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Are Crypto Assets Connected to Real World Shocks? The Nexus Between Terrorist Attacks, Bitcoin and NFTs*

Kripto Varlıklar Gerçek Dünya Şokları ile Ilişkili mi? Terörist Saldırıları, Bitcoin ve NFT'ler Arasındaki Bağlantı

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ABSTRACT
This study investigates the impact of terrorist attacks on the price fluctuations of Bitcoin prices and NFT sales. Although the value proposition of cryptocurrencies, Decentralized Finance, and the whole blockchain revolution is a quicker, cheaper, and more transparent kind of finance, various terrorist organizations tend to use cryptocurrency anonymously to finance their terrorist activities around the world by bypassing the banking system of the regulated countries. The analyses reveal that returns of Bitcoin and NFT markets are positively associated with the organization and funding phases of the terrorist attacks but negatively associated with the post-terrorist attack circumstances, meaning that it generates positive abnormal returns (AR) prior to the attack but creates negative AR right after the attack. Furthermore, while the Bitcoin news impact curve (NIC) is nearly symmetric, the NFT NIC is asymmetric, with positive shocks having significantly more impact on future volatility than negative shocks of the same magnitude. Since previous studies claim that terrorist attack news is good news for Bitcoin returns, we will enrich our AR analysis results with NICs results.

Keywords: Cryptocurrencies, Terror Attacks, Returns, Volatility, Event Study, News Impact Curves
Jel Classification: C22, G15, D81

ÖZ
Bu çalışmada, terörist saldırılarının Bitcoin fiyatlarındaki ve Değiştirilemez Jeton (NFT) satışlarındaki fiyat dalgalanmalarına etkisi araştırılmaktadır. Kripto paraların temel değer önermesi, Merkezi Olmayan Finans (DeFi) ve blokzincir teknolojisi daha hızlı, daha ucuz ve daha şeffaf bir finansal sistem için devrim niteliğinde gelişmelerdir. Buna karşın birçok terör örgütü, dünyanın dört bir yanındaki terörist faaliyetlerini finanse etmek için gelişmiş ülke ekonomilerinin güçlü bir şekilde regüle edilmiş konvansiyonel bankacılık sistemlerini kripto paraların anonim özelliğini kullanarak suistimal etme eğilimindedir. Makalemizdeki analizler, Bitcoin ve NFT piyasalarının getirilerinin terör saldırılarının organizasyon ve finansman aşamaları ile pozitif olarak ilişkili olduğunu, ancak terör sonrası

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oluşan koşullar ile negatif ilişkili olduğunu, yani saldırıdan önce pozitif anormal getiriler (AG) ürettiğini ancak saldırı sonrasında negatif anormal getiriler (AG) ürettiğini göstermektedir. Ek olarak Bitcoin haber etki eğrisi (HEE) neredeyse simetrik iken, NFT HEE'leri asimetriktir ve pozitif şokların oynaklık üzerindeki etkisi aynı büyüklükteki negatif şoklardan önemli ölçüde daha fazladır. Önceki çalışmalar terörist saldırı haberlerinin Bitcoin getirileri için iyi haber olduğunu savunduğu üzere, AG analiz sonuçlarının HEE sonuçlarıyla birleştirilmesi araştırmacılara daha sağlıklı sonuçlar sunacaktır.

Anahtar Kelimeler: Kripto paralar, Terör saldırıları, Getiri, Oynaklık, Olay çalışması, Haber etki eğrileri
Jel Sınıflaması: C22, G15, D81

1. Introduction

Cryptocurrency markets experienced numerous crashes and rallies in the last three years compared to the last three decades of traditional financial markets. In such a volatile environment, it is still a phenomenon whether Bitcoin is a new inflation hedge investment, a safe haven, digital gold, or digital money. Through Bitcoin having a dual nature as an investment tool and digital money and/or payment tool, it has become a significant source of interest not only for investors but also for policymakers and academicians. According to a report by Goldman Sachs[1], crypto assets and blockchain rapidly evolved from their infancy. We can briefly describe the process of its development in four major stages:

1. Blockchain 1.0 (2008–13):

- Satoshi Nakamoto created the idea of blockchain in Bitcoin in a white paper entitled "Bitcoin: A Peer-to-Peer Electronic Cash System."
- The industry assessed cryptocurrency through blockchain as the pure technology infrastructure.

2. Blockchain 2.0 (2013–17):

- Ethereum was introduced with smart contract technology.
- In the financial services industry, the blockchain expanded significantly.

3. Blockchain 3.0 (2017–20):

- Starting in 2017, the transition to Blockchain 3.0 was experienced via an Initial Coin Offering (ICO) boom.
- Beyond the financial sector, the industry explored the commercial potential of blockchain technology.
- Numerous blockchain platforms were established.
- Business models evolved from Business-to-Business (B2B) to Business-to-Consumer (B2C).

4. Blockchain 4.0 (2020 onwards):

- New blockchain applications such as non-fungible tokens (NFTs), play-to-earn games, and the metaverse emerged.
- Governments begin to assess nationwide adaptations of cryptocurrency.

