# Estimating Crypto-Related Risk: Market-Based Evidence from FTX's Failure and Its Contagion on U.S. Banks

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## Abstract

*We use historical covariance between stock returns of U.S. banks and bitcoin returns to estimate a sensitivity measure that captures crypto-related risk in financial institutions. The measure effectively explains cross-sectional stock returns of 219 U.S. based financial institutions in response to the failure of FTX on November 11, 2022. Overall we document negative contagion effects on the market valuation of U.S. banks. We further show that this risk measure is unrelated to variables that have been used to explain operational risk in previous literature, i.e., corporate governance and business complexity. However, we document a significant relation with bank liquidity as measured by the Tier 1 capital adequacy ratio. We conclude that, on average, it is the banks with sufficient liquidity reserves that venture into the crypto sphere. Our approach offers individual investors and customers the opportunity to leverage market efficiency to evaluate the idiosyncratic level of crypto-related risk in a financial institution.*

**Keywords:**

operational risk, crypto-related risk, FTX, fraud, event study.

## 1. Introduction

November 11, 2022, marks a watershed moment in the crypto sphere. FTX, the world's second largest crypto currency exchange at that time, officially announced filing for Chapter 11 bankruptcy protection in the United States. Resulting investigations have shed a light on how traditional finance and banking firms are intertwined with the crypto sphere.

On December 07, 2022, members of the Senate Committee on Banking, House of Representatives, and Urban Affairs drafted a letter to the Federal Reserve, the Federal Deposit Insurance Corporation, and the Office of the Comptroller of the Currency.[1] The letter expressed concerns about close ties between traditional banking firms in the U.S. and the crypto sphere. These concerns about the crypto sphere's entanglement with traditional banking firms were sparked by Alameda Research's acquisition of stakes in Moonstone Bank. Alameda Research paid USD11.5 million, more than double the value at the time of Moonstone Bank, which was the 26th smallest bank in the U.S. with one branch and three employees. [2] Initial information about other banks that are also interwined with the crypto sphere was already disclosed on November 23, 2022. [3]

The letter also states that "the sudden implosion of the exchange triggered a contagion that spread across the industry, tanking crypto currency values and dragging other crypto firms into similar fates." However, it further states that "the banking system has been spared of the FTX-induced turmoil."

Our study addresses two central questions. What was the eventual net effect of the failure of FTX on the market valuation of U.S. based financial institutions? Are there differences in stock market reactions among financial institutions? We propose a market-based approach to derive crypto-related operational risk from

[1] https://www.warren.senate.gov/imo/media/doc/Letter%20to%20Regulators%20re%20Banking%20System%20Exposure%20to%20Crypto.pdf

[2] The New York Times, "Crypto Firm FTX's Ownership of a U.S Bank Raises Questions," Stephen Gandel, November 23, 2022, https://www.nytimes.com/2022/11/23/business/ftx-cryptocurrency-bank.html

[3] The Washington Post, "These Banks Were Left Holding the Bag in Crypto Implosion," Marc Rubenstein, November 23, 2022, https://www.washingtonpost.com/business/these-banks-were-left-holding-the-bag-in-crypto-implosion/2022/11/22/b8de2096-6a2b-11ed-8619-0b92f0565592_s

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the long-term covariance of historical stock prices with crypto returns drawing from the empirical approach of Hanke et al. (2020). We rely on the efficient market hypothesis (EMH, Fama, 1970) and assume that the stock market efficiently evaluates crypto-related risk in financial institutions. While the perception of an individual investor may not necessarily be accurate, the EMH implies that the aggregate perception of the market should be correct, on average. Extracting this information from historical stock price movements, i.e., measuring the market-implied risk, eliminates the need for tedious and expensive information gathering. Our model gives both customers and individual investors a new perspective on the level of operational risk in financial institutions, which seems of particularly importance in light of the current banking crisis in the U.S.

