmakers propose tax on incoming cryptocurrency miners (https://www.ccn.com/iceland-lawmakers-want-to-tax-expanding-crypto-miners).

[2] See Hughes et al. (2019) and Ali, Ally, Clutterbuck, and Dwivedi (2020) for a discussion on the state of Blockchain research, applications and emerging research themes, in general, and a systematic review of blockchain technology specifically within the financial services sector, respectively.

[3] See dark web and deep web market list with up and down daily updated market status Available at: (https://darkwebnews.com/dark-web-market-list/). Also see (https://www.gwern.net/DNM-survival)

[4] Silk Road, the first crypto-market (using Bitcoin), resembled an eBay marketplace to trade narcotics, weapons, and other illegal goods and services, as well as some legitimate counter-cultural products and artefacts.

Road provide an environment for drug transactions that circumvent the problems associated with traditional trafficking; crucially, such sites rely on cryptocurrencies.

3. Hypothesis development

Within a competitive market when supply of, and demand for, illicit drugs are equal—an equilibrium price is established. However, a drug market is not a typical market as enforcement agencies act to limit the supply of drugs. The idea behind the enforcement of drug production and consumption is based on the expectation that costs are added which hopefully decreases consumption. In line with Brown and Warner (1985), Ramiah, Martin, and Moosa (2013) and Ramiah, Wallace, Veron, Reddy, and Elliott (2019), who explore other financial instruments, we assume that the price is a function of cryptocurrency demand and supply.[5] Further, as observed by Zuesse (1998), the impact of enforcement is mostly on the supply side as the behaviour of consumers is highly inelastic. As the buying and selling of illicit drugs is prohibited in most developed countries, cryptocurrencies, as indicated by Foley et al. (2018), are a possible method by which individuals may attempt to hide their buying activity. Nonetheless, we assume that drug busts have the potential to impact cryptocurrency prices due to a couple of different situations. For instance, news of drug busts may induce an increase in the price of drugs resulting from an expected decrease in the availability of drugs. Thus, end users who use cryptocurrencies to buy drugs require more cryptocurrencies to cover the increase in drug prices. This, in turn, leads to an increase in the demand for cryptocurrency. According to da Gama Silva et al. (2019), an increase in the demand of cryptocurrency will lead to an increase in the price of cryptocurrency. Using this argument, we formulate the following hypothesis.

H1. Drug bust news leads to an increase in the price of cryptocurrency following a decrease in the supply of drugs and an increase in the price of drugs.

It is worth making the distinction that while the actions of drug enforcement agencies impact the supply of drugs, the market will only react to this information when it is known by the market, i.e., when news of the drug bust is released.

Another possible outcome is that news of drug busts leads to a decrease in cryptocurrency price. This scenario occurs when the shortage of drugs in the market leads to a decrease in the demand for drugs as consumers fear the ramifications (jail time or large fines) associated with the consumption of illegal products. As such, news of drug busts is viewed by the market as strong signals by law enforcement authorities. As per da Gama Silva et al. (2019), a decrease in the demand for cryptocurrency will result in a decrease in the price of cryptocurrency. Based on this second scenario, we postulate the following hypothesis.

H2. *Drug bust news leads to a decrease in the price of cryptocurrency following a decrease in the demand for drugs as consumers fear the penalties associated with the consumption of illegal products.*

For completeness, we note that the impact of drug bust news may have no observable change in the price of cryptocurrencies. This possibility may occur when neither demand nor supply change following the news of a drug bust with the cryptocurrency value not being affected by the news. Both Boermans (2010) and Zuesse (1998) suggest that this lack of a cryptocurrency price change in response to the public knowledge of drug enforcement is unlikely, though Boermans (2010) does indicate that the impact may be small.

According to Chan, Le, and Wu (2019) and Peng, Albuquerque, Camboim-de-Sâ, Padula, and Montenegro (2018), investors cannot ignore the risk associated with cryptocurrencies, especially in times of unusually high levels of cryptocurrency volatility. In addition, the cryptocurrency literature suggests that suspicious trading activity associated with cryptocurrencies tends to increase the uncertainty in the cryptocurrency market as illegal acts like drug trafficking lead to additional systematic risk (illegal activity risk). The existing literature fails to explain how drug-trading activity, in response drug bust news, affects the risk of cryptocurrencies. Hence, we posit, as Hypothesis 3 below, that the risk of cryptocurrencies will drop following the news announcement of a drug bust as this leads to an increase in the demand for cryptocurrencies originating from a shortage of drugs in the market.

H3. Drug bust news will reduce the risk of cryptocurrency whereby such busts signal lesser criminal activities associated with cryptocurrencies.

4. Research methodology

In this section, we explain the data and methodology; including return analysis, risk analysis and robustness tests. We deal with these items, in turn.

4.1. Data

We download daily cryptocurrency prices from CoinMarketCap as it provides historical prices and statistical data on cryptocurrency coins and tokens. Next, we download the risk-free rate, broad market, regional indices and world indices from Datastream. The additional variables used in the three-factor model (SMB), four-factor (momentum) and five-factor (trend) are downloaded from Kenneth R. French's data library.[6] We use intraday prices of the top 100 cryptocurrencies, based on market capitalization, as on 29 June 2018. Additionally, we use the MSCI AC World Index as a proxy for the global market, and the US three-month interbank rate as a proxy for the risk-free rate. The data covers the period April 2013 to June 2018. Cryptocurrency specific information is sourced from cryptocurrency specialist media websites such as Coin Desk, Coin Telegraph, Bitcoin Magazine, Crypto Coins News and 24/7 Crypto News.

4.2. Return analysis

We base our empirical analysis on the event study methodology, which we use to isolate the impact of drug bust news (as an event) from other general market movements. This technique allows us to detect the abnormal and cumulative abnormal returns of the 100 cryptocurrencies following each of the news announcements of the 24 drug busts we examine in this study. As investigating all 100 cryptocurrencies may introduce a degree of volatility from the smaller cryptocurrencies, we also repeat our analysis for the top eight cryptocurrencies. They are

[5] An increase in supply does not refer to newly mined cryptocurrencies but rather to the increase in the amount available for sale.

[6] The three, four and five factor models are commonly used portfolio factor models that are used to explain the returns of a diversified portfolio. The three-factor model uses the excess return on the broad stock market (beta) as the first factor, the difference in the cheapest and most expensive stocks, measured by their price to book ratio (SMB), as the second factor, and the return of the smallest stocks minus the return of the largest stocks, by market capitalisation (HML), as the third factor.The four-factor model uses the same three factors from the three-factor model but includes a momentum factor (UMD), measured as the return of the highest performing stocks minus the return of the lowest performing stocks.The five-factor model drops the momentum factor from the four-factor model and includes profitability (RMW) and investment (CMA) factors. The profitability factor is measured as the return of stocks with high operating profitability minus the return of stocks with low operating profitability. The investment factor measures the return difference of stocks that require little on-going capital investment to grow the business relative to stocks with large investment requirements.

chosen for two related reasons. Firstly, some of these eight cryptocurrencies are specifically designed to grant users greater anonymity thus be much more appealing to criminals.[7] Secondly, the eight chosen cryptocurrencies are amongst the largest and are therefore more liquid and easily tradable.[8] This is depicted in Fig. 1.

Following Brown and Warner (1985) and Ramiah et al. (2013), daily returns are adjusted to obtain ex-post abnormal returns where adjustments are approximated by asset pricing models such as the (i) rolling average model, (ii) market model, (iii) CAPM, (iv) Fama-French three-factor model, (v) Carhart four-factor model, and (vi) Fama-French five-factor model. The CAPM is widely used to show the relationship between the systematic risk and returns—originally from stocks. The Fama-French three-factor model (Fama & French, 2012) augments the CAPM by adding factors for firm size and value risk. Carhart (1997) added a momentum factor to the three-factor model, while Fama and French (2015) added two factors, namely a profitability factor and a factor for investment conservativeness to the three-factor model. While the CAPM is mainly used for equities, recent studies have shown a relationship between stock markets and cryptocurrencies, in general, and during the Covid-19 pandemic (see Nguyen, 2021 and Umar, Hung, Chen, Iqbal, & Jebran, 2020, respectively). Given the aforementioned research, we use stock market factors to evaluate the risk and return of cryptocurrencies. We cede that there is a significant amount of related news that may impact cryptocurrency prices occurring at both high and low frequencies. The information arriving at high frequencies may be transitory in nature, especially in the presence of pure speculation in cryptocurrency markets. We note that the event study methodology captures the aggregate impact of each drug bust news announcement and, as such, it also captures high frequency news arrivals that may, or may not be, endogenous to the drug bust news.[9] For each event, the standard t-statistic of the abnormal return is computed to find out whether it is significantly different from zero. By analysing the effect of each of drug bust announcement we can empirically test the aforementioned hypotheses. To test for H1, we calculate if the abnormal return is statistically significantly greater than zero (positive abnormal returns). As for H2, we calculate if the abnormal return is statistically significantly less than zero (negative abnormal returns).

