Crypto Risk in Financial System*

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Abstract

In this paper, we measure crypto risk of financial firms and crypto-driven systemic risk in the financial system. Firm-level crypto risk has been rising in recent years within the financial system. Crypto risk at a financial firm level lifts systemic risk in the financial system. However, the management of financial firms could perceive systemic risk exposure but are unable to perceive systemic risk transmission. While crypto risk raises systemic risk exposure through both blockchain technology and asset class channels, it drives up the systemic risk transmission only via the blockchain technology channel. Furthermore, the management of financial firms tends to pay less attention to systemic risk transmission via the blockchain technology channel. Therefore, our paper has a clear policy implication of the global regulation framework for crypto currencies.

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

JEL Codes: G10;G20;G30;E40

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1 Introduction

Fintech is a double-edged sword, which brings in social welfares and causes risks simultaneously. Crypto has been invented as a novel decentralized payment technology since the 2008 Bitcoin initiation (Nakamoto 2008). After the great breakthrough of technology, more and more crypto coins have been initiated in the market, and more traders trade them as a new asset class. The collapse of crypto exchange FTX in 2022 triggers much attention among market participants and a big concern among regulators[1]. Regulators are worried that crypto risk might harm financial stability and cause a financial crisis again[2]. The question of whether crypto is a new systemic risk becomes a center-stage topic and is worth digging deeper to understand it. Faced with this important topic, we raise three research questions: (1) is there crypto risk in the financial system? (2) Does crypto risk raise systemic risk in the financial system? (3) which channel does crypto risk impact the systemic risk in the financial system? These three research questions are worth exploring in part because we can understand clearly how crypto risk interacts with systemic risk in the financial system, and how crypto-driven systemic risk is transmitted in the financial system. To understand these questions better, regulators can design an efficient regulation framework.

Prior papers underexplore these important questions because of three big challenges. The first challenge is how to measure crypto risk at a financial firm level. Crypto holdings are a natural candidate measure. However, outsiders cannot observe financial firms' crypto holdings directly. For banks, regulators restrict them from holding any crypto assets. The second challenge is how to construct a measure which can capture systemic risk changes driven by crypto risk. Traditional systemic risk measures such as CoVaR and MES capture universal systemic risk sources such as the housing bubble, the credit crunch, and the financial crisis. The third challenge is to identify channels in which crypto risk at the financial firm contributes to systemic risk changes. Natural experiments are needed to pin down different channels.

To address three empirical challenges, we employ a series of novel methods. First, we create a crypto risk measure at the financial firm level by calculating the covariance between equity returns of financial firms and returns of bitcoin or crypto market index. This crypto measure captures all direct or indirect connections between a financial firm and the crypto market. Second, building on fundamental papers of CoVaR and MES(Adrian & Brunnermeier 2016; Acharya *et al.* 2017), we extend their framework to construct a crypto-driven CoVaR and MES. Crypto-driven systemic risk could capture system risk changes

[1] The wall street journal article of "How FTX's Sam Bankman-Fried Went from Crypto Golden Boy to Villain" reports this market-wide event in detail.

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

induced by the crypto market. Last, we obtain two types of crypto shocks: blockchain technology and asset class. The crypto shocks of blockchain technology are a series of cyber attacks which target only the blockchain technology of cryptos, while crypto shocks of asset class are a series of cyber attacks which only target the asset class of cryptos[3].

In this paper, we measure crypto risk of financial firms and crypto-driven systemic risk in the financial system. Specifically, we construct a crypto risk measure by calculating the beta from regression of equity returns of financial firms on crypto market returns[4]. Also, we construct a perceived crypto risk measure of the management at a financial firm level by text mining financial disclosures[5]. This subjective crypto risk measure is to detect or track the perception of the management on crypto risk. Recent papers argue that subjective measures are divergent from objective measures and can reflect the perception of the management(Baron *et al.* 2024; Gormsen & Huber 2024). Further, we decompose the systemic risk into two parts: systemic risk exposure and systemic risk transmission. Systemic risk exposure measures the financial losses of a financial firm during the crisis period. Systemic risk transmission measures the contribution of a financial firm to the financial system.

We find that firm-level crypto risk has been rising in recent years within the financial system. Crypto risk at the financial firm level lifts systemic risk in the financial system. However, the management of financial firms could perceive systemic risk exposure but are unable to perceive systemic risk transmission. While crypto risk raises systemic risk exposure through both blockchain technology and asset class channels, it drives up the systemic risk transmission only via the blockchain technology channel. Furthermore, the management of financial firms tends to pay less attention to systemic risk transmission via the blockchain technology channel.

We start our analysis by showing some important stylized facts. In terms of crypto risk, crypto risk at the financial firm level is rising after 2018, while it is falling before the that time. This evidence raises an alarm bell that crypto risk is rising in recent years and might be a source of systemic risk. Banks and trading companies are exposed to crypto risk significantly. However, insurance companies and real estate companies are not exposed to crypto risk significantly. The perceived crypto risk of the management shares

[3] Online Appendix C discuss how we collect and categorize two types of shocks.
[4] Specifically, we use two crypto returns: bitcoin returns and crypto coin market index return. Bitcoin is the most valuable coin in the crypto market. Crypto coin market index return is constructed by calculating the average return of top 20 valuable crypto coins.
[5] We follow the same text mining methods to have three text measures(Hassan *et al.* 2019) (Hassan *et al.* 2023)and use the large language model to construct one measure. Four measures capture perceived crypto risk of the management.

similar patterns with our crypto risk. The management of financial firms perceived firm-level crypto risk and pays attention to this new risk source.

As for crypto-driven systemic risk exposure, crypto MES and MES share the same time-series trend, but the magnitude of crypto MES is smaller than that of MES. This evidence shows crypto MES is one subcomponent of MES, which captures the general systemic risk exposure. Cross-sectionally, Real estate companies and trading companies are more exposed to the systemic risk exposure, compared with banks and insurance companies. As for crypto-driven systemic risk transmission, both CoVaR and crypto CoVaR are rising after 2018, which suggests systemic risk transmission is rising in recent years. Banks, insurance companies, and trading companies are more exposed to systemic risk transmission, relative to real estate companies.

Next, we continue our analysis by using a case study of FTX exchange run[6]. We use the case study of FTX exchange run to validate our crypto risk measures and to show that our crypto risk measures can predict the crypto-driven systemic events to some degree. The collapse of FTX exchange triggers a big selloff in the crypto market and leads to market-wide fear in the equity market. The FTX exchange run is that its founder Sam Bankman-fried used his connected hedge fund Alameda Research to conduct inside trading in the FTX exchange. Thus, FTX exchange run is a crisis event initiated from the crypto market. We use the buy-and-hold returns during the crisis period to measure the financial loss of a financial firm, and then use our previous crypto risk and perceived crypto risk measures to predict buy-and-hold returns during the crisis. We find that our crypto risk and perceived crypto risk measures can predict the crisis returns of financial firms. These results support the validity of our crypto risk and perceived crypto risk measures, and our measures indeed capture the crypto risk level of a financial firm.

We turn our analysis to crypto risk on systemic risk. We use panel regression to justify this association in the normal times. Crypto risk raises systemic risk exposure. When crypto risk rises by one percentage point, MES and crypto MES surge by 0.027 percentage points and 0.064 percentage points. Furthermore, crypto risk only lifts crypto-driven systemic risk transmission. When crypto risk rises by one percentage point, crypto CoVaR surges by 0.5 basis point. Therefore, crypto risk at the financial firm level raises the systemic risk in normal times. An interesting pattern is that crypto risk also lifts total risk of financial firms but does not impact their performance.

Does the management of financial firms perceive systemic risk in normal times? We replace crypto risk measures with the perceived crypto risk measures and redo analysis. We find that the management can

[6] We also apply the same approach to the TerraUSD run as a case study and get the similar results with the FTX exchange run. Two case studies show robust evidence of our measures.

perceive systemic risk exposure but are unable to perceive the systemic risk transmission in normal times. By contrast, perceived crypto risk affects the performance of financial firms but does not impact their total risk. When the management of financial firms discusses more crypto topics, investors require higher equity returns but the accounting performance of financial firms deteriorates. Perceived crypto risk could be a risk factor for equity pricing.

Then, we continue our analysis on channels of systemic risk. On one hand, the core technology of crypto is blockchain technology, a novel decentralized payment system. On the other hand, crypto coins are a new asset class like equities and bonds. Many retail and institutional investors flood into crypto markets and trade cryptos in the crypto exchange. Thus, crypto, as an entity, has dual roles: blockchain technology and asset class. Through which channel, does the firm-level crypto risk cause the systemic risk? We obtain two types of crypto shocks: blockchain technology shocks and asset class shocks. Blockchain technology shocks are that cyber attackers only target the blockchain technology directly of one specific crypto and does not cause the big price move in the crypto market. Asset class shocks are that cyber hackers breach specific crypto coins in the exchange or wallet, leading to a big price move of crypto[7]. With two types of crypto shocks at hand, we use the stacked Difference-in-Difference research design to identify a specific channel.

Crypto risk of financial firms raises the systemic risk exposure via both blockchain technology and asset class channels. In terms of economic magnitude, when financial firms are exposed to a one change in crypto risk's standard deviation, they experience 4.86 percentage points, 11.06 basis points, and 3.15 percentage points, up in crypto MES after blockchain, exchange, and wallet shocks, respectively, compared with their counterfactuals. The main treatment effects come from banks and trading companies, which are exposed to systemic risk exposure via blockchain technology and asset value channels.

Crypto risk of financial firms lifts the systemic risk transmission through the blockchain technology channel, while it reduces the systemic risk transmission through the asset class channel. In terms of economic magnitude, when financial firms see a one change in crypto risk' standard deviation, they experience 0.59 basis points up, 0.07 basis points down, and 0.41 basis points up, in crypto CoVaR after blockchain, exchange, and wallet shocks, respectively, relative to their counterfactuals. Banks are the main drivers of systemic risk transmission via the blockchain technology channel, while trading companies are dominant for the systemic risk transmission via the asset value channel. Two reasons to explain this pattern. The first is regulation restrictions. Banks are strictly restricted from holding any crypto assets. Trading

[7] Recent papers point out the vulnerabilities of cryptos as a decentralized payment system and some flaws of this technologies (Hinzen *et al.* 2022; Budish 2024).

companies are allowed to hold but are regulated highly. The second is the blockchain technology itself, which has decentralized and non-transparent features.

How do the market and management perceive the systemic risk? The equity market reacts negatively to the asset value channels but pays no attention to the blockchain technology channel. The management of financial firms discusses or talks more about crypto topics, it can perceive systemic risk exposure via both blockchain technology and asset value channels. However, the management of financial firms discusses more about crypto topics, it can perceive the systemic risk transmission via the asset value channel but is unable to detect the systemic risk transmission via the blockchain channel. These findings show that the market and management pay less attention to the blockchain technology channel, or it is harder for the market and the management to detect the blockchain technology channel.

