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FULL LENGTH ARTICLE

The implications of virtual money on travel and tourism

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ABSTRACT

We obtain daily data of Bitcoin, Ethereum, Travala token, Kemacoin and Guider to investigate the implications of history's most famous five heists on travel and tourism. We find a statistically significant spillover effect in the cryptocurrency and tourism token markets with a limited impact on travel and tourism companies' stock prices. We also find evidence of herding behaviour and observe that overall market quality deteriorated because of the heists. To deal with these negative implications, we propose implementing tools based on artificial intelligence algorithms, emphasising the two leading cryptocurrencies – Bitcoin and Ethereum. Tracking major crypto wallets and 'whales' can help regulators identify potential hacks and mitigate systemic risk caused by spillovers in cryptocurrency markets.

Introduction

Research background

Before the COVID-19 pandemic, travel and tourism were among the most significant economic sectors, accounting for 333 million (1 in 4) new jobs created worldwide and $9.6 trillion (10.3 %) of global Gross Domestic Product. Statista's Digital Market Outlook estimation suggests that the worldwide revenue of mobile apps in the travel segment has increased by $296 million (38 %) in 2021 with projected revenue increase to approximately $613 billion by 2025 (Statista.com, 2023). Furthermore, the gross domestic product of travel and tourism is forecasted to grow by 5.8 % annually between 2022 and 2032, surpassing the projected economic growth of 2.7 % per year (World Travel & Tourism Council report, 2022).

The use of cryptocurrencies in travel and tourism

With the predicted growth in travel and tourism, the value of cryptocurrencies has surged in recent years, prompting many companies in these sectors to accept cryptocurrency payments and even develop their own tokens. Cryptocurrencies are the native assets of blockchains and crypto tokens are crafted on established blockchains. These tokens, fulfilling diverse roles within their platforms, are created based on different standards for non-interchangeable tokens and tokens that integrate with the Ethereum ecosystem (Meghmala, 2023).

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A recent study commissioned by Traders of Crypto (2023) suggests that travel companies are the most prominent cryptocurrency users out of any industry or particular business sector. Similarly, Dogan (2021) reports that 58 % of global luxury tourism increasingly relies on cryptocurrencies as legal tender, with blockchain technology allowing tourism companies to facilitate cryptocurrency-based transactions in place of services, develop loyalty programs, and tokenise resort places. It has been well documented that cryptocurrency payments provide several advantages, including avoiding intermediaries such as banks and other financial institutions (Valeri & Baggio, 2021), eliminating credit card fraud during travel (Rashideh, 2020), mitigating foreign currency exchange rate risk (Nam et al., 2021); the opportunity to transfer unlimited funds and very low or no transaction fees (Melkić & Čavlek, 2020) and the opportunity to immediately execute a transaction compared to several days for conventional credit cards (Willie, 2019). Kwok and Koh (2019) report that using cryptocurrencies in the tourism industry provides discounted travel services, enhanced public relations support, and facilitates various loyalty programs. Table 1 in the appendices of this paper comprehensively summarises the travel and tourism companies that use cryptocurrency payments or develop new crypto tokens. This information is current as of 1st of March 2023.

Research motivations

Tsihitas (2023) estimates that hackers steal cryptocurrencies worth more than $9 billion over the last few years. If this amount were converted at the end of February 2023, hackers would accumulate over $47 billion. On the one hand, research on the topic mainly focuses on the general application of blockchain technology to the travel and tourism segments (for systematic literature reviews, see Calvaresi et al., 2019, Antoniadis et al., 2020, and more recently, Rana et al., 2022). On the other hand, when referring to blockchain, the emphasis is usually on Bitcoin as the most appropriate illustration of blockchain technology (Yli-Huumo et al., 2016). Moreover, Balasubramarian et al. (2022) argue that the current understanding of blockchain technology in tourism is limited because previously published studies are primarily fragmented and narrowly scoped regarding technology application and scope. Kwok and Koh (2019), Treiblmaier and Önder (2019), and Yadav et al. (2021) all suggest that more empirical research is required to illustrate the real potential of blockchain technology in tourism.

Research aims and objectives

Our work is the first empirical study to examine the implications of hacker cyber-attacks on the travel and tourism sectors by obtaining data from the two most widely used cryptocurrencies and three of the most significant market capitalisation travel and tourism tokens. To the best of our knowledge, this is not only the first such empirical study in travel, tourism and hospitality but in general. Our study is timely and essential for several reasons. According to the World Travel and Tourism Council report (2022), travel and tourism sectors suffered losses of approximately $4.9 trillion during the Covid-19 pandemic, with the sectors' global contribution to the gross domestic product decreasing by 50.4 % on an annual basis, compared to only a 3.3 % shrink of the worldwide economy. However, what implications could the most significant hacker attacks have on travel and tourism companies using cryptocurrencies and related tokens as legal tender? As Fig. 1 shows, cyber-attacks from hackers occur daily with various magnitudes, with a significantly increased likelihood of occurrence between May 2021 and February 2023. Fig. 1 also reveals that the total amount stolen by hackers is over $47 billion in today's money, more than the gross domestic product of 104 countries worldwide (https://www.worldometers.info/gdp/gdp-by-country/). Furthermore, as Yousaf et al. (2022) suggest, most travel and tourism tokens are developed relatively recently, having contrasting characteristics with financial markets regarding operational structure, transaction speed and access to market participants. Therefore, we would like to investigate the relationship between frequently occurring cyber-attacks by hackers and travel and tourism operational activities. More specifically, our research aims to gain a deeper understanding of the effects of hacker network attacks on the travel and tourism industry, uncovering the security disparities among different tokens in the cryptocurrency market and the market's response to these disparities. This facilitates more accurate risk assessment and management for decision-makers and practitioners, enabling them to implement appropriate security measures to safeguard digital assets and user interests.

Research contributions

Our research contributions are threefold. We examine five of the largest heists in cryptocurrency history, as described in Table 2, to investigate the implications of significant crypto heists on the travel and tourism sectors. Our Dynamic Conditional Correlation - Generalised AutoRegressive Conditional Heteroskedasticity test statistical results reveal statistically significant spillover effects between Bitcoin, Ethereum and the three tourism tokens in the four months following each of the five crypto heists. This critical finding implies that the heists have affected the volatility of both crypto asset classes, and there is a spillover effect in the mainstream cryptocurrency market and the tourism token market. One real-life practical implication of this finding is that heists of mainstream cryptocurrencies raise concerns among investors about the security of tourism tokens based on Bitcoin or Ethereum chains, leading to panic trading and affecting the price fluctuations of mainstream cryptocurrencies and tourism tokens.

We are the first to empirically investigate herding behaviour in travel and tourism digital assets. We observe that Bitcoin, Ethereum and the three tourism tokens experience herding behaviour when the prices of the digital instruments are declining. Our empirical findings also suggest that Bitcoin and Ethereum drive the behaviour of the three tourism tokens.

We conduct a market quality examination by deploying several liquidity measures. We observe wider spreads and higher levels of illiquidity, indicating higher transaction costs and less liquid digital assets for market participants in the two weeks

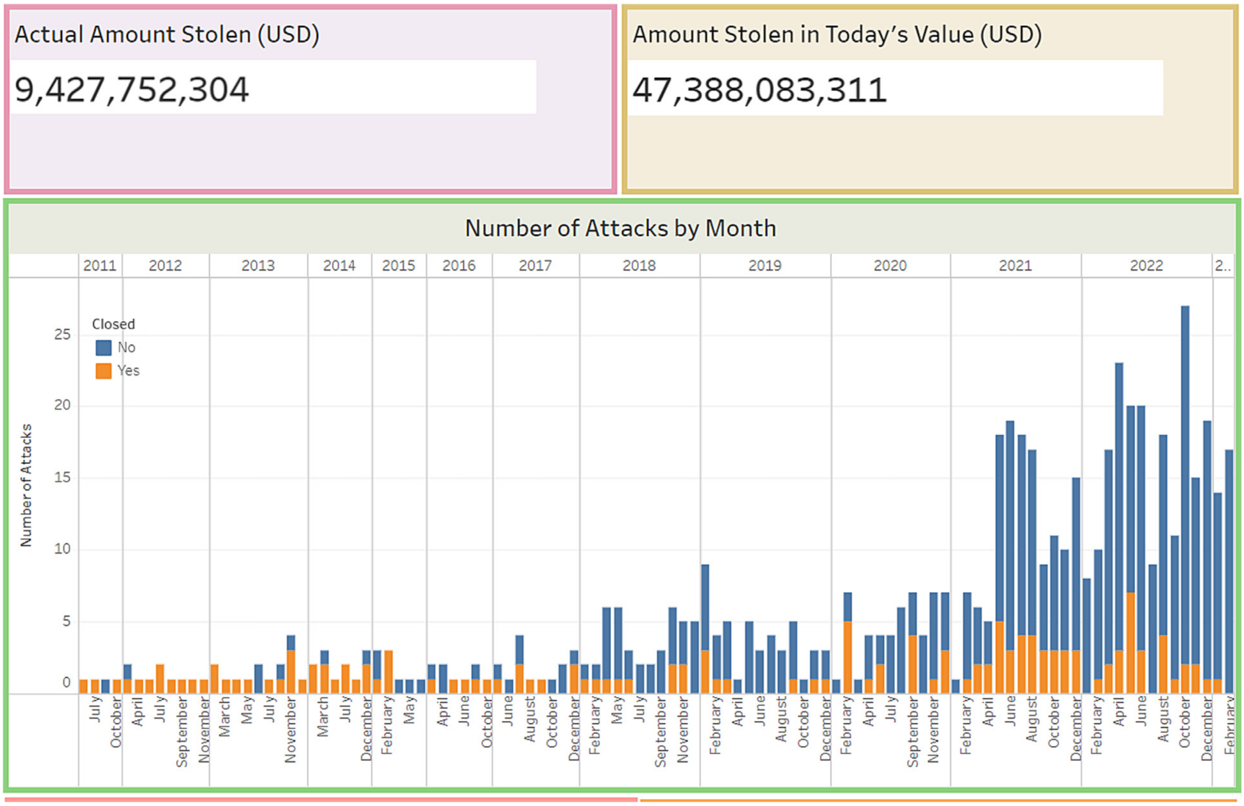

Fig. 1. Statistics of worldwide cryptocurrency and token cyber-attacks between June 2011 and February 2023.
Source: https://www.comparitech.com/crypto/biggest-cryptocurrency-heists/.

following each heist, which is likely to lead to lower certainty of trading order execution. We also observe that the smaller tokens are characterised by greater liquidity fluctuations than the two major cryptocurrencies during each heist. We conclude that overall market quality deteriorated because of the heists, evident by the higher liquidity measure values.