EMH postulates that markets react instantly to the arrival of new information as prices instantly reflect all available information content of an event (Fama, 1970). Although drug trafficking requires planning and financing to facilitate transfer and distribution, this planning is completed before smuggling takes place. Due to the secrecy of these operations, the market does not have a clear picture of the transportation and delivery of the drugs and, for the same reason, the market would not know if drug enforcement agencies are planning to disrupt distribution—which is an extension to Fama (1970). Accordingly, we do not expect any abnormal return linked to the news of a specific drug bust prior to the event. As a result, our focus is on the abnormal returns that materialize following the release of the drug bust news. Unlike stock market participants, we posit that drug dealers and end-users do not necessarily react instantly—there may be a delay in their responses representing a violation of Fama (1970). To that end, we estimate the cumulative abnormal return (CAR) of up to 90 days after the drug bust news. No theoretical justification possibly presented for the choice of 90 days; rather this window, based on empirical observations as well as the nature of the underlying financial instrument. We use the t-test to determine the statistical significance of cumulative returns.

[7] We thank an anonymous reviewer for this comment.

[8] The individual cryptocurrencies (the top eight) are Bitcoin, Ethereum, Bitcoin Cash, Litecoin, Monero, Dash, Zcash, and Dogecoin.

[9] The event study methodology also does not infer causality, rather it infers in this study, correlations between the drug bust announcement and cryptocurrency price before, at the same time or after the drug bust announcement. We thank the anonymous reviewer for this helpful suggestion.

4.3. Risk analysis

As indicated by Chan et al. (2019) and Peng et al. (2018) cryptocurrency investors are aware of the impact of cryptocurrency volatility and that suspicious trading activities associated with cryptocurrencies tends to increase uncertainty in the cryptocurrency market. To test the impact of news of enforcement agency drug busts, we modify the asset-pricing models to incorporate interaction variables capturing drug bust news. The first risk model captures the average change in risk resulting from the news of all 24-drug busts. Following Ramiah et al. (2013), we use an aggregate dummy variable (AD) to represent these busts, such that the dummy variable takes the value of one on the event date and zero otherwise. The AD is also multiplied by the market risk premium to form the first interaction variable (multiplicative dummy variable). Accordingly, the model takes the following form:

$$r\widetilde{_{St}} - \widetilde{r}_{ft} = \beta_S^0 + \beta_S^1\left[\widetilde{r}_{mt} - \widetilde{r}_{ft}\right] + \beta_S^2\left[\widetilde{r}_{mt} - \widetilde{r}_{ft}\right] * AD_t + \beta_S^3 AD_t + \varepsilon\widetilde{_{it}} \tag{1}$$

where $r\widetilde{_{St}}$ is the cryptocurrency return at time *t*, $\widetilde{r}_{ft}$ is the risk-free rate at time *t*, $\widetilde{r}_{mt}$ is the market return at time *t*, *AD* is a dummy variable that takes the value of one on the date of the news announcement of a drug bust and zero otherwise, $\varepsilon\widetilde{_{it}}$ is the error term. β_S^0 is the intercept of the regression equation ($E(\beta_S^0) = 0$), β_S^1 is the cryptocurrency beta, β_S^2captures the change in the cryptocurrency beta and β_S^3 measures the change in the intercept of Eq. (1). As such, Eq. 1 regresses the cryptocurrency return in excess of the risk-free rate ($r\widetilde{_{St}} - \widetilde{r}_{ft}$) on the excess return on the market $\beta_S^1(\widetilde{r}_{mt} - \widetilde{r}_{ft})$ and the change in the cryptocurrency beta when news of a drug bust is announced $\left(\beta_S^2(\widetilde{r}_{mt} - \widetilde{r}_{ft}) * AD_t\right)$. As such, Eq. 1 is estimated to calculate the aggregate effect of the announcement of drug busts on the cryptocurrency market. To test our risk hypothesis (H3), we focus on the variable of interest in Eq. (1), the change in the cryptocurrency beta (β_S^2). The sign on this variable is expected to be negative indicating that the risk has decreased following the announcement of a drug bust.

Different announcements may cancel out each other out, which makes it necessary to identify the effects of each drug bust, using an individual dummy variable (ID) that takes a value of one on the date when the drug bust is announced and zero otherwise. Each individual dummy variable is multiplied by the market risk premium to obtain interaction variables whose coefficients capture short-term changes in systematic risk following a particular drug bust news. With 24 ID variables, we write the model as follows:

$$r\widetilde{_{St}} - \widetilde{r}_{ft} = \beta_S^0 + \beta_S^1\left[\widetilde{r}_{mt} - \widetilde{r}_{ft}\right] + \sum_{g=1}^{N} \beta_{S,n}^2\left[\widetilde{r}_{mt} - \widetilde{r}_{ft}\right] * ID_{gt} + \varepsilon\widetilde{_{it}} \tag{2}$$

Furthermore, we study the long-term effects on cryptocurrency systematic risk. For this purpose, Eqs. (1) and (2) are re-estimated using adjusted dummy variables (ID_{gt}) that take the value of zero prior to the drug bust news date and one thereafter. The variables used are the same as Eq. 1 however we note that in Eq. 2 we identify the effect of the news of each drug bust individually. Eq. 2 provides coefficients for each drug bust and represents the change in risk following the release of news for each drug bust. Following the work of Narayan and Popp (2010, 2013); Narayan and Liu (2015) and Narayan, Liu, and Westerlund (2016), we conduct structural break tests on all the regression equations.

4.4. Robustness Tests

We undertake additional tests to check the robustness of the results. The Corrado (1989) non-parametric ranking procedure and the non-parametric conditional distribution approach proposed by Chesney, Reshetar, and Karaman (2011) are utilized to address the problem of non-normality in abnormal returns. Moreover, we follow Bekaert, Harvey, and Ng (2005), Chesney et al. (2011), Bilson, Brailsford, Hallett,