Last, we end our analysis by showing a series of placebo tests. A big identification concern is that all cyber attacks might have a common but unobserved factor, which might move the systemic risk in the financial system. In this case, our treatment effects of crypto shocks come from this common factor rather than our crypto risk measures(Florackis *et al.* 2023). To address this big concern, we use the individual financial firm's cyber-security attacks as placebo shocks. Placebo shocks are cybersecurity attacks, whose targets are financial firms not cryptos and hacks the cyber or digital infrastructure of financial firm. Placebo results support our main treatment effects.

Our paper contributes to the literature of financial stability. Diamond and Dybvig (1983) novelly argues that self-fulfilling belief of depositors leads to bank run and financial instability. Goldstein *et al.* (2024) think asset commonality could a source of systemic risk. Furthermore, off-balance activities of financial firms (Brunnermeier *et al.* 2020b), asset bubble (Brunnermeier *et al.* 2020a), and rare disaster risk(Baron *et al.* 2024) are systemic sources. Our paper contributes to the literature by identifying a new systemic risk source: crypto risk in the financial system.

Our paper adds on the literature of FinTech and digital currencies. Prior papers have been paying attention to new technology adoption in the financial systems. Buchak *et al.* (2018) find that regulation arbitrage is main reason of the Fintech rise in recent years compared with technology advantage. Digital currencies are other waves of new technology. Central Bank Digital Currency (CBDC) might threat traditional banking system and cause the deposits outflows(Keister & Sanches 2023; Berg *et al.* 2024). Crypto is a decentralized currency whose technology is the blockchain(Liu *et al.* 2024). Crypto is a new security class, which is priced by common factors(Liu *et al.* 2022; Huang & Yang 2024). Some papers focus on the application of this new decentralized technology(Cong & He 2019; Sockin & Xiong 2023), while other papers point this new technological vulnerabilities(Hinzen *et al.* 2022; Pagnotta 2022; Budish 2024).

Liu *et al.* (2023) argue that crypto run is more complicated than bank run by using the Terra Luna as a case study. Our paper contributes to the literature by showing a crypto risk can be transmitted to the traditional financial system via the blockchain technology and asset class channels.

Our paper relates to the literature of systemic risk measures in the financial system. After the great recession of 2008, systemic risk is the central topic for regulators and scholars who measure it to predict the crisis. CoVaR (Adrian & Brunnermeier 2016) and MES (Acharya *et al.* 2017) are two prominent systemic measures. Based on the their framework, lots of papers extend it to measure some new systemic risk(Jourde & Moreau 2022; Marfè & Pénasse 2024). Systemic climate risk is a good example. Our paper contributes to this literature by extending the CoVaR and MES framework 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. Section 4 presents our empirical results. Section 5 concludes the paper.

2 Data and Sample

2.1 Data and Sample

We construct our yearly-panel sample of financial firms from 2014 and 2022 by retrieving all firms, whose SIC code is between 6000 and 6799, in the Compustat database. Initially. Our sample of financial firms contains 15,082 observations of firm-year, with 2233 unique financial firms. Finally, our sample has 15,020 observations of firm-year, with 2228 unique financial firms. Among unique financial firms, there are 1075 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 firms returns in the CRSP and crypto returns in the CoinMarketCap database. We add crypto risk measures and systemic risk measures to our sample of financial firms.

Next, we merge our sample financial firms with perceived crypto risk measures, which are constructed by the text mining methods in financial firm's 10- K Files and earnings call transcripts. We download financial firms' 10- K files from EDGAR and earning call transcripts from Capital IQ in the Compustat.

Last, our final yearly-panel sample of financial firms are constructed merging financial variables from the Compustat database[8].

[8] Table A1 in the online appendix describes this process in detail.

For our shock samples, our crypto shocks are obtained from multiple sources[9] and our crypto shocks sample are at the event level. Our crypto shock samples are built at daily level, weekly level, and quarterly, respectively. Specifically, we build a daily crypto shock sample by merging the crypto shocks sample with the daily outcome variable of financial firms' equity returns; We build a weekly crypto sample by merging the crypto shocks sample with the weekly outcomes of CoVaR and Crypto CoVaR. We build a quarterly sample by merging the crypto shocks sample with the quarterly outcomes of MES, crypto MES, equity returns, and total risk[10].

2.2 Measuring Crypto Risk

Crypto assets are associated with financial firms through many direct and indirect links. Direct links are crypto holdings and the adoption of blockchain technology. Indirect links are financial service provided by financial firms to crypto customers or traders. Thus, we employ the covariance between financial firms' equity return and crypto return to detect the associations between a financial firm and crypto market. For a given financial firm i, we run the time series regression given each fiscal year y:

$$R_{iyt} = \alpha_{iy} + \beta_{iy} \times crypto\ return_{yt} + \epsilon_{iyt} \quad (1)$$

Where R_{iyt} is the financial firm i's equity return 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 year fiscal year y. We use bitcoin returns and coin market index return to estimate the crypto risk and have two crypto risk variables: bitcoin beta and index beta, respectively. Bitcoin beta and index beta are objective crypto risk measures, which reflect direct and indirect associations between a financial firm and the crypto market, using all available market information to borrow the wisdom of crowd[11].

Further, we want to know whether the management of a financial firm perceives this crypto risk subjectively. We construct perceived crypto risk measures by using the text mining approach(Hassan *et al.* 2019; Hassan *et al.* 2023). Considering subtle differences in the management's perception, we construct two groups of perceived crypto risk measures based on raw financial documents: 10-K files and earnings call transcripts. So, we have two groups of measures: perceived crypto risk in 10-k files and perceived crypto risk in the transcripts. For perceived crypto risk in the 10-K file, we have four variables to measure crypto risk: *tenk exposure*, *tenk risk*, *tenk sentiment*, and *tenk LLM*. The first three variables are constructed by the dictionary of crypto key words. The last variable is constructed by the large language model:

[9] We collect two types of crypto shocks from the firm disclosures, SEC disclosures, Twitter posts, and media reports. Online Appendix C discusses the construction process of the crypto shocks.
[10] Online Appendix table A3 provides the summary statistics of crypto shock samples.
[11] Keller (2024) measures a bank's exposure to the exchange market using the same method.

ChatGPT. For perceived crypto risk in the transcript, we use the same methods to construct the four variables: *trans exposure*, *trans risk*, *trans sentiment*, and *trans LLM*[12].

2.3 Measuring Systemic Risk

Generally, systemic risk measures measure spillover and network effects of financial risk in the financial system and regulatory authority has paid much attention to systemic risk since the 2008 financial crisis. Systemic risk can be decomposed 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 captures each financial firm's contribution to the loss of the financial system during the systemic crisis period.

Based on a pioneer paper(Acharya *et al.* 2017), we use marginal expected shortfall (MES) to measure the systemic risk exposure.

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

Where R_{it} is the equity return of financial firm i at 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.

Based on a pioneer paper(Adrian & Brunnermeier 2016), we use 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 institution i.

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

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:

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

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

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 bubble, the subprime mortgage crisis, and rare natural

[12] Online Appendix B1 discuss the construction process of perceived crypto risk measures.

disasters. Now, we want to know magnitudes of systemic risk, which are caused by the crypto market events rather than other non-crypto market events. We need to construct crypto-driven systemic risk exposure and systemic transmission.

Building on contribution of their papers(Acharya *et al.* 2017), we extend their framework to construct 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.

Building on contributions of their paper(Adrian & Brunnermeier 2016), we extend your framework 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 a financial firm i's exposure to 5% tail events of crypto market, $CoVaR^{S|i=50\%\ crypto\ events}_{50\%}$ measures the Value-at-Risk(VaR) of a financial system s conditional on a financial firm i's exposure to 50% tail events of crypto market.

We continue to apply the CoVaR's framework to measure a financial firm i's exposure to crypto events using crypto market index returns. A financial firm i's exposure to 5% and 50% tail events of 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 $VaR^{crypto}_{5\%}$ is the 5% quantile Value-at-Risk of crypto market index returns and it measures the 5% tail events of crypto market. Where $VaR^{crypto}_{50\%}$ is the 50% quantile Value-at-Risk of crypto market index returns and it measures the 50% tail events of crypto market.

Thus, crypto CoVaR measures each financial firm i's contribution to the financial systems conditional on the crypto market crisis periods relative to its normal periods[13].

For all other variables definition and source, please see the table A2 in the online appendix

2.4 Summary Statistics

Table 1 reports 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 crypto MES is larger than that of crypto MES, which supports our argument that crypto MES captures crypto-driven part of systemic risk exposure, while MES captures full part of systemic risk exposure. The mean in CoVaR is 68.25 percentage points with a standard deviation of 45.30 percentage points. For comparison, the mean in 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 mean, which elaborates our statement that crypto CoVaR only captures crypto-driven systemic risk exposure, while CoVaR captures full scale of systemic risk exposure.

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 and 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 case of perceived crypto risk measures, perceived crypto risk measures in 10-K files almost share similar descriptive statistics with those in transcripts. The only interesting difference is that the management perceives the crypto risk negatively on average in the ten k files' content sentiment while it perceives the crypto risk positively in the transcript's content sentiment.

*** Table 1***

3 Empirical Strategy

3.1 A Case Study

We use the collapse of crypto exchange FTX as a case study to test the prediction power of our crypto risk measures and perceived crypto risk measures. The collapse of FTX triggers a market-wide systemic risk exposure in the financial system because FTX's founder Sam Bankman-Fried conducted the fraud trading

[13] Online Appendix B2 describes the construction process of the crypto systemic risk measures.

in the exchange through his hedge fund Alameda Research. This fraud led to a crypto-market selloffs and the value of bitcoin tumbled. Consequently, crypto market fear also drove the equity market down. Thus, crypto market run posed a systemic threat to the financial system in the FTX crisis. We use the buy-and-hold returns of each financial firm during the FTX crisis period to measure its real systemic risk exposure to crypto market tail events, which has the same economical meaning as our crypto MES(Fahlenbrach *et al.* 2012). For the prediction setting, our predictive measures, consisting of crypto risk and perceived crypto risk, are used at least one year before the year 2022 of FTX crisis. The prediction specification is as follows:

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

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

3.2 Crypto Risk and Systemic Risk

We want to know if crypto risk of a financial firm raises the systemic risk in the financial system and construct the yearly panel sample from 2014 to 2022. The specification is a standard panel specification as follows:

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

Where Y_{iy} is outcome of variables, the coefficient of the interest is β, which measures relationship between crypto risk and systemic risk. X are 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} is the financial firm type× year fixed effects, which compare the effects at the same financial firm type given a same year and removes time-variant factors at the financial firm type level. For example, crypto risk might target each financial firm type over time. Robust standard errors are clustered at the financial firm level.