[1] Overview of Digital Assets and Blockchain Goldman Sachs (Asia) L.L.C. Investment Banking Division, November 2021

NFTs emerged following Bitcoin and other crypto assets, especially after the COVID-19 outbreak. However, Bitcoin and NFTs vary in function and structure: Bitcoin is a payment and exchange tool, while NFTs are assets. Glaser et al. (2014) classify Bitcoin as a currency and indicate that most Bitcoin users tend to hold it for speculation rather than to use it as a payment tool. Yermack (2015) and Ciaian, Rajcaniova and d'A Kancs (2016) claim that Bitcoin cannot satisfy three functions of a currency: a medium of exchange, a store of value, and a unit of account. What determines the exchange rate of a virtual currency then? Bolt and van Oordt (2020) argue for three main determinants: the current use of digital money to make actual payments, investors' decision to buy virtual currency soon, and the items that induce consumer adoption and merchant acceptance of digital money.

Due to its stability, gold is mainly accepted as a safe haven by investors in financial markets or politics in the face of rising fluctuations or risks. However, the limited supply and production of Bitcoin by non-governmental organizations make gold and Bitcoin (so-called digital gold) similar, where portfolio managers prefer gold to hedge against stocks. Although Bitcoin can be classified as an investment, it differs from gold because it has unexampled risk-return traits that do not correlate with other assets (Baur, Dimpfl and Kuck, 2018). Recently, Bitcoin prices dropped more than 50 percent over a six-month period. This market-wide downturn wiped over $1.5 trillion from the crypto market, which would have triggered global turmoil if it had happened in conventional financial markets. Bitcoin has not fallen this far since the start of 2021, meaning if the sell-off continues, it may be stuck in an uncharted range.

Before they are permitted to deal with financial transactions via regulated financial products, market players are usually obliged to register their identities. Although Blockchain technologies promote anonymity with a weak, flexible central authority oversight, these aspects are the main characteristics that attract the attention of illegal entities, such as money launderers, drug lords, and terrorists, who seek prompt and unidentifiable financing channels. Supporting Gandal et al.'s (2018) findings on the Mt. Gox Bitcoin currency exchange, our study assumes that suspicious trading activity can cause Bitcoin price fluctuations.

The lack of oversight leads the cryptocurrency market to roam freely, with evidence of price manipulation and speculation, and become an unidentifiable exploitable venue for illegal funding. Due to its anonymous nature, Foley, Karlsen and Putnins (2018) contend that cryptocurrencies lure illegal activities such as weapons trading, drug dealing, funding terrorist attacks, or even hiring killers. For instance, from 2009 to 2017, Foley et al. (2018) find that 26% of all users and 46% of Bitcoin operations were in some way connected with illegal activity. Although their research contemplates the nature of the transactions, it does not provide context for the purpose of these transactions.

This study seeks to determine the impact of major terrorist attacks on Bitcoin and NFT markets by investigating the price of Bitcoin and NFTs before and after terrorist actions. In order to grasp the sole effect of terrorist actions, we only include a limited number of terrorist attacks that are globally significant events. As such, we explore previously unknown effects of terrorist attacks on Bitcoin and NFT markets as well as the wider market. Although the rise of an ecosystem of various financial services, namely decentralized finance (DeFi), is expected to allocate power to individuals, not to concentrate it, money laundering utilizes the gray zone of services nested between the conventional banking system and Ethereum. The value proposition of cryptocurrencies, DeFi, and the whole blockchain revolution is a quicker, cheaper, and more transparent kind of finance, even though dirty money finds its way through the system and there is extensive energy use in mining operations. The future of this technical architecture and ideology challenge is uncertain, yet it still claims to transform how money works.

Bitcoin and NFT data used in this study are drawn from investing.com and nonfungible.com, while terrorist attack data are from the Global Terrorism Database. In our study, we will utilize two concepts, the Event Study approach and News Impact Curves, and combine our results in the conclusion section. Since the nature of crypto assets is complicated, even within only digital assets classes, and is influenced by various information sources and technical inputs, analyzing the hypothesis with more than one approach leads us to more coherent outputs and analyses.

Following the previous line of work, we employ abnormal returns (AR) of markets on the dates of the terrorist events (e.g., Chen and Siems, 2004; Richman, Santos and Barkoulas, 2005; Barros and Gil-Alana, 2009; Ramiah, Martin and Moosa, 2013; Ramiah, 2012; Graham and Ramiah, 2012; Ramiah and Graham, 2013; Cam and Ramiah, 2014; Ramiah et al., 2019; Aslam and Kang, 2015; Apergis and Apergis, 2016; Veron et al., 2017; Almaqableh et al., 2022). This article offers an unexplored area in the literature by linking the AR of Bitcoin and NFT markets to a global list of selected terrorist attacks. The CAPM models for Bitcoin and NFTs utilized in AR analysis will be embedded in the EGARCH approach, and News Impact Curves (NICs) based on these models will be analyzed to understand the impact of news and volatility structures of Bitcoin and NFTs.

The analyses reveal that Bitcoin and NFT returns are positively associated with the organization and funding phases of the terrorist attacks and negatively associated with the post-terrorist attack circumstances, meaning that Bitcoin and NFT generate positive ARs prior to the attack but create negative ARs right after the attack. Furthermore, Bitcoin NIC is nearly symmetric, though positive shocks slightly affect the future volatility more than negative shocks of the same magnitude. Nevertheless, NFT NIC is asymmetric, with positive shocks having significantly more effect on future volatility than negative shocks of the same magnitude. Since previous works claim that terrorist attack news is good news for Bitcoin returns, we will enrich our AR analysis with the results from NICs. Amiram, Jørgensen and Rabetti (2022) also merge different approaches in their recent paper, concluding that fund trails have predictive power in out of sample analysis. Due to the limitations of the methods, the paper incorporates forensic accounting techniques and machine learning algorithms.

