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Cybercrime on the Ethereum Blockchain*

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Abstract

We examine how cybercrime impacts victims' risk-taking and returns. The results from our difference-in-differences analysis of a sample of victim and matched non-victim investors on the Ethereum blockchain are in line with prospect theory and suggests that victims increase their long-term total risk-taking after losing part of their wealth, leading to lower risk-adjusted returns in the post-cybercrime period. Victims' long-term total risk-taking increases because they increase diversifiable risk due to victims' post-cybercrime withdrawal from altcoins. At the same time, the reduction in risk-adjusted returns correlates with increased trading activity and churn, due plausibly to managing cybercrime exposure. In the cross-section of Ethereum addresses, we show that the most affluent victims take a systematic approach to restore their pre-cybercrime wealth level, while the least affluent victims turn into gamblers. Finally, a parsimonious forensic model explains a good part of the addresses' probability of being involved in cybercrime, on both the victim and the cybercriminal side.

Keywords: Ethereum blockchain, market manipulation, financial fraud, token investment scam, cybercrime, cryptocurrency
JEL Codes: G14, G24, G30, L26, M13, O16

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1 Introduction

Public attention to the price of Bitcoin and the increasing popularity of token-funded startups have attracted investors to crypto markets, yet the new opportunities also come with significant risks. In addition to classic blockchain scams, in which fraudsters exchange tokens for cash and then disappear with the money, there is also cybercrime such as online shopping fraud in which cryptocurrencies are used as a means of payment. Together, these crypto-related scams have been on the rise, with $1 out of every $4 reported lost to fraud between 2021 and 2022 being stolen in cryptocurrency (Federal Trade Commission, 2022).[1] While many recent studies have focused on the type and severity of illegal activities through cryptocurrency (e.g., pump-and-dump schemes in Hamrick et al., 2018; Gandal et al., 2018; Li et al., 2021b; Dhawan and Putniņš, 2023); Drobetz et al., 2024; token-based Ponzi schemes in Securities and Exchange Commission, 2013; Bartoletti et al., 2020; moral hazard in signaling ICO venture quality in Momtaz, 2021b; general vulnerabilities in smart contracts as a source of cyberattacks in Kalra et al., 2018; Luu et al., 2016; Dhanani and Hausman, 2022; Harvey et al., 2021; cybercrimes linked to terrorist activities in Amiram et al., 2022; Cong et al., 2022; Karapapas et al., 2020; and various other types of fraud associated with cryptocurrencies in Hornuf et al., 2022; Trozze et al., 2022), relatively little is known about how investors react to such fraud in the crypto market. Understanding this question is important from a regulatory standpoint for investor protection. Moreover, as more traditional financial institutions are providing services on public blockchains, on-chain fraud can spill over to traditional financial markets (Cumming et al., 2025b).[2] The granularity of address-level transaction data from the Ethereum blockchain provides an interesting experimental setting to track and test investor responses to various types of cybercrime, which can shed light beyond the crypto sphere.

In this study, we investigate whether and how the experience of crypto-related cybercrime affects investor risk-taking and returns. The investor response to fraud is not obvious ex ante. While prospect theory suggests investors may take more risks to recover losses (Kahneman and

[1] Foley et al. (2019) document that 26% of all Bitcoin users and 46% of Bitcoin transactions are related to illegal activity. Makarov and Schoar (2021) report a smaller figure of 3%, and this difference is driven by including exchange-related volume and different classifications of participants.

[2] For example, private equity firm KKR tokenized part of its $4 billion Health Care Strategic Growth Fund II to the Avalanche blockchain, which allowed retail investors to engage in the fund. See https://www.forbes.com/sites/michaeldelcastillo/2022/09/24/kkr-blockchain-access-to-4-billion-fund-opens-door-to-crypto-investors/?sh=555c3ef84fce (retrieved July 25, 2023).

Tversky, 1979; Thaler and Johnson, 1990), losses due to fraud can also erode trust, potentially making investors more risk-averse, divesting from riskier assets (Giannetti and Wang, 2016; Gurun et al., 2018). Thus, the impact of cybercrime on investors' behavior remains uncertain.

Our study is among the first to explore primary blockchain data from Ethereum to study investors' responses to on-chain market misconduct and fraud. To test our research question, we implemented a pre- versus post-cybercrime comparison of victim addresses and matched non-victim addresses with the instant at which a cybercrime became public knowledge as the event date.

Methodologically, this involves three preparatory steps. First, for the purpose of identifying cybercrimes on Ethereum as such, we rely on crowd-reported incidents of alleged scams on *Etherscan*, cooperating with market experts from *ScamAlert* to validate reported scams. Although we verified with external experts each individual cybercrime, we did not always have the exact date on which a cybercrime was publicly identified. Thus, to determine the precise event timing of when a cybercrime became public knowledge, we manually researched social media for the first mention of a certain activity being a scam. Second, given the high dimensionality and imbalance of our primary ledger data, we implemented a Euclidean distance approach to pair victim addresses with matching non-victim/non-cybercriminal addresses to ensure that our difference-in-differences approach correctly identifies average treatment effects. Third, for each address on the Ethereum blockchain, we estimated Liu et al.'s (2022) three-factor crypto-asset pricing model in order to characterize victim and matching non-victim addresses by risk-taking levels and risk-adjusted returns (i.e., alphas).

We find that victims' *raw* returns (i.e., non-risk-adjusted returns) increase after a cybercrime. We follow Barber and Odean (2000) in measuring gross monthly raw returns as the change in address-level token prices at the end of the month relative to the beginning-of-month prices for all tokens held at the beginning of the month. By implication, Barber and Odean (2000) monthly raw returns only account for the *behavioral* effect of cybercrime on returns, not for the misappropriated funds due to the cybercrime *per se*.

Although victims' raw returns *increase* after a cybercrime, their risk-adjusted returns *decrease* statistically and economically significantly. We regress address-level alphas from Liu et al.'s (2022) three-factor crypto-asset pricing model in a difference-in-differences model and find highly significant marginal effects, suggesting that victims' alphas respond significantly negatively to cybercrime. In terms of economic magnitude, we find that victims' risk-adjusted returns in the post-cybercrime

period decreased by 55.2 to 96.4% relative to matched non-victims. Therefore, while cybercrime victims' raw returns respond positively to cybercrime, their risk-adjusted returns respond negatively, indicating that victims may increase their risk-taking levels after being scammed.

Consistent with our conjecture that the discrepancy between positive raw and negative risk-adjusted returns for cybercrime victims can be explained by higher post-cybercrime risk-taking, we confirm that total risk-taking increases in the long term. The average treatment effect of cybercrime on victims' total risk-taking twelve months after the event is in the 5.7 to 8.1 percentage-point range. It should be noted, however, that cybercrime victims' total risk-taking level reduces in the short term (i.e., three to six months after the cybercrime), increases in the medium term (i.e., six to twelve months after the cybercrime), and then remains permanently at a level that is higher than the initial risk-taking level in the long term (i.e., after twelve months). This result is consistent with recent literature showing that investor behavior, such as risk appetite, can change over time and that the level of risk—such as the level of risk of falling victim to cybercrime—is itself a determinant of such changes (Dicle, 2019).

Further, we conduct a risk decomposition and split total address-level risk-taking into diversifiable and non-diversifiable risk-taking levels per address. Interestingly, we find that the post-cybercrime response of victims in terms of *total* risk-taking is mostly driven by changes in their *diversifiable* risk-taking, both in terms of economic magnitude and the time structure of the treatment effects (i.e., lower risk-taking in the short term and higher risk-taking in the long term). As for non-diversifiable risk-taking, we report average treatment effects of cybercrime that constantly decrease in the post-cybercrime period, reaching a permanent level that is between 0.8% and 4.6% lower than the initial pre-cybercrime level after twelve months. Taken together, the negative average treatment effect of cybercrime on victims' risk-adjusted returns is driven by increased diversifiable risk-taking, while non-diversifiable risk-taking reduces.

We also examine the heterogeneous responses of victims to different cybercrime categories. Post-cybercrime blockchain address-level risk-adjusted returns and risk-taking critically depend on the type of cybercrime a victim fell for. Fake token scams, darkweb activity, and sextortion have a positive effect on victims' post-event alphas for risk-adjusted returns, while Ponzi schemes, phishing scams, investment scams, hacks, and exploits have a negative effect. Meanwhile, Ponzi schemes, events on the darkweb, and sextortion increase victims' total risk-taking levels, while giveaways,

investment scams, hacks, and exploits reduce them. By far the economically most significant increase in total risk-taking occurs after *darkweb-related scams*, when victims double their total risk-taking. In contrast, the economically most significant reduction in total risk-taking occurs after *investment scams*, when victims reduce their total risk-taking by more than half.

Given the overarching result that victims of cybercrime increase total risk-taking and thereby reducing their risk-adjusted returns, we next explore potential mechanisms that help explain the finding. The evidence from triple difference models suggests two behavioral explanations for how cybercrime changes victims' risk–return trade-off. First, victims of cybercrime significantly increase their trading activity and churn rate, which loads significantly negatively on the alpha-related triple difference estimator. This suggests that higher trading activity reduces risk-adjusted returns, which is in line with the evidence by Odean and Barber (1999) for traditional finance and Sokolov (2021) for decentralized finance. Second, address-level token diversification and ownership of different token categories (including altcoins and stablecoins) load positively on risk-adjusted returns and non-diversifiable risk and negatively on diversifiable risk. Overall, the collective evidence indicates that the increase in diversifiable risk, which reduces risk-adjusted returns, is largely caused by victims divesting altcoins.

Additionally, we investigate heterogeneous treatment effects for Ethereum addresses of various wealth levels (i.e., comparing the top 10% to the bottom 10% in terms of pre-cybercrime address balance). We document that the least affluent Ethereum addresses' risk-adjusted returns decrease more than those of the most affluent addresses. Again, the discrepancy in responses of cybercrime victims of differential wealth can be explained by their responses in risk-taking levels. The least affluent addresses dramatically increase their total risk-taking relative to the most affluent addresses following a cybercrime. However, the least affluent only increase their address-level diversifiable risk relative to the most affluent, while they decrease their non-diversifiable risk-taking. Our evidence suggests that the least affluent victims respond to cybercrime by becoming gamblers, while the most affluent victims respond to cybercrime in a more systematic way in order to restore their pre-cybercrime wealth level.

We also formulate a graph convolutional network (GCN) that serves the purpose of ex-ante detection of cybercriminal addresses on the Ethereum blockchain. Specifically, we use a heterogeneous graph structure, where both addresses and transactions are considered as nodes rather than

edges in order to effectively represent the Ethereum network, and we train the model on numerous dynamic on-chain characteristics, motivated by the preceding results from our linear models. Our GCN model correctly predicts cybercriminals with an accuracy of 72.5%, suggesting that almost 3 out of 4 cybercriminals are correctly detected as such based solely on publicly available ledger data even before committing a cybercrime. Our model also correctly predicts non-cybercriminal wallets with an accuracy of 71.1%, and our model's F1 score is 0.70. The results illustrate that on-chain transaction behavior can be used to inform the ex-ante detection of illicit activity on the Ethereum blockchain. As such, our results yield novel insights to protect investors through private platforms or governmental supervisory bodies.

In what follows, we describe our data, show aggregate statistics for cybercrime on the Ethereum blockchain, derive our cybercrime taxonomy, and develop empirical predictions in Section 2. Section 3 introduces our empirical design, including our difference-in-differences model and matching method. Section 4 discusses our results, and Section 5 concludes.

2 Data and Empirical Predictions

2.1 Transaction-Level Data

A novelty of our empirical setting is the granularity of transaction-level data to identify victims who interacted with cybercriminals, a level of detail so far rarely examined on the Ethereum blockchain. Notable exceptions of studies using extensive on-chain data are Easley et al. (2019), Foley et al. (2019), Sokolov (2021), and Hoang and Baur (2022); however, all of these investigate transactions on the Bitcoin blockchain. Unlike Bitcoin, the Ethereum blockchain acts not only as a payment network but also as the basis for numerous decentralized applications (dApps), facilitating a more diverse range of financial activities. It is thus not surprising that the Ethereum blockchain hosts a broader range of cybercrimes. In the following section, we describe our method of identifying cybercriminals and victims, leading to our comprehensive taxonomy of cybercrime on the Ethereum blockchain.

2.1.1 Identifying Cybercriminals

To identify the extent of fraud on the Ethereum blockchain, we acquired a list of blockchain addresses of cybercriminals from *Etherscan* and *ScamAlert*. *Etherscan*, a block explorer and analytics platform for Ethereum, assigns public name tags and labels to addresses that are of public interest. Any address associated with fraudulent activities has a brief warning message attached, providing investors with details of the purported scam. We include in our list of cybercriminals all blockchain addresses that *Etherscan* labeled as *exploit*, *hack*, *heist*, *phish*, *Ponzi scheme*, and/or *scam*.

In the next step, we cross-validate the list of blockchain addresses of cybercriminals with proprietary data from *ScamAlert*, which is operated by *WhaleAlert*, a blockchain analytics engine that tracks the activities of cybercriminals. Users can submit scam reports to and request address and website verifications from *ScamAlert*. They maintain a team of blockchain crime experts who collaborate closely with law enforcement agencies and consumer protection initiatives, such as the FBI's Internet Crime Complaint Center (IC3) (www.ic3.gov), to detect and monitor crypto-related crime more effectively and analyze this information in real time.[3] The list includes detailed information about each scam, such as the type of scam, total earnings per address, payments received, and the date of the first scam report. The list of cybercriminal blockchain addresses includes 5,644 unique addresses.

We chose *ScamAlert* over other sources, such as the California Department of Financial Protection and Innovation's (DFPI) Crypto Scam Tracker,[4] because of its global coverage and specialized focus on Ethereum scams. While the DFPI's tracker is valuable, it primarily focuses on scams affecting consumers within California, limiting its applicability for a global analysis of cybercrime on the Ethereum blockchain. *ScamAlert* aggregates data from users worldwide, offering a more comprehensive and timely dataset. *ScamAlert* also maintains an extensive database of Ethereum scam addresses, updated regularly, making it an ideal resource for analyzing cybercrime patterns on the Ethereum blockchain.

[3] *ScamAlert* (https://scam-alert.io) is affiliated with *WhaleAlert* (https://whale-alert.io/index.html), a blockchain analytics engine. *WhaleAlert*, headquartered in the Netherlands, specializes in tracking and analyzing a vast number of blockchain transactions daily. It is particularly recognized for reporting significant and noteworthy transactions in real time. With a following on X (formerly known as Twitter) of over 2.3 million, *WhaleAlert* frequently tracks large blockchain transaction movements, including those related to major scams. This connection underscores the reliability and relevance of the data provided by *ScamAlert* for our research purposes. For more information, visit https://scam-alert.io/.

[4] https://dfpi.ca.gov/consumers/crypto/crypto-scam-tracker/

To identify the event date for each scam, we first use the data provided by *ScamAlert*, which includes when the scam was first reported. Because *ScamAlert* provides real-time updates and anyone can search for an address to check whether it is related to a scam, this offers a reliable way to verify the event dates used in our study. To ensure accuracy and enhance our data's reliability, we conduct additional cross-checks by manually searching for related posts on social media platforms such as Twitter and Reddit. This method helps us corroborate the dates and ascertain when the events became widely known to the public.

For scams not listed in the *ScamAlert* database, we rely on the earliest relevant posts on Twitter, Reddit, and other social media platforms to understand when the incident first came to public attention. Our study relies on the assumption that the event date corresponds to the point when the scam became known to the victims. These platforms are primary hubs for cryptocurrency discussions and are often the first places where new scams are reported by the community. We used specific keywords related to each incident (e.g., scam name, wallet addresses, relevant hashtags) and sorted posts chronologically to identify the earliest mentions.

In cases where ambiguity remained, we extended our search to include other platforms such as cryptocurrency forums (e.g., Ethereum Stack Exchange), blockchain news websites (e.g., CoinDesk, CoinTelegraph), and official statements from affected projects or exchanges.

We acknowledge that this process is more likely to identify larger-scale crimes, as these are the events that tend to generate discussion on social media platforms. As a result, smaller-scale crimes for which we were unable to ascertain the event date via social media have not been included in our dataset. Consequently, this method may indeed underrepresent smaller-scale crimes, which are less likely to be discussed extensively in such public forums. This approach, while limiting the scope to more prominent incidents, ensures a higher likelihood that victims are aware of the scam, contrasting with smaller-scale crimes that might go unnoticed by the victims.

It should be noted that it is difficult to clearly distinguish between a failed project, which may collapse due to various non-fraudulent reasons, and an outright scam. In our study, we acknowledge this complexity and adopt a conservative approach in our classification. We only categorize a project as fraudulent if our collaborator, ScamAlert, has verified evidence supporting this classification.

2.1.2 Identifying Cybercrime Victims

As a public blockchain, Ethereum stores all transaction records on its distributed ledger, which we use as our primary data source for victim address identification. The public transaction data allows us to observe the transaction history of those who have interacted with and fallen victim to fraudsters operating on the Ethereum blockchain. Based on the identified and externally verified cybercriminal blockchain addresses, as described in Section 2.1.1, we extracted a list of addresses from all transactions on the Ethereum blockchain in which a positive sum of funds was transferred to cybercriminal addresses, starting with the Ethereum genesis block on July 30, 2015, and ending on December 31, 2021.

To mitigate the risk of mistakenly identifying cybercriminals as victims, we excluded addresses repeatedly transacting with cybercriminals since these could potentially be involved in the cybercrime themselves. Furthermore, if the list of victim addresses appeared in the *Etherscan Public Name Tags and Labels*, we assumed that they belong to public entities and excluded them from our sample. It is also possible that a user falls victim to multiple crimes. Including these cases in our sample could be problematic since any exposure to any cybercrime prior to the event date could have altered the behavior. Therefore, we only focus on wallets that have fallen victim to scams once.

Importantly, this study relies on the assumption that one wallet address corresponds to one investor. We acknowledge that this is indeed a simplification of the more complex reality where an investor may use multiple wallets. However, this assumption is a necessary limitation of our study, primarily due to the anonymous nature of blockchain transactions.

Our final sample includes 200,865 unique victim addresses. [5]

2.1.3 The Evolution of Cybercrime on Ethereum

Figure 1 plots the evolution of cybercrime on the Ethereum blockchain over time. Panel A shows the dollar value of funds lost due to fraudulent transactions on the Ethereum blockchain over time.

[5] To effectively implement a difference-in-differences setting, victims of cybercrimes must have interacted with the fraudsters before the fraud became public so that victim behavior before and after the scam can be compared. Nonetheless, in our dataset, a non-negligible number of victims initiated transactions with fraudulent accounts even after public disclosure of the scam, a circumstance which falls outside the scope of suitability for a difference-in-differences framework, because the victim may have known the fraudster or might have even been part of the scam. Consequently, these addresses have been removed from our sample.

Across the entire time period analyzed, the median value of funds lost due to fraudulent activities per address is $506.76. The mean value of funds lost per address is considerably higher at $1,476.64. This skewness is driven by a number of extremely large losses by some victims.

