Crypto Risk in the Financial System*

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Abstract

In this paper, we trace how crypto risk from the crypto ecosystem transmits systemic risk to the financial system. First, we measure crypto risk and crypto-driven systemic risk at the financial firm level. Using these metrics, we show that firm-level crypto risk has been rising significantly in recent years, thus leading to greater systemic risk exposure and transmission through two different channels. Specifically, crypto risk affects systemic risk exposure through both blockchain technology and asset class channels but elevates systemic risk transmission mainly via the blockchain technology channel. Notably, financial firms' management tends to neglect the transmission of risk through the blockchain technology channel. Our findings highlight the integration of two parallel systems and underscore the importance of a global regulatory framework.

Keywords: Crypto Risk; Systemic Risk; Blockchain Technology; Asset Class

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1 Introduction

Cryptocurrencies, a technological innovation introduced with Bitcoin in 2008 (Nakamoto, 2008), have established a sophisticated crypto ecosystem. At the first layer, blockchain technology validates and securely executes transactions, addressing the double-spending problem without requiring centralized intermediaries. The second layer features smart contracts that enable advanced decentralized financial entities, including decentralized exchanges, lending platforms, and Decentralized Autonomous Organizations (DAOs). The third user-oriented layer is composed of centralized exchanges and digital wallets, providing accessible gateways for investors to interact with the crypto ecosystem. Collectively, these layered innovations form an intricate financial infrastructure that is increasingly interconnected with the traditional financial system (Makarov & Schoar, 2022).[1]

Nevertheless, this growing integration could introduce substantial systemic risks, as vulnerabilities within the crypto ecosystem increasingly permeate traditional finance through many direct and indirect channels,[2] including financial crypto-asset exposure and technological integration. Financial firms directly engage with crypto markets through investments and credit arrangements with crypto entities. The FTX collapse in 2022[3] illustrates that these direct exposures can cause significant investor losses and liquidity crises for financial firms. Indirectly, financial firms face risks from technological integrations, including blockchain-based infrastructures, potentially exposing traditional finance to technological disruptions (e.g., cybersecurity breaches). Such incidents have raised critical concerns among regulators and market participants regarding the integration of the crypto ecosystem and the traditional financial system, highlighting the systemic implications of crypto risk and its potential role in amplifying financial instability.[4]

[1] Unlike the crypto ecosystem, the financial system consists of financial intermediaries such as banks, insurance companies, real estate firms, and trading firms. In our conceptual framework, Fintech firms are part of the traditional financial system because Fintech firms employ similar financial infrastructures as banks but apply only some new technologies, such as machine learning and AI, to increase overall efficiency.

[2] The Fed's policy report titled "The Financial Stability Implications of Digital Assets" finds that potential systemic risks arise from the crypto ecosystem and could be transmitted from the crypto ecosystem to the traditional financial system. In addition, this policy report points out some potential connections between the crypto ecosystem and the traditional financial system.

[3] *The Wall Street Journal* article titled "How FTX's Sam Bankman-Fried Went from Crypto Golden Boy to Villain" reports this market-wide event in detail.

[4] Federal agencies, including the Fed, the FDIC, and the OCC, jointly issued a statement on "Crypto-Asset Risks to Banking Organizations" after the FTX run. This joint statement identifies several possible crypto-related risks and emphasizes the close monitoring of crypto risk exposure for bank organizations. The website of the joint statement is here: https://www.federalreserve.gov/newsevents/pressreleases/files/bcreg20230103a1.pdf.

Against this backdrop, our paper investigates three critical questions: (1) Is there crypto risk in the financial system? (2) Does crypto risk elevate systemic risk in the financial system? (3) Through which channel—blockchain technology or asset class—does crypto risk affect systemic risk? Addressing these questions is essential for understanding the intricate ways in which crypto risk from the crypto ecosystem interacts with systemic vulnerabilities in the broader financial system. This study can also help provide regulators with the necessary tools to design effective regulatory frameworks.

Previous studies have underexplored these important questions due to three big challenges. The first challenge is discovering how to measure crypto risk at a financial firm level. This novel measure needs to capture closeness and co-movement through direct or indirect connections between two parallel systems.[5] While financial firms' direct crypto holdings are a natural candidate for measuring exposure, much of crypto risk stems from indirect connections. For example, banks, despite regulatory discouragement of crypto asset ownership, remain indirectly exposed by lending to crypto firms,[6] servicing institutional crypto clients, facilitating stablecoin transactions, and holding reserves.[7] The second challenge is constructing a measure that can capture systemic risk changes driven by the crypto market. Conventional systemic risk measures such as Conditional Value-at-Risk (CoVaR) and Marginal Expected Shortfall (MES) capture universal systemic risk sources such as the housing bubble, the credit crunch, and the financial crisis. The third challenge is identifying the transmission mechanisms through which financial firms' exposures to the crypto ecosystem contribute to systemic risk fluctuations.[8] Natural experiments that are purely based in the crypto ecosystem are needed to distinguish whether crypto risk affects systemic risk through blockchain technology or asset class channels.

To address these empirical challenges, we employed a series of novel methods. First, we created a financial firm-level crypto risk measure by calculating the co-movement between the equity returns of financial firms and the returns of Bitcoin or a broader crypto market index. Cryptocurrencies (Crypto coins) returns represent the most critical price signals within the crypto ecosystem, and their co-movement with financial firms' equity returns effectively captures essential information links across both markets. This measure captures both direct and indirect connections between financial firms and the crypto ecosystem. Second, building on foundational research on CoVaR and MES (Adrian & Brunnermeier, 2016; Acharya et

[5] The origin of crypto risk should come from the integration of the crypto ecosystem and the traditional financial system.
[6] Silvergate Capital Bank has issued bitcoin-collateralized loans, and Signature Bank provides deposit services to crypto businesses.
[7] Generally, banks that conduct any crypto activities need to receive non-objection approval from their regulators. Online Appendix D discusses the regulatory framework on crypto activities in U.S. banking industries.
[8] Financial firms might be impacted through their crypto holdings, exposure to crypto-related firms or households, or reliance on crypto-based payment infrastructures.

al., 2017), we extended these frameworks to construct crypto-driven CoVaR and MES, enabling us to capture systemic risk variations caused by the crypto ecosystem. Lastly, we employed clean crypto shocks: cryptocurrency-related cyber-attacks, from the crypto ecosystem and divided them into two types of channels: (1) blockchain technology, with core blockchain vulnerabilities that threaten the security and functionality of the blockchain infrastructure itself; and (2) asset class, with financial asset-targeted breaches that exploit the storage, transfer, and custodial aspects of cryptocurrencies.[9]

The building blocks of the crypto ecosystem are programs and scripts; indeed, in the crypto ecosystem, codes are rules and laws. The clean shocks from the crypto ecosystem could come from cyber-attacks on codes, which power the function and operation of the crypto ecosystem. Blockchain technology shocks threaten the bottom and second layers of blockchain architecture.[10] In contrast, asset class shocks harm the third application layer of blockchain architecture, including central exchange hacks and digital wallet exploits.[11]

In this paper, we measured the crypto risk of financial firms and crypto-driven systemic risk in the financial system. Specifically, we constructed a crypto risk measure by calculating the beta from a regression of financial firms' equity returns on crypto coin returns.[12] Also, we developed a perceived crypto risk measure at a financial firm level by text mining financial disclosures to capture financial firm management' perception of crypto risk.[13] The objective beta-based measure could instantly capture all the information that causes the co-movement of returns through the interconnections of two systems. In contrast, the subjective text measures could reflect the management' perception of or attention to crypto risk. Previous papers have suggested there is a divergence between subjective and objective risk assessments (Baron et al., 2024; Gormsen & Huber, 2024). Furthermore, we divided the systemic risk into two key components: systemic risk exposure and systemic risk transmission. Systemic risk exposure quantifies a firm's financial losses during crisis periods, while systemic risk transmission evaluates a firm's contribution to the broader financial system's stability. This approach provides a comprehensive framework for

[9] Online Appendix C discusses the steps we took to collect and categorize these two distinct types of shocks.
[10] These shocks cause the disruption or delay of payments, the outage or termination of transactions, and the dysfunction of smart contracts.
[11] These shocks cause the loss of crypto traders and liquidity holders, the fund outflow, and the withdrawal of the stablecoin holders.
[12] Specifically, we used two crypto returns: bitcoin returns and crypto coin market index returns. Bitcoin is the most valuable coin in the crypto market. Crypto coin market index returns are constructed by calculating the average return of the top twenty most valuable crypto coins.
[13] We employed text mining methods to build three text measures (Hassan et al., 2019; Hassan et al., 2023) and leverage the large language model (LLM) to construct one measure. Four different measures were used to capture the management' perceived crypto risk.

understanding and managing the multifaceted impact of crypto risks on financial institutions and the broader financial system.

Overall, we found that firm-level crypto risk has been rising in recent years within the financial system. Crypto risk at the financial firm level increases systemic risk in the financial system. However, while the management of financial firms could perceive systemic risk exposure, they are unable to perceive systemic risk transmission. Crypto risk raises systemic risk exposure through two channels. However, it drives up systemic risk transmission only through the blockchain technology channel.[14]

We begin our analysis by presenting some important, stylized facts. Crypto risk at the financial firm level has been rising since 2018, but it was declining prior to that year. This pattern signals that crypto risk could become a source of systemic risk, thereby threatening financial stability. Banks and trading firms are significantly exposed to crypto risk, while insurance companies and real estate firms show minimal exposure. Notably, the pattern of perceived crypto risk indicates that financial firm management is aware of—and paying attention to—this emerging risk.

In terms of crypto-driven systemic risk exposure, we show that MES and crypto MES share similar time-series trends, though the magnitude of crypto MES is smaller. This evidence suggests that crypto MES is a subset of MES, capturing specific components of general systemic risk exposure. Cross-sectionally, real estate firms and trading firms are more exposed to systemic risk exposure than banks and insurance companies. Regarding systemic risk transmission, both CoVaR and crypto CoVaR have been rising since 2018, which suggests an increase in systemic risk transmission in recent years. Banks, insurance companies, and trading firms are more vulnerable to systemic risk transmission than real estate firms.

Next, we extend our analysis with a case study of the FTX exchange run.[15] This case study validates our crypto risk measures and demonstrates their prediction power for crypto-driven systemic events. The collapse of the FTX exchange triggered a massive sell-off in the crypto ecosystem and increased fear in the broader equity market. The crisis originated from misconduct by FTX's founder, Sam Bankman-Fried, who leveraged his affiliated hedge fund, Alameda Research, for insider trading. Using buy-and-hold returns during the crisis period, we quantify the financial losses of financial firms and evaluate the extent to which

[14] The management and the market could perceive or react negatively to asset class channels but not to blockchain technology channels in the crypto and equity markets, as shown in Table 10 and Figure A7. The main effects of asset class channels come from direct crypto asset holdings, whereas those of blockchain technology channels come from indirect connections because the blockchain technology functions as service providers for crypto-traded firms or households. Consequently, the management can better control systemic risk transmission through asset channels.

[15] We also applied the same approach to a new case study of the TerraUSD run, and the results were similar to those of the FTX exchange run. Two case studies show robust evidence of our measures.

our crypto risk and perceived crypto risk measures can predict these financial losses.[16] Our findings confirm that two types of measures effectively predict financial firm losses during the crisis, reinforcing the validity of our metrics in capturing crypto risk-related risk.

We further analyze the impact of crypto risk on systemic risk using panel regressions during normal periods. Our results show that crypto risk raises systemic risk exposure, with a 1 percentage point increase in crypto risk resulting in a 0.027 percentage point rise in MES and a 0.064 percentage point rise in crypto MES. Crypto risk also elevates systemic risk transmission, with a 1 percentage point increase in crypto risk causing crypto CoVaR to rise by 0.5 basis points. Thus, crypto risk at the financial firm level contributes to systemic risk during normal periods. Interestingly, while crypto risk raises the total risk of financial firms, it does not affect their performance.

Does financial firm management perceive systemic risk in normal times? To address this question, we replace our crypto risk measures with perceived crypto risk measures and replicate our analysis. Our findings reveal that the management can identify systemic risk exposure but fail to detect systemic risk transmission. In addition, perceived crypto risk affects financial firms' performance but does not influence their total risk. When the management discusses crypto-related topics more frequently, investors demand higher equity returns, while firms' accounting performances deteriorate. In normal periods, crypto risk measures are risk sensitive, while perceived crypto risk measures are performance sensitive.

We then extend our analysis to the channels through which systemic risk can emerge. Does it arise through the blockchain technology, where vulnerabilities threaten its infrastructure and the stability of its permissionless financial framework? Or does it primarily arise when cryptocurrencies function as a financial asset, subject to breaches that can target their value without compromising the blockchain's foundational system?[17]

Using these two shocks, blockchain technology and asset class shocks from the crypto ecosystem, we employ a stacked Difference-in-Differences (DID) research design to analyze how firm-level crypto risk from the crypto ecosystem contributes to systemic risk in the financial system.

Our findings indicate that crypto risk at the financial firm level increases systemic risk exposure through both blockchain technology and asset class channels. Economically, when financial firms experience a 1 standard deviation change in crypto risk, their crypto MES rises by 4.36 percentage points; 71.89 basis

[16] Figure 4 and Table A4 report the results of the FTX exchange run, while Figure A6 and Table A5 report the results of the TerraUSD run.
[17] Recent papers have pointed out the vulnerabilities of crypto as a decentralized payment system and the flaws of this technology (Hinzen et al., 2022; Budish, 2024).

points; and 3.76 percentage points following blockchain, exchange, and wallet shocks, respectively, compared to their counterfactuals. The main treatment effects are striking among banks and trading firms, which are highly exposed to systemic risk through both blockchain and asset channels.

In contrast, crypto risk affects systemic risk transmission differently depending on channels. It increases systemic risk transmission through the blockchain technology channel but reduces it through the asset channel. Specifically, a 1 standard deviation change in crypto risk results in a 0.59 basis point increase; a 0.07 basis point decrease; and a 0.41 basis point increase in crypto CoVaR following blockchain, exchange, and wallet shocks, respectively, relative to their counterfactuals. Banks are the primary contributors to systemic risk transmission through the blockchain technology channel, while trading firms dominate the asset class channel. These patterns can be satisfactorily explained. First, regulatory authorities closely monitor and track banks' crypto activities, which discourages banks from directly holding crypto assets. This thus indirectly exposes banks to crypto ecosystems,[18], whereas trading firms are allowed to hold and trade cryptocurrencies but also face high regulatory scrutiny from their regulators. Second, blockchain technology channels spill over shocks through blockchain networks and cause global shocks,[19] while asset class channels are limited to one or two specific exchanges or wallets and lead to local shocks.

How do the market and management perceive systemic risk? The equity market reacts negatively to the asset class channel but shows no significant response to the blockchain technology channel.[20] Financial firm management, when discussing or focusing more on crypto-related topics, perceives systemic risk exposure through both the blockchain technology and asset class channels. However, while the management can perceive systemic risk transmission via the asset class channel, they fail to detect systemic risk transmission through the blockchain technology channel. These findings suggest that both the market and management pay less attention to the blockchain technology channel—or it may simply be more challenging for them to detect systemic risks arising from it.

Finally, we conclude our analysis with a series of placebo tests. A significant identification concern is that our treatment effects might come from common factors of cyber-attacks rather than clean shocks from the crypto ecosystem itself (Florackis et al., 2023). To address this concern, we used individual financial firms' cybersecurity attacks as placebo shocks. These placebo shocks target the cybersecurity or digital

[18] Online Appendix D provides the regulatory framework for U.S. banking industries.
[19] The crypto ecosystem is connected by a series of blockchain networks, such as Bitcoin networks, Ethereum networks, Solana networks, and XRP networks. Each blockchain network is connected to each other by crypto bridges.
[20] The crypto shocks of the asset class impact market liquidity and erode investors' confidence in cryptocurrency as an asset class. However, the crypto shocks of the blockchain technology do not destroy investors' trust in the system.

infrastructure of financial firms rather than cryptocurrencies. The results from these tests support our main treatment effects, validating the robustness of our findings.

We also present a battery of robustness tests. Those tests reaffirm our main findings: (1) Our crypto risk and perceived crypto risk measures can effectively predict crypto-driven systemic events, and that prediction power also applies to the TerraUSD run. (2) Our main findings regarding crypto shocks are robust using an alternative classification approach, and we can thus reclassify the types of crypto shocks within the framework of core versus non-core technological attacking methods. (3) The results of the differential market reactions to the two channels are still consistent in the crypto trading market.

Our paper contributes to the overall literature on financial stability. Diamond and Dybvig (1983) novelly argued that depositors' self-fulfilling beliefs could lead to bank runs and financial instability. Goldstein et al. (2024) suggested that asset commonality could be a source of systemic risk. Furthermore, financial firms' off-balance activities (Brunnermeier et al., 2020b), the asset bubble (Brunnermeier et al., 2020a), and rare disaster risk (Baron et al., 2024) are all systemic sources. Our paper contributes to the literature by identifying a new systemic risk source: crypto risk in the financial system.

Our study also adds to the literature on Fintech and digital currencies. Prior papers have primarily focused on the adoption of new technology in the financial systems. For example, Buchak et al. (2018) argued that regulation arbitrage, rather than technological advantage, is the primary driver of the recent Fintech rise. Digital currencies are another wave of technological innovation. Central Bank Digital Currency (CBDC) might threaten the traditional banking system by causing deposit outflows (Keister & Sanches, 2023; Berg et al., 2024).

Cryptocurrencies, as decentralized currencies, are based on the blockchain technology (Liu et al., 2024). They represent a new asset class, and they are priced by common factors (Liu et al., 2022; Huang & Yang, 2024). Some papers have focused on the application of this new decentralized technology (Cong & He, 2019; Sockin & Xiong, 2023), while other papers have pointed out its technological vulnerabilities (Hinzen et al., 2022; Pagnotta, 2022; Budish, 2024). Liu et al. (2023) explored the complexity of a crypto run by using Terra (LUNA) as a case study. Our paper contributes to the literature by showing how crypto risk from the crypto ecosystem can be transmitted to the traditional financial system through blockchain technology and asset class channels. Moreover, our paper empirically provides a concrete case for the two conflicting roles of money, which Goldstein et al. (2023) had theoretically argued.

Our paper relates to the literature on systemic risk measures in the financial system. Since the Great Recession of 2008, systemic risk has become a central topic for regulators and scholars, who aim to measure it to predict a potential crisis. CoVaR (Adrian & Brunnermeier, 2016) and MES (Acharya et al., 2017) are

two prominent systemic measures. Many studies have extended these frameworks to measure emerging systemic risk (Jourde & Moreau, 2022; Marfè & Pénasse, 2024), using the example of systemic climate risk. Our paper contributes to this literature by extending the CoVaR and MES frameworks to construct crypto-driven systemic risk measures.

The rest of the paper is structured as follows. Section 2 describes our data and sample. Section 3 discusses our empirical strategies for different samples. Section 4 presents our empirical results. Section 5 provides our robustness tests regarding our main findings. Finally, Section 6 concludes the paper.