The following sections review the literature of Bitcoin and NFTs' positioning in mainly financial markets and the relationship between terrorist attacks and these crypto instruments. This study's methods and data are then presented, followed by the empirical findings and concluding remarks.

2. Literature

2.1. History of Bitcoin and NFT Markets

With the introduction of the Nakamoto (2008) whitepaper, Bitcoin grabbed the attention of investors by being a digital currency with a Peer-to-Peer (P2P) electronic payment system. Since then, as the foundation behind Bitcoin, Blockchain has been the common element of all cryptocurrency systems (Nofer, Gomber and Hinz, 2017). The P2P system eliminates the double spending problem by allowing online payments from one party to another without the need for any trusted third parties (Van Alstyne, 2014).

An NFT is a form of cryptographic financial security that cannot be replicated and essentially consists of digital data stored in a blockchain. The authenticity of ownership of an NFT is recorded in the blockchain, and the digital asset's ownership can be transferred, allowing the token to be traded. So Bitcoin and NFTs differ in function and structure; while Bitcoin is a payment and exchange tool, NFTs are assets. With regard to this, while cryptocurrencies are fungible, NFTs are uniquely identifiable digital files that are non-fungible. NFTs typically contain digital files of photos, videos, and audio, and the market value of that NFT is determined by the digital file it references.

The NFT market has grown dramatically with the COVID-19 pandemic and increased attention to digital financial currencies. While the trading of NFTs raised 94.9 million US Dollars in 2020, 2021 witnessed an immense increase, with 24.9 billion US Dollars' worth of trade (Howcroft, 2022). Since there is no limitation, regulation, or control over NFT trades, NFTs can easily be used for speculative investments. NFTs can also be used for transferring funds, but lack the absolute anonymity of Bitcoin.

2.2. The Value of Bitcoin

The existing literature on the financial impact of the cryptocurrency market is in an earlier phase, with little empirical research. Li and Wang (2017) find that the Bitcoin exchange rate is more related to economic fundamentals, such as Gross Domestic Product and inflation, and less to technological factors. Hayes (2017) reaches a different determinant of cryptocurrency value: “Bitcoins’ value is derived from its cost of production” (p. 1309). From the behavioral finance point of view, Poyser (2018) indicates that herding theory has a significant role in determining the prices of cryptocurrencies. Furthermore, Rotta and Parana (2022) claim that Bitcoin is not money but a digital commodity with value but no value-added.

2.3. Terrorism and Its Effect on Markets

The financial effects of terrorism have been well studied in the preexisting research, with a broad focus on equity markets. Eldor, Hauser, Kroll and Shoukair (2012) used a unique dataset and econometric models to examine the effect of terrorism on the financial markets of both sides of the barricade in the Israeli-Palestinian conflict. One of their most important outcomes was that the share prices on the Israeli side declined significantly due to terror attacks, specifically by 0.43%.

Most of the studies reveal that equity markets are in some way affected by terrorist attacks (see Chen and Siems, 2004; Richman et al., 2005; Barros and Gil-Alana, 2009; Ramiah et al., 2013; Ramiah, 2012; Graham and Ramiah, 2012; Ramiah and Graham, 2013; Cam and Ramiah, 2014; Aslam and Kang, 2015; Apergis and Apergis, 2016; Veron et al., 2017; Almaqableh et al., 2022). As one of the most shocking terrorist attacks, the September 11 terrorist attack had the most significant effect on the financial markets. Terrorist attacks continue to affect the domestic markets of the attack locations. The literature has yet to develop research on terrorist attacks’ effects on cryptocurrency markets.

Ahmad et al. (2022) examine the impact of terrorism on stock market returns through an extensive dataset of 23 countries from 2001 to 2017. According to their study, assaults in the capital city and the severity of attacks negatively influence the index returns. Also, targeting specific locations with strategic advantages, these assaults have a higher effect on the stock market returns. Almaqableh et al. (2022) explore the impact of 21 terrorist attacks on the returns of 100 cryptocurrencies. They find that terrorist attacks positively contribute to cryptocurrency returns, becoming good news for cryptocurrency. Moreover, Lo et al. (2022) examine the impact of the Russo-Ukrainian war on financial markets, based on a country’s dependence on Russian commodities and employing a large panel of 73 countries, concluding that the effect of the war on commodity returns was significant for countries with a dependence beyond the 0–20% level.

The anonymity aspect of Bitcoin and other cryptocurrencies allows sponsors of terrorist groups to donate assets without being recognized. Some terrorist groups have started using virtual assets like Bitcoin to move funds. As Tupman and Harvey (2009) note, several terrorist groups obtain funding through donations. For instance, one far-right organization in South Africa has created its stablecoin that operates on a one-to-one ratio with the local currency, in which sponsors can donate without being identified (FATF, 2021). Another evidence of donation was revealed through the financial investigation of the Christchurch Mosque shooter who carried out the terror attack in New Zealand in 2019. The investigation uncovered that the perpetrator had made multiple donations to extreme right-wing entities overseas (FATF, 2021). Likewise, Irwin and Milad (2016) find strong evidence linking several terror attacks in Europe and Indonesia to the use of Bitcoins and other cryptocurrencies. For instance, from 2009 to 2017, nearly one-quarter of all users and one-half of Bitcoin operations were related to illicit activity. As a result, our main focus is exploring the extent of funding terrorist activities using Bitcoin and NFTs and the effects of attacks on market returns.