During bullish phases of the cryptocurrency market, when the value of cryptocurrencies typically increases significantly, we observe a significant rise in the mean and median values of funds lost to fraud. Panel B of Figure 1 presents the number of transactions to fraudulent accounts and the average share of blockchain address balance lost due to scam activities on the Ethereum blockchain.

During phases of relative stability or downturns in the crypto market, the proportion of balance lost to scams tends to rise. In contrast, during periods of market upswings, the share of balance lost to scams appears to decrease.

[Place Figure 1 about here.]

2.2 A Taxonomy of Cybercrime on the Ethereum Blockchain

Based on our sample, we derive a taxonomy of 19 unique categories of cybercrime on the Ethereum blockchain, following and extending Hornuf et al.'s (2022) approach for categorizing fraud in ICOs. We quantify the total amount of funds transferred from victims to cybercriminals' addresses and show that the 5,644 cybercriminals' addresses received an average of $1.78 million from victims' blockchain addresses, totaling $1.65 billion. This amount exceeds the self-disclosed figures of stolen funds reported by victims to the FTC by a factor of almost 16, which highlights the significant underreporting of cybercrime to regulators.[6]

Table 1 outlines our taxonomy and describes each fraud category in detail. *Ponzi schemes*—the most common scam involving cryptocurrency, accounting for 60% of the aggregate stolen funds on Ethereum—promise high returns to investors with little or no risk. These scams are not new and constitute a digital adaptation of fraudulent activities seen in traditional finance (e.g., Hofstetter et al., 2018). The difference lies in the fact that the digital nature of blockchain technology, combined

[6]Note that while our data starts with the Ethereum genesis block and runs from July 2015 to December 2021, the FTC refers to complaints between January 2018 and March 2022. Since not all complaints were received by the FTC immediately after the fraud, the two observation periods are roughly identical, especially because most of the fraud only started in 2018. Thus, if anything, we may be slightly underestimating the volume of transfers relative to the FTC. The different estimates are therefore likely to be due primarily to the fact that the FTC statistics are based on reports from fraud victims, whereas our data represent an estimate of the total on-chain fraud volume.

with the anonymity of blockchain addresses and lax regulatory oversight, has largely enhanced the impact and potential reach of Ponzi schemes. Almost a billion dollars were transferred into on-chain Ponzi-related accounts. Off-chain transactions and scams are also common in crypto Ponzi schemes, with the aim of soliciting funds from non-tech-savvy investors. When these off-chain Ponzi schemes are factored in, the true magnitude of the financial impact is likely even greater. One of the largest crypto Ponzi schemes, *PlusToken*, is purported to have defrauded $4 billion in 2019,[7] of which only a small part is recorded on-chain and the larger part happened off-chain in blockchain addresses of crypto exchanges.

With the rise of cryptocurrency and blockchain technology, new forms of cybercrimes have also emerged, exploiting the unique characteristics of digital assets. The *giveaway* scam is one notable example, representing the second-largest cybercrime, with 18% of the aggregate stolen funds on Ethereum. It involves the misrepresentation of the identities of reputable companies, exchanges, or influential individuals. These scams are primarily disseminated via social media platforms and are structured to mimic authentic promotions by crypto companies or exchanges.[8] In some well-known giveaway scams, the perpetrators imitate the largest cryptocurrency exchange, Binance, in order to inspire trust among investors.[9]

Investors are then invited to send a fixed amount of cryptocurrency, usually Bitcoin or Ethereum, with the promise of high returns or rewards—a sign of an illegitimate operation. Once the investor transfers the funds, the fraudster does not uphold the initial promise. On-chain transaction data indicates that giveaway scams resulted in transfers totaling $274 million to addresses associated with this type of fraud as of the end of December 2021.

Another major scam is *exploits*, a phenomenon unique to digital systems such as blockchains. An exploit occurs when an individual or group discovers and takes advantage of a vulnerability or bug within a system. Unlike a hack, the vulnerability is accidentally left in the code by the developer. On the blockchain, exploits often involve manipulation of smart contracts. Because they are automatically executed if certain conditions are met, a small bug or overlooked vulnerability can

[7] See, e.g., https://www.wsj.com/articles/cryptocurrency-scams-took-in-more-than-4-billion-in-2019-11581184800.

[8] Legitimate giveaways are often used as marketing tools to enhance brand awareness, facilitate product promotion, and drive user acquisition. They have become a popular method for engaging with potential customers while simultaneously promoting the products or services. In a legitimate giveaway, the organizer will not ask participants to send any cryptocurrency and the offerings are typically modest.

[9] See, for example https://www.binance.com/en/blog/community/know-your-scam-protect-yourself-from-binance-imposter-scams-8186206274508844717, retrieved July 31, 2023.

result in significant financial losses if exploited by malicious actors. A notable example is the DAO exploit in 2016, where an attacker exploited a code vulnerability of a decentralized autonomous organization on the Ethereum blockchain, resulting in a loss of about $50 million (Dhanani and Hausman, 2022), underscoring the potential magnitude and sophistication of blockchain exploits.

Rug pulls and *exit scams* are types of fraudulent activities that have specifically emerged with the advent of cryptocurrencies and ICOs. These scams involve the intentional abandonment of a project after attracting investments, often leading to significant losses for investors. In an exit scam, the founders or promoters of a blockchain project, after raising funds through an ICO, disappear with the invested capital. Rug pulls, a relatively newer form of scam, are particularly prevalent in the decentralized finance (DeFi) sector. Developers abruptly abandon a project and withdraw the liquidity from decentralized exchanges, causing a significant drop in the value of the project's token. The sudden removal of liquidity makes the tokens almost worthless, leaving investors unable to offload their holdings. In a *fake token scam* fraudsters pretend to offer well-known tokens by using similar token names and symbols. Unsuspecting users will exchange funds for worthless tokens, which have no inherent value and cannot be traded.

[Place Table 1 about here.]

2.3 Empirical Predictions

Prospect theory posits that individuals place greater weight on losses than on an equivalent gain (Kahneman and Tversky, 1979; Kahneman et al., 1990). Once people are confronted with losses, they tend to become more risk-seeking to offset the potential losses as long as the losses have not yet been realized and mentally acknowledged (Thaler and Johnson, 1990). There is also evidence of such behavior in the financial markets, where traders regularly take above-average risk in the afternoon in order to recover from losses in the morning (Coval and Shumway, 2005).

Shefrin and Statman (1985) emphasizes that, once the loss is realized (meaning the investor has sold the losing asset and mentally acknowledged the loss), the psychological pain associated with the loss is again mitigated. Consequently, investors often return to a more risk-averse stance because the urgency to recover losses diminishes, and the focus shifts back to preserving capital and avoiding further losses.

In our empirical setting, it is unclear whether the information of fraud is immediately evaluated as a realized loss by investors. Fraudsters often promise recovery of funds and claim that the situation is only temporary, keeping victims engaged and hopeful. This is especially true for Ponzi schemes that rely on existing investors not withdrawing their money. Moreover, investors often still have the hope of getting their money back somehow through legal action. Thus, in line with prospect theory, investors should become more risk-seeking after experiencing fraud in an attempt to break even.

However, the recent empirical literature on portfolio formation by private households has arrived at the opposite results. Investors who are exposed to negative events such as corporate fraud, Ponzi schemes, or nearby firm bankruptcies in the community can make investors risk-averse via the loss of trust (Giannetti and Wang, 2016; Gurun et al., 2018; Laudenbach et al., 2021). However, these results are mostly based on indirect exposure to negative events in the surrounding area rather than being experienced directly by the investors. Cybercrime victims in our setting experience the losses themselves. In line with prospect theory, we therefore conjecture:

Hypothesis 1. *Victims of fraud become more risk-seeking after the event of fraud.*

While prospect theory does not predict changes in returns as a result of increased risk preferences, the Capital Asset Pricing Model (CAPM) assumes that higher market risks are also associated with higher expected raw returns (Lintner, 1965; Mossin, 1966; Sharpe, 1964). However, on a risk-adjusted basis, the returns should be identical for efficient portfolios, regardless of whether investors take more risks or not. That is, the higher raw returns in neoclassical capital market theory are only achieved through higher risks. Thus, the risk-adjusted returns remain constant if the portfolio remains on the efficient frontier.

Empirical evidence also shows that unexpected losses are often associated with higher transaction costs and divestment. Coval and Shumway (2005) show that losing traders who become more risk-seeking often buy securities at higher prices and sell them at lower prices than those that prevailed previously, which can also have a negative impact on their risk-adjusted returns. In a similar vein, Dorfleitner et al. (2023) show that German marketplace lending investors stop investing in new loans and cease diversifying their portfolio after experiencing a loan default. This behavior can significantly worsen the risk–return profile of their loan portfolios, reducing the expected

risk-adjusted returns. We therefore conjecture:

Hypothesis 2. *Increased risk-taking after falling victim to fraud increase the investor's raw returns.*

Hypothesis 3. *After falling victim to fraud, risk-adjusted returns decrease because of higher transaction costs and reduced diversification.*

3 Empirical Design

This study aims to identify the causal impact of blockchain-related cybercrimes on victims' investment behavior. Therefore, we adopt a difference-in-differences approach that consists of a pre- versus post-cybercrime comparison between victims of cybercrime and a matched sample of non-victims/non-cybercriminals. To test our hypotheses, our main model investigates investment behavior, especially risk-taking and returns per address, based on monthly address-level panel data. We specify the following baseline regression model:

$$\begin{aligned} Y_{i,t} = \; & \beta_1 \times \mathbb{1}[\text{After cybercrime}]_{i,t} + \beta_2 \times \mathbb{1}[\text{Cybercrime victim}]_{i,t} + \\ & \beta_3 \times \mathbb{1}[\text{After cybercrime}]_{i,t} \times \mathbb{1}[\text{Cybercrime victim}]_{i,t} + \Omega_{i,t}\gamma \end{aligned} \tag{1}$$

where i indexes blockchain addresses and t indexes months, and $Y_{i,t}$ captures measures of risk-taking such as total risk, diversifiable risk, and non-diversifiable risk, as well as risk-adjusted returns computed as alphas, which we obtained using the cryptocurrency asset pricing model (Liu et al., 2022). $\mathbb{1}[\text{After cybercrime}]_{i,t}$ denotes an indicator that takes the value of 1 in the month of a cybercrime and thereafter, 0 otherwise. $\mathbb{1}[\text{Cybercrime victim}]_{i,t}$ denotes an indicator that takes the value of 1 if the focal blockchain address fell victim of a cybercrime and 0 if the blockchain address belongs to a matched non-victim/non-cybercriminal. $\Omega_{i,t}$ represents a matrix of controls and fixed effects, including blockchain address age, calendar-month $\times$ calendar-year fixed effects, and cybercrime-type fixed effects. Finally, note that we sample only from one-time victims in order to ensure that the identification of the average treatment effects in our model is not confounded by overlapping periods with other cybercrime events affecting the blockchain address. In our model, the average treatment effect is thus measured as the difference-in-differences estimator β_3.

3.1 Matching Cybercrime Victims with Non-Victims

Our study draws on the entire population of Ethereum blockchain transactions, which is high-dimensional in its scope. Due to the size and complexity of the data, there exists a notable imbalance whereby the number of non-victims substantially exceeds that of victims.[10] In the context of our study, this high dimensionality combined with the imbalance between victims and non-victims could lead to significant attenuation bias. To address this issue, we use a Euclidean distance matching procedure to match each victim's address (treatment group) to a non-victim/non-cybercriminal address (control group) that is most similar, according to a multidimensional vector consisting of blockchain address balance, blockchain address age, trading activity, and address diversification. The similarity is measured by minimizing the Euclidean distance between these vectors, based on data from the three months preceding the scam being identified to the public. This approach allows us to create a balanced representation of the treatment and control groups. Furthermore, we recognize that the substantial price fluctuations in crypto markets could affect our nominal variables; hence, we compare investor addresses that entered the market in the same month, allowing for a more balanced and fair comparison of risk and return developments.

Table 2 shows that the matching of victims and non-victims/non-cybercriminals was successful, substantially reduced the bias, and draws the sample densities of our treatment and control groups closer together. The standardized bias for each covariate is calculated as the difference in means in the treatment and control groups, divided by the standard deviation in the control group. This value is then represented as a percentage. A lower standardized % bias post-matching indicates a better balance between the treatment and control groups in terms of that specific covariate. The matching process led to significant reductions in bias for all variables. That is, our matching reduced the bias for blockchain address age by 100% (perfect matches), for blockchain address balance by 81.7% (with the remaining difference being statistically non-significant, with a p-value of 0.55), for trading activity by 97.8%, and for diversification by 96.6%.

[Place Table 2 about here.]

[10] In our study, we regard each address as an individual portfolio. One limitation of this approach is that individuals can create multiple addresses; thus, one address may not fully represent an individual's portfolio or investment behavior.

3.2 Matching Quality and Parallel Trends

As another plausibility check for our matching quality, we look at parallel trends in a non-matched variable. It would be reassuring if the trends between treatment and control observations are parallel in a non-matched variable because this would suggest that the matching dimensions also capture more fundamental and unobserved behavior at the observational level. In particular, we plot monthly raw returns for victims and matched non-victims/non-cybercriminals in Figure 2. Barber and Odean (2000) raw returns, as defined in Table A.1, are especially well-suited to illustrate the matching quality because they do not merely reflect a single trading dimension of victims and matched non-victims/non-cybercriminals, but rather result from the cumulative investment decisions of blockchain address owners along all dimensions. Figure 2 shows reconfirming evidence that our matching was successful. Specifically, we observe parallel and mostly identical trends in the twelve months leading up to the cybercrime. However, as one would expect, in the month of the cybercrime trends start to diverge. Victims of cybercrime make investment decisions that increase their Barber and Odean (2000) raw returns relative to matched non-victims/non-cybercriminals.[11] The cumulative effect 12 months after the cybercrime amounts to a positive return differential of 0.3% for victims of cybercrime, which is statistically highly significant.[12] That is, in line with Hypothesis 2, cybercrime impacts victims in a way that is beneficial for their raw returns.

[Place Figure 2 about here.]

3.3 Variable Construction

3.3.1 Outcome Variables: Risk and Risk-Adjusted Return

To test Hypothesis 1, we adopt an empirical approach based on a state-of-the-art asset pricing model to understand the risk–return dynamics at the level of individual blockchain addresses. Specifically, we estimate the cryptocurrency three-factor model developed by Liu et al. (2022) as the basis for constructing risk-related variables. This model was designed to effectively capture the

[11] We confirm in unreported robustness tests that winsorizing the return data at 0.1, 0.5, and 1% levels does not materially change the graphical evidence in Figure 2.

[12] Note that in order not to compare apples to oranges, we consider victims' pure behavioral response and do not consider the loss caused by the scam when calculating returns. When we look at fraud losses and behavioral responses together, we find that over a 12-month period after being defrauded, cybercrime victims perform 10% worse than non-victims/non-cybercriminals.

unique risk factors inherent in the cryptocurrency market using trading data from cryptocurrencies listed on *CoinMarketCap*. The cryptocurrencies were weighted according to their respective market capitalizations. The factors employed in our analysis were directly obtained from Liu et al., 2022,[13] which is suitable given that we exclusively focus on ERC-20 tokens in our sample, for which price data were available on *CoinMarketCap*.[14]

$$Return_{i,t} = \alpha_{i,t} + b_{\text{mkt},i,t} \times MKT + b_{\text{size},i,t} \times SIZE + b_{\text{mom},i,t} \times MOM + \epsilon_{i,t} \tag{2}$$

The total risk is quantified as the variance of the return of wallet i in month t, giving a sense of how much risk the investor is exposed to due to their investment choices. From this, two types of risk are derived through variance decomposition. The *diversifiable* risk is determined as the variance of the error term $\epsilon_{i,t}$ in the model, representing the wallet-specific idiosyncratic risk. This represents the portion of risk that could be eliminated through effective portfolio diversification. High levels of *diversifiable* risk suggest that the investor is holding a portfolio that is not well-diversified, indicating a potential lack of risk mitigation strategies. The *non-diversifiable* risk is then calculated by subtracting the *diversifiable* risk from the total risk. This portion of risk is attributed to factors inherent to the market and is not reducible through diversification. High levels of *non-diversifiable* risk imply that the investor is taking positions in higher-risk crypto market segments. To test Hypothesis 3, we calculate risk-adjusted returns by $\alpha_{i,t}$, which is the excess return that is not explained by the market, size, and momentum factors. It essentially

[13] An objection to our approach of obtaining risk factors from Liu et al. (2022) is that those factors may be calculated based on a set of cryptocurrencies that differs from the set used in our study. To address this concern, we compared key characteristics of the sample in Liu et al. (2022) and our sample by year and find that they are relatively similar in terms of the number of cryptocurrencies available to calculate risk factors and their average annual market capitalization. Thus, a natural next question is which of the two sets of risk factors should be preferred. Given the survivorship bias in *CoinMarketCap* data used in Liu et al. (2022) and our study, the risk factors from Liu et al. (2022) should be preferred, given that they are based on data obtained in late-2021/early-2022, while we obtained the data in early-2023. As such, Liu et al.'s (2022) data is a better representation of cryptocurrency risks at the time of the cybercrimes studied in our article. We thank an anonymous reviewer for pointing this out.

[14] Given that Ethereum is the largest smart contract blockchain, a significant proportion of the tokens listed on *CoinMarketCap* include ERC-20 tokens. As of March 2024, the top 20 tokens listed on *CoinMarketCap* have a collective market capitalization of approximately $2.38 trillion. This figure represents around 89% of the total crypto market. Importantly, 19 out of these 20 tokens are also traded on Ethereum. This includes not only native Ethereum-based tokens but also ERC-20 wrapped versions of major cryptocurrencies from other blockchains, such as Bitcoin and Binance coin. Similarly, the top 100 tokens have a market capitalization of $2.58 trillion, representing 96% of the total market, and most of these tokens can also be found on Ethereum in ERC-20 form. We also identify potential anomalies or extreme values in our data, and cross-reference the prices of these tokens with other cryptocurrency price-tracking websites, such as *CoinGecko* and *Coinbase*. We have identified 14 such tokens which are then removed from our sample.

captures the unique return of the wallet i in excess of what would be predicted by these common risk factors at time t.

To test Hypothesis 2, the gross monthly portfolio *return* at the address level is computed using the beginning-of-day position statements. Following Barber and Odean (2000), we make two simplifying assumptions. First, we assume that all tokens are bought or sold at the end of the month. Second, we ignore intra-month trading. By tracking these measures over time, we can infer changes in an investor's risk appetite and evaluate how exposure to fraud events impacts portfolio returns. Table A.1 reports detailed definitions of these variables.

3.3.2 Other Measures of Investor Behavior

To further investigate Hypothesis 3, we also construct investor behavior variables at the address level using blockchain transaction data. We measure the investment horizon denoted by *churn rate*, that is, how frequently an address rotates its positions, and *diversification*, the number of unique tokens that an address holds at the end of each month. We also look at trading activity, which measures the number of transactions per address within a month. Trading activity provides insights into the investor's market engagement and potential responsiveness to fraud events.