2 Data and Sample

2.1 Data and Sample

We constructed our yearly panel sample of financial firms from 2014 and 2022 by retrieving all firms whose SIC codes are between 6000 and 6799 from the Compustat database. Initially, our sample of financial firms contained 15,082 observations of firm-year, including 2,233 unique financial firms. Finally, our sample included 15,020 observations of firm-year, with 2,228 unique financial firms. Among the unique financial firms, there were 1,075 unique banks, 232 unique insurance companies, 144 unique real estate firms, and 777 trading firms.

Then, we merged our sample of financial firms with financial firm returns in the CRSP and crypto returns in the CoinMarketCap database. We added crypto risk measures and systemic risk measures to our sample of financial firms.

Next, we merged our sample financial firms with perceived crypto risk measures, which were constructed with the text mining financial firm's 10-K filings and earnings call transcripts. We downloaded the financial firms' 10-K filings from EDGAR and earnings call transcripts from Capital IQ in the Compustat database.

Lastly, our final yearly panel sample of financial firms was constructed by merging financial and accounting variables from the Compustat database.[21]

We constructed our shock samples to analyze the impacts of the crypto shocks, which were obtained from multiple sources,[22] and then identified them at the event level. These samples were constructed at three different frequencies: daily, weekly, and quarterly, respectively. Specifically, we built a daily crypto

[21] Table A1 in Online Appendix A describes this process in detail.
[22] We collected three types of crypto shocks from the firm disclosures, SEC disclosures, Twitter posts, and media reports. Online Appendix C discusses how the crypto shocks were constructed.

shock sample by merging the crypto shocks sample with the daily outcome variables, such as financial firms' equity returns. We built a weekly crypto sample by merging the crypto shocks sample with the weekly outcomes, including CoVaR and Crypto CoVaR. Finally, we built a quarterly sample by merging the crypto shocks sample with the quarterly outcomes, such as MES, crypto MES, equity returns, and total risk.[23]

2.2 Measuring Crypto Risk

The crypto ecosystem is associated with financial firms through both direct and indirect links. Direct links are crypto holdings.[24] Indirect links involve the adoption of smart contracts, financial services provided by financial firms to crypto-related clients, and investments provided by financial firms to crypto-related firms.[25] To detect any possible associations between a financial firm and the crypto ecosystem, we employed the covariance between financial firms' equity returns and crypto returns. For a given financial firm *i*, we ran a time series regression for each fiscal year *y*:

$$R_{iyt} = \alpha_{iy} + \beta_{iy} \times cryptoreturn_{yt} + \gamma_{iy}^{'} X_{yt} + \epsilon_{iyt} \ (1),$$

where R_{iyt} is the equity return of the financial firm *i* in the year *y* and trading day *t*. $Crypto\ return_{yt}$ is the crypto return at the fiscal year *y* and trading day *t*. β_{iy} is the time-varying crypto risk for each financial firm *i* in the fiscal year *y*. Control variables *X* consist of Fama-French three factors: equity market index, size factor, and value factor, which could remove common confounding factors at the macro level. We used bitcoin returns and coin market index returns to estimate the crypto risk, resulting in two crypto risk variables: bitcoin beta and coin beta, respectively. Bitcoin beta and coin beta are objective crypto risk measures that reflect direct and indirect associations between a financial firm and the crypto ecosystem, leveraging all available market information to borrow the wisdom of crowd.[26]

Further, we aimed to determine whether the financial firm management perceives this crypto risk subjectively. We constructed perceived crypto risk measures by using the text mining approach (Hassan et al., 2019; Hassan et al., 2023). Considering the subtle differences in management' perceptions, we constructed two groups of perceived crypto risk measures based on two types of financial documents: 10-K filings and earnings call transcripts. Thus, we had two groups of measures: perceived crypto risk in 10-K filings and perceived crypto risk in the transcripts. For perceived crypto risk in the 10-K filings, we constructed four variables to measure crypto risk: *tenk exposure*, *tenk risk*, *tenk sentiment*, and *tenk LLM*.

[23] Table A3 in Online Appendix A provides the summary statistics of the crypto shock samples.
[24] Banks such as Silvergate, Signature, and Customers Bancorp hold cryptocurrencies in their deposits, as documented in *The Wall Street Journal* article titled "Crypto Is Taking a Few Small Banks on a Wild Ride," published on August 15, 2022.
[25] Aiello et al. (2023) tracked customers' crypto transactions by using a proprietary dataset of U.S. banks.
[26] Keller (2024) measured a bank's exposure to the exchange market using the same method.

The first three variables were constructed with the dictionary of crypto-related keywords, while the last one was constructed with ChatGPT, a large language model (LLM). For perceived crypto risk in the transcripts, we used the same methods to construct four variables: *trans exposure*, *trans risk*, *trans sentiment*, and *trans LLM*.[27]

2.3 Measuring Systemic Risk

Systemic risk measures generally assess spillover and network effects of financial risk within the financial system, and since the 2008 financial crisis, regulatory authorities have paid close attention to systemic risk. Systemic risk can be divided into two aspects: systemic risk exposure and systemic risk transmission. Systemic risk exposure captures each financial firm's loss during the systemic crisis period, while systemic risk transmission reflects each financial firm's contribution to the financial system's loss during the systemic crisis period.

Inspired by Acharya et al.'s (2027) paper, we used marginal expected shortfall (MES) to measure the systemic risk exposure.

$$MES^{i}_{5\%} = -E[R_{it}|I_{5\%}] \text{ (2)},$$

where R_{it} is the equity return of financial firm *i* on day *t*. $I_{5\%}$ is an indicator, indicating the 5% worst trading day of equity market returns. *MES* measures the average loss during a simulated systemic crisis.

Encouraged by a pioneer paper (Adrian & Brunnermeier, 2016), we used conditional Value-at-Risk (CoVaR) to measure the systemic risk transmission. CoVaR is defined as $CoVaR_q^{s|c(x^i)}$, the Value-at-Risk (VaR) of financial system *s*, conditional on some events $C(X^i)$ of financial firm *i*.

$$Pr\left(X^s \middle| C(X^i) \leq \ CoVaR_q^{s|c(x^i)}\right) = q\% \text{ (3)},$$

where X_s and X_i are equity returns of a financial system *s* and a financial firm *i*, respectively. $q\%$ is the q quantile of the probability distribution.

The systemic risk transmission is finally defined as follows:

$$\Delta CoVaR_q^{s|i} = CoVaR_q^{s|x^i=VaR_q i} - CoVaR_q^{s|x^i=VaR_{50} i} \text{ (4)}$$

Thus, $\Delta CoVaR_q^{s|i}$ measures the contribution of financial firm *i* to the tail loss of the financial system *s* in the crisis period relative to the normal period.

[27] Online Appendix B1 discusses how we constructed perceived crypto risk measures.

However, MES and CoVaR capture systemic risk in the financial system caused by universal risk sources, such as the stock market bubble, the housing market bubbles, the subprime mortgage crisis, and natural disasters.

We then aimed to understand the magnitudes of systemic risk caused specifically by the crypto ecosystem rather than other non-crypto market events. To achieve this goal, we needed to construct crypto-driven systemic risk exposure and systemic transmission.

Building on Acharya et al.'s (2017) framework, we constructed the crypto-driven systemic risk exposure: crypto marginal expected shortfall (crypto MES):

$$crypo\ MES^{i}_{5\%} = -E[R_{it}|I_{5\%}(crypto\ market\ return)] \quad (6),$$

where $R_{i,t}$ is the equity return of financial firm *i* on trading day *t*. $I_{5\%}(cryptomarketreturn)$ is an indicator variable, indicating 5% the worst trading day of crypto market events during a period. Crypto MES measures the average loss of a financial firm during a simulated crypto market run period.

We extended the framework of Adrian & Brunnermeier (2016) to construct the crypto-driven systemic risk transmission: crypto Conditional Value-at-Risk (crypto CoVaR):

$$\Delta CoVaR^{S|i=crypto\ events}_{5\%} = CoVaR^{S|i=5\%\ crypto\ events}_{5\%} - \ CoVaR^{S|i=50\%\ crypto\ events}_{50\%} \quad (7),$$

where $CoVaR^{S|i=5\%\ crypto\ events}_{5\%}$ measures the Value-at-Risk (VaR) of a financial system *s* conditional on the exposure of a financial firm *i* to 5% tail events of the crypto market. $CoVaR^{S|i=50\%\ crypto\ events}_{50\%}$ measures the Value-at-Risk (VaR) of a financial system *s*, conditional on the exposure of a financial firm *i* to 50% tail events of the crypto market.

We continued to apply the CoVaR framework to measure the exposure of a financial firm *i* to crypto events using crypto market index returns. The exposure of a financial firm *i* to 5% and 50% tail events of the crypto market are measured by their Value-at-Risk (VaR), conditional on crypto market crisis and normal periods:

$$i's\ exposure\ to\ 5\%\ crypto\ events = CoVaR^{i|\ VaR^{crypto}_{5\%}}_{5\%} \quad (8)$$

$$i's\ exposure\ to\ 50\%\ crypto\ events = CoVaR^{i|\ VaR^{crypto}_{50\%}}_{50\%} \quad (9),$$

where $VaR_{5\%}^{crypto}$ is the 5% quantile Value-at-Risk (VaR) of crypto market index returns, and it measures the 5% tail events of the crypto market. Where $VaR_{50\%}^{crypto}$ is the 50% quantile Value-at-Risk (VaR) of crypto market index returns, and it measures the 50% tail events of the crypto market.

Thus, crypto CoVaR measures the contribution of each financial firm *i* to the financial system *s*, conditional on the crypto market crisis periods relative to its normal periods.[28]

For all other definitions and sources, please see Table A2 in the Online Appendix.

2.4 Summary Statistics

Table 1 reports the summary statistics of our yearly panel sample. The average MES of financial firms is 2.1 percentage points, with a standard deviation of 2.0 percentage points. The average crypto MES of financial firms is 0.66 percentage points, with a standard deviation of 1.26 percentage points. The magnitude of MES is larger than that of crypto MES, which supports our argument that crypto MES captures the crypto-driven portion of systemic risk exposure, while MES captures all systemic risk exposures. The mean CoVaR is 68.25 percentage points, with a standard deviation of 45.30 percentage points. For comparison, the mean crypto CoVaR is 3.87 percentage points, with a standard deviation of 6.46 percentage points. The magnitude of CoVaR's mean is larger than that of crypto CoVaR's mean, which demonstrates that crypto CoVaR captures only crypto-driven systemic risk exposure, while CoVaR captures all systemic risk exposures.

In terms of crypto risk measures, the average bitcoin beta of financial firms is 0.23 percentage points, with a standard deviation of 4.56 percentage points. On the contrary, the average coin beta of financial firms is 0.11 percentage points, with a standard deviation of 2.33 percentage points. Two crypto risk variables share similar description statistics.

In the case of perceived crypto risk measures, perceived crypto risk measures in 10-K filings are identical to those in the transcripts. The only notable difference is that management perceives crypto risk negatively on average in the 10-K filings' content sentiment, while they perceive crypto risk positively in the transcripts' content sentiment.

*** Table 1***

[28] Online Appendix B2 describes how we constructed the crypto systemic risk measures.

3 Empirical Strategy

3.1 A Case Study of FTX Run

We used the collapse of crypto exchange FTX as a case study to test the predictive power of our crypto risk measures and perceived crypto risk measures. As previously mentioned, the collapse of FTX triggered market-wide systemic risk exposure in the financial system. This fraud led to crypto-market sell-offs, causing the value of bitcoin to tumble. Consequently, fear in the crypto market drove the equity market down. Thus, this crypto market run posed a systemic threat to the financial system during the FTX crisis.

We measured the real systemic risk exposure of each financial firm to crypto market tail events during the FTX crisis periods by using its buy-and-hold returns. This measure has the same economical interpretation as our crypto MES (Fahlenbrach et al., 2012). For the prediction setting, our predictive measures, consisting of crypto risk and perceived crypto risk, were used at least one year before 2022, the year of the FTX crisis. The prediction specification is as follows:

$$B\&H\ return\ in\ FTX_i = \alpha + \beta \times crypto\ risk_i\ (perceived\ crypto\ risk) + X^{'}\gamma + \epsilon_i\ (10),$$

where $B\&H\ return\ in\ FTX$ is the outcome variable of financial firm i, and the coefficient of interest is β, which measures the predictive relationship between our prior crypto risk variables and the real systemic loss exposure for each financial firm i. X represents the previous control variables. The R-squared value of each regression for each crypto risk or perceived crypto risk indicates the predictive powers. The specification is at the cross-sectional level, and standard errors are robust.

3.2 Crypto Risk and Systemic Risk in Normal Periods

We aimed to investigate whether the crypto risk of a financial firm raises systemic risk in the broader financial system. To do so, we constructed a yearly panel sample spanning the period from 2014 to 2022. The specification is a standard panel specification as follows:

$$Y_{iy} = \beta \times crypo\ risk_{iy} + X^{'}\gamma + \delta_i + \eta_{fy} + \epsilon_{iy}\ (11),$$

where Y_{iy} represents outcomes of variables, and the coefficient of interest is β, which captures the relationship between crypto risk and systemic risk. X denotes a series of control variables. δ_i are the financial firm fixed effects, which removed unobserved time-invariant factors such as the financial firm's corporate culture and risk management capacity. η_{fy} represents the financial firm type multiplied by the year fixed effects, comparing the effects at the same financial firm type within the same year, thereby removing time-variant factors at the financial firm-type level. For example, this accounts for the possibility that crypto risk might disproportionately target specific types of financial firms over time. Robust standard errors are clustered at the financial firm level.

3.3 Crypto Shock Transmission

To identify the channels through which crypto risk from the crypto ecosystem can be transmitted to the broader financial system, the blockchain technology channel, or the asset class channel, we collected and categorized two distinct types of crypto cyber shocks: blockchain technology shocks (core blockchain vulnerabilities) and asset class shocks (financial asset-targeted breaches). Blockchain technology shocks occur when attacks exploit vulnerabilities within the blockchain infrastructure, threatening its core operations at layers one and two. Asset class shocks, on the other hand, result from breaches targeting cryptocurrencies as financial assets, such as exchange hacks or wallet hacks, without undermining the blockchain's permissionless framework as an alternative financial system. By using two types of crypto shocks, we could distinguish the systemic risk caused by crypto risk through the blockchain technology channel or the asset class channel. Thus, we created three categories of crypto shocks: blockchain, exchanges, and wallet. In a similar spirit, Goldstein et al. (2023) theoretically argued that the payment and non-payment roles of money encounter delays and disruptions, while Gonzalez et al. (2024) empirically used the technological disruptions of the instant payment system as instrumental variables.

For each crypto shock, we identified a specific crypto coin targeted by cyber hackers. Given each cyber shock, we used returns of targeted crypto coin to construct the treatment variable of each financial firm.[29] We then ran a time-series regression of the targeted crypto returns for every financial firm that experienced a specific crypto shock during the pre-shock period:

$$R_{eit} = \alpha + \beta_{ei} \times crypto\ return_{et} + \epsilon_{eit} \quad (12),$$

where R_{eit} is the equity return of financial firm i on the trading day t in the crypto shock e, and $crypto\ return_{et}$ is the return of the targeted crypto coin in the crypto shock e. β_{ei} measures the association of a financial firm i with a targeted crypto coin return before the crypto shock e. (We named it crypto beta.) Crypto beta is a treatment variable in the crypto shock setting because crypto beta captures the closeness between a financial firm and a specific network of the crypto ecosystem before the shock. The more closely linked financial firms suffer more during a specific crypto shock. Unlike bitcoin or coin beta, the crypto beta is estimated without adding Fama-French three factors as control variables because treatment status variables require only relative magnitudes among financial firms in the exogenous shock setting.

[29] Figure A1 in Online Appendix A shows the estimation strategy for three date frequencies: daily, weekly, and quarterly, respectively. Specifically, Figure A1 shows the length of the estimation window and the event window. The estimation window is the first stage regression, which was used to estimate the treatment variable, while the event window is the second stage regression, which was used to estimate the treatment effects.

In the second stage, we stacked multiple crypto shocks together to have a stacked difference-in-difference (DID) research design by using crypto beta as the treatment variable from the first stage (de Chaisemartin & D'Haultfœuille, 2020).

$$Y_{eit} = \gamma \times \beta_{ei} \times post + \delta_{ei} + \lambda_{et} + \upsilon_{eit} \ (13),$$

where Y_{eit} is the outcome variable of a financial firm *i* on the time *t* in the crypto shock *e*. The coefficient of interest is γ, which is the Average Treatment Effects on the Treated (ATT). δ_{ei} is the crypto shock multiplied by the financial firm fixed effects, and this removes a time-invariant observable component at a financial firm level given the event. λ_{et} is the crypto shock multiplied by the time fixed effects, and this controls the time-trends for each crypto shock. Robust standard errors are clustered at the financial firm level. The time interval of *t* depends on the frequency of the main outcomes variables and includes the frequency at daily, weekly, and quarterly levels.[30]

We ran a dynamic stacked difference-in-difference (DID) research design.[31]

$$Y_{eit} = \sum_{q \neq -1} \gamma_t \times \beta_{ei} \times 1(t = q) + \delta_{ei} + \lambda_{et} + \upsilon_{eit} \ (14)$$

4 Empirical Results

4.1 Some Stylized Facts

In this subsection, we provide some stylized facts about crypto risk and systemic risk in the financial system. First, we provide descriptive evidence to shed light on the financial firm's crypto risk. Second, we provide descriptive evidence to show systemic risk in the financial system.

Figure 1 shows the crypto risk in the financial system. Panel A of Figure 1 shows the time series of crypto risk in the financial system. While crypto risk was steadily falling during the period between 2015 and 2018, it rose rapidly between 2018 and 2022. This graph shows that crypto risk in the financial system has been a massive concern in recent years. Furthermore, the graph suggests that management' perceived crypto risk has also been increasing, and the management has been paying close attention to this rising crypto risk.[32] Panel B of Figure 1 shows the crypto risk distribution in financial firms. Banks, real estate

[30] Similarly to Butters et al. (2022), , we used the event-study style specification to estimate the ATT by using multiple shocks.
[31] Figure A1 in Online Appendix A shows the empirical strategies for crypto shocks. Specifically, this figure shows the different parameters of the estimation window and the event window for daily, weekly, and quarterly samples, respectively. The estimation window was used to estimate the crypto beta for the time series regressions, while the event window was used to estimate the ATT using a stacked DID research design.
[32] Figure A2–Figure A5 in Online Appendix A show descriptive evidence of perceived crypto risk.

firms, and trading firms show positive crypto risk, while insurance companies show negative crypto risk. Crypto risks in banks and trading firms are significantly different from 0. In the financial system, banks and trading firms are more exposed to crypto risk.

*** Figure 1***

Next, we explored descriptive patterns of systemic risk and crypto systemic risk. Figure 2 shows the time series of systemic risk and crypto systemic risk. For systemic risk exposure, MES and crypto MES share similar time trends, and the COVID 2020 crisis marked the peak of this trend. Crypto MES is merely a subset of MES, which measures universal systemic risk exposure. In terms of systemic risk transmission, before 2018, CoVaR was more volatile, while crypto CoVaR was relatively stable. After 2018, CoVaR rose, and so did crypto CoVaR. Therefore, CoVaR and crypto CoVaR capture different parts of systemic risk transmission. Worryingly, both CoVaR and crypto CoVaR indicate that systemic risk transmission has risen in recent years.