3. Methodology

We will use two different approaches (Event Study and News Impact Curves) to understand the complex relationship between Bitcoin, NFTs, and terrorist attacks. First, we fill a gap in the literature by linking AR of Bitcoin and NFT markets to a global list of selected terrorist attacks. Secondly, the CAPM models for Bitcoin and NFTs utilized in AR analysis will be embedded in the EGARCH approach, and NICs based on these models will be analyzed to understand the impact of news and volatility structures of Bitcoin and NFTs. Our main goal is to link ARs of Bitcoin and NFTs with terrorist attacks, and the news impact on the volatility structure of Bitcoin and NFTs.[2]

a. Event Study

The event study methodology focuses on detecting ARs of assets from a particular event. If investors react favorably to an event, in our case a terrorist attack, it is expected that we would detect positive ARs close to the event data. In contrast, if investors react unfavorably to an event, it is expected that negative ARs would be detected. As discussed later, the efficient markets hypothesis (Fama et al., 1969) is the essence of the event-study methodology. According to this hypothesis, investors consider and assess new information's current and future impact whenever it is salient.

[2] The internet bubble of 2000 was an expensive experience for the markets that put technologies/assets in a position synonymous with volatility. In this context, the market's main question is whether 2022's crypto winter is a reboot of the same movie with a new generation of actors.

The daily return of cryptocurrencies ($Ret_{i,t}$) for each of *i = 1, 2, 3...N* through *t = 1, 2, 3... T* days is formulated as:

$Ret_{i,t} = Ln\frac{P_{i,t}}{P_{i,t-1}}$ where $Ret_{i,t}$ is the cryptocurrency's return i for date t. $P_{i,t}$ is taken as the closing price for cryptocurrency i for day t.

For each i = 1, 2, 3... N assets through t = 1, 2, 3... T days the ARs are formulated as: $AR_{i,t} = Ret_{i,t}$ and $E(R_{i,t})$ is cryptocurrency i's daily expected return.

The famous Capital Asset Pricing Model (CAPM) leads the calculation for cryptocurrency i's the daily expected return at time t in the following way:

$$E(R_{i,t}) = \beta_{0\,i,t} + \beta_{1i,t}\,(r_{m,t} - r_{f,t}) + \varepsilon_{i,t} \qquad [1.1]$$

b. News Impact Curves

A crucial issue with a standard GARCH model is that it is mandatory to ensure that all of the estimate coefficients are positive, however, the EGARCH model allows for the asymmetric effect of the news. In this context, Nelson (1991) proposed a specification in which non-negativity constraints are not required.

Let's define the natural logarithm of in the following equation:

$$\ln(h_t) = \alpha_0 + \alpha_1\left(\frac{\varepsilon_{t-1}}{h_{t-1}^{0.5}}\right) + \lambda_1 \left| \frac{\varepsilon_{t-1}}{h_{t-1}^{0.5}} \right| + \beta_1 \ln(h_{t-1}) \qquad [1.2]$$

Equation (1.2) refers to the exponential-GARCH (EGARCH) model. Three essential items about the EGARCH model are noted below:

1. Conditional variance in the equation is in log-linear structure. The implied value of h_t cannot be smaller than zero regardless of its magnitude. Hence, it allowed for the coefficients to be negative. This specification eases the non-negativity constraint of GARCH models.

2. The EGARCH model utilizes the level of standardized value of ε_{t-1}^2 [i.e., ε_{t-1}^2 divided by $(h_{t-1})^{0.5}$] instead of the value of ε_{t-1}^2. Nelson (1991) claims that this standardization enables a more natural interpretation of the shocks' size and persistence. Consequently, the standardized value of ε_{t-1}^2 is a unit-free measure.

3. According to the model results, if $\varepsilon_{t-1}^2/(h_{t-1})^{0.5}$ is bigger than zero, the effect of the shock on the log of conditional variance is $\alpha_1+\lambda_1$. If $\varepsilon_{t-1}^2/(h_{t-1})^{0.5}$ is smaller than zero, the effect of the shock on the log of the conditional variance is $-\alpha_1+\lambda_1$. In this

context, the EGARCH model provides us with the leverage effects to detect the asymmetric relationship of the volatility structure.

Most financial decisions rely on the trade-offs between future risks and asset returns, which is the essence of Markowitz's portfolio theory. Correlations of financial assets and volatility are the two factors that constitute a risk. New information is distributed to all financial markets for all asset classes due to the frequently changing economy. Considering the high volatility of cryptocurrencies and crypto assets, frequent market crashes, and the impact of COVID-19, such regime switches or market structure changes are more expected.

The news impact curve driven by EGARCH models exponentially increases in both directions with different parameters. The curve also has its minimum at $\varepsilon_{t-1}=0$.

The conditional variances equation for the related model helps us construct the NICs. The given coefficient estimates and the lagged conditional variance set to the unconditional variance are also the outputs of the same process.

