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# A flight-to-safety from Bitcoin to stock markets: Evidence from cyber attacks

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ABSTRACT

We discover a novel flight-to-safety (FTS) effect from cryptocurrency markets to stock markets, triggered by a series of hacking attacks on cryptocurrency exchanges. This phenomenon is driven by heightened uncertainty, which increases investors' risk awareness and prompts asset reallocation in favour of safer stock markets over riskier cryptocurrency markets. We conduct an extensive global examination of this effect across 39 countries and confirm this novelty. This effect is amplified by frequent attacks when investors' risk awareness is strengthened. Notably, social media sentiment surrounding these attacks serves as both a timely warning indicator for upcoming hacking events and a measure of the FTS pressure following such attacks. We conclude that the collapsed investor confidence and increased risk aversion are the primary cause of such an effect. We further substantiate the FTS hypothesis by offering evidence of significant abnormal fund flows into US mutual funds following these hacking events. As such, through the lens of cyber attacks, we document how a shock in cryptocurrency markets is transmitted into stock markets via investors' FTS behaviour.

## 1. Introduction

Over the past decade, Bitcoin, the most popular cryptocurrency, has attracted enormous attention. This unregulated market operates 24/7, is characterized by anonymity, and facilitates borderless transactions. The adoption of privacy-enhanced cryptocurrencies has been increasing and a significant proportion of their usage has been linked to illicit and criminal activities (Foley, Karlsen, & Putniņš, 2019). According to the Internet Organized Crime Threat Assessment Report 2024, hacking attacks over cryptocurrency have become more evident over the past few years, partially driven by the growing adoption of cryptocurrencies.[1] As a result, cryptocurrency users have become the targets of cybercriminals. In 2019 alone, there were 10 publicly confirmed hacking attacks on cryptocurrency exchanges, resulting in stolen cryptocurrencies valued at 244 million euro.

Users approaching digital currencies perhaps may not be primarily interested in an alternative transaction system but rather seek to engage with an alternative investment vehicle for a novel experience (Glaser, Zimmermann, Haferkorn, Weber, & Siering, 2014). These cryptocurrency investors may lack adequate financial literacy to navigate the inherently complex, risky, and volatile nature of these financial instruments (Panos & Karkkainen, 2019). Frequent hacking attacks on cryptocurrency exchanges may dampen investors' interest in cryptocurrencies. Investors may realize that they are ill-equipped to make financial decisions within such a complex system, especially as they are not protected by central authorities or law enforcement. Consequently, they tend to favour regulated asset markets, resulting in the FTS effect from cryptocurrency markets to stock markets.

A flight-to-safety (FTS) is characterized as an episode of the co-occurrence of heightened economic uncertainty, declining equity prices, and low real interest rates (Barsky, 1986). During volatile times, increased risk aversion among market participants drives investment transfer, from equity markets to bond markets, in pursuit of liquidity and quality (Vayanos, 2004). In this study, we characterize the FTS phenomenon between cryptocurrencies and stocks by the shifting risk perception and resultant capital reallocation from an alternative high-risk digital investment vehicle to a safer conventional investment vehicle. Cryptocurrency investors[2] are typically risk takers or

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[1] Internet Organized Crime Threat Assessment (IOCTA, 2024) can be found at https://www.europol.europa.eu/publication-events/main-reports/internet-organised-crime-threat-assessment-iocta-2024

[2] Bitcoin is an investment vehicle of the highest risk worldwide. According to Yermack (2024) the volatility of Bitcoin-dollar exchange rate was 142%, higher than the dynamic movement of the riskiest stock of a volatility of 100%. Widely traded stocks normally had volatility in the range of 20% to 30%, other fiat currency had volatility between 7% and 12%, and gold, an alternative investment for hedging risk, had a volatility of 22% in 2013 based on dollar-denominated exchange rate.

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speculators seeking higher returns (Smutny, Sulc, & Lansky, 2021). These "risk-taking" investors, when confronted with hacking attacks on cryptocurrency markets, are more likely to redirect their investments to stock markets. Consequently, a FTS effect emerges as cryptocurrency investors and hesitant potential investors shift away from cryptocurrency markets towards stock markets.

Baele, Bekaert, Inghelbrecht, and Wei (2020) propose three criteria to identify a FTS from stock markets to bond markets and employ different models to measure the FTS.[3] Given the unique nature of cryptocurrency markets and the inherent difficulty in tracing capital flows, using conventional approaches to identifying a FTS between cryptocurrency markets and stock markets is challenging. Building on theories and expectations of FTS dynamics in conventional financial markets during periods of market uncertainty, we address this challenge by conducting a range of strategically designed analyses. First, we focus on temporal market reactions following hacking attacks[4] on cryptocurrency markets. Risk-averse investors tend to be more prevalent in the wake of cyber-attacks (Caporale, Kang, Spagnolo, & Spagnolo, 2020). Investors, perhaps frustrated by their limited financial literacy in the cryptocurrency markets, lack confidence in navigating these complex systems. Cyber-attacks heightens investors' risk perception and awareness, prompting them to seek safer investment options and hence triggering redemptions and asset re-allocation across different asset classes, for instance, moving away from alternative assets towards equity markets. We expect counter-movements of market performance — decreasing in cryptocurrency markets and increasing in stock markets, thereby providing global evidence for the FTS behaviour across these two markets. Then, we focus on the strength of stock market reactions and hypothesize a more pronounced FTS effect during consecutive hacking attacks on cryptocurrency exchanges, based on the argument that repeated attacks significantly erode market participants' confidence and further heighten their risk awareness.

Next, we explore the transmission mechanisms of this novel FTS effect, through which shocks in cryptocurrency markets propagate to stock markets. We focus on the role of social media, a key information exchange platform for the cryptocurrency community, given that unregulated cryptocurrency markets are less transparent than regulated stock markets. Hackers often target cryptocurrency exchanges with weak security and initiate small attacks before launching larger breaches (Gandal, Hamrick, Moore, & Oberman, 2018). Victims of these testing incidents are inclined to spread attack alerts to their communities via social media platforms and thus informed players within cryptocurrency markets, such as exchange founders, cybersecurity experts, and affected investors, possess advanced awareness of attacks prior to official announcements. We conjecture that social media sentiment has the predictive power for the upcoming announcements of hacking events, which triggers investors' FTS behaviour towards safer stock markets.

Finally, we validate this novel FTS effect by analysing abnormal fund flows in stock markets. As it is impossible to directly trace the capital flows from cryptocurrency markets to stock markets, we partially address the issue by focusing on the fund flow dynamics in the stock markets in the context of US mutual funds. Following hacking events in cryptocurrency markets, with the presence of FTS behaviours, we expect to observe substantial capital movement into mutual funds, which are from both existing and hesitating cryptocurrency investors. Moreover, to ensure the robustness of our results, we perform additional tests using various event windows and firm-level analyses. Furthermore, we present a set of supplementary analyses to further comprehend our understanding of this novel FTS behaviour across country characteristics in the online Appendix.

Addressing the borderless nature of cryptocurrency markets, with investors spanning the globe, we examine the FTS effect across a global sample of 39 countries and regions. Identifying the event date of a breach in cryptocurrency exchanges, more specifically the event time stamp confirmed by exchanges, is critical to this study. We manually collect information on hacking events reported by the mainstream press such as Reuters, The Guardian and BBC and disclosed on blockchain forums or cryptocurrency exchange websites.[5] Between January 2011 and December 2019, a total of 45 attacks were recorded, with an average of US$ 29.19 million stolen per event. As shown in Fig. 1, the likelihood of attacks appears to be correlated with cryptocurrency market prices, as evidenced by the cryptocurrency bubble period in 2018, potentially driven by elevated prices.[6]

Based on this unique sample, we document a novel FTS effect from cryptocurrency markets to stock markets, triggered by a series of hacking attacks on cryptocurrency exchanges. This phenomenon is driven by heightened uncertainty, which increases investors' risk awareness and prompts the reallocation of assets in favour of safer stock markets over riskier cryptocurrency markets. We observe opposing movements in market performance between Bitcoin and stock markets pre- and post-formal announcements of hacking events. Under the threat of hacking attacks on cryptocurrency markets, stock markets emerge as a safe haven for investors. This effect is amplified by frequent attacks induced by the heightened investors' risk awareness. Exploring the working channel of this FTS effect, we find that social media sentiment surrounding these attacks serves as both a timely warning indicator for upcoming hacking event announcements and as a measure of the FTS pressure following such attacks. A sharp decline in social media sentiment precedes a steep downward plunge in Bitcoin returns and a corresponding rise in stock market returns. We attribute the underlying causes of this phenomenon to the collapse of investor confidence, as captured by social media sentiment and increased risk perception, which prompts a shift in investor interest from alternative investment vehicles to conventional ones, such as stocks. Furthermore, we find evidence of significant abnormal flows into US mutual funds after the announcements of hacking events on the cryptocurrency market, further substantiating the FTS hypothesis. Our results are robust to a range of event window periods and a firm-level analysis in the context of S&P500.

This study contributes to the literature in three aspects. Firstly, this study extends the literature by documenting a novel FTS effect from alternative asset markets (e.g., cryptocurrency markets) to conventional financial markets, triggered by cyber-attacks. Extant research has examined FTS episodes during market downturns or crisis periods, such as the 1997 Asian crisis, the 1998 Russian crisis, and the Enron crisis in 2011 (Baur & Lucey, 2009), which is in alignment with investment managers' stronger tendency to transfer capital to relatively safe assets during more volatile periods (Adrian, Crump, & Vogt, 2019). The FTS effect has been explored under the dimensions of market uncertainty, spanning sovereign debt (Nasir, Le, Ghabri, &

[3] The three criteria are (1) the bond and stock market have a large positive and negative return, respectively; (2) bond and stock returns are negatively correlated; and (3) a high equity market volatility.

[4] In this paper, the terms "cyber-attacks" and "hacking attacks" are used interchangeably. Cyber-attacks refer to intentional attempts to steal, alter, or destroy data through unauthorized access, as defined by IBM (https://www.ibm.com/topics/cyber-attack). Hacking attacks are a subset of cyber-attacks, focusing on a decentralized system framework.

[5] Attacks covered by these outlets are considered to have significant impact. This paper analyses the daily effects of these hacking events at the time of their occurrence and afterwards. We filter the hacking-related news based on the specific calendar dates reported in mainstream media. To avoid potential bias or manipulation, no thresholding criteria were applied to the reported value of stolen assets.

[6] We also observe that the attacks were particularly frequent during the early phase of exchanges' establishment, which is large due to inadequate security infrastructure. The breach suffered by the Mt. Gox exchange in 2014 with a total loss of US$ 460 million is the most notable example.

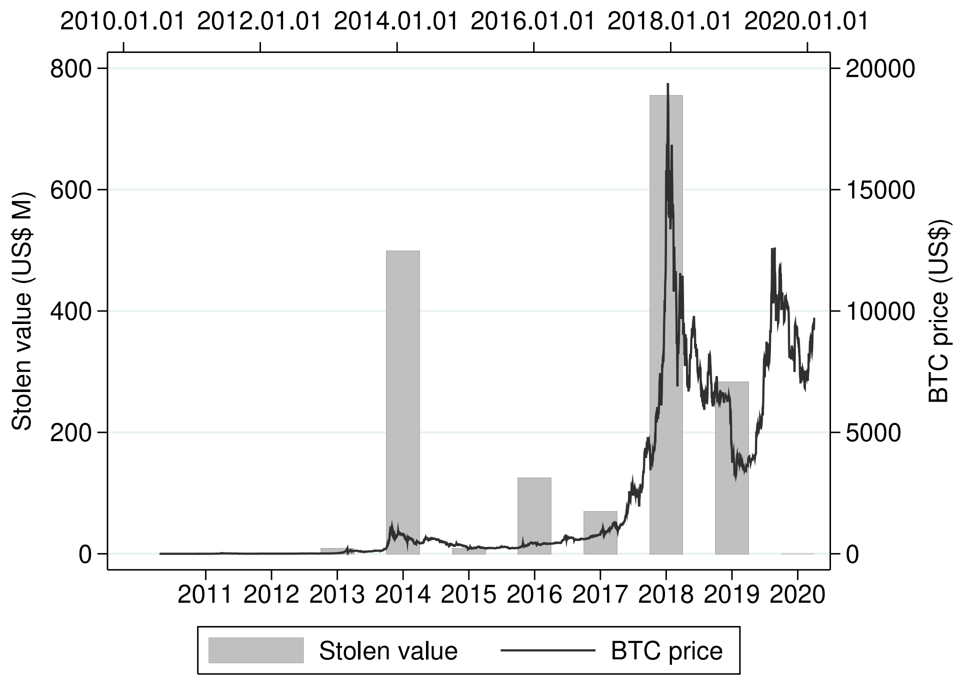


**Fig. 1.** Stolen value versus Bitcoin price.
This figure plots stolen value by hacking attacks in US dollar million (the left $y$-axis) and Bitcoin (BTC) price in US dollar (the right $y$-axis) during the period 2011–2020.

Huynh, 2023), bonds (Baele et al., 2020), gold and foreign exchange as potential safe havens (Bouri & Jalkh, 2024). Our study uncovers a new paradigm of the FTS effect from the digital asset markets to the conventional asset markets.

Secondly, this study contributes to the ongoing debate regarding the relationship between cryptocurrency markets and traditional financial markets. Akyildirim, Corbet, Sensoy, and Yarovaya (2020) demonstrate contagion channels between stock markets and cryptocurrency markets, noting that changes in corporate names to blockchain-related names can affect their stock market performance. In contrast, Liu and Tsyvinski (2021) finds no strong correlation between cryptocurrency returns and traditional asset classes. While Klein, Thu, and Walther (2018) reject the view of Bitcoin serving as a safe haven or hedging tool, other researchers argue that Bitcoin shares similar features with gold (Xu & Kinkyo, 2023), can serve as a hedging tool (Guesmi, Saadi, Abid, & Ftiti, 2019), or act as a diversifier for short-term investments (Corbet, Meegan, Larkin, Lucey, & Yarovaya, 2018). These studies attempt to establish a link between cryptocurrency markets and conventional financial markets by exploring the potential role of cryptocurrencies as an alternative investing or hedging vehicle. Our study examines how shocks within cryptocurrency markets propagate to stock markets and explores the underlying working mechanism, documenting a direct link between these asset classes.