3.3 Crypto Shock Transmission

To test the dual roles of crypto: technology or asset, we collect two bundles of crypto cyber shocks: blockchain technology shocks and crypto asset shocks. Blockchain technology shocks are that cyber hackers attack the blockchain technology directly and did not lead to the great price move of the crypto return. On the other hand, crypto asset shocks are that cyber hackers attack crypto's exchange and wallets, which moves the crypto returns but do not affect the blockchain technology itself. With two types of crypto

shocks at hand, we can pin down the channel of systemic risk transmission caused by crypto risk via the technology channel or asset channel. Thus, we have three types of crypto shocks: blockchain, exchange and wallet.

For each crypto shock, we can identify a specific crypto currency targeted by cyber hackers. Give each cyber shock, we use returns of crypto attacked to construct the treatment variable of each financial firm. So we run the time-series regression of the target crypto returns for every financial firms given 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 a financial firm i on the trading day t in the crypto shock e and $crypto\ return_{et}$ is the return of attacked crypto in the crypto shock e. β_{ei} measures a financial firm i's association with a attacked crypto return before the crypto shock e and we name it crypto beta. Crypto beta is a treatment variable in the crypto shock setting.

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

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

Where Y_{eit} is the outcome variables of a financial firm i on the time t in the crypto shock e. the coefficient of interest is the γ, which is average treatment effects of treated. δ_{ei} is the crypto shock × financial firm fixed effects, which removes a time-invariant observable component of a financial firm given the event. λ_{et} is the crypto shock × time fixed effects, which controls the time-trends for each crypto shock. Robust standard errors are clustered at the financial level. The time interval t depends on main outcomes variable frequency and have daily, weekly, and quarterly[14].

For the dynamic plot of the stacked DID design, we run the dynamic stacked difference-in-difference research design[15].

[14] Similar to the method of this paper(Butters *et al.* 2022), we use the event-study style specification to estimate the treatment effects of treated by using multiple shocks.

[15] Online Appendix figure A1 shows the empirical strategies for crypto shocks. Specifically, this figure shows different parameters of the estimation window and the event window for daily, weekly, quarterly sample, respectively. The estimation window is to estimate the crypto beta for the time series regressions, while the event window is to estimate the treatment effects of treated using the stacked difference-in-difference research design.

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

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 is steadily falling during the period between 2015 and 2018, it is rising rapidly from 2018 to 2022. This graph evidence raises an alarm that crypto risk in the financial system is a big concern in recent years. Furthermore, the graph evidence of text measures suggests that the perceived crypto risk by the management is also jumping high and management pays enough attention to this rising crypto risk[16]. Panel B of figure 1 shows the crypto risk distribution in the financial firms. Bank, real estate companies 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 explore 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 is marks the peak of the trend. Crypto MES is just a chunk of MES, which measures the universal systemic risk exposure. In terms of systemic risk transmission, Before the year 2018, CoVaR is more volatile while crypto CoVaR is almost stable. After the year 2018, CoVaR is rising and crypto CoVaR is also ladder hiking. Thus, CoVaR and crypto CoVaR capture different information of systemic risk transmission. An urgent pattern is that both CoVaR and crypto CoVaR indicate the systemic risk transmission shows a hiking trend in recent years.

Figure 2

Figure 3 shows systemic risk and crypto systemic risk distributions over financial firms. The upper panel of figure 3 shows the systemic risk exposure. Real estate companies and trading companies have higher systemic risk exposure than Insurance companies and banks have. In terms of systemic risk

[16] Figure A2-Figure A5 in the appendix A shows descriptive evidence of perceived crypto risk.

transmission, banks, insurance companies, and trading firms show higher CoVaR and crypto CoVaR than real estate companies. 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: 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. The basic idea is to measure the financial loss of each financial firm during the crypto-driven crisis, which is the real crypto systemic risk exposure, while our crypto MES is to simulate systemic crisis by using the tail returns in the normal times.

The FTX run is a crypto-driven systemic crisis and leads to a market-wide selloffs of crypto assets, which also triggers the free fall of equity markets and a temporary crisis period. The collapse of FTX is triggered by its cofounder's fraud because its cofounder Sam Bankman-Fried uses his connected hedge fund to trade against retail investors in the FTX exchange.

The FTX run is a good experiment because this is a completely crypto-driven systemic crisis. We measure realized systemic risk exposure by calculating the buy-and-hold returns of financial firms during the FTX crisis period. Specifically, FTX filed the Chapter 11 bankruptcy protection on November 11, 2022, which is the benchmark of the event window. The buy-and-hold returns are calculated by using the event widow of ten days before and after the benchmark. Last, we test the prediction power of our crypto and perceived crypto measures.

Figure 4 shows the scatterplot of buy-and-hold returns against crypto risk in the FTX crisis. The top panel shows results of bitcoin, 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 real systemic risk exposure perfectly. In addition, we mark the most vulnerable financial firms in this crisis such as the Signature Bank and the Silvergate Capital Bank and mark the Big Four banks in the financial system. An eyeball-catching pattern is that most vulnerable financial firms in this crisis have higher realized systemic risk exposure with higher pre-crisis crypto risk. The Big Four banks are very stable and robust in 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. 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 a 1 percent significant 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 in the FTX run. The R squares is about 6 percentage points. The evidence suggests that our crypto risk has some prediction powers of crypto-drive systemic risk exposure. The perceived crypto risk measures also show some prediction powers to some degree. 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 this subsection, we examine whether crypto risk of financial firms raises the systemic risk in the financial system. Specifically, we decompose the systemic risk into two types: systemic risk exposure and systemic risk transmission. Next, we assess whether perceived crypto risk of the financial firms' management could perceive the systemic risk to some degree. Last, we test crypto risk of financial firms affects performance and total risk of financial firms.

Table 3 presents the impacts of crypto risk on systemic risk exposure, measured by the MES and crypto MES. Column 1 and column 2 presents results of MES, while column 3 and column 4 reports results of crypto MES. All results are positively and statistically significant at a 1 percentage point level. When crypto risk rises by 1 percentage point, MES and crypto MES lifts by 0.027 and 0.064 percentage points, respectively. A one 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 the larger part of economic effects come from crypto-driven systemic risk exposure not from the 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 results of CoVaR, and the last two columns show results of crypto CoVaR. An interesting pattern is that only results of crypto CoVaR are positively and statistically significant at a 5 percentage points level but the result of CoVaR are not. When crypto risk rises by 1 percentage points, a financial firm transmits by 0.5 basis points. This magnitude is not neglectable because this is equivalent to 0.29 billion dollars[17] loss of the financial system due to a financial firm's risk

[17] Here should be calculated by using the 0.5 basis points times the average market value of financial system between 2014 and 2022 (5824.49 billions).

transmission. 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 the financial firm's management affect the systemic risk? Table 5 and table 6 present results of perceived crypto risk on systemic risk exposure and transmission, respectively. According to results of table 5, we use 8 text variables to detect the financial firm management crypto risk perception and find that all text variables except for transcript sentiment are significantly associated with the crypto MES. The evidence suggests when the management of a financial firm perceives more crypto risks, it can detect more systemic risk exposure. Based on results of table 6, neither of all 8 text measures is significantly associated with crypto CoVaR. This evidence indicates that the management of a financial firm does not detect or track systemic risk transmission in the financial system, although it discusses or perceives crypto risk in their financial disclosures. In sum, the management of a financial firm tends to pay enough attention to systemic risk exposure but not enough attention to systemic risk transmission.

*** Table 5 and Table 6***

Last, we test whether our crypto risk and perceived crypto risk measures impact the financial performance and total risk of financial firms. Panel A of table 7 presents results of crypto risk measures, while panel B of table 7 presents results of perceived risk measures. Based on results of panel A, we find that the crypto risk of a financial firm does not affect the equity returns and accounting performances ROA. However, it lifts the total risk in the financial system. In contrast, panel B of table 7 shows that when the management of a financial firm perceives or discusses more crypto-related risks, the financial firm's equity returns would rise but its ROA declines. Because when the management discusses more crypto risks, investors require more compensation for equity returns. Crypto risk might cause financial loss, which leads to a decline in ROA. The management pays less attention to the total risk, measured by the equity volatility.

Table 7

4.4 Crypto Shocks Transmission Channel: Technology or Asset?

In this subsection, we identify cryptocurrency's dual roles: blockchain technology and asset class. On the one hand, crypto is a kind of decentralized payment technology. On the other hand, crypto is like a kind of security class such as equities, bonds and derivatives. Crypto has its own exchange market, including the initial coin offering and the second-market trading. Therefore, we test what roles the crypto's dual roles

play in systemic risk. We employ two types of crypto shocks to identify two different channels: blockchain technology and asset class. The blockchain technology shocks of crypto shocks are the blockchain shocks, while asset class shocks of crypto shocks are exchange and wallet[18].

Table 8 presents the results of crypto risk on systemic risk exposure in crypto shocks. Panel A of table 8 presents the results of 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 a 1 percentage point level. When financial firms are exposed to a one change in crypto risk' standard deviation, they experience 4.24 percentage points up (1.5 times of MES's standard deviation), 5.53 basis points up (1.9 percentage points of MES's standard deviation), and 2.7 percentage points up (93 percentage points 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 one change in crypto risk' standard deviation, they experience 4.86 percentage points up (2 times of crypto MES's standard deviation), 11.06 basis points up (4.8 percentage points of crypto MES's standard deviation), and 3.15 percentage points up(1.37 times of crypto MES's standard deviation) in 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. Whatever channel is technology or asset value, crypto risk lifts the systemic risk exposure in both channels. Figure 5 and Figure 6 show the dynamic effects of crypto risk on MES and crypto MES. A clean pattern is that the effects are rising.

Panel B presents results by financial firm's types, including banks, insurance companies, real estate companies, and trading companies. The main treatment effects come from banks and trading companies, while insurance companies and real estate companies 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 financial firm's types. 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 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 results of CoVaR and the last three

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

columns present results of crypto CoVaR. When financial firms see a one change in crypto risk' standard deviation, they experience 7.94 basis points up (7.43 percentage points of CoVaR's standard deviation), 0.68 basis points down (0.64 percentage point of CoVaR's standard deviation), and 5.87 basis points down (5.48 percentage point 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 one change in crypto risk' standard deviation, they experience 0.59 basis points up (4.62 percentage points of crypto CoVaR's standard deviation), 0.07 basis points down (0.59 percentage point of crypto CoVaR's standard deviation), and 0.41 basis points up (3.18 percentage point 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 technology channel, while it lowers the systemic risk transmission through the asset value channel. In addition, the magnitude of systemic risk transmission is much larger through the technology channel than through the asset value channel.