This is also the first study to investigate the implications of each crypto heist on the traditional travel and tourism sector and the broader economy. We demonstrate that the impact of cryptocurrency heists on the traditional travel and tourism market appears relatively limited. However, it still significantly affects companies primarily using tourism tokens as payment methods.

Finally, we propose appropriate regulatory measures based on our empirical findings. Using the proposed 'Bitcointracker' and 'Ethereumtracker' for tracking major crypto wallets and 'whales' can help regulators identify suspicious activity, such as potential hacks and scams and help mitigate systemic risk caused by spillovers in cryptocurrency markets.

Literature review

The travel and tourism sectors are increasingly adopting cryptocurrencies and tokens as payment methods. Cryptocurrencies offer advantages like minimal transaction fees, avoiding intermediaries, cost savings, and streamlined travel payments (Filimonau & Naumova, 2020; Nam et al., 2021; Trieblmaier et al., 2020). Although cryptocurrencies have many benefits in travel and tourism, several issues remain unresolved. Treiblmaier (2020) argues that cryptocurrencies still lack extensive implementation and understanding of the underlying blockchain mechanism. Many companies in the travel and tourism sectors are reluctant to accept cryptocurrencies as legal tender due to a lack of sufficient knowledge and concerns related to crypto assets' stability. In addition, using cryptocurrencies could pose regulatory issues as most countries do not currently regulate virtual assets, making it challenging for travel and tourism companies to use them legally. Önder and Treiblmaier (2018) and Treiblmaier and Önder (2019) suggest that Bitcoin conversion into fiat money and cryptocurrency transaction taxation may sometimes be complicated.

Most research on applying cryptocurrencies to travel and tourism mainly provided future recommendations. Leung and Dickinger (2017) survey 183 European travellers and find that the use of Bitcoin for payments is not frequent, although there is interest in its future use for online services. In another early study, Önder and Treiblmaier (2018) propose that the increased implementation of cryptocurrencies will likely lead to new consumer-to-consumer and customer-to-customer relationships. Tyan et al. (2020) advocate for local cryptocurrencies to boost tourism economies, but note the theoretical nature of their research; therefore, empirically orientated studies are needed to examine and confirm their statements. More recently, Nam et al. (2021) predict that major cryptocurrencies will lead in travel and tourism but cannot specify which ones due to their study's small sample size.

Yousaf et al. (2022) deploy a generalised vector autoregressive model to investigate return and volatility connections between virtual assets such as bitcoin and travel and tourism tokens and WTI oil, gold, the US dollar, gold and travel and tourism equity represented by the Dow Jones Travel and Tourism Sector index between February 2019 and August 2022.

The authors observe a weak static relationship between travel and tourism tokens and the other financial instruments under investigation during regular economic times. However, their analysis suggests significantly more volatility and return spillovers between travel and tourism tokens and other financial instruments at the beginning of 2020. This study concludes that the two travel tokens provide greater diversification during periods of economic downturn. While Kwok and Koh (2019) suggest that government cryptocurrencies can benefit small islands' tourism by offering greater opportunities to diversify financial portfolios away from international banks, Özgit and Adalier (2022) find similarities in stakeholders' understanding of cryptocurrencies after conducting telephone interviews with sixteen managers in North Cyprus casino hotels. However, a potential limitation of this study is the small sample size of interview participants.

A string of literature investigates the use of cryptocurrency payments in medical tourism. Skiba (2017) and Till et al. (2017) argue that cryptocurrencies improve efficiency and competitiveness for medical tourists and institutions due to free international transfers. Rajeb et al. (2020) and Tyan et al. (2021) generally agree that blockchain technology is advantageous for medical tourism. However, Tyan et al. (2020) note a limitation in their study due to its narrow focus on certain stages of medical tourism. In a larger-scale study, Çapar (2021) uses regression analysis on data from 555 tourists and reports a statistically significant correlation between cryptocurrency transactions and medical tourism, with monetary risk mitigation being the most significant variable in the sample.

In contrast to the above studies, Trieblmaier et al. (2020) conduct an explorative questionnaire survey. They observe the positive and negative aspects of cryptocurrencies among 161 Asia-Pacific travellers who use crypto assets to purchase travel-related services. As mentioned by the authors, however, this study has several limitations, such as geographical bias, which does not allow generalising the findings and issues with the modelling variables.

Methodology

Research models

We deploy the Dynamic Conditional Correlation - Generalised AutoRegressive Conditional Heteroskedasticity model (Engle, 2002) to investigate whether mainstream cryptocurrencies, such as Bitcoin and Ethereum, have a volatility spillover effect on tourism tokens during each cryptocurrency heist described in Table 2. The advantage of this model is that it can be combined with different univariate models of the same category to handle various return distributions and heteroskedastic structures flexibly. At the same time, the model's parameters can be estimated using the Maximum Likelihood Estimation method, and the solving process is simple and stable (Cappiello et al., 2006; Engle, 2002). Compared to other multivariate volatility models, the Dynamic Conditional Correlation - Generalised AutoRegressive Conditional Heteroskedasticity model can effectively capture the dynamic changes in the volatility of financial asset returns and the correlation between multiple assets when the external market environment changes, thereby reflecting the degree of risk propagation in the market (Engle, 2002). We compute the model as follows:

$$H_t = D_t R_t D_t \tag{1}$$

Where H_t represents the conditional covariance matrix, D_t is a diagonal matrix that consists of diagonal elements that represent the conditional volatility of each crypto asset under investigation, and R_t represents the time-varying correlation matrix.

Considering our empirical finding that the spillover effects are mainly related to Bitcoin and Ethereum, we investigate the implications of the two cryptocurrencies on the tourism tokens affected by the spillovers. To examine the presence of herding behaviour in the digital markets, we first compute each cryptocurrency and tourism token return daily as follows:

$$r_{i,t} = \frac{(P_t - P_{t-1})}{P_{t-1}} \tag{2}$$

where P_t represents the cryptocurrency and tourism token price at time t.

Christie and Huang (1995) suggest that market participants tend to disregard their private information about financial instruments during periods of extreme market stress and mimic the collective behaviour of the market. Therefore, market participants exhibit herding behaviour by adopting more uniform actions.

Given that crypto hacker attacks and the related heists provide conditions for extreme cryptocurrency market stress, we investigate the presence of herding behaviour in the travel and tourism sectors by dividing the cryptocurrency and tourism token returns when the entire digital market is up or down. We adopt the cross-sectional absolute deviation of returns models by Vidal-Tomás et al. (2019) and Chiang and Zheng (2010) to develop our regressions as follows:

$$\begin{aligned} Cross - Sectional - Absolute - Deviation_{CM,t} = {} & \lambda_0 + \lambda_1 (1 - Dummy) R_{CM,t} + \lambda_2 Dummy R_{CM,t} + \lambda_3 (1 - Dummy) R_{CM,t}^2 \\ & + \lambda_4 Dummy R_{CM,t}^2 + \varepsilon_t \end{aligned} \tag{3}$$

where $CM_{,t}$ denotes the cross-sectional deviation of cryptocurrency and tourism token market returns in absolute terms; (1 – *Dummy*) and *Dummy* are two dummy variables which equal 1 when $r_{m,t} \geq 0$ and $r_{m,t} < 0$, respectively; $R_{CM,t}$ measures the cross-sectional of the N returns at t in average terms; and $R^2_{CM,t}$ is the cross-sectional cryptocurrency and tourism token returns squared term.

We also investigate whether the tourism tokens affected by the spillover effect behave the same way as Bitcoin and Ethereum by dividing the dataset into two sub-samples.

The first sub-sample consists of Bitcoin and Ethereum, while the second sub-sample Travala token, Kemacoin and Guider tourism tokens. We estimate the following regression for the two sub-samples:

$$\begin{aligned} Cross-Sectional-Absolute-Deviation_{TT,t} = \lambda_0 + \lambda_1(1-Dummy)R_{TT,t} + \lambda_2 DummyR_{TT,t} + \lambda_3(1-Dummy)R^2_{TT,t} \\ + \lambda_4 DummyR^2_{TT,t} + \lambda_5 Cross-Sectional-Absolute-Deviation_{BE,t} + \varepsilon_t \end{aligned} \quad (4)$$

where the subscript *TT is* presented in *Cross-Sectional-Absolute-Deviation*$_{TT,t}$, $(1-Dummy)R_{TT,t}$,$DummyR_{TT,t}$, $(1-Dummy)R^2_{TT,t}$ and $DummyR^2_{TT,t}$ is the tourism tokens sub-sample, while *Cross-Sectional-Absolute-Deviation*$_{BE,t}$ represents the cross-sectional deviation of Bitcoin and Ethereum sub-sample returns in absolute terms.