Finally, this paper advances the literature on cryptocurrency markets by examining the interaction of cybercrime and investor behaviour. Extensive academic attention has focused on driving factors of cryptocurrency price dynamics, including the network effect of cryptocurrency adoption (e.g., Cong, Li, & Wang, 2021), the marginal cost of production (e.g., Cong, He, & Li, 2019), stablecoins valuation (e.g., Griffin & Shams, 2020), and the influence of traditional asset classes (e.g., Schilling & Uhlig, 2019). As cryptocurrency users have become a prime target for cybercriminals (Foley et al., 2019), researchers have paid more attention to various security threats, including forking, mining botnets, and private key issues (Biais, Bisiere, Bouvard, & Casamatta, 2019; Li, Jiang, Chen, Luo, & Wen, 2020; Spathoulas, Giachoudis, Damiris, & Theodoridis, 2019). A recent study by Cheraghali, Molnár, Storsveen, and Veliqi (2024) investigates the effects of cyberattacks on cryptocurrencies and other asset classes. While their study focuses on asset dynamics such as returns, volatility, and trading volumes, our paper adopts a broader perspective by exploring the implications of hacking attacks on global stock markets. By highlighting how cyberattacks influence investor risk perceptions and asset reallocation behaviours, this paper contributes novel insights into the cross-market effects of cybersecurity breaches.

The remainder of the paper is organized as follows. Section 2 reviews the literature and develops hypotheses. Section 3 describes the sample and key variables. Section 4 specifies empirical models and interprets the results. Section 5 presents evidence for FTS from mutual funds, and Section 6 concludes.

## 2. Theoretical background and hypothesis

### 2.1. Risky cryptocurrency trading and vulnerable cryptocurrency exchanges

Interest in cryptocurrency has become unprecedented in recent years, fuelled not only by the emergence of a new form of currency but also by a disruptive and innovative payment technology. However, this enthusiasm comes with significant risks. Unlike conventional financial assets (i.e., stocks or bonds), which are typically insured and regulated by government authorities, cryptocurrency trading is fraught with security vulnerabilities. Cybercriminals increasingly employ sophisticated and holistic strategies to exploit these vulnerabilities, putting investors at risk. For instance, traditional financial markets are backed by regulatory safeguards, such as the Federal Deposit Insurance Corporation (FDIC) in the US, which insures depositors in the event of bank failures, ensuring the protection of their funds during liquidation or restructuring (Buser, Chen, & Kane, 1981). However, in the cryptocurrency world, no similar regulatory framework exists. There are no protections or schemes supported by authorities or third parties to recover losses caused by cyber-attacks. In 2018, the U.S. Securities and Exchange Commission (SEC) has called cryptocurrency exchanges “potentially unlawful online platforms” as none of these exchanges are registered with securities regulators . In the event of a cyber-attack on exchanges, it is often extremely difficult or impossible to trace the stolen assets because of the privacy-enhanced payment techniques. This contrasts sharply with traditional financial markets, where stolen securities can be traced back to their original owners since every single account is linked with a government-authenticated identity. This regulatory gap further heightens the risks for investors, as they are exposed to the possibility of losing their investments without any recourse for recovery.

Cryptocurrency exchanges have become prime targets for cyberattacks, and investors continue to face significant risks related to security breaches. According to a Hackernoon report,[7] many exchanges are poorly rated for security,[8] struggling to prevent or mitigate the frequency and severity of cyber-attacks. A combination of factors makes cryptocurrency exchanges attractive to hackers, including the rapid increase in coin values, the centralized business operation model, the reliance on hot wallets for storing customer funds, and the inability to trace stolen coins. First, the explosive growth in cryptocurrency value, especially Bitcoin, has made exchanges a lucrative target for hackers. For instance, Bitcoin's price reached an all-time high of US$ 64,550 in April 2021. Between April 2017 and February 2020, there were 30 reported hacking attacks on exchanges, with a total stolen value of $1108 million. The stolen value appears to be positively correlated with Bitcoin prices, as shown in Fig. 1, with notable spikes during the cryptocurrency bubble in 2018 when the stolen value peaked at $755 million.

The second factor is the centralized operation model. Approximately 99% of cryptocurrency transactions are conducted through centralized exchanges, significantly increasing the probability of cybercrime compared to traditional stock exchanges. Unlike stock exchanges that primarily facilitate trading, cryptocurrency exchanges also serve as custodians, holding cryptocurrencies on behalf of investors. Specifically, cryptocurrency exchanges typically maintain full control of Bitcoin storage, enabling the execution of buying and selling orders in real-time. These centralized storage practices, akin to cash holding in banks, create single points of vulnerability, making exchanges a prime target for cybercriminals (Russolillo & Jeong, 2018). When an exchange is under attack, traders often face delays in withdrawing funds due to the centralized approval process, exacerbating losses caused by high price volatility. The Mt. Gox attack exemplifies these vulnerabilities, with traders unable to access their funds during critical price fluctuations.

The third factor is the hot wallet storage practices. Cryptocurrency exchanges typically store the coins for their customers in hot wallets, which keep private key information online to facilitate real-time transactions. This poses significant security risks. A private key serves as the unique identifier of ownership and security credentials for cryptocurrencies.[9] If hackers gain access to these private keys stored in centralized pools of cryptocurrency exchanges, the potential for catastrophic losses increases. For users, losing their private keys equates to losing access to their cryptocurrency assets, permanently severing their connection to the blockchain ecosystem.

Finally, the anonymity afforded by cryptocurrencies, coupled with the lack of a clear ownership identification, makes cryptocurrency exchanges particularly attractive to hackers. From a technical standpoint, cryptocurrency transactions are built on privacy-enhanced payment systems, meaning traders' identities are not verified through transaction records. The underlying structure of Bitcoin and other cryptocurrencies makes it nearly impossible to trace stolen coins and funds. Once hackers successfully transfer stolen coins into their private wallets, they can obfuscate their trail by creating millions of wallet addresses through blockchain networks (Foley et al., 2019). These stolen coins and funds often embark on a "mystery journey" across multiple token addresses, tendering law enforcement efforts to trace payments nearly futile. This lack of traceability further emboldens cybercriminals and undermines the ability to recover stolen assets.

### 2.2. Literature review of flight-to-safety

The FTS phenomena, initially observed by Barsky (1986), describes the divergent movement between equity and bond markets during periods of economic uncertainty. This dynamic has been extensively studied in shaping market behaviour of shifting investments from riskier assets to safer ones during financial crises (Adrian et al., 2019; Baele et al., 2020; Baur & Lucey, 2009). The primary driver of FTS behaviour is a shift in investor risk aversion. Changes in risk appetite are widely recognized as key determinants of asset class dynamics (Bekaert et al. 2022). When markets experience stress, investor risk aversion tends to increase, accompanied by perceived wealth shrinkage (Lehnert, 2022). Based on FTS episodes across 23 countries, Baele et al. (2020) finds that price changes are marked by risk transfer during the period of market stress. They demonstrate how mutual fund investors actively rebalance their holdings from riskier into safer assets in response to FTS effects. This reallocation reflects a sudden increase in risk aversion.

A substantial collection of research explores the FTS effect across different economic contexts. While early studies focused on developed countries (e.g., Baur & Lucey, 2009), more recent work has extended to emerging economies. For instance, Ahmed (2023) investigates the FTS effect in the context of U.S. monetary spillovers, and Janus (2023) examines its role in sovereign bond markets. The COVID-19 pandemic has further exploration of FTS under the new dimensions of market stress. In the context of the G-7 and E-7 economies, Nasir et al. (2023) highlight the heterogeneous effect of the COVID-19 pandemic on sovereign bond yields, suggesting that the developed economies with more developed sovereign bond markets are still seen as a safe haven during times of crisis. For assessing FTS timing, Bouri and Jalkh (2024) explores the predictive power of US stock volatility on the implied volatility of safe haven assets, such as gold, cryptocurrency, foreign exchange rates, and US Treasury notes. Moreover, studies have also expanded the scope of FTS research, including the strengths of FTS (Boucher & Tokpavi, 2019), the nonlinear relationship between stock and bond markets (Adrian et al., 2019), retail investor behaviour (Lehnert, 2022), and the detection of FTS in the labour market (Bernstein, Townsend, & Xu, 2024). However, the FTS dynamic between decentralized markets and centralized regulated markets remains underexplored. Our study addresses this gap by offering insight into a novel FTS from cryptocurrency markets to equity markets during the period of cryptocurrency market uncertainty.

### 2.3. Hypothesis development

The main cause driving the FTS activity can be attributed to a shift in risk aversion. As highlighted in a global FTS study (Baele et al., 2020), more risk-averse investors, typically retail investors, rebalance their portfolios towards safe assets, while less risk-averse provide the insurance of alternative investments, earning elevated risk premiums afterwards. The same scenario happens in the cryptocurrency markets. Cyber-attacks on cryptocurrency exchanges disrupt market functionality by compromising private keys, leaking sensitive information, and resulting in stolen funds. Retail investors, characterized by lower financial literacy and higher sensitivity to risk, are more vulnerable to uncertainty. Such events that elevate risk perception prompt them to reasonably seek refuge in safer and regulated traditional assets.

Cyber-attacks on cryptocurrency exchanges create a reverse contagion effect, where shocks in the decentralized cryptocurrency market influence centralized stock markets. According to asset management pricing theory (Vayanos, 2004), funding constraints driven by market volatility amplify these effects, as uncertainty prompts a flight to

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[7] https://hackernoon.com/security-problems-of-crypto-exchanges-d5e2f595fb79.

[8] No cryptocurrency exchange offers complete security, with none achieving an A+ in security measures and most rated B. Approximately 30%–40% are vulnerable to Clickjacking and DoS attacks, leading to frequent data breaches and asset losses.

[9] A hot wallet is preferable to a cold wallet, considering the expense and speed of online selling, buying or trading orders.

safer assets. Furthermore, investors tend to favour assets with familiar features for better information acquisition (Massa & Simonov, 2006). In the context of cryptocurrency markets, hacking-induced volatility and uncertainty collapse investors' confidence, trigger risk aversion behaviours, and hence stimulate investment redemption, leading to a FTS effect towards stock markets. As such, we propose the following hypothesis:

**Hypothesis 1.** Cyber attacks on crypto markets undermine existing and prospective cryptocurrency investors' confidence, increase their risk awareness, and simultaneously heighten their caution, resulting in a FTS effect on stock markets

Consecutive hacking attacks can further erode investor confidence in cryptocurrency markets and push up their risk perception. This conjecture draws in parallel with crises in traditional stock markets, where successive waves of negative news significantly impact investor confidence and lead to capital flight. When hacking attacks become more prevalent and intense, investors are increasingly sensitive to such threats and exacerbate risk aversion, prompting them to move away from the cryptocurrency markets and seek safer investments such as stocks. As such, we propose the following hypothesis:

**Hypothesis 2.** Consecutive hacking attacks strengthen the FTS effect towards stock markets

Social media discussion, where users report and discuss attacks and their associated losses before broader public awareness, could provide early warning signals for upcoming major cyberattacks. Bitcoin users and traders are frequently active on social media platforms, as the relatively opaque nature of cryptocurrency markets and social media platforms are highly responsive to current events (Linton, Teo, Bommes, Chen, & Härdle, 2017). This channel enables the swift transmission of mood and sentiment among users. Research by Chen, Guo, and Renault (2019) highlights that social media activity is closely tied to future market performance and can serve as a reliable predictor of price movements and market volatility. Markets tend to react more strongly to negative events than positive news (Medovikov, 2016). Informed users, such as sophisticated traders, cybersecurity professionals and victims of wallet theft, could share early warnings, making social media a critical tool for detecting impending disruptions.

In the context of cyberattacks on cryptocurrency exchanges, social media sentiment amplifies risk aversion, leading to FTS behaviour. Discussions of negative events, such as economic crises or cyberattacks, often trigger sharp price movements as investors react to amplified fears and uncertainties. This dynamic is consistent with the findings of Sprenger, Tumasjan, Sandner, and Welpe (2014), who noted that spikes in negative sentiment precede significant sell-offs. Within cryptocurrency markets, informed investors possess advanced knowledge of hacking incidents, while the majority of retail investors lack timely access to such information and hence remain vulnerable to unexpected shocks. When hacking news emerges, the surge in related discussions on social media creates a contagion effect, aligning with risk aversion theory and driving FTS behaviour, pushing investors to safer assets. Based on the above discussion, we formulate the following hypothesis:

**Hypothesis 3.** The social media sentiment towards attacks serves as a timely warning indicator for impending major attack announcements, triggering FTS behaviour

## 3. Sample and key variables

### 3.1. Data source and sample construction

We collect data on a series of hacking events, mainly from Reuters, The Guardian, other mainstream press and cryptocurrency exchanges' official websites that report hacking events and information leakage regarding investors' private keys. Our analysis starts in 2011 when cyber-attack was first recorded online and reported by mainstream press. We collect the daily market price of Bitcoin and its bid–ask spread from Bitcoinity, a platform that uses API to gather data directly from cryptocurrency exchanges, including Coinbase, Bitfinex, Bitstamp, Kraken, BitX, BTCE, CEX.IO, EXNO, Gemini, itBit, LakeBTC, Okcoin and among others. Over the period from January 2011 to November 2019, we ended up with 45 hacking attacks in our sample, as listed in Appendix Table B.3.

Stock market data for this study were sourced from DataStream. To address potential discrepancies in stock market performance among different countries such as different numbers of constituents between indices like the S&P 500 and the FTSE 100, we primarily utilized data from the MSCI. MSCI data were chosen for their consistency and comprehensive coverage, which help mitigate inconsistencies in various global markets. Data were downloaded to cover daily market activities from 2011 to 2019, Relevant financial indicators were obtained the World Bank's world development indicators (WDI) database. Given the inconsistent format between the two databases, DataStream often uses full country names, while WDI sometimes uses abbreviations. Therefore, we develop a name translation form to match these two databases. In the end, aligning with the designated sample period for hacking events, we are left with 84,747 daily observations in 39 countries across 6 continents, of which 59% are developed economies and 41% are emerging economies.[10]

### 3.2. Key variables

The performance of cryptocurrency markets is measured by Bitcoin returns - $R_{j,t}^{BTC}$ and Bitcoin liquidity - $Spread_{j,t}$, defined as the logarithms of daily changes in Bitcoin price - $log(BTC\ price_{i,t}/BTC\ price_{i,t-1})$ and the daily bid–ask spread, from the $j$th cryptocurrency exchange at date $t$, respectively. A smaller return implies worse Bitcoin performance, while a larger spread indicates higher liquidity costs and risk. The stock market performance of country $i$ at date $t$, $R_{i,t}$, is defined as the daily changes in stock market return - $log(stock_{i,t}/stock_{i,t-1})$.[11]

To assess the temporal impact of hacking attacks, we consider a three-day window encompassing the announcement date and the subsequent two trading days and define three indicator variables - $D_0$, $D_1$, $D_2$, that take a value of 1 for the announcement date, the first trading day after the announcement, and the second trading day after the announcement, respectively.