Figure 2

Figure 3 shows systemic risk and crypto systemic risk distributions over financial firms. The top panel of Figure 3 shows the systemic risk exposure. Real estate firms and trading firms have higher systemic risk exposure than insurance companies and banks. The bottom panel of Figure 3 shows systemic risk transmission. Banks, insurance companies, and trading firms have higher CoVaR and crypto CoVaR than real estate firms. A striking pattern is that banks experience lower systemic risk exposure but higher systemic risk transmission, relative to other financial firm types.

Figure 3

4.2 A Case Study: The FTX Run

In this subsection, we use the FTX run as a case study to test the prediction power of our crypto and perceived crypto risk measures. We measured the financial loss of each financial firm during the crypto-driven crisis, which is the real crypto systemic risk exposure, while crypto MES simulates the systemic crisis by using tail returns in normal times.

The FTX run was a crypto-driven systemic crisis that led to market-wide sell-offs of crypto assets. It also triggered the free fall of equity markets and a temporary crisis period. As noted previously, FTX's collapse was triggered by its cofounder's misconduct.

The FTX run is a good experiment because it was a completely crypto-driven systemic crisis. We measured realized systemic risk exposure by calculating the buy-and-hold returns of financial firms during

the FTX crisis period. Specifically, FTX filed for Chapter 11 bankruptcy protection on November 11, 2022, which we used for the benchmark of the event window. The buy-and-hold returns were calculated by using the event window of ten days before and after the benchmark. Lastly, we tested the prediction power of our crypto and perceived crypto measures.

Figure 4 shows the scatterplot of buy-and-hold returns against crypto risk during the FTX crisis. The top panel shows the results of bitcoin beta, while the bottom panel shows the results of coin beta. Two graphs show a clearly negative relationship between our crypto risk and real systemic risk exposure, which suggests that our crypto risk measures can predict realized systemic risk exposure effectively. In addition, we marked the most vulnerable financial firms during this crisis, such as Signature Bank and Silvergate Capital Bank, as well as the Big Four banks in the financial system. A striking pattern is that during this crisis, the most vulnerable financial firms had higher realized systemic risk exposure, with higher pre-crisis level of crypto risk. The Big Four banks, in contrast, were very stable and sound during this crisis.

Figure 4

Table 2 reports a case study of the FTX run. The outcome variable is the buy-and-hold returns during the FTX crisis periods.[33] The prediction variables are at least one year before the FTX event. Column 1 and Column 2 present the prediction results of realized systemic risk exposure on our crypto risk measures. Our crypto measures are negatively associated with realized systemic risk exposure at the 1% significance level. When crypto risk increases by 1 percentage point in the pre-crisis period, a financial firm experiences 0.12 percentage points rise in systemic risk exposure during the FTX run. The R-squared value is about 6 percentage points. The evidence suggests that our crypto risk measure can predict crypto-driven systemic risk exposure, to some extent. The perceived crypto risk measures also, to some degree, show predictive powers. The case study of FTX supports the validity of our crypto risk and perceived crypto risk measures.

Table 2

4.3 Crypto Risk and Systemic Risk in Normal Periods

In this subsection, we examine whether crypto risk of financial firms raises the systemic risk in the financial system during the normal periods. Specifically, we divided the systemic risk into two types: systemic risk exposure and systemic risk transmission. Next, we assessed whether financial firm management' perceived crypto risk could predict the systemic risk, to some degree. Lastly, we tested whether financial firms' crypto risk affects performance and total risk of financial firms.

[33] Table A4 presents the results of all crypto risk measures, including objective and subjective measures.

Table 3 presents the impacts of crypto risk on systemic risk exposure, measured by the MES and crypto MES. Column 1 and Column 2 present the results of MES, while Column 3 and Column 4 report the results of crypto MES. All the results are positive and statistically significant at the 1% significance level. When crypto risk rises by 1 percentage point, MES and crypto MES increase by 0.027 and 0.064 percentage points, respectively. A 1 standard deviation change in the crypto risk translates to 0.12 percentage points of MES and 0.29 percentage points of crypto MES, respectively, which are equivalent to 6.3 percentage points of MES's standard deviation and 23 percentage points of crypto MES's standard deviation. Therefore, financial firm-level crypto risk raises the systemic risk exposure, and many economic effects primarily stem from crypto-driven systemic risk exposure rather than from general systemic risk exposure.

Table 3

Table 4 presents the impacts of crypto risk on systemic risk transmission, measured by the CoVaR and crypto CoVaR. The first two columns show the results of CoVaR, and the last two columns show the results of crypto CoVaR. An interesting pattern is that only the results of crypto CoVaR are positively and statistically significant at the 5% significance level; the results of CoVaR, on the other hand, are not. When crypto risk rises by 1 percentage point, a financial firm transmits by 0.5 basis points. This magnitude is not negligible because it is equivalent to a $290 million loss in the financial system.[34] Therefore, the financial firm-level crypto risk lifts the crypto-driven systemic risk transmission. Our crypto risk measures could detect or track the crypto-driven systemic risk transmission in the financial system.

Table 4

Next, does the crypto risk perception of financial firm management affect the systemic risk? Table 5 and Table 6 present the results of perceived crypto risk on systemic risk exposure and transmission, respectively. According to the results of Table 5, we used 8 text-based variables to detect financial firm management' crypto risk perception, and we found that all text variables except for transcript sentiment are significantly associated with the crypto MES. The evidence suggests that when financial firm management perceives more crypto risks, they can detect more systemic risk exposure. Based on the results of Table 6, none of the 8 text-based measures are significantly associated with crypto CoVaR. This evidence indicates that the financial firm management does not detect or track systemic risk transmission in the financial system, although they may discuss or perceive crypto risk in their financial disclosures. In sum, financial firm management tends to pay attention to systemic risk exposure but not enough attention to systemic risk transmission.

[34] This should be calculated by using the 0.5 basis points times the average market value of the financial system between 2014 and 2022 ($5824.49 billion).

*** Table 5 and Table 6***

Lastly, we tested whether our crypto risk and perceived crypto risk measures could impact the financial performance and total risk of financial firms. Panel A of Table 7 presents the results of our crypto risk measures, while Panel B of Table 7 presents the results of our perceived risk measures. Based on the results of Panel A, we can conclude that a financial firm's crypto risk does not affect the equity returns and accounting performances ROA. However, it does increase the total risk in the financial system. In contrast, Panel B of Table 7 shows that when financial firm management perceives or discusses crypto-related risks, the financial firm's equity returns rise, but its ROA declines. When management discusses crypto risks, investors require more compensation for equity returns. Crypto risk might cause financial loss and lead to a decline in ROA. The management pays less attention to the total risk, as measured by the equity volatility. Therefore, crypto risk measures are sensitive to risk in normal periods. In contrast, perceived crypto risk measures are sensitive to performance in normal periods.

Table 7

4.4 Crypto Shocks Transmission Channel: Technology or Asset?

In this subsection, we identify the channels through which crypto risk transmits in the financial system, looking specifically at blockchain technology and asset class channels. We employed two distinct types of crypto shocks: blockchain technology shocks (core blockchain technology vulnerabilities) and asset class shocks (financial asset-targeted breaches). Blockchain technology shocks have one category of *blockchain*, while asset class shocks have two categories of *exchange* and *wallet*.[35]

Table 8 presents the results of crypto risk on systemic risk exposure in crypto shocks. Panel A of Table 8 presents the results of the full sample. The first three columns show the results of MES, while the last three columns show the results of crypto MES. In terms of MES, all three coefficients are positively and statistically significant at the 1% significance level. When financial firms are exposed to a 1 percentage point change in crypto risk's standard deviation, they experience an increase of 3.32 percentage points (1.14 times of MES's standard deviation), an increase of 16.59 basis points (5.7 percentage points of MES's standard deviation), and an increase of 3.04 percentage points (1.05 times of MES's standard deviation) in MES after blockchain, exchange, and wallet shocks, respectively, compared with their counterfactuals. In terms of crypto MES, when financial firms are exposed to a 1 percentage point change in crypto risk's standard deviation, they experience an increase of 4.37 percentage points (1.9 times of crypto MES's standard deviation), an increase of 71.89 basis points (31.26 percentage points of crypto MES's standard deviation), and an increase of 3.76 percentage points (1.63 times of crypto MES's standard deviation) in

[35] See the definition and identification of two types of crypto shocks in Online Appendix C.

crypto MES after blockchain, exchange, and wallet shocks, respectively, compared with their counterfactuals. Therefore, financial firms' crypto risk drives up the systemic risk exposure in the financial system, and the economic magnitudes are sounder for crypto-driven systemic risk exposure. For both blockchain technology and asset class channels, crypto risk increases the overall systemic risk exposure.

Panel B presents the results by financial firm type, including banks, insurance companies, real estate firms, and trading firms. The main treatment effects come from banks and trading firms, while insurance companies and real estate firms do not work for one or two channels. In terms of crypto MES, blockchain and exchange channels work for all four types of financial firms. Figure 5 shows the dynamic effects of crypto risk on crypto MES by each financial firm type. This figure shows all four types of financial firms' systemic risk exposure is climbing in all three types of crypto shocks.

Table 8

Figure 5

Table 9 presents the results of crypto risk on systemic risk transmission in the crypto shocks. Panel A presents the results of the full sample. The first three columns present the results of CoVaR, and the last three columns present the results of crypto CoVaR. When financial firms see a 1 percentage point change in crypto risk's standard deviation, they experience an increase of 7.94 basis points (7.43 percentage points of CoVaR's standard deviation), a decrease of 0.68 basis points (0.64 percentage points of CoVaR's standard deviation), and a decrease of 5.87 basis points (5.48 percentage points of CoVaR's standard deviation) in CoVaR after blockchain, exchange, and wallet shocks, respectively, relative to their counterfactuals. In terms of crypto CoVaR, when financial firms see a 1 percentage point change in crypto risk's standard deviation, they experience an increase of 0.59 basis points (4.62 percentage points of crypto CoVaR's standard deviation), a decrease of 0.07 basis points (0.59 percentage points of crypto CoVaR's standard deviation), and an increase of 0.41 basis points (3.18 percentage points of crypto CoVaR's standard deviation) in crypto CoVaR after blockchain, exchange, and wallet shocks, respectively, relative to their counterfactuals. Crypto risk of financial firms raises systemic risk transmission through the blockchain technology channel, while it lowers the systemic risk transmission through the asset class channel. In addition, the magnitude of systemic risk transmission is much larger through the blockchain technology channel than through the asset class channel.

Panel B presents the results by financial firm types. A striking pattern is that most of the systemic risk transmission via the blockchain technology channel is from banks, while most of the systemic risk transmission via the asset class channel is from trading firms. Banks are the main drivers of systemic risk transmission via the blockchain technology channel, in part because regulatory authorities in banking

industries actively monitor or check banks' crypto activities, thereby discouraging banks from holding cryptocurrencies. Therefore, banks are holding fewer cryptocurrencies, but they are indirectly connected to crypto markets as the service providers for crypto-trading firms or households. The second reason for this is because crypto shocks in the blockchain technology channel are global shocks, while those in the asset class channel are local shocks. Trading firms reduce systemic risk transmission via the asset class channel, in part because regulatory authorities pay attention to trading firms' risk management, even though trading firms are allowed to hold cryptocurrencies as assets in their balance sheets. Insurance companies transmit crypto-driven systemic risk only via the blockchain technology channel. Real estate firms raise crypto-driven systemic risk transmission via the wallet. Figure 6 shows the dynamic effects of crypto risk on systemic risk transmission by financial firm type, and the results are similar to those of Table 9.

Table 9

***Figure 6 ***

Does the equity market react to the two channels? Table 10 presents the results of crypto risk on equity returns in the crypto shocks. The first three columns show the results of daily returns, and the last three columns show the results of daily abnormal returns.[36] The coefficients of exchange and wallet are negatively and statistically significant at the 1% significance level, while the coefficients of blockchain are not precisely estimated. In crypto shocks, the crypto risk of financial firms leads to lower equity returns via the asset class channel, but it does not impact the equity returns via the blockchain technology channel. A potential explanation is that the asset class shocks are financial asset-targeted breaches, which impact the market liquidity and erode investors' confidence in cryptocurrencies as an asset class. However, the blockchain shocks are core technology vulnerabilities that cause only delays or disruptions in the infrastructure but do not erode investors' trust in the system.

Table 10

Does financial firm management perceive systemic risk exposure and systemic risk transmission? Panel A of Table 11 presents the results of perceived crypto risk on systemic risk exposure. We find that two main variables of *tenk risk* and *tenk sentiment* detect systemic risk exposure via the blockchain technology or asset class channels. Panel B presents the results of perceived crypto risk on systemic risk transmission. We find that many variables, such *as tenk risk* and *trans risk*, indicate that financial firm management perceives systemic risk transmission via the asset class channel. However, the management hardly detects or perceives

[36] Abnormal returns are calculated by using the raw returns minus the market index returns.

systemic risk transmission via the blockchain technology channel. Therefore, the management tends to not pay enough attention to systemic risk transmission through the blockchain technology channel.

Table 11

4.5 Placebo Shocks: Cyber Attack

In this subsection, we employ placebo shocks of cyber-attacks to rule out an identification concern that our crypto shocks might capture common but unobservable systemic risk factors for all kinds of cyber shocks. In this case, we needed to validate that our crypto shocks do, indeed, capture the effects of crypto-driven systemic risk. Cyber-attacks are cyber shocks in which financial firms' information systems are attacked or breached maliciously by professional hackers. Under these attacks, financial firms' information systems or infrastructure can potentially be paralyzed or dysfunctional for a long time. In cyber-attacks, financial firms are the main target, while cryptocurrencies are the main target in crypto shocks. We ensured that cyber-attacks in our sample are unrelated to cryptocurrencies. Cyber-attacks have three main types: financial, personal, and other. For cyber-attacks, we used the same stacked DID identification as our crypto shocks and replaced only crypto beta with cyber-attack, which indicates whether a particular financial firm is currently under a cyber-attack.

Table 12 presents the placebo tests of cyber-attacks on systemic risk. Panel A presents the results of systemic risk exposure. We find that cyber-attacks of financial firms do not impact the systemic risk exposure, measured by MES and crypto MES. Panel B presents the results of systemic risk transmission. Cyber-attacks do not contribute to systemic risk transmission, as measured by CoVaR and crypto CoVaR. Therefore, we could state that these crypto shocks are not due to unobservable systemic factors that are common to all cyber shocks.

Table 12

5 Robustness Results

In this section, we conduct a multitude of robustness tests to support our main findings.

The first robustness tests are a case study of the TerraUSD run.[37] In our paper, we validated our crypto risk and perceived crypto risk measures by using a case study of the FTX exchange run. A potential concern was that the prediction power of our measures was limited only to a specific event and would not apply to

[37] Liu et al. (2023) studied the crypto-driven systemic events of a stablecoin: the TerraUSD run.

general and crypto-driven events. To address this challenge, we applied the same approach to the TerraUSD run. Table A5 and Figure A6 present similar results as those of the FTX run.

Table A5 and Figure A6

The second robustness tests are findings of crypto shocks within the framework of core versus non-core technological attacking methods. A specification concern is that we might misclassify blockchain technology channels and asset class channels by using only blockchain, exchanges, and wallet categories. To address this concern, we manually read the word descriptions of crypto shocks and reclassified them into three categories: core blockchain technology, non-core blockchain technology, and unidentified groups.[38] Table A6 presents the results of core versus non-core technology, which show that our results are robust to classification methods of crypto shocks regarding statistical significance and economic magnitudes.

Table A6

The third robustness tests are the results of crypto market reactions to crypto shocks. In our paper, we found that the equity market reacts negatively to the asset class channel but does not react to the blockchain technology channel. Crypto shocks in blockchain technology channels compromise the structure of the blockchain itself and therefore alter the blockchain protocol, which leads only to the delay or disruption of the blockchain. However, these attacks do not break the trust of the system. In contrast, crypto shocks in asset class channels impact the market liquidity and erode investors' confidence in cryptocurrencies as an asset class (Goldstein et al., 2023). We employed a crypto three-factor pricing model, proposed by Liu et al. (2022), to conduct event studies for all crypto shocks. Figure A7 supports our argument that the differential market reactions to two channels are consistent in the crypto trading market.

Figure A7

6 Conclusion

In this paper, we measured crypto risk and crypto-driven systemic risk within the financial system. Stylized facts show that crypto risk and crypto-driven systemic risk have been rising in recent years. Financial firms' crypto risk increases systemic risk exposure via both the blockchain technology and asset class channels. However, crypto risk raises the systemic risk transmission via the blockchain technology channel but reduces the systemic risk transmission via the asset class channel. The market and financial

[38] Online Appendix C discusses reclassification process in detail.

firm management can perceive the asset class channel but are unable to detect the blockchain technology channel.

Our paper sheds light on the regulation debate.[39] We suggest that regulatory authorities might fail to regulate crypto as a new asset class because the systemic risk can be transmitted through blockchain technology. Furthermore, individual countries might struggle to regulate cryptocurrencies independently as crypto shocks are cross-border activities without geographical boundaries. Therefore, effective crypto regulation requires international cooperation; only then can we build a global regulation framework.

Our paper proposes a general framework that can be used to evaluate crypto risk in any other country's financial system. For example, in 2021, China banned all crypto exchanges and activities in the mainland.[40] Future research can build on our framework to evaluate this policy shift in China.

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[39] Critics and advocates of crypto in the U.S. argue over crypto regulation. Crypto critics, such as SEC Chair Gary Gensler, point out that the crypto market is the Wild West, which might pose a threat to the financial system. There could be widespread crypto fraud and market manipulation. Thus, crypto should be regulated like an asset class. See *The Wall Street Journal* article titled "Big Battles Loom in SEC's War on Crypto," published on December 28,2023. Crypto advocates, such as President Donald Trump and Elon Musk, argue that crypto is a new kind of technology and asset. Trump vowed to deregulate crypto when he became president. See *The Wall Street Journal* article titled "The Crypto World is Preparing for a Renaissance Under Trump," published on November 10, 2024.

[40] *The Wall Street Journal* article titled "China Latest Crackdown on Bitcoin, Other Cryptocurrencies Shakes Market," published on May 24, 2021, reported this regulatory shift on the Chinese mainland.