Our regression allows us to investigate whether the behaviour of the tourism tokens follows the mean return of their sub-sample $(r_{s,t})$ or the mean return of the Bitcoin and Ethereum sub-sample $(r_{l,t})$.

Chung and Zhang (2014) suggest the *Roll's spread*, *Zeros1* and *Zeros2*, and the *Amihud illiquidity measure* to estimate the level of liquidity in daily data. We use the suggested four measurement models to test the liquidity levels two weeks before and after each cryptocurrency heist.

Roll (1984) demonstrates that the bid-ask spread can be computed by using the sample serial covariance as:

$$S = 2\sqrt{-Cov(\Delta P_t, \Delta P_{t-1})} \quad (5)$$

where P_t denotes the closing price of a digital asset on day t, while Δ represents the change operator. As Chung and Zhang (2014), we estimate the *Roll's Spread* in Table 7 by dividing S by the average digital asset price during the estimation data sample period. Goyenko et al. (2009) suggest that the *Roll's Spread* $= 0$ when $Cov(\Delta P_t, \Delta P_{t-1}) > 0$.

Lesmond et al. (1999) argue that the number of days with zero returns can be a proxy for transaction costs (lower transaction cost means higher liquidity). Similar to Lesmond et al. (1999) and Chung and Zhang (2014), we implement two procedures for trading days with zero returns:

$$Zeros1 = (\text{Number of days with zero returns})/(\text{Number of trading days}) \quad (6)$$

$$Zeros2 = (\text{Number of positive}-\text{volume days with zero returns})/(\text{Number of positive}-\text{volume trading days}) \quad (7)$$

This is based on Lesmond et al. (1999) two assumptions that the likelihood of zero-volume days and, therefore, zero-return days is greater for financial instruments with higher trading costs, and the likelihood of zero returns even in positive-volume days is also greater for financial instruments with higher trading costs.

Our final liquidity measure is based on Amihud (2002), who proposes the following price impact on trading liquidity measure:

$$Illiquidity = Average\left(\frac{|r_t|}{Volume_t}\right) \quad (8)$$

where r_t denotes the digital asset's return on day *t*, and $Volume_t$ represents the dollar trading volume on day *t*. This measure intends to capture the illiquidity in our digital assets under investigation.

Data description

We use the daily prices of two mainstream cryptocurrencies, Bitcoin and Ethereum, and three tourism tokens, Travala token, Kemacoin, and Guider, to analyse the volatility spillover effect over four months following five cryptocurrency heists. Bitcoin and Ethereum are chosen for their broad acceptance in travel, tourism, and hospitality, as shown in Table 1.

The Travala token is the leading tourism token by market value, with Kemacoin and Guider also being prominent in tourism. Therefore, we choose these three tokens as samples of tourism tokens. The data for Bitcoin, Ethereum, Travala token and Kemacoin comes from *CoinGecko*, while the data for Guider comes from *CoinMarketCap*. The observations for each cryptocurrency are the same for each heist, but the data range varies depending on the date of the heist. Table 3 shows the range of data we used for each heist.

Empirical findings

The implications of the cryptocurrency heists of travel and tourism sectors

Table 4 shows that all tokens return reject the unit root hypothesis in the data set. Therefore, we conclude that the series in the dataset is stationary. We use the Autocorrelation function to examine autocorrelation in the residuals of the mean equation. If the autocorrelation effects of the lags in the plot exceed the significance level (blue line), the null hypothesis of no autocorrelation is rejected, indicating the presence of autocorrelation. Although some lags show effects beyond the significance level, they do not form a consistent pattern, suggesting the residuals are approximately uncorrelated. Additionally, we use the Autocorrelation function to test for AutoRegressive Conditional Heteroskedasticity effects in the tokens. Suppose the autocorrelation effects of the lags in the plot exceed the significance level. In that case, the null hypothesis of no AutoRegressive Conditional Heteroskedasticity effect is rejected, indicating the presence of such an effect. Figs. 2 and 3 show the test results of autocorrelation and AutoRegressive Conditional Heteroskedasticity effects that can be used later to build the Dynamic Conditional Correlation - Generalised AutoRegressive Conditional Heteroskedasticity model.

The test results in Table 5 reveal statistically significant spillover effects between Bitcoin, Ethereum and the three tourism tokens in the four months following each of the five crypto heists. Four months following each heist, the β values (dccb1) and $\alpha + \beta$ values (dcca1 + dccb1) of these seven token pairs approached 1, indicating a robust long-term correlation between mainstream

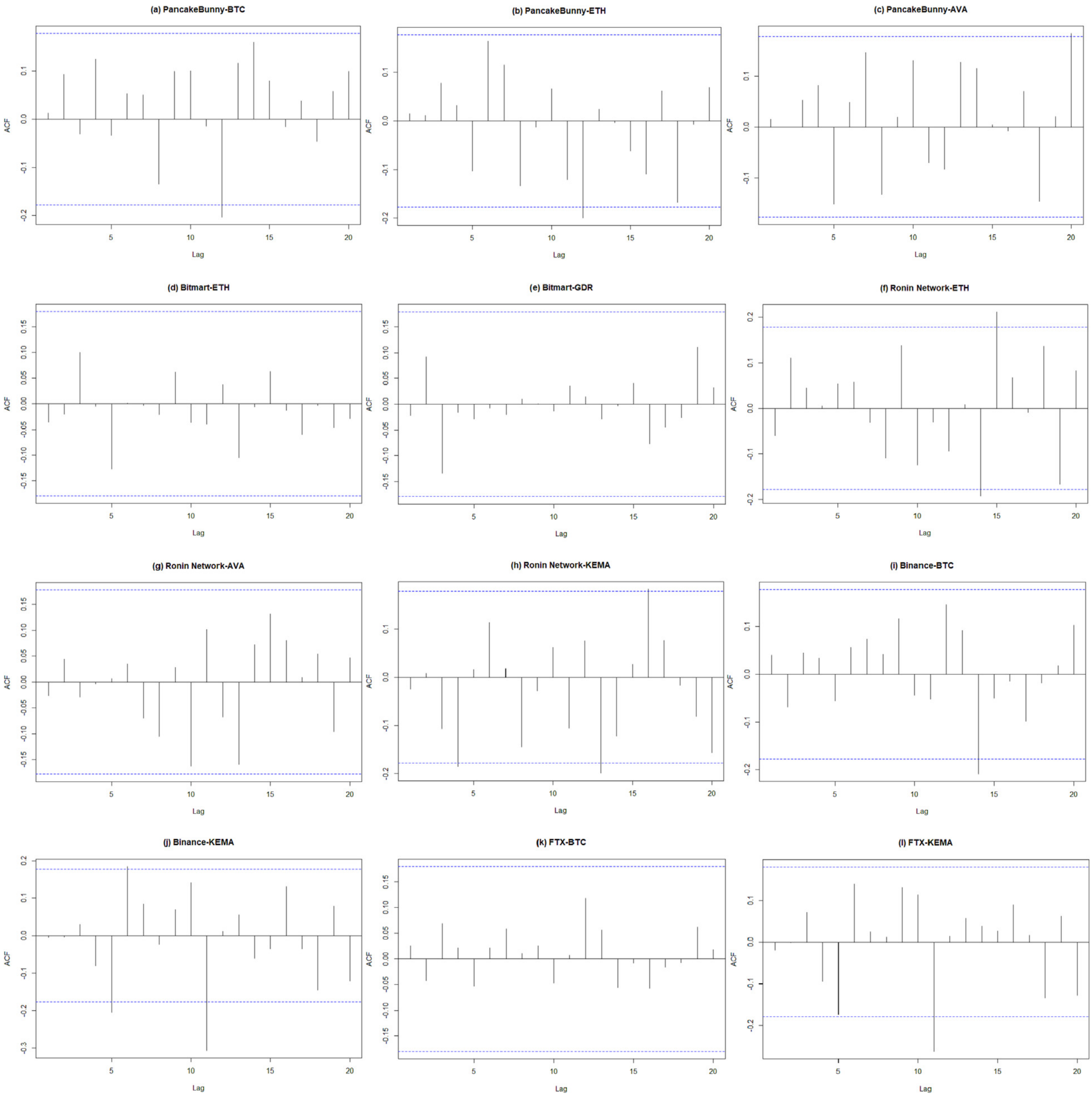

Fig. 2. Residual correlation results for the mean equation.
BTC: Bitcoin; **ETH**: Ethereum; **AVA**: Travala token; **GDR**: Guider; **KEMA**: Kemacoin.