Using the address-level monthly portfolio compositions, we also quantify the share of different classes of crypto assets, which measures the proportion of the investor's total portfolio allocated to *lottery tokens*, *stablecoins*, and *altcoins* at the end of each month. The share of different classes of crypto assets offers insights into the change in investment preferences and risk tolerance by investors with respect to their overall portfolio composition. Arguably, a larger share of Ether in an address-level portfolio is associated with more fraudulent activity, because scams are typically conducted in the native currency rather than a specific lottery or altcoin. Therefore, a higher share of lottery tokens, stablecoins, and altcoins in an address-level portfolio is most likely associated with less fraud. All variables are defined in Table A.1 in the Appendix.

3.4 Summary Statistics

Table 3 presents summary statistics for blockchain addresses that fell victim to cybercrimes, reporting a broad spectrum of address characteristics. An average victimized blockchain address

experienced a Barber and Odean (2000) raw return of 13.2% over the entire sample period; the median figure of 0 indicates that more than half of these addresses realized no or negative returns. Therefore, there are significant differences in investment results across different blockchain addresses.

Regarding portfolio activity, an average victimized address has a turnover rate of 5.5% and holds an average of 2.3 tokens. The size of addresses is right-skewed with an average blockchain address balance of $9,218 and a median value of $16. The age of addresses varied, averaging at 18 months, with a median age of 16 months, indicating that many victims were relatively new to the Ethereum blockchain. In terms of investment preferences, 14.6% of these addresses invested in lottery tokens, with an average portfolio share of 4.3%. Stablecoins were less popular, with just 4.8% of addresses investing in them and dedicating an average of 0.6% of their portfolio to this asset type.

Examining risk measures, the average victim blockchain address assumed a diversifiable risk of 0.311, a non-diversifiable risk of 0.095, and consequently a total risk of 0.407. Notably, despite these risks, the alpha value, which measures the blockchain address's return in excess of its expected return, averaged at a positive 6.4%. The average loading on the size factor is 0.551, which suggests that these addresses have a mild sensitivity to changes in the size factor, with a tilt towards larger cap assets. The average loading on the momentum factor is -0.370, implying that the returns of these blockchain addresses tend to move in the opposite direction to changes in the momentum factor. Thus, these blockchain addresses likely hold assets that have recently underperformed in the market.

[Place Table 3 about here.]

Table 4 presents the summary statistics for a matched sample of victims and non-victims/non-cybercriminals over the short-term period of three months prior to and after the scam became public. Victims showed a higher average return in both periods compared to their matched non-victims/non-cybercriminals. Before the scam became public, victims and non-victims displayed broadly similar behaviors and characteristics in several aspects. Returns, for example, were similar, with averages of 9.0% and 8.5% for victims and non-victims/non-cybercriminals, respectively. This similarity extends to metrics like trading activity and diversification, where both groups had close

averages. Blockchain address balance, churn rate, and blockchain address age also were generally similar in the pre-scam phase. The average age at the time of the revelation of scams is identical, indicating that we compare addresses that entered the market in the same month, which allows us to account for the effect of macroeconomic trends on our outcome variables.

In the realm of risk factors, there was also a broad similarity between victims and non-victims/non-cybercriminals during the pre-scam phase. The means for diversifiable risk, non-diversifiable risk, total risk, market, momentum, size, and alpha were all largely similar between the treatment and control group. However, there were some minor pre-scam disparities in terms of excess returns, particularly in terms of investments in lottery tokens, stablecoins, and altcoins.

[Place Table 4 about here.]

Table 5 offers a comprehensive view of the mean and median summary monthly statistics for victims by the type of scams they fell victim to for the entire sample period. Regarding returns, victims of Ponzi schemes, hacking, and stolen crypto incidents reported the highest average returns at 14.5% and 14.3%, respectively, while victims of exploit and hardfork scams showed the lowest average return at 4.7%.

In terms of churn rate, victims of exploits and hardfork scams had the highest average at 0.401, while those affected by Ponzi schemes and hacks had the lowest average churn rate, indicating a lower frequency of switching from one investment to another. Diversification, a measure of the number of tokens held by an address, is highest on average for victims of fake token sales and lowest for those affected by Ponzi schemes, hacks, and stolen crypto scams. Victims of exploits and hardfork scams held the highest average balances at $176,000, while victims of hacks and stolen crypto scams had the lowest at $684. The average trading activity was highest for victims of investment scams, while those affected by hacks and stolen crypto scams reported the lowest average trading activity.

Victims of sextortion and other scams had the oldest accounts; those who fell victim to Ponzi schemes had the youngest. Interestingly, victims of fake token sales and phishing scams were the most likely to invest in lottery tokens, with average participation shares of 73% and 67%, which constitute the highest shares of lottery token investments. Conversely, Ponzi scheme and hack victims had the lowest involvement in lottery token investments, indicating that they were

generally less eager to take risky positions. Notably, individuals who fell prey to darkweb, exchange, or charity scams had a higher likelihood of having stablecoins in their portfolios and allocate a higher share of their portfolio to stablecoins. Given the nature of these scams, it is possible that these types of fraudulent activities may frequently involve or target stablecoins.

[Place Table 5 about here.]

4 Results

4.1 Treatment Effects of Cybercrime on Investor Risk-Taking

The graphical evidence in Figure 2 suggests that victims of cybercrime change their investment behavior in a way that increases their post-cybercrime *non*-risk-adjusted Barber and Odean (2000) monthly returns relative to matched non-victims/non-cybercriminals, not accounting for the loss that results from the scam itself. In this and the following Section 4.2, we study what drives this investment pattern and whether victims' post-cybercrime risk-adjusted returns are equally positive.

To test Hypothesis 1, we estimate our main difference-in-differences model, as defined in Equation 1, with three different dependent variables: total, diversifiable, and non-diversifiable risk-taking. We also estimate the models for symmetric event windows of 3 and 12 months before and after the cybercrime event in Tables 6 and 7, respectively, accounting for the dynamic structure of how victims of cybercrime adjust their risk-taking levels. Figure 3 shows that the 3-month window is well-suited to capture the short-term response of victims to cybercrime, while the 12-month window captures a more permanent effect of cybercrime on address-level risk-taking. Finally, we estimate *average treatment effects* based on all observations in our sample to quantify the aggregate impact cybercrime had on users of the Ethereum blockchain. We also estimate *heterogeneous treatment effects* for individual cybercrime categories to gauge the variance in treatment effects across different cybercrime types. All our models include granular calendar-month $\times$ calendar-year fixed effects and the model for the average treatment effect estimation also includes cybercrime-type fixed effects. Note that our analysis for the symmetric 3-month event window draws on more than 4.5 million blockchain address–month observations and the one for the symmetric 12-month event window draws on more than 7.8 million blockchain address–month observations. Finally, note the

limitation that we measure treatment effects of cybercrime victimization for *on-chain* (and not *off-chain*) trading behavior.[15]

The difference-in-differences results for the symmetric 3-month event window in Table 6 show the effects of cybercrime on blockchain address-level total, diversifiable, and non-diversifiable risk-taking in Panels A, B, and C, respectively. Again, the first two models estimate *average treatment effects* and models (3) to (11) estimate *heterogeneous treatment effects*.

Comparing the short-term effects for the 3-month event window with the more long-term effects for the 12-month event window is interesting because prospect theory suggests that investors become more risk-loving after incurring an unrealized loss, but return to their previous risk aversion after realizing the loss. During the 3-month event window, investors may not have yet fully realized a loss caused by fraud, because they think they might get the money back somehow. Thus, they should seek more risk. In the long-term, however, investors are more likely to mentally process and realize a loss due to fraud and return to their original risk preferences. Consequently, the identified effects should reverse.

We find that the average treatment effects in the between-cybercrime model in column (1) are negative (–0.0157), positive (0.0043), and negative (–0.0200) for the 3-month window in Table 6 and positive (0.0230), negative (–0.0027), and positive (0.0257) for the 12-month window in Table 7 for total (Panels A), diversifiable (Panels B), and non-diversifiable risk-taking (Panels C), respectively.

The structure of the average treatment effects is similarly reversed in the within-cybercrime model in column (2). For brevity, we only provide an overarching comparison of the heterogeneous treatment effects. A number of cybercrimes entail similar effects over the 3- and 12-month event windows, although the longer window mostly exhibits stronger effects in terms of both statistical and economic magnitude. In particular, the effects for Ponzi schemes, hacks, and exploits are consistent across the event windows. In contrast, several cybercrimes yield either reversed effects or are non-significant in the shorter event window. These include giveaways, phishing scams, investment scams, fake token scams, darkweb shop-related cybercrime, and sextortion.

[Place Table 6 about here.]

[15] While this is admittedly an important limitation to the generalizability of our results, we note that this is not a limitation specific to our approach, rather it is a restriction to all studies of cryptocurrency investor behavior because off-chain cryptocurrency exchanges are not disclosing their trading books in a sufficient manner to trace per-address transactions.

Table 7 presents the difference-in-differences results for the symmetric 12-month event window for blockchain address-level total, non-diversifiable, and diversifiable risk-taking in Panels A, B, and C, respectively. Our first two models estimate *average treatment effects*. In Panel A (total risk), the *between*-cybercrime-type model (i.e., the model without cybercrime-type fixed effects) in the first column estimates an average treatment effect of 0.023, which is statistically significant at the 0.1% level. In economic terms, the estimate suggests that, given the full-samples average total risk-taking of 0.407, victims of any type of cybercrime increase their total risk-taking levels by 5.7% (= 0.023 / 0.407) as a response to the scam event. The average treatment effect in the *within*-cybercrime-type model (i.e., the model with cybercrime-type fixed effects) in the second column is only 0.0033; that is, victims increase their post-cybercrime risk-taking level by 8.1%, although the within-cybercrime-type effect is statistically non-significant. The non-significant effect on the total risk-taking level is caused by counteracting effects for non-diversifiable (positive effects) and diversifiable (negative effects) risk-taking levels in Panels B and C, respectively. Panel B (non-diversifiable risk) shows that post-cybercrime victims reduce their blockchain address-level non-diversifiable risk-taking. The highly statistically significant difference-in-differences estimators of –0.0027 and –0.0142 for the between- and within-cybercrime-type models suggest that victims decrease their non-diversifiable risk-taking by 0.8% and 4.6%, respectively, given the full-sample non-diversifiable risk-taking average of 0.311. Panel C (diversifiable risk) shows that post-cybercrime victims increase their blockchain address-level diversifiable risk-taking in the long term. The highly statistically significant difference-in-differences estimates of 0.0257 and 0.0175 for the between- and within-cybercrime-type models suggest that victims increase their diversifiable risk-taking by 27.1% and 18.4%, respectively, given the full-sample diversifiable risk-taking average of 0.095.

While the dynamic pattern of risk-taking is in line with prospect theory for diversifiable risk, it is not for overall risk and non-diversifiable risk. However, the dynamic pattern might differ for specific cybercrime types. For example, in Ponzi schemes, fraudsters often promise to refund the money and claim that the inability to pay back the money is only a temporary situation in order to keep victims interested and give them hope. Thus, losses are initially not realized by victims and are only mentally accepted over time. On the other hand, if a wallet is hacked and the money is no longer there, a victim may immediately perceive that the loss has been realized, which is unlikely to increase risk appetite in the short term. To test this conjecture, the models in columns (3) to (11)

contain *heterogeneous treatment effects* by cybercrime type. Overall, we find that post-cybercrime blockchain address-level risk-taking critically depends on the type of cybercrime a victim fell for.

Cybercrime categories that lead to an increase in victims' total risk-taking levels are Ponzi schemes, events on the darkweb, and sextortion. Ponzi scheme-related cybercrime increases victims' total risk-taking levels by 14.8% (= 0.0604 / 0.407), which is associated with a reduction in non-diversifiable risk-taking and an increase in diversifiable risk-taking of –23.1% (= –0.0219 / 0.095) and 26.4% (= 0.0822 / 0.311), respectively. Darkweb-related cybercrime increases victims' total risk-taking levels by 114.6% (= 0.4665 / 0.407), which is associated with increases in non-diversifiable risk-taking and diversifiable risk-taking of 156.9% (= 0.1519 / 0.095) and 101.2% (= 0.3147 / 0.311), respectively. Sextortion-related cybercrime increases victims' total risk-taking levels by 114.6% (= 0.4665 / 0.407), which is associated with increases in non-diversifiable risk-taking and diversifiable risk-taking of 64.9% (= 0.0617 / 0.095) and 21.0% (= 0.0653 / 0.311), respectively.

Cybercrime does not alter victims' total risk-taking levels if the event was a phishing scam or involved a fake token. At least for phishing scams, the non-significant total risk-taking effect is statistically non-significant, while the non-diversifiable and diversifiable effects are statistically significant. Victims of phishing scams increase their non-diversifiable risk-taking level by 162.1% (= 0.0154 / 0.095), while they reduce their diversifiable risk-taking level by 212.9% (= 0.0662 / 0.311).

Cybercrimes that lead to a reduction in victims' total risk-taking levels are giveaways, investment scams, hacks, and exploits. Giveaway-related cybercrime reduces victims' total risk-taking levels by –12.2% (= –0.0495 / 0.407), which is associated with an increase in non-diversifiable risk-taking and a reduction in diversifiable risk-taking of 9.4% (= 0.0089 / 0.095) and –21.3% (= –0.0662 / 0.311), respectively. Investment scam-related cybercrime reduces victims' total risk-taking levels by –58.7% (= –0.239 / 0.407), which is associated with an increase in non-diversifiable risk-taking and a reduction in diversifiable risk-taking of 29.1% (= 0.0276 / 0.095) and –85.7% (= –0.2666 / 0.311), respectively. Hack-related cybercrime reduces victims' total risk-taking levels by –52.8% (= –0.215 / 0.407), which is associated with reductions in non-diversifiable risk-taking and diversifiable risk-taking of –13.7% (= –0.013 / 0.095) and –220.1% (= –0.6846 / 0.311), respectively. Exploit-related cybercrime reduces victims' total risk-taking levels by –167.5% (= –0.6818 / 0.407), which is associated with an increase in non-diversifiable risk-taking and a reduction in diversifiable

risk-taking of 2.9% (= 0.0028 / 0.095) and 220.1% (= –0.6846 / 0.311), respectively.

[Place Table 7 about here.]

The results from Tables 6 and 7 suggest that post-cybercrime risk-taking changes with time. This result is consistent with recent literature showing that investor behavior changes over time and that, for example, the perceived risk of fraud can itself be a determinant of risk-taking by investors (Dicle, 2019). To shed light on the dynamics of the treatment effects, we plot the difference-in-difference estimates for total risk, non-diversifiable risk, and diversifiable risk in Panels A, B, and C of Figure 3. Total and diversifiable risk follow similar trends. Cybercrime slightly reduces risk-taking along these two dimensions for the first 5 months after the fraud became public, and, starting in month 6, risk-taking starts to climb back to the pre-cybercrime level, around months 10 to 12. This is consistent with previous research showing that indirect exposure to fraud in a community makes investors risk averse due to a loss of trust (Giannetti and Wang, 2016; Gurun et al., 2018) and that negative events in investors' portfolios lead to lower risk-taking (Laudenbach et al., 2021; Dorfleitner et al., 2023). Ultimately risk-taking exceeds the pre-fraud level, which has been normalized in Figure 3 by construction to 0%, and then permanently stays at a constantly higher level after months 12 to 15. Subsequent risk-taking is consistent with prospect theory, which assumes that investors take higher risks after an incident of fraud in order to break even. For non-diversifiable risk, the pattern is somewhat different. Post-cybercrime non-diversifiable risk-taking decreases constantly over the first 12 months post-event, after which it starts to recover slowly, though never returning to the pre-cybercrime level over the 24-month observation period.

[Place Figure 3 about here.]

4.2 Treatment Effects of Cybercrime on Risk-Adjusted Returns

The evidence in the preceding section indicates that cybercrime victims, on average, reduce risk-taking relative to the pre-event level in the first year following the event. A natural next question is whether and how the adjustment to risk-taking levels is reflected in victims' risk-adjusted returns. Panels A and B of Table 8 present the results for the 3- and 12-month event windows, respectively.

Columns (1) and (2) of Table 8 report the *average treatment effects* from the difference-in-differences analyses for blockchain address-level alphas. Note that the results are consistent with Hypothesis 3 throughout all four model specifications, regardless of whether we look at between- or within-cybercrime-type models, or the different event windows. The coefficients are all highly statistically significant and range from –0.0353 (within-cybercrime-type model; 3-month window) to –0.0617 (between-cybercrime-type model; 12-month window). In economic terms, victims' risk-adjusted returns in the post-cybercrime period reduce by 55.2% (= –0.0353 / 0.064) to 96.4% (= –0.0617 / 0.064) relative to matched non-victims/non-cybercriminals.

The *heterogeneous treatment effects analyses by cybercrime type* again suggest that victims' risk-adjusted returns can be both positively and negatively impacted by the various categories of cybercrime. For the symmetric 12-month event window, cybercrime categories that have a *negative* effect on victims' post-event risk-adjusted returns are Ponzi schemes, phishing scams, investment scams, hacks, and exploits. Ponzi scheme-related cybercrime increases victims' risk-adjusted returns in the post-event period by 124.5% (= –0.0797 / 0.064). Phishing scam-related cybercrime increases victims' risk-adjusted returns in the post-event period by 29.1% (= –0.0186 / 0.064). Investment scam-related cybercrime increases victims' risk-adjusted returns in the post-event period by 18.8% (= –0.012 / 0.064). Hack-related cybercrime increases victims' risk-adjusted returns in the post-event period by 36.7% (= –0.0235 / 0.064). Exploit-related cybercrime increases victims' risk-adjusted returns in the post-event period by 298.6% (= –0.1911 / 0.064).

For the symmetric 12-month event window, cybercrime categories that have a *positive* effect on victims' post-event risk-adjusted returns are fake token scams, darkweb activity, and sextortion. Fake token-related cybercrime increases victims' risk-adjusted returns in the post-event period by 26.4% (= 0.0169 / 0.064). Darkweb-related cybercrime increases victims' risk-adjusted returns in the post-event period by 45.9% (= 0.0294 / 0.064). Sextortion-related cybercrime increases victims' risk-adjusted returns in the post-event period by 44.7% (= 0.0286 / 0.064).

Unlike for victims' post-cybercrime risk-taking levels, the treatment effects on victims' risk-adjusted returns is relatively consistent throughout the symmetric 3- and 12-month event windows. Therefore, we only briefly discuss commonalities and differences at an overarching level, without going into detail. In general, the 3-month model yields slightly smaller treatment effects than the 12-month model. This can be explained by the time-series pattern in Figure 4 below, which

suggests that cybercrime impacts victims' alphas permanently negatively, with the treatment effect reaching its peak around month 10 after the cybercrime. A few heterogeneous treatment effects differ for the two event windows. While investment scams and fake token scams significantly reduce victims' alphas over the 12-month window, the treatment effects are statistically non-significant for the 3-month event window.

[Place Table 8 about here.]