We adopt investor sentiment measures developed by Chen et al. (2019), based on social media messages from two leading social microblogging platforms — StockTwits and Reddit, where the cryptocurrency players are actively enrolled for sharing information and expressing opinions in real-time. Under the supervised learning, the authors

[10] The countries and economies include Argentina, Australia, Austria, Belgium, Brazil, Canada, Chile, China, Colombia, Denmark, Egypt, Finland, France, Germany, Hungary, India, Indonesia, Ireland, Italy, Japan, Korea, Malaysia, Mexico, Netherlands, New Zealand, Norway, Philippines, Poland, Portugal, Russia, Singapore, South Africa, Spain, Sweden, Switzerland, Thailand, Turkey, UK and USA. We are unable to match cryptocurrency exchanges and stock markets by geographical location for two reasons. First, Bitcoin trading volume of online exchanges is highly concentrated. According to Statista (https://tinyurl.com/4pbm277e), more than 85% of total global Bitcoin trading in 2020 was conducted in the top 10 countries (i.e., USA, Russia, Nigeria, China, and UK). Second, cryptocurrency exchanges are online platforms serving different countries. For example, Binance, headquartered in Shanghai (China), operates in over 40 countries and serves more than 180 countries across the world.

[11] When the closing index on date $t-1$ or $t$ is unavailable, we treat the stock market return as missing. An alternative method is to use a different time horizon (i.e., weekly) to calculate the returns. However, we consider that longer intervals cannot fully capture market volatility and are likely to result in greater distortion.

apply the Natural Language Processing technique to construct a novel lexicon tailored for the cryptocurrency-specific semantic distillation on a daily basis over the period from January 2014 to December 2018.[12] We denote $Stwits_t$ as the measure of investor sentiment in the StockTwist community, ranging from −1 (negative sentiment) to +1 (positive sentiment) and the smaller the sentiment value, the more pessimistic investors become. The daily log changes in *Stwits* is $\Delta \ln(Stwits_t)$. Using the crypto-specific lexicon,[13] We also quantify the sentiment from messages on the Reddit website. The daily log changes, $\Delta \ln(Reddit_t)$, is an alternative measure of sentiment movement.[14]

Del Guercio and Tkac (2008) developed the event study approach for mutual fund flows, later applied by Ferriani (2021) to the FTS effect during COVID-19. Building on this method, we examine investor responses to exogenous events of hacking episodes in cryptocurrency markets, treating fund flow dynamics as evidence for the FTS effect. We measure abnormal flow for each mutual fund using the following regression, which captures the unexplained net flow after excluding the effect of the past fund dynamics and other performance determinants:

$$AF_{i,t} = F_{i,t} - \hat{F_{i,t}} \tag{1}$$

where

$$F_{i,t} = \alpha + \beta_1 SF_{i,t} + \beta_2 RET_{i,t-1} + \beta_3 F_{i,t-1} + \epsilon_{i,t}$$

$AF_{i,t}$ represents the abnormal flow of fund i in day t and $\hat{F_{i,t}}$ is the forecast flow estimated on the basis of the benchmark regression. We quantify $AF_{i,t}$ to examine fund flows towards hacking attacks.

Finally, we also include a set of control variables that have proven influences on stock market outcomes in the literature. To save space, we elaborate these variables in more detail in Section 4 along with the discussion of empirical results. Moreover, given the comprehensiveness of our analysis, we present our empirical model specifications in Section 4 and Section 5 along with empirical analysis for convenience.

### 3.3. Summary statistic

Table 1 Panel A reports descriptive statistics for our full sample. Daily changes in stock return ($R_{i,t}$) has a mean of 0.025% with a standard deviation of 1.2%, while Bitcoin return ($R^{BTC}_{j,t}$) has a mean of 0.22% with a standard deviation of 3.8%. Bitcoin spread ($Spread_{j,t}$) has a mean of 64.3% with a standard deviation of 199%. A total of 1.2% of our sample have cryptocurrency exchanges making hacking attack announcements ($D_0$). The corresponding figures for the first trading day ($D_1$) and the second trading day ($D_2$) after the attack announcement date are both about 1.7%.[15] 7.8% of our sample have experienced multiple crypto-exchange attacks within one month ($M$). Global equity growth rate (*SP*) shows an increase in stock market growth, on average, by 2.48% per annum and its standard deviation of 21.27% indicates a wide gap across countries. Stock market development (*MKT*) and credit market development (*CREDIT*) have mean values of 78.53% and 101.91% with standard deviations of 57.8% and 50.7%, respectively. During the sample period, investor sentiment ($Stwits_t$)[16] on average is 0.21 and its changes ($\Delta \ln(Stwits_t)$) is negative (−0.2%), while the changes in the sentiment measure from Reddit ($\Delta \ln(Reddit_t)$) is positive (0.1%). Table 1 Panel B reports comparative statistics for a sub-sample with a pre- and post-event two-day window $(-2, +2)$.

## 4. Empirical model specification and results

### 4.1. The flight-to-safety effect

Cybercrime undermines investors' confidence in crypto markets, inducing asset re-allocation to less risky investments such as stocks. We expect hacking attacks to have a negative impact on cryptocurrency markets but a positive impact on stock markets, thereby signifying a FTS effect. We first investigate how the announcements of attacking events affect crypto markets in terms of Bitcoin returns and Bitcoin liquidity, as shown in Eqs. (2) and (3), respectively.

$$R^{BTC}_{j,t} = \alpha + \beta_0 D_0 + \beta_1 D_1 + \beta_2 D_2 + \beta_3 \Delta BTC_{t-1} + \gamma_j + \epsilon_t \tag{2}$$

$$Spread_{j,t} = \alpha + \beta_0 D_0 + \beta_1 D_1 + \beta_2 D_2 + \beta_3 \Delta BTC_{t-1} + \gamma_j + \epsilon_t \tag{3}$$

Where the dependent variable $R^{BTC}_{j,t}$ in Eq. (2) and $Spread_{j,t}$ in Eq. (3) denotes the daily Bitcoin return and the bid–ask spread of the $j$th crypto exchange at date $t$, respectively.[17] $D_0$, $D_1$ and $D_2$ are dummy variables for dating hacking events. $D_0$ denotes the attack announcement date reported by the mainstream media, while $D_1$ and $D_2$ denote the first and second calendar day after the attack announcement, respectively. Note that $D_0$, $D_1$, $D_2$ are set according to calendar days which may slightly depart from the trading days defined in Section 3 and applied to Eq. (4), given that the crypto markets operate 24/7. $\Delta BTC_{t-1}$ is the lagged average daily changes in Bitcoin price across Bitcoin exchanges, $\gamma_j$ is the crypto exchange fixed effect, and $\epsilon$ is an error term.

Estimation results from Eqs. (2) and (3) are reported in Table 2 and all regressions control for Bitcoin price fluctuations and the crypto exchange fixed effect.[18] Columns (1) to (3) show that the average contemporaneous estimate of $\beta_0$ on $D_0$ is significantly different from zero across a range of specifications, suggesting a decline in Bitcoin returns with respect to hacking attack announcements. The effect is economically sizeable and statistically significant. On average, following attack announcements, the Bitcoin returns attenuate by about 43% compared with those of no attack periods. This effect dies out rapidly as the coefficients on $D_1$ and $D_2$ are insignificant, suggesting that crypto markets react to hacking events instantly without any delay. Regarding the impact of hacking attacks on Bitcoin liquidity, we bring liquidity costs into our regression analysis and columns (4)-(6) present the estimation results from Eq. (3). We find that after hacking attack announcements, Bitcoin liquidity becomes worse and liquidity risk emerges in the crypto markets. The attack announcement increases the bid–ask spread by about 30 percentage points every day during the hacking attacks period ($D_0$, $D_1$, $D_2$) and the effect is more statistically and economically significant at $D_1$. The overall evidence shows that hacking attacks on average are associated with a decrease in Bitcoin

[12] The processing procedure includes normalizing text to lowercase, filtering repeated words, and developing a cryptocurrency-specific lexicon based on the frequency and sentiment context of terms. The effectiveness and reliability of the sentiment value have been validated using the out-of-sample test.

[13] Data can be downloaded from Cathy Y. Chen's website https://sites.google.com/site/professorcathychen/resume.

[14] The authors accessed and download messages related to digital currency discussions via StockTwits' API and Python Reddit API Wrapper (PRAW). The authors have got 1,533,975 messages from 38,812 distinct users related to 465 cryptocurrencies for StockTwits, and 1,392,587 messages for Reddit, posted on the eight subreddits with the highest number of subscribers: "CryptoCurrency", "CryptoCurrencyTrading", "CryptoMarkets", "Bitcoin", "Bit-coinMarkets", "BTC", "Ethereum", and "Ethtrader".

[15] The reason for $D_0$, $D_1$, $D_2$ having different sample statistics is that when a hacking event is announced during the weekend, there is no corresponding stock market return on the attack announcement date ($D_0$) and such observations are excluded from our sample.

[16] The standard for identifying investor sentiment from −1(totally negative) to +1(totally positive).

[17] Bitcoin returns from exchanges such as Bitfinex, Bitstamp, BitX, CEX.IO, Coinbase, EXMO, Gemini, itBit, Kraken, and Others; and Bitcoin bid–ask spreads from exchanges such as Bitfinex, Bitstamp, BTCE, CEX.IO, Coinbase, Gemini, ItBit, LakeBTC, Okcoin, and Others.

[18] As our key variables, $D_0$, $D_1$, $D_2$, are dummy variables, we cannot use the fixed effect estimator. Instead, we employ the OLS estimator while controlling for exchanges and year-fixed effect.

**Table 1**
Summary statistic.

| | No. Obs | Mean | SD | Min | Max |
|---|---|---|---|---|---|
| Panel A: Full sample | | | | | |
| $R_{j,t}$ | 84,708 | 0.025 | 1.165 | −13.9518 | 12.9684 |
| $R_{j,t}^{BTC}$ | 21,328 | 0.22 | 3.766 | −75.644 | 72.447 |
| $Spread_{j,t}$ | 17,606 | 64.264 | 198.8 | 0.010 | 3333.15 |
| $\Delta BTC$ | 33,090 | 0.004 | 0.046 | −0.415 | 0.606 |
| $D_0$ | 84,747 | 0.012 | 0.109 | 0 | 1 |
| $D_1$ | 84,747 | 0.017 | 0.131 | 0 | 1 |
| $D_2$ | 84,747 | 0.017 | 0.131 | 0 | 1 |
| M | 84,747 | 0.078 | 0.268 | 0 | 1 |
| Bubble | 84,747 | 0.120 | 0.325 | 0 | 1 |
| SP | 84,747 | 2.479 | 21.274 | −49.144 | 71.655 |
| Volatility | 71,175 | 18.34 | 5.525 | 7.500 | 41.230 |
| MKT | 84,747 | 78.53 | 57.750 | 6.274 | 352.156 |
| CREDIT | 84,747 | 101.91 | 50.731 | 13.668 | 256.200 |
| GDP growth | 81,989 | 0.660 | 1.191 | −6.300 | 22.340 |
| GDP percap | 84,747 | 9.946 | 1.036 | 7.252 | 11.436 |
| M3 | 82,790 | 0.594 | 1.274 | −5.250 | 16.832 |
| Inflation | 84,747 | 3.581 | 5.786 | −2.855 | 50.623 |
| Saving | 84,747 | 25.172 | 8.185 | 9.593 | 49.233 |
| Popurban | 84,747 | 74.325 | 15.513 | 31.280 | 100.000 |
| $\text{Stwits}_t$ | 1,929 | 0.213 | 0.170 | −0.255 | 0.587 |
| $\Delta \ln(Stwits_t)$ | 41,964 | −0.002 | 0.563 | −5.256 | 4.345 |
| $\Delta \ln(Reddit_t)$ | 44,499 | 0.001 | 0.218 | −1.520 | 1.169 |
| Panel B: Two-day window subsample (−2,+2) | | | | | |
| $R_{j,t}$ | 7,254 | 0.022 | 1.166 | −11.028 | 7.238 |
| SP | 7,254 | 0.572 | 20.25 | −49.144 | 71.655 |
| Volatility | 4,563 | 18.07 | 5.642 | 7.5 | 41.23 |
| MKT | 7,254 | 79.03 | 57.973 | 6.274 | 352.156 |
| CREDIT | 7,254 | 102.2 | 51.606 | 13.668 | 256.200 |
| GDP growth | 7,045 | 0.662 | 1.354 | −6.3 | 22.34 |
| GDP percap | 7,254 | 9.968 | 1.029 | 7.252 | 11.436 |
| M3 | 7,127 | 0.508 | 1.140 | −4.820 | 9.742 |
| inflation | 7,254 | 3.691 | 6.453 | −2.855 | 50.623 |
| Saving | 7,254 | 25.294 | 8.055 | 9.593 | 49.233 |
| Popurban | 7,254 | 74.622 | 15.400 | 31.28 | 100 |
| $\Delta \ln(Stwits_t)$ | 4,056 | −0.028 | 0.389 | −1.520 | 1.022 |
| $\Delta \ln(Reddit_t)$ | 4,212 | −0.008 | 0.271 | −1.520 | 0.682 |

This table reports summary statistics for the data set used in this study, covering the period 2011 to 2019. Panel A reports the summary statistics of the full sample, while Panel B reports those of a sub-sample with a pre- and post-two-day window period. $R_{i,t}$ measures daily changes in stock market index return at the country level, defined as $log(stock_{i,t}/stock_{i,t-1})$. $R_{j,t}^{BTC}$ measures the daily Bitcoin return at the crypto exchange level, defined as $log(BTC\ price_{i,t}/BTC\ price_{i,t-1})$. $Spread_{j,t}$ denotes the daily bid–ask spread at the crypto exchange level. $\Delta BTC$ is the average daily change in Bitcoin price across cryptocurrency exchanges. $D_0$, $D_1$, $D_2$ are indicator variables, taking a value of 1 for the attack announcement date, the first, and second trading day after the attack announcement date, respectively. *M* is a binary variable and takes a value of 1 if there is more than one hacking events announced within the same month and 0 otherwise. *Bubble* is a time dummy for Bitcoin market bubble in 2018 and 0 otherwise. *SP* denotes the annual changes in global stock index. *Volatility* denotes the annual standard deviation of stock market. *MKT* denotes the ratio of listed companies' market capitalization over GDP. *CREDIT* denotes the ratio of domestic credit to private sectors over GDP. *GDP growth* denotes the quarterly GDP growth rate. *GDP percap* is the logarithmic GDP per capita (in USD). *M3* is the monthly broad money growth rate. *Inflation* is measured by GDP deflator. *Saving* denotes the ratio of saving over GDP. *Popurban* denotes the proportion of people living in urban areas. $Stwits_t$ is a measure of investor sentiment in the StockTwists community, ranging from −1 (negative sentiment) to +1 (positive) and $\Delta \ln(Stwits_t)$ denotes the daily changes in *Stwits* . $\Delta \ln(Reddit_t)$ denotes the daily changes in a sentiment measure from the Reddit website.

return by 43% and a rise in liquidity costs amounts to an additional 30 percentage points in bid–ask spread.