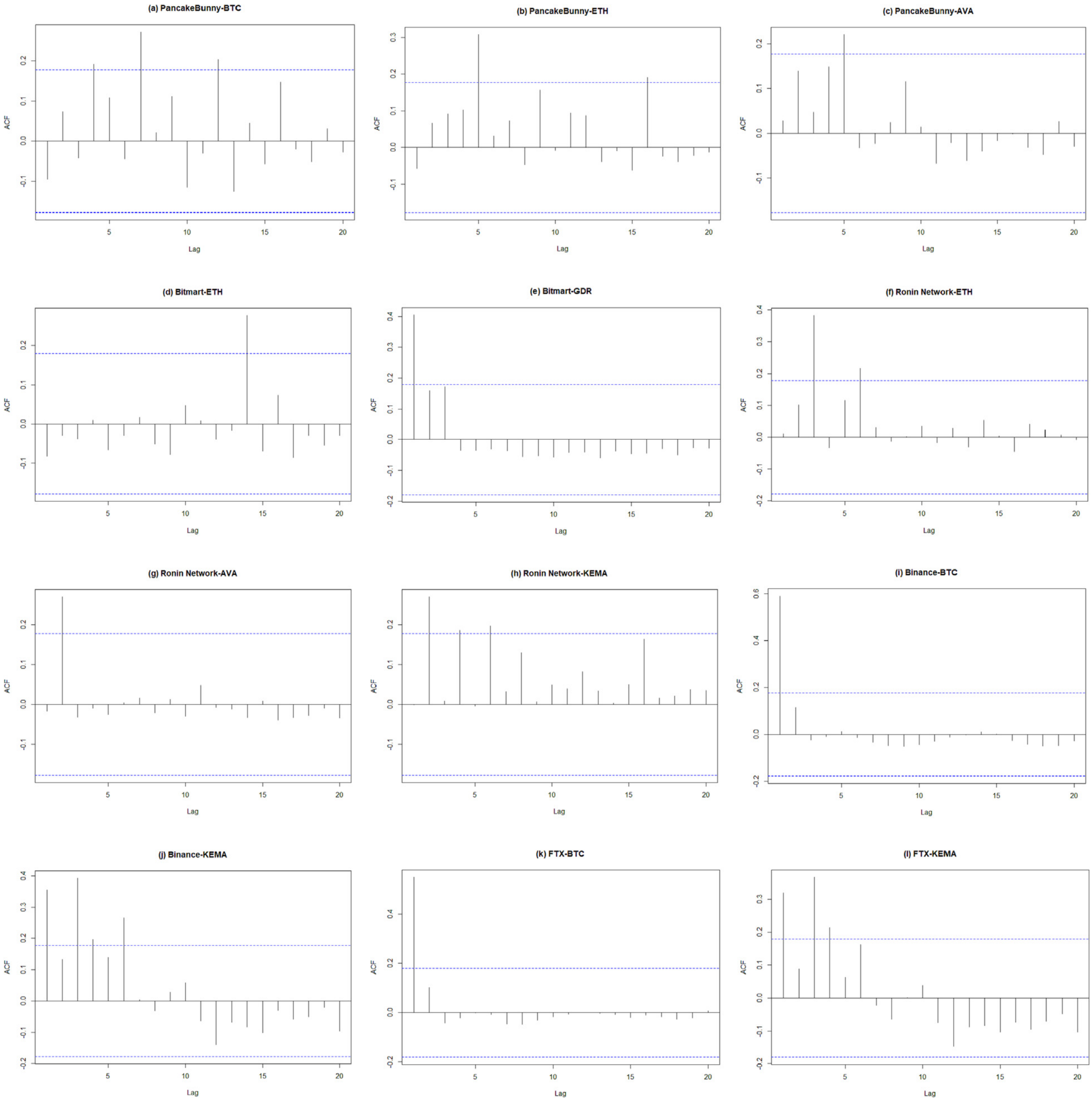

Fig. 3. Autoregressive conditional heteroskedasticity results.
BTC: Bitcoin; **ETH**: Ethereum; **AVA**: Travala token; **GDR**: Guider; **KEMA**: Kemacoin.

cryptocurrencies and tourism tokens, which is highly persistent. Heists have a similar impact on the mainstream cryptocurrency and tourism token markets, causing the price changes to remain consistent in the long run.

In addition, the Dynamic Conditional Correlation - Generalised AutoRegressive Conditional Heteroskedasticity values show fluctuations, and the correlation coefficients significantly increase after each heist. This suggests that the heists affect the volatility of both crypto asset classes, and there is a spillover effect in the mainstream cryptocurrency market and the tourism token market. In real-life trading activity, the heists of mainstream cryptocurrencies raise concerns among investors about the security of tourism tokens based on Bitcoin or Ethereum chains, leading to panic trading and affecting the price fluctuations of mainstream cryptocurrencies and tourism tokens.

Notably, in the *Binance* exchange heist, although there is a spillover effect between Bitcoin and Kemacoin, their $\alpha + \beta$ value is the smallest, only 0.685296. This may be because *Binance* quickly freezes many stolen tokens after discovering the heist, limiting the spread of the volatility spillover effect and mitigating the negative impact of the heist on the cryptocurrency market. In contrast, in the *Bitmart* exchange heist, the $\alpha + \beta$ value of the spillover effect between Ethereum and Guider is the largest, 0.994826.

This may be because *Bitmart*'s stolen assets include up to 20 tokens on the Ethereum blockchain and the Binance Smart Chain. The wide-ranging stolen assets and the lack of timely remedial measures significantly negatively impact the entire cryptocurrency market, making the spillover effect more pronounced.

Our Dynamic Conditional Correlation - Generalised AutoRegressive Conditional Heteroskedasticity test results in Fig. 4 provide visual evidence of a significant spillover effect between Bitcoin, Ethereum and the three tourism tokens during the five crypto heists. The spillover effect between the cryptocurrency and tourism token markets can be explained from a micro perspective. First, the cryptocurrency market typically exhibits high market connectivity because digital assets can freely move between cryptocurrency exchanges around the clock. This connectivity enables rapid dissemination of price information across various exchanges. When cryptocurrency heists or similar events occur in the cryptocurrency market, traders quickly seek information and react, leading to spillover effects across different token markets. Second, the cryptocurrency market typically exhibits a high level of market depth, meaning that a sufficient number of buyers and sellers are willing to engage in large-scale transactions. Investors may attempt to adjust their positions when cryptocurrency heists occur, leading to significant trading activity. This substantial trading activity can impact cryptocurrency market prices and propagate spillover effects to the tourism token market. Third, the cryptocurrency market, being an emerging market, often experiences issues related to information asymmetry, where specific traders may possess more information than others. Following cryptocurrency heists, traders with critical information may react promptly, leading to price fluctuations. These price fluctuations can, in turn, propagate through spillover effects to other markets.

Ji et al. (2019) conduct a comprehensive analysis of dynamic connectedness and integration in cryptocurrency markets using the Dynamic Conditional Correlation - Generalised AutoRegressive Conditional Heteroskedasticity model. Their results indicate that cryptocurrency markets exhibit higher integration over time. Furthermore, our empirical spillover findings align with the existing literature on the interconnectedness in the cryptocurrency markets. In an early study, Fry and Cheah (2016) demonstrate a spillover effect from Ripple to Bitcoin in their investigation of crashes in the cryptocurrency market. Ji et al. (2019) examine interconnectedness in six leading cryptocurrencies, suggesting that Bitcoin and Litecoin are the primary driving forces of connected cryptocurrency returns. Antonakakis et al. (2019) look into the transmission process in nine prominent cryptocurrencies and conclude that Ethereum is the prime transmitting cryptocurrency, but Bitcoin remains one of the main transmitters.

The regression results for the five heists in Table 6 suggest that Bitcoin, Ethereum and the three tourism tokens experience herding behaviour when the prices of the digital instruments are declining. This is evident by the significant negative coefficient $DummyR^2_{CM,t}$ reported in Panel A of Table 6. The negative values of the generalised form in Panel A of Table 6 confirm this finding.

Our herding behaviour findings align with some current studies, even though these studies do not examine tourism tokens. Vidal-Tomás et al. (2019) collect data from 65 cryptocurrencies of various sizes and use a cross-sectional standard deviation of returns model to investigate herding behaviour in cryptocurrency markets. The authors report that smaller cryptocurrencies herd with the largest ones. Poyser (2018) gathers data on an even more extensive set of 100 cryptocurrencies and captures significant herding behaviour. Similarly, Leclair (2018) obtains high-frequency five-minute data of the 12 mainstream cryptocurrencies and provides evidence of herding behaviour.

Bouri et al. (2019) acquire a similar dataset containing the leading 14 cryptocurrencies between 2013 and 2018. They document time-varying herding behaviour, primarily driven by economic policy uncertainty, while King and Koutmos (2021) also present evidence of cryptocurrency herding behaviour. More recently, Manahov (2023) documents the presence of herding behaviour in the entire cryptocurrency market when prices of the more prominent cryptocurrencies decreased on the 5th of September 2018.

The regression results $\textit{Cross-Sectional-Absolute-Deviation}_{TT,t}$ are presented in Panel B of Table 6. The negative and significant values that Bitcoin and Ethereum drive the behaviour of the three tourism tokens. An essential further observation is that the coefficient of $\textit{Cross-Sectional-Absolute-Deviation}_{BE,t}$ in Panel B of all tables is positive and significant, suggesting the superior influence of the Bitcoin and Ethereum return dispersions in the cryptocurrency market. We also observe in Panel B that the mean return of the three tourism tokens is less related to the market dynamics, which is evident by the positive insignificant coefficients $(1 - Dummy)R^2_{TT,t}$ and $DummyR^2_{TT,t}$. One possible explanation of this finding could be the relatively limited information available about small crypto assets such as tourism tokens.

Information asymmetry often exists between mainstream cryptocurrency markets and smaller token markets like tourism. The smaller scale and lower liquidity of the tourism token market make it more sensitive to influences like news or social media. When prices dip, investors, fearing unknown market events, might follow the downward trend, exhibiting classic herding behaviour. In addition, tourism tokens are often relatively new, and their whitepapers and project websites often lack detailed fundamental data. Therefore, investors struggle to determine their true price, making them more susceptible to market sentiment. Finally, tourism tokens typically have smaller market capitalisations, and their price volatility may be higher. These tokens attract speculative traders who often prioritise quick profits over strategic investments, further amplifying herding tendencies in the tourism token sphere. Therefore, herding behaviour in the tourism token market can be explained as a prevalent phenomenon.