Panel B presents the results by financial firm types. A striking pattern is that most of systemic risk transmission via the blockchain technology are from banks, while most of systemic risk transmission via the asset value channel are from trading companies. Banks are the main drivers of systemic risk transmission via the blockchain channel in part because regulatory authorities in banking industries restrict banks from crypto asset holdings directly. The second reason is that blockchain technology itself has features of opaqueness, decentralization, and anonymization which is hard for regulators to track or monitor. Trading companies reduce systemic risk transmission via the asset value channel in part because regulatory authorities pay enough attention to trading companies' risk management, even though trading companies are allowed to hold cryptos as assets in their balance sheet. Insurance companies only transmit crypto-driven systemic risk via the blockchain channel. Real estate companies raise crypto-driven systemic risk transmission via the wallet. Figures 6 shows the dynamic effects of crypto risk on systemic risk transmission by financial firm types and this figure shows similar patterns with results in table 9.

Table 9

***Figure 6 ***

Does the equity market react to two channels? Table 10 presents results of crypto risk on equity returns in the crypto shocks. The first three columns show results of daily returns, and the last three columns show results of daily abnormal returns. The coefficients of exchange and wallet are negatively and statistically significant at a 1 percentage point level, while the coefficients of blockchain are not precisely estimated. In crypto shocks, crypto risk of financial firms leads to lower equity returns via the asset value channel, but it

does not impact the equity returns via the technology channels. A potential explanation is that it is easy for the equity markets to perceive asset value channels, but it is hard for equity markets to perceive the blockchain technology channel. Thus, asset value channels gain much more attention in the equity market, while the blockchain technology channels are ignored by the equity market.

Table 10

Does the management of financial firms perceive systemic risk exposure and systemic risk transmission? Panel A of table 11 presents results of perceived crypto risk on systemic risk exposure. We find that two main variables of tenk risk and tenk sentiment detect the systemic risk exposure via the blockchain technology or asset value channels. Panel B presents results of perceived crypto risk on systemic risk transmission. We find that many variables such as tenk risk and trans risk indicate the management of financial firms does perceive the systemic risk transmission via the asset value channel. When it comes to perceive the systemic risk transmission via the blockchain technology channel, few text measures has marginal effects, and the management hardly detect or perceive it via the blockchain technology channel. Therefore, the management tends not to pay enough attention to systemic risk transmission via the blockchain technology channel.

Table 11

4.5 Placebo Shocks: Cyber Attack

In this subsection, we employ placebo shocks: cyber attacks to rule out the identification concern that our crypto shocks might capture common and unobservable systemic risk factor for all kinds of cyber shocks. In this case, we need to validate that our crypto shocks indeed capture the effects of crypto-driven systemic risk. Cyber attacks are cyber shocks in which cyber or information system of financial firms are attacked or breached maliciously by professional hackers. Under attacks, the information system or infrastructure of financial firms could been paralyzed or dysfunctional for a long time. In the cyber attacks, individual financial firm is the main target, while crypto coin is the main target in the crypto shocks. We ensure that cyber attacks in our sample have nothing to do with crypto coins. Cyber attacks have three main types: financial, personal, and other. For cyber attacks, we use the same stacked DID identification as our crypto shocks and only replace crypto beta with cyber attack, which indicates which financial firm is under cyber attacks.

Table12 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 results of systemic risk transmission. Cyber attacks dost not contribute to the systemic risk transmission, measured by the CoVaR and crypto CoVaR.

Therefore, we could state that our main results of crypto shocks are not from unobservable systemic factors common to all cyber shocks.

Table 12

5 Conclusion

In this paper, we measure crypto risk and crypto-driven systemic risk in the financial system. Stylized facts show that crypto risk and crypto-driven systemic risk have been rising in recent years. Crypto risk of financial firms raises systemic risk exposure via both the blockchain technology and asset class channels. However, crypto risk raises the systemic risk transmission via the blockchain channel while it reduces the systemic risk transmission via the asset class channel. The market and the management of financial firms can perceive the asset value channel but are unable to detect the blockchain technology channel.

Our paper could throw light on the regulation debate[19]. Our paper suggests that regulatory authorities might fail to regulate crypto as a new asset class because the systemic risk can be transmitted via blockchain technology. Furthermore, each country could fail to regulate the crypto separately because the crypto shocks are cross-border. Thus, the globe needs to cooperate with each other to build a global regulation framework.

Our paper is a general framework to evaluate crypto risk in any other country's financial system. China in 2021 banned all crypto exchanges and activities in the mainland[20]. The future research can build on our framework to evaluate this policy shift in China.

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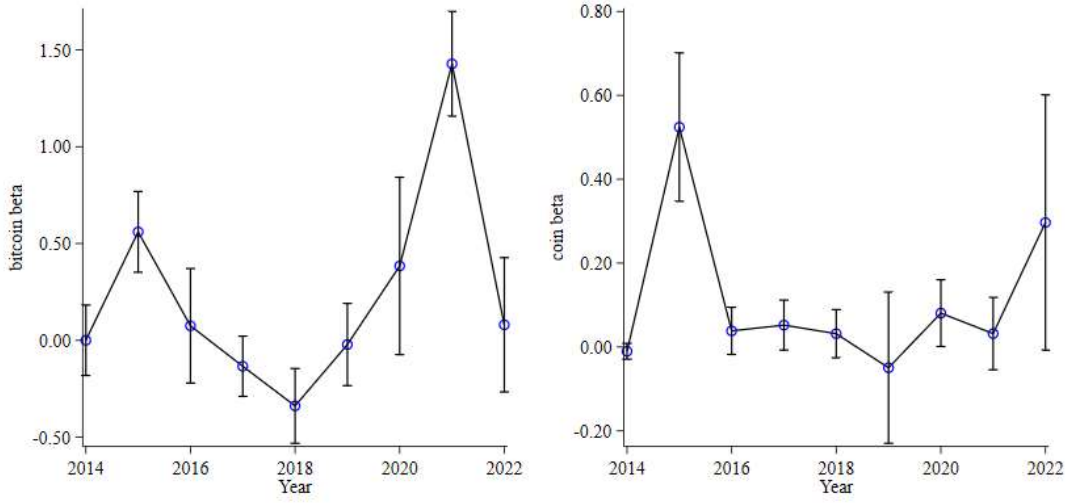
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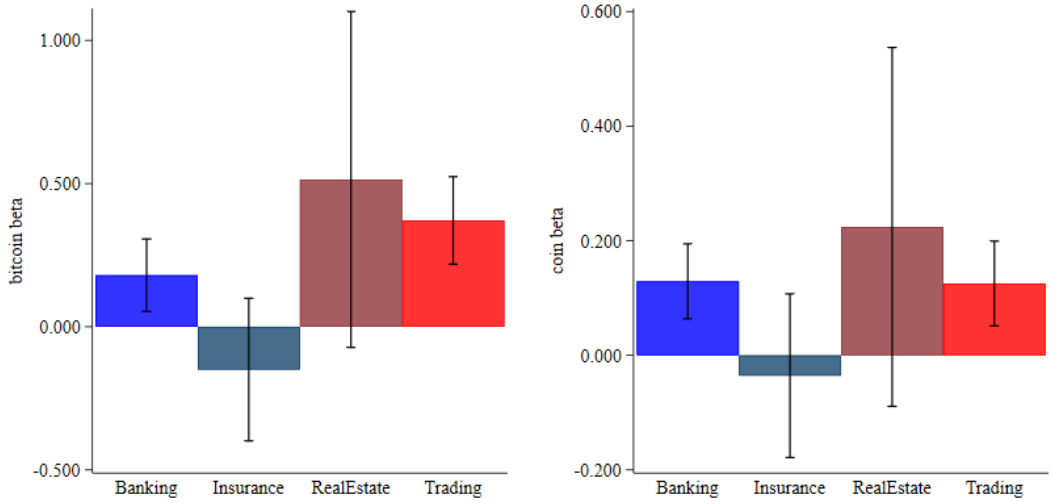
[19] Critics and advocates of cryptos in the US argue over the crypto regulation. Crypto critics such as the SEC chair Gary Gensler point out that crypto market is the wild west which might pose a threat to the financial system such as the crypto fraud and market manipulation. Thus, crypto should regulated like an asset class. See Wall Street Journal article "Big battles Loom in SEC's War on Crypto" on Dec 28,2023. Crypto advocates such as the former and president-elect Donald Trump and the famous businessman Elon Musk argue crypto is new technology and asset. President-elect Donald Trump vows to deregulate cryptos when he will take over the white house. See Wall Street Journal article "The Crypto World is preparing for a Renaissance Under Trump" on Nov 10, 2024.

[20] Wall Street Journal article "China Latest Crackdown on Bitcoin, Other Cryptocurrencies Shakes Market" reported this regulation shift in Chinese mainland on May 24, 2021.

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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 with the 95% confidence interval. Panel B shows the average crypto risk in the financial firms, including banks, insurance companies, real estate companies, and trading firms. The left panel shows the crypto risk measured by bitcoin beta; The right panel shows the crypto risk measured by the coin beta.