We also conducted a robustness test by adding sentiment controls from both StockTwits and Reddit. The estimation results for daily Bitcoin returns and the bid–ask spread remain robust and consistent, and are available upon request.

As a response to security concerns, the declining confidence and rising uncertainty around crypto markets are likely to trigger and enhance FTS behaviours. To justify this conjecture, we treat hacking attacks in crypto markets as exogenous shocks to stock markets and examine how stock markets react to those shocks under a global investigation. Our baseline model is shown in Eq. (4), with control for heterogeneity across countries and over the years.

$$R_{i,t} = \alpha + \beta_0 D_0 + \beta_1 D_1 + \beta_2 D_2 + \delta_i X_{i,t} + \gamma_i + \gamma_{year} + \epsilon_{i,t} \tag{4}$$

$R_{i,t}$ is daily changes in stock market return of the $i$th country at date $t$.[19] We pay our attention to the dummy variables - $D_0$, $D_1$, $D_2$, dating hacking attacks for the announcement date, the first, and the second trading day after the announcement date, respectively. $X_{i,t}$ is a set of control variables in country $i$ at date $t$; $\gamma_i$ and $\gamma_{year}$ are the country and year fixed effects, respectively; and $\epsilon_{i,t}$ is an error term.

Table 3 reports estimation results from our baseline model in Eq. (4). We account for heteroscedasticity robust standard errors in the panel. The coefficients on $D_0$ and $D_1$ are statistically significant with a positive sign as expected in all model specifications, while the coefficient on $D_2$ is insignificant. As shown in column (3), stock market returns increase by 15% on the announcement date, compared to those

[19] The results remain robust when using dividend-adjusted returns.

**Table 2**
BTC markets towards hack events.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Dependent variable: | $R^{BTC}_{j,t}$ | | | $Spread_{j,t}$ | | |
| $D_0$ | −0.427** | −0.429** | −0.428** | 29.12* | 29.63* | 30.08* |
| | (−2.02) | (−2.03) | (−2.02) | (1.89) | (1.92) | (1.95) |
| $D_1$ | | −0.14 | −0.139 | | 31.23** | 31.68** |
| | | (−0.50) | (−0.49) | | (1.96) | (1.99) |
| $D_2$ | | | 0.09 | | | 29.56* |
| | | | (0.40) | | | (1.76) |
| $\Delta BTC_{t-1}$ | 22.48*** | 22.47*** | 22.47*** | 53.94 | 55.64 | 56.66 |
| | (8.55) | (8.55) | (8.55) | (1.03) | (1.07) | (1.09) |
| Constant | 0.151* | 0.153** | 0.152* | 7.61*** | 7.08*** | 6.62*** |
| | (1.94) | (1.96) | (1.94) | (15.12) | (12.45) | (10.57) |
| Exchange FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 21,326 | 21,326 | 21,326 | 13,822 | 13,822 | 13,822 |
| R-squared | 0.048 | 0.048 | 0.048 | 0.354 | 0.354 | 0.355 |

This table reports regression results for the impact of hacking attack announcements on crypto markets in terms of Bitcoin return and Bitcoin liquidity over the period 2011–2019. All coefficients are presented in percent. We consider heteroscedasticity and robust standard errors. $R^{BTC}_{j,t}$ measures the daily Bitcoin return at the crypto exchange level, defined as $log(BTC\ price_{i,t}/BTC\ price_{i,t-1})$. $Spread_{j,t}$ denotes the daily bid–ask spread at the crypto exchange level. $D_0$, $D_1$, $D_2$ are indicator variables, taking a value of 1 for the attack announcement date, the first, and the second calendar day after the attack announcement date, respectively. $\Delta BTC_{t-1}$ is the lagged average daily change of Bitcoin price across cryptocurrency exchanges. Exchange FE denotes the exchange fixed effect. T-statistics are reported in parentheses and ***, **, * signify the 1%, 5%, and 10% significance level, respectively.

on the days without attack announcements. This effect continues with a further increase by 7% on the first trading day ($D_1$) after the attack announcement but vanishes on the second trading day ($D_2$).

We investigate stock returns across countries by incorporating key control variables reflecting financial and economic contexts (Baele et al., 2020; Levine, Loayza, & Beck, 2000). We include stock market development (*MKT*) and credit market development (*CREDIT*) to capture financial market sophistication (Levine et al., 2000). To account for risk and uncertainty (Lee & Rui, 2002), we control for stock market volatility (*Volatility*) and global equity market changes (*SP*). Macroeconomic factors like *GDP growth*, *GDP percap* (GDP per capita), *M3* (broad money growth rate), and *Inflation*, capture the broader economic environment, while *Saving* (savings) and *Popurban* (urban population ratio) are addressed to market sensitivity (Fresard, 2012) and wealth distribution (DellaVigna & Pollet, 2007). As shown, we control for global stock change in column (4), financial development in column (5), and macroeconomic factors in column (6). Hacking announcements consistently lead to an 11% increase in stock market returns, highlighting their significant impact.

Although we control for stock market characteristics and macroeconomic conditions, our model may still face potential omitted variable problems. To address this, we conduct additional tests. First, we include dummy variables for major religions (*Buddhism*, *Catholic*, *Muslim*, *Protestant*) to account for the influence of religious backgrounds on investment behaviour (Callen & Fang, 2015). Second, recognizing the role of cryptocurrencies in shadow economies, we control the size of the shadow economy. Third, we include cultural factors such as cultural tightness, individualism, and trust behaviour, which reflect social norms, self-perception, and trust in society (Eun, Wang, & Xiao, 2015; Gelf et al., 2011). Results and detailed variable definitions are reported in the Appendix — Table B.4. With the inclusion of these additional controls, our main results hold.

To address the potential issue of inflated statistical power in our pooled regression setting, we cluster the standard errors by continent, income group and developed or developing country group, respectively. Our results hold, with at least one of the coefficients on the post-event period ($D_0$, $D_1$, $D_2$) being positive and statistically significant. We also run regressions by income groups separately and our results hold for high and upper-middle income country groups but not for the lower-middle income country group. We further consider the geographical location and run regression by continents separately and our results hold except for Africa and South America.[20]

In short, we have found robust evidence for the FTS effect. Given the hacking attacks, we observe rising stock returns, along with declining Bitcoin returns and liquidity across cryptocurrency exchanges for at least 2 trading days. This effect turns out to be worldwide, supporting our hypothesis (H1) that *Cyber attacks on crypto markets undermine existing and prospective cryptocurrency investors' confidence, increase their risk awareness, and simultaneously heighten their caution, resulting in a FTS effect on stock markets*.

### 4.2. The impact of consecutive attacks

As shown in Fig. 1, attacks arrive consecutively, resulting in huge losses in terms of the dollar value of stolen coins. Concerning that consecutive attacks may weaken the confidence in crypto markets and increase investors' risk perception, we test whether recurring attacks in crypto markets amplify the FTS effect. In this respect, we define a period as under consecutive attacks if there is more than one attack in the same month. Furthermore, we introduce an additional dummy variable, $M$, and its interaction terms with $D_j, j \in (0,2)$ to our baseline model in Eq. (4). We examine whether and how stock markets react differently during high-frequency attack episodes relative to low-frequency periods. The empirical specification is delineated in Eq. (5):

$$R_{i,t} = \alpha + \beta_j D_j + \theta M_t + \lambda_j D_j * M_t + \delta_i X_{i,t} + \gamma_i + \gamma_{year} + \epsilon_{i,t} \quad (5)$$

Estimation results are reported in Table 4. The coefficients on the interaction terms $D_j \times M$ ($j$=0,1,2) are of our particular interest to assess the impact of consecutive attacks on stock markets. As shown in columns (1)-(6), the point estimates of the effect of multiple attacks at the attack announcement date ($D_0 \times M$) are positively and statistically significant at the 1% or 5% level. This effect is insignificant on the following first trading day ($D_1 \times M$) but significant on the second trading day ($D_2 \times M$). As shown in column (6), after controlling for a set of country-specific factors, stock market return on average is higher by 5.8% during a period of frequent attacks compared with that of those months with one or no cyber attacks on crypto markets,

[20] Results are not reported for the sake of brevity, but they are available from the authors on request.

**Table 3**
Flight to safety during hack attacks.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Dependent variable: | $R_{i,t}$ | | | | | |
| $D_0$ | 0.145*** | 0.147*** | 0.147*** | 0.113** | 0.147*** | 0.117** |
| | (3.94) | (3.98) | (3.99) | (2.37) | (3.99) | (2.43) |
| $D_1$ | | 0.064** | 0.065** | 0.116*** | 0.065** | 0.106*** |
| | | (2.11) | (2.11) | (2.97) | (2.11) | (2.69) |
| $D_2$ | | | 0.006 | 0.041 | 0.006 | 0.057 |
| | | | (0.18) | (1.06) | (0.18) | (1.44) |
| SP | | | | 0.003*** | | 0.003*** |
| | | | | (9.14) | | (8.67) |
| Volatility | | | | −0.0001 | | 0.0001 |
| | | | | (−0.05) | | (0.07) |
| MKT | | | | | 0.0004 | −0.0004 |
| | | | | | (1.26) | (−1.08) |
| CREDIT | | | | | −0.0002 | 0.0005 |
| | | | | | (−0.40) | (0.73) |
| GDP growth | | | | | | 0.005 |
| | | | | | | (1.24) |
| GDP percap | | | | | | −0.078 |
| | | | | | | (−0.56) |
| M3 | | | | | | −0.008** |
| | | | | | | (−2.12) |
| Inflation | | | | | | 0.001 |
| | | | | | | (0.61) |
| Saving | | | | | | 0.001 |
| | | | | | | (0.32) |
| Popurban | | | | | | 0.004 |
| | | | | | | (0.43) |
| Constant | −0.103*** | −0.104*** | −0.104*** | −0.030 | −0.101*** | 0.250 |
| | (−3.80) | (−3.82) | (−3.82) | (−0.43) | (−3.61) | (0.21) |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 84,708 | 84,708 | 84,708 | 71,136 | 84,708 | 67,990 |
| R-squared | 0.002 | 0.002 | 0.002 | 0.003 | 0.002 | 0.003 |

This table reports regression results for the FTS effect over the period 2011–2019. We consider heteroscedasticity and robust standard errors. The dependent variable $R_{i,t}$ measures daily changes in stock market index return at the country level, defined as $log(stock_{i,t}/stock_{i,t-1})$. $D_0$, $D_1$, $D_2$ are indicator variables, taking a value of 1 for the attack announcement date, the first, and the second trading day after the attack announcement date, respectively. *SP* denotes the annual changes in global stock index. *Volatility* denotes the annual standard deviation of stock market. *MKT* denotes the ratio of listed companies' market capitalization over GDP. *CREDIT* denotes the ratio of domestic credit to private sectors over GDP. *GDP growth* denotes quarterly GDP growth rate. *GDP percap* measured by the logarithmic GDP per capita (in USD). *M3* is the monthly broad money growth rate. *Inflation* denotes inflation measured by GDP deflator. *Saving* denotes as the ratio of saving over GDP. *Popurban* denotes the proportion of people living in urban areas. Country FE is the country fixed effect and Year FE is the year fixed effect. T-statistics of the test are reported in parentheses and ***, **, * signify the 1%, 5%, and 10% significance level, respectively.

indicated by the positive and significant coefficient on $M$. Under a sequence of attacks, on average, the stock markets experience a rise in returns by 27% on the date of announcement ($D_0 \times M$), no extra gain on the following first trading day ($D_1 \times M$),[21] and a surge by 43.5% on the second trading day ($D_2 \times M$). When introducing interaction terms, the meaning of the coefficients on $D_j$ ($j$=0,1,2) are not directly comparable to those in Table 3. We focus on the overall marginal effect of consecutive attacks and we find that stock market returns increase by 26% on $D_0$ and 33% on $D_2$ (insignificant on $D_1$). The overall impact of consecutive attacks on stock market return is stronger compared with those in Table 3.[22] Our results reveal investors' differential behaviour. With the initial attack, some risk-sensitive investors react acutely on the announcement day, whereas others hesitate and take a "wait-and-see" action until their confidence eventually collapses after further attacks. The overall evidence supports Hypothesis 2 that *Consecutive attacks strengthen the FTS effect.*

### 4.3. The flight-to-safety effect: The role of social media

Social media have become prevalent platforms for sharing information, which is particularly true for the cryptocurrency community. Early study has found that messages written by Bitcoin developers and investors are a rich source of information (Linton et al., 2017), and messages and discussions on social media affect the movement of Bitcoin prices. The information on crypto markets is neither as abundant nor as efficient as that on stock markets, hence investors or traders are inclined to gather and exchange information via social media.

In this section, we advance our analysis by exploring the underlying pressure of the FTS. We consider a sentiment measure developed by Chen et al. (2019) based on social media messages from StockTwits, where players share information, express opinions and moods instantly. The smaller the sentiment value, the more pessimistic investors become. Fig. 2 shows a boxplot of the changes in sentiment during a 3-day pre- and post-attack event window period (−3,+3). Prior to the event date, a number of pessimistic outliers emerge and the greatest dispersion is exhibited from $t-3$ to $t-2$, reflecting diverse opinions.

[21] The stock return increases 12.7% at ($D_1$) regardless of the consecutive attack period or not.

[22] As the FTS effect tends to be short-term while it does not happen frequently, we define the consecutive attack period in the same-month interval. Employing an alternative two-week rolling window to define the consecutive attack period, results are consistent (unreported results are available from the authors on request).