Table 7 compares the *Roll's spread*, *Zeros1* and *Zeros2*, and the *Amihud illiquidity measure* two weeks before and after each crypto heist. It is evident from the table that each of the four liquidity measures has higher values in the two weeks after each heist for the five digital assets. For example, the *Roll's spread* for Bitcoin and Ethereum are 0.416 and 0.483 two weeks before the *PancakeBunny* exchange heist on 20 May 2021 and 0.489 and 0.527 two weeks after. At the same time, the *Amihud illiquidity*

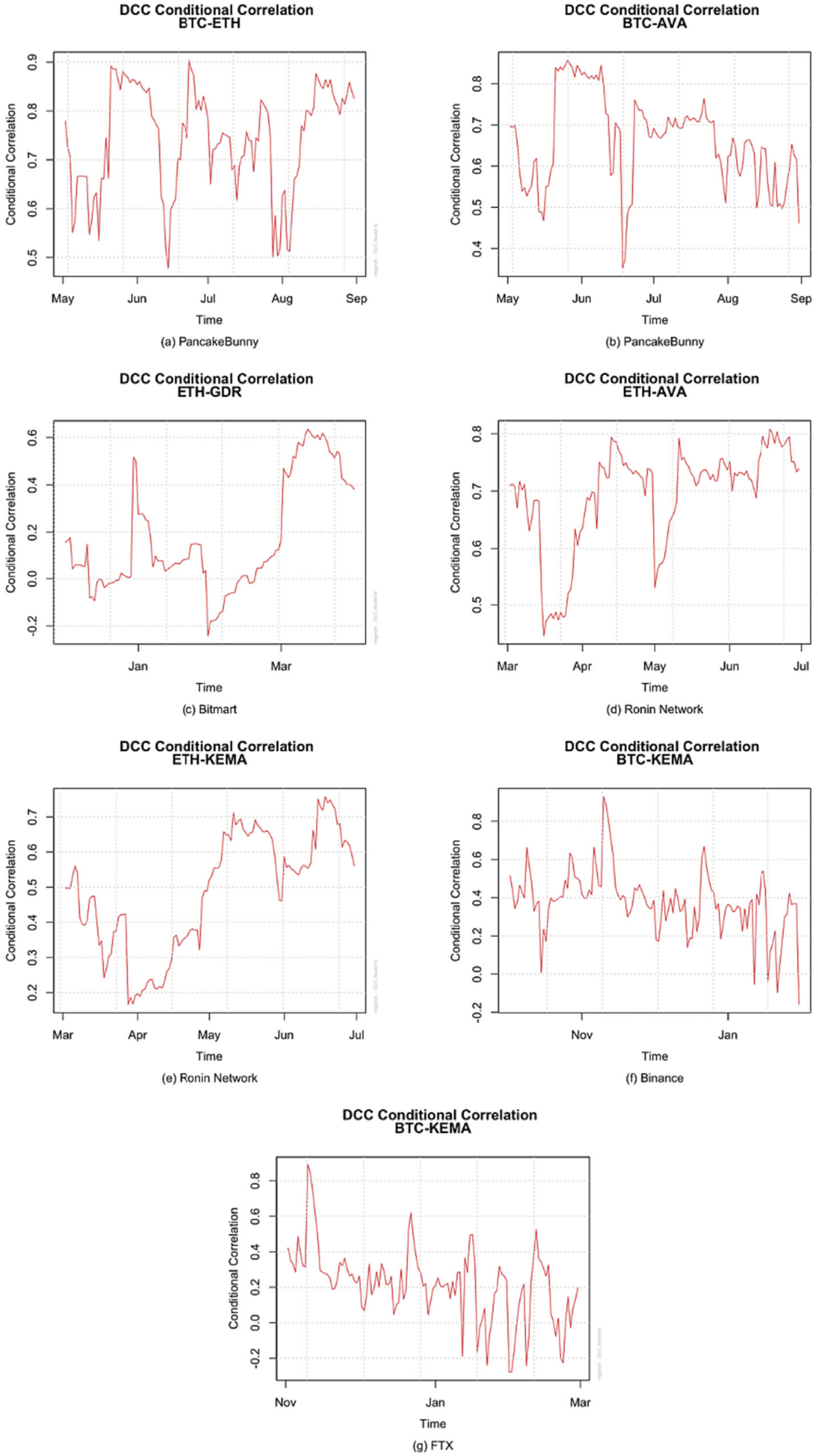

Fig. 4. Volatility spillover effect for Bitcoin, Ethereum, Travala token, Guider and Kemacoin.
BTC: Bitcoin; **ETH**: Ethereum; **AVA**: Travala token; **GDR**: Guider; **KEMA**: Kemacoin.

measure is 0.763 for Bitcoin and 0.801 for Ethereum two weeks before the same heist and 0.815 and 0.846 two weeks after. These wider spreads and higher levels of illiquidity indicate higher transaction costs and less liquid digital assets for market participants in the two weeks following each heist, leading to lower certainty of trading order execution.

Moreover, a direct comparison between the liquidity values of the five digital assets in Table 7 reveals that the smaller tokens are characterised by greater liquidity fluctuations than the two major cryptocurrencies during each heist. The *Roll's spread* of Guider increases from 0.285 to 0.372, while *Zeros2* of Travala token rises from 0.418 to 0.493 two weeks before and after the *PancakeBunny* exchange heist. Two weeks before and after the *Bitmart* exchange heist, the *Roll's spread* of Guider soars from 0.309 to 0.419, while *Zeros1* values of Travala token increase from 0.413 to 0.487. Kemacoin *Roll's spread* and *Amihud illiquidity* values surge from 0.276 to 0.343 and from 0.402 to 0.486 two weeks before and after the *Ronin Network* heist. Similarly, Travala token's *Amihud illiquidity* values increase from 0.585 to 0.663 compared to Bitcoin and Ethereum's smaller increase from 0.699 to 0.729 and 0.773 to 0.815 in the same heist. We observe a similar increase in the *Amihud illiquidity* values of Guider and Kemacoin compared with Bitcoin and Ethereum in the *Binance* exchange heist. In addition, the *Roll's spread* and *Zeros2* of Travala token and Kemacoin grow from 0.402 to 0.489 and 0.281 to 0.314 in the same heist.

In the *FTX* exchange heist, the *Roll's spread* and *Zeros2* of Travala token and Kemacoin also rise from 0.327 to 0.394 and 0.247 to 0.315. At the same time, we observe relatively smaller liquidity fluctuations in the two major cryptocurrencies two weeks before and after each heist.

Brauneis et al. (2021) highlight that the difference in liquidity fluctuations can be explained by various factors specific to the cryptocurrency market. A regression analysis conducted by the authors shows that cryptocurrency liquidity largely remains independent of other financial markets, such as the equity or FX markets.

Due to larger market capitalisation and greater liquidity, Bitcoin and Ethereum experience a smaller magnitude of liquidity decline in each of the heists we investigate. Therefore, cryptocurrency market participants may prefer to keep their funds in Bitcoin to mitigate risks during turbulent market conditions. In contrast, smaller-cap tokens like tourism tokens are less liquid, and investors often sell these tokens at lower prices, leading to significant liquidity fluctuations, especially during events such as crypto heists. Yao et al. (2022) observe that fewer market participants invest in cryptocurrencies with small market value and low idiosyncratic volatility. Therefore, their transactions are inactive, and the marginal impact of investor attention on their liquidity is more intense. The authors conclude that trading activities significantly affect liquidity when investors pay close attention to these cryptocurrencies.

Furthermore, the persistent negative implications on the liquidity of the five digital assets two weeks after each heist represent another research contribution. Yue et al. (2021) apply four liquidity measures to the largest 100 cryptocurrencies. They report that negative news announcements harmed liquidity only for four days, while we observe such negative implications for longer periods.

We can conclude that overall market quality deteriorated because of the heists, evident by the higher liquidity measure values. Therefore, such crypto heists could negatively impact cryptocurrency market participants and travel and tourism users.

The implications of the cryptocurrency heists on the general stock market

Table 1 presents the current list of publicly listed and non-listed travel and tourism companies that use cryptocurrency or tourism tokens as payment methods. We investigate the impact of stock prices of these six publicly listed travel and tourism companies (*Airbnb*, *AXA*, *Despegar*.com, *Expedia Group*, *Norwegian Air*, and *Webjet*) during cryptocurrency heists. Due to the suspension of trading in the stock market during weekends and holidays, while the cryptocurrency market operates 24/7, the data range used here differs from the range used to analyse the spillover effects between mainstream cryptocurrencies and tourism tokens. However, both data sets cover the period before and after the cryptocurrency heists. Table 8 shows the range of data we used for each heist.

Table 9 shows the cryptocurrencies and stocks in each heist that pass the AutoRegressive Conditional Heteroskedasticity test and can be used to build the Dynamic Conditional Correlation - Generalised AutoRegressive Conditional Heteroskedasticity model. Since neither Bitcoin nor Ethereum passes the test in the *Ronin Network* heist, we do not build any model under this heist. The results of Table 9 show that the α value (dcca1) and β value (dccb1) are not simultaneously significant in all token-stock pairs, indicating no significant spillover effects between Bitcoin, Ethereum and stock prices during the five heists. We also collect index data at the same data range from the Dow Jones Travel & Tourism Index and NASDAQ Composite Index to avoid sample selection bias. Similarly, the results of Table 10 show that Bitcoin, Ethereum, and the traditional travel and tourism market have no significant spillover effects. Therefore, the heists do not directly influence traditional travel and tourism companies' stock prices and business operations.

The stock prices and business performance are more influenced by internal factors within the traditional economy and industry, with limited correlation to cryptocurrency market events.