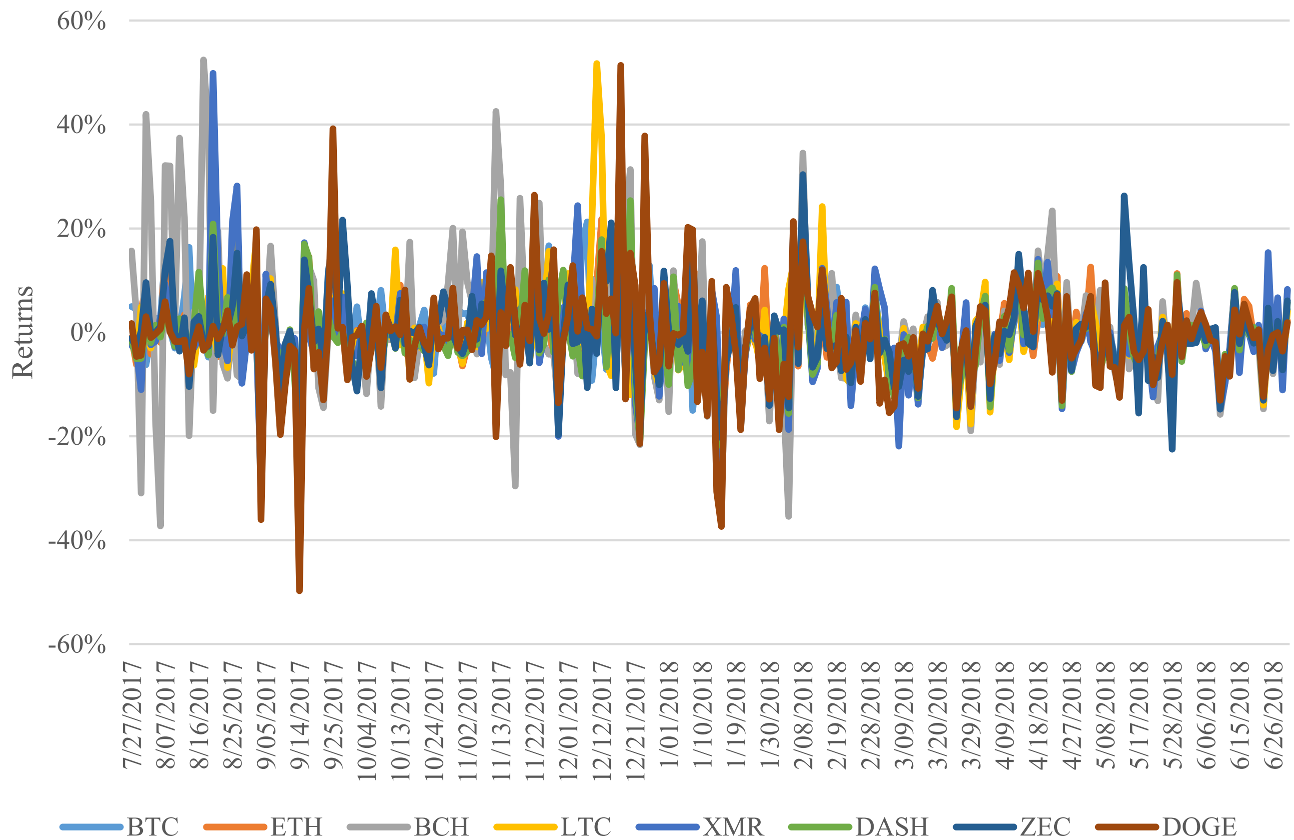

Fig. 1. The 8 Crypto returns over time.

and Shi (2012), Graham and Ramiah (2012) to control for asynchronicity, stock market integration, and spillover effects. For this purpose, asset-pricing models are augmented with three additional market risk premia representing Asia $\left(\tilde{r}_{mt}^{Asia} - \tilde{r}_{ft}^{Asia}\right)$, Europe $\left(\tilde{r}_{mt}^{Europe} - \tilde{r}_{ft}^{Europe}\right)$ and the US$\left(\tilde{r}_{mt}^{US} - \tilde{r}_{ft}^{US}\right)$.

Another issue that we may encounter is the influence of cryptocurrency specific information on abnormal returns. Examples of cryptocurrency specific information are outages and security breaches, mining botnets, Ponzi schemes, technical issues, design challenges, denial-of-service attacks, theft of "brain" wallets, and any relevant regulation announcements. Hence, if cryptocurrency specific information appears in the estimation period, it will not be possible to differentiate between abnormal returns arising from drug bust news and those produced by cryptocurrency-specific information. Consequently, we use a third robustness test, involving the exclusion of announcements that intersect with cryptocurrency specific information 15 days on either side of the drug bust news date.[10] Cryptocurrency specific information is obtained from public forums on the cryptocurrency.

So far in this section, we discuss all the methodologies used in our study but according to Kar (2020), Kar and Dwivedi (2020) and Kushwaha, Kar, and Dwivedi (2021) it is important to explain why these methodologies have been used. The daily data used is of high frequency and the original version of event study methodology used in the 1980′s suffers from a series of statistical and econometrics problems. The extensive approaches used address the statistical and econometrics problems so that we generate robust results.

[10] In addition to applying a 15-day window around drug bust news, we also check for any major news arrival around our wide range of abnormal returns.

5. Empirical results

5.1. Return analysis

The 24 major drug busts analyzed in this study are listed in Table 1. For each drug bust we display a short descriptive name, the estimated value (in US dollars) of the drugs seized, the date on which news of the bust is released to the market, and the country where the operation took place. The drug busts we study have a range of seized dollar value—with the largest being valued at $1.5 billion.

Table 2 shows the effects of the news of the 24 drug busts on the 100 cryptocurrencies estimated by different asset pricing models. The general conclusion we draw is that the overall cryptocurrency market experiences a marginal impact resulting from information on drug busts. The aggregated model produces little to indicate that drug bust news affect the cryptocurrency market. Some statistically significant negative reactions to drug bust news occur which are supported by the robustness tests. One possible explanation for the non-statistical significance of abnormal returns is that the change in demand for, and supply of, drugs resulting from drug busts do not affect cryptocurrencies. While this result indicates that cryptocurrencies are used as a medium of exchange in cryptomarkets, and not for trafficking purposes, it is possible that drug transactions are completed via only a few of the 100 cryptocurrencies used in this work. Specifically, it may be likely that due to factors that restrict the ability of participants in the distribution and trafficking of drugs, only a few useable cryptocurrencies exist, to settle transactions in this manner.

5.2. Return analysis of the top eight cryptocurrencies

Table 3 shows the impact of the news announcements of the 24 drug busts on the potential top eight cryptocurrencies acceptable in the cryptomarkets as a medium of exchange.

Table 1
Details of Drug Busts.

No.	Drug Busts Description	Value	Date	Day	Country of Operation
1	KSA amphetamine pills bust	$267 M	14/4/14	Mon	Saudi Arabia
2	NY heroin bust	$11 M	19/5/14	Mon	USA
3	Perth methamphetamine bust	$63 M	10/10/14	Fri	Australia
4	Sydney MDMA bust	$1.5 B	29/11/14	Sat	Australia
5	Dutch cocaine bust	$149 M	2/12/14	Tue	Netherlands
6	California marijuana bust	$19 M	27/2/15	Fri	USA & Mexico
7	U.S. Coast Guard cocaine bust I	$424 M	16/4/15	Thu	USA
8	Royal Navy cocaine bust	$785 M	30/4/15	Thu	UK
9	The multi-agency cocaine bust	$408 M	19/12/15	Sat	UK, Spain & Dubai
10	U.S. Coast Guard cocaine bust II	$400 M	8/4/16	Fri	USA
11	The Mexico-CA drug tunnel bust	$23 M	20/4/16	Wed	USA & Mexico
12	"Clan Úsuga" gang cocaine bust	$240 M	16/5/16	Mon	Colombia
13	Sydney cocaine bust	$30 M	29/8/16	Mon	Australia
14	Florida cocaine bust	$420 M	28/3/17	Tue	USA
15	India heroin bust	$545 M	31/7/17	Mon	India
16	Ontario cocaine bust	$250 M	28/8/17	Mon	Canada
17	"Gulf Clan" gang cocaine bust	$360 M	8/11/17	Wed	Colombia
18	Spain cocaine bust	$250 M	5/12/17	Tue	Spain
19	Geraldton methamphetamine bust	$1.04 B	22/12/17	Fri	Australia
20	Myanmar methamphetamine bust	$54 M	18/1/18	Thu	Myanmar (Burma)
21	Adelaide methamphetamine bust	$270 M	18/2/18	Sun	Australia
22	Vietnam heroin bust	$2.5 M	26/2/18	Mon	Vietnam & China
23	Thailand methamphetamine bust	$22.4 M	3/4/18	Tue	Thailand
24	Algeciras cocaine bust	$609 M	25/4/18	Wed	Spain

The abnormal returns of the eight cryptocurrencies, in aggregate and individual forms, is displayed in Table 3. The results show that some cryptocurrencies are preferred to others within this narrow set. For instance, Bitcoin produces no statistically significant results for any horizon, indicating that drug bust news have no effect on Bitcoin returns. However, for other cryptocurrenices, such as Bitcoin cash, Monero, Dash and Dogecoin, we find some evidence that drug bust news affect the prices of these cryptocurrencies. The underlying proposition is that drug traffickers/participants prefer to use liquid and easily convertible cryptocurrencies (through ATM's) (Goldman, Maruyama, Rosenberg, Saravalle, & Solomon-Strauss, 2017)—however, the results indicate that these participants are even more particular in their choice of cryptocurrency, which possibly may determine the quality of the encryption algorithms. For instance, Monero, Dash and Zcash are commonly accepted as having stronger protection and anonymity than others, such as Bitcoin (Hilmola, 2021).