**Table 4**
Flight to safety during repeated attacks.

| Dependent variable: | (1) $R_{i,t}$ | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| $D_0$ | 0.071 | 0.073 | 0.071 | 0.003 | 0.071 | −0.003 |
| | (1.46) | (1.50) | (1.46) | (0.05) | (1.46) | (−0.06) |
| M | 0.008 | 0.010 | −0.011 | 0.062** | −0.011 | 0.058** |
| | (0.49) | (0.60) | (−0.59) | (2.46) | (−0.59) | (2.28) |
| $D_0 \times$ M | 0.171** | 0.169** | 0.189** | 0.240** | 0.189** | 0.27*** |
| | (2.26) | (2.23) | (2.49) | (2.38) | (2.49) | (2.65) |
| $D_1$ | | 0.097** | 0.094** | 0.143*** | 0.094** | 0.127*** |
| | | (2.56) | (2.51) | (2.99) | (2.51) | (2.64) |
| $D_1 \times$ M | | −0.100 | −0.079 | −0.133 | −0.079 | −0.112 |
| | | (−1.51) | (−1.19) | (−1.55) | (−1.19) | (−1.29) |
| $D_2$ | | | −0.093** | −0.126*** | −0.093** | −0.106** |
| | | | (−2.48) | (−2.65) | (−2.48) | (−2.19) |
| $D_2 \times$ M | | | 0.297*** | 0.450*** | 0.297*** | 0.435*** |
| | | | (4.50) | (5.26) | (4.50) | (5.03) |
| SP | | | | 0.003*** | | 0.003*** |
| | | | | (9.14) | | (8.67) |
| Volatility | | | | −0.0001 | | 0.0001 |
| | | | | (−0.05) | | (0.07) |
| MKT | | | | | 0.0004 | −0.0004 |
| | | | | | (1.26) | (−1.08) |
| CREDIT | | | | | −0.0002 | 0.0005 |
| | | | | | (−0.40) | (0.72) |
| GDP growth | | | | | | 0.005 |
| | | | | | | (1.14) |
| GDP percap | | | | | | −0.077 |
| | | | | | | (−0.55) |
| M3 | | | | | | −0.008** |
| | | | | | | (−2.11) |
| Inflation | | | | | | 0.001 |
| | | | | | | (0.61) |
| Saving | | | | | | 0.001 |
| | | | | | | (0.32) |
| Popurban | | | | | | 0.004 |
| | | | | | | (0.43) |
| Constant | −0.103*** | −0.104*** | −0.103*** | −0.029 | −0.100*** | 0.245 |
| | (−3.79) | (−3.82) | (−3.79) | (−0.41) | (−3.58) | (0.21) |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 84,708 | 84,708 | 84,708 | 71,136 | 84,708 | 67,990 |
| R-squared | 0.002 | 0.002 | 0.002 | 0.003 | 0.002 | 0.003 |

This table reports regression results for the FTS effect under consecutive hacking attacks in crypto markets over the period 2011–2019. All coefficients are presented in terms of percent. We consider heteroscedasticity and robust standard errors. $R_{i,t}$ measures daily changes in stock market index return at the country level, defined as $log(stock_{i,t}/stock_{i,t-1})$. $D_0$, $D_1$, $D_2$ are indicator variables, taking a value of 1 for the attack announcement date, the first, and the second trading day after the attack announcement date, respectively. *M* is a binary variable and takes a value of 1 if there is more than one hacking events announced within the same month and 0 otherwise. *SP* denotes the annual changes in global stock index. *Volatility* denotes the annual standard deviation of stock market. *MKT* denotes the ratio of listed companies' market capitalization over GDP. *CREDIT* denotes the ratio of domestic credit to private sectors over GDP. *GDP growth* denotes quarterly GDP growth rate. *GDP percap* measured by the logarithmic GDP per capita (in USD). *M3* is the monthly broad money growth rate. *Inflation* denotes inflation measured by GDP deflator. *Saving* denotes as the ratio of saving over GDP. *Popurban* denotes the proportion of people living in urban areas. Country FE is the country fixed effect and Year FE is the year fixed effect. T-statistics are reported in parentheses and ***, **, * signify the 1%, 5%, and 10% significance level, respectively.

The blue dots in the first two days are the maximum negative sentiment exceeding the estimation for a 95% confidence level. The observed outliers are the extremely bearish sentiment expressed by the social media users who suffer from huge losses. The boxplots at $t-1$ and $t$ display a left-skewed distribution, implying the predominance of bearish mood. Although the median changes slightly, the mean is implied to be much lower than the median given the asymmetric skewness. We may conclude that social media sentiment conveys attack information prior to the official announcements.

To empirically test whether hacking events announcements can be predicted by the changes in investor sentiment, we construct panel data for each event and adopt a logistic model shown in Eq. (6), where $p_t = P(D_{0,t} = 1)$ indicates the probability of the occurrence of attacks. The sentiment indicator is the explanatory variable for such prediction in probability.

$$\log \frac{p_t}{1-p_t} = \alpha + \beta Sentiment_{t-j} + \epsilon_t, \qquad j \in (1,3), \quad Sentiment_t \in \{Stwits_t, \Delta \ln(Stwits_t), \Delta \ln(Reddit_t)\} \tag{6}$$

We employ a variety of sentiment measures from different social media channels, either at the level or in the log changes to ensure the robustness of our results. $Stwits_t$ is a sentiment measure from StockTwits, ranging from −1 to +1. $\Delta \ln(Stwits_t)$ is the daily log changes of $Stwits_t$ from *t-1* to *t*, and $\Delta \ln(Reddit_t)$ is applied to Reddit data. These two social media platforms potentially attract users with different interests (Chen et al., 2019). The discussions on StockTwits focus more on cryptocurrency speculation and investment, while the messages on Reddit are more about crypto technology and other general topics.

Columns (1) and (2) of Table 5 show the results from the full sample with the year and event fixed effect controlled. The estimate

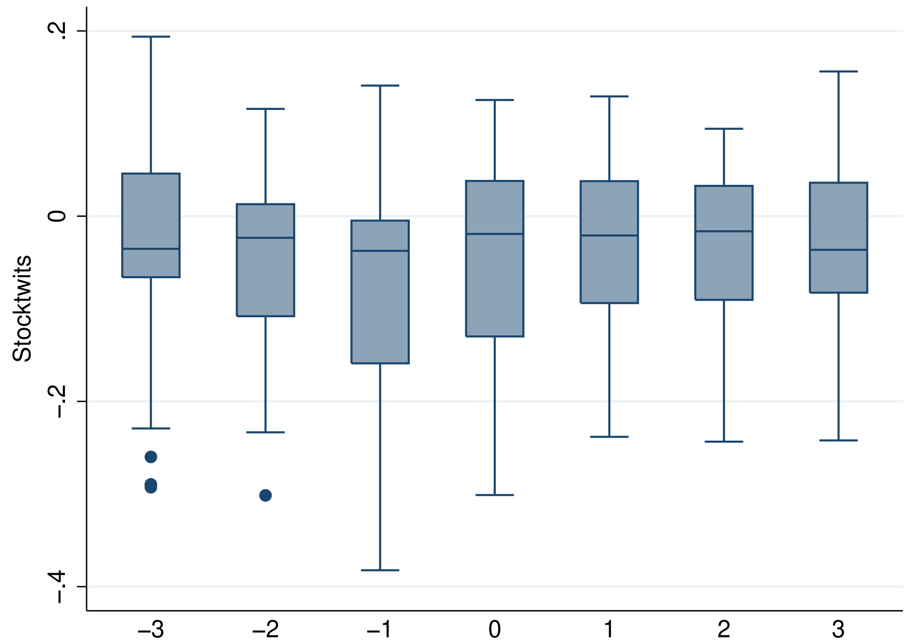


**Fig. 2.** Sentiment variation around hacking event announcement.
This figure presents boxplot of the changes in sentiment during the hacking period with pre- and post-event 3-day window. The horizontal line in the boxes represents the median, while blue dots are the outliers. The sentiment is extracted from Stocktwits from 2014 to 2018.

on $Stwits_{t-1}$ is statistically significant at the 1% level in most specifications, confirming our conjecture that social media sentiment is able to predict the probability of hacking news. As the number of cybercrimes rocketed during the crypto bubble period in 2018, we limit our attention to the year 2018 to further examine the predictive power of investor sentiment. The analysis focuses on changes in sentiment and results from $\Delta \ln(Stwits_{t-j})$ and $\Delta \ln(Reddit_{t-j})$ , $j \in (1,3)$, are reported in columns (3)-(4) and columns (5)-(6), respectively. Those results consistently show a strong predictive power of sentiment in forecasting subsequent cybercrime announcements. We, therefore, confirm that discussions about hacking activities among social media users, have the predictive power for upcoming official cyber-attack announcements by cryptocurrency exchanges.[23]

To address the economic importance, we use the estimates in column (2) and document that a decrease by one standard deviation in sentiment at $t-1$, irrespective of the level of other regressors, increases the probability of observing attacks by $\frac{1}{1+\exp^{8\times0.17}} = 20\%$. A fall in investor sentiment assigns a higher probability of the occurrence of attacks, which supports the literature in the context of the information content and predictability of social media messages (Chen et al., 2019).

Given the discovered insights into investor sentiment during the hacking period (Fig. 2), we pay particular attention to a sub-sample of the event period with a pre- and post-event two-day window (−2,+2) to mitigate the potential impact of noisy sentiment during the non-event period. We replace the hacking attack announcement indicators $(D_j)$ $j \in (0,2)$ in Eq. (4) with the changes in sentiment ($\Delta \ln(Stwits_t)$ or $\Delta \ln(Reddit_t)$), as shown in Eq. (7). This allows us to directly examine how changes in sentiment-related hacking events in crypto markets, as a measure of FTS pressure, affect stock market returns. Unlike the lagged value of sentiment (sentiment prior to the event date) in Eq. (6), which reflects the sentiment from the informed investors, a contemporaneous change in sentiment at the event date captures a sentimental variation among uninformed investors. This group, comprising a large number of people, has been unaware of fragmentary attacks and far behind in accessing information.

$$R_{i,t} = \alpha + \beta_1 Sentiment_t + \delta_i X_{i,t} + \gamma_i + \gamma_{year} + \epsilon_{i,t},$$
$$Sentiment_t \in \{\Delta \ln(Stwits_t), \Delta \ln(Reddit_t)\} \tag{7}$$

Estimation results from Eq. (7) are reported in Table 6. In columns (1) and (2), we observe a reverse movement between sentiment and stock returns, inferred by the negative sign of the coefficient on $\Delta \ln(Stwits_t)$ with the statistical significance at the 1% level. In the full specification after accounting for stock market characteristics, macroeconomic factors, and country and year fixed effect, a 1% decrease in $\Delta \ln(Stwits)$ is associated with an increase in stock market return by 0.19% during the attacking period. The results from $\Delta \ln(Reddit)$ in the last three columns, in general, show a consistent picture.[24] All in all, we find that before the event is formally announced, social media sentiment serves as a warning indicator for hacking events. At the event episode, the sentiment is capable of capturing FTS pressure among groups of investors.

To inspect whether the FTS is concentrated on the bubble period, we undertake additional exploration by introducing *Bubble*, a time dummy for the Bitcoin bubble in 2018. Investors who crowded into crypto markets during the bubble period with speculative intentions are susceptible to unexpected shocks. A certain proportion of investors lack financial and technological literacy and they are unlikely to make a wise financial decision. For instance, they may hold poorly diversified portfolios. Using microdata from 15 countries, Panos and Karkkainen (2019) find that financial literacy has a negative impact on the probability of owning cryptocurrency; in other words, those who are more financially literate are less likely to engage in highly volatile assets. They conclude that crypto markets are largely comprised of unsophisticated investors. During the bubble period, a skyrocketed cryptocurrency price attracts more unsophisticated investors than the

[23] The date of the cyber-attack precedes the official announcement date. It normally takes some time for cryptocurrency exchanges to discover the breach, conduct a security review, and fix the problems. A hacking announcement is submitted only when losses are beyond the exchange's capacity to cover it up. In Table 5, we provide evidence that social media users' negative sentiment may exert pressure on cryptocurrency exchanges to release the hacking news and can predict the official announcement of hacking events.

[24] In this small sample regression, we employ a range-based daily volatility $Var_{RS}$.

**Table 5**
The likelihood of posting attacked news with sentiment change.

| | Full sample | | Sub-period:year 2018 | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Dependent variable: | $P(D_{0,t}=1)$ | | $P(D_{0,t}=1)$ | | | |
| $Stwits_{t-1}$ | −6.489*** | −8.025*** | | | | |
| | (−3.59) | (−4.00) | | | | |
| $Stwits_{t-2}$ | | 2.166 | | | | |
| | | (1.19) | | | | |
| $Stwits_{t-3}$ | | 3.515* | | | | |
| | | (1.95) | | | | |
| $\Delta\ln(Stwits_{t-1})$ | | | −1.289*** | −1.928*** | | |
| | | | (−3.19) | (−2.98) | | |
| $\Delta\ln(Stwits_{t-2})$ | | | | −1.399* | | |
| | | | | (−1.68) | | |
| $\Delta\ln(Stwits_{t-3})$ | | | | −0.818 | | |
| | | | | (−1.41) | | |
| $\Delta\ln(Reddit_{t-1})$ | | | | | −1.789*** | −2.089*** |
| | | | | | (−3.30) | (−2.98) |
| $\Delta\ln(Reddit_{t-2})$ | | | | | | −0.046 |
| | | | | | | (−0.05) |
| $\Delta\ln(Reddit_{t-3})$ | | | | | | −0.802 |
| | | | | | | (−1.05) |
| Year FE | Yes | Yes | No | No | No | No |
| Event FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Constant | −28.67 | −32.695 | −3.072*** | −3.293*** | −3.187*** | −3.28*** |
| | (−0.01) | (−0.00) | (−4.25) | (−3.98) | (−4.23) | (−4.05) |
| Pseudo R-square | 0.085 | 0.112 | 0.053 | 0.062 | 0.063 | 0.068 |
| Observations | 985 | 918 | 440 | 418 | 440 | 418 |

This table reports regression results for the informativeness of investor sentiment in forecasting hacking event announcements, over the period of 2014–2018. We consider heteroscedasticity and robust standard errors. The dependent variable $P_t = P(D_{0,t}=1)$ indicates attack events announced at date $t$, and $D_{0,t}=0$ otherwise. We employ three measures of sentiment: (1) $Stwits_t$, distilled from StockTwits and in the range of −1 to +1; (2) $\Delta\ln(Swits_t)$, denotes the daily changes in *Stwits*; (3) $\Delta\ln(Reddit_t)$ , denotes the daily changes in a sentiment measure from the Reddit website. Exchange FE is the exchange fixed effect. Year FE is the year fixed effect. T-statistics are reported in parentheses and ***, **, * signify the 1%, 5%, and 10% significance level, respectively.

usual time. When the bubble bursts following attacks by malicious hackers, we expect an unprecedented FTS pressure, which is examined in Eq. (8).

$$R_{i,t} = \alpha + \sum_{j=0}^{2}\theta_j D_j \times Sentiment_t \times Bubble + \sum_{j=0}^{2}\zeta_{jt} D_j \times Sentiment_t + \sum_{j=0}^{2}\eta_j D_j \times Bubble + \sum_{j=0}^{2}\beta_j D_j + \rho Sentiment_t + \lambda Sentiment_t \times Bubble + \nu Bubble + \delta_i X_{i,t} + \gamma_i + \gamma_{year} + \epsilon_{i,t} \tag{8}$$

where $j \in (0,2)$, $Sentiment_t \in \{\Delta\ln(Stwits_t), \Delta\ln(Reddit_t)\}$.