Let us assume the EGARCH (1,1) model as the following:

$$\ln(h_t) = \alpha_0 + \beta \ln(h_{t-1}) + \alpha_1 z_{t-1} + \gamma(|z_{t-1}|) - E(|z_{t-1}|) \tag{1.3}$$

where . The news impact curve is

$$h_t = \begin{cases} A exp\left[\frac{\alpha_1+\gamma}{\sqrt{h_t}}\right] & for\ \varepsilon_{t-1} > 0 \\ A exp\left[\frac{\alpha_1-\gamma}{\sqrt{h_t}}\right] & for\ \varepsilon_{t-1} < 0 \end{cases} \tag{1.4}$$

$$A \equiv h_t^{\beta} exp\left[\alpha_0 - \gamma\sqrt{2/\pi}\right] \tag{1.5}$$

$$\alpha_1 < 0 \qquad \alpha_1 + \gamma > 0 \tag{1.6}$$

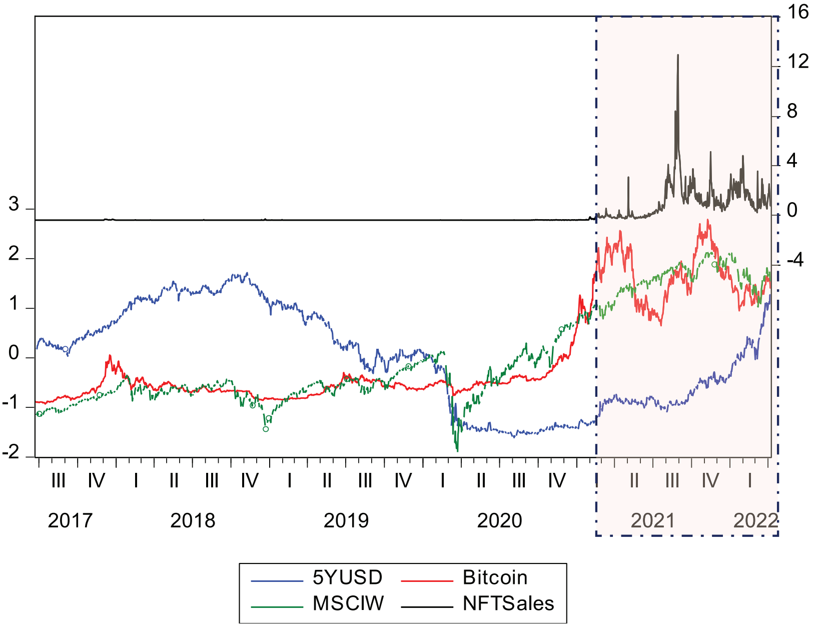
According to the existing finance literature, the impact of "bad" news is more persistent on volatility changes than "good" news, an essential asset price aspect. For example, most stocks are negatively correlated from a risk (volatility) and return aspect. In this context, volatility tends to decrease when returns increase and vice versa, thereby identifying the leverage effect.

4. Data

We use daily data for the study's main five variables: 5 years US bonds (*5YUSD*) as a proxy for the risk-free rate, bitcoin prices (*Bitcoin*), the MSCI AC World Index (*MSCIW*) as a proxy for the global market, price of gold per ounce (*Gold*), and second market non-fungible tokens sales data (*NFT*). The original data covers 21 June 2017 to 07 April 2022. Hence, to differentiate the impact of COVID-19, which is an intense period for news impact on all financial assets, we reduced the dataset from 21 June 2017 to 31 December 2019 and performed EGARCH models for two different periods. Event study results also depend on the period for 21 June 2017 to 31 December 2019. Our data on a short time frame of 30 months is attractive and cohesive for several reasons. First, even though cryptocurrencies were traded prior to June 2017, the public data were relatively sporadic in their availability. Second, we do not hold regional limitations and instead have a global outreach regarding terrorist events. Lastly, we have eliminated the effect of the COVID-19 pandemic by censoring our time frame from the end of 2019 onwards. All the financial data are from Investing.com, and NFT data is from nonfungible.com. Since Bitcoin and NFT markets do not close, the daily price is the last price of a day, where times align with a UTC zone.

Figure 1 exhibits the normalized graphs of the level prices of the variables. The NFT move (indicated as the black line), in particular, shows that after the second half of 2021, NFT markets experienced an outperforming jump compared to Bitcoin.

Figure 1: Normalized Graphs of All Variables



Next, the return of each market is calculated as follows:

$ln(P_t) - ln(P_{t-1})$

where R5YUSD, RBitcoin, RMSCIW, RGold, and RNFTs refer to the return series of 5 years US bonds (*5YUSD*), Bitcoin prices (*Bitcoin*), the MSCI AC World Index (*MSCIW*), price of gold per ounce (*Gold*), and non-fungible tokens sales data (*NFT*), respectively. This is exhibited in Figure 2.

Figure 2: Daily Returns of Data Set

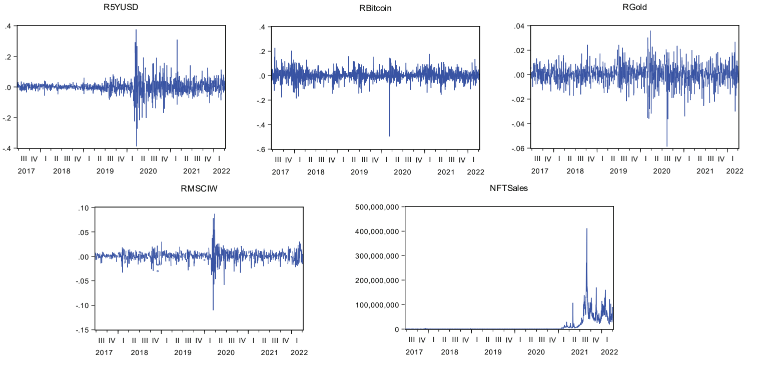


Table 1 presents the descriptive statistics for the returns. For all the return series, the mean values are close to zero. In addition, the Jarque-Bera statistic of all return series is significantly different from zero, which spoils the normality. Further, we ensured that all the series are stationary via Augmented Dickey-Fuller (ADF) unit root test results.