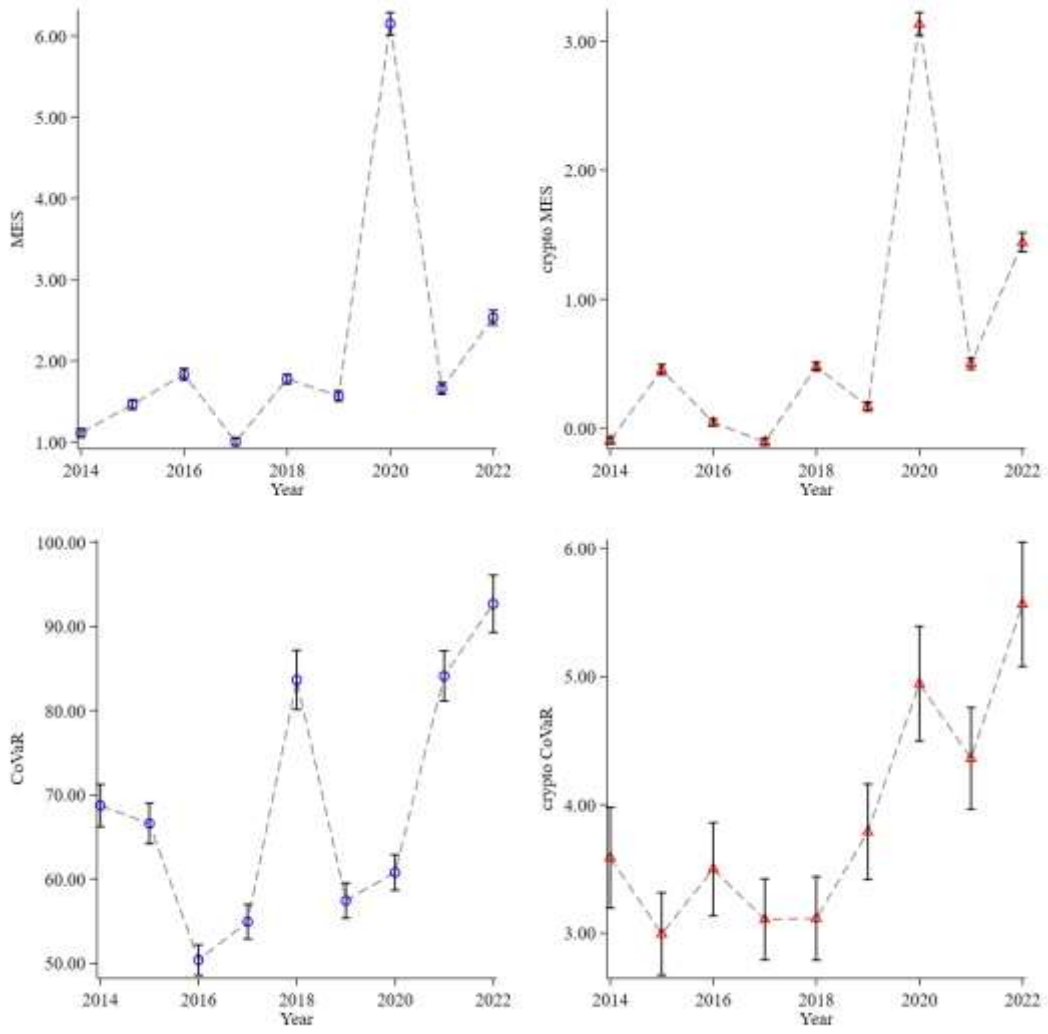


Figure 2: the time series of systemic risk and crypto systemic risk

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

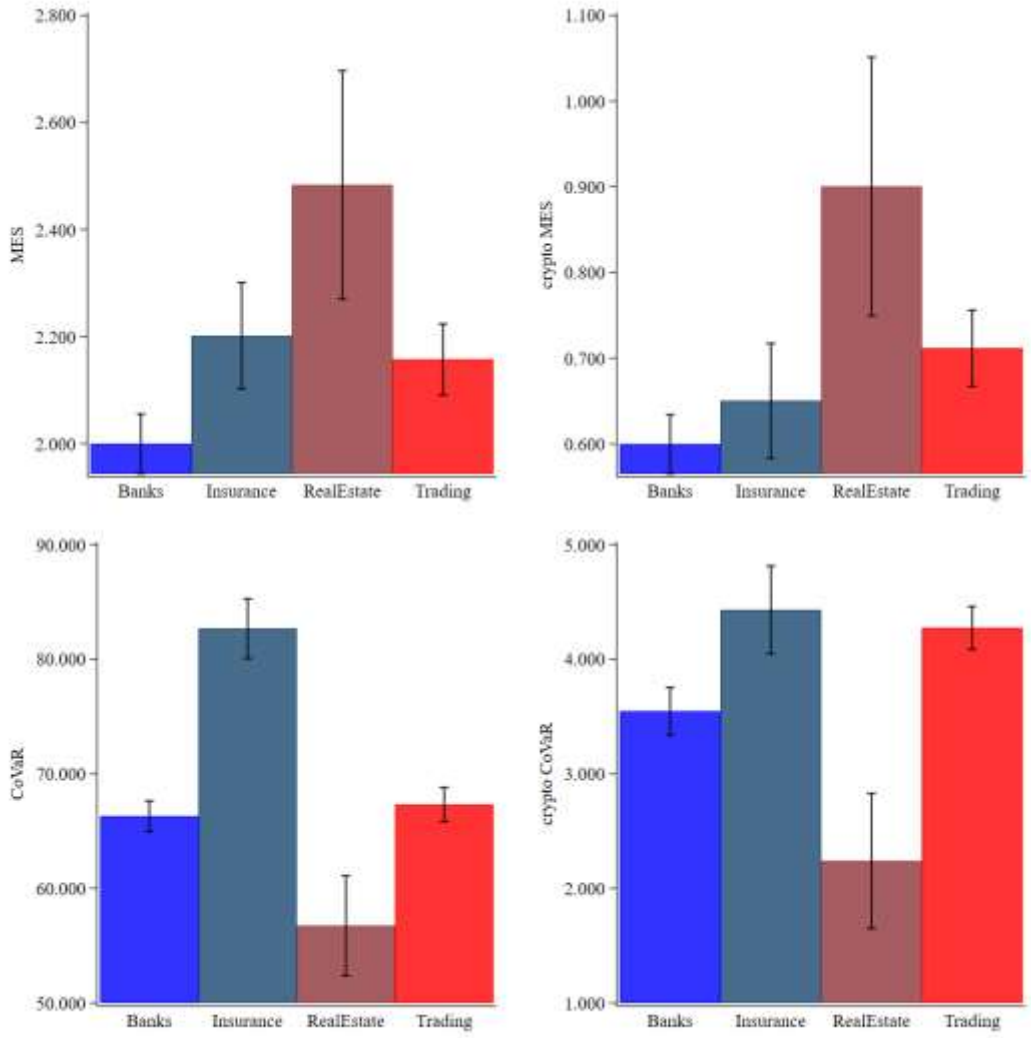


Figure 3: systemic risk and crypto systemic risk in financial firms

Note: this figure shows systemic and crypto systemic risk in financial firms, calculated by group mean with 95% confidence intervals. The upper panel shows systemic risk exposure: MES and crypto MES; The lower panel shows systemic risk transmission: CoVaR and crypto CoVaR.

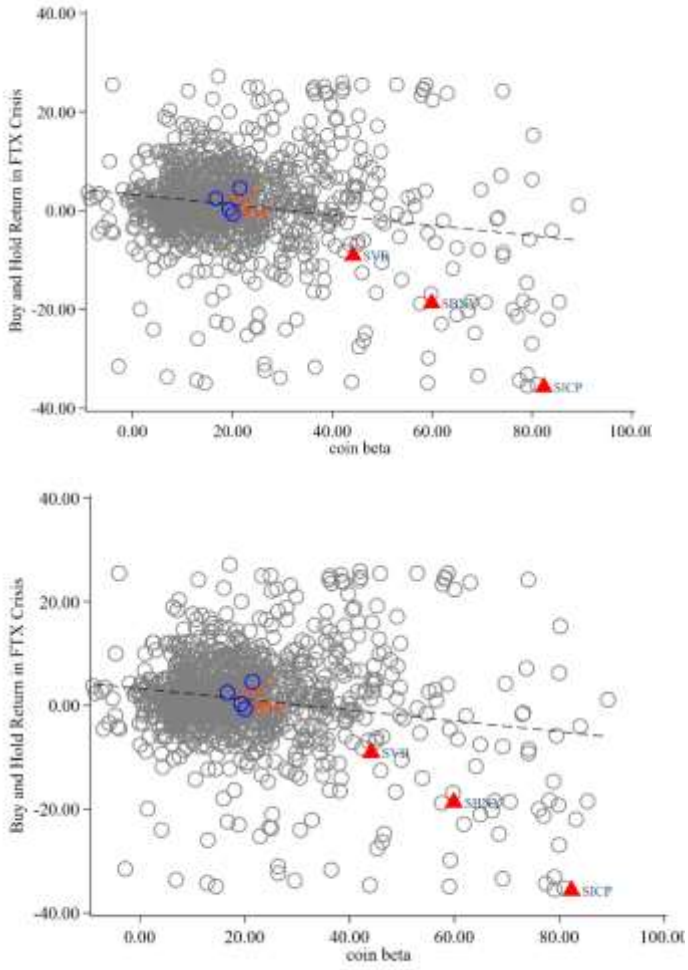


Figure 4: the scatterplot of buy-and-hold returns in the FTX crisis against crypto risk

Note: the figure shows the scatterplot of buy-and-holding returns in the FTX crisis against crypto risk. The upper panel shows this relationship of two variables by bitcoin beta; The lower panel panels shows this relationship of two variables by coin beta. The relationship of two variables has been remove 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), Citi Group Bank(C); Red triangles mark Silicon Valley Bank (SVB),SignatureBank(SBNY),SilvergateCapital(SICP).

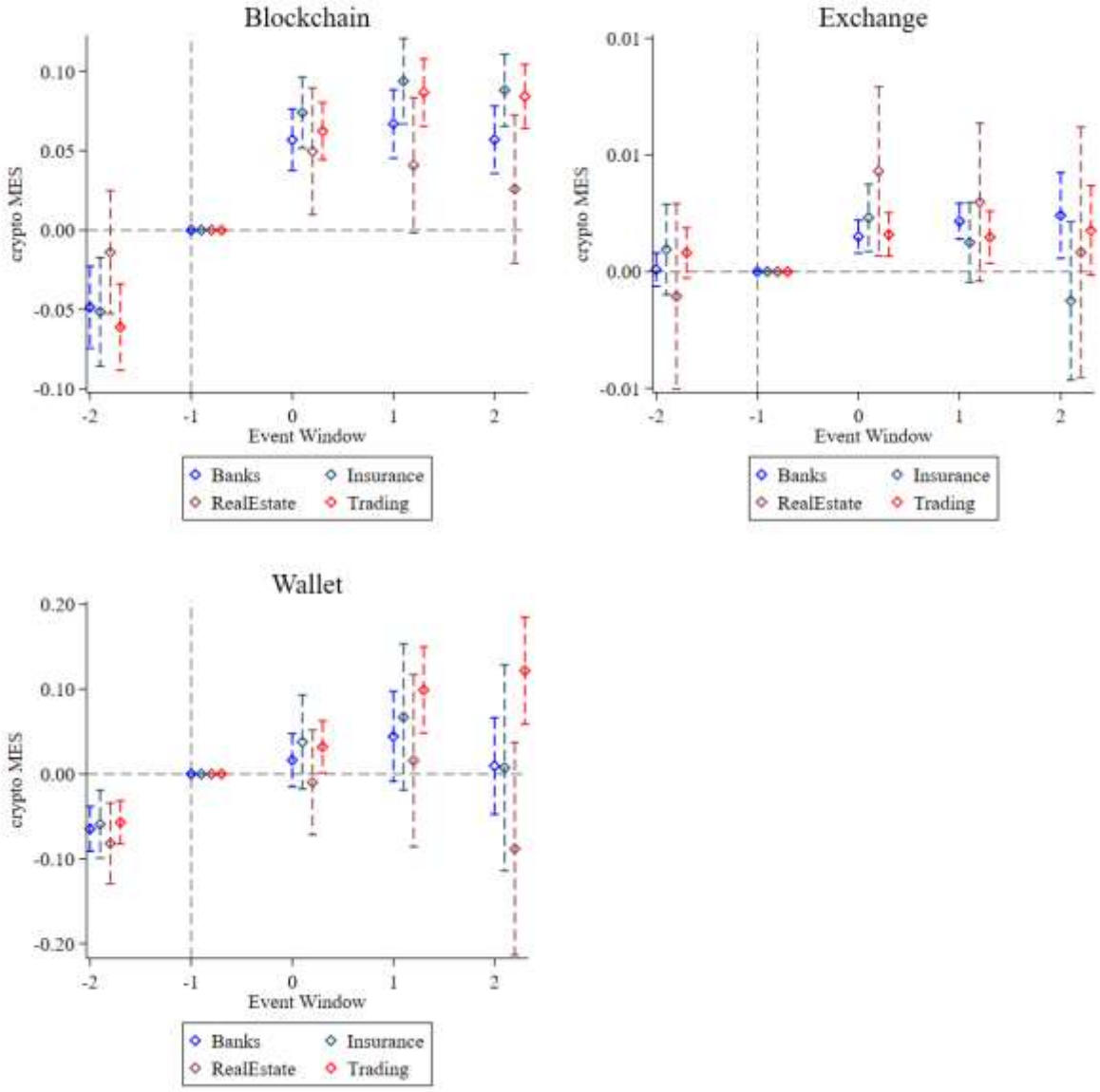


Figure 5: dynamic coefficients of crypto MES on crypto beta in the Stacked DID design by Financial firms.