Figure 4 plots the average treatment effects from the difference-in-differences model for the monthly alphas for the 1- to 24-month post-cybercrime period. That is, we estimate our main model with alphas as the dependent variable for 24 different event windows. Figure 4 illustrates that, in line with Hypothesis 3, victims' post-cybercrime alphas take a strong hit of around –3% in the month right after the cybercrime and then continue to decline to slightly more than –6% in month 10, and thereafter remain relatively stable at that level.

[Place Figure 4 about here.]

4.3 Investor Behavior, Risk-Taking, and Returns

Given that the collective evidence so far suggests that, in line with Hypothesis 1, cybercrime victims increase total risk-taking and, in line with Hypothesis 3, have lower risk-adjusted returns, a natural next question to investigate is which dimensions of investor behavior help explain these patterns. To test the channels underlying Hypothesis 3, we simultaneously regress several characteristics of investor behavior on risk-taking and risk-adjusted returns in a correlational triple differences model. Specifically, we are interested in the triple interactions of the victim and post-scam indicators with the measures of risk-taking and risk-adjusted returns. To explain the diverging patterns for risk-taking and risk-adjusted returns in the period following a cybercrime, we would expect that at least some investor behavior characteristics load positively for the risk-related triple difference estimates and negatively for the return-related triple difference estimates, and vice versa. As measures of investor behavior, we explore blockchain address-level trading activity, churn rate, diversification, lottery token, stablecoin, and altcoin blockchain address weights, which we define in Section 3.3.

Table 9 presents the regression results for the 3- and 12-month event windows in Panels A and B, respectively.

Overall, our results yield three important insights. First, *trading-related investor behavior*—that is, trading frequency and investment horizon—appears to be the primary driver of the negative treatment effects on alphas for victims in the post-cybercrime period. Second, *investment strategy-related investor behavior*—that is, reduced diversification and ownership of different token categories—appears to be the main factor behind the increases in alphas and non-diversifiable risk and the reduction in diversifiable risk. Third, alpha and risk-taking are explained by these investor behavior measures with heterogeneous quality. In terms of the adjusted R-squared (for the 12-month window in Panel B), the altcoin weight (adjusted R-squared of 29.3%) and diversification (adjusted R-squared of 13.3%) are most meaningful in terms of the variation explained by alpha and risk-taking in these variables, followed by the lottery token blockchain address weight (adjusted R-squared of 8.0%), churn rate (adjusted R-squared of 5.3%), stablecoin blockchain address weight (adjusted R-squared of 2.7%), and trading activity (adjusted R-squared of 0.6%). These findings are in line with Dorfleitner et al. (2023), who show that marketplace lending investors cease diversifying their loan portfolio after experiencing a loan default and that fraud erodes trust, leading investors to divest from riskier assets (Giannetti and Wang, 2016; Gurun et al., 2018).

More precisely, Table 9 shows that (i) trading activity loads significantly negatively on alpha but has no significant relation with diversifiable or non-diversifiable risk-taking, while (ii) churn rate, our measure of how quickly investors rotate their portfolio, loads significantly negatively on alpha and diversifiable risk-taking and significantly positively on non-diversifiable risk-taking. Both results suggest that their risk-adjusted returns are falling as investors trade more after being hit by a scam. This finding is consistent with findings from Odean and Barber (1999) for traditional capital markets that investors who trade more tend to underperform. Moreover, (iii) diversification, (iv) stablecoin blockchain address weight, (v) altcoin blockchain address weight, and (vi) lottery token blockchain address weight all load significantly positively on alpha and non-diversifiable risk-taking but significantly negatively on diversifiable risk-taking. The fact that diversification, which can also be represented by a higher share of lottery tokens, stablecoins, and altcoins, increases returns and negatively relates to diversifiable risk-taking appears intuitive. The fact that lottery tokens, stablecoins, and altcoins often represent early investments, especially when compared to

the native cryptocurrency Ether, and in many cases offer unique DeFi use cases, could explain excess returns represented by larger alphas. However, the fact that a higher proportion of lottery tokens, stablecoins, and altcoins is positively associated with undiversifiable risk-taking may be due to the fact that these tokens are associated with other forms of undiversifiable risk. These forms of market-wide risk may stem from investors' doubts about the ability of stablecoin issuers to maintain a currency peg, which consequently raises doubts about the premise of stablecoins and blockchain technology in general.[16]

Two observations support the meaningfulness of our results. First, the positive relation between alpha and non-diversifiable risk-taking and the negative relation between alpha and diversifiable risk-taking are consistent with arbitrage pricing theory (Fama and French, 1992, 1993; Roll and Ross, 1980). Second, although we document a dynamic structure of risk-taking levels on the event window in the post-cybercrime period, the coefficients in Panel A (3-month window) and Panel B (12-month window) in Table 9 are largely consistent, suggesting that these investor behaviors drive alphas and risk-taking independent of the observation period, reflecting some fundamental associations.

[Place Table 9 about here.]

4.4 Heterogeneous Treatment Effects

4.4.1 Rich versus poor address victims

Do affluent blockchain addresses react differently to cybercrime than non-affluent ones? To address the question, Figure 5 plots treatment effects for alphas, total risk, diversifiable risk-taking, and non-diversifiable risk-taking for the top 10% richest and bottom 10% poorest blockchain addresses as measured by blockchain address balance in the month prior to the focal cybercrime. Poor blockchain addresses yield significantly lower alphas over the 24 months following the cybercrime. For example, two years after the cybercrime, blockchain addresses of the richest victims yield an alpha of –4% relative to non-victim/non-cybercriminal matched control blockchain addresses, while blockchain addresses of the poorest victims yield an alpha of –5.5% relative to non-victim/non-cybercriminal matched control blockchain addresses.

[16] For a comprehensive list of failed stablecoins, see https://chainsec.io/failed-stablecoins/

The heterogeneous treatment effect on risk-adjusted returns between rich and poor cybercrime victims can be explained by different levels of risk-taking in the post-scam period. Rich blockchain addresses take substantially less total risk than poor blockchain addresses, although risk-loading by rich vs. poor blockchain addresses differs by risk type. That is, rich blockchain addresses take on less diversifiable risk and more non-diversifiable risk than poor blockchain addresses as a response to a cybercrime event. Hence, financially vulnerable investors have historically faced a dual burden: first, losing their funds to scams, and second, compounding their losses further by adopting a speculative approach after falling victim to the scam. Consequently, the role of regulators and consumer authorities becomes doubly crucial in combating cryptocurrency scams and protecting these vulnerable individuals.

[Place Figure 5 about here.]

A concern with the analysis above is that the cybercrime type and the balance of a blockchain address may be correlated and, hence, any identified treatment effect potentially endogenous. In unreported results, we compared summary statistics for the average victim's balance for each cybercrime. The average wallet size of a victim that fell for a hack, steal, or mal-/ransomware cybercrime is \$1,146 (smallest average balance per cybercrime type), the average wallet size of a Ponzi scheme victim is \$5,414, and the average wallet size of a darkweb shop-, charity-, or exchange-related cybercrime is \$6,692, while exploits and hardfork scam victims' average wallet size is \$108,934 (largest average balance per cybercrime type), investment scam victims' average wallet size is \$58,300, and sextortion and other cybercrime victims' average wallet size is \$45,526. Next, we modified our difference-in-differences model by including dummies for the 10% richest and 10% poorest addresses, and we re-estimated all regressions with the triple difference model in each cybercrime category. Although we observed heterogeneous treatment effects by cybercrime type and rich versus poor victims, the evidence is not systematical. Thus, we conclude that the correlation between address balance and cybercrime types does not confound our inferences from Figure 5.

4.4.2 Bull versus bear markets

We also explore heterogeneous treatment effects on cybercrime victims in bear versus bull markets. To that end, we classify our sample into periods of increasing prices (i.e., bull markets, e.g., between 01/2017 and 01/2018), decreasing prices (i.e., bear markets, e.g., between 02/2018 and 01/2019), and stagnating prices (i.e., sideways markets, e.g., between 02/2019 and 09/2020), following the definition in Drobetz et al. (2024). With these market phases in hand, we re-estimate all our results to contrast full-sample within- and between-cybercrime-type average treatment effects for all our outcome variables for bear versus bull markets. We focus on the 3-month measurement period and estimate average treatment effects on total, diversifiable, and non-diversifiable risk-taking, and risk-adjusted returns. Table 10 shows the results.

First, victims' total risk-taking reacts to cybercrime events only in bull markets, not in bear markets, with the effect being mostly driven by diversifiable risk-taking. Plausibly, altcoin prices are disproportionately low in bear markets, making exiting more costly, which ultimately reduces the divestment rate and keeps diversifiable risk-taking at the pre-cybercrime level. In contrast, non-diversifiable risk-taking increases in both bear and bull markets. Second, cybercrime victims experience positive treatment effects on risk-adjusted returns when they are scammed in bull markets. These results are robust when also examining a 12-month measurement period.

[Place Table 10 about here.]

4.4.3 Large- versus small-scale scams

Table 1 indicates that some types of cybercrimes affected large groups of victims, while others affected relatively small groups. Here, we explore whether victims that fell for a cybercrime alongside a larger mass of victims versus in a relatively idiosyncratic manner differ in their trading behaviors following the cybercrime event. To explore whether treatment effects between those two victim groups differ, we divided the number of transactions associated with a specific scam by the number of addresses of scammers in the specific scam category, and then split our sample into the top and bottom 25% of the distribution in this new variable to measure the relative size of the group that has been affected by a particular scam. The top 25% subsample corresponds to victims that fell for a cybercrime as part of a relatively large group of victims, while the bottom 25% subsample

corresponds to victims that were among a relatively small group of victims. We then rerun all our main models for risk-taking and risk-adjusted returns. Table 11 shows the results.

First, total risk-taking of victims in a relatively small group decreases, while that of victims in relatively large victim group increases. Decomposing the differential risk-taking effects, we find that small-group victims increase non-diversifiable risk and decrease diversifiable risk, while large-group victims decrease non-diversifiable risk and increase diversifiable risk. These treatment effects are consistently estimated in our within- and between-cybercrime-type models. Second, risk-adjusted returns (alphas) do not exhibit different treatment effects for small- versus large-group victims. Both victim types have lower alphas after a cybercrime event. The treatment effects are not sensitive to the measurement period and consistently estimated for the reported 3- and the unreported 12-month horizons.

[Place Table 11 about here.]

4.4.4 Victims with versus without DEX experience

Finally, in unreported results, we explore whether investor sophistication, as proxied by investors' previous transaction relations with decentralized exchanges (DEXs), moderates our main average treatment effects of cybercrime on investor risk-taking and returns. To this end, for each address, we identified all transactions that had a DEX counterparty and defined a *DEX dummy* for every Ethereum address that interacted with DEXs at least once (DEX dummy = 1) and those that never interacted with DEXs (DEX dummy = 0). We use the *DEX dummy* to split our sample into two subsamples and re-run our main analyses. First, we find heterogeneous treatment effects between the DEX- and non-DEX-interacting addresses on risk-adjusted returns (alpha). The impact of becoming a victim of cybercrime on alpha is significantly negative for both subsamples. Looking at the within-cybercrime-type model, we find that the negative effects are more pronounced for the sample without DEX experience, and hence arguably the less-sophisticated group of investors. As a consequence, the evidence suggests that investor sophistication, as proxied by previous DEX interactions, mitigates the negative impact of cybercrime victimization on risk-adjusted returns. Second, we also find heterogeneous treatment effects between the DEX- and non-DEX-interacting addresses on risk-taking over the 3- and 12-month horizons. The impact of becoming a victim of

a cybercrime is mixed for both subsamples. For total risk-taking, DEX-interacting addresses show consistently lower total risk-taking, while DEX-non-interacting addresses do not show a reaction in the within-cybercrime-type model. Continuing with the within-cybercrime-type model, we find that DEX-interacting addresses increase their levels of diversifiable risk and reduce their levels of non-diversifiable risk, whereas we observe diametrically opposed patterns for DEX-non-interacting addresses, as they reduce diversifiable risk and increase their non-diversifiable risk post-cybercrime. This is in line with the reasoning that more sophisticated investors are more active investors that manage their token portfolios post-cybercrime in a way that they divest altcoins that are often exploited by cybercriminals for attacks, which increases diversifiable risk in those investors' addresses.

4.5 A Forensic Approach to Cybercriminal Detection

4.5.1 Linear model

Table 12 shows blockchain address characteristics predicting cybercriminals across various crime categories. First, the age of the blockchain address does not appear to have predictive power with respect to cybercriminals, while addresses engaged in these illicit activities tend to diversify their assets. It is technically feasible to transfer ownership of an existing blockchain address, and darkweb markets may have emerged allowing cybercriminals to impersonate an old blockchain address if they do not already have one. The diversification might be a direct consequence of the nature of the crimes committed. If a criminal engages in various types of fraud that yield different types of tokens, this will naturally lead to a more diversified portfolio relative to those who do not. This theory could hold particularly true for cases where cybercriminals accept or demand payment in the victims' tokens, leading to an assortment of different assets in their portfolios. Moreover, stolen tokens and hacks, for example, could naturally lead to greater diversification in cybercriminals' portfolios, while cybercriminals that distribute malware often only accept a few cryptocurrencies.

Lottery token and stablecoin share are both negatively associated with criminals' blockchain addresses in all types of cybercrimes. In other words, cybercriminals appear to be highly discriminating in their choice of cryptocurrencies, avoiding both extremes of the spectrum (i.e., highly regulated stablecoins and overly speculative assets such as lottery tokens). While stablecoins provide a certain level of predictability due to their regulation and stability, their enhanced traceability

and centralization may deter cybercriminals who value anonymity and control. On the other hand, lottery tokens, often associated with high-risk, high-reward speculative investing, could pose a significant risk even for cybercriminals. Despite the potential for high returns, the extreme volatility and uncertain nature of such assets could lead to substantial losses. Furthermore, the relative lack of establishment and recognition of these tokens might pose challenges in terms of liquidity and ease of transaction, making them less suitable for illicit activities.

In contrast to stablecoins and lottery tokens, we find a positive relationship between the share of altcoins in the criminals' blockchain addresses and most cybercrime types. Altcoins may offer a balance between anonymity, risk, and reward that may be appealing to cybercriminals. Unlike stablecoins, they are typically not as heavily regulated. They are also more established and less speculative than lottery tokens, reducing the risk of substantial losses due to volatility. Importantly, the nature of altcoins may provide opportunities for exploitation by cybercriminals. For example, many startups in the blockchain space often raise funds through ICOs or similar mechanisms, where they sell tokens to early investors. These tokens can sometimes be obtained in significant volumes and at lower prices during these initial phases, making them attractive to cybercriminals. Moreover, although these tokens are not as widely accepted as more established cryptocurrencies, they often have sufficient liquidity for criminals to convert them into other assets or fiat currency when needed.

[Place Table 12 about here.]

4.5.2 Non-linear model

We use the insights from our preceding analyses to formulate a graph neural network (GNN) model that serves the purpose of ex-ante detection of cybercriminal addresses on the Ethereum blockchain. Cakici et al. (2024) and Momtaz and Urban (2025) demonstrate that machine learning may outperform traditional approaches to explaining behavior in crypto markets. We augment an existing fraud-detection GNN model from Kim et al. (2023). Specifically, the model builds on the idea that blockchain transactions naturally form a graph structure, where addresses are connected by transactions. Because the graph data does not exist in Euclidean space, it is challenging to employ existing machine-learning algorithms, and hence we rely on GNNs. Intuitively, a GNN

learns the representation of a target node by iteratively propagating the neighbor information for the node, edge, or graph-level prediction. On the Ethereum blockchain, while many other algorithms use homogeneous graphs where addresses are considered as nodes and transactions are considered as edges (e.g., Chen et al., 2020, and Li et al., 2021a), we use a heterogeneous graph (i.e., *ATGraph*), where transactions are considered as nodes rather than edges in order to effectively represent the Ethereum network. This means that *ATGraph* has two types of nodes: account nodes and transaction nodes. To extract the features from nodes, we follow Kim et al. (2023), who have used the statistical, topological, and temporal features, including total, minimum, maximum, and average values for the amount of received and sent assets, number of transactions, lifetime of the account, and time intervals between transactions. There are 13 features for the account nodes: in-degree defined as the number of received transactions in this account; out-degree defined as the number of sent transactions in the account; in-value defined as the sum of the received value; out-value defined as the sum of the sent value; average in-value defined as the average of the received value; average out-value defined as the average of the sent value; min in-value defined as the minimum received value; min out-value defined as the minimum sent value; max in-value defined as the maximum received value; max out-value defined as the maximum sent value; lifetime defined as the active time of the account; balance defined as the balance over the lifetime of the account; and average inter-tx time defined as the average time interval between transactions. For the transaction nodes, there are two features: the timestamp when a transaction was issued and the amount of value in the transaction. We have implemented an augmented graph convolutional network (GCN) using *ATGraph* twice: once with the features that Kim et al. (2023) used and another time adding all the characteristics we constructed for our linear empirical analysis above (i.e., the averages and standard deviations of account balance, diversification, lower-bound return, upper-bound return, churn rate, trading activity, Barber-Odean return, and account age). For the hyperparameters, the number of layers is 6, batch size is 128, and the hidden unit is 64. Due to computational limitations, we selected the scam and non-scam addresses whose involved number of transactions is less than 200,000. To handle the imbalanced dataset, we assigned appropriate weights to different classes.

Figure 6 shows the results. Our augmented GCN model correctly predicts cybercriminals in the test set with an accuracy of 72.5%, suggesting that almost 3 out of 4 cybercriminals are correctly

detected as such even before committing a cybercrime. Further, our F1 score of 0.70 compares favorably to that in the Kim et al. (2023) benchmark model of 0.67. Our model also correctly predicts non-cybercriminal wallets with an accuracy of 71.1%, which compares to the 55.5% of correctly predicted non-cybercriminal addresses in the benchmark model by Kim et al. (2023), representing a significant improvement. The improvement in reducing false positives illustrates the economic significance of the variables tested in the linear models above. The results illustrate that on-chain transaction behavior can be used to inform the ex-ante detection of illicit activity on the Ethereum blockchain.[17]

[Place Figure 6 about here.]

5 Conclusion

This article is among the first to provide a comprehensive analysis of cybercrime on the Ethereum blockchain. We identify more than 1.78 million transactions that are externally verified to be linked to cybercrime, corresponding to an aggregate amount of $1.65 billion of funds lost. In a first step, our analysis shows that fraud reported to the FTC understates the amount of abducted funds on the Ethereum blockchain by a factor of 16.[18] Furthermore, our data enables us to develop a taxonomy grounded in the economic impact of each cybercrime, yielding 19 overarching categories. With the data and taxonomy in hand, we develop a causal approach to estimating how cybercrime impacts victims' risk-taking, risk-adjusted returns, and investor behavior. Using a difference-in-differences approach on victim and non-victim/non-cybercriminal matched addresses, we find that victims increase their overall risk-taking after an incident of fraud, which is generally consistent with the predictions of prospect theory. Moreover, in line with the CAPM, we find that investors who take higher market risks after a fraud event also earn higher raw returns. Although neither prospect theory nor the CAPM provides an unconditional statement on whether higher risk-taking also affects risk-adjusted returns, it is clear that higher transaction costs and lower diversification

[17] A replication package for our GCN model of ex-ante cybercrime detection on the Ethereum blockchain is available at pypi.org.