We also investigate the performance of non-listed companies listed in Table 1 during the heists. The only available financial data we could obtain is from *Travala.com*, the largest travel booking platform currently using tourism tokens. They utilise the Travala token as their travel token, allowing travellers worldwide to book flights, hotels, and other travel products with discounts and loyalty rewards. Table 11 presents *Travala.com*'s financial data. The fluctuations in monthly revenue indicate the impact of cryptocurrency heists on the company's performance. For instance, the *PancakeBunny* exchange heist in late May resulted in a mere 5.42 % growth in revenue, significantly lower than the 20.19 % growth in May. The *Bitmart* exchange heist in early December caused a 34.53 % revenue decline in the same month. Similarly, the *Ronin Network* heist in late March led to a 14.64 % drop in revenue for April. The *Binance* and *FTX* exchange heists in early October and November resulted in revenue declines of 2.85 % and 23.09 % for those months. Thus, we observe that cryptocurrency heist impacts the performance of travel and tourism companies that utilise tourism tokens as payment methods.

In conclusion, the impact of cryptocurrency heists on the traditional travel and tourism market appears relatively limited. Still, it has a more significant effect on companies that primarily use tourism tokens as payment methods. This could be attributed to companies utilising tourism tokens being generally smaller in scale and mostly privately owned, resulting in their relatively limited influence on the overall travel and tourism market.

However, with an increasing number of companies adopting and utilising tourism tokens and the corresponding growth in their market value, the impact of cryptocurrency heists on the travel and tourism market may become more pronounced. As tourism tokens gain widespread adoption and their market size expands, these companies may become more attractive potential targets for attacks. In the event of a heist, investors may become more concerned about the security and reliability of tourism tokens, leading to heightened stock price fluctuations and panic trading. While the current cryptocurrency heists may have a limited impact on the overall travel and tourism market, we still need to continue monitoring the cryptocurrency market's security and volatility to ensure the stable development of emerging areas like tourism tokens. Additionally, understanding the interaction between the cryptocurrency market and the traditional travel industry is vital for fostering the synergistic growth of both innovative applications in the travel and tourism sectors.

These findings align with Yousaf et al. (2022), who suggest that there might be a certain isolation level between the traditional travel and tourism sectors and the cryptocurrency market. A recent large-scale report by the European Systemic Risk Board published in May 2023 demonstrates that the cryptocurrency market has few interlinkages with the traditional financial sector and the real economy. None of those links are currently significant. However, the report concludes that cryptocurrency's interconnectedness with the conventional financial markets may increase over time, especially when traditional finance implements most blockchain technologies.

As an urgently needed regulatory measure, the report indicates the requirement to closely monitor potential interconnectedness between the cryptocurrency market and traditional financial markets and within the crypto industry.

Robustness checks

We filter the original dataset into Bitcoin individual decline price changes, Ethereum individual decline price changes and collective decline price changes that occur concurrently in multiple cryptocurrencies and tourism tokens.

We identify the collective price changes as events occurring in no less than two cryptocurrencies and tourism tokens. We apply the divided datasets to the liquidity models presented in Eqs. (5), (6), (7) and (8).

Table 12 reveals ten Bitcoin individual decline price changes, twelve Ethereum individual decline price changes and twenty-one collective decline price changes, implying that the virtual assets negatively affected in each crypto heist mimic the behaviour of each other. This very high decline in price changes in the five digital assets could describe the frequency of collective decline in price changes occurring in the crypto heists.

Furthermore, we observe different market quality values in individual and collective price declines. The *Roll's spread, Zeros1, Zeros2 and the Amihud illiquidity measure* values are higher during the Bitcoin and Ethereum individual decline price changes, indicating higher transaction costs for market participants. For instance, the *Roll's_spread* is higher for the Bitcoin and Ethereum individual decline price changes than collective decline price changes (0.473, 0.495 and 0.226, respectively). We report similar findings for the other three market quality measures – *Zeros1*, *Zeros2 and the Amihud illiquidity measure*.

Overall, our robustness checks confirm our initial observations that herding behaviour with Bitcoin and Ethereum drives the behaviour of the three tourism tokens in each crypto heist, resulting in diminished market quality.

Policy implications

Cryptocurrencies and virtual tokens have gained traction in tourism-focused countries, prompting various governmental initiatives (Kwok & Koh, 2019; Rashideh, 2020). As early as 2014, destinations like Bangkok and Pattaya in Thailand began accepting Bitcoin, driven by prevalent credit card and ATM frauds (Irannezhad & Mahadevan, 2021). The Bahamas and seven Eastern Caribbean Union nations introduced the Sand Dollar and Dcash cryptocurrencies in 2020. Meanwhile, nations like Mexico, Jamaica, India, Nigeria, Sweden, China, the US, the UK, and the Eurozone are exploring or developing their digital currencies. Notably, El Salvador emerged as the first Latin American country to legalise Bitcoin and envision a Bitcoin city. Countries like Australia, Japan, and Switzerland have also recognised cryptocurrencies as legal tender (www.complyadvantage.com).

Our empirical findings suggest that the spillover effect in the mainstream cryptocurrency market and the tourism token market could raise concerns among investors about the security of tourism tokens based on Bitcoin or Ethereum chains, leading to panic trading and affecting the price fluctuations of mainstream cryptocurrencies and tourism tokens. We also observe that overall market quality deteriorated because of the heists, resulting in real-life negative implications for cryptocurrency market participants and travel and tourism users. Therefore, we suggest governments worldwide develop stricter regulatory measures on cryptocurrency crime detection and reporting by requiring cryptocurrency exchanges to implement advanced scam and hacker attack detection tools mainly related to Bitcoin and Ethereum.

To bolster the stability of cryptocurrency and tourism token markets and boost investor confidence, we also suggest AI-driven tools, notably focused on the primary cryptocurrencies, Bitcoin and Ethereum. These tools, called 'Bitcointracker' and

'Ethereumtracker', would monitor key cryptocurrency wallets and transaction flows, tracing the origins and destinations of potential scam proceeds. By observing transactions, regulators can gain insights into fund flows, track assets post-heist, and preemptively address systemic risks arising from market spillovers. Recent research by Xu et al. (2021) indicates growing interconnectedness among cryptocurrencies, with Ethereum emerging as a prime systemic risk emitter. To counteract this, tools like 'Bitcointracker' and 'Ethereumtracker' can monitor the activities of crypto 'whales', entities holding significant amounts of cryptocurrency. Typically, ownership of 10 % of a specific cryptocurrency marks one as a 'whale' (Whitfield, 2023). Observing these major players' trading patterns can shed light on market influences and allow regulators to foresee systemic risks. Tracking these 'whales' can also hint at which tokens major participants are trading, holding, or mining. Our proposed regulatory approach aims to stabilise the tourism token market, reinforcing investor trust and promoting growth in the travel and tourism sectors.

To sum up, these measures primarily aim to ensure cryptocurrency market stability, which in turn would safeguard related markets like tourism tokens, thus fortifying the overall integrity of the tourism and travel sectors. However, a primary hurdle to the proposed regulatory measures is the unresolved classification of cryptocurrencies in the U.S. market: Are they currencies, commodities, or securities? This distinction matters since different financial instruments follow distinct trading rules. Should cryptocurrencies be considered securities, they'd fall under the Securities and Exchange Commission's purview. Conversely, the Commodity Futures Trading Commission would oversee their regulation if viewed as currencies or commodities. Additionally, excessive regulation risks undermining cryptocurrency's decentralised foundation and stymying its innovative progress.

Conclusions

Although blockchain technology and the broader adaptation of cryptocurrencies dramatically transformed the travel and tourism sectors, their use also increased the risk of financial fraud and hacker attacks. This is the first empirical study examining the implications of hacker cyber-attacks on travel and tourism. We obtain daily data of the leading two cryptocurrencies and three tourism tokens to investigate the implications of history's most famous five heists on the travel and tourism sectors.

Our results reveal statistically significant spillover effects between Bitcoin, Ethereum and the three tourism tokens in the four months following each of the five crypto heists. This implies a spillover effect in the mainstream cryptocurrency, the tourism token market. In real-life trading, this could raise concerns among market participants about the security of tourism tokens based on Bitcoin or Ethereum chains, leading to panic trading activity and affecting the price fluctuations of mainstream cryptocurrencies and tourism tokens. Furthermore, we observe that Bitcoin, Ethereum and the three tourism tokens experience herding behaviour when the prices of the digital instruments are declining. Our empirical findings also suggest that Bitcoin and Ethereum drive the behaviour of the three tourism tokens.

We conduct a market quality examination by deploying several liquidity measures. We observe wider spreads and higher levels of illiquidity, indicating higher transaction costs and less liquid digital assets for market participants in the two weeks following each heist, which is likely to lead to lower certainty of trading order execution. We also observe that the smaller tokens are characterised by greater liquidity fluctuations than the two major cryptocurrencies during each heist. We conclude that overall market quality deteriorated because of the heists, evident by the higher liquidity measure values.

We also demonstrate that the impact of cryptocurrency heists on the traditional travel and tourism market appears relatively limited but still has a more significant effect on companies that primarily use tourism tokens as payment methods.

We propose appropriate regulatory tools based on our empirical findings to mitigate the negative implications for cryptocurrency market participants. Using the proposed 'Bitcointracker' and 'Ethereumtracker' for tracking major crypto wallets and 'whales' can help regulators identify suspicious activity, such as potential hacks and scams and help mitigate systemic risk caused by spillovers in cryptocurrency markets.