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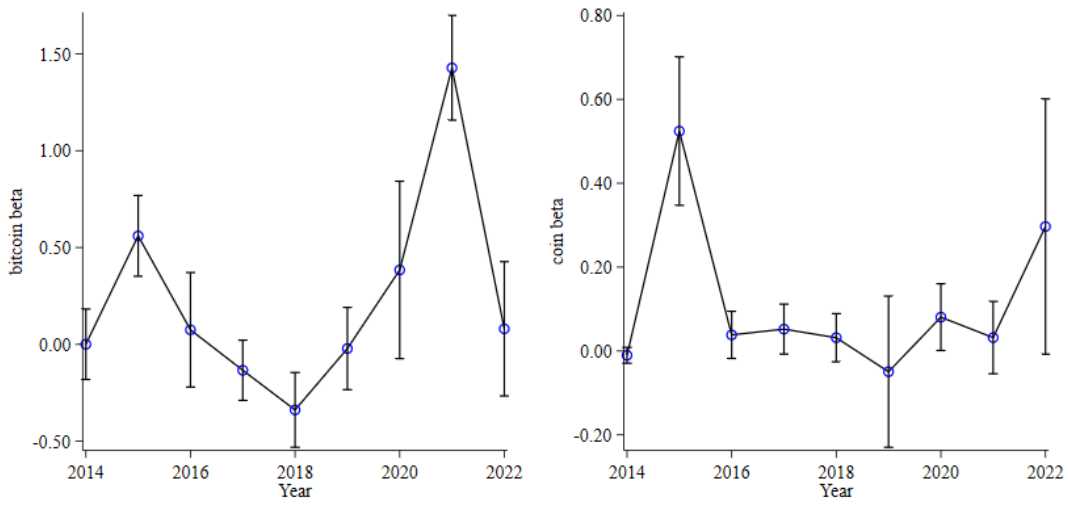
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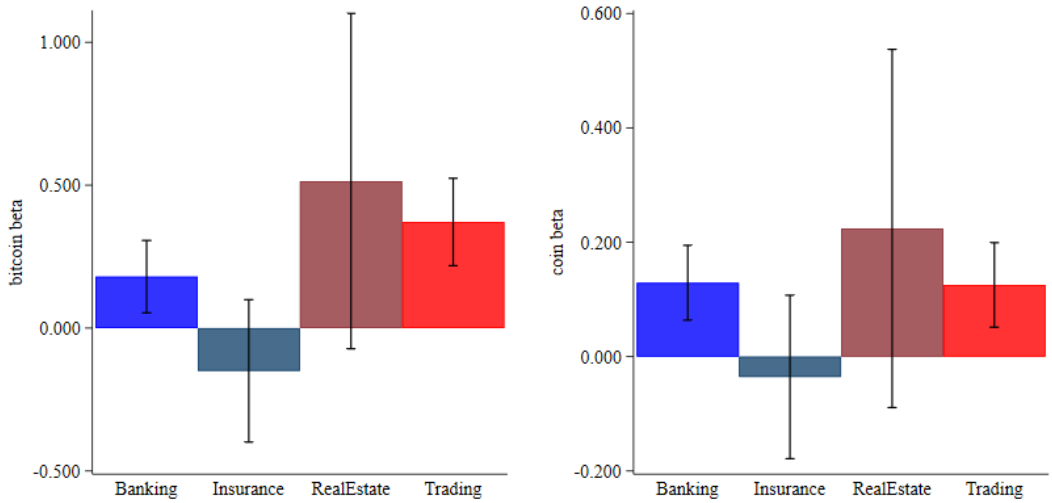
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Panel A: Time Series of Crypto Risk



Panel B: Crypto Risk in Financial Firms

Figure 1: Crypto Risk

Note: This figure shows the crypto risk. Panel A shows the time series of crypto risk, calculated by yearly mean at the 95% confidence interval. Panel B shows the average crypto risk in financial firms, including banks, insurance companies, real estate companies, and trading firms. The left panel shows the crypto risk measured by bitcoin beta, and the right panel shows the crypto risk measured by coin beta.

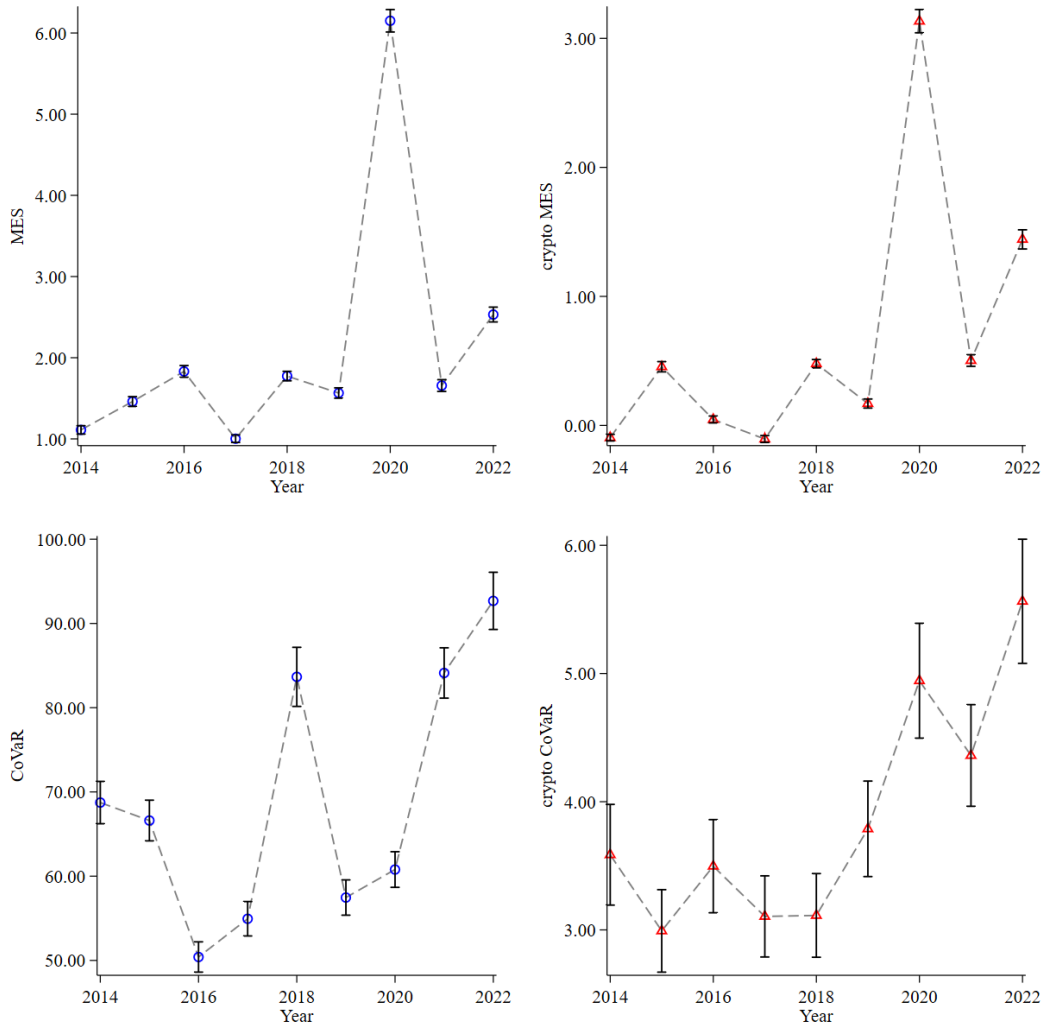


Figure 2: The Time Series of Systemic Risk and Crypto Systemic Risk

Note: This figure shows the time series of systemic and crypto systemic risk, calculated by yearly mean at the 95% confidence interval. The upper panel shows systemic risk exposure: MES and crypto MES. The lower panel shows systemic risk transmission: CoVaR and crypto CoVaR.

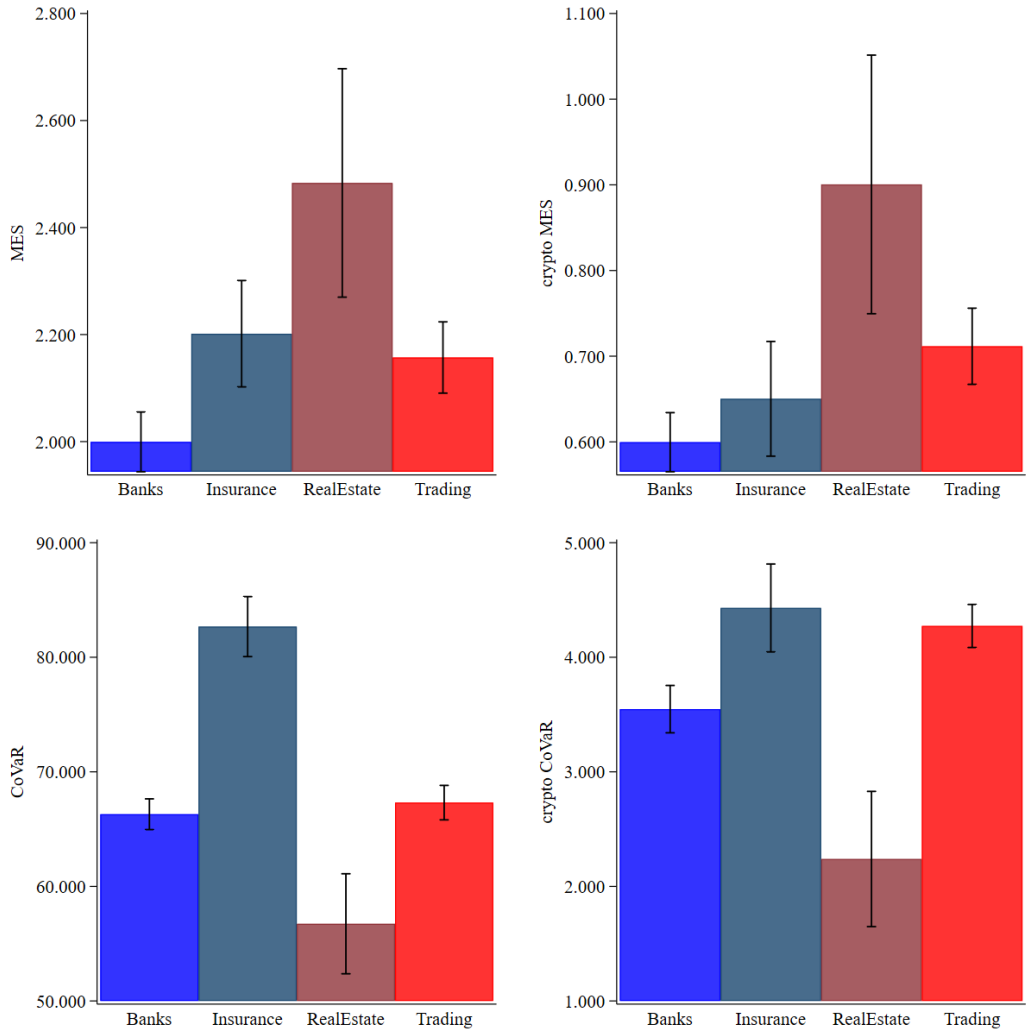


Figure 3: Systemic Risk and Crypto Systemic Risk in Financial Firms

Note: This figure shows systemic and crypto systemic risk in financial firms, calculated by group mean at the 95% confidence interval. The upper panel shows systemic risk exposure: MES and crypto MES. The lower panel shows systemic risk transmission: CoVaR and crypto CoVaR.

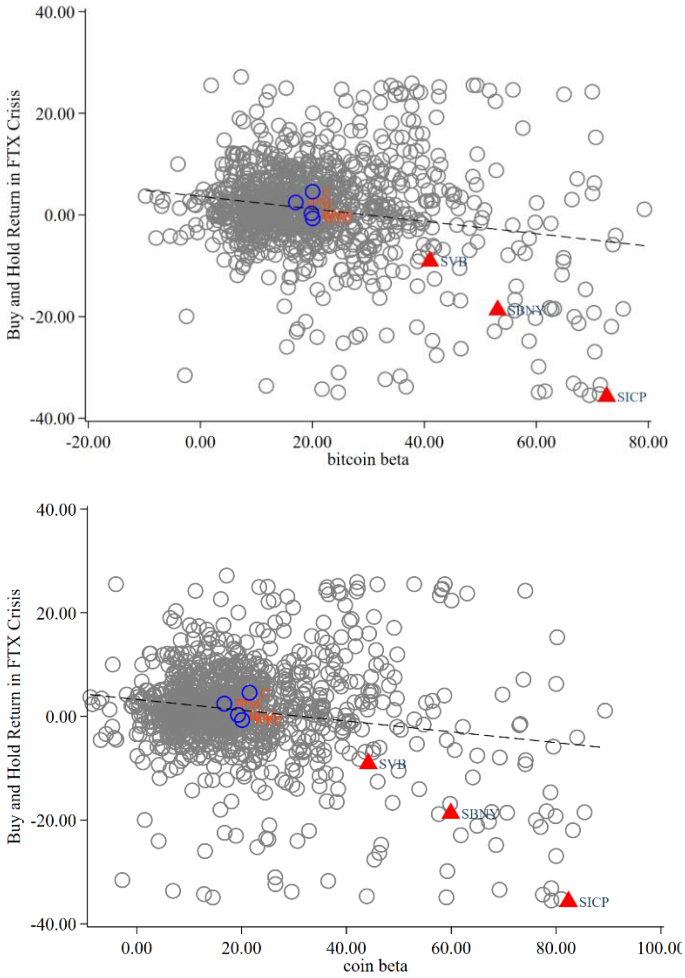


Figure 4: The Scatterplot of Buy-and-Hold Returns in the FTX Crisis Against Crypto Risk

Note: This figure shows the scatterplot of buy-and-hold returns in the FTX crisis against crypto risk. The upper panel shows this relationship with two variables by bitcoin beta. The lower panel shows this relationship with two variables by coin beta. The relationship of two variables has removed the effects of size and capital. The dash line has been fitted by linear regression: $\text{B\&H Return in FTX}_i = \alpha + \beta \times \textit{crypto}\ \text{risk}_i + \text{size}_i + \text{capital}_i + \epsilon_i$. The blue squares mark the Bank of America (BOC), JP Morgan Chase (JPM), Wells Fargo Bank (WFC), and Citi Group Bank (C), and the red triangles mark Silicon Valley Bank (SVB), Signature Bank (SBNY), and Silvergate Capital (SICP).

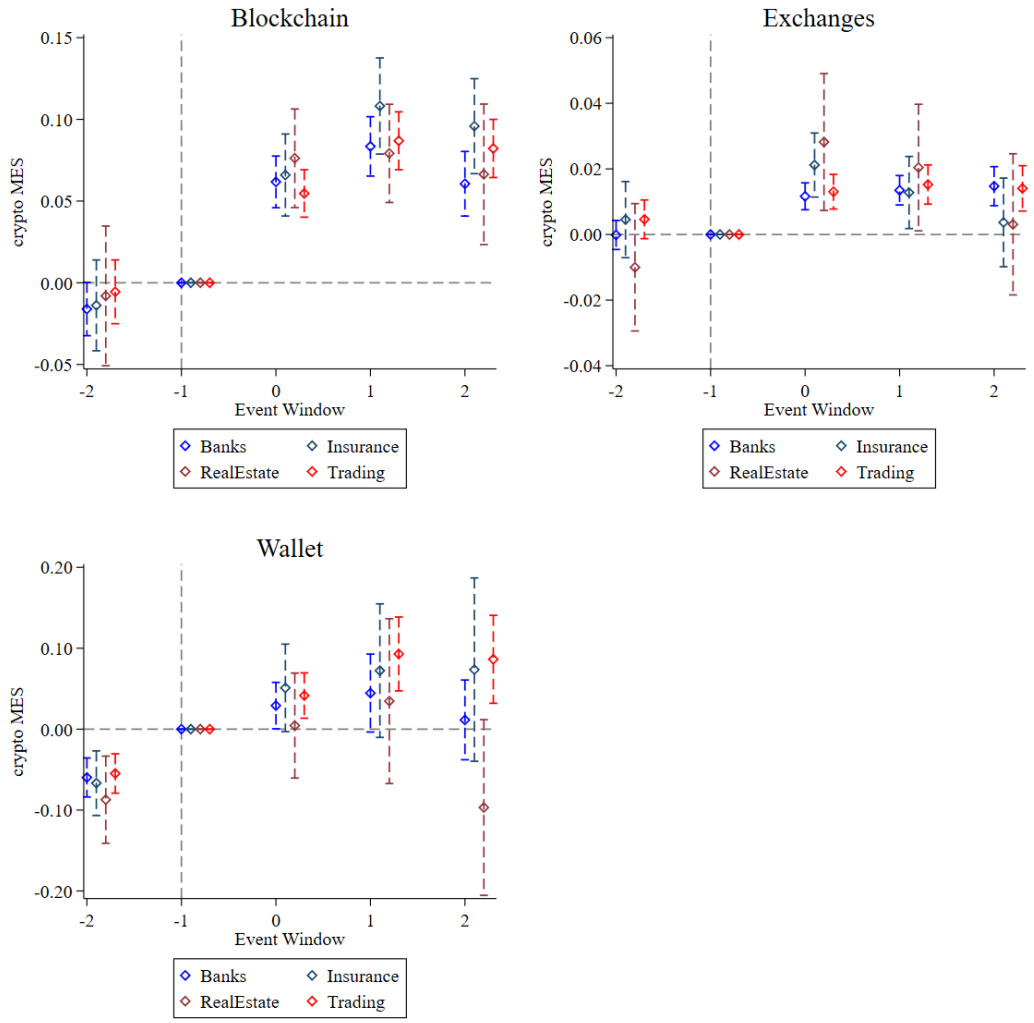


Figure 5: Dynamic Coefficients of Crypto MES on Crypto Beta in the Stacked DID Design by Financial Firms.

Note: This figure shows the dynamic coefficients of crypto MES on crypto beta in the stacked DID design. The coefficients in the graph are estimated in the equation: $y_{eit} = \sum_{q \neq -1} \gamma_t \times \beta_{ei} \times 1(t = q) + \delta_{ei} + \eta_{et} + \epsilon_{eit}$. The confidence interval is constructed at the 99% level, and the time interval is at the quarterly level. The crypto shocks in the stacked DID design are blockchain, exchange, and wallet. The blue, navy, maroon, and red markers show the coefficients of banks, insurance companies, real estate companies, and trading firms, respectively.