As mentioned earlier, our focus is on the abnormal returns generated following the release of news on drug busts. This is different from the abnormal returns arising before drug busts, which do not reflect market reactions to these actions based on the confidentiality implementation of drug bust operations. We note the consistent negative abnormal returns for the majority of the eight cryptocurrencies following drug bust news. We observe that these negative abnormal returns are consistent with our expectation stipulated in hypothesis H2 in that a smaller quantity of drugs is available (or expected to be available) for purchase after a drug bust, from a "middle-man supplier" or the end user, which, in turn, lowers the demand for cryptocurrencies. This decline in demand for cryptocurrencies leads, ceteris paribus, to lower cryptocurrency prices.

Table 4 reports the empirical results for the top eight cryptocurrencies associated with the news of each drug bust over a 30-day horizon after the drug bust announcement (CAR30). For each drug bust, we report the cumulative abnormal returns and their t-statistics, using the CAPM as well as the 3, 4 and 5 factor models and the market integration model. The results indicate that the drug busts numbered 1, 14, 17, 19 and 21 are busts where returns on the cryptocurrencies are statistically significant. For instance, event 19 (the Geraldton methamphetamine bust) produces a CAR30 of − 1.01% after the announcement of the bust, with a t-statistic of − 1.99, indicating that this value is statistically different from zero. Similarly, drug bust 21 (the Adelaide methamphetamine bust) produces a significant negative result after 30 days following the announcement of the bust. These results again support hypothesis H2 such that, in the aftermath of these drug busts, participants in the trafficking or consumption of drugs have no need (or at least a lesser need) to utilize the cryptocurrency market as smaller quantities of drugs are available for purchase through this channel. Only a few drug busts produce statistically significant and positive CAR30 (drug bust 1, 14 and 17) which indicates that drug prices go up in response to drug bust news. This empirical evidence supports hypothesis H1, and indicates that since smaller amounts of drugs are available for purchase through any means (cash or cryptocurrencies), the demand for cryptocurrencies will shrink.

Table 2
Overall Market Reaction to Drug Busts.

Abnormal Returns	CAPM		3 Factor model		4 Factor model		5 Factor model		Market integration	
	%	t-stat	%	t-stat	%	t-stat	%	t-stat	%	t-stat
CAR-90	24.48	1.85	-4.77	-0.32	-6.12	-0.41	-4.14	-0.28	-2.40	-0.18
CAR-60	12.32	1.01	-6.68	-0.52	-8.22	-0.64	-6.93	-0.54	-4.58	-0.43
CAR-30	-3.87	-0.45	-9.49	-0.94	-9.89	-0.98	-9.50	-0.93	-7.11	-0.76
CAR-15	7.20	1.66	2.43	0.48	1.84	0.36	2.27	0.43	3.96	0.78
CAR-10	4.57	1.10	2.58	0.59	2.21	0.50	2.51	0.56	3.91	0.87
CAR-5	-0.76	-0.32	-0.85	-0.32	-1.24	-0.48	-0.92	-0.33	-0.17	-0.07
AR	-1.34	-1.07	-0.59	-0.46	-0.69	-0.53	-0.61	-0.48	-0.50	-0.39
CAR+ 5	4.21	0.79	-0.85	-0.37	-0.70	-0.31	-1.20	-0.51	-0.33	-0.15
CAR+ 10	4.64	0.67	-1.81	-0.46	-1.74	-0.44	-2.05	-0.52	-0.77	-0.21
CAR+ 15	3.51	0.44	-6.41	-0.96	-6.14	-0.92	-6.66	-0.99	-4.53	-0.73
CAR+ 30	5.88	0.57	-13.24	-1.14	-12.71	-1.09	-13.27	-1.13	-9.02	-0.86
CAR+ 60	-1.85	-0.13	-26.37	-1.56	-26.01	-1.53	-26.47	-1.58	-21.07	-1.42
CAR+ 90	-7.86	-0.48	-42.80	-2.44	-42.44	-2.39	-42.49	-2.45	-36.98	-2.52

Table 3
Reaction of the Top 8-Cryptocurrencies to Drug Busts.

Abnormal Returns	Top-8 Crypto	Bitcoin	Ethereum	Bitcoin Cash	Litecoin	Monero	Dash	Zcash	Dogecoin
CAR-90 (%)	5.04	-10.16	25.94	10.45	-18.54	7.94	-31.60	56.07	6.93
t-stat	0.31	-0.86	1.17	0.74	-1.25	0.44	-1.28	1.72	0.50
CAR-60 (%)	-2.81	-11.22	1.40	3.85	-14.59	4.77	-15.80	18.86	-10.59
t-stat	-0.24	-1.24	0.08	0.30	-1.48	0.30	-0.91	1.09	-0.71
CAR-30 (%)	-2.62	-7.51	-10.64	2.55	-7.53	-1.39	2.64	4.19	-5.18
t-stat	-0.30	-1.07	-1.05	0.27	-0.93	-0.12	0.21	0.38	-0.44
CAR-15 (%)	3.83	1.58	-1.12	5.26	1.15	8.93	0.84	8.25	4.70
t-stat	0.80	0.43	-0.18	0.88	0.23	1.02	0.11	1.54	0.78
CAR-10 (%)	4.23	0.42	0.52	7.75	3.41	8.68	1.46	7.04	4.52
t-stat	1.00	0.12	0.14	1.34	0.82	1.05	0.21	1.55	0.86
CAR-5 (%)	-0.81	-1.46	-3.02	-0.85	-1.02	4.05	-0.46	-1.11	-2.95
t-stat	-0.38	-0.73	-1.58	-0.28	-0.47	0.89	-0.10	-0.50	-1.00
AR (%)	-0.27	0.11	-1.72	-6.77	0.09	3.29	-0.61	0.05	-1.95
t-stat	-0.21	0.11	-1.22	-3.25	0.06	0.87	-0.39	0.02	-1.49
CAR+ 5 (%)	0.10	1.50	-2.66	-3.41	5.82	0.03	-2.33	-1.01	-0.79
t-stat	0.04	0.78	-1.29	-0.90	1.24	0.01	-0.59	-0.39	-0.25
CAR+ 10 (%)	-1.43	1.89	-1.32	-1.51	4.97	-5.34	-5.63	0.90	-3.29
t-stat	-0.38	0.67	-0.39	-0.40	0.80	-0.66	-1.22	0.21	-0.54
CAR+ 15 (%)	-6.63	-3.86	-5.03	0.37	-1.09	-15.95	-13.05	0.42	-6.17
t-stat	-1.12	-0.93	-0.93	0.05	-0.16	-1.67	-2.11	0.07	-0.64
CAR+ 30 (%)	-8.35	-8.91	-2.86	-10.38	-4.82	-15.96	-19.44	-0.76	-6.20
t-stat	-0.81	-1.32	-0.27	-0.99	-0.35	-1.36	-1.45	-0.07	-0.41
CAR+ 60 (%)	-17.87	-19.56	7.20	-22.84	-20.42	-38.26	-65.67	35.84	-28.62
t-stat	-1.30	-1.87	0.26	-2.13	-1.05	-2.27	-3.03	0.90	-1.51
CAR+ 90 (%)	-16.77	-34.33	38.94	-26.07	-38.80	-41.34	-94.58	82.15	-43.16
t-stat	-0.91	-2.55	0.93	-1.85	-1.71	-1.59	-3.33	1.46	-2.33

Table 4
Cumulative Abnormal Returns 30-days after the Drug Busts.