Our main interest is on the triple interaction terms presented in Table 7, $D_j \times Bubble \times \Delta\ln(Stwits_t)$. In Panel A, the coefficient on the tripe interaction term is negative, statistically and economically significant, implying that the FTS pressure during the bubble period is more prominent than that of the non-bubble period. In column (3), given a decline in sentiment by 1%, the difference in stock market reaction between the bubble period and the non-bubble period is 0.35% on the date of the attacking announcement. This effect peaks at 1.08% on the first trading day after the announcement and slows down to a further 0.51% increase on the second trading day, showing a discernible economic significance in the bubble period. In Panel B, we employ an alternative sentiment measure of $\Delta\ln(Reddit_t)$ and we also find evidence for the FTS effect with a slightly different pattern - a much stronger effect on the event date and the second trading day after the hacking announcement. For 1% decline in sentiment, the stock market return is higher by 0.85% on the event date and 5.49% on the second trading day after the event announcement during the bubble period compared to those in the non-bubble period. We attribute the different results to the diverse soft information on the two social media platforms that the discussions on StockTwits are more about speculative opportunities while the messages on Reddit are more about crypto-related technology. To better gauge the timing of the FTS effect and constantly monitor the FTS pressure revealed in social media, we suggest future research to explore sentiment on StockTwits.[25]

In sum, the presence of a bubble attracts unsophisticated investors as well as greedy hackers. With intensive attacks by hackers, investors rectify their over-excitement and risk attitudes towards digital assets. The collapse of confidence among clusters of existing and prospective investors, whilst a bubble bursts, is the major cause of this phenomenon. Our argument coincides with the FTS episodes interacting with VIX, a measure of market sentiment (Baele et al., 2020).

In our supplementary analysis, we examine the strength of stock market responses across different countries. Our findings reveal a pronounced FTS reversal in stock markets that exhibited poor performance prior to the hacking events, with variations strongly influenced by national economic indicators such as economic freedom and financial literacy. These insights contribute to understanding the interplay between investor behaviour and economic conditions during periods of financial uncertainty. The Online Appendix Part A further details the discussion.

## 5. Evidence from stock mutual fund and robustness test

### 5.1. Flight-to-safety effect: Evidence from mutual fund

The previous section provides the global stock market depiction of cyber attacks, providing evidence that global stock markets have a simultaneous reaction towards this type of shocking news. While

[25] To address the potential multicollinearity issue when the *Bubble* is a year dummy for 2018 along with year fixed effect, following Petersen (2009), we exclude the year fixed effect in the model with standard errors clustered by year, results are consistent.

**Table 6**
Flight to safety under investor sentiment channel.

| Dependent variable: | (1) $R_{i,t}$ | (2) | (3) | (4) $R_{i,t}$ | (5) | (6) |
|---|---|---|---|---|---|---|
| | Panel A: $\Delta\ln(Stwits_t)$ | | | Panel B: $\Delta\ln(Reddit_t)$ | | |
| Sentiment | −0.121*** | −0.185*** | −0.186*** | −0.383*** | −0.507*** | −0.498*** |
| | (−3.06) | (−3.46) | (−3.48) | (−7.03) | (−8.57) | (−8.43) |
| $Var_{RS}$ | | −10.377*** | −10.304*** | | −10.685*** | −10.615*** |
| | | (−10.29) | (−10.22) | | (−10.37) | (−10.36) |
| SP | | 0.005* | 0.005 | | 0.004 | 0.005 |
| | | (1.69) | (1.61) | | (1.60) | (1.56) |
| MKT | | | 0.001 | | | 0.000 |
| | | | (0.27) | | | (0.14) |
| CREDIT | | | 0.001 | | | 0.001 |
| | | | (0.29) | | | (0.25) |
| GDP growth | | | −0.056 | | | −0.050 |
| | | | (−0.99) | | | (−0.92) |
| GDP percap | | | 2.271 | | | 1.439 |
| | | | (1.14) | | | (0.78) |
| M3 | | | 0.046* | | | 0.052** |
| | | | (1.88) | | | (2.15) |
| Inflation | | | 0.022 | | | 0.024 |
| | | | (0.64) | | | (0.72) |
| Saving | | | −0.021 | | | −0.011 |
| | | | (−0.74) | | | (−0.42) |
| Popurban | | | −0.119 | | | −0.096 |
| | | | (−1.34) | | | (−1.16) |
| Constant | 0.302 | 0.231** | −14.082 | 0.258 | 0.194** | −7.204 |
| | (1.40) | (2.47) | (−0.79) | (1.21) | (2.13) | (−0.44) |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 4,056 | 2,125 | 2,078 | 4,212 | 2,204 | 2,157 |
| R-squared | 0.013 | 0.071 | 0.075 | 0.021 | 0.087 | 0.090 |

This table reports regression results explaining the FTS effect in terms of investor sentiment. All coefficients are presented in terms of percent. We consider heteroscedasticity and robust standard errors. The sample is restricted to a sub-sample of a two-day pre- and post-event window (−2,+2) over the period 2014–2018. The dependent variable $R_{i,t}$ measures daily changes in stock market index return at the country level, defined as $log(stock_{i,t}/stock_{i,t-1})$. We use two measures of sentiment: $\Delta\ln(Swits_t)$, denotes the daily changes in *Stwits* and $\Delta\ln(Reddit_t)$ denotes the daily changes in a sentiment measure from the Reddit website. *SP* denotes the annual changes in global stock index. $Var_{RS}$ denotes the daily ranged-based volatility of stock market across different countries (Rogers & Satchell, 1991). *MKT* denotes the ratio of listed companies' market capitalization over GDP. *CREDIT* denotes the ratio of domestic credit to private sectors over GDP. *GDP growth* denotes quarterly GDP growth rate. *GDP percap* measured by the logarithmic GDP per capita (in USD). *M3* is the monthly broad money growth rate. *Inflation* denotes inflation measured by GDP deflator. *Saving* denotes as the ratio of saving over GDP. *Popurban* denotes the proportion of people living in urban areas. Country FE is the country fixed effect and Year FE is the year fixed effect. T-statistics are reported in parentheses and ***, **, * signify the 1%, 5%, and 10% significance level, respectively.

we are unable to provide specific information on the inflows and outflows for stock markets, we assess the FTS effect in relation to capital flows in the U.S. mutual fund market. Previous research indicates a significant proportion of cryptocurrency retail holders are based in the U.S., and more than half of U.S. households hold mutual funds, which allow us to observe retail investors' reactions to cryptocurrency-related cybercrimes.

### 5.1.1. Sample construction and measurements

Daily data on mutual funds from January 2013 through January 2019 are sourced from Bloomberg. Following the research by Ben-David, Franzoni, and Moussawi (2018), we choose to limit our sample to sector and broad-based US Equity. U.S. investors are more likely to seek familiar domestic markets during international market shocks. US-focused funds provide a clearer picture of FTS behaviour by reducing exposure to foreign policies, exchange rates, and macroeconomic uncertainties. This approach allows us to better trace the FTS effect among U.S. investors. The supplementary fund characteristics and index returns are also gathered from Bloomberg. We remove funds with more than one share class and those with fewer than 6 months of observations. The net sample consists of 436 funds.

In accordance with Del Guercio and Tkac (2008), we intend to employ an event-study approach to differentiate the increased flow generated by the exogenous hacking events towards the mutual fund. To calculate the expected flow, we regress the following benchmark model for each fund under cyber-attacks:

$$F_{i,t} = \alpha + \beta_1 SF_{i,t} + \beta_2 RET_{i,t-1} + \beta_3 F_{i,t-1} + \epsilon_{i,t} \tag{9}$$

where

$$F_{i,t} = \frac{TNA_{i,t}}{TNA_{i,t-1}} - (1 + RET_{i,t}),$$

In line with Barber, Huang, and Odean (2016) method to calculate flow $F_{i,t}$, where $TNA_{i,t}$ is the total net assets under fund i at day t, and $RET_{i,t}$ is the return of closing price for fund i in day t. $SF_i$ reflects the aggregated net flow to all funds in the same style category at week t[26]; $RET_{i,t-1}$ is the return of fund i at day t-1 while $F_{i,t-1}$ is the lagged flow to fund i at day t-1. The style categories are used to classify family funds with the same features and we apply three style categories: capitalization, issue and index. Detailed procedures for producing these style flow benchmarks are provided in the appendix. The initial day on which an investor would have access to the official announcements is designated as t=0. We use a total of 12 months of data ending with 3 months prior to time 0 (event date −14 months to −3 months) as our estimation period to regress the coefficients for the benchmark flow regression.

[26] The detailed information on fund categories under different groups is listed in the appendix Table B.5.

**Table 7**
Flight to safety during bubble period.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Dependent variable: | $R_{i,t}$ | | | $R_{i,t}$ | | |
| *Sentiment* | Panel A: $\Delta\ln(Stwits_t)$ | | | Panel B: $\Delta\ln(Reddit_t)$ | | |
| $D_0$ × Bubble × Sentiment$_t$ | −0.308 | −0.343* | −0.351* | −0.327 | −0.835* | −0.853* |
| | (−1.57) | (−1.66) | (−1.69) | (−0.73) | (−1.65) | (−1.71) |
| $D_1$ × Bubble × Sentiment$_t$ | −1.213*** | −1.036*** | −1.078*** | 0.447* | 0.222 | 0.224 |
| | (−5.00) | (−3.26) | (−3.34) | (1.76) | (0.69) | (0.69) |
| $D_2$ × Bubble × Sentiment$_t$ | −0.251* | −0.511*** | −0.508*** | −5.131*** | −5.676*** | −5.490*** |
| | (−1.84) | (−3.14) | (−3.17) | (−8.93) | (−8.43) | (−7.86) |
| $D_0$ | −0.277*** | −0.324*** | −0.299*** | −0.261*** | −0.360*** | −0.337*** |
| | (−5.07) | (−5.08) | (−4.69) | (−3.32) | (−4.09) | (−3.82) |
| Sentiment$_t$ | 0.015 | 0.014 | 0.019 | −0.005 | −0.005 | −0.006 |
| | (1.42) | (1.05) | (1.37) | (−0.16) | (−0.10) | (−0.13) |
| $D_0$ × Sentiment$_t$ | −0.056 | −0.061 | −0.060 | −0.013 | 0.395 | 0.411 |
| | (−0.48) | (−0.49) | (−0.47) | (−0.03) | (0.83) | (0.87) |
| $D_0$ × Bubble | 0.473*** | 0.584*** | 0.560*** | 0.440*** | 0.603*** | 0.582*** |
| | (5.91) | (6.51) | (6.24) | (4.45) | (5.57) | (5.36) |
| $D_1$ | 0.137*** | 0.164** | 0.139** | 0.174*** | 0.197*** | 0.175*** |
| | (2.70) | (2.37) | (1.98) | (3.56) | (2.95) | (2.59) |
| $D_1$ × Sentiment$_t$ | 0.709*** | 0.459* | 0.492* | −1.012*** | −1.002*** | −1.012*** |
| | (3.81) | (1.83) | (1.92) | (−5.69) | (−4.26) | (−4.28) |
| $D_1$ × Bubble | −0.134* | −0.100 | −0.071 | −0.160** | −0.116 | −0.090 |
| | (−1.75) | (−1.03) | (−0.72) | (−2.12) | (−1.23) | (−0.94) |
| $D_2$ | −0.092 | −0.117 | −0.103 | −0.247*** | −0.285*** | −0.279*** |
| | (−1.34) | (−1.25) | (−1.12) | (−4.00) | (−3.65) | (−3.51) |
| $D_2$ × Sentiment$_t$ | 0.106 | 0.167 | 0.166 | 5.060*** | 5.377*** | 5.195*** |
| | (0.99) | (1.23) | (1.25) | (8.91) | (8.07) | (7.51) |
| $D_2$ × Bubble | 0.021 | 0.093 | 0.089 | 0.161* | 0.241** | 0.244** |
| | (0.24) | (0.82) | (0.79) | (1.90) | (2.39) | (2.39) |
| Bubble | −0.177*** | −0.191*** | −0.243*** | −0.083*** | −0.081*** | −0.095* |
| | (−7.70) | (−6.22) | (−4.53) | (−3.88) | (−2.79) | (−1.86) |
| Bubble × Sentiment$_t$ | 0.015 | 0.065 | 0.064 | −0.076 | 0.000 | 0.002 |
| | (0.40) | (1.39) | (1.37) | (−1.41) | (0.00) | (0.03) |
| Constant | 0.111* | 0.225*** | −9.786 | 0.019 | 0.109*** | −4.169 |
| | (1.69) | (6.28) | (−1.59) | (0.31) | (3.19) | (−0.71) |
| Stock market controls | No | Yes | Yes | No | Yes | Yes |
| Country economics controls | No | No | Yes | No | No | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 41,964 | 21,770 | 21,075 | 44,499 | 23,071 | 22,340 |
| R-squared | 0.004 | 0.033 | 0.032 | 0.007 | 0.034 | 0.032 |

This table reports regression results for a stronger FTS effect driven by sentiment during the Bitcoin bubble period. All coefficients are presented in terms of percent. The sample period is restricted to 2014 to 2018 due to sentiment data availability and we consider heteroscedasticity and robust standard errors. The dependent variable $R_{i,t}$ measures daily changes in stock market index return at the country level, defined as $log(stock_{i,t}/stock_{i,t-1})$. $D_0$, $D_1$, $D_2$ are indicator variables, taking a value of 1 for the attack announcement date, the first, and the second trading day after the attack announcement date, respectively. We use two measures of sentiment. $\Delta\ln(Stwits_t)$ denotes the daily changes in sentiment measure of StockTwits. $\Delta\ln(Reddit_t)$ denotes the daily changes in a sentiment measure from the Reddit website. *Bubble* is a dummy variable, taking a value of 1 for the year 2018, and 0 otherwise. Control variables in column (2) and (5) include *SP* - the annual changes in global stock return and $Var_{RS}$ - a ranged-based daily volatility measure of stock market. Macro economic controls in column(3) and (6) include *MKT* denotes the ratio of listed companies' market capitalization over GDP; *CREDIT* denotes the ratio of domestic credit to private sectors over GDP; *GDP growth* denotes quarterly GDP growth rate; *GDP percap* measured by the logarithmic GDP per capita (in USD); *M3* is the monthly broad money growth rate; *Inflation* denotes inflation measured by GDP deflator; *Saving* denotes as the ratio of saving over GDP; *Popurban* denotes the proportion of people living in urban areas. Country FE is the country fixed effect and Year FE is the year fixed effect. T-statistics are reported in parentheses and ***, **, * signify the 1%, 5%, and 10% significance level, respectively.

The selective benchmark model's regressors are the ones expected to influence mutual funds and change over time, similar to a market model for estimating stock returns. Specifically, the net flow aggregation within a particular style category ($SF_t$) is a uniform measure among all funds in that category, and flows related to different styles show dramatic time variation.[27] We measure how sensitive each fund responds to the popularity of each style ($\beta_i$) to consider this effect on the fund flow during the cyber-attack activities.

Furthermore, we incorporate fund-specific indicators of lagged return and flow, since these variables have been intensively identified as an influence on flow in the empirical analysis (Del Guercio & Tkac, 2008; Wagner, Lee, & Margaritis, 2022).