Note: the 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 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 coefficients of banks, insurance companies, real estate companies, and trading firms, respectively.

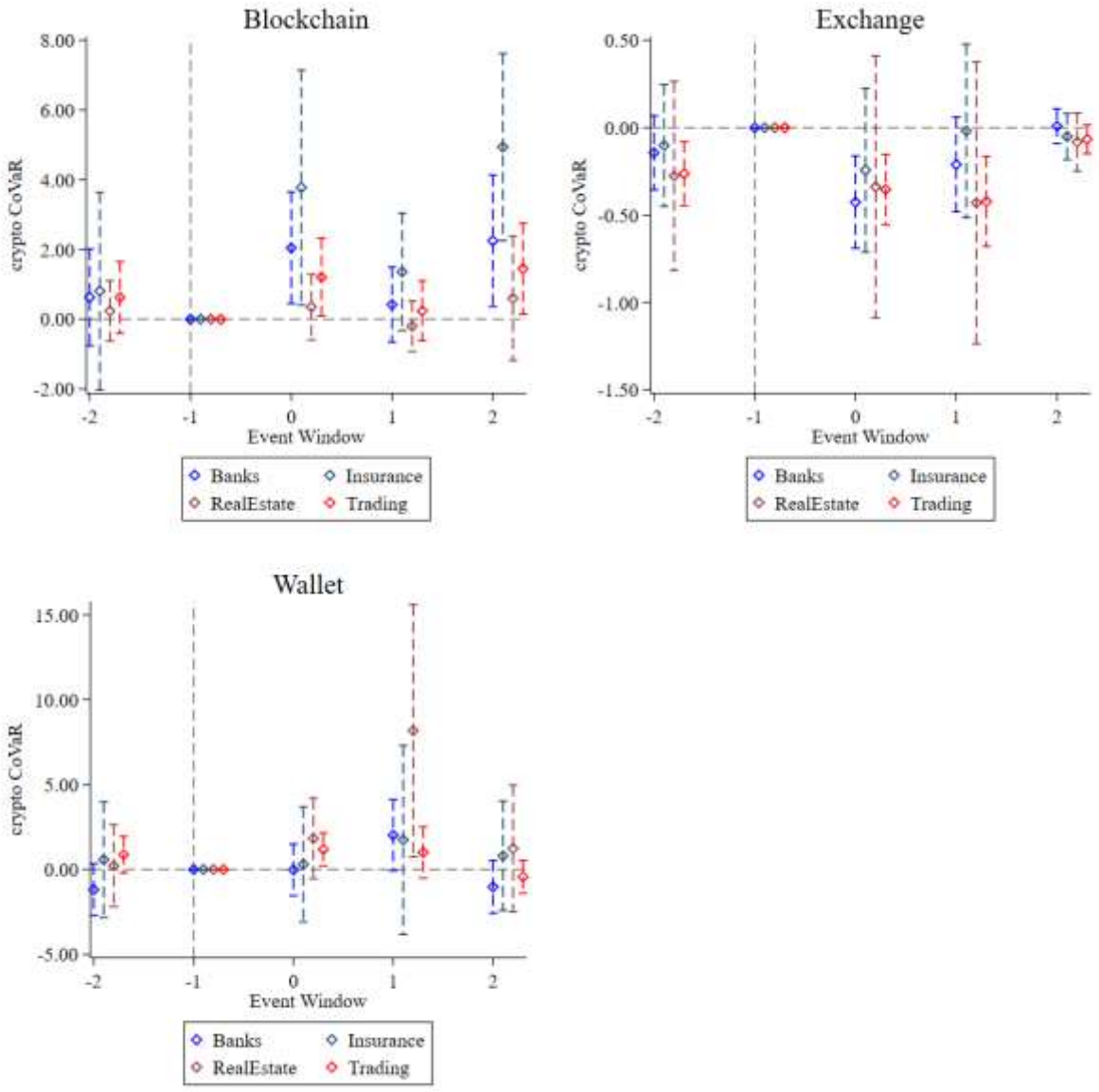


Figure 6: dynamic coefficients of crypto CoVaR on crypto beta in the Stacked DID design by financial firms

Note: the 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 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 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 the parentheses and significance level with the 0.1,0.05,0.01 level is 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
Bank 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 the parentheses and significance level with the 0.1,0.05,0.01 level is 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
Bank 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 the parentheses and significance level with the 0.1,0.05,0.01 level is 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
Bank 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 ten 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 the parentheses and significance level with the 0.1,0.05,0.01 level is 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
Bank 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 ten 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 the parentheses and significance level with the 0.1,0.05,0.01 level is 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
Bank 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 the parentheses and significance level with the 0.1,0.05,0.01 level is 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 firm's 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 ten 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 the parentheses and significance level with the 0.1,0.05,0.01 level is 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	0.080***	0.001***	0.049***	0.088***	0.002***	0.057***
	(0.006)	(0.000)	(0.006)	(0.009)	(0.000)	(0.007)
Observations	119,495	99,148	26,576	119,400	99,063	26,552
R^2	0.80	0.74	0.83	0.75	0.69	0.78
# of Events	24	21	7	24	21	7
# of Fin Firms	1933	2324	1961	1933	2324	1961
Event×Bank 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 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 returns on returns of crypto attacked by each crypto shock. The heteroscedasticity robust standard errors, clustered at the financial firm level, are in the parentheses and significance level with the 0.1,0.05,0.01 level is 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	Exchange	Wallet	Blockchain	Exchange	Wallet
Banks	0.069***	0.000	0.048***	0.079***	0.002***	0.048***
	(0.008)	(0.000)	(0.009)	(0.011)	(0.000)	(0.011)
Insurance	0.086***	0.000	0.017	0.110***	0.001*	0.068***
	(0.017)	(0.001)	(0.013)	(0.012)	(0.001)	(0.018)
Real Estate	0.059***	0.002**	0.030*	0.046*	0.004***	0.023
	(0.017)	(0.001)	(0.017)	(0.025)	(0.001)	(0.019)
Trading	0.097***	0.001***	0.052***	0.107***	0.001***	0.075***
	(0.007)	(0.000)	(0.009)	(0.007)	(0.000)	(0.012)

Note: this table reports the stacked DID regressions of systemic risk exposure using multiple crypto shocks by financial firm's types. Systemic risk exposure is measured by MES and crypto MES. Multiple crypto shocks consist of three main types: Blockchain, Exchanges, and Wallet. Financial firm's types consist 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 returns on returns of crypto attacked by each crypto shock. The heteroscedasticity robust standard errors, clustered at the financial firm level, are in the parentheses and significance level with the 0.1,0.05,0.01 level is 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×Bank 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 returns on returns of crypto attacked by each crypto shock. The heteroscedasticity robust standard errors, clustered at the financial firm level, are in the parentheses and significance level with the 0.1,0.05,0.01 level is 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's types. Systemic risk transmission is measured by CoVaR and crypto CoVaR. Multiple crypto shocks consist of three main types: Blockchain, Exchanges, and Wallet. Financial firm's types consist 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 returns on returns of crypto attacked by each crypto shock. The heteroscedasticity robust standard errors, clustered at the financial firm level, are in the parentheses and significance level with the 0.1,0.05,0.01 level is 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×Bank 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 returns on returns of crypto attacked by each crypto shock. The heteroscedasticity robust standard errors, clustered at the financial firm level, are in the parentheses and significance level with the 0.1,0.05,0.01 level is 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 exposusre×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 by at least one year before each crypto shock. The heteroscedasticity robust standard errors, clustered at the financial firm level, are in the parentheses and significance level with the 0.1,0.05,0.01 level is 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 by at least one year before each crypto shock. The heteroscedasticity robust standard errors, clustered at the financial firm level, are in the parentheses and significance level with the 0.1,0.05,0.01 level is 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×Bank 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 by at least one year before each crypto shock. The heteroscedasticity robust standard errors, clustered at the financial firm level, are in the parentheses and significance level with the 0.1,0.05,0.01 level is 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×Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Event×Time FE	Yes	Yes	Yes	Yes	Yes	Yes

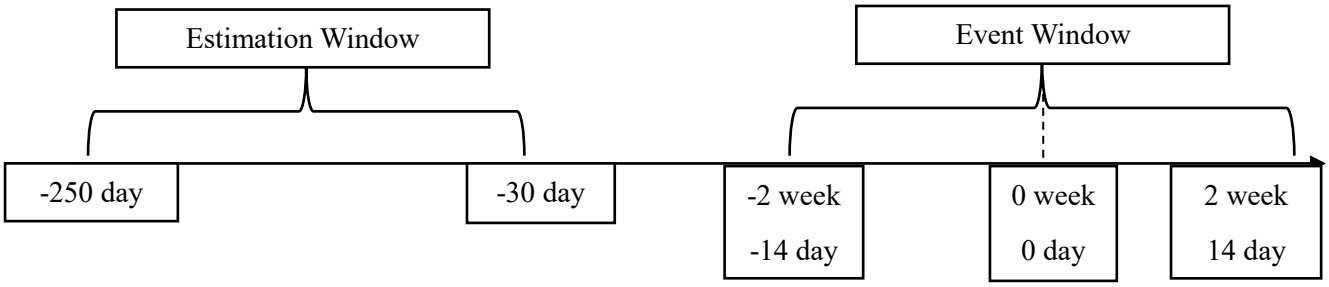
Note: this table reports the stacked DID regressions of systemic risk transmission using placebo cyber-attack shocks. Systemic risk transmission is measured by CoVaR and crypto CoVaR. Placebo cyber-attack shocks consist of three main types: Financial, Personal, and Other. The treatment variable is previously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