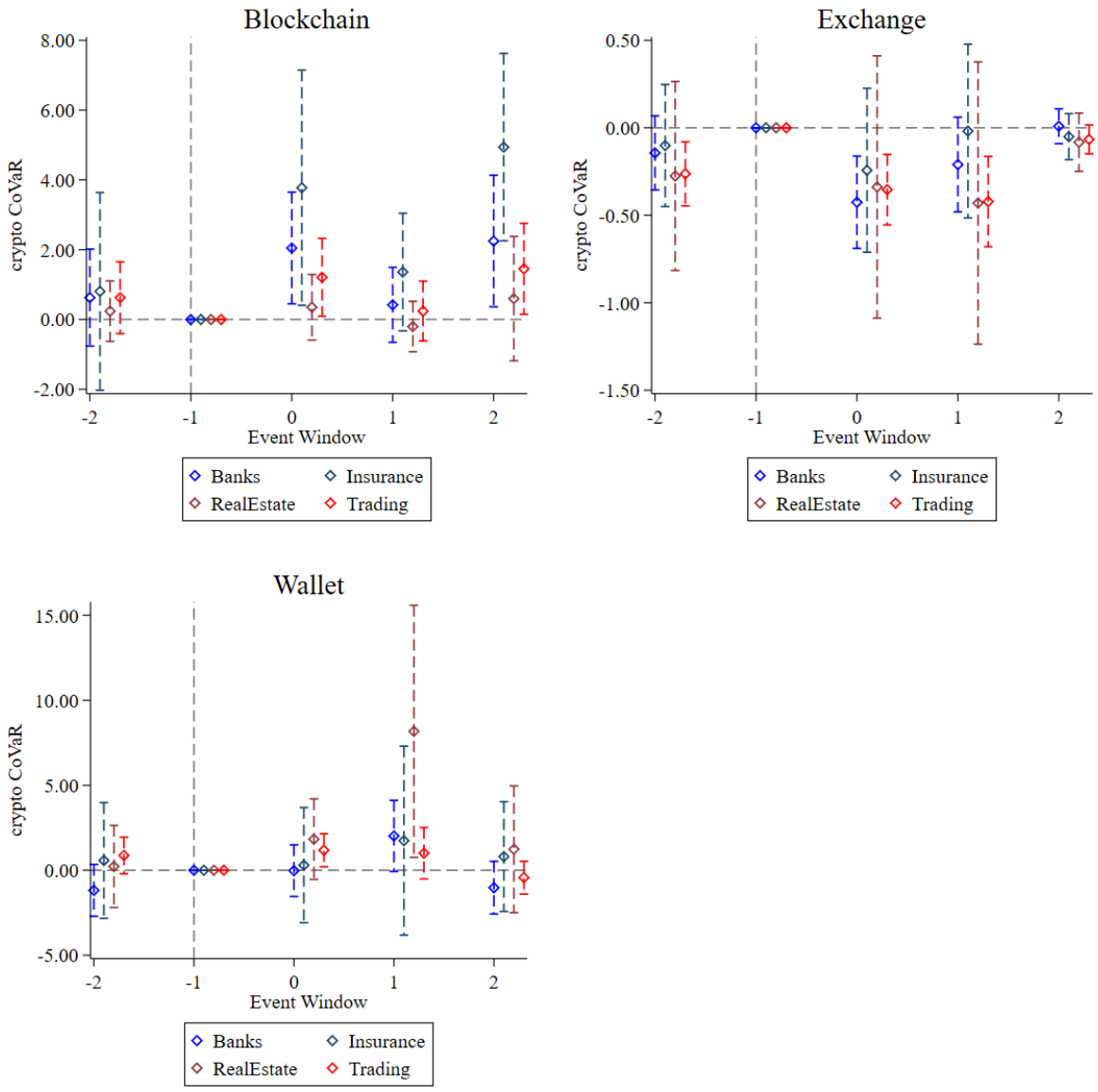


Figure 6: Dynamic Coefficients of Crypto CoVaR on Crypto Beta in the Stacked DID Design by Financial Firms

Note: This figure shows the dynamic coefficients of crypto CoVaR on crypto beta in the stacked DID design. The coefficients in the graph are estimated in the equation: $y_{eit} = \sum_{q \neq -1} \gamma_t \times \beta_{ei} \times 1(t = q) + \delta_{ei} + \eta_{et} + \epsilon_{eit}$. The confidence interval is constructed at the 99% level, and the time interval is at the weekly level. The crypto shocks in the stacked DID design are blockchain, exchange, and wallet. The blue, navy, maroon, and red markers show the coefficients of banks, insurance companies, real estate companies, and trading firms, respectively.

Table 1

Summary Statistics

Variable	N	Mean	Median	STD
MES	9,650	2.105	1.643	1.954
crypto MES	9,636	0.661	0.283	1.268
CoVaR	9,284	68.275	63.345	45.307
crypto CoVaR	9,513	3.872	2.659	6.467
return	10,197	-17.199	4.578	191.621
ROA	12,883	2.604	2.220	17.094
B&H return	10,197	-1.301	0.000	10.726
total risk	10,195	40.525	27.259	40.475
bitcoin beta	9,690	0.226	-0.073	4.566
coin beta	9,690	0.112	0.000	2.336
tenk exposure	486	0.176	0.023	0.558
tenk risk	486	0.015	0.000	0.064
tenk sentiment	486	-0.039	0.000	0.185
tenk LLM	465	0.187	0.150	0.149
trans exposure	575	1.247	0.528	2.201
trans risk	575	0.044	0.000	0.123
trans sentiment	575	0.203	0.006	0.701
trans LLM	552	0.514	0.475	0.167
size	15,020	14.369	14.357	2.615
capital	15,020	0.273	0.151	0.300

Note: This table reports the summary statistics in our sample. The summary statistics include the number of observations, sample mean, sample median, and sample standard deviation.

Table 2

A Case Study of the FTX Run

	B&H Return in FTX Run					
	(1)	(2)	(3)	(4)	(5)	(6)
bitcoin beta	0.122***					
	(0.031)					
coin beta		0.104***				
		(0.028)				
tenk exposure			16.864***			
			(1.644)			
trans exposure				1.953***		
				(0.414)		
tenk LLM					3.090	
					(6.642)	
trans LLM						-10.076
						(6.306)
Observations	1,046	1,046	112	170	106	159
R^2	0.06	0.05	0.28	0.16	0.01	0.09
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports the prediction regressions of buy-and-hold returns during the FTX crisis on crypto risk measures. Buy-and-hold returns in the FTX crisis are estimated in the event window of [-10,10]. Crypto risk measures include crypto risk, measured by bitcoin beta and coin beta, and perceived crypto risk, measured by text mining from *tenk* files and earnings call transcripts. Crypto risk and perceived crypto risk are measured at least one year before the FTX event. Control variables are size and capital. The heteroscedasticity robust standard errors are in parentheses, and the 0.1, 0.05, and 0.01 significance levels are indicated: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Table 3

Crypto Risk on Systemic Risk Exposure

	MES		crypto MES	
	(1)	(2)	(3)	(4)
bitcoin beta	0.027***		0.064***	
	(0.005)		(0.004)	
coin beta		0.026***		0.088***
		(0.007)		(0.006)
Observations	9,547	9,547	9,530	9,530
Adj.R2	0.74	0.74	0.70	0.67
Control Variables	Yes	Yes	Yes	Yes
Year×Firm Type	Yes	Yes	Yes	Yes
Fin Firm FE	Yes	Yes	Yes	Yes

Note: This table reports the regression of systemic risk exposure on crypto risk. Systemic risk exposure is measured by MES and crypto MES. The crypto risk is measured by bitcoin beta and coin beta. Control variables are size and capital. The heteroscedasticity robust standard errors, clustered at the financial firm level, are in parentheses, and the 0.1, 0.05, and 0.01 significance levels are indicated: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Table 4

Crypto Risk on Systemic Risk Transmission

	CoVaR		crypto CoVaR	
	(1)	(2)	(3)	(4)
bitcoin beta	0.047		0.005**	
	(0.042)		(0.002)	
coin beta		0.066		0.013**
		(0.087)		(0.006)
Observations	9,221	9,221	9,453	9,453
Adj.R2	0.86	0.86	0.98	0.98
Control Variables	Yes	Yes	Yes	Yes
Year×Firm Type	Yes	Yes	Yes	Yes
Fin Firm FE	Yes	Yes	Yes	Yes

Note: This table reports the regression of systemic risk transmission on crypto risk. Systemic risk exposure is measured by CoVaR and crypto CoVaR. The crypto risk is measured by bitcoin beta and coin beta. Control variables are size and capital. The heteroscedasticity robust standard errors, clustered at the financial firm level, are in parentheses, and the 0.1, 0.05, and 0.01 significance levels are indicated: *$p <$ 0.1; **$p < 0.05$; ***$p < 0.01$.

Table 5

Perceived Crypto Risk on Systemic Risk Exposure

	crypto MES							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
tenk exposure	0.802***							
	(0.241)							
tenk LLM		0.642**						
		(0.283)						
tenk risk			7.204***					
			(2.172)					
tenk sentiment				-2.177***				
				(0.799)				
trans exposure					0.130***			
					(0.050)			
trans LLM						0.246***		
						(0.089)		
trans risk							1.300**	
							(0.564)	
trans sentiment								0.089
								(0.089)
Observations	9,530	9,530	9,530	9,530	9,530	9,530	9,530	9,530
Adj.R2	0.65	0.65	0.65	0.65	0.65	0.65	0.65	0.65
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year×Firm Type	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fin Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports the regression of systemic risk exposure on perceived crypto risk. Systemic risk exposure is measured by crypto MES. The perceived crypto risk is measured by text measures from 10-K files and earnings call transcripts. Control variables are size and capital. The heteroscedasticity robust standard errors, clustered at the financial firm level, are in parentheses, and the 0.1, 0.05, and 0.01 confidence levels are indicated: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Table 6

Perceived Crypto Risk on Systemic Risk Transmission

	crypto CoVaR							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
tenk exposure	0.047							
	(0.226)							
tenk LLM		0.167						
		(0.366)						
tenk risk			0.418					
			(3.837)					
tenk sentiment				-1.398*				
				(0.774)				
trans exposure					0.016			
					(0.038)			
trans LLM						-0.199		
						(0.133)		
trans risk							-1.094	
							(0.676)	
trans sentiment								0.087
								(0.099)
Observations	9,460	9,460	9,460	9,460	9,460	9,460	9,460	9,460
Adj.R2	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.98
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year×Firm Type	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fin Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports the regression of systemic risk transmission on perceived crypto risk. Systemic risk transmission is measured by crypto CoVaR. The perceived crypto risk is measured by text measures from 10-K files and earnings call transcripts. Control variables are size and capital. The heteroscedasticity robust standard errors, clustered at the financial firm level, are in parentheses, and the 0.1, 0.05, and 0.01 confidence levels are indicated: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Table 7

Crypto Risk on Performance and Total Risk

Panel A

Beta Measure

	return		B&H return		ROA		total risk	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
bitcoin beta	-0.602		-0.037		0.007		0.181*	
	(0.581)		(0.033)		(0.033)		(0.094)	
coin beta		2.040		0.096		0.054		0.457**
		(1.322)		(0.072)		(0.047)		(0.196)
Observations	9,509	9,509	9,509	9,509	7,994	7,994	9,509	9,509
Adj.R2	0.17	0.17	0.21	0.21	0.77	0.77	0.52	0.52
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year×Firm Type	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fin Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports the regression of performance and total risk on crypto risk. Performance is measured by return, buy-and-hold return, and ROA. Total risk is measured by total volatility of equity returns. The crypto risk is measured by bitcoin beta and coin beta. Control variables are size and capital. The heteroscedasticity robust standard errors, clustered at the financial firm level, are in parentheses, and the 0.1, 0.05, and 0.01 significance levels are indicated: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Panel B

Perceived Crypto Risk

Perceived crypto risk	Return	B&H Return	ROA	Total Risk
tenk exposure	75.803***	4.059***	-8.946***	1.322
	(24.277)	(1.175)	(2.127)	(5.319)
tenk risk	747.195***	39.443***	-52.321***	34.332
	(155.573)	(7.810)	(15.573)	(52.885)
tenk sentiment	-241.991***	-13.139***	16.178**	-13.278
	(65.917)	(3.336)	(6.818)	(17.368)
tenk LLM	-7.956	-0.654	-6.966**	2.494
	(46.617)	(2.416)	(2.727)	(6.365)
trans exposure	14.039**	0.743**	0.171	1.949
	(5.764)	(0.347)	(0.493)	(1.323)
trans risk	319.663***	17.901***	2.949	23.440*
	(106.126)	(5.905)	(6.069)	(14.008)
trans sentiment	32.400**	1.677**	-0.205	6.154**
	(14.390)	(0.853)	(0.888)	(2.978)
trans LLM	-21.564	-1.138	-1.816**	2.613
	(21.749)	(1.195)	(0.863)	(2.960)

Note: This table reports the regressions of perceived crypto risk on financial firms' performance and total risk. Performance is measured by return, buy-and-hold return, and ROA. Total risk is measured by total volatility of equity returns. The perceived crypto risk is measured by text measures from 10-K files and earnings call transcripts. Control variables are size and capital. The heteroscedasticity robust standard errors, clustered at the financial firm level, are in parentheses, and the 0.1, 0.05, and 0.01 significance levels are indicated: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Table 8

Crypto Risk on Systemic Risk Exposure in the Crypto Shocks

Panel A

Full Sample Results

	Crypto Shocks					
	MES			crypto MES		
	Blockchain	Exchanges	Wallet	Blockchain	Exchanges	Wallet
	(1)	(2)	(3)	(4)	(5)	(6)
crypto beta×post	0.060***	0.003***	0.055***	0.079***	0.013***	0.068***
	(0.004)	(0.001)	(0.006)	(0.004)	(0.001)	(0.006)
Observations	119,495	99,148	26,576	119,400	99,063	26,552
R^2	0.80	0.73	0.85	0.75	0.68	0.80
# of Events	24	21	7	24	21	7
# of Fin Firms	1933	2324	1961	1933	2324	1961
Event×Fin Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Event×Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports the stacked DID regressions of systemic risk exposure using multiple crypto shocks. Systemic risk exposure is measured by MES and crypto MES. Multiple crypto shocks consist of three main types: blockchain, exchanges, and wallet. The treatment variable in crypto shocks is the crypto beta, estimated by the regression of each bank equity return on returns of crypto that were attacked by each crypto shock. The heteroscedasticity robust standard errors, clustered at the financial firm level, are in parentheses, and the 0.1, 0.05, and 0.01 significance levels are indicated: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Panel B

Crypto Risk on Systemic Risk Exposure by Financial Firms

	Crypto Shocks					
	MES			crypto MES		
Fin Firm	Blockchain	Exchanges	Wallet	Blockchain	Exchanges	Wallet
Banks	0.053***	0.000	0.050***	0.077***	0.013***	0.058***
	(0.006)	(0.002)	(0.010)	(0.007)	(0.001)	(0.010)
Insurance	0.070***	0.005	0.034**	0.095***	0.013***	0.087***
	(0.015)	(0.003)	(0.013)	(0.011)	(0.003)	(0.017)
Real Estate	0.075***	0.006	0.046**	0.079***	0.024***	0.042**
	(0.018)	(0.005)	(0.020)	(0.014)	(0.007)	(0.020)
Trading	0.067***	0.004**	0.053***	0.076***	0.012***	0.079***
	(0.006)	(0.002)	(0.009)	(0.006)	(0.002)	(0.010)

Note: This table reports the stacked DID regressions of systemic risk exposure using multiple crypto shocks by financial firm type. Systemic risk exposure is measured by MES and crypto MES. Multiple crypto shocks consist of three main types: blockchain, exchanges, and wallet. Financial firm type consists of banks, insurance companies, real estate firms, and trading firms. The treatment variable in crypto shocks is the crypto beta, estimated by the regression of each bank equity return on returns of crypto that were attacked by each crypto shock. The heteroscedasticity robust standard errors, clustered at the financial firm level, are in parentheses, and the 0.1, 0.05, and 0.01 significance levels are indicated: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Table 9

Crypto Risk on Systemic Risk Transmission in The Crypto Shocks

Panel A

Full Sample Results

	Crypto Shocks					
	CoVaR			crypto CoVaR		
	Blockchain	Exchanges	Wallet	Blockchain	Exchanges	Wallet
	(1)	(2)	(3)	(4)	(5)	(6)
crypto beta×post	12.617***	-1.087***	-9.318**	0.951***	-0.123***	0.655**
	(3.606)	(0.237)	(3.932)	(0.294)	(0.026)	(0.286)
Observations	158,581	224,094	51,490	158,418	223,867	51,437
R^2	0.94	0.94	0.94	0.97	0.97	0.97
# of Events	33	46	12	33	46	12
# of Fin Firms	1091	1305	1134	1091	1305	1134
Event× Fin Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Event×Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports the stacked DID regressions of systemic risk transmission using multiple crypto shocks. Equity return is measured by CoVaR and crypto CoVaR. Multiple crypto shocks consist of three main types: blockchain, exchanges, and wallet. The treatment variable in crypto shocks is the crypto beta, estimated by the regression of each bank equity return on returns of crypto that were attacked by each crypto shock. The heteroscedasticity robust standard errors, clustered at the financial firm level, are in parentheses, and the 0.1, 0.05, and 0.01 significance levels are indicated: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Panel B

Crypto Risk on Systemic Risk Transmission by Financial Firms

	Crypto Shocks					
	CoVaR			crypto CoVaR		
Fin Firm	Blockchain	Exchange	Wallet	Blockchain	Exchange	Wallet
Banks	12.478**	-0.584*	-8.322	1.257***	-0.140***	0.881
	(5.606)	(0.338)	(6.994)	(0.464)	(0.041)	(0.569)
Insurance	17.424	-1.139*	-30.614**	2.950***	-0.053	0.610
	(15.842)	(0.579)	(14.592)	(0.763)	(0.072)	(1.249)
Real Estate	-1.196	-0.794	33.911	0.128	-0.146	3.420**
	(4.018)	(1.034)	(20.517)	(0.452)	(0.115)	(1.310)
Trading	10.325*	-1.201***	-12.465***	0.653*	-0.151***	0.176
	(5.779)	(0.447)	(4.580)	(0.338)	(0.034)	(0.260)

Note: This table reports the stacked DID regressions of systemic risk transmission using multiple crypto shocks by financial firm type. Systemic risk transmission is measured by CoVaR and crypto CoVaR. Multiple crypto shocks consist of three main types: blockchain, exchanges, and wallet. Financial firm type consists of banks, insurance companies, real estate firms, and trading firms. The treatment variable in crypto shocks is the crypto beta, estimated by the regression of each bank equity return on returns of crypto that were attacked by each crypto shock. The heteroscedasticity robust standard errors, clustered at the financial firm level, are in parentheses, and the 0.1, 0.05, and 0.01 significance levels are indicated: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Table 10

Crypto Risk on Equity Returns in the Crypto Shocks

	Crypto Shocks					
	Daily Return			Daily Abnormal Return		
	Blockchain	Exchanges	Wallet	Blockchain	Exchanges	Wallet
	(1)	(2)	(3)	(4)	(5)	(6)
crypto beta×post	-0.053	-0.025***	-0.705***	-0.040	-0.027***	-0.799***
	(0.180)	(0.008)	(0.171)	(0.174)	(0.008)	(0.187)
Observations	525,477	864,288	185,245	525,477	864,288	185,245
R^2	0.28	0.26	0.36	0.13	0.10	0.11
# of Events	34	55	13	34	55	13
# of Fin Firms	1308	1510	1314	1308	1510	1314
Event× Fin Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Event×Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports the stacked DID regressions of equity returns using multiple crypto shocks. Systemic risk transmission is measured by daily return and daily abnormal return. Multiple crypto shocks consist of three main types: blockchain, exchanges, and wallet. The treatment variable in crypto shocks is the crypto beta, estimated by the regression of each bank equity return on returns of crypto that were attacked by each crypto shock. The heteroscedasticity robust standard errors, clustered at the financial firm level, are in parentheses, and the 0.1, 0.05, and 0.01 significance levels are indicated: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Table 11