Drug bust No.	CAPM		3 Factor model		4 Factor model		5 Factor model		Market Integration	
	CAR+ 30	t-stat	CAR+ 30	t-stat	CAR+ 30	t-stat	CAR+ 30	t-stat	CAR+ 30	t-stat
1	0.28	3.87	0.00	0.17	0.01	0.66	0.00	0.10	-0.02	-0.64
2	-0.17	-1.10	-0.11	-1.38	-0.12	-1.56	-0.13	-1.62	-0.07	-1.00
3	-0.25	-0.84	0.01	0.07	0.05	0.24	0.06	0.30	-0.05	-0.24
4	-0.31	-1.05	-0.23	-1.18	-0.25	-1.22	-0.21	-1.08	-0.28	-1.37
5	-0.37	-1.25	-0.33	-1.70	-0.35	-1.70	-0.31	-1.61	-0.37	-1.83
6	0.23	0.64	0.16	0.64	0.17	0.64	0.17	0.68	0.08	0.31
7	0.18	0.51	0.26	0.95	0.29	0.98	0.25	0.92	0.27	0.99
8	0.27	0.71	0.32	1.06	0.35	1.11	0.30	1.00	0.28	0.95
9	0.32	1.13	0.12	0.52	0.10	0.46	0.11	0.50	0.13	0.61
10	-0.07	-0.24	-0.11	-0.54	-0.08	-0.40	-0.15	-0.72	-0.12	-0.62
11	0.08	0.31	0.05	0.25	0.06	0.31	0.02	0.10	0.04	0.23
12	0.15	0.59	0.17	1.04	0.16	1.03	0.15	0.93	0.18	1.07
13	-0.08	-0.39	-0.06	-0.45	-0.06	-0.44	-0.09	-0.62	-0.07	-0.49
14	0.83	2.43	0.73	2.61	0.73	2.63	0.74	2.64	0.72	2.58
15	0.39	0.95	0.16	0.45	0.17	0.48	0.17	0.45	0.17	0.45
16	-0.37	-0.88	-0.46	-1.20	-0.46	-1.21	-0.45	-1.17	-0.44	-1.15
17	0.96	2.36	0.95	2.35	0.96	2.38	0.95	2.33	0.97	2.39
18	0.18	0.38	0.20	0.45	0.19	0.43	0.23	0.52	0.18	0.41
19	-1.01	-1.99	-0.98	-2.02	-0.98	-2.02	-0.96	-1.98	-0.99	-2.06
20	-0.36	-0.68	-0.53	-1.02	-0.51	-0.99	-0.54	-1.03	-0.31	-0.64
21	-0.91	-1.66	-1.20	-2.10	-1.21	-2.11	-1.21	-2.12	-0.93	-1.80
22	-0.85	-1.56	-1.15	-2.01	-1.18	-2.05	-1.15	-2.01	-0.87	-1.69
23	0.14	0.29	-0.16	-0.31	-0.17	-0.33	-0.15	-0.30	0.08	0.17
24	-0.52	-1.12	-0.67	-1.40	-0.67	-1.39	-0.68	-1.41	-0.53	-1.22

To identify the influence of drug bust news, we further analyse the specific drug busts at two other horizons (CAR60 and CAR90) to identify the dynamics of the demand for, and supply of, the cryptocurrency. Tables 5 and 6 document the results of the CAR60 and CAR90 abnormal returns, respectively. The results reported in Table 5 for CAR60 show that there may be an influence of time whereby the news effects of a drug bust is filtered through a short-term increase in drug prices to a long-term decline in the demand for cryptocurrencies as participants change their drug purchasing behavior. For instance, the statistically significant positive CAR30, produced by drug bust 1, reverses to a statistically significantly negative CAR60. Drug bust 17 produces a statistically significant positive CAR30 but does not produce a statistically significant CAR60. With respect to the negative results for the CAR60 abnormal returns, drug busts 1, 2, 19 and 20 produce significantly negative abnormal returns.

The results of CAR90 reported in Table 6 is similar to the pattern documented in Table 4 and Table 5 whereby there are more statistically significant negative reactions than positive. This transition over time provides some evidence indicating that those engaged in drug trafficking (to certain degree) utilize the cryptocurrency markets to facilitate the purchase of drugs. Additionally, the results suggest that drug bust news led to a short-term (30-day) increase in the price of drugs and consequently an increase in the demand for cryptocurrencies (on the assumption that the demand for drugs is inelastic).

Table 5
Cumulative Abnormal Returns 60-days after the Drug Busts.

Drug bust No.	CAPM		3 Factor model		4 Factor model		5 Factor model		Market Integration	
	CAR+ 60	t-stat	CAR+ 60	t-stat	CAR+ 60	t-stat	CAR+ 60	t-stat	CAR+ 60	t-stat
1	-0.22	-2.06	-0.32	-3.83	-0.30	-3.64	-0.33	-3.81	-0.30	-3.54
2	-0.76	-2.40	-0.41	-2.04	-0.44	-2.15	-0.42	-2.06	-0.43	-2.06
3	-0.35	-0.77	-0.02	-0.07	-0.02	-0.06	0.06	0.21	-0.11	-0.34
4	-0.22	-0.49	-0.15	-0.52	-0.19	-0.61	-0.11	-0.35	-0.22	-0.68
5	-0.18	-0.40	-0.18	-0.61	-0.21	-0.66	-0.14	-0.46	-0.24	-0.77
6	0.21	0.40	0.25	0.66	0.26	0.66	0.25	0.65	0.13	0.36
7	0.67	1.12	0.71	1.51	0.73	1.46	0.70	1.50	0.71	1.52
8	0.71	1.14	0.77	1.57	0.82	1.57	0.76	1.57	0.70	1.42
9	0.66	2.02	0.23	0.88	0.15	0.56	0.17	0.72	0.24	0.97
10	0.03	0.09	0.07	0.31	0.12	0.52	0.03	0.12	0.07	0.34
11	0.09	0.29	0.15	0.79	0.20	1.06	0.11	0.60	0.16	0.84
12	0.02	0.05	0.07	0.40	0.07	0.41	0.06	0.38	0.10	0.57
13	-0.42	-1.30	-0.31	-1.48	-0.30	-1.52	-0.35	-1.64	-0.33	-1.59
14	1.44	2.44	1.17	2.36	1.17	2.37	1.18	2.33	1.15	2.31
15	0.06	0.10	-0.23	-0.41	-0.22	-0.40	-0.22	-0.39	-0.23	-0.41
16	-0.18	-0.34	-0.40	-0.73	-0.40	-0.73	-0.38	-0.70	-0.41	-0.75
17	0.11	0.19	0.11	0.21	0.12	0.22	0.14	0.25	0.11	0.21
18	-0.44	-0.68	-0.56	-0.86	-0.55	-0.85	-0.54	-0.83	-0.38	-0.63
19	-1.44	-1.90	-1.68	-2.18	-1.67	-2.18	-1.67	-2.17	-1.41	-2.01
20	-1.12	-1.43	-1.58	-1.90	-1.60	-1.92	-1.58	-1.90	-1.09	-1.52
21	-0.83	-1.16	-1.41	-1.77	-1.43	-1.78	-1.42	-1.77	-0.91	-1.38
22	-0.67	-0.97	-1.23	-1.58	-1.26	-1.60	-1.23	-1.57	-0.73	-1.16
23	-0.44	-0.74	-0.47	-0.69	-0.48	-0.70	-0.47	-0.68	-0.50	-0.92
24	-0.88	-1.51	-0.67	-1.00	-0.67	-1.00	-0.68	-1.01	-0.89	-1.66

Table 6
Cumulative Abnormal Returns 90-days after the Drug Busts.