Consequently, our indicator of anomalous flow in response to the cryptocurrency hacking shocks is as follows:

$$AF_{i,t} = F_{i,t} - \hat{\alpha} - \hat{\beta}_1 SF_{i,t} - \hat{\beta}_2 RET_{i,t} - \hat{\beta}_3 F_{i,t-1} \tag{10}$$

Under the setting, the abnormal flow to fund i at day t is the difference between the actual flow at time t and the expected flow, determined by the aggregate style flow, lagged flow, and lagged return, adjusted by the average abnormal flow for fund i. This average abnormal flow $SF_{i,t}$ represents fund-specific flow determinants that remain constant over time. It is important to be aware that the sign of abnormal flow should not be interpreted in the same meaning as net flow. The expected abnormal flow can be either positive or negative. For instance, a negative abnormal flow does not indicate the outflow of the mutual fund. Instead, it suggests that the fund is receiving a lower

[27] To ensure a more consistent and robust estimation of mutual fund flows $F_{i,t}$, we use three categories to quantify the aggregated net flow: capitalization (Cap), parent issuers (Issue), and index weighting (Index).

**Table 8**
Summary statistics for mutual fund.

| Variable | N | Mean | S.D. | p10 | p50 | p90 |
|---|---|---|---|---|---|---|
| Cap | 1,410,798 | 0.0003 | 0.323 | −0.209 | 0.00004 | 0.214 |
| Issue | 1,410,798 | 0.0005 | 0.322 | −0.207 | 0.00023 | 0.210 |
| Index | 1,410,798 | 0.0004 | 0.321 | −0.208 | 0.00007 | 0.208 |
| Flow | 1,337,522 | 1.351 | 139.000 | 0.000 | 0.000 | 5.273 |
| D_week | 1,419,912 | 0.059 | 0.236 | . | . | . |
| M | 1,404,662 | 0.226 | 0.418 | . | . | . |
| D0 | 1,419,912 | 0.008 | 0.092 | . | . | . |
| D1 | 1,419,912 | 0.008 | 0.092 | . | . | . |
| D2 | 1,419,912 | 0.008 | 0.092 | . | . | . |
| D3 | 1,419,912 | 0.008 | 0.092 | . | . | . |
| D4 | 1,419,912 | 0.008 | 0.092 | . | . | . |
| D5 | 1,419,912 | 0.008 | 0.092 | . | . | . |
| D6 | 1,419,912 | 0.008 | 0.092 | . | . | . |
| D7 | 1,419,912 | 0.008 | 0.092 | . | . | . |
| L.Alpha | 1,345,570 | 0.017 | 0.268 | −0.276 | 0.009 | 0.311 |
| log(TNA) | 1,417,403 | 3.821 | 0.591 | 3.179 | 3.717 | 4.687 |
| Expense | 1,419,912 | 0.344 | 0.646 | 0.050 | 0.270 | 0.620 |
| log(age) | 1,337,459 | 1.699 | 0.900 | 0.000 | 1.946 | 2.708 |
| log(N) | 1,419,912 | 4.144 | 0.770 | 3.296 | 4.060 | 5.069 |
| VIX | 1,364,651 | −0.00006 | 0.083 | −0.086 | −0.006 | 0.092 |
| indpro | 1,364,651 | 0.002 | 0.005 | −0.005 | 0.002 | 0.008 |
| PDI | 1,364,651 | 0.021 | 0.020 | −0.015 | 0.020 | 0.043 |
| CND | 1,364,651 | 0.012 | 0.037 | −0.028 | 0.014 | 0.038 |
| var_GK | 1,364,651 | 0.0001 | 0.0001 | 0.000005 | 0.00002 | 0.00012 |

This table presents summary statistics for the mutual funds sample from 2013 to December 2019.

volume of inflows than anticipated, a fund may exhibit a high positive abnormal flow due to its style's popularity this month or its market sensitivity towards exogenous events (rate upgrade, M&A, event with other financial markets such as hacking crypto-exchange market).

Table 8 presents descriptive statistics for the abnormal flows and main control variables of the mutual fund. The statistics include mean, standard deviation, and several quantiles in our whole sample. The abnormal flow in the Cap (capitalization), Issue (main issuers), and Index (index weighting) categories highlights the divergence between actual and expected daily flows. It is evident that the average values for each category are centred around small numbers, but the standard deviations are relatively large. This suggests that each mutual fund, grouped by a different style, experiences varying abnormal flows, indicating a wide dispersion in our sample.

Flow refers to the net movement of inflow and outflow under the US dollars which is regarded as the robustness measurement for the abnormal flow. The overall statistics of flow measurements are consistent with the frequency of daily data and a relatively low turnover rate (Khorana, 1996). The D0–D7 represent dummy variables that capture the timing of the hack and the subsequent days following the event.

### 5.1.2. Fund flow-performance relation towards hacking events

In this section, we provide an analysis to explore whether the mutual fund flow is responsive to hacking events. The abnormal flow is built up to trace the daily variation of fund flow. In line with the original setting for cross-country regressions, we include dummy time variables to account for the day effect during and after the event.

$$AF_{i,t} = \alpha + \sum_{i=0}^{7} \beta_j D_j + \theta_1 Fund\ controls_{i,t} + \theta_2 market\ controls_{i,t} + \gamma_{event} + \gamma_{year} + \epsilon_{i,t} \tag{11}$$

where $j \in (0, 7)$

Where AF is the abnormal flow of mutual funds in day t. $D_0$, $D_1$, $D_2$, $D_3$, $D_4$, $D_5$, $D_6$, and $D_7$ are indicator variables that take the value of 1 for the attack announcement date, the first trading day after the attack, and subsequent trading days up to the seventh day, respectively. We add a series of variables to control the characteristics of mutual fund. $L.Alpha$ (Jensen's alpha) represents the week-lagged abnormal return of each fund, calculated using the CAPM model over a rolling window of six months.[28] $log$(TNA) refers to the natural logarithm of the fund's total net assets (TNA). $Expense$ is the fund's expense ratio, reflecting its commission fees. $log(age)$ is the natural logarithm of the fund's age in years. $log(N)$ represents the natural logarithm of the total number of funds managed by the same parent company. Besides that, a list of market control variables is under consideration. $\Delta VIX_t$ denotes the daily change in the VIX (Volatility Index). $\Delta INDPRO_t$ refers to the monthly changes in the U.S. Industrial Production Index. $\Delta PDI_t$ represents the quarterly changes in Personal Dividend Income. $\Delta CND_t$ denotes the quarterly change in the corporate net dividends paid. $Var_{GK}$ is a range-based daily volatility measure of the U.S. stock market.

In the regression of Table 9, abnormal flow, as the dependent variable, is measured through three groups: Cap, Issue, and Index. These categories represent distinct features such as capitalization, family issuers, and index weighting. The independent variables are time dummies (D0–D7).

In our empirical setting, one research question is targeted to address whether the variation of abnormal flow is caused by external hacking incidents or not. After controlling fund-related variables and market-related variables, the positive and statistically significant D0 indicates that the mutual fund market experiences an unexpectedly increasing abnormal flow on the date of hack accountment. This could suggest that the initial response of the FTS effect is addressed on the day of the announcement itself (D0). D1–D5 correspond to the consecutive days after the first hacking notification. The "temporary price pressure hypothesis" appears interpretable due to the lack of significance for these time dummies (Ben-Rephael, Kandel, & Wohl, 2011). It suggests that the sudden change of risk aversion by retail investors generates

[28] To evaluate the performance of mutual funds, we employ the rolling-window time-series regressions over the past 6 months to estimate the average weekly alpha of each fund. More specifically, we use the intercept from a regression of excess mutual fund returns on excess aggregated stock market returns and risk-free rates. Extensive research supports using the Capital Asset Pricing Model (CAPM) for estimating alpha, as it outperforms other multi-factor models (Barber et al., 2016; Gu, Kelly, & Xiu, 2020). A positive (or negative) alpha during a window suggests information-motivated or liquidity-motivated trading (Edelen, 1999), making alpha essential for guiding investment and redemption decisions.

**Table 9**
Mutual fund: Flight to safety under hacking attacks.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Cap | Issue | Index | Cap | Issue | Index |
| D0 | 0.006* | 0.005* | 0.006** | 0.006* | 0.005* | 0.006** |
| | (1.86) | (1.74) | (2.10) | (1.82) | (1.73) | (2.08) |
| D1 | −0.002 | −0.001 | 0.000 | −0.002 | −0.001 | 0.000 |
| | (−0.51) | (−0.18) | (0.13) | (−0.55) | (−0.19) | (0.11) |
| D2 | 0.002 | −0.005 | 0.001 | 0.002 | −0.005 | 0.001 |
| | (0.58) | (−1.42) | (0.27) | (0.54) | (−1.43) | (0.24) |
| D3 | | | | −0.001 | 0.003 | 0.004 |
| | | | | (−0.47) | (1.00) | (1.44) |
| D4 | | | | 0.002 | 0.004 | 0.001 |
| | | | | (0.56) | (1.38) | (0.26) |
| D5 | | | | 0.003 | 0.000 | −0.000 |
| | | | | (0.94) | (0.15) | (−0.14) |
| D6 | | | | −0.006** | −0.002 | −0.005 |
| | | | | (−2.04) | (−0.57) | (−1.62) |
| D7 | | | | −0.006* | −0.008*** | −0.005 |
| | | | | (−1.90) | (−2.70) | (−1.63) |
| L.Alpha | 0.036*** | 0.035*** | 0.034*** | 0.036*** | 0.035*** | 0.034*** |
| | (33.27) | (32.08) | (31.73) | (33.27) | (32.08) | (31.73) |
| log(TNA) | 0.00002 | 0.0002 | −0.001 | 0.00003 | 0.0002 | −0.001 |
| | (0.04) | (0.40) | (−1.40) | (0.05) | (0.40) | (−1.40) |
| Expense | 0.00045 | 0.0002 | 0.0003 | 0.0004 | 0.0002 | 0.0003 |
| | (0.97) | (0.50) | (0.64) | (0.97) | (0.50) | (0.64) |
| log(age) | −0.00002 | 0.00012 | −0.001* | −0.00002 | 0.00012 | −0.001* |
| | (−0.05) | (0.33) | (−1.66) | (−0.05) | (0.33) | (−1.66) |
| log(N) | 0.00009 | −0.002*** | 0.0003 | 0.00009 | −0.002*** | 0.0003 |
| | (0.22) | (−5.28) | (0.80) | (0.22) | (−5.28) | (0.80) |
| $\Delta VIX$ | −0.078*** | −0.108*** | −0.102*** | −0.078*** | −0.108*** | −0.102*** |
| | (−22.15) | (−30.95) | (−29.35) | (−22.13) | (−30.98) | (−29.32) |
| $\Delta INDPRO$ | −0.012 | −0.014 | 0.076 | −0.007 | −0.013 | 0.079 |
| | (−0.18) | (−0.22) | (1.16) | (−0.11) | (−0.19) | (1.22) |
| $\Delta PDI$ | −0.026 | −0.046 | −0.029 | −0.024 | −0.044 | −0.026 |
| | (−0.62) | (−1.08) | (−0.67) | (−0.56) | (−1.02) | (−0.62) |
| $\Delta CND$ | 0.018 | 0.020 | 0.023* | 0.019 | 0.020 | 0.024* |
| | (1.32) | (1.44) | (1.66) | (1.39) | (1.46) | (1.71) |
| $VAR_{GK}$ | 40*** | 60.9*** | 50.05*** | 41.09*** | 60.93*** | 50.02*** |
| | (11.54) | (17.26) | (14.23) | (11.57) | (17.27) | (14.22) |
| Constant | 0.00049 | 0.008** | 0.003 | 0.00046 | 0.008** | 0.003 |
| | (0.13) | (2.22) | (0.84) | (0.12) | (2.20) | (0.82) |
| Event FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 1,216,979 | 1,216,979 | 1,216,979 | 1,216,979 | 1,216,979 | 1,216,979 |
| R-squared | 0.0014 | 0.0018 | 0.0017 | 0.0014 | 0.0018 | 0.0017 |

This table provides the analysis of the FTS effect on US mutual fund. The dependent variable, abnormal flow, is measured across three categories: Cap, Issue, and Index. $D_0$, $D_1$, $D_2$, $D_3$, $D_4$, $D_5$, $D_6$, and $D_7$ are indicator variables that take the value of 1 for the attack announcement date, the first trading day after the attack, and subsequent trading days up to the seventh day, respectively. $L.Alpha$ represents the week-lagged abnormal flow of each fund, calculated using the CAPM model over a 6-month rolling window. $log$(TNA) refers to the natural logarithm of total net assets (TNA) of the fund. $Expense$ is the fund's expense ratio, reflecting its commission fees. $log(age)$ is the natural logarithm of the fund's age in years. $log(N)$ represents the natural logarithm of the total number of funds managed by the same parent company. $\Delta VIX_t$ denotes the daily change in the VIX (Volatility Index). $\Delta INDPRO_t$ refers to the monthly changes in the U.S. Industrial Production Index. $\Delta PDI_t$ represents the quarterly changes in Personal Dividend Income. $\Delta CND_t$ denotes the quarterly change in the corporate net dividends paid. $Var_{GK}$ is a range-based daily volatility measure of the U.S. stock market. Event FE represents event fixed effects, and Year FE represents year fixed effects. T-statistics are reported in parentheses. Significance levels are denoted as follows: ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

non-fundamental price pressure on mutual fund movement that reverts in the short term. This is consistent with previous research (Baele et al., 2020; Lehnert, 2022) showing that more risk-averse retail investors reallocate their portfolios towards safer assets such as mutual fund in reaction to FTS episodes.

Furthermore, the study finds that fund past performance (L.Alpha) is a robust indicator of abnormal flow, in accordance with existing research (e.g., DeMiguel, Gil-Bazo, Nogales, & Santos, 2023), that investors are attracted to funds with outstanding performance. Macroeconomic variables such as VIX and volatility have a greater explanatory power than fund-related factors (fund size, expense ratio, fund family, and fund age).

The significance of D0 in Table 9 underlines the timing of specific security-related events to drive investor decisions. Our result corresponds with the existing body of research, especially in the study of Del Guercio and Tkac (2008), which demonstrates the substantial impact of external events, such as market-wide shocks or fund-specific changes, on investor behaviour and fund flows.

To establish the robustness of Table 9, we use an alternative proxy of fund flow from Bloomberg. It is the net movement of investments into and out of mutual funds. Table B.6 in the appendix illustrates that the impact of hacking events has a short-lived FTS effect on the mutual fund real inflow. The retail investor's immediate transfer to the mutual fund market when suddenly facing the shock of stolen announcements from the crypto-exchange, supports the investment strategy of choosing high-quality, low-risk 'alpha funds' to secure safer assets (Ben-David, Li, Rossi, & Song, 2022). Overall, a significant abnormal flow in mutual funds indicates that retail households exhibit FTS behaviour driven by heightened risk aversion in response to cryptocurrency-related cybercrimes.