Table 1: Descriptive Statistics

	R5YUSD	RBITCOIN	RGOLD	RMSCIW	RNFTSALES
Mean	0.000444	0.003091	0.000480	0.000503	0.010628
Median	0.001110	0.002716	0.000910	0.001440	-0.012750
Maximum	0.308637	0.263831	0.072362	0.077931	4.169862
Minimum	-0.389525	-0.497278	-0.062552	-0.110182	-4.635.257
Std. Dev.	0.049182	0.057394	0.010082	0.012631	0.620714
Skewness	-0.612586	-0.599094	-0.212838	-0.990580	0.073142
Kurtosis	12.82714	11.39665	8.704205	15.09310	12.35272
Jarque-Bera	3730.888	2736.694	1244.691	5712.642	3328.445
Probability	0.000000	0.000000	0.000000	0.000000	0.000000
Observations	913	913	913	913	913

We collected terrorist attack data from the Global Terrorism Database (START, 2021) to include terrorist attacks as a proxy in our analysis. Terrorist events with more than 100 deaths are considered major terrorist attacks that could potentially affect the Bitcoin and NFT markets. This event selection method differs from Almaqableh et al. (2022), who chose events based on a global agreement on what is regarded as a terrorist attack and one that the global news had reported as a terrorist attack. Our selection method is not based on relative perceptions of terrorist attacks and therefore is not limited to any geographical area or subjective prioritizations.

Table 2 exhibits the major terrorist events that are included. Our dataset includes 14 major terrorist events from 21 June 2017 to 31 December 2019; five of the events occurred in the Sub-Saharan Africa region, five in South Asia, and four in the Middle East and North Africa. Some of the terrorist organizations in our sample are the Taliban, with four occurrences, Boko Haram with three events, and the Islamic State of Iraq and the Levant (ISIL) with two events. The deadliest terrorist attack is by Al-Shabaab, with 588 deaths in October 2017 in Mogadishu, Somalia. Earlier attacks are omitted from the dataset because cryptocurrency and NFT data are unavailable.

Table 2: Major Terrorist Attacks

#	Year	Month	Day	Country	Region	City	Attack Type	Name	#Kill
1	2017	9	28	Syria	Middle East & North Africa (MENA)	Qaryatayn	Bombing/Explosion	Islamic State of Iraq and the Levant (ISIL)	153
2	2017	10	2	Syria	MENA	Qaryatayn	Hostage Taking (Kidnapping)	ISIL	128
3	2017	10	14	Somalia	Sub-Saharan Africa (SSA)	Mogadishu	Bombing/Explosion	Al-Shabaab	588
4	2017	11	24	Egypt	MENA	Al-Rawda	Bombing/Explosion	Sinai Province of the Islamic State	311
5	2018	1	27	Afghanistan	South Asia (SA)	Kabul	Bombing/Explosion	Taliban	104
6	2018	5	15	Afghanistan	SA	Farah	Bombing/Explosion	Taliban	330
7	2018	7	13	Pakistan	SA	Darengarh	Bombing/Explosion	Khorasan Chapter of the Islamic State	150
8	2018	8	10	Afghanistan	SA	Ghazni	Bombing/Explosion	Taliban	466
9	2018	11	19	Nigeria	SSA	Mitile	Armed Assault	Boko Haram	118
10	2018	12	16	Democratic Republic of the Congo	SSA	Bongende	Hostage Taking (Kidnapping)	Tribesmen	339
11	2019	1	21	Afghanistan	SA	Maydan Shahr district	Bombing/Explosion	Taliban	129
12	2019	6	9	Cameroon	SSA	Darak	Armed Assault	Boko Haram	101
13	2019	8	25	Yemen	MENA	Kitaf wa al-Boqee district	Hostage Taking (Kidnapping)	Houthi extremists (Ansar Allah)	200
14	2019	12	10	Niger	SSA	Inates	Armed Assault	Boko Haram	128

The hypotheses for the effects of terrorist attacks on Bitcoin and NFT returns are as follows:

Hypothesis 1: Bitcoin and NFT returns are expected to increase prior to the terrorist attacks.

Hypothesis 2: Bitcoin and NFT returns are expected to decrease following the terrorist attacks.

We assume that the return of a cryptocurrency or NFT is a direct function of the demand and supply of these payment tools and assets. Sponsors of the terrorist attacks will transfer the funds to the terrorist groups to organize a terrorist attack, increasing the demand for cryptocurrency right before the attack. Although NFTs are assets, they could also be a vehicle for transferring necessary funds to terrorist organizations. Therefore, we expect higher returns for Bitcoin and NFTs prior to the terrorist attacks. However, as a relatively stable payment system compared to the NFTs, we expect terrorist attacks to affect Bitcoin more than NFTs.

Regarding Hypothesis 2, after terrorist attacks have been executed, supporters of terrorist attacks will decrease their funding to terrorist organizations. In addition, NFTs will receive a harder blow than Bitcoin in the case of an unclear market environment.

The efficient market hypothesis contends that asset prices reflect available new information. By extending this hypothesis to unregulated markets such as Bitcoin and NFTs, we will check the validity of the efficient market hypothesis with terrorist attacks as the new information. Terrorist attacks take time to organize, plan, and finance; the required time ranges from years to weeks prior to the event. Since there is no consensus on an approximate amount of time required to plan an attack, we measure ARs for 361 days as 180 days before and after the attack, within varying time windows.