Drug bust No.	CAPM		3 Factor model		4 Factor model		5 Factor model		Market Integration	
	CAR+ 90	t-stat	CAR+ 90	t-stat	CAR+ 90	t-stat	CAR+ 90	t-stat	CAR+ 90	t-stat
1	-1.01	-3.39	-0.77	-3.46	-0.78	-3.46	-0.79	-3.47	-0.82	-3.47
2	-1.15	-2.53	-0.93	-2.74	-0.99	-2.75	-0.95	-2.74	-0.98	-2.70
3	-0.49	-0.84	-0.17	-0.45	-0.18	-0.43	-0.04	-0.10	-0.26	-0.61
4	0.18	0.30	0.13	0.32	0.11	0.25	0.18	0.43	-0.02	-0.06
5	0.16	0.27	0.10	0.24	0.07	0.17	0.13	0.33	-0.05	-0.13
6	0.67	0.90	0.73	1.25	0.76	1.23	0.72	1.24	0.58	1.03
7	0.59	0.76	0.54	0.88	0.58	0.89	0.55	0.91	0.51	0.83
8	0.29	0.38	0.47	0.79	0.52	0.81	0.47	0.80	0.40	0.66
9	0.53	1.74	0.19	0.77	0.08	0.33	0.09	0.41	0.20	0.95
10	-0.04	-0.11	0.03	0.14	0.07	0.36	0.00	-0.03	0.05	0.27
11	0.18	0.54	0.24	1.25	0.28	1.58	0.21	1.21	0.26	1.39
12	0.22	0.64	0.29	1.54	0.28	1.61	0.26	1.49	0.32	1.69
13	0.16	0.40	-0.28	-0.98	-0.27	-0.99	-0.31	-1.08	-0.28	-0.99
14	0.88	1.16	0.61	0.97	0.61	0.99	0.61	0.96	0.58	0.94
15	0.54	0.77	0.12	0.17	0.13	0.19	0.13	0.19	0.14	0.20
16	0.46	0.67	0.27	0.40	0.27	0.41	0.29	0.44	0.28	0.42
17	-0.31	-0.39	-0.57	-0.77	-0.56	-0.77	-0.56	-0.76	-0.28	-0.41
18	-1.24	-1.37	-1.64	-1.84	-1.66	-1.86	-1.63	-1.83	-1.20	-1.52
19	-1.37	-1.45	-1.95	-2.00	-1.97	-2.01	-1.93	-1.99	-1.39	-1.67
20	-1.15	-1.29	-1.87	-1.94	-1.88	-1.94	-1.87	-1.94	-1.17	-1.52
21	-1.36	-1.70	-1.65	-1.88	-1.66	-1.87	-1.66	-1.88	-1.42	-2.07
22	-1.22	-1.55	-1.47	-1.70	-1.50	-1.71	-1.47	-1.70	-1.29	-1.91
23	-0.48	-0.69	-0.47	-0.60	-0.48	-0.61	-0.47	-0.60	-0.54	-0.90
24	-0.88	-1.37	-0.67	-0.90	-0.67	-0.90	-0.68	-0.91	-0.89	-1.58

5.3. Risk analysis

Based on the results of the return analysis, changes in systematic risk are unknown to the extent that the risk is expected to rise for some cryptocurrencies and fall for others. The average change in systematic risk, calculated from Eq. (1) and is reported in Table 7. The beta for all 100 cryptocurrencies is 0.229, whilst the betas for Bitcoin, Ethereum, Bitcoin Cash, Litecoin, Monero, Dash, Zcash and Dogecoin are − 0.004, 0.604, − 0.213, 0.079, 0.389, 0.647, 0.548 and 0.416, respectively. Bitcoin and Bitcoin Cash have negative betas which supports hypothesis H3, implying that they move against the market—this property provides a potential hedging instrument as suggested by Chan et al. (2019). The remaining six cryptocurrencies are less risky than the market as their

Table 7
Aggregate Changes in Short-term Systematic Risk.

Cryptocurrencies	Beta	Change in beta	t-stat	Intercept change	t-stat
Bitcoin	-0.004	-1.262	-0.56	0.006	0.60
Ethereum	0.604	7.050	1.01	-0.030	-1.48
Bitcoin Cash	-0.213	8.303	0.46	-0.054	-1.12
Litecoin	0.079	-6.569	-6.64	-0.026	-3.69
Monero	0.389	-1.134	-0.37	0.003	0.20
Dash	0.647	2.306	0.63	-0.019	-1.69
Zcash	0.548	12.704	1.89	-0.019	-0.61
Dogecoin	0.416	-0.504	-0.31	-0.012	-1.54
100-Cryptos	0.229	1.449	0.18	-0.004	-0.14

betas fall between zero and one. Of specific interest is the multiplicative dummy variable, (β_S^2), in Eq. (1), which captures changes in systematic risk following the news of a drug bust. Note that a positive coefficient on the multiplicative dummy reflects an increase in systematic risk caused by the 24 drug busts. The results documented in Table 7 show that following drug bust news, the beta of Litecoin changed from 0.08 to − 6.49 while the beta of Zcash changed from 0.55 to 12.16. This result suggests that cryptocurrency markets react to drug bust news, which provides support for the intuitive proposition that drug traffickers and users may be utilizing cryptocurrencies to settle transactions.

Due to the inherent issues with using Eq. (1) to identify short-term effects, we estimate Eq. (2) to capture daily changes in short-term systematic risk. The results, represented by Fig. 2, are mixed to the extent that we find major short-term risk shifting behavior for many cryptocurrencies between drug bust 13 (the Sydney cocaine bust) and 17 (the “Gulf Clan” gang cocaine bust). For these drug busts, we observe both increase and decrease in systematic risk, implying that drug bust news have different impacts on risk for different cryptocurrencies. For instance, we identify an increase in the systematic risk associated with drug busts 17 (the “Gulf Clan” gang cocaine bust) and 20 (Myanmar methamphetamine bust), while we observe a decrease in systematic risk, a result of drug bust 7 (U.S. Coast Guard cocaine bust I). Last, but not least, we note that changes in systematic risk can have opposing effects for different cryptocurrencies such as for drug bust 16 (Ontario cocaine bust) where Litecoin and Ethereum experienced increases in risk, while Monero, Bitcoin Cash and Dash experienced decreases in risk.

We now make several observations, based on the results represented by Fig. 2. First, the news of initial drug busts appear to have had little influence on the risk structure of the cryptocurrency market. Subsequent busts, however, appear to have a larger influence on the risk structure, which indicates a greater degree of uncertainty following drug busts. Whether this is due to drug traffickers utilizing the cryptocurrency market more prolifically (as cryptocurrencies gained popularity), or as a result of other factors, is yet to be determined. Second, in a number of drug busts the effects of drug bust news releases vary from one cryptocurrency to another. Third, we observe several significant divergences in changes in systematic risk from one drug bust to another, to the extent that changes in systematic risk can be positive for one cryptocurrency and negative for another, indicating asymmetric reactions.

6. Discussion

This study’s goal is to shed light on the influence of drug enforcement activities in the form of drug busts on cryptocurrency markets. Cryptocurrency markets have become a talking point for speculators, individuals who dislike fiat currencies and regulators. Due to cryptocurrency anonymity, individuals and organisations can hide their activity from the usual checks regulators normally implement on monetary transactions. The buying and selling of drugs using cryptocurrencies, hypothesized by Foley et al. (2018) leads us to investigate the cryptocurrency market impact of drug bust news. In this study/paper, we propose three hypotheses to test whether news of drug busts influence the cryptocurrency market.

Hypothesis H1 tests whether news of drug busts positively affect cryptocurrency returns. We find some evidence to support this hypothesis. More specifically, we find positive CAR30 following drug busts 1, 14 and 17 which are statistically significant at 1% level of confidence. For example, for drug bust 1, the CAR30 is 0.28 with a t-statistics of 3.87. In other words, the argument that “drug bust news lead to an