**Table 10**
Flight to safety under various window group.

| Window: | (1) (−1,+1) | (2) (−2,+2) | (3) (−3,+3) | (4) (−6,+6) | (5) (−10,+10) | (6) (−15,+15) | (7) (−30,+30) |
|---|---|---|---|---|---|---|---|
| D | 0.198*** | 0.156*** | 0.214*** | 0.250*** | 0.236*** | 0.162*** | 0.036*** |
| | (3.73) | (4.14) | (7.09) | (11.12) | (13.16) | (10.68) | (2.89) |
| SP | 0.003 | 0.003* | 0.003** | 0.003*** | 0.002*** | 0.003*** | 0.003*** |
| | (1.27) | (1.91) | (2.56) | (3.25) | (3.16) | (5.23) | (6.59) |
| Volatility | −0.002 | 0.008 | 0.007 | 0.008 | 0.003 | 0.001 | 0.001 |
| | (−0.21) | (0.90) | (0.91) | (1.49) | (0.63) | (0.15) | (0.40) |
| MKT | 0.001 | −0.001 | −0.002 | −0.001 | −0.000 | −0.000 | −0.000 |
| | (0.27) | (−0.64) | (−1.21) | (−0.62) | (−0.35) | (−0.42) | (−0.85) |
| CREDIT | 0.002 | 0.002 | 0.002 | 0.001 | 0.001 | 0.001 | 0.001 |
| | (0.61) | (0.60) | (0.75) | (0.72) | (0.70) | (1.37) | (0.77) |
| GDP growth | −0.002 | 0.001 | 0.007 | 0.007 | 0.003 | 0.008 | 0.007 |
| | (−0.08) | (0.04) | (0.45) | (0.72) | (0.42) | (1.06) | (1.09) |
| GDP percap | 1.414 | 0.680 | 0.220 | −0.243 | 0.084 | 0.051 | −0.097 |
| | (1.53) | (0.95) | (0.37) | (−0.57) | (0.25) | (0.18) | (−0.45) |
| M3 | 0.065** | 0.009 | 0.007 | 0.001 | −0.003 | −0.010 | −0.014** |
| | (2.52) | (0.44) | (0.45) | (0.06) | (−0.38) | (−1.25) | (−2.43) |
| Inflation | 0.009 | 0.013 | 0.004 | 0.006 | 0.002 | 0.002 | 0.006 |
| | (0.38) | (0.82) | (0.34) | (0.64) | (0.34) | (0.30) | (1.29) |
| Saving | −0.020 | −0.017 | −0.008 | 0.002 | −0.002 | 0.002 | 0.003 |
| | (−0.86) | (−1.03) | (−0.56) | (0.16) | (−0.31) | (0.24) | (0.64) |
| Popurban | −0.036 | −0.006 | 0.021 | 0.003 | 0.012 | 0.016 | 0.009 |
| | (−0.50) | (−0.10) | (0.48) | (0.10) | (0.47) | (0.81) | (0.60) |
| Constant | −9.425 | −6.245 | −4.255 | 1.607 | −2.002 | −1.970 | −0.206 |
| | (−1.05) | (−0.88) | (−0.75) | (0.41) | (−0.63) | (−0.77) | (−0.11) |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 2,545 | 4,379 | 6,251 | 10,769 | 16,367 | 22,489 | 38,690 |
| R-squared | 0.044 | 0.019 | 0.020 | 0.022 | 0.015 | 0.010 | 0.003 |

This table reports results from robustness tests for the FTS effect, under different window period from 2011–2019. All coefficients are presented in terms of percent. We consider heteroscedasticity and robust standard errors. The dependent variable $R_{(-t,+t),i,t}$ is measured daily changes in stock market index return at the country level under different sub-sample, defined as $log(stock_{i,t}/stock_{i,t-1})$. $D$ is an indicator variable, taking a value of 1 for the attack announcement date and after during the respective window days. *SP* denotes the annual changes in global stock index. *Volatility* denotes the annual standard deviation of stock market. *MKT* denotes the ratio of listed companies' market capitalization over GDP. *CREDIT* denotes the ratio of domestic credit to private sectors over GDP. *GDP growth* denotes quarterly GDP growth rate. *GDP percap* measured by the logarithmic GDP per capita (in USD). *M3* is the monthly broad money growth rate. *Inflation* denotes inflation measured by GDP deflator. *Saving* denotes as the ratio of saving over GDP. *Popurban* denotes the proportion of people living in urban areas. Country FE is the country fixed effect and Year FE is the year fixed effect. T-statistics are reported in parentheses and ***, **, * signify the 1%, 5%, and 10% significance level, respectively.

### 5.2. Robustness tests

To enhance the robustness of the results, we carry out two tests around the baseline model. The first robustness test is formulated in Eq. (12) where we focus on the stock return reactions during the event window period and lengthen the window further to test the duration of the FTS effect.

$$R_{i,t} = \alpha + \beta_0 D_\tau + \delta_i X_{i,t} + \gamma_i + \gamma_{year} + \epsilon_{i,t}, \qquad t \in (-\tau, \tau) \tag{12}$$

$$D_\tau = \begin{cases} 1, & 0 \le t \le \tau \\ 0, & -\tau \le t < 0 \end{cases}$$

Clearly, $\tau = 0$ indicates the event date. We pay our attention to an indicator variable - $D_\tau$, splitting the observations in the window period into the pre- and post-event groups. $X_{i,t}$ are vectors of country-specific control variables in country $i$ at date $t$; $\gamma_i$ and $\gamma_{year}$ are the country and year fixed effects, respectively; and $\epsilon_{i,t}$ is an error term. In Table 10, the coefficients on $D_\tau$ over a range of $\tau$ are overwhelmingly significant until a window of 30 trading days. The positive sign indicates the stock index returns during the post-event window are pumping up, compared to those in the pre-event period. By lengthening the window period, one observes that the FTS effect is persistent, lasting up to 30 trading days.

In the second robustness check, we conduct a firm-level data as a supplementary verification to the study on the country-level data. To ensure that the FTS is applied to the firm-level investigation, for the dependent variables in the baseline model we consider the log returns of the stocks that are the constituents of the S&P 500 index.[29]

$$R_{f,t} = \alpha + \beta_j D_j + \theta X_t + \gamma_s + \gamma_{year} + \epsilon_{i,t} \qquad j \in (0,2) \tag{13}$$

where $R_{f,t}$ is the daily change of stock price of the $f$-th firm at date $t$. $D_j$ is a set of dummy variables as usual. In order to control the fluctuation of economic uncertainty, we add a list of control variables from the CBOE[30] and the Board of Governors of the Federal Reserve System[31] respectively. $\Delta VIX_t$, from the CBOE is the daily log difference of the daily VIX index. $\Delta INDPRO_t$ measures the monthly industrial production growth. $\Delta PDI$ is the change in personal dividend payment, and $\Delta NFDP_t$ denotes the change ratio for non-financial dividends paid. We expect the coefficients on $D_j$ to be consistent with our preceding findings. We also control the sector and year-fixed effects.

Regression results are reported in Table 11 with robust standard errors, the year and the sector fixed effects. Unsurprisingly, the evidence from the firm-level analysis is consistent with our main results. As it is shown in Panel A that all coefficients on $D_0$ and $D_2$ are statistically significant, the constituents of the S&P 500 index appear to be the safe haven. In column (3), the firm-level stock returns, on average, increase sharply by 13.8% on the announcement date. After experiencing a moderate downward adjustment by 9.2% on the following trading day,

29 For the purpose of robustness, we accentuate the US market for the reason that, Bitcoin trading in the US market has occupied more than half of the trading volume worldwide.

30 https://www.cboe.com/tradable_products/vix/

31 https://fred.stlouisfed.org

**Table 11**
Flight to safety under firm-level.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Dependent variable: | Panel A: $R_{f,t}$ | | | | Panel B: $R_{p,t}$ | | | |
| $D_0$ | 0.139*** | 0.137*** | 0.138*** | | 0.145** | 0.144** | 0.146** | |
| | (9.81) | (9.66) | (9.73) | | (2.56) | (2.54) | (2.56) | |
| $D_1$ | | −0.093*** | −0.092*** | | | −0.049 | −0.048 | |
| | | (−7.46) | (−7.38) | | | (−0.85) | (−0.83) | |
| $D_2$ | | | 0.039*** | | | | 0.052 | |
| | | | (3.18) | | | | (1.08) | |
| $D_{(0,2)}$ | | | | 0.019** | | | | 0.042 |
| | | | | (2.51) | | | | (1.30) |
| Δ VIX | −10.076*** | −10.074*** | −10.073*** | −10.076*** | −9.588*** | −9.587*** | −9.586*** | −9.588*** |
| | (−377.42) | (−377.36) | (−377.26) | (−377.42) | (−100.73) | (−100.71) | (−100.65) | (−100.72) |
| Δ INDPRO | −1.826*** | −1.793*** | −1.808*** | −1.786*** | −1.024 | −1.006 | −1.027 | −1.008 |
| | (−4.40) | (−4.33) | (−4.36) | (−4.31) | (−0.62) | (−0.61) | (−0.62) | (−0.61) |
| Δ PDI | −0.212*** | −0.211*** | −0.212*** | −0.214*** | −0.870*** | −0.870*** | −0.871*** | −0.872*** |
| | (−8.34) | (−8.34) | (−8.35) | (−8.43) | (−9.18) | (−9.18) | (−9.19) | (−9.21) |
| Δ NFDP | 0.081*** | 0.081*** | 0.081*** | 0.082*** | −0.072*** | −0.072*** | −0.072*** | −0.071*** |
| | (13.03) | (13.03) | (13.03) | (13.24) | (−3.37) | (−3.37) | (−3.37) | (−3.32) |
| Constant | −0.006 | −0.005 | −0.005 | −0.006 | 3.647*** | 3.648*** | 3.647*** | 3.647*** |
| | (−0.79) | (−0.67) | (−0.71) | (−0.76) | (118.17) | (118.15) | (118.11) | (118.10) |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Sector FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 928,885 | 928,885 | 928,885 | 928,885 | 72,504 | 72,504 | 72,504 | 72,504 |
| R-squared | 0.196 | 0.196 | 0.196 | 0.196 | 0.716 | 0.716 | 0.716 | 0.716 |

This table reports results from robustness tests for the FTS effect, using USA firm level data from 2011–2019. All coefficients are presented in terms of percent. We consider heteroscedasticity and robust standard errors. The dependent variable $R_{f,t}$ is measured daily individual stock return at the USA firm-level, defined as $log((stock_{f,t} - stock_{f,t-1})/stock_{f,t-1})$. We also use alternative measure $R_{p,t}$ to define the return for equally weighted portfolio across 38 industries. $D_0$, $D_1$, $D_2$ are indicator variables, taking a value of 1 for the attack announcement date, the first, and the second trading day after the attack announcement date, respectively. An alternative measure $D_{(0,2)}$ presents the event period covering the episodes from announcement dates to the second trading days. $\Delta VIX_t$ is the daily change in VIX index. $\Delta INDPRO_t$ denotes the monthly changes of Industrial Production index in US. $\Delta PDI_t$ is the quarterly changes of Personal dividend income. $NFDP_t$ denotes the quarterly change ratio of non-financial dividend paid. Sector FE is the sector fixed effect and Year FE is the year fixed effect. T-statistics are reported in parentheses and ***, **, * signify the 1%, 5%, and 10% significance level, respectively.

the returns rebound by 3.9% at $D_2$. On average, the firm-level return gains of 1.9% change over the attacking period, from $D_0$ to $D_2$ denoted by the employed $D_{(0,2)}$, as shown in column (4). In sum, it appears that the economic impact of cyber hacking incidents is stronger in the US than the worldwide average of 11% in Table 3.

In Panel B, we carry out an additional test based on portfolio returns denoted as $R_{p,t}$, an equally weighted portfolio across various industries at date $t$.[32] Results are generally consistent but weaker in terms of both economic and statistical significance.

## 6. Conclusion

We uncover a novel FTS effect from alternative asset markets to stock markets in the context of cyber attacks on cryptocurrency exchanges. Such attacks raise investors' concerns about the uncertainty and risk of investing in cryptocurrencies and undermine their confidence in crypto markets. We find that the official announcements of hacking events instantly wiped out Bitcoin returns by 43%, while pumping up Bitcoin liquidity costs by 30 percentage points in terms of the bid–ask spread. The resultant market panic prompts a widespread capital reallocation, which contributes to stock market returns of 27% on the date of announcement and 44% on the second trading day during a high-incident period. We also find that investor sentiment embedded in messages on social media platforms serves as an early warning indicator prior to the events and measures the FTS pressure during and after the events. In addition, the magnitude and timing of the FTS effect vary by country characteristics. Our results are robust regarding the firm-level investigation and the length of the event window. Finally, we observe the mutual fund market and obviously detect that the FTS effect is addressed as well during the event window.

To the best of our knowledge, this is the first study examining the impact of cybercrime in crypto markets on financial markets. Crypto markets have been generally deemed to be closely related to underground unlawful activities (Foley et al., 2019) and are isolated from the real economy. We document a link between crypto markets and the real economy. The examination of transmitted shocks from unregulated crypto markets to regulated stock markets has significant policy implications. Stock markets might become more volatile in response to the exogenous shocks from alternative asset markets. More importantly, social media play a pivotal role in conveying soft information relating to crypto markets to investors. For the purpose of stock market stability, keeping a close eye on social media sentiment towards cryptocurrencies can aid the task of monitoring stock market fluctuation. Policymakers can utilize social media information to help safeguard the real economy. Since early 2021, crypto markets have gained increased attention from some principal players in the financial markets. For instance, in March J.P. Morgan and Morgan Stanley started to offer 'crypto exposure' products or offer clients access to Bitcoin funds. It seems likely that the conventional financial markets and cryptocurrency markets will become more connected, providing a fascinating area for future research. With more information available, future research may focus on each exchange or clustered group and potentially trace fund flows.

[32] We collected 39 industries across the S&P 500. They are aerospace and defense, automobiles and parts, banks, beverages, chemicals, construction and materials, electricity, electronic and electrical equipment, financial services (sector), fixed-line telecommunications, food producers, food and drug retailers, forestry and paper, gas, water and multi utilities, general industrials, general retailers, health care equipment and services, household goods and home construction, industrial engineering, industrial metals and mining, industrial transportation, leisure goods, life insurance, media, mining, nonlife insurance, oil equipment and services, oil and gas producers, personal goods, pharmaceuticals and biotechnology, real estate investment trusts, real estate investment and services, software and computer services, support services, technology hardware and equipment, tobacco, travel and leisure, unclassified.

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## 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.

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## Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.irfa.2025.104093.

## Data availability

Data will be made available on request.

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