Perceived Crypto Risk on Systemic Risk in the Crypto Shocks

Panel A

Perceived Crypto Risk and Systemic Risk Exposure in the Crypto Shocks

		Crypto Shocks crypto MES	
Risk Perception×Post	Blockchain	Exchange	Wallet
tenk exposure×post	5.653**	-2.809	0.975
	(2.292)	(5.972)	(7.457)
tenk risk×post	44.089***	29.501**	85.203***
	(3.280)	(15.001)	(21.810)
tenk sentiment×post	-15.901***	-3.391	-30.710***
	(2.851)	(9.827)	(9.770)
tenk LLM×post	0.004*	0.000	-0.009
	(0.003)	(0.003)	(0.006)
trans exposure×post	0.185	0.061	-0.388
	(0.420)	(0.470)	(0.770)
trans risk×post	3.772	3.181	2.579
	(5.258)	(6.941)	(18.382)
Trans sentiment×post	0.955	1.456	-0.821
	(1.565)	(1.095)	(1.880)
trans LLM×post	0.000	-0.002*	-0.009***
	(0.001)	(0.001)	(0.002)

Note: This table reports the stacked DID regressions of systemic risk exposure using multiple crypto shocks. Systemic risk transmission is measured by MES and crypto MES. Multiple crypto shocks consist of three main types: blockchain, exchanges, and wallet. The treatment variable is previously perceived crypto risk, measured at least one year before each crypto shock. The heteroscedasticity robust standard errors, clustered at the financial firm level, are in parentheses, and the 0.1, 0.05, and 0.01 significance levels are indicated: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Panel B

Perceived Crypto Risk on Systemic Risk Transmission in the Crypto Shocks

		Crypto Shocks crypto CoVaR	
Risk Perception×Post	Blockchain	Exchange	Wallet
tenk exposure×post	10.059	162.035	354.744**
	(82.074)	(165.194)	(148.600)
tenk risk×post	-1483.825	3390.947**	11348.130***
	(2455.405)	(1622.881)	(4271.915)
tenk sentiment×post	-3.001	-280.939	-1457.308*
	(348.292)	(352.481)	(865.317)
tenk LLM×post	-0.578*	0.299	0.156
	(0.322)	(0.230)	(0.467)
trans exposure×post	-41.711*	71.952**	18.654
	(21.933)	(34.347)	(72.892)
trans risk×post	-972.447*	1574.300***	438.744
	(586.701)	(577.594)	(1199.856)
trans sentiment×post	-48.777	45.314	49.921
	(72.609)	(113.210)	(143.381)
trans LLM×post	-0.138	0.390***	0.183*
	(0.098)	(0.115)	(0.106)

Note: This table reports the stacked DID regressions of systemic risk transmission using multiple crypto shocks. Systemic risk transmission is measured by CoVaR and crypto CoVaR. Multiple crypto shocks consist of three main types: blockchain, exchanges, and wallet. The treatment variable is previously perceived crypto risk, measured at least one year before each crypto shock. The heteroscedasticity robust standard errors, clustered at the financial firm level, are in parentheses, and the 0.1, 0.05, and 0.01 significance levels are indicated: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Table 12

Placebo Tests of Cyber Attacks and Systemic Risk

Panel A

Placebo Tests of Cyber Attacks and Systemic Risk Exposure

	Cyber Attack Shocks					
	MES			crypto MES		
	Financial	Personal	Other	Financial	Personal	Other
	(1)	(2)	(3)	(4)	(5)	(6)
cyber attack×post	0.001	-0.000	0.007*	0.002*	0.000	0.004
	(0.001)	(0.001)	(0.004)	(0.001)	(0.001)	(0.003)
Observations	266,874	384,768	96,564	266,448	384,298	96,423
R^2	0.72	0.75	0.75	0.65	0.69	0.69
# of Events	55	78	20	55	78	20
# of Fin Firms	2337	2337	2254	2337	2337	2254
Event× Fin Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Event×Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports the stacked DID regressions of systemic risk exposure using placebo cyber-attack shocks. Systemic risk exposure is measured by MES and crypto MES. Placebo cyber-attack shocks consist of three main types: financial, personal, and other. The treatment variable is previously perceived crypto risk, measured at least one year before each crypto shock. The heteroscedasticity robust standard errors, clustered at the financial firm level, are in parentheses, and the 0.1, 0.05, and 0.01 significance levels are indicated: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Panel B

Placebo Tests of Cyber Attacks and Systemic Risk Transmission

	Cyber Attack Shocks					
	CoVaR			crypto CoVaR		
	Financial	Personal	Other	Financial	Personal	Other
	(1)	(2)	(3)	(4)	(5)	(6)
cyber attack×post	0.226	-1.994	-2.716	0.084	-0.411*	0.329
	(5.226)	(2.790)	(5.916)	(0.322)	(0.235)	(0.242)
Observations	320,137	446,822	100,516	319,801	446,356	100,408
R^2	0.94	0.95	0.95	0.98	0.97	0.98
# of Events	68	94	22	68	94	22
# of Fin Firms	1305	1305	1254	1305	1305	1254
Event× Fin Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Event×Time FE	Yes	Yes	Yes	Yes	Yes	Yes

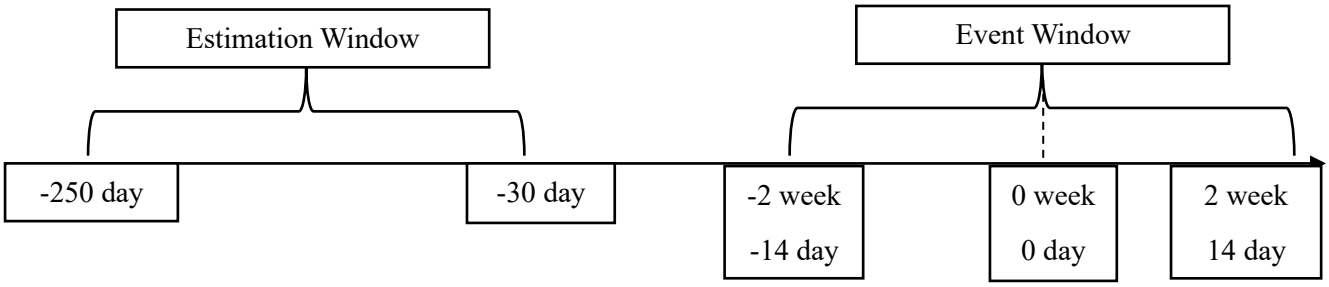
Note: This table reports the stacked DID regressions of systemic risk transmission using placebo cyber-attack shocks. Systemic risk transmission is measured by CoVaR and crypto CoVaR. Placebo cyber-attack shocks consist of three main types: financial, personal, and other. The treatment variable is previously perceived crypto risk, measured at least one year before each crypto shock. The heteroscedasticity robust standard errors, clustered at the financial firm level, are in parentheses, and the 0.1, 0.05, and 0.01 significance levels are indicated: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Online Appendix