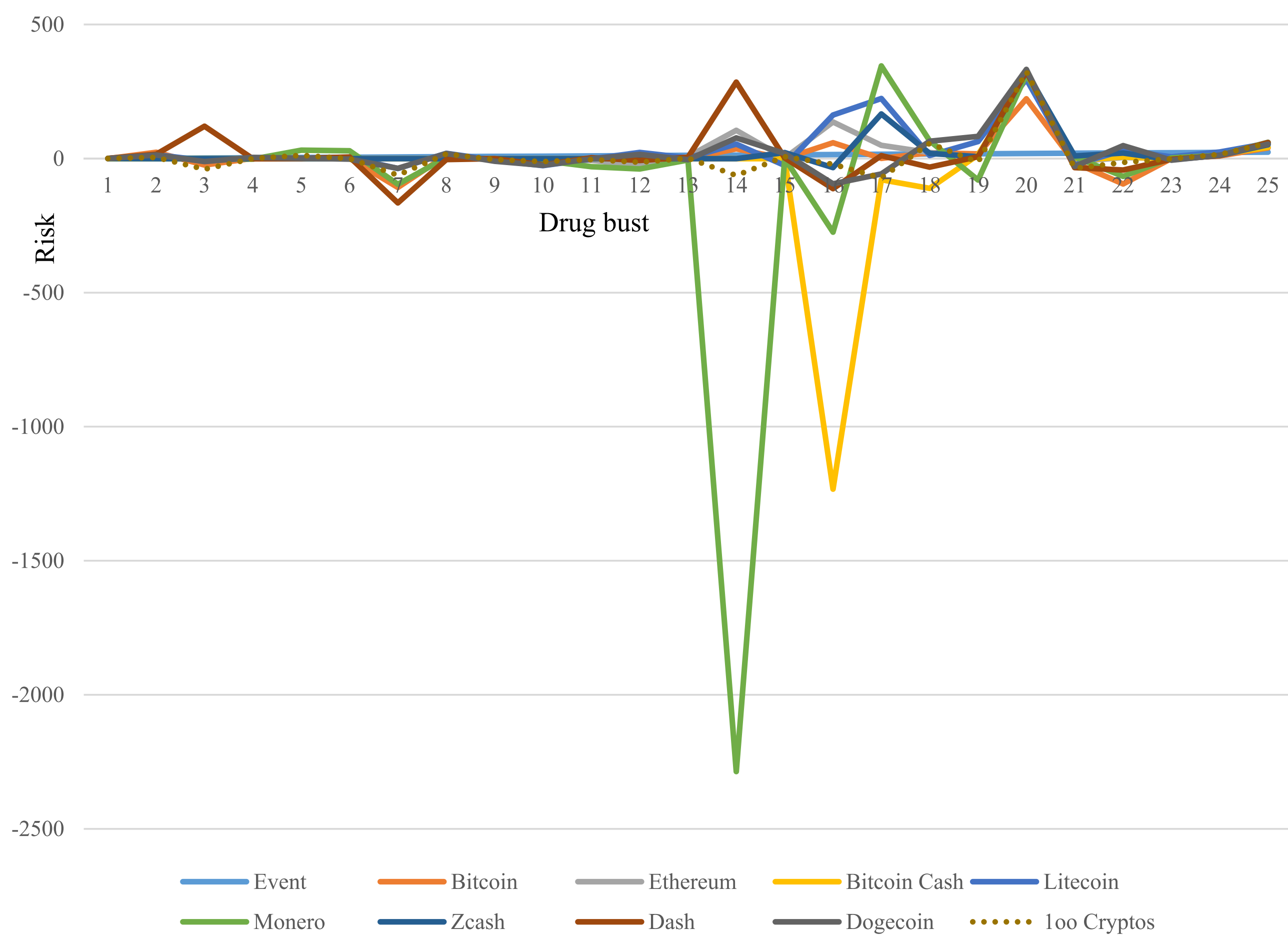

Fig. 2. The Impact of each Drug Bust on Short-term Systematic Risk.

increase in the price of cryptocurrency following (1) a decrease in the supply of drugs and (2) an increase in the price of drugs" is of rare occurrence but can prevail. Nonetheless, our hypothesis H1 extends the work of da Gama Silva et al. (2019) in that we explain how (1) the decrease in the supply of drugs and (2) an increase in the price of drugs following drug busts news affect the demand for cryptocurrency which in turn leads to an increase in the price of cryptocurrency.

Hypothesis H2 tests whether news of drug busts negatively affect cryptocurrency returns. We find strong support for hypothesis H2 in that we document significant negative CAR over 30-, 60- and 90-day periods following the news announcement of drug busts. Most of our results are statistically significant at 1% level of confidence. For instance, drug bust number 2 has a CAR60 of − 0.76 with a t-statistics of − 2.40. In other words, the perception of lesser drugs usage following drug busts leads to a decrease in abnormal returns and is consistent with the arguments made by da Gama Silva et al. (2019) in terms of lower demand for cryptocurrency.

Hypothesis 3 tests whether the news of these drug busts decrease cryptocurrency risk and we find support for this hypothesis. For example, the empirical evidence provided from Litecoin suggests that this cryptocurrency is less risky in that the beta decreased by 6.569 (with a t-statistics of −6.64), following the news arrival of the 24 drug busts. It is indirect evidence that market participants view the cryptocurrency market as less risky as we posit that the market assumes lesser drug related activities are carried out within these networks. Such evidence is consistent with Chan et al. (2019) and Peng et al. (2018) who explain that market participants who suspect illegal activities tend to perceive cryptocurrency markets as a risky one.

Please see Table 8 for a summary of the hypotheses. The theoretical implications arising our investigation are presented in Section 6.1 while we highlight the practical implications in Section 6.2. Lastly, we provide a discussion on the limitations of the research and directions for future research in Section 6.3.

6.1. Theoretical contributions and implications

There is a burgeoning body of literature focusing on the role and impact of cryptocurrencies in an emerging trans-national market (Branzei & Abdelnour, 2010; Coviello et al., 2017; Fisch et al., 2021). Specifically, the use of cryptocurrencies to transfer money due to the low transaction costs and anonymity is on the increase (Fisch et al., 2021). A relatively new area of literature focuses on the use of cryptocurrencies for illegal activities. This alarming externality of the popularity and characteristics of cryptocurrencies allows individuals to facilitate these criminal activities. Foley et al. (2018) indicate that almost half of all Bitcoin transactions are associated, in some way, with illegal activities. With an increase in speculation and "pump and dump" strategies, we have seen an emerging literature that investigates the value of a cryptocurrency. A number of authors link cryptocurrency value to technical factors and determinants of demand and supply (see, for instance, Bolt & van Oordt, 2016; Li & Wang, 2017; Hayes, 2017). As suggested by Yermack (2015) and Ciaian et al. (2016b), Bitcoin and, by extension other cryptocurrencies, do not satisfy the conditions to be classified as a currency which gives rise to speculation as a determinant in the value of cryptocurrencies. Further, in a world of digital media, Urquhart (2017)

Table 8
Summary of the Acceptance or Rejection of the Hypotheses.

Hypothesis	Description (in short form)	Accept / Reject
H1	Drug bust news have a positive effect on cryptocurrency prices.	Accept
H2	Drug bust news have a negative effect on cryptocurrency prices.	Accept
H3	Drug bust news have a negative association with cryptocurrency risk.	Accept

consider the impact of news and media on cryptocurrency price. Activities by drug enforcement agencies, such as drug busts, specifically disclosed as news announcements, may affect the demand and supply characteristics from a purely economic perspective as well as a speculative component. As such, in this paper we present an empirical model to test the impact of the news of a drug bust on the price and volatility of cryptocurrencies. Our unique contribution in this vein of the literature is that we show how the news announcement of 24 international drug busts have affected the risk and return of cryptocurrencies. More specifically, we (1) show how individual international drug bust news affect the return of cryptocurrencies, (2) identify the eight most sensitive cryptocurrencies to drug busts, (3) provide strong evidence of delayed reactions, and (4) document the first risk shifting behaviour following drug bust news in the cryptocurrency market.

Our study adds to the cryptocurrency literature in a couple of ways. First, we provide evidence that drug trafficking, or more specifically, the announcement of a drug bust by enforcement agencies influence cryptocurrency prices. Further, we highlight that criminals use major cryptocurrencies more often than the minor, less well-known cryptocurrencies. These results suggest that illegal activities, such as drug trafficking, mould cryptocurrency markets, to the detriment of more orthodox business users.

As argued in our theoretical section above, convenience theory suggests that wrongdoers make choices based on ease. In our case, given the linkages between cryptocurrency and drug busts, one might argue that it simplifies complex activities and reduces the space for detection. However, we find a focus on immediate benefits, and this had little concern for social consequences down the line, even though the consequences could be telling (Gottschalk, 2017b). In other words, such criminal usage of cryptocurrencies may deter conventional users and investors of cryptocurrencies, because criminals add to the costs incurred through choosing convenience. In addition, as we witness high cryptocurrency volatility, given the instability of the global economy, we see that the tensions induced by such criminal behavior actually undermines the feasibility of the medium itself, as we discussed in our literature (c.f. Barratt et al., 2016). Hence, the findings and linkages to the effects of criminal usage of cryptocurrencies on their volatility, helps confirm the predictions of convenience theory, when it comes to the discounting of future consequences. Further, linking the social foundations approaches, the apparent lack of social and regulatory dampers (Pace, 2017), with convenience choices (Gottschalk, 2017b), proves to have an affect input (criminal usage) on output (volatility). This confirms our argument that the risk of a self-reinforcing cycle of negative feedback loops, as criminals are likely to be less concerned with volatility. This is because they factor it into convenience choices further undermining their limited social footprint, as we argued above again, because of the eroding of the legitimacy of the currency, which in turn tends to drive out other more legitimate users, thus predictably making the future effects of drug busts more pronounced.