One potential limitation of our study is the linear nature of our empirical models. Future research on the topic could eventually involve using more sophisticated machine learning and artificial intelligence models. Such models require significant computational power and precise calibration but could be especially useful in crypto heist detection and reporting. For example, appropriate artificial intelligence models can prevent hackers and crypto scammers from transferring stolen assets and funds to suspected virtual wallets.

CRediT authorship contribution statement

Viktor Manahov: Conceptualization, Methodology, Writing - Original draft preparation, Validation, Reviewing and Editing.
Mingnan Li: Data curation, Software, Investigation, Methodology, Reviewing and Editing.

Data availability

Data will be made available on request.

Declaration of competing interest

None.

Appendix A

Table 1
Travel and tourism companies using cryptocurrencies and tourism tokens.

	Company name	Used tokens/crypto platform
Non-listed company	Air Baltic	Bitcoin, Ethereum, Binance coin, Dogecoin
	Ariva World	Ariva
	Berkley Travel	Bitcoin
	CheapAir	Bitcoin, Ethereum, Bitcoin Cash
	Destinia	Bitcoin, Bitcoin Cash
	Emirates Airlines	Bitcoin
	GetYourGuide	Bitcoin, Ethereum, Litecoin, Dogecoin
	Guider.travel	Guider
	LockTrip	Ethereum, LockTrip
	LOT Polish Airlines	Bitcoin
	Northern Pacific Airways	Flycoin
	One Shot Hotels	Bitcoin
	TamTam Travels	Bitcoin, Ethereum
	Touriscoin.com	Bitcoin, Ethereum
	Travala.com	Bitcoin, Ethereum, Travala token
	Trippki	Tripcoin
	Winding Tree	Winding Tree
	XcelTrip	Bitcoin, Ethereum, XcelToken Plus
Listed company	Airbnb	Book with Bitcoin via Fold App
	AXA	Bitcoin
	Despegar.com	Book with cryptocurrency via Binance Pay
	Expedia Group	Bitcoin
	Norwegian Air	Bitcoin
	Webjet	Bitcoin
Government & international organisations	Agistri island, Greece	NautilusCoin
	The German National Tourist Board	Bitcoin
	World Tourism Forum Institute	TourismX Token

Table 2
Description of some of the biggest hacker cyber-attacks in history.

Platform	Date	Amount	Tokens	Description
Ronin network	29 March 2022	$620 million	Ethereum	Ronin Network, supporting the Axie Infinity game, suffered the largest crypto heist of nearly $620.5 million due to compromised validator nodes. The US Treasury Department attributed the theft to North Korea's Lazarus group.
Binance	7 October 2022	$570 million	Binance coin	Hackers stole 2 billion Binance coin from the Binance Smart Chain Bridge, but Binance acted quickly and most of the Binance coin were frozen, resulting in an actual loss of $110 million in Binance coin.
FTX	11 November 2022	$477 million	Bitcoin	FTX cryptocurrency exchange was hacked and lost funds, leading to a bankruptcy filing. The exchange moved the remaining funds to cold storage to prevent further unauthorised transactions.
PancakeBunny	20 May 2021	$200 million	Pancake Bunny token, Binance coin	Hackers used flash loans of Binance coin to manipulate its price and acquire substantial Pancake Bunny token. After selling all the Pancake Bunny token, causing a price drop, they repaid the Binance coin via PancakeSwap.
Bitmart	4 December 2021	$196 million	Binance coin	Hackers accessed employee accounts to steal private keys, leading to the theft of two Bitmart hot wallets on the Ethereum and Binance Smart Chain blockchains.

Table 3
The data range for five cryptocurrency heists.

Heist	Data range
PancakeBunny	1 May 2021 to 31 August 2021
Bitmart	1 December 2021 to 31 March 2022
Ronin Network	1 March 2022 to 30 June 2022
Binance	1 October 2022 to 31 January 2023
FTX	1 November 2022 to 28 February 2023

Table 4
Augmented Dickey-Fuller test of return for Bitcoin, Ethereum, Travala token, Guider and Kemacoin.

Heist	Bitcoin	Ethereum	Travala token	Guider	Kemacoin
PancakeBunny	– 4.9562***	– 5.3252***	– 5.7716***	– 5.6558***	– 6.5639***
Bitmart	– 5.6863***	– 5.0921***	– 4.9155***	– 6.5721***	– 8.9665***
Ronin network	– 4.4294***	– 4.535***	– 4.7268***	– 5.4981***	– 8.3336***
Binance	– 5.1786***	– 5.2673***	– 6.0522***	– 4.9426***	– 8.9196***
FTX	– 5.0242***	– 5.7098***	– 5.9494***	– 5.4291***	– 8.3709***

*** indicates significance at the 1 % level.

Table 5
Statistical properties of volatility spillover effect in the five cryptocurrency heists.

Heist incident	Token-Token	Parameter	Estimate	Std. error	t-Value	***P_r*** (>|***t***|)
PancakeBunny	Bitcoin - Ethereum	dcca1	0.146849	0.053739	2.732628	0.006283
		dccb1	0.761955	0.078690	9.683028	0.000000
	Ethereum - Travala token	dcca1	0.105867	0.050810	2.083570	0.037199
		dccb1	0.822971	0.053406	15.409730	0.000000
Bitmart	Ethereum - Guider	dcca1	0.120546	0.034217	25.053136	0.000427
		dccb1	0.874280	0.034897	25.053136	0.000000
Ronin Network	Ethereum - Travala token	dcca1	0.068981	0.033022	2.089000	0.036712
		dccb1	0.856763	0.042217	20.294100	0.000000
	Ethereum - Kemacoin	dcca1	0.063004	0.021121	2.983000	0.002854
		dccb1	0.901038	0.031118	28.955300	0.000000
Binance	Bitcoin - Kemacoin	dcca1	0.204934	0.098348	2.083750	0.037183
		dccb1	0.480362	0.162593	2.954380	0.003133
FTX	Bitcoin - Kemacoin	dcca1	0.232754	0.103979	2.238500	0.025190
		dccb1	0.477507	0.220678	2.163800	0.030478

Table 6
The *Cross-Sectional-Absolute-Deviation*$_{CM,t}$ and Cross-Sectional-Absolute-Deviation$_{TT,t}$ regression results for the five crypto heists.

	PancakeBunny	Bitmart	Ronin Network	Binance	FTX
Panel A					
λ_0	0.0036***	0.0328**	0.0042***	0.0014***	0.0038***
	(0.0012)	(0.0014)	(0.0136)	(0.0028)	(0.0044)
$R_{CM,t}$	0.0087**	0.0714**	0.0338**	0.0404**	0.0801**
	(0.0110)	(0.0029)	(0.0451)	(0.0499)	(0.0335)
$R^2_{CM,t}$	– 0.2038***	– 0.4348***	– 0.2005***	– 0.0662***	– 0.0883***
	(0.1105)	(0.1140)	(0.1092)	(0.0622)	(0.1144)
$(1-Dummy)R_{CM,t}$	0.2884***	0.5288***	0.0103***	0.5244***	0.3037***
	(0.0059)	(0.0136)	(0.0052)	(0.0106)	(0.0386)
$DummyR_{CM,t}$	– 0.3278***	– 0.4549***	– 0.4714***	– 0.0258***	– 0.0104***
	(0.0142)	(0.0188)	(0.0018)	(0.0046)	(0.0049)
$(1-Dummy)R^2_{CM,t}$	0.4060**	0.9014**	0.3246***	0.9921	0.7746**
	(0.5367)	(0.9002)	(0.1173)	(0.9247)	(0.3212)
$DummyR^2_{CM,t}$	– 0.7039***	– 0.7144***	– 0.4408***	– 0.0233***	– 0.0106***
	(0.1033)	(0.0313)	(0.0715)	(0.0341)	(0.2233)
$AdjR^2$	0.84	0.82	0.83	0.83	0.82
Panel B					
λ_0	0.5002**	0.4991**	0.3216**	0.0446**	0.0457**
	(0.0010)	(0.0161)	(0.0442)	(0.0333)	(0.0389)
$(1-Dummy)R_{TT,t}$	0.6477**	0.1863***	0.0261***	0.0212***	0.0882***
	(0.3992)	(0.0074)	(0.3011)	(0.0089)	(0.0117)
$DummyR_{TT,t}$	– 0.0093***	– 0.0326***	– 0.0019***	– 0.0019***	– 0.0019***
	(0.0028)	(0.0258)	(0.0228)	(0.0277)	(0.0020)
$(1-Dummy)R^2_{TT,t}$	3.104	0.0316**	0.0403**	0.0028**	0.0073**
	(0.8993)	(0.3203)	(0.0277)	(0.4133)	(0.0022)
$DummyR^2_{TT,t}$	0.8102	0.2783**	0.03173**	0.4002**	0.8992
	(0.9650)	(0.1152)	(0.0425)	(0.0515)	(0.9134)
$CSAD_{BE,t}$	0.0077***	0.0033***	0.0035***	0.0017***	0.0035***
	(0.0152)	(0.0009)	(0.0024)	(0.0133)	(0.0024)
$AdjR^2$	0.83	0.81	0.84	0.83	0.83

***indicates significance at the 1 % level; **indicates significance at the 5 % level.

Table 7
Cryptocurrency market quality measures two weeks before and after each crypto heist.