[18] Given the heightened exposure of token investors to cybercrime, a growing literature argues that decentralized finance might benefit from more intermediaries, such as crypto funds, to manage cybercrime risk for individual investors (Cumming et al., 2025a; Dombrowski et al., 2023; Fisch and Momtaz, 2020; Momtaz, 2024; Zetzsche et al., 2020).

generally do not have a positive impact on risk-adjusted returns. We find that, as a result of increased overall risk-taking, investors earn lower risk-adjusted returns as measured by alphas from a state-of-the-art crypto factor model. Theses lower risk-adjusted returns can be explained by higher transaction costs due to fraud victims trading more after the fraud, and lower diversification, for example, as fraud victims withdraw from stablecoins and altcoins.

We find heterogeneous post-cybercrime risk-taking effects. Although total risk increases, a risk decomposition leads to higher diversifiable risk-taking and lower non-diversifiable risk-taking at the address level in the long term. We also evidence time dependencies: diversifiable risk-taking decreases in the short term and increases permanently in the long term, while non-diversifiable risk-taking decreases in the short and medium term, but does not return to pre-cybercrime levels within a 24-month period. We show that various measures for investor behavior, including trading behavior and investment strategy, explain the differential impact of cybercrime on risk-taking and risk-adjusted returns. Finally, in post-hoc additional analysis, we show that victim and cybercrime addresses differ systematically, leading to variation that can be exploited in predictive models to screen for cybercriminals ex ante.

Certain limitations should be acknowledged to contextualize our findings. First, our focus on cryptocurrency investors interacting with the Ethereum blockchain means our findings may not be generalizable to the broader investor population. Cryptocurrency investors may differ systematically from traditional investors in demographics, risk tolerance, and susceptibility to cybercrime. Second, our methodology may bias the dataset toward larger, more prominent scams that generate significant public attention, potentially underrepresenting smaller-scale scams. Third, an evaluation of the relative merits of various investor protection measures (e.g., jurisdiction-level regulations (Cumming et al., 2025b), protocol-level governance mechanisms (Fuchs and Momtaz, 2024), or relational trust-based mechanisms (Momtaz, 2021a)) seems to be a promising avenue for future research to inform policymaking.

Despite these limitations, our study provides important insights into the behavior of cryptocurrency investors following exposure to scams. Future research could address these limitations by incorporating more diverse investor populations, developing methods to detect smaller-scale scams.

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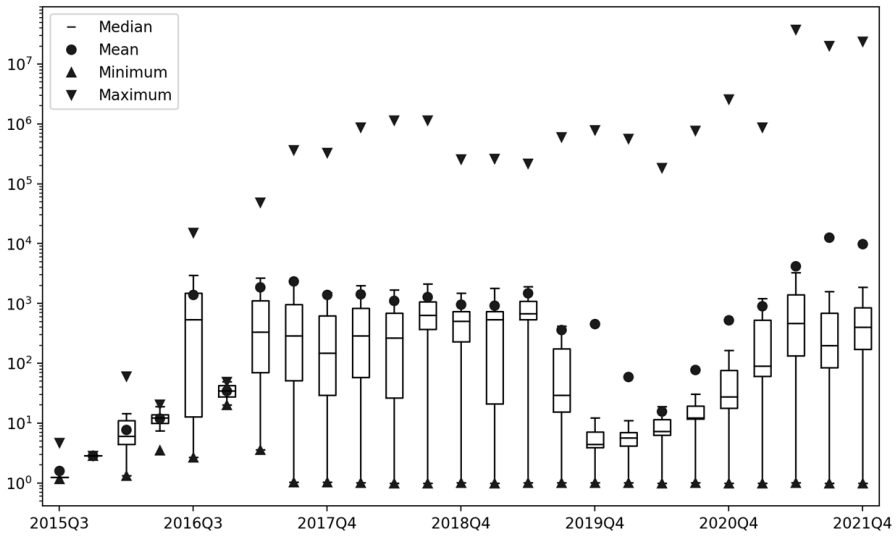
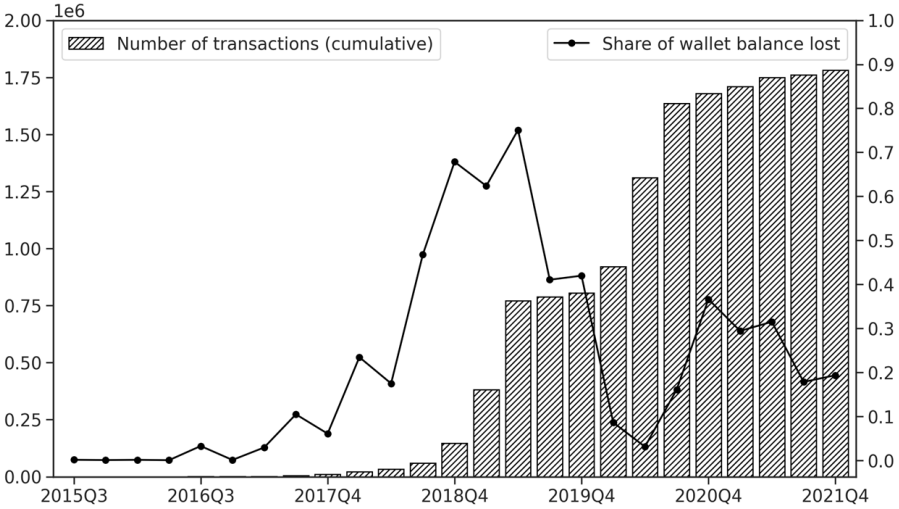
Exhibits

Figure 1: **Cybercrime on the Ethereum blockchain**

Panel A: Funds transferred to fraudulent accounts per blockchain address, in $

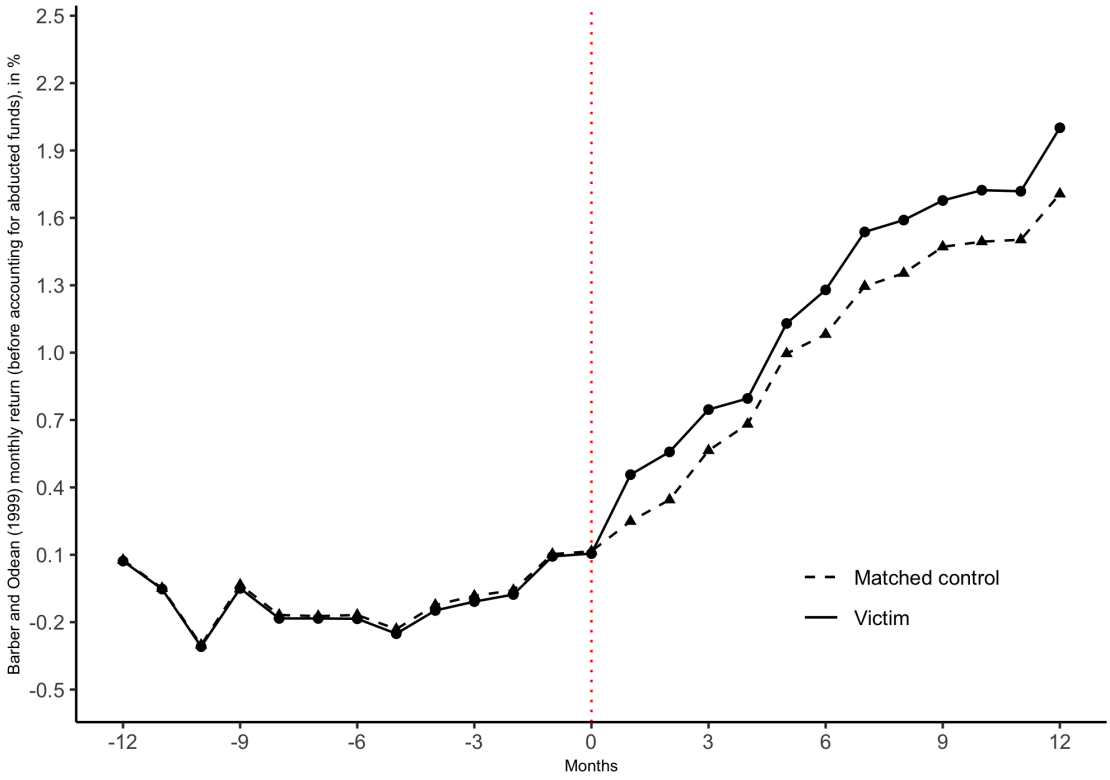


Panel B: Transactions to fraudulent addresses and the share of funds lost due to scams



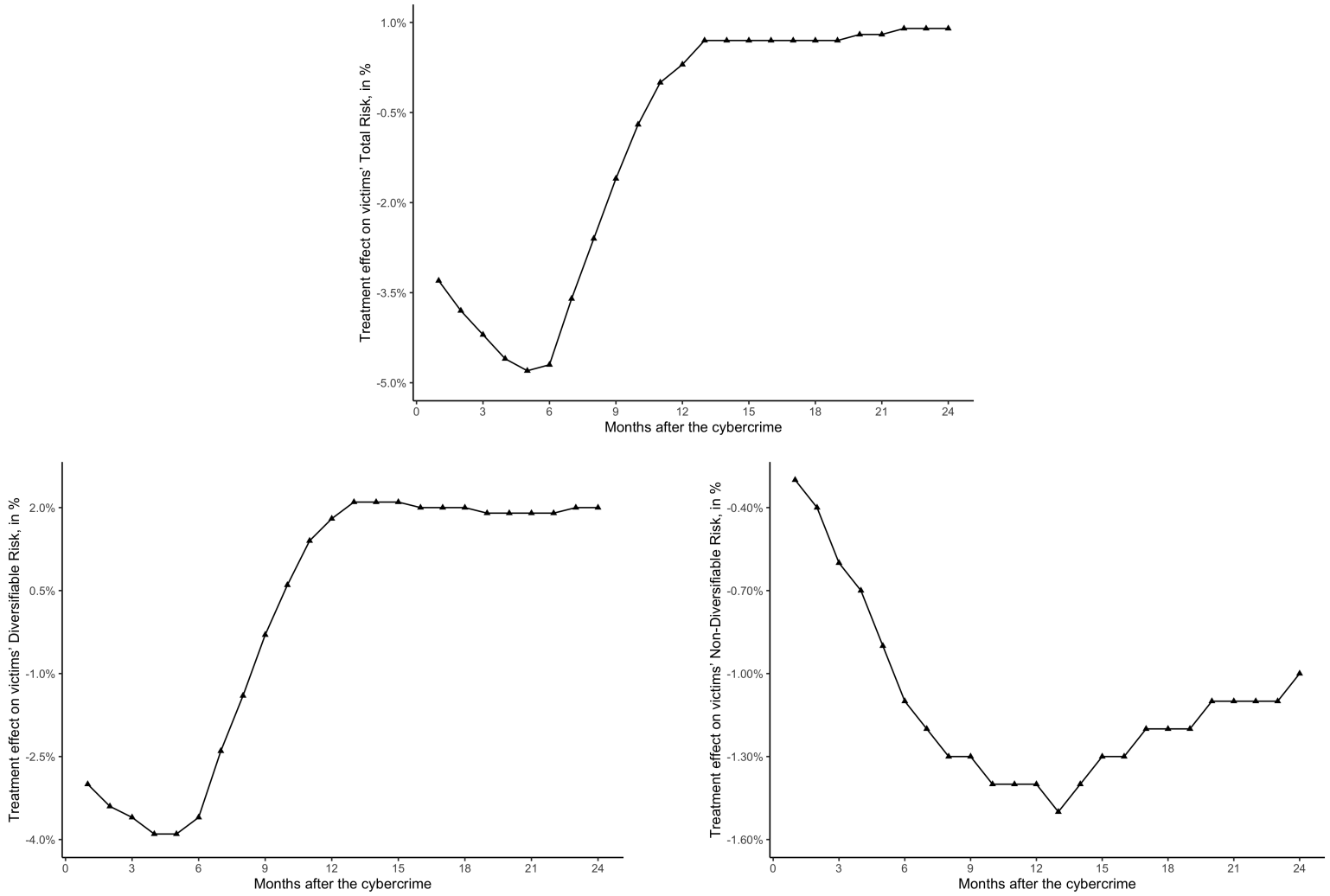
Note: The first figure shows the interquartile range, mean, and the maximum and minimum amounts of funds transferred to fraudulent accounts. The second figure shows the cumulative sum of the number of transactions to fraudulent accounts (left axis) and the share of blockchain address balance lost due to scams (right axis).

Figure 2: **Parallel trends and treatment effect of cybercrime on victims' *raw* returns**



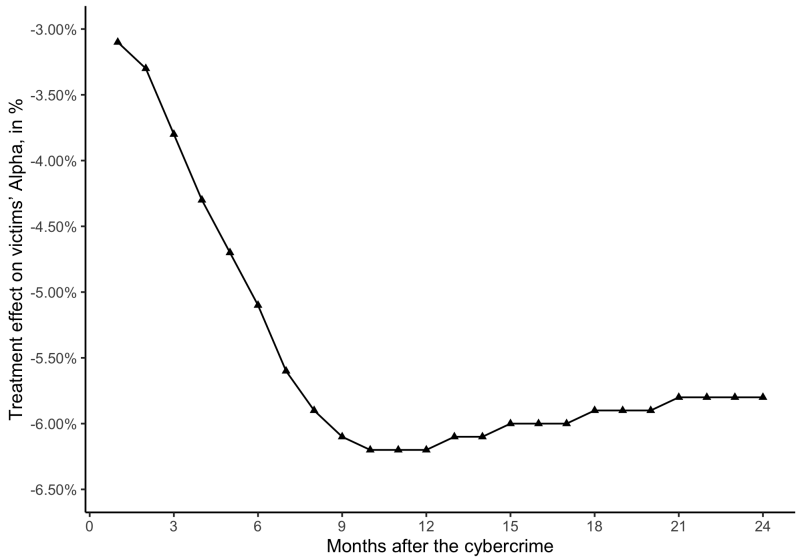
Note: This graph plots Barber and Odean (2000) monthly raw returns, as defined in Table A.1, for victims and matched non-victims for the time period of –12 to +12 months with respect to the focal cybercrime. Barber and Odean (2000) monthly raw returns only account for the *behavioral* effect of cybercrime on returns, not for the abducted funds due to the cybercrime *per se*. The graph illustrates that victims become better investors post-cybercrime. However, if one were to account for the nominal value of abducted funds due to the cybercrime, cybercrime victims have lost 10% of their wealth 12 months after the cybercrime relative to matched non-victims. Thus, on average, cybercrime victims lose one-tenth of their address-level wealth in a cybercrime. Note that the plot illustrates nearly perfect parallel trends for the treatment (cybercrime victims) and control observations (matched non-victims), suggesting the identification of a causal effect of cybercrime on victim behavior.

Figure 3: **Changes in post-scam blockchain address-level risk-taking (treatment effects) over time**



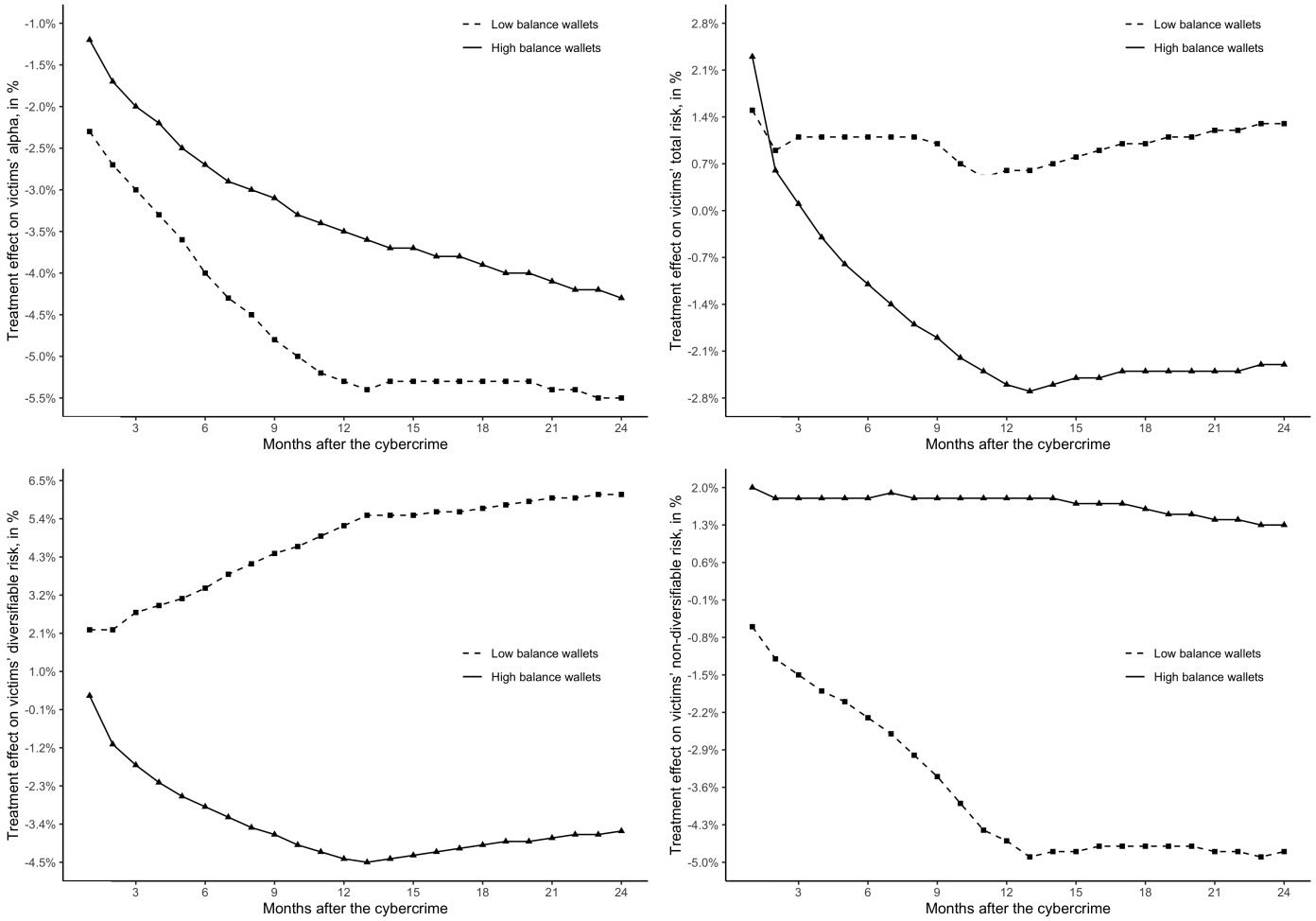
Note: These plots illustrate the time structure of our identified treatment effects for victims' post-cybercrime risk-taking levels in terms of total risk (top), diversifiable risk (bottom-left), and non-diversifiable risk (bottom-right). The graphs plot the monthly coefficients from difference-in-differences models for the post-cybercrime months 1 to 24. Definitions of all variables appear in Table A.1.