Based on standard event study methodology, we find that contagion effects dominate in the overall U.S. banking sector after the default of FTX. However, we note substantial and significant differences in the market reaction of those banks that have a higher level of crypto-related risk according to our model compared to more traditional and conservative banks. The results are robust in multivariate OLS regressions. Mapping the measure with determinants that explained operational risk in financial institutions in prior literature, i.e., corporate governance, business complexity, and banks liquidity, we find that our measure is largely independent of these variables. Banks' liquidity, as proxied by Tier 1 capital adequacy ratio, is significantly, yet positively related to our measure of crypto-related risk. Thus, our results imply that, on average, it is the banks with sufficient liquidity reserves that take the risk and venture into the crypto sphere. However, our findings open up discussions and avenues for further research on the characterization and measurement of crypto-related risks in financial institutions, not least in light of the Basel Accords of the Basel Committee on Banking Supervision.

This study makes two significant contributions to the existing literature. Firstly, it provides empirical evidence regarding the impact of the default of FTX on financial markets, with a particular focus on exploring the relationship between centralized financial institutions and the crypto sphere. Second, we leverage the empirical approach of Hanke et al. (2020) to a different sort of event, thereby offering investors and customers a simple and easy to replicate model to identify crypto-related risk in financial institutions.

The remainder of the paper is structured as follows. Section 2 depicts the theoretical background. Section 3 explains the empirical strategy. Section 4 presents the results. Section 5 concludes.

## 2. Literature

### 2.1. Contagious and Competition Effects of Bankruptcies

Previous literature has examined the failure of financial institutions and the associated economic impact on industry peers (e.g., Dumontaux and Pop, 2013; Ferris et al., 1997; Haensly et al., 2001; Lang and Stulz, 1992; Schiereck et al., 2016. The resulting stock market reaction, however, is theoretically ambigious. Lang and Stulz (1992) distinguish between contagion and competitive intra-industry effects of bankruptcy announcements. The bankruptcy of an individual firm may alter overall profitability expectations within the industry if it reveals unfavorable information about cash flow components that are common to all firms in the industry, commonly referred to as the information transmission channel (Chakrabarty and Zhang, 2012). Conversely, the collapse of a competitor may also have a positive impact on the valuation of the remaining competitors (Altman, 1984). Lang and Stulz (1992) define the competitive effect as the "wealth gain experienced by competitors because the bankruptcy announcement conveys information about the present and future competitive positions of firms in the bankrupt firm's industry."

The failure of FTX has brought to light the close ties between some conventional U.S. banks and the crypto sphere. As a result, the reputation of the overall U.S. banking industry seem to have suffered. At the same time, two factors may strengthen the competitive position of U.S. banks, namely, (expected) enhanced regulatory stringency and users trust. The difference in regulatory stringency is what constitutes an essential difference between the crypto sphere and the traditional banking sector. Crypto assets and the crypto sphere itself have remained largely unregulated thus far. This is in stark contrast to the highly regulated finance and banking industry. In response to the default of FTX, voices became louder calling for stronger regulation of the crypto sphere. Hester M. Peirce, a crypto-friendly commissioner at the Securities and Exchange Commission (SEC) and commonly known as ”Crypto Mom”, stated that the implosion of FTX could be a catalyst for authorities to tighten the reins and formulate clear regulations (CoinDesk, 2022). The expected tighter regulatory stringency may significantly strengthen the competitive position of traditional, centralized financial services providers, thereby positively affecting expectations about future cash flows and eventually stock prices.

By the same token, the second key factor supporting the competitive hypothesis is users trust. Digital financial services and crypto assets both rely on a variety of underlying technologies to secure transactions, except that crypto assets eliminate the need for institutional backing by a central authority (Marella et al., 2020). While traditional financial services benefit from institutional trust, the use of cryptography enhances user trust in decentralized assets and products where central authorities and intermediaries are largely absent. Hence, the security of financial transactions depends on the underlying technology and requires trust not in people but in technology (Jarvenpaa and Teigland, 2017; Marella et al., 2020). Mukherjee and Nath (2003) note that, particularly in online banking, trust issues arise due to the physical separation of customer and bank, the complexity of supervising relationships, and the lack of well-defined regulation on the internet. Two of the essential pillars of trust in online banking services are reliability (Clay and Strauss, 2000) and reputation (Ba, 2001).