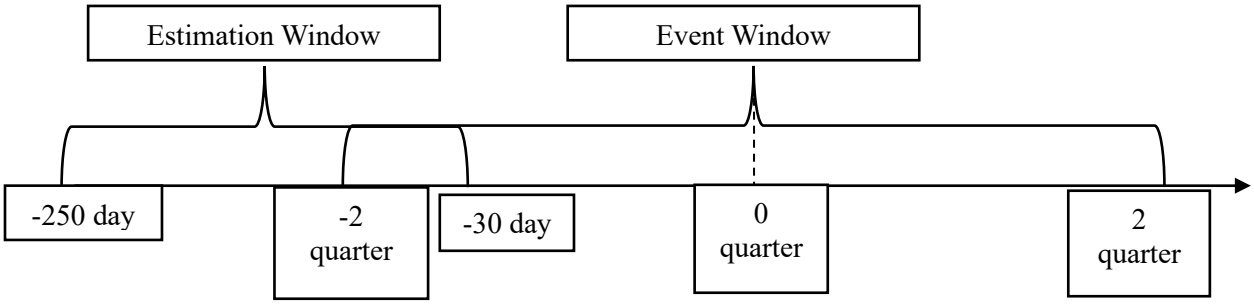
A: Additional Figures and Tables



Panel A: Daily-Frequency Sample



Panel B: Weekly-Frequency Sample



Panel C: Quarterly-Frequency Sample

Figure A1: Empirical Strategy of the Crypto Shocks

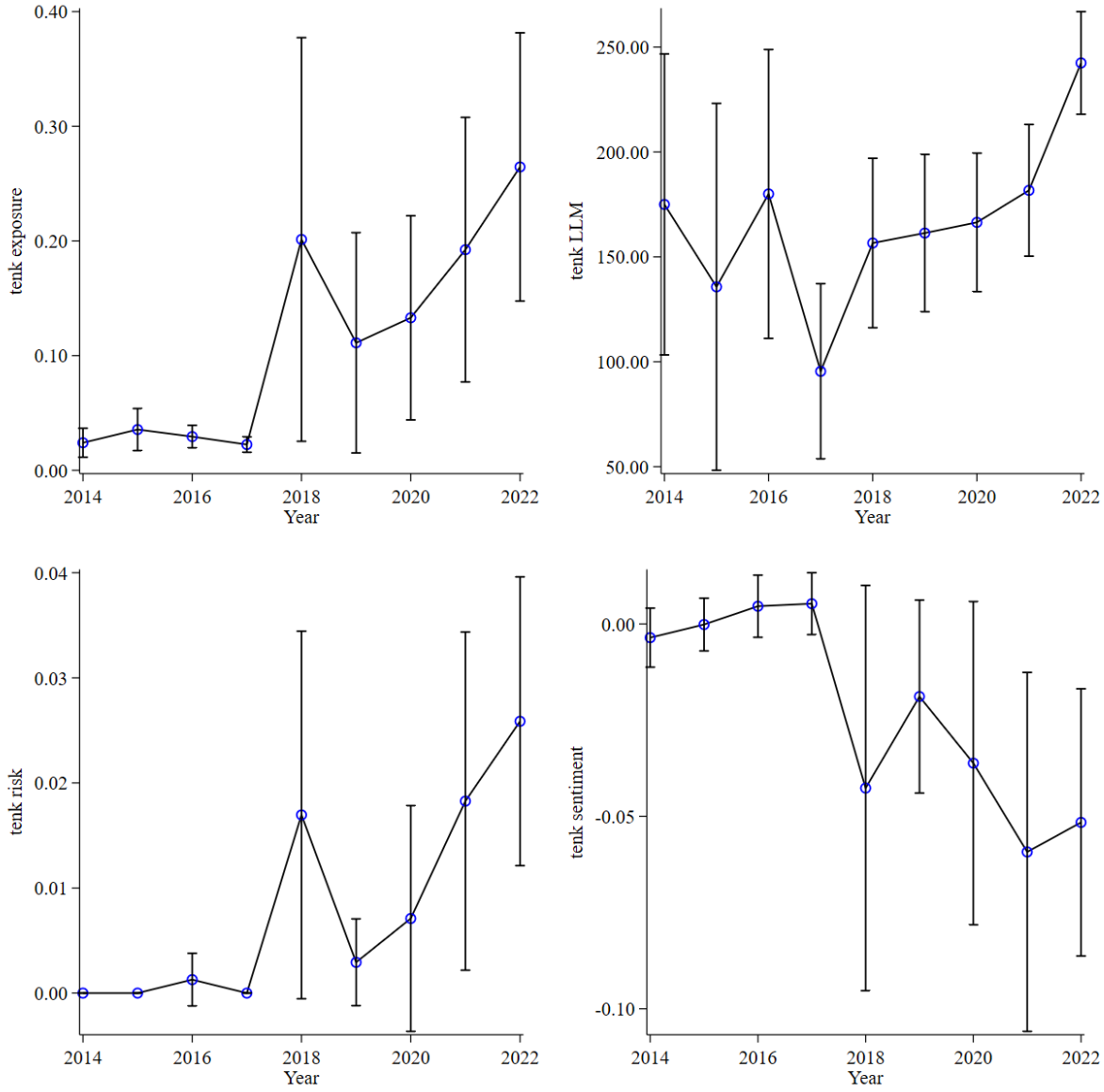


Figure A2: Time Series of Perceived Crypto Risk Measured by 10-K Files

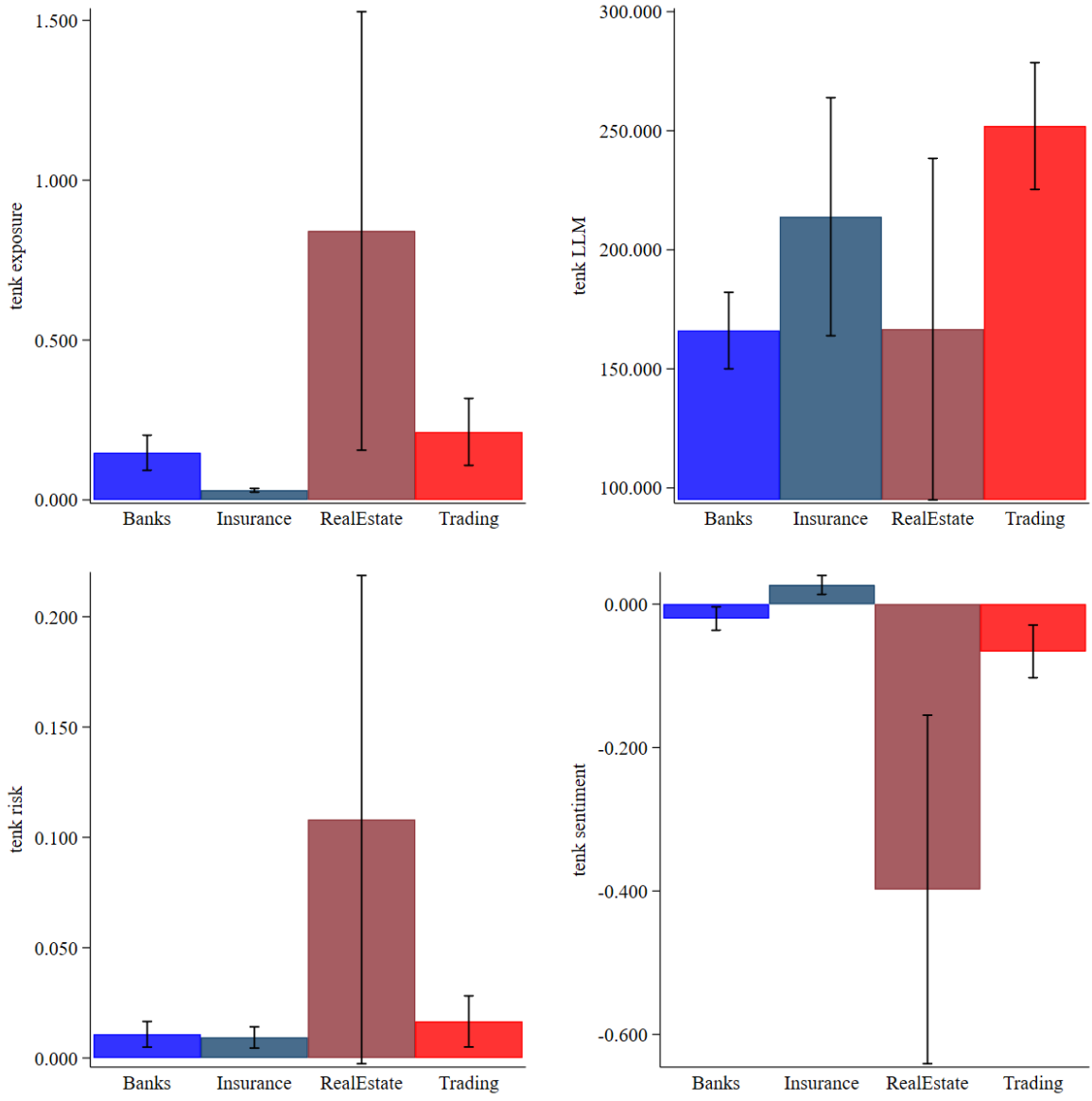


Figure A3: Perceived Crypto Risk of Financial Firms Measured by 10-K Files

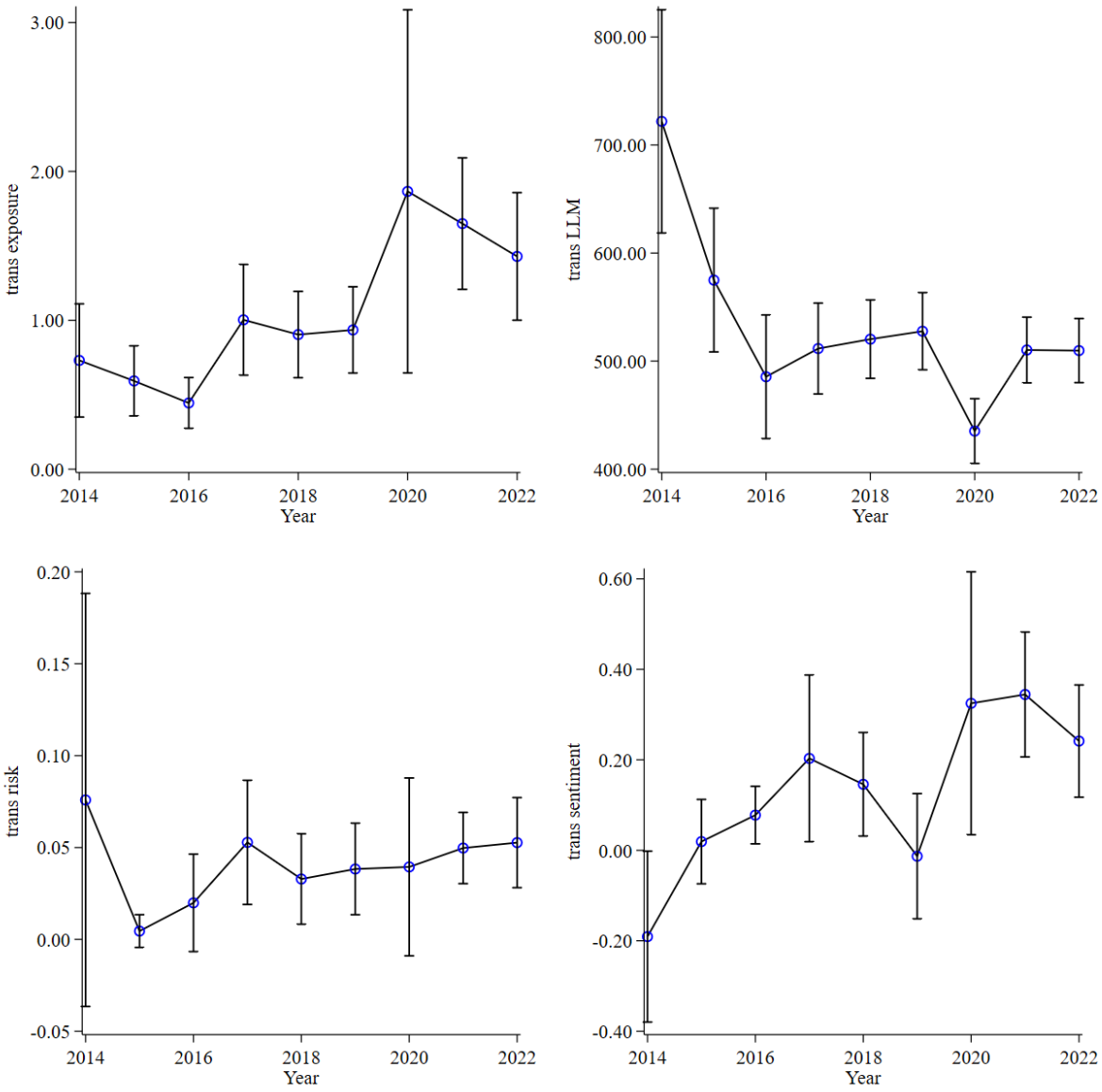


Figure A4: Perceived Crypto Risk of Financial Firms Measured by Transcript Files

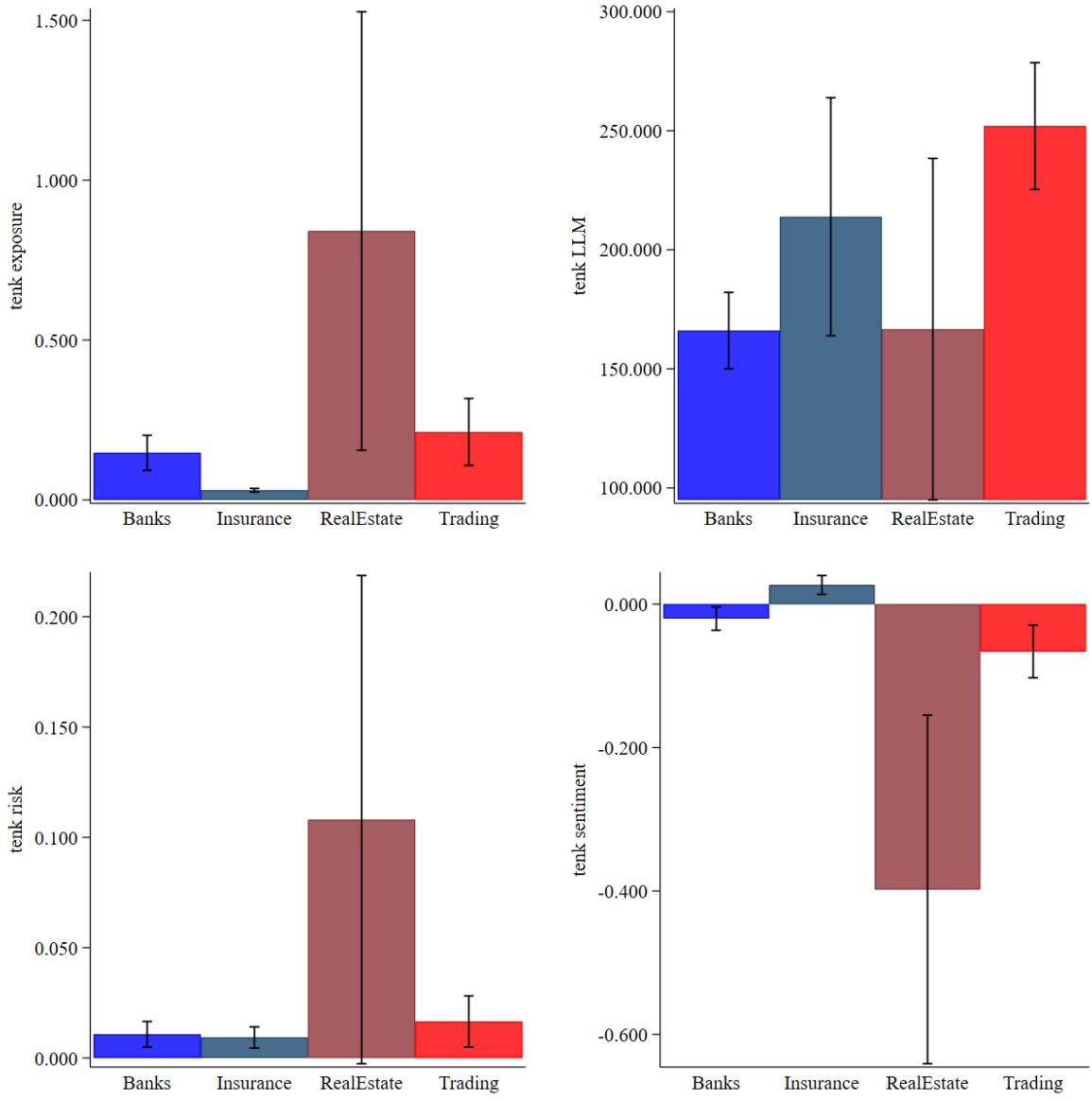


Figure A5: Perceived Crypto Risk of Financial Firms Measured by Transcript Files

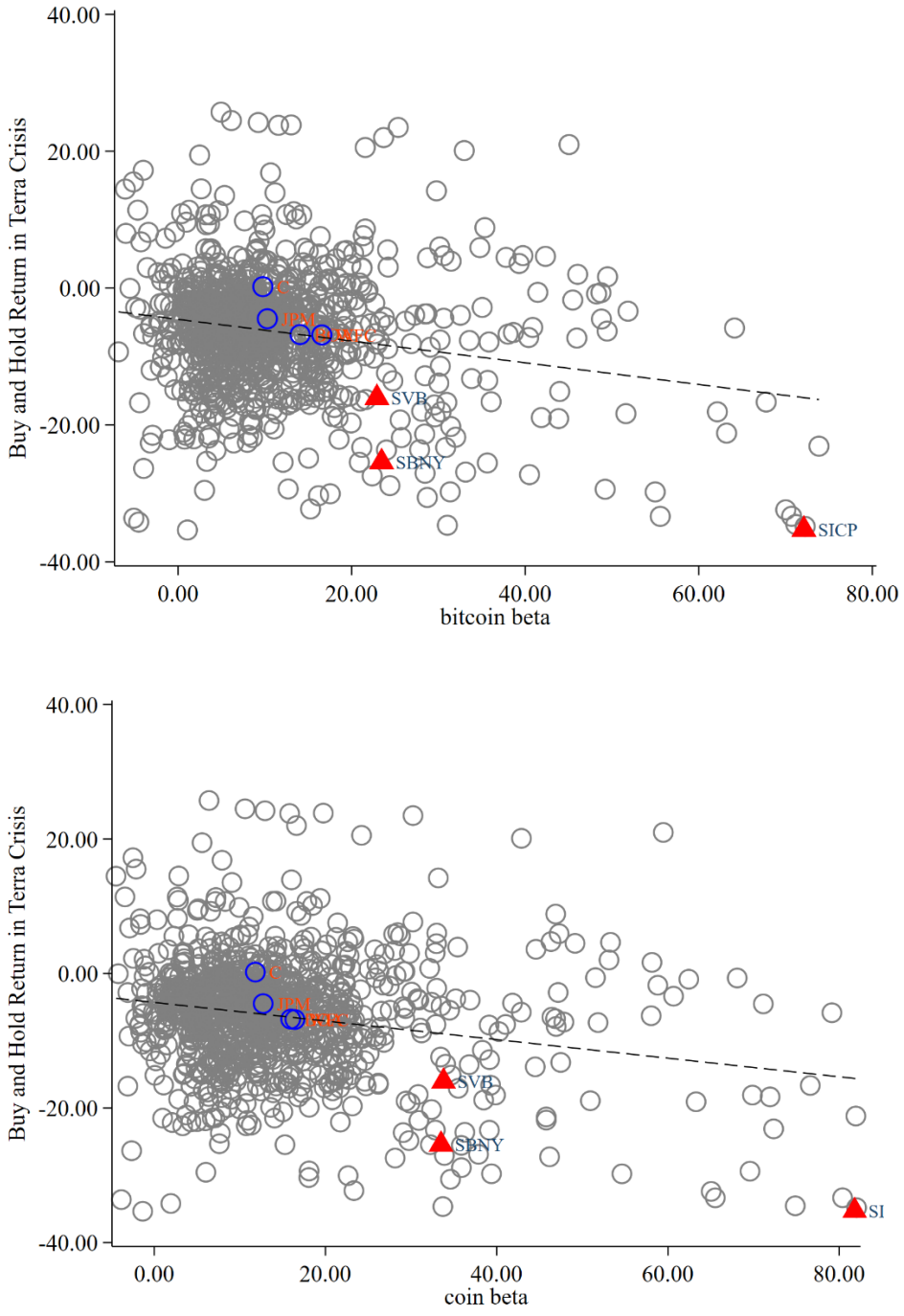


Figure A6: The Scatterplot of Buy-and-Hold Returns in the TerraUSD Run Against Crypto Risk

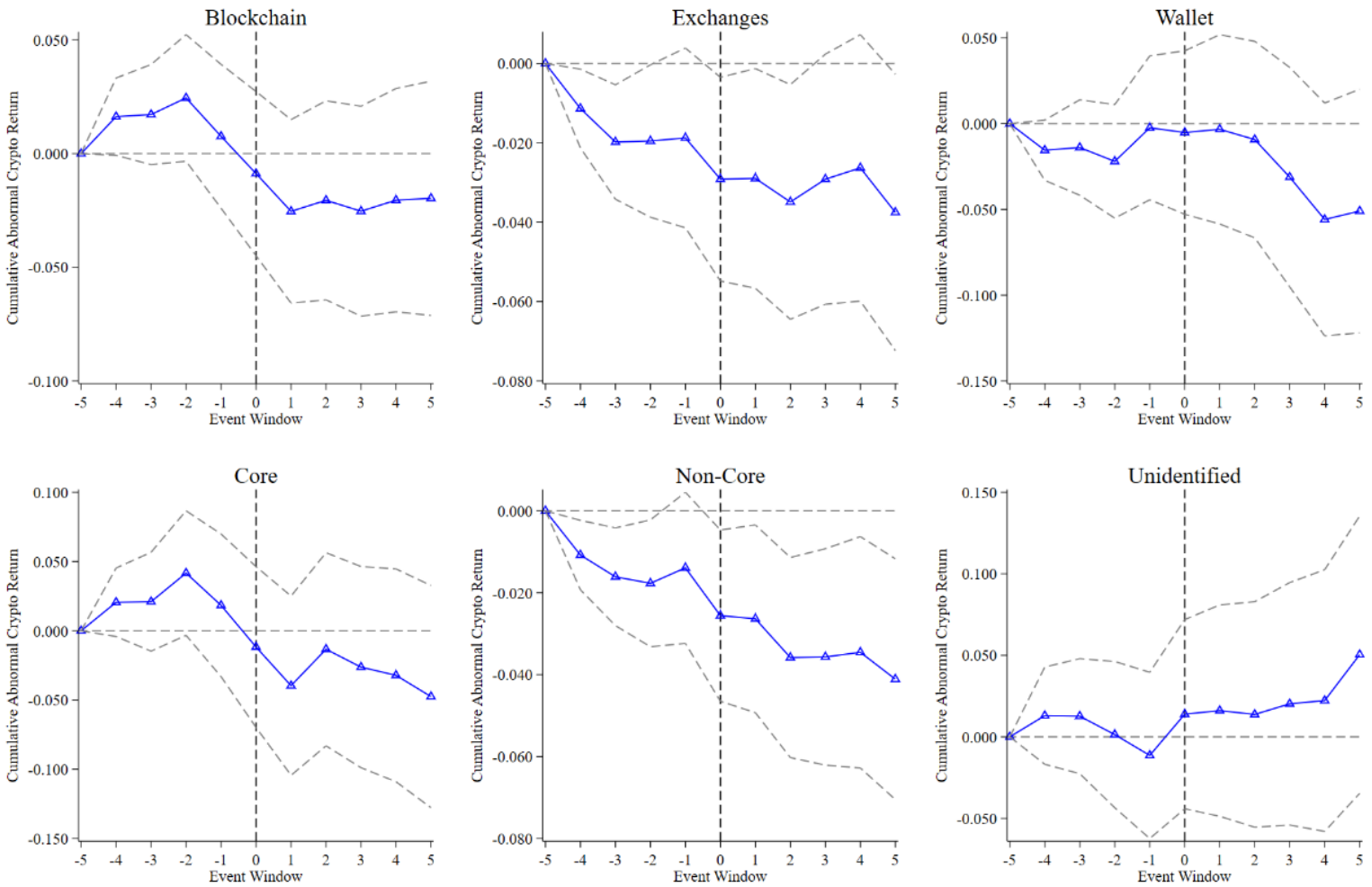


Figure A7: Crypto Market Reactions to Crypto Shock

Table A1

Sample Creation

Sample creation criteria	# of unique financial firms	# of unique observations
Keep SIC of financial firms between 6000 and 6799 from 2014 and 2022	2,233	15,082
Drop observations whose total assets is missing	2,228	15,020
Final sample	2,228	15,020
Banks	1,075	7,204
Insurance	232	1,611
Real estate	144	890
Trading	777	5,315

Table A2

Variable Definition and Source

variable name	variable definition	source
MES	Financial firm's Marginal Expected Shortfall (MES), conditional on the worst 5% market outcomes	CRSP
crypto MES	Financial firm's Marginal Expected Shortfall (MES), conditional on the worst 5% crypto market outcomes	CRSP
CoVaR	Systemic risk transmission. The VaR of financial system, conditional on each financial firm's distress	CRSP
crypto CoVaR	Crypto systemic risk transmission. The VaR of financial system, conditional on each financial firm's distress from crypto market distress	CRSP
return	Average equity return of financial firm during the window ten days before and after 10-K form disclosure date	CRSP
B&H return	Buy-and-hold return of the financial firm during the window ten days before and after 10-K form disclosure date	CRSP
total risk	Annual equity return volatility of the financial firm during the window ten days before and after 10-K form disclosure date	CRSP
ROA	Return on asset of the financial firm	Compustat
bitcoin beta	The sensitivity of financial firm equity return to bitcoin return, conditional on the Fama-French three-factor model	CRSP and Coinmarketcap
coin beta	The sensitivity of financial firm equity return to crypto market index return, conditional on the Fama-French three-factor model	CRSP and Coinmarketcap
tenk exposure	The number of crypto-related key words divided by the total number of words in the financial firm's ten K form	10-K form
tenk risk	The number of risk-meaning words around the crypto-related keywords, divided by the total number of words in the financial firm's 10-K form	10-K form

tenk sentiment	Sentiment scores of text analysis in the financial firm's 10-K form	10-K Form
tenk LLM	Crypto risk score in the 10-K form, generated from the Large Language Model (LLM) ChatGPT	10-K Form and Open AI
trans exposure	The number of crypto-related keywords, divided by the total number of words in the financial firm's 10-K form	Earnings Call Transcript
trans risk	The number of risk-meaning words around the crypto-related keywords, divided by the total number of words in the financial firm's earnings call transcript	Earnings Call Transcript
trans sentiment	Sentiment scores of text analysis in the financial firm's earnings call transcript	Earnings Call Transcript
trans LLM	Crypto risk score in the earnings call transcript generated from the Large Language Model (LLM) ChatGPT	Earnings Call Transcript and Open AI
size	Financial firm size, the natural logarithm of the total assets	Compustat
capital	Financial firm capital, the ratio of total equity to total asset	Compustat

Table A3

Summary Statistics of Shock Sample

variable	N	Mean	STD	Min	P25	Median	P75	Max
			Daily Sample					
daily Return	1,597,057	0.064	2.356	-7.659	-1.003	0.008	1.093	8.527
daily Abreturn	1,597,057	-0.007	2.112	-7.073	-0.990	-0.013	0.959	7.498
crypto beta	1,575,259	-0.156	0.715	-5.634	-0.076	-0.019	0.002	0.293
			Weekly Sample					
CoVaR	439,617	148.323	106.971	0.383	69.339	131.652	202.343	524.694
crypto CoVaR	439,169	8.278	12.967	-20.395	0.261	5.857	14.396	55.554
crypto beta	435,458	-0.142	0.634	-4.786	-0.070	-0.017	0.002	0.207
			Quarterly Sample[42]					
MES	251,625	0.023	0.029	-0.020	0.007	0.016	0.027	0.160
crypto MES	251,426	0.012	0.023	-0.027	-0.001	0.006	0.017	0.122
crypto beta	249,198	-0.125	0.553	-3.896	-0.057	-0.014	0.001	0.228
size	367,000	14.604	2.543	6.495	13.344	14.568	15.983	21.065
capital	367,000	0.265	0.285	-0.723	0.095	0.150	0.425	0.992

[42] Quarterly sample is winsorized at a 3% level, while weekly sample and daily sample are winsorized at a 1% level.

Table A4

A Case Study of the FTX Run

Panel A

Beta Measures and Main Text Measures

	B&H Return in FTX Run					
	(1)	(2)	(3)	(4)	(5)	(6)
bitcoin beta	-0.122***					
	(0.031)					
coin beta		-0.104***				
		(0.028)				
tenk exposure			-16.864***			
			(1.644)			
trans exposure				-1.953***		
				(0.414)		
tenk LLM					-3.090	
					(6.642)	
trans LLM						10.076
						(6.306)
Observations	1,046	1,046	112	170	106	159
R^2	0.06	0.05	0.28	0.16	0.01	0.09
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes

Panel B

Components of Text Measures

	B&H Return in FTX Run			
	(1)	(2)	(3)	(4)
tenk risk	104.181**			
	(48.992)			
tenk sentiment		-25.517		
		(18.907)		
trans risk			21.043**	
			(10.362)	
trans sentiment				3.666*
				(1.891)
Observations	112	112	170	170
R^2	0.13	0.08	0.09	0.10
Control Variables	Yes	Yes	Yes	Yes

* $p<0.1$; ** $p<0.05$; *** $p<0.01$

Table A5

A Case Study of the TerraUSD Run

Panel A

Beta Measures and Main Text Measures

	B&H Return in Terra Run					
	(1)	(2)	(3)	(4)	(5)	(6)
bitcoin beta	-0.159***					
	(0.035)					
coin beta		-0.138***				
		(0.030)				
tenk exposure			-10.996***			
			(2.555)			
trans exposure				-1.335***		
				(0.486)		
tenk LLM					-8.379	
					(5.950)	
trans LLM						8.460*
						(4.971)
Observations	1,055	1,055	111	174	105	163
R^2	0.05	0.05	0.18	0.13	0.04	0.08
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes

Panel B

Components of Text Measures

	B&H Return in Terra Run			
	(1)	(2)	(3)	(4)
tenk risk	-77.661*			
	(39.558)			
tenk sentiment		21.881		
		(14.108)		
trans risk			6.094	
			(6.539)	
trans sentiment				-3.342**
				(1.365)
Observations	111	111	174	174
R^2	0.11	0.08	0.05	0.11
Control Variables	Yes	Yes	Yes	Yes

* $p<0.1$; ** $p<0.05$; *** $p<0.01$

Table A6

Core Technology Shocks VS Non-Core Technology Shocks

Panel A

Crypto Risk on Systemic Risk Exposure in the Crypto Shocks

	Crypto Shocks					
	MES			crypto MES		
	Core	Non-core	Unidentified	Core	Non-core	Unidentified
	(1)	(2)	(3)	(4)	(5)	(6)
crypto beta×post	0.058***	0.010***	0.075***	0.077***	0.021***	0.083***
	(0.005)	(0.001)	(0.008)	(0.004)	(0.001)	(0.007)
Observations	77,404	138,874	28,941	77,340	138,765	28,910
R^2	0.80	0.79	0.78	0.76	0.7	0.73
# of Events	15	31	6	15	31	6
# of Fin Firms	1933	2324	1889	1933	2324	1889
Event×Fin Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Event×Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel A

Crypto Risk on Systemic Risk Transmission in the Crypto Shocks

	Crypto Shocks					
	CoVaR			crypto CoVaR		
	Core	Non-core	Unidentified	Core	Non-core	Unidentified
	(1)	(2)	(3)	(4)	(5)	(6)
crypto beta×post	7.486	-1.065***	-0.759	1.575***	-0.118***	-0.028
	(5.670)	(0.234)	(1.239)	(0.399)	(0.025)	(0.148)
Observations	84,687	301,668	47,810	84,602	301,359	47,761
R^2	0.93	0.94	0.95	0.96	0.97	0.99
# of Events	17	64	10	17	64	10
# of Fin Firms	1091	1305	1088	1091	1305	1088
Event×Fin Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Event×Time FE	Yes	Yes	Yes	Yes	Yes	Yes

* $p<0.1$; ** $p<0.05$; *** $p<0.01$

B: Main Variables Construction

B1: Perceived Crypto Risk Construction

In this subsection, we discuss how to construct the perceived crypto risk measures. In sum, we text mined 10-K files and earnings call transcripts to construct the three text measures and one LLM measure, respectively.