Figure 4: **Post-cybercrime evolution of victims' blockchain address-level risk-adjusted returns**



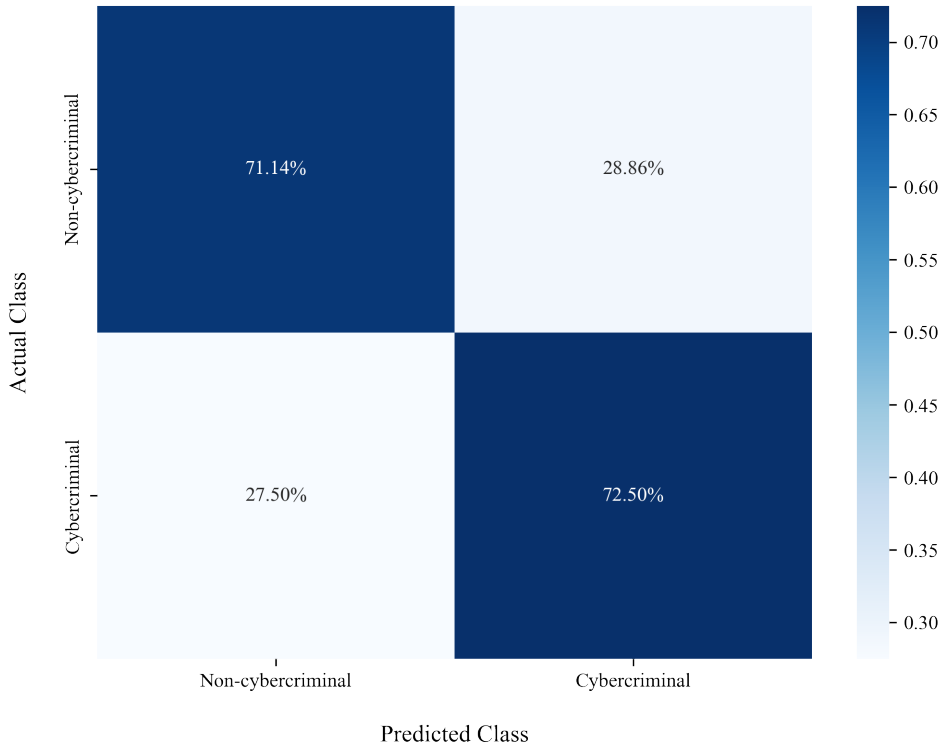
Note: This plot illustrates the time structure of our identified treatment effect for victims' post-cybercrime risk-adjusted returns (i.e., alphas from the three-factor model introduced by Liu et al., 2022). The graphs plot the monthly coefficients from difference-in-differences models for the post-cybercrime months 1 to 24. Definitions of all variables appear in Table A.1.

Figure 5: **Heterogeneous treatment effects by blockchain address balance**



Note: These plots show heterogeneous treatment effects for affluent (top 10% richest addresses by pre-cybercrime balance) and non-affluent (bottom 10% poorest addresses) cybercrime victims. The outcome variables are victims' risk-adjusted returns (top-left), total risk (top-right), diversifiable risk (bottom-left), and non-diversifiable risk (bottom-right). The graphs plot the monthly coefficients from difference-in-differences models for the post-cybercrime months 1 to 24. Definitions of all variables appear in Table A.1.

Figure 6: **Accuracy of a graph neural network model for cybercrime detection**



Note: The plot shows the accuracy of a our graph neural network (GNN) model for ex-ante cybercriminal detection on the Ethereum blockchain. We augment the Fraud Detection Graph Neural Network (FDGNN) model by adding all features that have been shown to be economically meaningful to understanding cybercrime-related activity on the Ethereum blockchain in our study. The F1 score of the augmented model is around 0.7.

Table 1: **A taxonomy of cybercrime on Ethereum**

Scam category	Description	# addresses	# transactions	$ received
Ponzi Scheme	A type of investment fraud whereby cybercriminals lure investors with purportedly high returns with little to no risk. Without real underlying businesses, it focuses mainly on attracting new investors to make promised payments to existing investors.	124	1,539,927	989,408,032
Giveaway	A scammer poses as a major company, exchange, or celebrity hosting a giveaway and promises to send back, for instance, double the amount received from the investor. As one of the most prevalent forms of scam, it is often advertised on social media platforms.	1,914	18,814	297,119,907
Exploit	Instances where an exploiter takes advantage of a vulnerability or bug to cause unintended or unanticipated behavior to occur.	51	3,099	214,021,559
General Phishing Scam	A type of social engineering where a fraudulent message is sent by an attacker in an attempt to gain access to private data, resulting in stolen funds. When a scam lacks information on a specific fraud type, it is included in our data set as a general phishing scam.	2,453	93,558	80,618,544
Hack	An attempt to gain access to private data, which can range from stolen private keys to illegitimate or counterfeit hardware wallets, designed to steal funds.	110	87,247	22,269,413
Exchange	Fake cryptocurrency exchanges posing as legitimate exchanges. Trading volumes on these exchanges are often manipulated to appear credible. Users may be lured with additional giveaway tokens. Once the money is received by scam exchanges, users are in many cases burdened with high fees and/or denied crypto withdrawals.	113	10,529	11,092,274
Stolen crypto	Instances whereby users had their private key stolen, or their wallets hacked.	279	9,893	9,917,668
Investment	Cybercriminals pose as investment managers and contact victims offering crypto investment products. They often require an upfront fee and may also ask for private information to get access to the user's assets.	313	12,515	9,773,136
Rug Pull/Exit Scam/ICO Scam	Exit scammers are protocol founders or promoters who, during or after an initial coin offering (ICO), disappear with funds raised by investors. A rug pull is a newer form of exit scam where developers abandon a project and pull liquidity away from decentralized exchanges entirely, causing the token value to plummet to zero.	39	798	5,671,271

Fake Token Scam	Tokens that pose as well-known tokens by using similar token names and symbols. Unsuspecting users will exchange them using real tokens. These scam tokens usually have no value and cannot be traded.	35	1,280	2,974,719
Malware	A type of phishing scam where malicious software is planted into a device in order to gain access to the user's funds.	18	1,320	1,871,751
Fake Token Sale Scam	Scams propagated through malicious advertisements that imitate legitimate new token launches. Scammers may also pose as well-known entities, promoting fake new token sales tricking investors into purchasing their new fraudulent crypto tokens.	21	373	956,928
Honeypot	An attacker creates a seemingly vulnerable contract to lure users into believing that the money can be drained if a particular sum of funds are sent to the contract beforehand. The user's fund will be trapped, and can only be recovered by the attacker.	1	2	474,236
Darkweb Shop	Darkweb-related activity and/or fake illegal shops designed to steal funds.	13	192	85,625
Charity	Crypto projects impersonating charities after major events and asking for donations using phishing emails and websites.	11	111	79,802
Ransomware	A type of phishing scam whereby software is planted on the user's device in order to encrypt files. This can compromise crypto private key information as well as other credentials stored in the network unless a ransom is paid.	7	36	77,836
Hardfork Scam	Cybercriminals create a fake network upgrade of major blockchains and ask users to send respective tokens with the promise of new coins from the alleged new protocols.	1	36	13,293
Sextortion	Cybercriminals evoke fear by threatening victims with sharing their online behaviors such as visiting adult websites. Users are coerced into paying a ransom.	4	70	7,475
Other		137	4,181	4,974,454
Total		5,644	1,783,981	1,651,407,924

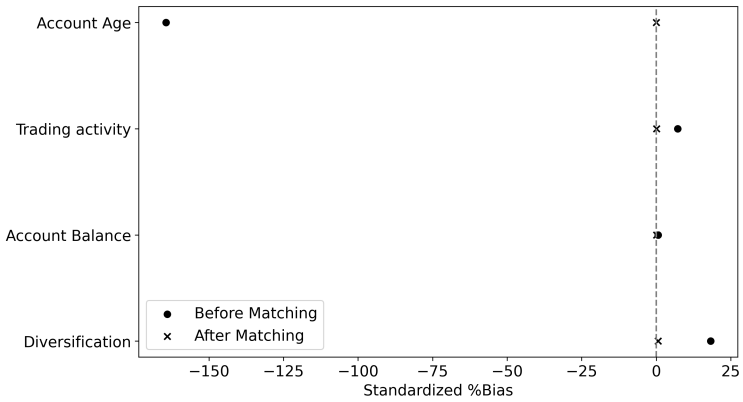
Note: This table presents 19 cybercrime categories observed on the Ethereum blockchain. The list is derived from two primary sources: *Etherscan* and *ScamAlert*. *Etherscan*, a block explorer and analytics platform for Ethereum, assigns public name tags and labels to addresses that are of public interest. Any address associated with fraudulent activities has a brief warning message attached to it, providing investors with details of the purported scam. All blockchain addresses that *Etherscan* labeled as exploit, hack, heist, phish, Ponzi scheme, and/or scam are included. The authors have

reclassified the scams into 19 finer categories based on the detailed information in the warning messages.

Table 2: **Matched variables and matching results**

	Matching	Mean Treated	Mean Control	% bias	% bias reduction
Blockchain address age	Before	7.6929	21.1131	-164.41	-
	After	7.6929	7.6929	0.00	1.00
Trading activity	Before	4.2794	0.5966	7.18	-
	After	4.2794	4.1992	0.16	97.83
Blockchain address balance	Before	5,712.05	3,271.02	0.66	-
	After	5,712.05	5,266.08	0.12	81.73
Diversification	Before	1.6438	1.1025	18.25	-
	After	1.6438	1.6254	0.62	96.60

Note: This table presents mean values of matching variables for both the treatment (victims) and control (non-victims) groups. Each of our 200,865 victims is matched with a non-victim control with the lowest Euclidean distance score. These scores are determined based on blockchain address balance, blockchain address age, trading activity, and diversification, using data from the three months leading up to the public revelation of the scam. Our final sample comprises address–month observations from both our victim group (200,865) and our non-victim group (200,865). Definitions of all variables appear in Table A.1.



Note: Standardized % bias for each covariate is calculated as the difference in means in the treatment and control groups, divided by the standard deviation in the control group. This value is then represented as a percentage.

Table 3: **Summary statistics for victims of cybercrime (treatment group)**

Variable	mean	stddev	min	max	q1	median	q3
return	0.132	0.749	-1	176.271	-0.162	0	0.259
churn rate	0.055	0.358	0	59.656	0	0	0
diversification	2.346	6.408	1	637	1	1	1
blockchain address balance	9,218.949	3,145,094.447	0	2,826,598,945.187	2.52	15.702	75.566
trading activity	4.27	125.818	0	48,091	0	0	0
blockchain address age (month)	18.445	12.99	1	77	8	16	27
lotterytoken investor (dummy)	0.146	0.353	0	1	0	0	0
lotterytoken share	0.043	0.179	0	1	0	0	0
stablecoin investor (dummy)	0.048	0.214	0	1	0	0	0
stablecoin share	0.006	0.065	0	1	0	0	0
altcoin share	0.269	0.427	0	1	0	0	0.762
3-factor model:							
diversifiable risk	0.311	0.975	0	211.339	0.175	0.179	0.223
non-diversifiable risk	0.095	0.161	0	38.843	0.081	0.102	0.109
total risk	0.407	1.075	0	214.245	0.273	0.279	0.301
market	3.609	2.355	-5.053	41.774	2.666	3.996	4.484
momentum	-0.37	5.999	-21.289	58.54	-4.321	-2.552	0.158
size	0.551	2.178	-32.429	15.428	0.176	0.407	0.64
alpha	0.064	0.103	-0.485	1.335	0.001	0.077	0.132

Note: This table reports summary statistics for victims of all fraud types. Variables are constructed monthly and our final sample includes address–month observations from 200,865 unique victim addresses. Definitions of all variables appear in Table A.1.

Table 4: **Summary statistics for victims (treatment group) and non-victims/non-cybercriminals (matched control group)**

		(1)	(2)	(3)	(4)
		3 months prior		**3 months post**	
Variable	Statistics	Victims	Non-victims	Victims	Non-victims
Return	mean	0.090	0.085	0.214	0.147
	(median)	(0.000)	(0.000)	(0.043)	(0.064)
Diversification	mean	1.644	1.625	2.104	1.663
	(median)	(1.000)	(1.000)	(1.000)	(1.000)
Blockchain address balance	mean	5,712.046	5,266.077	8,178.883	6,686.706
	(median)	(11.968)	(11.796)	(11.821)	(7.137)
Churn rate	mean	0.088	0.09	0.081	0.071
	(median)	(0.000)	(0.000)	(0.000)	(0.000)
Trading activity	mean	4.279	4.199	6.082	1.864
	(median)	(0.000)	(0.000)	(0.000)	(0.000)
Blockchain address age	mean	7.693	7.693	10.345	10.345
	(median)	(5.000)	(5.000)	(8.000)	(8.000)
Lottery token investor	mean	0.107	0.127	0.118	0.127
	(median)	(0.000)	(0.000)	(0.000)	(0.000)
Lottery token share	mean	0.028	0.041	0.034	0.038
	(median)	(0.000)	(0.000)	(0.000)	(0.000)
Stablecoin investor	mean	0.070	0.129	0.075	0.136
	(median)	(0.000)	(0.000)	(0.000)	(0.000)
Stablecoin share	mean	0.009	0.03	0.008	0.023
	(median)	(0.000)	(0.000)	(0.000)	(0.000)
Altcoin share	mean	0.098	0.111	0.225	0.137
	(median)	(0.000)	(0.000)	(0.000)	(0.000)
3-factor model:					
Diversifiable Risk	mean	0.105	0.106	0.301	0.218
	(median)	(0.099)	(0.099)	(0.176)	(0.176)
Non-diversifiable Risk	mean	0.199	0.195	0.117	0.108
	(median)	(0.18)	(0.167)	(0.114)	(0.102)
Total Risk	mean	0.305	0.300	0.418	0.325
	(median)	(0.307)	(0.307)	(0.293)	(0.289)
Market	mean	0.106	0.098	0.075	0.076
	(median)	(0.000)	(0.000)	(0.088)	(0.088)
Momentum	mean	2.584	2.464	3.374	3.608
	(median)	(3.498)	(3.122)	(4.36)	(4.36)
Size	mean	2.351	2.223	0.257	-1.179
	(median)	(0.000)	(0.000)	(-2.734)	(-2.283)
Alpha	mean	-1.93	-1.773	0.569	-0.104
	(median)	(0.000)	(0.000)	(0.601)	(0.263)

Note: This table presents the mean and median summary statistics for address–month observations for victims and matched non-victims for 3 months pre- (columns 1 & 2) and post-treatment (columns 3 & 4). Definitions of all variables appear in Table A.1.

Table 5: **Summary statistics for victims by scam type**

Variable	Statistics	Ponzi Schemes	Giveaways	Phishing Scams	Investment Scams	Fake Token Sales	Hack/ Stolencrypto	Exploit/ Hardfork Scams	Darkweb Shop/ Exchange/ Charity	Sextortion Other
	N	3,174,851	149,386	529,074	55,961	21,477	1,807,369	18,849	139,386	63,363
Return	Mean	0.145	0.074	0.081	0.115	0.066	0.143	0.047	0.058	0.067
	(Median)	(0.077)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Churn Rate	Mean	0.032	0.141	0.168	0.286	0.25	0.027	0.401	0.266	0.145
	(Median)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Diversification	Mean	1.459	5.302	8.696	6.095	11.063	1.174	8.129	4.92	6.442
	(Median)	(1.00)	(2.00)	(3.00)	(1.00)	(3.00)	(1.00)	(1.00)	(2.00)	(2.00)
Blockchain address Balance	Mean	7,082.8	24,254.2	33,635.6	39,536.9	29,149.4	684.6	176,969.9	5,494.3	41,710.9
	(Median)	(15.404)	(105.626)	(32.89)	(63.112)	(156.371)	(12.544)	(72.779)	(133.73)	(84.418)
Trading Activity	Mean	1.235	28.519	13.967	67.978	12.847	1.002	27.323	11.556	16.671
	(Median)	(0.00)	(0.00)	(0.00)	(1)	(0.00)	(0.00)	(1.00)	(0.00)	(0.00)
Blockchain address Age (Month)	Mean	14.162	23.511	23.604	15.04	24.621	23.793	15.601	19.206	25.167
	(Median)	(12.00)	(22.00)	(22.00)	(12.00)	(23.00)	(24.00)	(10.00)	(16.00)	(24.00)
Lotterytoken Investor (Dummy)	Mean	0.063	0.575	0.674	0.43	0.731	0.042	0.575	0.414	0.608
	(Median)	(0.00)	(1.00)	(1.00)	(0.00)	(1.00)	(0.00)	(1.00)	(0.00)	(1.00)
Lotterytoken Share	Mean	0.016	0.156	0.23	0.116	0.203	0.014	0.133	0.065	0.148
	(Median)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Stablecoin Investor (Dummy)	Mean	0.038	0.092	0.109	0.3	0.115	0.006	0.421	0.352	0.073
	(Median)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Stablecoin Share	Mean	0.005	0.01	0.009	0.034	0.011	0.001	0.036	0.039	0.008
	(Median)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Altcoin Share	Mean	0.045	0.417	0.443	0.277	0.495	0.586	0.296	0.344	0.371
	(Median)	(0.00)	(0.17)	(0.298)	(0.00)	(0.016)	(1.00)	(0.506)	(0.037)	(0.069)

Note: This table presents the mean and median summary statistics for address–month observations for victims of various scam types. Definitions of all variables appear in Table A.1.