Twenty years later, similar reasoning may apply to the adaption of crypto currencies and decentralized payment services. The reputation of the crypto sphere has undoubtedly suffered as a result of the current developments. The bank run on FTX shortly upon knowledge of its issues became public illustrates the fragility of trust in crypto-related products and services, as investors and customers questioned the reliability and trustworthiness of associated actors. Even though blockchain technology and the crypto currency such as Bitcoin are not subject to any central authority, and thus are not subject to any direct organization-related counterparty risk, the sustained loss of trust may have severely delayed mass adoption of cryptocurrencies and decentralized financial services, thereby strengthening the competitive position of and trust in traditional service providers and banks. Hence, the first contribution of our study is to assess whether contagion or competitive effects dominate the aggregate effect on the stock market valuation of U.S. banks after the failure of FTX.

## 2.2. Innovation and Operational Risk

Blockchain technology and crypto currencies are commonly seen as a disruptive threat to traditional, centralized financial services providers (Underwood, 2016), severely affecting business models, i.e., accounting, auditing, and bank transfer (Chen and Bellavitis, 2020; Wang and Kogan, 2018; Weking et al., 2020). Business models based on blockchain technology rest on the concept of two-sided markets (Glaser, 2017), eliminating the necessity of an intermediary third party. One such example is international payments. With blockchain technology, payments can be settled within seconds, without the need to entrust a third party with the settlement and circumventing any exchange fees (Weking et al., 2020). Hence, payment service providers which are increasingly threatened by low-cost decentralized payment networks (Chen and Bellavitis, 2020). To counter the threat of decentralized payment services and the disruptive business models of the crypto sphere, banks need to adapt to these patterns and dynamically implement technologies.

Adapting to new technologies and business models and diversifying into nonbanking activities, however, may increase operational risk (Peters et al., 2016). Operational risk is a major concern for financial institutions, encompassing a broad range of risks that are not directly related to market or credit risks but internal failures, such as human error or system breakdowns. The Basel Committee on Banking Supervision (BCBS) defines operational risk as the risk of loss resulting from ”inadequate or failed internal processes and systems, human error, or external events” (BCBS, 2006). Operational risk under Basel is measured through standardized approaches (such as the Basic Indicator Approach and the Standardized Approach) or advanced internal models, and it is calculated and reported by individual banks as part of their regulatory capital adequacy requirements. Amorello (2016), however, notes that the Basel III framework is subject to fourfold inefficiencies: (i) extreme complexity; (ii) continued reliance on internal model-based rules to calculate capital requirements, particularly regarding operational risk; (iii) incomplete capture of a range of off-balance sheet risks, i.e., the residual risk arising from non-banking activities, such as business models around crypto-related services and assets; and (iv) incompleteness of disclosure requirements.

Prior literature has analyzed the determinants and drivers of operational risk in financial institutions. Chernobai et al. (2011) analyze a sample of 925 publicly reported operational risk events among 176 U.S. financial institutions from 1980 to 2005. Their results reveal that the frequency of operational risk events depends negatively on corporate governance. They show that most operating losses are due to a failure of internal control and that companies experiencing such losses tend to be younger, larger, more complex, have higher credit risk, make more provisions for acquisitions, and have chief executive officers (CEOs) with higher stock options and bonuses relative to salary. Chernobai et al. (2021) analyze operational risk in U.S. bank holding companies related to business complexity. They find that both frequency and magnitude of operational risk events increases significantly with business complexity. The authors note that complexity is multidimensional, encompassing corporate diversification, geographic diversification, and network interconnectedness.

As noted above, the net impact on U.S. bank stock market valuations is theoretically ambiguous. Our second contribution is therefore to provide an ex ante estimate of crypto-related risk among financial institutions. Specifically, we address the question of whether market reactions differ across financial institutions and whether we can divide financial institutions into groups that are intertwined in the crypto sphere and those that are more conservative about adopting new technologies. We finally test whether our measure is related to any of the variables known to explain operational risk in financial institutions.