Thus, the existing literature on convenience theory and cryptocurrencies suggest that criminals opt for the latter because of ease in transactions and the opportunities they provide. Further, criminals are unlikely, deterred by the impact of their activities on others making usage of cryptocurrencies or, indeed, the consequences of their actions on their own future activities (Nolasco Braaten & Vaughn, 2021).

Second, via our results and the explicit understanding that the social foundations and regulation of cryptocurrencies are relatively weak (Pace, 2017), our study extends this work through highlighting how the interpenetration of crime into cryptocurrency markets can be so extensive as to mould criminals fortunes. Indeed, this process can be so extensive that a single drug bust directly affects the worth of the currency involved. Herding behaviour as well as the weak regulatory framework of the cryptocurrency markets, used as explanations as to why players are sensitive to the signals provided by law enforcement agencies (da Gama Silva et al., 2019); however, a hypersensitivity to law enforcement activity might itself be indicative of the scale of criminal involvement. Of course, it is of no little concern that news of a single drug bust can impart volatility to an entire currency unit— a phenomenon is more commonly associated with peripheral criminal states. The extent to which these patterns of behaviour repeat themselves indicates the short-term opportunism of criminals and their lack of concern for the impact on the future interests of others, and, indeed themselves. It also suggests the need for more extensive comparative work on the internal and external regulation of different cryptocurrencies, and how this impacts on their relative social embeddedness, and, in turn, how this affects the relative interpenetration of crime.

Lastly, our study sheds light on the influence of criminal activity on the volatility of cryptocurrencies. Businesses may secure profits through the generation and/or sale of goods and services, or via speculative activities; firms making usage of cryptocurrencies necessarily will have a speculative element built into their business model, given the volatility of such units. Over time, convenience behaviour by criminals could help drive volatility and intensify the speculative element.

6.2. Implications for practice

Our findings, while providing theoretical implications, also provides guidance and information specific to cryptocurrency market participants, regulators and enforcement agencies. The analysis of the impact of the use of cryptocurrencies for illegal activities may have wide reaching implication for these actors.

Our research has practical implications for regulators and enforcement. Our results show that buyers and sellers of drugs use cryptocurrencies to some degree for the transactions. Further the use of cryptocurrencies, by criminals, appears to be constrained to those cryptocurrencies that have access via an ATM. Removing the anonymity of cryptocurrencies is impossible, especially for individuals, however regulators should consider implementing, or expanding in some jurisdictions, a register for entities acting as cryptocurrency exchanges. As such, these entities would be required to be able to identify and verify their users if required (which defeats the purpose of anonymity—hence resulting in a paradox). They would also need to maintain records to comply with anti-terrorism and laundering rules – these laws would need implementing.

The ability of data driven algorithms used by regulators for stock exchanges is now useable to track transaction cryptocurrency transactions. While the individuals for each transaction are anonymous, the cryptocurrency transaction, through an exchange, is possible to track through the block-chain to identify where the funds originated. For instance, if the funds originated in a dark-web marketplace there is a higher likelihood that the transaction was for nefarious outcomes. In conjunction with the above register for cryptocurrency exchanges, criminals will have a smaller chance of converting to cash or transferring their cryptocurrency to a safe-haven. Additionally, if the objective of policy makers and regulators is, at least implicitly, to reduce the consumption and externalities of the use of drugs, monitoring of cryptocurrency ATMs for buyers can well prove useful in tracking back to the suppliers of illicit drugs.

For cryptocurrency speculators, while it is difficult to predict drug intervention acts in advance, speculators in the cryptocurrency market can identify which cryptocurrencies to avoid in the advent of such an intervention. Further, in order to remove, or mitigate, the impact of drug interventions on speculators portfolio of cryptocurrencies, speculators may choose to diversify away from the eight major cryptocurrencies that criminals may use to traffic their wares. Speculators, if aware of the outcome of drug enforcement activities, may use the news to change their positions in chosen cryptocurrencies. As news of drug-busts can take time to impound into prices, speculators have sufficient time to buy cryptocurrencies in expectation that prices will increase over the following 30 days.

6.3. Limitations and future research direction

Drawing on the well-used event study methodology we test whether drug bust news have an influence on the risk and return of cryptocurrencies. As with every empirical study, the findings of the research needs consideration vis-à-vis their limitations. First, we use daily data to identify the impact of the news of drug busts. In the context of the model, the other factors incorporated in the model, such as the risk-free rate, also needs to be confined to daily rates. The granular nature of markets may not seem estimated well for the aggregate trading activity, for a cryptocurrency, over the entire day. Although daily data captures the trading over the day it does not capture the possible asymmetries within the day and, accordingly, more research may be required to capture the effect of drug bust news at higher frequencies.

Another limitation is that our results seem based on data provided by CoinMarketCap. The cryptocurrency market appears decentralized with data, as is provided and received from multiple sources which is then aggregated by CoinMarketCap. Based on these data providers there may be embedded transposition or translation errors. More research is necessary, using different data providers, to verify our results. Additionally, using higher frequency data to aggregate manually would remove the dependence on external sources of data.

Our identification of the impact period (that is over 30 days) for drug bust news on cryptocurrencies may not capture the full effect of a drug bust. We envisage identification of a number of windows of observation, within the event-study methodology framework; however, there is no rule for identifying what the 'best' window length may be in a market such as a cryptocurrency market. Further research may optimise these windows through a selection algorithm to better estimate the impact of drug bust news on cryptocurrency markets.

7. Conclusions

We witness the blaming of cryptocurrency markets for harbouring illegal activities such as drug trafficking. Indeed, recent work has confirmed the scale of criminal infiltration of the cryptocurrency market (Kethenini and Cao, 2019). Additionally, there exists an ongoing debate on the fundamental value of cryptocurrencies and the reasons behind the fluctuations in their prices (da Gama Silva et al., 2019). Consequently, the objective of this paper is to document the impact of drug trafficking operations, through news of interdictions by law enforcement agencies, on the risk and return of the cryptocurrency market. Our results provide empirical evidence that links drug trafficking activities with the cryptocurrency market—in particular, major cryptocurrencies. These results suggest that illegal activities, such as drug trafficking, mould cryptocurrency markets, to the detriment of more orthodox business users. As such, our study extends the work of Pace (2017) and Nolasco, Braaten and Vaughn (2021) through highlighting how the impact of crime into cryptocurrency markets can be so extensive that the news of a single drug bust directly affects the individual cryptocurrency value.

CRediT authorship contribution statement

Laith Almaqableh: Conceptualization, Methodology, Software, Data curation, Writing – original draft preparation, Visualization, Investigation. Supervision, Validation, Writing – reviewing & editing. **Damien Wallace:** Conceptualization, Methodology, Software, Data curation, Writing-Original draft preparation, Visualization, Investigation. Supervision, Validation, Writing- Reviewing and Editing. **Vikash Ramiah**: Conceptualization, Methodology, Software, Data curation, Writing – original draft preparation, Visualization, Investigation. Supervision, Validation, Writing – review & editing. **Geoffrey Wood**: Conceptualization, Methodology, Software, Data curation, Writing – original draft preparation, Visualization, Investigation. Supervision, Validation, Writing – review & editing. **Imad Moosa**:

Conceptualization, Methodology, Software, Data curation, Writing – original draft preparation, Visualization, Investigation. Supervision, Validation, Writing – review & editing. **Alastair Watson:** Conceptualization, Methodology, Software, Data curation, Writing – original draft preparation, Visualization, Investigation. Supervision, Validation, Writing – review & editing.

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