Table 6: **Post-scam changes in blockchain address-level risk-taking (treatment effects for victims vs. matched non-victims/non-cybercriminals), 3-month**

	Average Treatment Effects		**Heterogeneous Treatment Effects by Cybercrime Type**								
	All scams (1)	All scams (2)	Ponzi scheme (3)	Give-away (4)	Phishing scam (5)	Investment (6)	Fake token scam (7)	Hack (8)	Exploit (9)	Darkweb shop (10)	Sextortion (11)
Panel A: Total Risk											
Post-scam	0.0284***	0.0417	-0.01***	0.015	-0.004	-0.015	-0.01	0.122***	0.187**	-0.134	-0.056**
	(0.002)	(0.003)	(0.002)	(0.018)	(0.012)	(0.033)	(0.014)	(0.004)	(0.066)	(0.082)	(0.018)
Victim	0.1033***	0.1165***	-0.014***	0.071***	0.13***	0.217***	0.035**	0.454***	0.111⋆	-0.161⋆	-0.046**
	(0.002)	(0.003)	(0.002)	(0.014)	(0.018)	(0.067)	(0.013)	(0.005)	(0.043)	(0.076)	(0.015)
Post-scam × Victim	-0.0157***	-0.0421***	0.021***	-0.028	-0.011	-0.094	0.031	-0.231***	-0.345***	0.27	0.109***
	(0.004)	(0.005)	(0.004)	(0.025)	(0.024)	(0.077)	(0.023)	(0.008)	(0.108)	(0.154)	(0.029)
Blockchain address age	0.0033***	0.0035⋆	0.003***	-0.001	-0.001	-0.002	-0.001⋆	0.011***	0.001**	0.004***	0.003***
	(0.000)	(0.000)	(0.0)	(0.001)	(0.0)	(0.001)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)
Calendar-month FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Scam-type FEs	✗	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗
Adj. R^2	0.020	0.020	0.003	0.001	0.001	0.0	0.011	0.116	0.006	0.004	0.0
No. obs.	4,540,665	4,540,665	2,462,468	96,288	308,302	57,112	11,745	1,290,330	33,374	190,849	90,197
Panel B: Non-Diversifiable Risk											
Post-scam	-0.0045***	0.0005***	0.001***	-0.001	-0.005***	-0.025***	-0.007	0.008***	-0.011⋆	-0.041***	-0.034***
	(0.000)	(0.000)	(0.000)	(0.002)	(0.001)	(0.006)	(0.004)	(0.001)	(0.006)	(0.009)	(0.006)
Victim	0.0011***	0.0062***	0.011***	0.001	-0.001	0.007	-0.002	-0.0	-0.034***	-0.044***	-0.029***
	(0.000)	(0.000)	(0.000)	(0.002)	(0.002)	(0.012)	(0.003)	(0.001)	(0.005)	(0.009)	(0.006)
Post-scam × Victim	0.0043***	-0.0058***	-0.007***	0.005	0.01***	0.027	0.018**	-0.014***	0.031***	0.081***	0.067***
	(0.001)	(0.001)	(0.001)	(0.003)	(0.002)	(0.014)	(0.006)	(0.002)	(0.009)	(0.018)	(0.012)
Blockchain address age	-0.0003***	0.0002***	-0.004***	-0.0	-0.001***	-0.0	-0.001***	-0.001***	0.001***	-0.001***	0.0
	(0.000)	(0.000)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)
Calendar-month FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Scam-type FEs	✗	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗
Adj. R^2	0.007	0.014	0.011	0.028	0.01	0.002	0.05	0.03	0.052	0.028	0.037
No. obs.	4,540,665	4,540,665	2,462,468	96,288	308,302	57,112	11,745	1,290,330	33,374	190,849	90,197
Panel C: Diversifiable Risk											
Post-scam	0.0329***	0.0412***	-0.011***	0.016	0.002	0.01	-0.002	0.114***	0.198**	-0.094	-0.022
	(0.001)	(0.003)	(0.002)	(0.017)	(0.011)	(0.028)	(0.012)	(0.003)	(0.064)	(0.073)	(0.016)
Victim	0.1022***	0.1103***	-0.025***	0.07***	0.131***	0.21***	0.038***	0.454***	0.144***	-0.117	-0.017
	(0.002)	(0.003)	(0.002)	(0.013)	(0.017)	(0.056)	(0.011)	(0.004)	(0.041)	(0.067)	(0.012)
Post-scam × Victim	–0.0200***	–0.0363***	0.028***	-0.032	-0.021	-0.121	0.013	-0.217***	-0.376***	0.189	0.042
	(0.004)	(0.005)	(0.003)	(0.023)	(0.023)	(0.064)	(0.019)	(0.007)	(0.104)	(0.137)	(0.024)
Blockchain address age	0.0037***	0.0036⋆	0.004***	-0.0	-0.001	-0.001	0.0	0.01***	0.002***	0.003***	0.003***
	(0.000)	(0.000)	(0.0)	(0.001)	(0.0)	(0.001)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)
Calendar-month FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Scam-type FEs	✗	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗
Adj. R^2	0.023	0.024	0.004	0.002	0.001	0.0	0.019	0.139	0.011	0.003	0.003
No. obs.	4,540,665	4,540,665	2,462,468	96,288	308,302	57,112	11,745	1,290,330	33,374	190,849	90,197

Note: These are difference-in-differences regressions to estimate the treatment effects of cybercrime on victim addresses' risk-taking. The dependent variables are total, diversifiable, and non-diversifiable risk-taking in Panels A, B, and C, respectively. The independent variables are a post-scam dummy that takes the value of 1 in the post-scam period, 0 otherwise; a victim dummy that takes a value of 1 for victims and 0 for matched non-victims, and their interaction term, i.e., the difference-in-differences estimator. We also control for blockchain address age, and include calendar-month and cybercrime-type fixed effects. The first two columns show the *average* treatment effects across all cybercrime types, while columns 3 to 11 show *heterogeneous* treatment effects for each cybercrime type separately. The regressions are estimated over the symmetric [–3, +3] event window with respect to the cybercrime month 0. Definitions of all variables appear in Table A.1.

Table 7: **Post-scam changes in blockchain address-level risk-taking (treatment effects for victims vs. matched non-victims/non-cybercriminals), 12-month**

	Average Treatment Effects		**Heterogeneous Treatment Effects by Cybercrime Type**								
	All scams (1)	All scams (2)	Ponzi scheme (3)	Give-away (4)	Phishing scam (5)	Investment (6)	Fake token scam (7)	Hack (8)	Exploit (9)	Darkweb shop (10)	Sextortion (11)
Panel A: Total Risk											
Post-scam	0.0058***	0.0158***	–0.0314***	0.0287***	0.0130***	0.0475**	0.0115	0.1109***	0.3913***	–0.2327***	–0.0617***
	(0.001)	(0.001)	(0.001)	(0.012)	(0.008)	(0.023)	(0.009)	(0.003)	(0.092)	(0.052)	(0.012)
Victim	0.0871***	0.0970***	–0.0320***	0.0787***	0.1532***	0.2993***	0.0555***	0.4487***	0.2433***	–0.2592***	–0.0583***
	(0.001)	(0.001)	(0.001)	(0.008)	(0.010)	(0.049)	(0.009)	(0.003)	(0.059)	(0.051)	(0.009)
Post-scam × Victim	0.0230***	0.0033	0.0604***	–0.0495***	-0.0508	–0.2390***	–0.0109	–0.2150***	–0.6818***	0.4665***	0.1270***
	(0.002)	(0.003)	(0.002)	(0.017)	(0.0014)	(0.064)	(0.014)	(0.006)	(0.150)	(0.100)	(0.019)
Blockchain address age	0.0031***	0.0034***	0.0029***	0.000***	–6.338e-05	–0.0024***	3.465e-05	0.0134***	0.0003***	0.0033***	0.0030***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Calendar-month FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Scam-type FEs	✗	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗
Adj. R^2	0.001	0.018	0.002	0.000	0.001	0.000	0.009	0.117	0.009	0.004	0.001
No. obs.	7,837,125	7,837,125	4,661,547	152,595	520,739	84,237	19,133	1,985,775	35,379	268,411	109,309
Panel B: Non-Diversifiable Risk											
Post-scam	–0.0019***	0.0039***	0.0069***	–0.0032***	–0.0084***	–0.0274**	–8.606e-05	0.0082***	0.0036	–0.0747***	–0.0305***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.004)	(0.002)	(0.000)	(0.005)	(0.007)	(0.003)
Victim	0.0054***	0.0112***	0.0199***	–0.0020**	–0.0030***	0.0082	0.0045**	–0.0010**	–0.0206***	–0.0815***	–0.0272***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.009)	(0.002)	(0.000)	(0.004)	(0.007)	(0.003)
Post-scam × Victim	–0.0027***	–0.0142***	–0.0219***	0.0089***	0.0154***	0.0276**	0.0035	–0.0130***	0.0028***	0.1519***	0.0617***
	(0.000)	(0.000)	(0.000)	(0.002)	(0.001)	(0.012)	(0.003)	(0.001)	(0.080)	(0.013)	(0.006)
Blockchain address age	–0.0001***	0.0000***	–2.068e-05***	–0.0005***	–0.0003***	–0.0012***	–0.0008***	0.0006***	–0.0013***	0.0002***	0.0003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Calendar-month FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Scam-type FEs	✗	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗
Adj. R^2	0.003	0.008	0.012	0.015	0.005	0.001	0.029	0.020	0.049	0.013	0.033
No. obs.	7,837,125	7,837,125	4,661,547	152,595	520,739	84,237	19,133	1,985,775	35,379	268,411	109,309
Panel C: Diversifiable Risk											
Post-scam	0.0077***	0.0119***	–0.0383***	0.0319**	0.0214***	0.0115***	0.018	0.1027***	0.3877***	–0.1580***	–0.0312***
	(0.001)	(0.001)	(0.001)	(0.011)	(0.007)	(0.020)	(0.008)	(0.002)	(0.089)	(0.046)	(0.011)
Victim	0.0817***	0.0858***	–0.0519***	0.0807***	0.1562***	0.2912	0.0510***	0.4497***	0.2639***	–0.1776***	–0.0311***
	(0.001)	(0.001)	(0.001)	(0.008)	(0.010)	(0.041)	(0.007)	(0.003)	(0.057)	(0.046)	(0.008)
Post-scam × Victim	0.0257***	0.0175***	0.0822***	–0.0584***	-0.0662***	–0.2666**	–0.0144	–0.2020***	-0.6846***	0.3147***	0.0653***
	(0.000)	(0.002)	(0.001)	(0.015)	(0.014)	(0.012)	(0.003)	(0.005)	(0.145)	(0.088)	(0.017)
Blockchain address age	0.0032***	0.0034***	0.0029***	0.0006	0.0002	–0.0013**	0.0008***	0.0127***	0.0017***	0.0031***	0.0027***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Calendar-month FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Scam-type FEs	✗	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗
Adj. R^2	0.021	0.021	0.002	0.001	0.001	0.000	0.018	0.140	0.013	0.003	0.002
No. obs.	7,837,125	7,837,125	4,661,547	152,595	520,739	84,237	19,133	1,985,775	35,379	268,411	109,309

Note: These are difference-in-differences regressions to estimate the treatment effects of cybercrime on victim addresses' risk-taking. The dependent variables are total, diversifiable, and non-diversifiable risk-taking in Panels A, B, and C, respectively. The independent variables are a post-scam dummy that takes the value of 1 in the post-scam period, 0 otherwise; a victim dummy that takes a value of 1 for victims and 0 for matched non-victims, and their interaction term, i.e., the difference-in-differences estimator. We also control for blockchain address age, and include calendar-month and cybercrime-type fixed effects. The first two columns show the *average* treatment effects across all cybercrime types, while columns 3 to 11 show *heterogeneous* treatment effects for each cybercrime type separately. The regressions are estimated over the symmetric [–12, +12] event window with respect to the cybercrime month 0. Definitions of all variables appear in Table A.1.

Table 8: **Treatment effects of cybercrime on victims' risk-adjusted returns (alphas)**

	Average Treatment Effects		**Heterogeneous Treatment Effects by Cybercrime Type**								
	All scams (1)	All scams (2)	Ponzi scheme (3)	Give-away (4)	Phishing scam (5)	Investment (6)	Fake token scam (7)	Hack (8)	Exploit (9)	Darkweb shop (10)	Sextortion (11)
Panel A: Alpha, 3-month event window											
Post-scam	0.0156***	0.0171***	0.021***	0.002	0.007***	-0.001	-0.0	0.013***	0.101***	-0.006	-0.02***
	(0.000)	(0.000)	(0.0)	(0.002)	(0.001)	(0.004)	(0.005)	(0.001)	(0.01)	(0.005)	(0.006)
Victim	0.0148***	0.0163***	0.029***	-0.001	-0.001	-0.013***	-0.02***	-0.011***	0.086***	-0.018***	-0.024***
	(0.000)	(0.000)	(0.0)	(0.002)	(0.001)	(0.004)	(0.005)	(0.0)	(0.008)	(0.004)	(0.006)
Post-scam × Victim	–0.0353***	–0.0383***	-0.044***	-0.001	-0.01***	0.009	0.009	-0.023***	-0.201***	0.02⋆	0.039***
	(0.000)	(0.001)	(0.001)	(0.003)	(0.001)	(0.006)	(0.009)	(0.001)	(0.017)	(0.009)	(0.011)
Blockchain address age	–0.0032***	–0.0030***	-0.004***	-0.004***	-0.002***	-0.002***	-0.003***	-0.003***	-0.001***	-0.002***	-0.003***
	(0.000)	(0.000)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)
Calendar-month FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Scam-type FEs	✗	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗
Adj. R^2	0.185	0.191	0.13	0.051	0.037	0.051	0.102	0.045	0.037	0.132	0.037
No. obs.	4,540,665	4,540,665	2,462,468	96,288	308,302	57,112	11,745	1,290,330	33,374	190,849	90,197
Panel B: Alpha, 12-month event window											
Post-scam	0.0214***	0.0285***	0.0380***	0.0014	0.0116***	0.0104***	–0.0030	0.0130***	0.0996***	–0.0091**	–0.0139***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.003)	(0.003)	(0.000)	(0.011)	(0.004)	(0.003)
Victim	0.0211***	0.0282***	0.0470***	-0.0027**	0.0033***	–0.0044	–0.0250***	–0.0113***	0.0785***	–0.0240***	–0.0189***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.003)	(0.003)	(0.000)	(0.008)	(0.004)	(0.003)
Post-scam × Victim	–0.0475***	–0.0617***	–0.0797***	0.0021	–0.0186***	–0.0120**	0.0169***	–0.0235***	–0.1911***	0.0294***	0.0286***
	(0.000)	(0.000)	(0.000)	(0.002)	(0.001)	(0.006)	(0.005)	(0.001)	(0.017)	(0.007)	(0.006)
Blockchain address age	–0.0031***	–0.0031***	–0.0039***	–0.0022***	–0.0015***	–0.0024***	–0.0026***	–0.0012***	–0.0018***	–0.0026***	–0.0021***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Calendar-month FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Scam-type FEs	✗	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗
Adj. R^2	0.179	0.184	0.091	0.050	0.034	0.046	0.108	0.049	0.031	0.137	0.036
No. obs.	7,837,125	7,837,125	4,661,547	152,595	520,739	84,237	19,133	1,985,775	35,379	268,411	109,309

Note: These are difference-in-differences regressions to estimate the treatment effects of cybercrime on victims' risk-adjusted returns. The dependent variable are address-level alphas estimated from the three-factor crypto-asset pricing model in Liu et al. (2022). Panels A and B show regression results for the 3- and 12-month symmetric event windows, respectively. The independent variables are a post-scam dummy that takes the value of 1 in the post-scam period, 0 otherwise; a victim dummy that takes a value of 1 for victims and 0 for matched non-victims, and their interaction term, i.e., the difference-in-differences estimator. We also control for blockchain address age, and include calendar-month and cybercrime-type fixed effects. The first two columns show the *average* treatment effects across all cybercrime types, while columns 3 to 11 show *heterogeneous* treatment effects for

each cybercrime type separately. Definitions of all variables appear in Table A.1.

Table 9: **Correlations between investor behavior, risk, and return in victims' post-scam blockchain addresses**

	Trading activity (1)	Churn rate (2)	Diversification (3)	% Stablecoins (4)	% Altcoins (5)	% Lottery tokens (6)
Panel A: 3-month						
Alpha × Post-scam × Victim	-20.067***	-0.478***	1.517***	0.081***	0.164***	0.024
	(3.543)	(0.083)	(0.309)	(0.005)	(0.048)	(0.014)
Alpha × Post-scam	4.698***	0.151⋆	-2.944***	-0.033***	-0.114***	-0.066***
	(1.207)	(0.068)	(0.163)	(0.003)	(0.02)	(0.009)
Alpha × Victim	-13.109***	-0.032	-5.912***	-0.129***	-0.421***	0.029***
	(2.259)	(0.033)	(0.226)	(0.004)	(0.04)	(0.007)
Non-diversifiable risk × Post-scam × Victim	2.142	0.083	0.626	0.083***	0.149	-0.029
	(3.714)	(0.088)	(0.615)	(0.013)	(0.113)	(0.022)
Non-diversifiable risk × Post-scam	-18.331***	-0.028	-1.079***	-0.071***	-0.137***	0.047**
	(2.28)	(0.075)	(0.318)	(0.009)	(0.039)	(0.016)
Non-diversifiable risk × Victim	4.435⋆	0.009	1.025⋆	-0.042***	0.125	-0.003
	(1.754)	(0.02)	(0.421)	(0.008)	(0.09)	(0.011)
Diversifiable risk × Post-scam × Victim	0.097	-0.022⋆	-0.544***	-0.009***	-0.106***	-0.024***
	(0.316)	(0.009)	(0.118)	(0.002)	(0.022)	(0.006)
Diversifiable risk × Post-scam	0.487⋆	0.024**	0.508***	0.009***	0.06***	0.024***
	(0.22)	(0.007)	(0.096)	(0.002)	(0.012)	(0.006)
Diversifiable risk × Victim	0.216	0.016***	0.237***	0.005***	0.068***	0.01***
	(0.185)	(0.005)	(0.061)	(0.001)	(0.018)	(0.003)
Post-scam × Victim	6.612***	0.036***	0.345***	-0.007***	-0.007⋆	-0.015***
	(0.284)	(0.002)	(0.017)	(0.0)	(0.003)	(0.001)
Calendar-month FEs	✓	✓	✓	✓	✓	✓
Scam type FEs	✓	✓	✓	✓	✓	✓
Adj. R^2	0.007	0.065	0.128	0.031	0.229	0.066
No. obs.	4,540,665	4,540,665	4,540,665	4,540,665	4,540,665	4,540,665
Panel B: 12-month						
Alpha × Post-scam × Victim	-20.525***	-0.132***	3.844***	0.111***	0.306***	0.018
	(2.517)	(0.033)	(0.211)	(0.004)	(0.032)	(0.01)
Alpha × Post-scam	2.998***	-0.03	-3.266***	-0.033***	-0.065***	-0.008
	(0.448)	(0.022)	(0.097)	(0.002)	(0.014)	(0.006)
Alpha × Victim	-11.687***	-0.215***	-7.623***	-0.15***	-0.577***	-0.015***
	(0.878)	(0.014)	(0.149)	(0.003)	(0.024)	(0.004)
Non-diversifiable risk × Post-scam × Victim	3.397	0.175***	0.818	0.123***	0.507***	0.104***
	(2.239)	(0.047)	(0.457)	(0.01)	(0.087)	(0.02)
Non-diversifiable risk × Post-scam	-14.604***	-0.088**	-1.745***	-0.101***	-0.465***	-0.055***
	(0.933)	(0.032)	(0.243)	(0.006)	(0.041)	(0.014)
Non-diversifiable risk × Victim	1.437**	-0.024	1.102***	-0.052***	0.089	-0.039***
	(0.482)	(0.013)	(0.294)	(0.006)	(0.059)	(0.008)
Diversifiable risk : Post-scam × Victim	0.239	-0.022***	-0.624***	-0.014***	-0.142***	-0.04***
	(0.153)	(0.005)	(0.077)	(0.001)	(0.015)	(0.005)
Diversifiable risk × Post-scam	0.453***	0.025***	0.566***	0.011***	0.084***	0.032***
	(0.087)	(0.003)	(0.06)	(0.001)	(0.01)	(0.004)
Diversifiable risk × Victim	0.018	0.013***	0.269***	0.006***	0.078***	0.017***
	(0.047)	(0.002)	(0.037)	(0.001)	(0.01)	(0.002)
Post-scam × Victim	7.368***	0.057***	0.386***	-0.004***	0.0	-0.009***
	(0.27)	(0.002)	(0.013)	(0.0)	(0.003)	(0.001)
Calendar-month FEs	✓	✓	✓	✓	✓	✓
Scam type FEs	✓	✓	✓	✓	✓	✓
Adj. R^2	0.006	0.053	0.133	0.027	0.293	0.080
No. obs.	7,837,125	7,837,125	7,837,125	7,837,125	7,837,125	7,837,125

Note: These are difference-in-differences-in-differences (i.e., triple differences) regressions to explore correlations between various proxies for investor behavior and the estimated treatment effects for risk-adjusted returns and risk-taking. The dependent variables are trading activity, churn rate, diversification, stablecoin, altcoin, and lottery token holdings in % in columns 1, 2, 3, 4, 5, and 6, respectively. The independent variables are our difference-in-differences variables (victim dummy, post-scam dummy, and their interaction), which are simultaneously interacted with risk-adjusted returns, non-diversifiable risk-taking, and diversifiable risk-taking. We also include calendar-month and cybercrime-type fixed effects. The regressions are estimated over the symmetric [–3, +3] and [–12, +12] event windows with respect to the cybercrime month 0 in Panels A and B, respectively. Definitions of all variables appear in Table A.1.