## 3. Methodology and Data

### 3.1. Empirical Model

Wagner et al. (2018) analyzed stock market reactions in the U.S. to the election of Donald J. Trump as the 45th president of the U.S. in 2016. Cash-effective tax rates and percentage of foreign income emerged as significant determinants of stock market reactions as a response to the anticipated economic impact of Trump's policies. However, myriad factors may determine the sign and magnitude of event-driven stock market reactions, and the eventual market reaction is the aggregate thereof.

The aggregation of these factors is complex and tedious for an individual investor, and encounters certain limitations, especially under the use of traditional axiomatic approaches. In light of these constraints, Hanke et al. (2020) leverage market efficiency to derive the aggregate economic impact. Assuming that changes in election outcome probabilities are priced efficiently in stock prices, changes in pre-event betting odds were used to derive stock specific sensitivities to electoral outcomes. These sensitivities were then used to form portfolios to allow investors to bet on a particular election outcome. Hanke et al. (2022) go even further and propose another application of the model. Based on historical pre-event data on betting odds and intraday stock returns the authors recovered intraday election outcome probabilities. Both results show that markets price event-induced information efficiently and anticipate event outcome probabilities. Thus, historical stock prices can in turn be used to eventually derive aggregated information on firm-level characteristics for a broad sample of stocks.

The question in our setting is whether the stock market was aware of traditional banks' exposure to crypto sphere and, consequently, priced crypto-related risk. If the market was indeed aware of the entanglement (and priced information efficiently), these risks should be reflected in historical share prices. A traditional empirical strategy requires the collection of a variety of data and variables from different sources, i.e., announcements of cooperations and joint ventures of traditional banks with crypto-related organizations, holdings of crypto assets, among others. The recent investigations have shown that the compilation of such information is indeed tedious, laborious, and eventually expensive. Assuming that the market is efficient and does this in fine granularity, an individual may leverage the EMH to derive a (market-implied) measure of crypto-related risk at the firm level from historical covariance of stock returns with crypto returns. Such an empirical approach is agnostic, that is, one cannot derive information on the specific type or source of crypto-related risk, e.g., adaption of crypto-related business models and resulting interdependencies or exposure resulting from holding crypto assets. However, one might infer information on whether a bank is at all exposed to any form of crypto-related risk, which is of valuable information for both investors and customers of financial institutions.

Drawing from the approach of Hanke et al. (2020), our empirical model reads as follows:

$$r_{i,t} = \alpha_i + \beta_i r_{m,t} + \theta_i r_{btc,t} + \epsilon_{i,t} \qquad (1)$$

where we regress the daily return of stock $i$ on day $t$ on the market return, proxied by the return of the Russell 3000 index on day $t$, denoted as $r_{m,t}$ and the return of Bitcoin on day $t$, denoted as $r_{btc,t}$. The term "return" refers to the discrete percentage change in the price of an asset between two consecutive (trading) days, i.e., banking stocks, the market index, and Bitcoin.

In the empirical model, $\alpha_i$ captures the idiosyncratic component, whereas $\beta_i$ captures the systemic market risk exposure and $\theta_i$ captures crypto-related risk exposure. The remaining error term is denoted by $\epsilon_{i,t}$ which is expected to have a mean of zero and variance $\sigma_i^2$. We treat the return of the market index as an exogenous factor, since the share of the individual security on the index itself is negligible. Alternatively, we apply a two step procedure where we first regress the returns of each bank on the market return. We then use the residuals from this regression and regress them on bitcoin returns. $\theta$ obtained from this procedure are virtually identical to $\theta$ obtained from Equation 1. The estimation period ranges from January 1, 2022 to

October 31, 2022.