Heist	Token	Roll's spread (before)	Roll's spread (after)	Zeros1 (before)	Zeros1 (after)	Zeros2 (before)	Zeros2 (after)	Amihud illiquidity (before)	Amihud illiquidity (after)
PancakeBunny	Bitcoin	0.416	0.489	0.513	0.571	0.624	0.675	0.763	0.815
	Ethereum	0.483	0.527	0.574	0.618	0.636	0.692	0.801	0.846
	Travala token	0.399	0.430	0.422	0.480	0.418	0.493	0.633	0.692
	Guider	0.285	0.372	0.360	0.395	0.367	0.428	0.552	0.613
	Kemacoin	0.266	0.304	0.305	0.367	0.323	0.395	0.447	0.516
Bitmart	Bitcoin	0.479	0.521	0.588	0.619	0.638	0.684	0.826	0.893
	Ethereum	0.512	0.586	0.636	0.682	0.671	0.703	0.880	0.928
	Travala token	0.411	0.477	0.413	0.487	0.420	0.488	0.721	0.779
	Guider	0.309	0.419	0.370	0.399	0.404	0.449	0.528	0.570
	Kemacoin	0.298	0.334	0.308	0.327	0.399	0.432	0.480	0.522
Ronin Network	Bitcoin	0.488	0.515	0.499	0.551	0.546	0.598	0.699	0.729
	Ethereum	0.497	0.536	0.516	0.593	0.603	0.668	0.773	0.815
	Travala token	0.410	0.468	0.387	0.421	0.437	0.496	0.585	0.663
	Guider	0.353	0.394	0.289	0.326	0.388	0.415	0.443	0.497
	Kemacoin	0.276	0.343	0.274	0.311	0.324	0.383	0.402	0.486
Binance	Bitcoin	0.512	0.608	0.605	0.685	0.644	0.705	0.727	0.798
	Ethereum	0.486	0.534	0.618	0.683	0.696	0.722	0.802	0.845
	Travala token	0.402	0.489	0.412	0.477	0.424	0.490	0.566	0.621
	Guider	0.367	0.399	0.310	0.365	0.305	0.369	0.479	0.551
	Kemacoin	0.233	0.295	0.296	0.334	0.281	0.314	0.323	0.412
FTX	Bitcoin	0.478	0.516	0.476	0.528	0.527	0.588	0.656	0.703
	Ethereum	0.493	0.537	0.520	0.577	0.540	0.607	0.711	0.780
	Travala token	0.327	0.394	0.429	0.493	0.367	0.398	0.488	0.536
	Guider	0.288	0.321	0.367	0.402	0.282	0.336	0.377	0.410
	Kemacoin	0.254	0.291	0.282	0.313	0.247	0.315	0.295	0.344

Table 8
The data range for five cryptocurrency heists.

Heist	Data range
PancakeBunny	3 May 2021 to 23 September 2021
Bitmart	1 December 2021 to 26 April 2022
Ronin Network	1 March 2022 to 25 July 2022
Binance	3 October 2022 to 27 February 2023
FTX	1 November 2022 to 28 March 2023

Table 9
Volatility spillover results between Bitcoin, Ethereum, and tourism stocks.

Heist	Token-Stock	Parameter	Estimate	Std. error	t-Value	$P_r(>\|t\|)$
PancakeBunny	Bitcoin - Despegar.com	dcca1	0.0176	0.0544	0.3235	0.7463
		dccb1	0.7383	0.1456	5.0721	0.0000
	Bitcoin - Expedia Group	dcca1	0.0330	0.0454	0.7264	0.4676
		dccb1	0.7253	0.1479	4.9041	0.0000
	Bitcoin - Norwegian Air	dcca1	0.0202	0.0641	0.3153	0.7526
		dccb1	0.9495	0.0308	30.8156	0.0000
	Ethereum - Despegar.com	dcca1	0.0000	0.0000	0.0014	0.9989
		dccb1	0.9247	0.0791	11.6908	0.0000
	Ethereum - Expedia Group	dcca1	0.0000	0.0000	0.0494	0.9606
		dccb1	0.8981	0.1371	6.5516	0.0000
Bitmart	Bitcoin - Airbnb	dcca1	0.0000	0.0000	0.0256	0.9796
		dccb1	0.9668	0.1857	5.2072	0.0000
	Bitcoin - Despegar.com	dcca1	0.0000	0.0002	0.0002	0.9998
		dccb1	0.9286	0.6131	1.5145	0.1299

(continued on next page)

Table 9 *(continued)*

Heist	Token-Stock	Parameter	Estimate	Std. error	t-Value	$P_r(>\|t\|)$
	Bitcoin - Expedia Group	dcca1	0.0000	0.0000	0.1229	0.9022
		dccb1	0.9288	0.3172	2.9278	0.0034
	Ethereum - Airbnb	dcca1	0.0000	0.0000	0.0021	0.9984
		dccb1	0.9236	0.1910	4.8359	0.0000
	Ethereum - AXA	dcca1	0.0063	0.0369	0.1713	0.8640
		dccb1	0.8708	0.0528	16.5077	0.0000
	Ethereum - Despegar.com	dcca1	0.0000	0.0000	0.0011	0.9991
		dccb1	0.9212	0.1486	6.2001	0.0000
	Ethereum - Expedia Group	dcca1	0.0000	0.0028	0.0000	1.0000
		dccb1	0.9364	2.2658	0.4133	0.6794
	Ethereum - Norwegian Air	dcca1	0.0000	0.0000	0.0003	0.9997
		dccb1	0.9284	0.2343	3.9625	0.0001
Binance	Bitcoin - Airbnb	dcca1	0.0000	0.0000	0.0016	0.9987
		dccb1	0.9261	0.1279	7.2414	0.0000
	Bitcoin - Expedia Group	dcca1	0.0371	0.0708	0.5234	0.6007
		dccb1	0.7405	0.2420	3.0604	0.0022
	Ethereum - Airbnb	dcca1	0.0000	0.0000	0.0015	0.9988
		dccb1	0.9183	0.3129	2.9344	0.0033
	Ethereum - Expedia Group	dcca1	0.0000	0.0001	0.0022	0.9983
		dccb1	0.9187	0.4413	2.0817	0.0374
FTX	Bitcoin - AXA	dcca1	0.0000	0.0000	0.0011	0.9991
		dccb1	0.9244	0.1586	5.8293	0.0000
	Ethereum - AXA	dcca1	0.0000	0.0000	0.0006	0.9995
		dccb1	0.9265	0.3112	2.9776	0.0029

Table 10
Volatility spillover results between Bitcoin, Ethereum, and stock indices.

Heist	Token-Index	Parameter	Estimate	Std. error	t-Value	$P_r(>\|t\|)$
PancakeBunny	Bitcoin - NASDAQ Composite Index	dcca1	0.0000	0.0000	0.0257	0.9795
		dccb1	0.9110	0.0810	11.2410	0.0000
	Bitcoin - Dow Jones U.S. Travel & Tourism	dcca1	0.0000	0.0000	0.0003	0.9998
		dccb1	0.9172	0.0792	11.5816	0.0000
	Ethereum - NASDAQ Composite Index	dcca1	0.0000	0.0002	0.0002	0.9998
		dccb1	0.9344	0.5241	1.7828	0.0746
	Ethereum - Dow Jones U.S. Travel & Tourism	dcca1	0.0000	0.0000	0.0049	0.9961
		dccb1	0.9234	0.0929	9.9352	0.0000
Bitmart	Bitcoin - NASDAQ Composite Index	dcca1	0.0533	0.0501	1.0653	0.2867
		dccb1	0.6611	0.1552	4.2606	0.0000
	Bitcoin - Dow Jones U.S. Travel & Tourism	dcca1	0.0000	0.0002	0.0005	0.9996
		dccb1	0.9397	0.9143	1.0279	0.3040
	Ethereum - NASDAQ Composite Index	dcca1	0.0000	0.0000	0.0111	0.9911
		dccb1	0.9165	0.1056	8.6774	0.0000
	Ethereum - Dow Jones U.S. Travel & Tourism	dcca1	0.0000	0.0000	0.0093	0.9925
		dccb1	0.9241	0.0891	10.3710	0.0000
Binance	Bitcoin - Dow Jones U.S. Travel & Tourism	dcca1	0.0000	0.0000	0.0292	0.9767
		dccb1	0.9197	0.0969	9.4896	0.0000
	Ethereum - Dow Jones U.S. Travel & Tourism	dcca1	0.0000	0.1233	0.0000	1.0000
		dccb1	0.9045	4.5020	0.2009	0.8408
FTX	Bitcoin - NASDAQ Composite Index	dcca1	0.0000	0.0011	0.0001	0.9999
		dccb1	0.9355	1.5860	0.5899	0.5553
	Ethereum - NASDAQ Composite Index	dcca1	0.0000	0.0053	0.0000	1.0000
		dccb1	0.9371	4.3183	0.2170	0.8282

Table 11
Travala.com's financial data before and after the heist.

Month	Revenue ($)	Change of revenue
Apr-21	2,832,389	
May-21	3,404,245	20.19 %
Jun-21	3,588,647	5.42 %
Nov-21	7,214,627	32.09 %
Dec-21	4,723,556	−34.53 %
Mar-22	7,356,003	46.87 %
Apr-22	6,278,867	−14.64 %
Oct-22	5,387,429	−2.85 %
Nov-22	4,143,703	−23.09 %

Source: https://www.travala.com/blog/category/reports/monthly-reports/.

Table 12
Bitcoin individual decline price changes, Ethereum individual decline price changes and collective decline price changes in the whole dataset during the five crypto heists.

	Bitcoin individual decline price changes		Ethereum individual decline price changes		Collective decline price changes	
	Mean	Std. dev	Mean	Std. dev	Mean	Std. dev
Number of DPCs	10		12		21	
Roll's_spread	0.473	0.390	0.495	0.414	0.226	0.113
Zeros1	0.551	0.536	0.580	0.720	0.304	0.199
Zeros2	0.607	0.304	0.672	0.633	0.416	0.286
Amihud_illiquidity	0.825	0.098	0.856	0.138	0.627	0.095

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