The choice of 180 days before and after the event is not based on any theoretical assumptions. We rely on the *t*-test to determine the statistical significance of ARs in specified windows. Some of the included terrorist attacks in our dataset are chronologically close; for example, in 2017, two ISIL attacks in Syria were only three days apart. This closeness of time could distort the cumulative ARs for some events. In spite of this, ARs would significantly present the effect if a terrorist event indeed affected the prices.

5. Empirical Results

Table 3 shows the effects of the 14 terrorist attacks on Bitcoin, NFT, gold, and oil markets. As expected, 30 days prior to the attack reflects a statistically significant positive association with the market returns of Bitcoin. On the other hand, ten days after the terrorist attack undergoes a negative turn in market returns. Both findings significantly support Hypotheses 1 and 2.

Overall, NFT market returns are positively associated with terrorist attacks. The results for prior to the attack and 90 to 180 days post-attack generate statistically significant positive cumulative ARs, while immediate post-attack returns indicate a negative association. These findings also support our expectations in Hypotheses 1 and 2. However, NFTs are overall more affected than Bitcoin by terrorist attacks. Following our previous argument that NFTs would receive a harder blow in the post-attack environment, the effects indeed reveal an almost 11% drop in NFT prices, while Bitcoin prices drop only by 1%.

15 to 60 days prior to the terrorist attacks reveal a minor but positive association with

gold market returns. Immediate post-attack gold market returns reflect a significant positive association. Although oil market returns are overall negatively associated with terrorist attacks, the immediate post-attack days estimation window shows a relatively higher association.

The general conclusion of Table 3 is that Bitcoin and NFT markets returns are positively associated with the organization and funding phases of the terrorist attacks and negatively associated with the post-terrorist attack circumstances, meaning that it generates positive ARs prior to the attack but creates negative ARs right after the attack. Despite this fluctuation in the pre- and post-attack environments, both prices resume their regular forms for the other window frames.

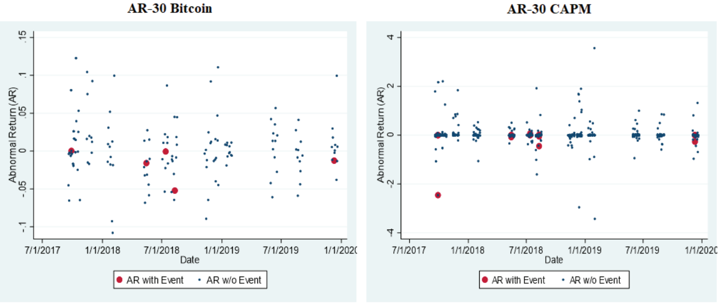
One explanation for the positive AR of Bitcoin and NFT prices prior to the terrorist attacks is related to the illegal funding through the purchasing of Bitcoin and NFTs of the terrorist organizations by their sponsors to organize and prepare for the terrorist attack. The negative cumulative AR observed following the terrorist attacks may indicate that the sponsors stop funding the terrorist organizations.

Table 3: Reaction of Bitcoin, NFT, Gold and Oil to Terrorist Attacks

CARS	Bitcoin		NFT		Gold		Oil	
	%	t-stat	%	t-stat	%	t-stat	%	t-stat
-180	-.11	-1.47	8.66	4.70	.01	1.35	-.34	-10.08
-120	-.16	-2.07	8.66	4.70	.02	1.84	-.31	-9.21
-90	-.12	-1.61	10.59	5.75	.00	.05	-.22	-6.56
-60	-.02	-.25	9.61	5.22	.05	4.35	-.22	-6.43
-30	.40	5.13	12.51	6.79	.05	4.75	-.17	-5.22
-15	.98	12.46	5.52	3.00	.05	4.50	-.26	-7.93
-10	.52	6.59	11.33	6.15	-.00	-.06	-.03	-1.17
-5	.62	7.81	6.54	3.54	.00	.64	-.28	-8.39
0	-	-	-	-	-	-	-	-
5	.43	5.55	-3.97	-2.15	.07	5.67	-.08	-2.51
10	-.45	-5.73	-5.16	-2.80	.02	1.91	-.05	-1.50
15	-1.42	-18.01	-12.27	-6.66	.00	.55	-.27	-8.19
30	-.63	-8.01	-2.05	-1.11	.01	.79	-.31	-9.20
60	-.62	-7.93	1.08	.58	-.00	.18	-.31	-9.26
90	-.43	-5.43	5.66	3.07	-.00	.63	-.31	-9.15
120	-.35	-4.47	7.37	3.99	.02	1.69	-.26	-7.76
180	-.31	-3.98	7.05	3.83	.01	1.04	-.27	-8.16

To clarify our findings, Figure 3 shows the ARs of Bitcoin and CAPM of 30 days prior to the terrorist attack. Overall, the ARs of events show a scattered but relatively positive pattern, indicating expected positive ARs.

Figure 3: 30 Days Abnormal Returns for Bitcoin only and CAPM



According to [1.1], we established two models to analyze the volatility asymmetry for Bitcoin and NFT returns, as exhibited in Table 4.