We expect that stocks show positive $\theta_i$ if investors are aware of the entanglement between a bank and the crypto sphere. Conversely, we expect $\theta_i$ to be approximately zero if returns on bank stocks are largely independent from crypto-related risk. Thus far, our empirical analysis incorporates only Bitcoin to derive $\theta_i$. Arguably, it would also be possible to employ, e.g., a weighted average crypto market portfolio. However, Bitcoin is the largest crypto asset by market capitalization and clearly dominates the price movements of such an index (Kaiser and Stöckl, 2020). Moreover, Bitcoin is considered a transfer currency and thus frequently serves as an general indicator of developments in the crypto sphere and is often used as a deonym for general crypto assets (Kaiser and Stöckl, 2020). In the remainder of the paper we will refer to banks with low $\theta_i$ as traditional, conservative banks and banks with high $\theta_i$ as crypto-friendly banks.

### 3.2. Data and Statistical Analysis

In the first part of our analysis, we estimate the effect of the default of FTX on the U.S. banking sector based on standard event study methodology following MacKinlay (1997). We control for event-induced volatility and serial correlation in abnormal returns by testing significance based on standardized abnormal returns following Boehmer et al. (1991).

The sample includes all 219 companies classified as "banks" under the GICS industry classification and included in the Russell 3000 Index as of Nov. 10, 2022. The sample thus covers the majority of publicly traded banks in the U.S. Data is retrieved from different sources. We retrieve firm-level stock returns and Russell 3000 index returns from Refinitiv. Remaining firm-level data is sourced from Worldscope. Data on risk-free rate and U.S. market factors are gratefully taken from the Kenneth French Data Library. Daily bitcoin returns are retrieved from Coinmarketcap. Formally, cumulative abnormal returns are calculated as the difference between observed returns and estimated returns, aggregated over the respective event period $[\tau_1 : \tau_2]$ formally written as:

$$CAR_{i,t} = \sum_{t=\tau_1}^{\tau_2} r_{i,t} - E[r_{i,t}|\phi_{i,t}] \tag{2}$$

Where $r_{i,t}$ is the realized return of stock $i$ at time $t$ and $E[r_{i,t}|\phi_{i,t}]$ denotes the expected return of stock $i$ at time $t$. We employ the standard market model and use the Russell 3000 to proxy U.S. market returns, formally written as:

$$r_{i,t} = \hat{\alpha}_i + \hat{\beta}_i r_{m,t} + \epsilon_{i,t} \tag{3}$$

We estimate $\hat{\alpha}_i$ and $\hat{\beta}_{n,i}$ over a period of 220 trading days. The estimation period ends ten trading days before the first day of our event period. We then use $\alpha_i$ and $\beta_{n,i}$ to estimate $E[r_{i,t}|\phi_{i,t}]$ and eventually calculate abnormal returns over the event periods.

Thereafter, we run cross-sectional regressions to determine the covariance of $\theta_i$ with firm-level variables that where associated with operational risk in prior literature, e.g., in Chernobai et al. (2021). The regression model is formally written as:

$$\theta_i = \alpha + \beta' X + \epsilon_{i,t} \tag{4}$$

We regress $\theta_i$ on governance scores, non-interest income ratios as a measure of business complexity, and Tier 1 capital adequacy ratios as a proxy for a bank's liquidity reserves. We control for profitability, measured as return on equity, firm size, measured as the natural logarithm of total assets, and leverage. The choice of variables and controls is based on Chernobai et al. (2021).

## 4. Empirical Results

### 4.1. Exploring Theta

We start our empirical analysis by exploring our derived sensitivity measure $\theta$ to confirm the validity of our empirical approach. We perform an out-of-sample pretest of $\theta$'s displayed in Fig. 1. The results confirm that $\theta$ captures the cross-sectional dependencies between bitcoin prices and market valuation of financial institutions effectively. The performance of out-of-sample strategies increases monotonically as more extreme sorting methods are applied.

We plot the cross-sectional distribution of $\theta$ in Fig. 2. It can be seen that there is a robust negative relationship between financial institution stock returns and Bitcoin. The vast majority of $\theta$s are below zero, with some individual values being positive. Interestingly, 104 out of 219 $\theta$s reach statistical significance, three of which are positive.