For the three text measures, we first constructed a crypto-related dictionary *C*. Then, we constructed the exposure measure by counting the frequency of keywords in crypto-related dictionaries, scaled by the length of the document.

$$Exposure_{i,t} = \frac{\sum_{b}^{B_{i,t}}(1[b \in C])}{B_{i,t}} \quad (B.1)$$

Where $b = 0,1,\ldots,B_{i,t}$ are the bigrams in the document of financial firm *i* in the time *t*, and $1[.]$ is the indicator function.

Next, we constructed the sentiment measure by counting positive or negative words around keywords in crypto-related dictionary *C*. The positive and negative words were from the dictionary of Loughran and McDonald (2011).

$$Sentiment_{i,t} = \frac{1}{B_{i,t}}\sum_{b}^{B_{i,t}}\{(1[b \in C]) \times \sum_{b}^{b \in S}\tau(b)\} \ (B.2)$$

Where *S* is the sentence containing the bigrams $b = 0,1,\ldots,B_{i,t}$, and $\tau(b) = 1(-1)$ if b has positive(negative) tone and zero, otherwise.

Next, we constructed the risk measures by counting words like "risk," "uncertainty," and their synonyms around keywords in crypto-related dictionary *C*.

$$Risk_{i,t} = \frac{1}{B_{i,t}}\sum_{b}^{B_{i,t}}(1[b \in C] \times 1[b, r \in S]) \ (B.3)$$

Where *r* contains the words "risk," "uncertainty," or a synonym.

For 10-K files and earnings call transcripts, we constructed two group measures, respectively. The first group included *tenk exposure*, *tenk sentiment*, and *tenk risk*. The second group included *trans exposure*, *trans sentiment*, and *trans risk*.

Table B1

***Crypto-Related Dictionary* C**

Blockchain	*crypto*	*Cryptocurrency*
Bitcoin	*Defi*	*Ethereum*
Digital Currencies	*Stablecoins*	*Coin Mining*
Smart contracts		

Lastly, we constructed the ChatGPT measures. To thoroughly evaluate the cryptocurrency-related risks that firms face, we utilized LLMs to analyze the dimensions of their exposure. Our process began by extracting relevant context words from a carefully curated vocabulary list, provided in Table B1. These context words were then inputted into the ChatGPT API to answer a series of questions using the following prompt:

"You are an assistant specializing in analyzing firms' exposure to cryptocurrency. Your task is to review the provided text and answer each of the following questions based on the information available. Responses should be either 'Yes' or 'No.' If there is insufficient information to determine an answer, respond with 'Uncertain.' Ensure that each question receives an answer."

These questions were designed to produce clear responses that could be converted into a numerical scoring framework. Each 'Yes' response received a value of +1, each 'No' received a value of -1, and each 'Uncertain' response received a value of 0. The aggregated result, termed the "LLM Score," provided a deeper analysis beyond traditional bag-of-words methods. This score enabled a more nuanced understanding of whether firm disclosures—such as 10-K files or earnings call transcripts—contain explicit information on these questions, thereby offering a more precise measure of firms' cryptocurrency exposure.

Finally, we constructed the two groups' LLM scores: *tenk LLM* for 10-K files and *trans LLM* for earnings call transcripts.

For this study, we employed ChatGPT-4 to address the following inquiries:

(1) **Overall Exposure:** Does the firm demonstrate exposure to cryptocurrencies, either through investments or customer transactions? (Yes/No)

(2) **Service Offering:** Does the firm provide cryptocurrency-related services, such as trading or custody services, to its customers? (Yes/No)

(3) **Risk Mitigation:** Has the firm implemented strategies to manage cryptocurrency-related risks, including volatility and regulatory uncertainty? (Yes/No)

(4) **Market Positions:** Does the firm hold substantial cryptocurrency positions or engage with entities significantly involved in the crypto market, such as mining or trading firms? (Yes/No)

(5) **Partnerships:** Does the firm engage in partnerships with cryptocurrency or blockchain companies, and if so, what risks and benefits are associated with these collaborations? (Yes/No)

(6) **Transaction Handling:** Does the firm process cryptocurrency transactions, and does it adhere to anti-money laundering (AML) and know-your-customer (KYC) regulations? (Yes/No)

(7) **Blockchain Usage:** Does the firm use blockchain technology in its operations? (Yes/No)

(8) **Crypto Holdings:** Does the firm possess cryptocurrency-related holdings or investments, or does it engage in trading activities? (Yes/No)

(9) **Risk Management:** Has the firm implemented measures to manage risks associated with cryptocurrency exposure, such as market volatility, liquidity, security, and regulatory compliance? (Yes/No)

(10) **Stablecoin Holdings:** Does the firm hold stablecoins? (Yes/No)

B2: Crypto Systemic Risk Construction

In this subsection, we discuss how to construct and estimate the crypto-driven systemic risk. First, we discuss how to estimate the marginal expected shortfall (MES) and crypto-driven marginal expected shortfall (crypto MES). Next, we discuss how to estimate the conditional value-at-risk (CoVAR) and crypto-driven conditional value-at-risk (crypto CoVaR).

For the MES, we calculated the average equity returns of each financial firm, conditional on the 5 percent worst trading days of stock market. We obtained daily equity returns of financial firms from CRSP and used the CRSP value-weighted index return to measure the stock market returns. We used the daily equity returns to estimate the quarterly and annual MES. The estimation equation is as follows:

$$MES_{5\%}^{i} = -E[R_{it}|I_{5\%}] \ (B.4)$$

For the crypto-driven MES, we calculated the average equity returns of financial firms, conditional on the 5 percent worst trading days of crypto market. We obtained the daily equity returns of financial firms

from CRSP and constructed crypto market index returns by using the top 20 market-cap cryptos from the CoinMarketCap. We used the daily equity returns of financial firms and daily crypto returns to estimate the quarterly and annual crypto MES. The estimation equation is as follows:

$$crypo\ MES^{i}_{5\%} = -E[R_{it}|I_{5\%}(crypto\ market\ return)]\ (B.5)$$

For the CoVaR, we used the quantile regression to estimate the CoVaR. X^{s}_{t} and X^{i}_{t} are equity returns of financial system *s* and financial firm *i* at the time *t*, respectively. M_{t-1} is the vector of lagged state variables. $CoVaR^{i}_{q,t}$ and $VaR^{i}_{q,t}$ are conditional value-at-risk and value-at-risk of financial firm *i* with quantile q at the time *t*. We estimated the quantile regression on weekly data.

$$X^{i}_{t} = \alpha^{i}_{q} + \gamma^{i}_{q} M_{t-1} + \epsilon^{i}_{q,t}\ (B.6)$$

We used this quantile regression to predict the VaR of financial firm *i*:

$$VaR^{i}_{q,t} = \widehat{\alpha^{i}_{q}} + \widehat{\gamma^{i}_{q}} M_{t-1}\ (B.7)$$

Then, we ran the quantile regression of the financial system to estimate the CoVaR:

$$X^{s|i}_{t} = \alpha^{s|i}_{t} + \gamma^{s|i}_{q} M_{t-1} + \beta^{s|i}_{q} X^{i}_{t} + \epsilon^{s|i}_{q,t}\ (B.8)$$

We used the quantile regression of the financial system to predict the CoVaR by inputting the VaR of the financial firm:

$$CoVaR^{i}_{q,t} = \widehat{\alpha^{s|i}_{q}} + \widehat{\gamma^{s|i}_{q}} M_{t-1} + \widehat{\beta^{s|i}_{q}} VaR^{i}_{q,t}\ (B.9)$$

Finally, we defined the $\Delta CoVaR^{i}_{q,t}$:

$$\Delta CoVaR^{i}_{q,t} = CoVaR^{i}_{q,t} - CoVaR^{i}_{50,t}\ (B.10)$$

$$= \widehat{\beta^{s|i}_{q}}\left(VaR^{i}_{q,t} - VaR^{i}_{50,t}\right)$$

For the Crypto CoVaR, we followed two steps. For the first step, we estimated the exposure CoVaR of each financial firm to the crypto market. For the second step, we inputted the financial firm's exposure CoVaR to the quantile regression of the financial system to estimate the contribution of the financial firm's crypto-driven VaR to the tail risk of the financial system.

For the first step, we ran the quantile regression of crypto market returns CR_{t-1}:

$$CR_{t-1} = \alpha^{CR}_{q} + \gamma^{CR}_{q} M_{t-1} + \epsilon^{CR}_{q,t}\ (B.11)$$

We used this regression to predict the value-at-risk of the crypto market with q quantile at the time t:

$$VaR_{q,t}^{CR} = \widehat{\alpha_q^{CR}} + \widehat{\gamma_q^{CR}} M_{t-1} \ (B.12)$$

Then, we ran the quantile regression of financial firm equity returns on the crypto market returns CR_{t-1} :

$$X_t^i = \alpha_q^i + \gamma_q^i M_{t-1} + \beta_q^{i|CR} CR_{t-1} + \epsilon_{q,t}^i \ (B.13)$$

We used the $VaR_{q,t}^{CR}$, Value-at-Risk (VaR) of crypto market returns of q quantile at time t, to estimate the VaR of each financial firm, conditional on crypto market tail events: $VaR_{q,t}^{CR}$, which is the exposure CoVaR of each financial firm to crypto tail events:

$$CoVaR_{q,t}^{i|CR} = \widehat{\alpha_q^{i|CR}} + \widehat{\gamma_q^{i|CR}} M_{t-1} + \widehat{\beta_q^{i|CR}} VaR_{q,t}^{CR} \ (B.14)$$

$$CoVaR_{50,t}^{i|CR} = \widehat{\alpha_q^{i|CR}} + \widehat{\gamma_q^{i|CR}} M_{t-1} + \widehat{\beta_q^{i|CR}} VaR_{50,t}^{CR} \ (B.15)$$

For the second step, we ran the quantile regression of financial system equity returns on financial firm equity returns:

$$X_{q,t}^{s|i} = \alpha_q^{s|i} + \gamma_q^{s|i} M_{t-1} + \beta_q^{s|i} X_t^i + \epsilon_{q,t}^{s|i} \ (B.16)$$

Then, we inputted the exposure CoVaR of each financial firm to estimate the crypto CoVaR:

$$\mathrm{CoVaR}_{q,t}^{s|i} = \widehat{\alpha_q^{s|\iota}} + \widehat{\gamma_q^{s|\iota}} M_{t-1} + \widehat{\beta_q^{s|\iota}} \mathrm{CoVaR}_{q,t}^{i|CR} \ (B.17)$$

$$\mathrm{CoVaR}_{50,t}^{s|i} = \widehat{\alpha_q^{s|\iota}} + \widehat{\gamma_q^{s|\iota}} M_{t-1} + \widehat{\beta_q^{s|\iota}} \mathrm{CoVaR}_{50,t}^{i|CR} \ (B.18)$$

Last, we defined the crypto CoVaR as $\Delta CoVaR_{q,t}^{s|i}$:

$$\Delta CoVaR_{q,t}^{s|i} = CoVaR_{q,t}^{s|i} - CoVaR_{50,t}^{s|i} \ (B.19)$$

$$\Delta CoVaR_{q,t}^{s|i} = \widehat{\beta_q^{s|\iota}} \left(CoVaR_{q,t}^{i|CR} - CoVaR_{50,t}^{i|CR} \right)$$

$$\Delta CoVaR_{q,t}^{s|i} = \widehat{\beta_q^{s|\iota}} \times \widehat{\beta_q^{i|CR}} \left(VaR_{q,t}^{CR} - VaR_{50,t}^{CR} \right)$$

C: Crypto Shocks Construction

Cryptocurrency has transformed the financial landscape in recent years by providing a means of conducting transactions without the need for an intermediary to oversee and verify the process. It addresses the double-spending problem and offers a permissionless consensus mechanism, enabling parties to transact without reliance on a financial institution. In this paper, we aim to establish a causality argument regarding firms' crypto risk exposure and the impact on systemic risk, using two distinct shocks as analytical tools. Contrary to popular belief, blockchain-based currencies are not immune to hacking. This misconception may stem from the immutable nature of blockchain, which, through cryptographic measures, ensures data integrity and authentication.

However, vulnerabilities remain, and malicious actors can still compromise private keys. Despite the decentralized structure of blockchain, certain nodes may be centralized because they are on the same server. For instance, if a significant number of nodes are hosted on an Amazon server, incapacitating that server would similarly impact those nodes.

The security of permissionless consensus and blockchain's immutability are often predicated on the assumption that a 51% attack is unlikely. Yet incidents like the attack on Ethereum Classic illustrate that this assumption is not entirely foolproof. This underscores the reality that cryptocurrency, like other digital assets, carries cybersecurity risks. In this study, we distinguish between different types of shocks to better understand how technological factors affect cryptocurrencies, especially Bitcoin.

We categorize shocks into two types: core-vulnerability shocks (which impact the fundamental technology of cryptocurrency) and non-core vulnerability shocks (which do not). For instance, a hack that compromises a wallet's private key or targets a cryptocurrency exchange does not undermine the core technological principles of blockchain; this is akin to password theft in traditional banking. Conversely, a 51% attack challenges blockchain's technological and foundational framework, targeting its essential architecture.

To classify these vulnerabilities, we have organized them into the following categories:

1. Core-Blockchain Vulnerabilities (Blockchain Technology Shocks)

These vulnerabilities exploit weaknesses in the fundamental blockchain architecture:

1.1: 51% Attack: Occurs when an entity gains control of over half the network's mining power, enabling them to manipulate transactions and potentially double-spend coins.

1.2: Double-Spend Attack: Involves spending the same cryptocurrency multiple times by reversing transactions or exploiting network delays.

1.3: Sybil Attack: Occurs when an attacker creates numerous fake identities or nodes to gain disproportionate influence over the network, potentially disrupting consensus mechanisms.

1.4: Eclipse Attack: Targets a specific node by isolating it from the network, allowing the attacker to control all the information received and sent by the node.

1.5: Routing Attack: Intercepts and manipulates data traveling between nodes, potentially delaying or censoring transactions.

2. Non-Core Blockchain Vulnerabilities (Asset Class Shocks)

These vulnerabilities affect systems that interact with the blockchain but are not part of its decentralized structure:

2.1: Phishing Attacks: Deceptive attempts to acquire sensitive information, such as private keys or login credentials, by impersonating a trustworthy entity.

2.2: Exchange Hacks: The act of targeting centralized cryptocurrency exchanges to steal funds, as these platforms often hold substantial assets in custodial wallets.

2.3: Wallet Exploits: The act of exploiting vulnerabilities in wallet software, which can lead to unauthorized access and theft of funds.

2.4: Distributed Denial of Service (DDoS) Attacks: The act of overwhelm a service with excessive requests to disrupt operations, affecting exchanges, wallet services, and/or network nodes.

In analyzing these categories, we seek to clarify the implications of both core and non-core vulnerabilities for systemic risk within cryptocurrency frameworks.

D: Crypto Regulation Framework in the U.S. Banking Industry

(1) Jul 22, 2020: Interpretive Letter 1170

Regulation Agency: OCC

The main policy requirement: The OCC allows banks to provide crypto-asset custody services.

Policy link: https://www.occ.gov/news-issuances/news-releases/2021/nr-occ-2021-121.html

(2) Sep 21, 2020: Interpretive Letter 1172

Regulation Agency: OCC

The main policy requirement: The OCC allows banks to hold dollar deposits serving as reserves that can back stablecoins in certain circumstances.

Policy link: https://www.occ.gov/news-issuances/news-releases/2021/nr-occ-2021-121.html

(3) Jan 4, 2021: Interpretive Letter 1174

Regulation Agency: OCC

The main policy requirement: The OCC allows banks to (1) act as nodes on an independent node verification network to verify customer payments and (2) engage in certain stablecoin activities to facilitate payment transactions on a distributed ledger.

Policy link: https://www.occ.gov/news-issuances/news-releases/2021/nr-occ-2021-121.html

(4) Nov 18, 2021: Interpretive letter

Regulation agency: OCC

The main policy requirement: The OCC limits banks to crypto activities.

Policy link: https://www.occ.gov/news-issuances/news-releases/2021/nr-occ-2021-121.html

(5) Apr 7, 2022: Policy Letter on Notification of Engaging in Crypto-Related Activities

Regulation Agency: FDIC

The main policy requirement: The FDIC requires banks to report their crypto activities to the FDIC.

Policy link: https://fdic.gov/news/financial-institution-letters/2022/fil22016.html#letter

(6) Aug 16, 2022: Policy Statement on Engagement on Crypto-Asset-Related Activities by Federal Reserve-Supervised Banking Organizations

Regulation Agency: Fed

The main policy requirement: The Fed requires Fed-supervised banks to notify the organization of any crypto-related activities.

Policy link: https://www.federalreserve.gov/supervisionreg/srletters/SR2206.pdf

(7) Jan 3, 2023: Join Statement on Crypto-Asset Risks to Banking Organizations

Regulation Agency: Fed, OCC, FDIC

The main policy requirement: This guideline reminds banks of the risks of crypto activities.

Policy link: https://www.federalreserve.gov/newsevents/pressreleases/files/bcreg20230103a1.pdf

(8) Jan 27, 2023: Policy Statement on Section 9(13) of the Federal Reserve Act

Regulation Agency: Fed

The main policy requirement: The Fed restricts banks from holding crypto assets, explicitly based on Section 9(13) of the Federal Reserve Act.

Policy link: https://www.federalreserve.gov/newsevents/pressreleases/files/bcreg20230127a1.pdf

(9) Feb 23, 2023: Joint Statement on Liquidity Risks to Banking Organizations Resulting from Crypto-Asset Market Vulnerabilities

Regulation Agency: Fed, OCC, FDIC

The main policy requirement: This joint statement reminds banks of the liquidity risks driven by crypto assets.

Policy link: https://www.federalreserve.gov/newsevents/pressreleases/files/bcreg20230223a1.pdf

(10) Mar 7, 2025: Interpretative letter 1183

Regulation agency: OCC

The main policy requirement: The OCC revokes the interpretive letter 1179 and lifts the limitations on banks' crypto activities.

Policy Link: https://www.occ.treas.gov/news-issuances/news-releases/2025/nr-occ-2025-16.html