Table 4: EGARCH Models for Bitcoin and NFTs

Model 1: Bitcoin			Model 2: NFTs		
Variable	Coefficient	z-Statistic	Variable	Coefficient	z-Statistic
R5YUSD	1,2404	16,624	R5YUSD	0,0492	3,145
RP	1,2809	14,327	RP	0,8914	1,036
C	0,0013	0,768	C	0,9984	1,026
α_0	-0,5233	-6,1539	α_0	-0,5798	-11,5037
$\lambda 1$	0,1867	8,3755	$\lambda 1$	0,5068	9,8995
$\alpha 1$	0,0083	0,6382	$\alpha 1$	0,1679	4,5434
$\beta 1$	0,9327	7,3671	$\beta 1$	0,8355	45,2089
R^2	0,007		R^2	-0,004	
DW	2,088		DW	2,681	

In Figure 4, the Bitcoin NIC is nearly symmetric; however, positive shocks have slightly more impact on future volatility than negative shocks of the same magnitude. Nevertheless, the NFT NIC is asymmetric, with positive shocks having significantly more impact on future volatility than negative shocks of the same magnitude. Moreover, the response of NFT returns to volatility shocks is significantly slower than Bitcoin returns. In Figure 4, we performed EGARCH models from 21 June 2017 to 31 December 2019 to be consistent with global terrorist attacks event data and to analyze the impact of the COVID-19 pandemic separately from the terrorist attacks.

Figure 4: News Impact Curves for Bitcoin (Model 1) and NFTs (Model 2)-All Period

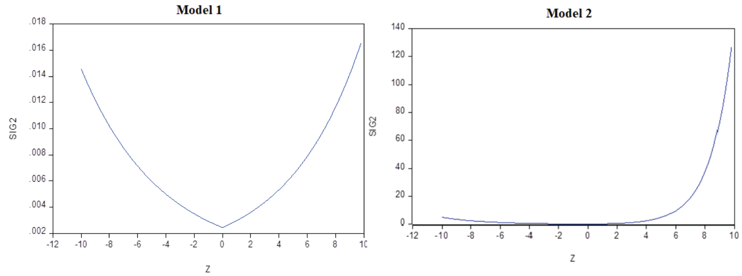
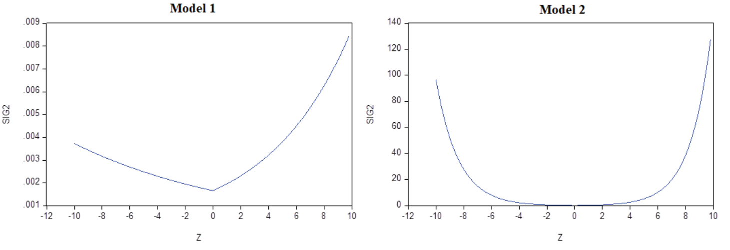


Table 5 presents the COVID -19 excluded models (for the period of 21 June 2017 to 31 December 2019), and Figure 4 shows the NICs based on these EGARCH models. Table 5 shows that before the COVID-19 period, both Bitcoin and NFT returns lose their connection with conventional markets, since the coefficients of return equation parameters are not statistically significant. In Figure 5, we also see that the structure of NICs for both Bitcoin and NFTs changes. While the symmetric structure of Bitcoin in Figure 4 changes to a more asymmetric shape in favor of good news, the asymmetric structure of NFTs evolves into a more symmetric shape, yet still having a dominant impact of good news.

Table 5: EGARCH Models for Bitcoin and NFTs (before COVID-19)

Model 1: Bitcoin			Model 2: NFTs		
Variable	Coefficient	z-Statistic	Variable	Coefficient	z-Statistic
R5YUSD	0,3725	1,385	R5YUSD	-3,9729	-1,106
RP	0,4101	1,489	RP	-5,0675	-1,288
C	0,0002	0,111	C	0,0404	1,676
α_0	-0,6350	-2,9011	α_0	-0,7873	-7,7356
λ1	0,1177	3,2064	λ1	0,6404	8,7177
α1	0,0414	2,3237	α1	0,0206	0,3461
β1	0,9120	29,2244	β1	0,6915	12,4816
R^2	0,005		R^2	0,003	
DW	1,970		DW	2,457	

Figure 5: News Impact Curves for Bitcoin (Model 1) and NFTs (Model 2)-Shorter Period



6. Conclusion

The study is the first to investigate the relationship between terror attacks and returns of Bitcoin and NFTs by conjointly applying news impact and event study approaches. Highly news-driven markets like crypto assets are subject to volatility turmoil and return crashes. The biggest price drivers in crypto are Bitcoin, Ethereum, and crypto dollars, representing about 70% of the total crypto market cap. Nonetheless, NFTs have been around since 2014, and they are becoming an increasingly popular way to buy and sell digital artwork. In this context, our analysis focuses on Bitcoin and NFTs. Even if cryptocurrency is threatened by most of the regulatory bodies of developed economies, central banks worldwide are trying to launch their cryptocurrencies as part of the digitization of the financial system. The digital revolution of finance has emerged rapidly despite the crypto market crashes, illegal usage accusations, and carbon emission issues due to high energy consumption for mining.

According to our results, Bitcoin and NFT markets returns are positively associated with the organization and funding phases of terrorist attacks and negatively associated with the post-terrorist attack circumstances, meaning that it generates positive ARs prior to the attack but creates negative ARs right after the attack. Furthermore, Bitcoin NIC is nearly symmetric, while NFT NIC is asymmetric, with positive shocks having significantly more impact on future volatility than negative shocks of the same magnitude.

Recent work has shown the scale of criminal penetration of the cryptocurrency market. The findings of this paper may help investors and portfolio managers understand the effect of terrorist attacks on Bitcoin and NFT returns and news impact on volatility to hedge their portfolio positions. These concerns are shared by global regulators and financial watchdogs, who explore cryptocurrencies as volatile and speculative. Many are concerned about criminal activities such as money laundering and terrorism financing being facilitated by digital assets. This study can be enriched by adding drug bust data to terrorist attacks in future research.

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