Online Appendix

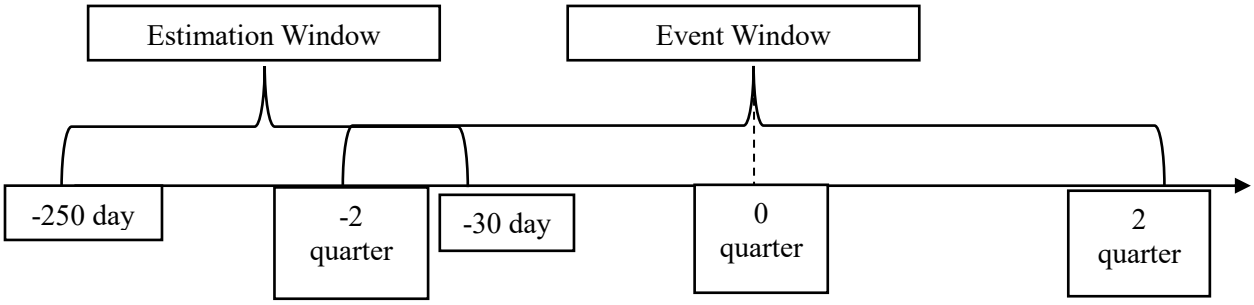
A Additional Figures and Tables



Panel A: daily-frequency sample



Panel B: weekly-frequency sample



Panel C: quarterly-frequency sample

Figure A1: empirical strategy of the crypto shocks

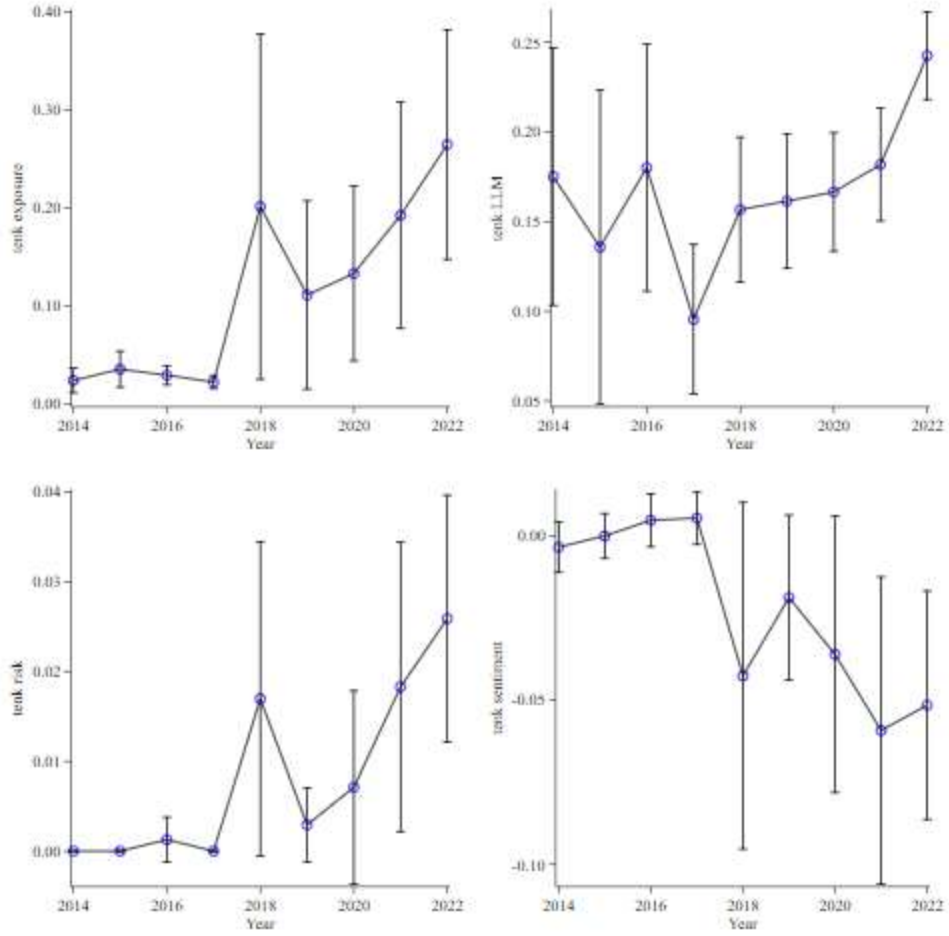


Figure A2: time series of perceived crypto risk measured by ten K files

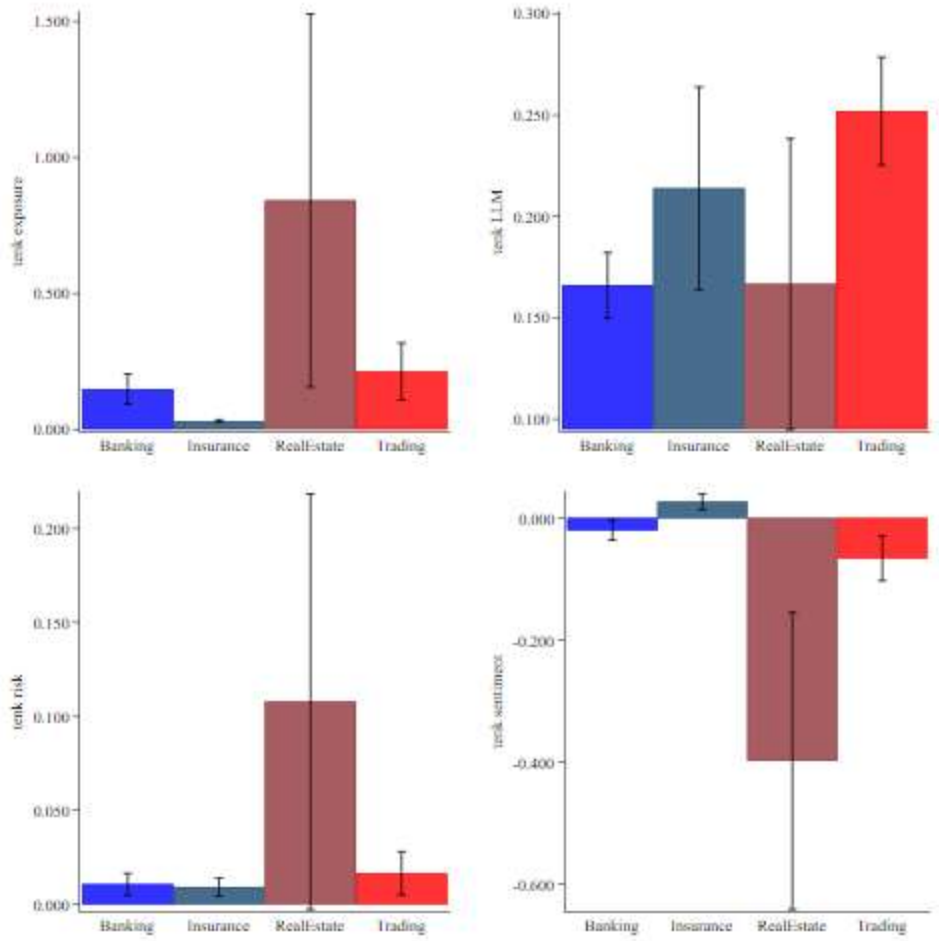


Figure A3: perceived crypto risk of financial firms measured by ten K files

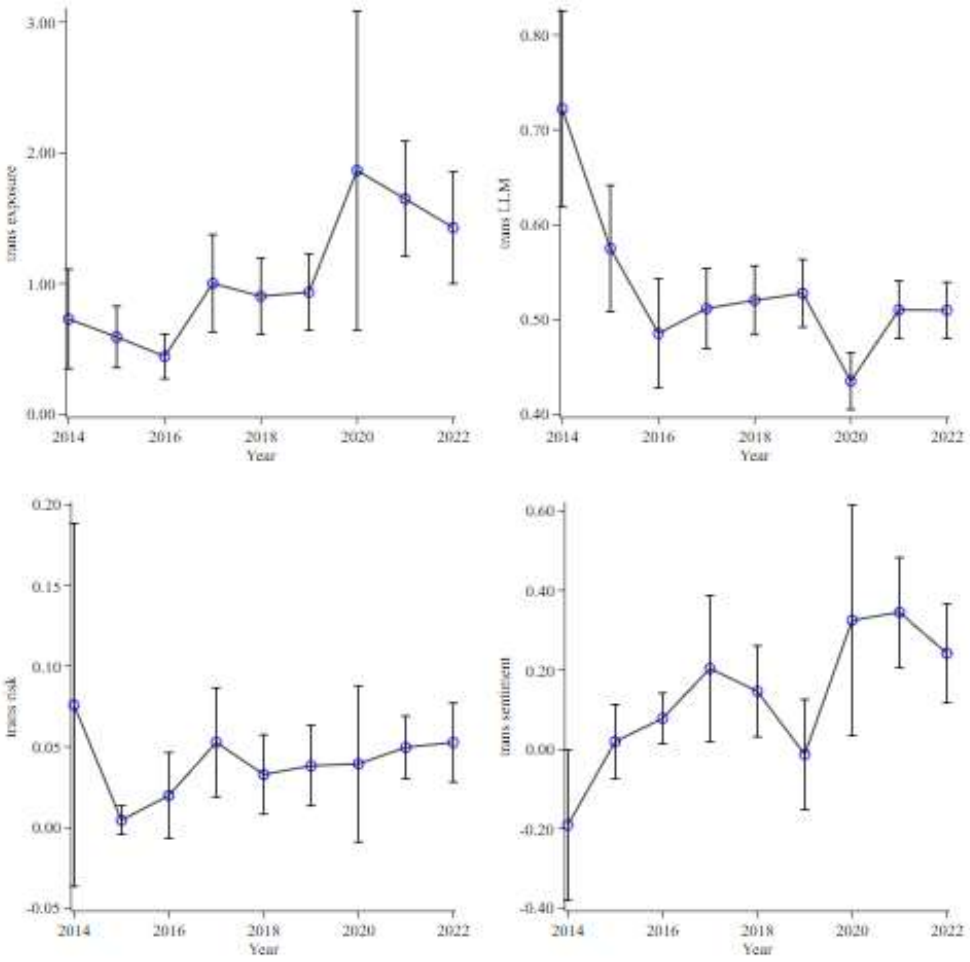


Figure A4: perceived crypto risk of financial firms measured by transcript files

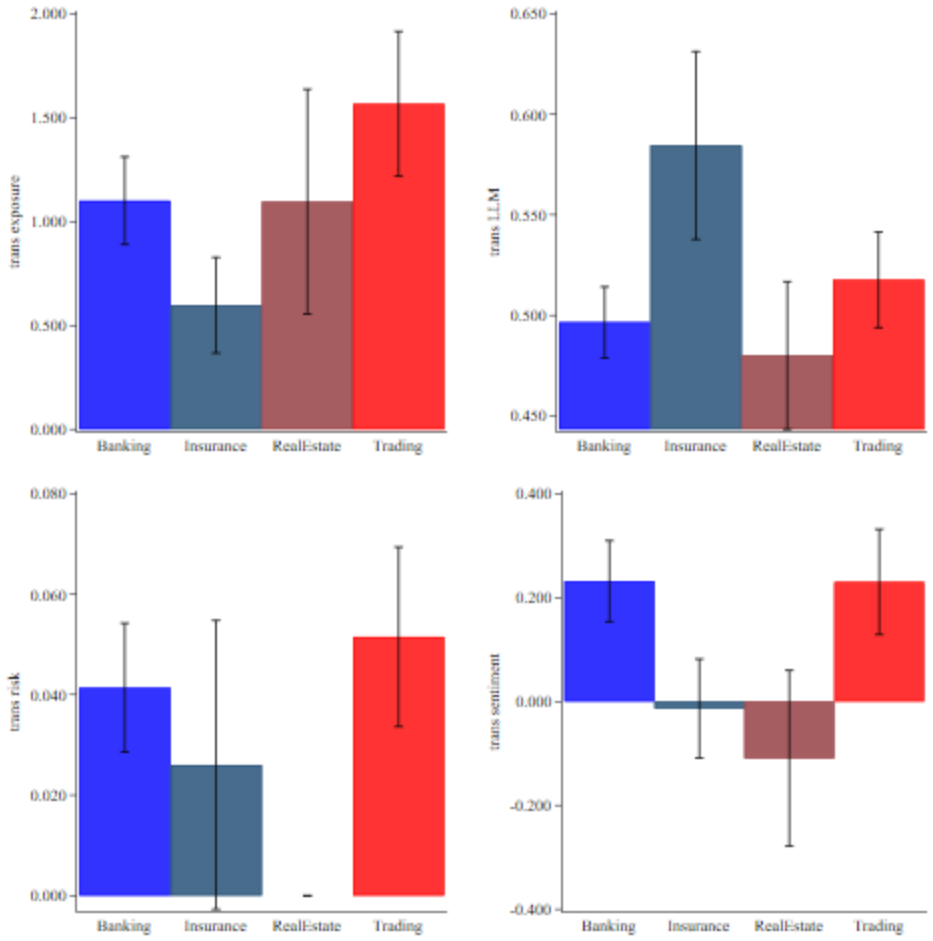


Figure A5: perceived crypto risk of financial firms measured by transcript files

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	2,32	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 ten K form disclosure date	CRSP
B&H return	Buy and hold return of the financial firm during the window ten days before and after ten K form disclosure date	CRSP
total risk	Annually equity return volatility of the financial firm during the window ten days before and after ten 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 Coinmarktcap
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 words in the financial firm's ten K form	Ten K form
tenk risk	The number of risk-meaning words around the crypto-related key words divided by the total words in the financial firm's ten K form	Ten K form
tenk sentiment	Sentiment scores of text analysis in the financial firm's ten K form	Ten K Form

tenk LLM	Crypto risk score in the ten k form generated from Large Language Model(LLM: ChatGPT)	Ten K Form and Open AI
trans exposure	The number of crypto-related key words divided by the total words in the financial firm's ten K form	Earnings Call Transcript
trans risk	The number of risk-meaning words around the crypto-related key words divided by the total 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 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 the 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	1597057	0.064	2.356	-7.659	-1.003	0.008	1.093	8.527
daily Ab return	1597057	-0.007	2.112	-7.073	-0.990	-0.013	0.959	7.498
crypto beta	1575259	-0.156	0.715	-5.634	-0.076	-0.019	0.002	0.293
			Weekly Sample					
CoVaR	439617	148.323	106.971	0.383	69.339	131.652	202.343	524.694
crypto CoVaR	439169	8.278	12.967	-20.395	0.261	5.857	14.396	55.554
crypto beta	435458	-0.142	0.634	-4.786	-0.070	-0.017	0.002	0.207
			Quarterly Sample					
MES	251625	0.023	0.029	-0.020	0.007	0.016	0.027	0.160
crypto MES	251426	0.012	0.023	-0.027	-0.001	0.006	0.017	0.122
crypto beta	249198	-0.125	0.553	-3.896	-0.057	-0.014	0.001	0.228
size	367000	14.604	2.543	6.495	13.344	14.568	15.983	21.065
capital	367000	0.265	0.285	-0.723	0.095	0.150	0.425	0.992

Table A4: A Case Study of the FTX Run

	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

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

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 mine ten k files and earnings call transcripts to construct the three text measures and one large language model measures, respectively.

For the three text measures, we first construct a crypto-related dictionary C. then we construct the exposure measure: count the frequency of key words which are in crypto-related dictionaries scaled by the length of the document.

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

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

Next, we construct the sentiment measure: count positive or negative words around key words which are in crypto-related dictionary C. The positive ad negative words are from the dictionary of Loughran and McDonald (2011).

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

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 construct the risk measures: count words of "Risk" "Uncertainty", or their synonyms around key words which are in crypto-related dictionary C.

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

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

For ten k and earnings call transcripts, we construct two group measures, respectively. The first group are "tenk exposure", "tenk sentiment", and "tenk risk". The second group are "trans exposure", "trans sentiment" and "trans risk".

Table B1: Crypto-related dictionary C

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

Last, we construct the ChatGPT measures. To thoroughly evaluate the cryptocurrency-related risks that firms face, we utilized large language models to analyze the dimensions of their exposure. Our process began by extracting relevant context words from a carefully curated vocabulary list, provided in the table B1. These context words were then input 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 are designed to produce clear responses that can be converted into a numerical scoring framework: each "Yes" response receives a value of +1, each "No" receives -1, and "Uncertain" receives 0. The aggregated result, termed the "LLM Score," provides a deeper analysis beyond traditional bag-of-words methods. This score enables a more nuanced understanding of whether firm disclosures—such as 10-K reports or earnings call transcripts—contain explicit information on these questions, thereby offering a more precise measure of firms' cryptocurrency exposure. Finally, we construct the two group of large language model scores: “tenk LLM” for 10-K reports 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, investments, or 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 will 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).