Table 10: **Treatment effects on victims in bull versus bear markets, 3-month**

	Bear Market		Bull Market	
Panel A: Total Risk				
Post-scam	-0.057^{***}	-0.059^{*}	-0.112^{***}	-0.013^{**}
	(0.004)	(0.004)	(0.001)	(0.001)
Victim	0.041	0.040	0.234^{***}	0.334^{**}
	(0.004)	(0.004)	(0.003)	(0.003)
Post-scam × Victim	0.088	0.092	0.268^{***}	0.068
	(0.005)	(0.005)	(0.003)	(0.003)
Account age	0.004	0.004	0.020^{***}	0.024^{**}
	(0.001)	(0.001)	(0.001)	(0.001)
Calendar-month FEs	Yes	Yes	Yes	Yes
Scam-type FEs	No	Yes	No	Yes
Adj. R^2	−0.0	−0.003	0.031	0.032
No. obs.	45718	45718	1123429	1123429
Panel B: Non-Diversifiable Risk				
Post-scam	-0.006^{***}	-0.008^{**}	-0.013^{***}	0.001^{*}
	(0.001)	(0.002)	(0.001)	(0.001)
Victim	-0.010^{***}	-0.012^{**}	-0.019^{***}	-0.005^{**}
	(0.001)	(0.002)	(0.001)	(0.001)
Post-scam × Victim	0.010^{***}	0.013^{**}	0.026^{***}	−0.001
	(0.002)	(0.003)	(0.001)	(0.001)
Account age	0.002^{***}	0.002^{**}	0.001^{***}	0.002^{**}
	(0.001)	(0.002)	(0.001)	(0.001)
Calendar-month FEs	Yes	Yes	Yes	Yes
Scam-type FEs	No	Yes	No	Yes
Adj. R^2	0.007	0.005	0.017	0.029
No. obs.	45718	45718	1123429	1123429
Panel C: Diversifiable Risk				
Post-scam	-0.051^{*}	-0.052^{*}	-0.1^{***}	-0.014^{**}
	(0.002)	(0.002)	(0.001)	(0.001)
Victim	0.052	0.051	0.253^{***}	0.339^{**}
	(0.002)	(0.002)	(0.003)	(0.003)
Post-scam × Victim	0.078	0.079	0.242^{***}	0.069^{**}
	(0.003)	(0.003)	(0.002)	(0.002)
Account age	0.002^{***}	0.002^{**}	0.018^{***}	0.022^{**}
	(0.001)	(0.002)	(0.001)	(0.001)
Calendar-month FEs	Yes	Yes	Yes	Yes
Scam-type FEs	No	Yes	No	Yes
Adj. R^2	−0.0	−0.003	0.032	0.034
No. obs.	45718	45718	1123429	1123429
Panel D: Alpha				
Post-scam	0.000	0.002	-0.018^{***}	-0.003^{**}
	(0.001)	(0.001)	(0.001)	(0.001)
Victim	-0.012^{***}	-0.011^{**}	-0.033^{***}	-0.019^{**}
	(0.001)	(0.001)	(0.001)	(0.001)
Post-scam × Victim	0.003	−0.000	0.035^{***}	0.005^{**}
	(0.002)	(0.002)	(0.001)	(0.001)
Account age	-0.001^{***}	-0.001^{**}	-0.003^{***}	-0.002^{**}
	(0.001)	(0.001)	(0.001)	(0.001)
Calendar-month FEs	Yes	Yes	Yes	Yes
Scam-type FEs	No	Yes	No	Yes
Adj. R^2	0.007	0.007	0.057	0.074
No. obs.	45718	45718	1123429	1123429

Note: These are difference-in-differences regressions to estimate the treatment effects of cybercrime on victim addresses' risk-taking and risk-adjusted returns in subsamples of victims that fell for a scam in a bull market (columns 1 and 2) and a bear market (columns 3 and 4). The dependent variables are total, diversifiable,

non-diversifiable risk-taking, and alphas in Panels A, B, C, and D, respectively. The independent variables are a post-scam dummy that takes the value of 1 in the post-scam period, 0 otherwise; a victim dummy that takes a value of 1 for victims and 0 for matched non-victims, and their interaction term, i.e., the difference-in-differences estimator. We also control for blockchain address age, and include calendar-month and cybercrime-type fixed effects. The regressions are estimated over the symmetric [–3, +3] event window with respect to the cybercrime month 0. Definitions of all variables appear in Table A.1.

Table 11: **Treatment effects for victims in small- versus large-scale cybercrimes, 3-month**

	Victims in a small group		Victims in a large group	
Panel A: Total Risk				
Post-scam	0.018^{***}	0.020^{**}	-0.011^{***}	-0.012^{**}
	(0.001)	(0.001)	(0.001)	(0.001)
Victim	0.202^{***}	0.206^{***}	-0.007^{*}	-0.008^{**}
	(0.003)	(0.003)	(0.002)	(0.002)
Post-scam × Victim	-0.051^{***}	-0.052^{**}	0.023^{***}	0.023^{**}
	(0.002)	(0.002)	(0.002)	(0.002)
Account age	0.001^{***}	0.001^{**}	0.003^{***}	0.003^{**}
	(0.000)	(0.000)	(0.000)	(0.000)
Calendar-month FEs	Yes	Yes	Yes	Yes
Scam-type FEs	No	Yes	No	Yes
Adj. R^2	0.005	0.006	0.003	0.003
No. obs.	1314067	1314067	1416688	1416688
Panel B: Non-Diversifiable Risk				
Post-scam	-0.005^{***}	-0.006^{**}	0.002^{***}	0.001^{**}
	(0.000)	(0.000)	(0.000)	(0.000)
Victim	-0.002^{**}	-0.003^{*}	0.014^{***}	0.014^{**}
	(0.000)	(0.000)	(0.000)	(0.000)
Post-scam × Victim	0.010^{***}	0.011^{**}	-0.010^{***}	-0.010^{**}
	(0.001)	(0.001)	(0.001)	(0.001)
Account age	-0.000^{***}	-0.000^{**}	-0.000^{***}	-0.000^{**}
	(0.000)	(0.000)	(0.000)	(0.000)
Calendar-month FEs	Yes	Yes	Yes	Yes
Scam-type FEs	No	Yes	No	Yes
Adj. R^2	0.012	0.016	0.016	0.018
No. obs.	1314067	1314067	1416688	1416688
Panel C: Diversifiable Risk				
Post-scam	0.023^{**}	0.026^{**}	-0.013^{**}	-0.013^{**}
	(0.001)	(0.001)	(0.001)	(0.001)
Victim	0.205^{***}	0.209^{***}	-0.021^{***}	-0.022^{**}
	(0.003)	(0.003)	(0.002)	(0.002)
Post-scam × Victim	-0.061^{***}	-0.063^{**}	0.033^{***}	0.034^{**}
	(0.002)	(0.002)	(0.002)	(0.002)
Account age	0.001^{***}	0.002^{**}	0.004^{***}	0.004^{**}
	(0.000)	(0.000)	(0.000)	(0.000)
Calendar-month FEs	Yes	Yes	Yes	Yes
Scam-type FEs	No	Yes	No	Yes
Adj. R^2	0.006	0.007	0.004	0.004
No. obs.	1314067	1314067	1416688	1416688
Panel D: Alpha				
Post-scam	0.008^{***}	0.009^{**}	0.018^{**}	0.018^{**}
	(0.000)	(0.000)	(0.000)	(0.000)
Victim	-0.004^{***}	-0.003^{**}	0.027^{***}	0.027^{***}
	(0.000)	(0.000)	(0.000)	(0.000)
Post-scam × Victim	-0.013^{**}	-0.013^{**}	-0.041^{***}	-0.041^{**}
	(0.001)	(0.001)	(0.001)	(0.001)
Account age	-0.002^{***}	-0.002^{**}	-0.004^{***}	-0.004^{**}
	(0.000)	(0.000)	(0.000)	(0.000)
Calendar-month FEs	Yes	Yes	Yes	Yes
Scam-type FEs	No	Yes	No	Yes
Adj. R^2	0.044	0.058	0.149	0.149
No. obs.	1314067	1314067	1416688	1416688

Note: These are difference-in-differences regressions to estimate the treatment effects of cybercrime on victim addresses' risk-taking and risk-adjusted returns in subsamples of victims that fell for a scam in a relatively small group (columns 1 and 2) and a relatively large group (columns 3 and 4). The dependent variables

are total, diversifiable, non-diversifiable risk-taking, and alphas in Panels A, B, C, and D, respectively. The independent variables are a post-scam dummy that takes the value of 1 in the post-scam period, 0 otherwise; a victim dummy that takes a value of 1 for victims and 0 for matched non-victims, and their interaction term, i.e., the difference-in-differences estimator. We also control for blockchain address age, and include calendar-month and cybercrime-type fixed effects. The regressions are estimated over the symmetric [–3, +3] event window with respect to the cybercrime month 0. Definitions of all variables appear in Table A.1.

Table 12: **Predictors of cybercriminals**

	All Scams	Ponzi scam	Give-away	Phishing	Investment scam	Fake token	Hack	Exploit shop	Darkweb	Sextortion
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Blockchain address age	-0.0	0.001⋆	-0.0	0.0	0.0	0.001	-0.0	-0.0	0.001	0.001
	(0.0)	(0.001)	(0.0)	(0.0)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.0)
Diversification	0.007***	0.01***	0.002***	0.008***	0.012***	0.017***	0.005***	0.009***	0.012***	0.017***
	(0.0)	(0.001)	(0.001)	(0.0)	(0.002)	(0.005)	(0.001)	(0.001)	(0.001)	(0.001)
Lottery token share	-0.459***	-0.534***	-0.371***	-0.49***	-0.483***	-0.538***	-0.462***	-0.367***	-0.584***	-0.623***
	(0.003)	(0.018)	(0.007)	(0.005)	(0.014)	(0.033)	(0.014)	(0.03)	(0.021)	(0.011)
Stablecoin share	-0.331***	-0.524***	-0.403***	-0.361***	-0.344***	-0.259***	-0.247***	-0.205***	-0.302***	-0.15***
	(0.005)	(0.016)	(0.01)	(0.009)	(0.014)	(0.049)	(0.017)	(0.058)	(0.021)	(0.029)
Altcoin share	0.202***	0.151***	0.19***	0.251***	0.016	-0.135**	0.155***	-0.37***	0.121***	0.146***
	(0.005)	(0.027)	(0.01)	(0.007)	(0.024)	(0.048)	(0.018)	(0.032)	(0.036)	(0.02)
Adj. R^2	0.138	0.212	0.081	0.177	0.152	0.156	0.211	0.141	0.187	0.164
No. obs.	82894	3580	24458	34714	6152	1182	4304	878	2498	5128

Note: This table reports regression results examining the characteristics of addresses that belong to cybercriminals (Panel A) and victims (Panel B). The dependent variable is a dummy variable which takes a value of 1 if the address belongs to a cybercriminal (victim). Robust standard error in parenthesis. Definitions of all variables appear in Table A.1.

Appendix

Table A.1: Variable definitions

Variable	Definition
Barber and Odean (2000) raw return	Gross monthly return on investment using the beginning-of-day position statements. Following Barber and Odean (2000), all tokens are assumed to be bought or sold at the end of the month and ignore intra-month trading. The monthly return on the investor i's portfolio is calculated as: $$return_{i,t} = \sum_{j \in Q} w_{j,t} R_{j,t}$$ where j refers to different tokens in investor i's portfolio at time t, w refers to the weight of the \$ value for the holdings of token j in the total portfolio value at the beginning of the month, and R is the gross monthly return of token j.
Total Risk	Total risk refers to the overall variability or volatility of the return for a specific address i at time t. It encompasses all sources of risk, including both diversifiable and non-diversifiable components.
Diversifiable Risk	Diversifiable risk, also known as idiosyncratic risk, represents the portion of the total risk of the return that can be eliminated through diversification. It refers to the risk specific to the address i at time t and is captured by the variance of $\epsilon_{i,t}$ in equation (2).
Non-Diversifiable Risk	Non-diversifiable risk, also known as systematic risk, is the portion of the total risk of the return that cannot be eliminated through diversification. It captures the common risk factors that affect a broad range of addresses and is measured by subtracting the diversifiable risk from the total risk.
Churn rate	We measure investment horizon by calculating for each blockchain address how frequently the holder's positions are rotated on all of the portfolio's tokens (Gaspar et al., 2005). The churn rate of address i at day t is calculated as: $$churn\ rate_{i,t} = \frac{\sum_{j \in Q} \lvert N_{j,i,t} P_{j,i,t} - N_{j,i,t-1} P_{j,i,t-1} - N_{j,i,t-1} \Delta P_{j,t} \rvert}{\sum_{j \in Q} \frac{N_{j,i,t} P_{j,i,t} + N_{j,i,t-1} P_{j,i,t-1}}{2}}$$ where $P_{j,t}$ and $N_{j,i,t}$ represent the price and the number of tokens of token j held by blockchain address i at month t.
Blockchain address balance	We measure the balance of each address by summing over the \$ value of all tokens held by a blockchain address: $$blockchain address\ balance_{i,t} = \sum_{j \in Q} N_{j,i,t} P_{j,i,t}$$ where $N_{j,i,t}$ and $P_{j,i,t}$ represent the number of tokens and the price of token j held by address i at month t.

(Continued)

Table A.1 – Continued

Variable	Definition
Diversification	Diversification refers to the number of unique tokens held within an address at the end of each month.
Trading activity	Trading activity represents the number of transactions, including purchases and sales, measured at the end of each month.
Blockchain address age	Blockchain address age denotes the duration in months since the address became active.
Lottery token investor	A dummy variable that takes a value of 1 if the investor has made investments in lottery tokens in that month. Lottery tokens are defined as tokens with a share price lower than 10 cents.
Lottery token share	Lottery token share corresponds to the proportion of the investor's total portfolio allocated to lottery tokens at the end of each month.
Stablecoin investor	A dummy variable that takes a value of 1 if the investor has made investments in stablecoins in that month. A token is deemed a stablecoin if it is designed to maintain a steady value, which can be achieved either by linking it to a specific commodity or currency, or by regulating its supply through algorithmic means.
Stablecoin share	Stablecoin share represents the percentage of the investor's total portfolio consisting of stablecoins at the end of each month.
Altcoin share	Altcoin share indicates the proportion of the investor's total portfolio allocated to altcoins at the end of each month. Altcoins are defined as tokens issued by start-ups to finance their blockchain projects. Currency tokens (ETH, WBTC, etc.) or stablecoins are excluded.

Table A.2: **Cybercriminals (all types)**

Variable	mean	stddev	min	max	q1	median	q3
return	0.069	0.779	-1	65.6	-0.021	0	0.058
churn rate	0.076	0.38	0	18.151	0	0	0
diversification	4.521	12.431	1	287	1	1	2
blockchain address balance	56,246.866	2,072,803.766	0	229,506,948.254	0	0.29	39.413
trading activity	301.238	16,916.938	0	2,400,319	0	0	0
blockchain address age (month)	19.68	13.757	1	76	7	17	30
lotterytoken investor (dummy)	0.296	0.457	0	1	0	0	1
lotterytoken share	0.109	0.288	0	1	0	0	0
stablecoin investor (dummy)	0.106	0.308	0	1	0	0	0
stablecoin share	0.024	0.138	0	1	0	0	0
altcoin share	0.211	0.388	0	1	0	0	0.082
3-factor model:							
diversifiable risk	0.24	0.621	0	12.844	0.023	0.123	0.191
non-diversifiable risk	0.075	0.152	0	3.607	0.004	0.048	0.111
total risk	0.316	0.699	0	16.451	0.053	0.221	0.292
market	2.597	4.751	-23.913	78.281	0.172	1.847	4.151
momentum	1.288	11.782	-145.027	218.3	-1.394	0	0.463
size	-0.473	6.888	-158.4	17.035	-0.205	0.006	0.635
alpha	0.023	0.173	-1.156	2.759	-0.016	0	0.053

Note: This table reports summary statistics for cybercriminals of all fraud types. Variables are constructed monthly and our final sample includes address–month observations from 1,467 unique cybercriminal addresses. Definitions of all variables appear in Table A.1.

Table A.3: **Non-cybercriminals (all types)**

Variable	mean	stddev	min	max	q1	median	q3
return	0.061	0.843	-1	89.998	-0.075	0	0.077
churn rate	0.087	0.586	0	56.487	0	0	0
diversification	2.615	4.825	1	89	1	1	2
blockchain address balance	50,663.996	1,158,625.327	0	83,760,132.375	0	2.252	205.02
trading activity	23.416	1,199.593	0	147,241	0	0	0
blockchain address age (month)	19.682	13.756	1	76	7	17	30
lotterytoken investor (dummy)	0.318	0.466	0	1	0	0	1
lotterytoken share	0.092	0.264	0	1	0	0	0
stablecoin investor (dummy)	0.11	0.313	0	1	0	0	0
stablecoin share	0.016	0.115	0	1	0	0	0
altcoin share	0.208	0.381	0	1	0	0	0.079
3-factor model:							
diversifiable risk	0.221	0.653	0	13.644	0.018	0.158	0.202
non-diversifiable risk	0.085	0.137	0	2.287	0.009	0.062	0.114
total risk	0.306	0.713	0	14.066	0.079	0.234	0.299
momentum	0.834	8.988	-79.788	123.634	-1.663	-0.002	0.436
size	-0.368	6.606	-138.591	29.716	-0.438	0	0.722
alpha	0.025	0.265	-0.696	7.623	-0.026	0	0.054

Note: This table reports summary statistics for non-cybercriminals of all fraud types. Variables are constructed monthly and our final sample includes address–month observations from 1,467 unique non-cybercriminal addresses. Definitions of all variables appear in Table A.1.

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