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

$$MES_{5\%}^{i} = -E[R_{it}|I_{5\%}] \ (B.1)$$

In the terms of crypto-driven MES, we calculate the average equity returns of financial firms conditional on the 5 percent worst trading days of crypto market. We obtain the daily equity returns of financial firms from CRSP and construct crypto market index returns by using the top 20 market-cap cryptos from the CoinMarketCap. We use 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:

$$crypo\ MES^i_{5\%} = -E[R_{it}|I_{5\%}(crypto\ market\ return)]\ (B.2)$$

In terms of CoVaR, we use the quantile regression to estimate the CoVaR. X^s_t and X^i_t are equity returns of financial systems s and a 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 estimate the quantile regression on weekly data.

$$X^i_t = \alpha^i_q + \gamma^i_q M_{t-1} + \epsilon^i_{q,t}\ (B.3)$$

We use this quantile regression to predict the VaR of financial firm i

$$VaR^i_{q,t} = \widehat{\alpha^i_q} + \widehat{\gamma^i_q} M_{t-1}\ (B.4)$$

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

$$X^{s|i}_t = \alpha^{s|i}_t + \gamma^{s|i}_q M_{t-1} + \beta^{s|i}_q X^i_t + \epsilon^{s|i}_{q,t}\ (B.5)$$

We use the quantile regression of financial system to predict the CoVaR by inputting the VaR of the financial firm.

$$CoVaR^i_{q,t} = \widehat{\alpha^{s|i}_q} + \widehat{\gamma^{s|i}_q} M_{t-1} + \widehat{\beta^{s|i}_q} VaR^i_{q,t}\ (B.6)$$

Finally, we define the $\Delta CoVaR^i_{q,t}$

$$\Delta CoVaR^i_{q,t} = CoVaR^i_{q,t} - CoVaR^i_{50,t}\ (B.7)$$

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

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

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

$$CR_{t-1} = \alpha^{CR}_q + \gamma^{CR}_q M_{t-1} + \epsilon^{CR}_{q,t}\ (B.8)$$

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

$$VaR^{CR}_{q,t} = \widehat{\alpha^{CR}_q} + \widehat{\gamma^{CR}_q} M_{t-1}\ (B.9)$$

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

$$X_t^i = \alpha_q^i + \gamma_q^i M_{t-1} + \beta_q^{i|CR} CR_{t-1} + \epsilon_{q,t}^i \ (B.10)$$

We use the $VaR_{q,t}^{CR}$, Value-at-risk of crypto market returns of q quantile at time t to estimate the value-at-risk 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.

$$CoVaR_{q,t}^{i|CR} = \widehat{\alpha_q^{i|CR}} + \widehat{\gamma_q^{i|CR}} M_{t-1} + \widehat{\beta_q^{i|CR}} VaR_{q,t}^{CR} \ (B.11)$$

$$CoVaR_{50,t}^{i|CR} = \widehat{\alpha_q^{i|CR}} + \widehat{\gamma_q^{i|CR}} M_{t-1} + \widehat{\beta_q^{i|CR}} VaR_{50,t}^{CR} \ (B.12)$$

For the second step, we run the quantile regression of financial system equity returns on financial firm equity returns.

$$X_{q,t}^{s|i} = \alpha_q^{s|i} + \gamma_q^{s|i} M_{t-1} + \beta_q^{s|i} X_t^i + \epsilon_{q,t}^{s|i} \ (B.12)$$

Then we input the exposure CoVaR of each financial firm to estimate the crypto CoVaR

$$\mathrm{CoVa}R_{q,t}^{s|i} = \widehat{\alpha_q^{s|\iota}} + \widehat{\gamma_q^{s|\iota}} M_{t-1} + \widehat{\beta_q^{s|\iota}} \mathrm{CoVa}R_{q,t}^{i|CR} \ (B.13)$$

$$\mathrm{CoVa}R_{50,t}^{s|i} = \widehat{\alpha_q^{s|\iota}} + \widehat{\gamma_q^{s|\iota}} M_{t-1} + \widehat{\beta_q^{s|\iota}} \mathrm{CoVa}R_{50,t}^{i|CR} \ (B.14)$$

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

$$\Delta CoVaR_{q,t}^{s|i} = CoVaR_{q,t}^{s|i} - CoVaR_{50,t}^{s|i} \ (B.15)$$

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

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

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 research, we aim to establish a causality argument

regarding firms' crypto risk exposure and its 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 malicious actors can still compromise private keys. Despite the decentralized structure of blockchain, certain nodes may be centralized by residing on the same server. For instance, if a significant number of nodes are hosted on an Amazon server, rendering that server incapacitated 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 will 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, akin to a 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:

These vulnerabilities exploit weaknesses in the fundamental blockchain architecture:

1. Core-Blockchain Vulnerabilities (Blockchain Technology Shocks)

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: 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 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: Targeting centralized cryptocurrency exchanges to steal funds, as these platforms often hold substantial assets in custodial wallets.

2.3: Wallet Exploits: Exploiting vulnerabilities in wallet software can lead to unauthorized access and theft of funds.

2.4: Distributed Denial of Service (DDoS) Attacks: Overwhelming a service with excessive requests to disrupt operations, affecting exchanges, wallet services, 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.