We can infer from the results that there is a direct negative correlation between traditional banks and Bitcoin returns, which seems to weaken somewhat the more a bank ventures into the crypto sphere. A side note as anecdotal evidence: among the banks with the highest $\theta$ are Silicon Valley Bank and Signature Bank.

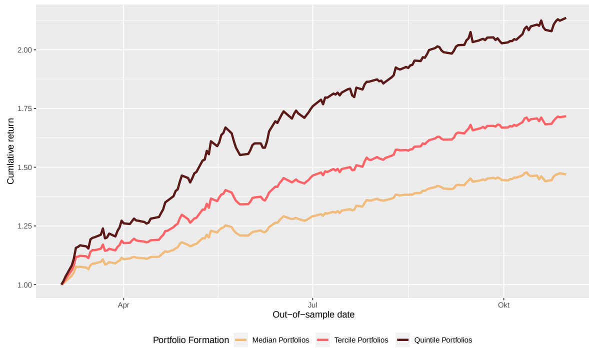


Figure 1: Out-of-sample evaluation of $\theta_{t,i}$ using long-short investments conditioned on the future movement of bitcoin. We construct median, tercile, and quintile portfolios based on daily $\theta_{t,i}$ calculated from January 1, 2022 until $t$. In this approach, when bitcoin prices exhibit an upward movement ($r_{BTC,t+1} >= 0$), we initiate a buy position in the top portfolio and sell the bottom portfolio. Conversely, for a negative bitcoin return, we reverse the investment strategy. A positive net performance of this strategy serves as evidence that $\theta$ effectively captures the cross-sectional dependencies between bitcoin prices and market valuation of financial institutions.

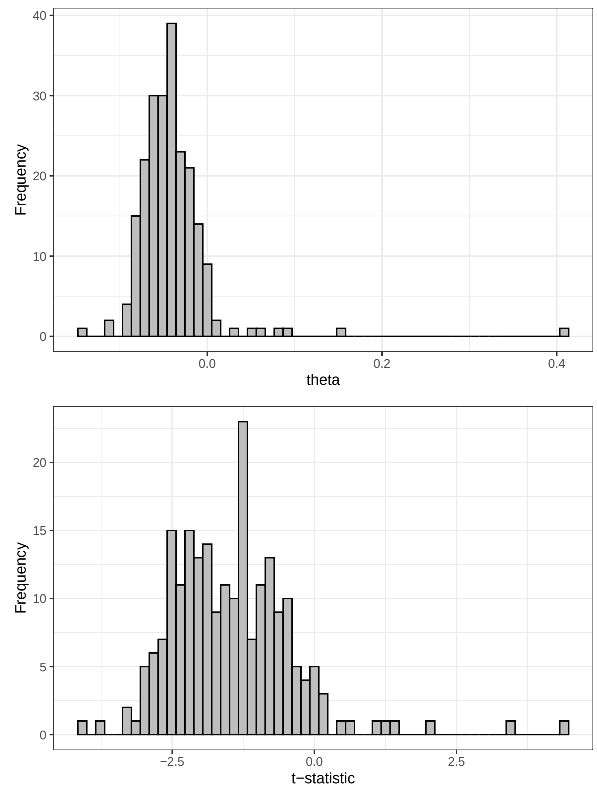


Figure 2: Empirical Distribution of $\theta_i$ in Panel A and respective t-values in Panel B. 104 of 219 are statistically significant at the 10% level, thereof 101 negative. $\theta_i$ is derived from Equation 1 as in Hanke et al. (2020).

## 4.2. Event Study Results

We then turn to the results of the event study shown in Table 1. Panel A shows the results for the full sample of all 219 U.S. banks. We test for significance using a standard t-test (mean) as well as the Wilcoxon signed-rank test (median). On the days before the default of FTX, the cumulative abnormal returns are positive on average, but not significant. However, the median is statistically significant. Interestingly, on the day of the event itself, November 11, 2022, abnormal returns are negative and statistically significant, indicating that contagion effects dominate. Cumulative abnormal returns remain negative on the first trading day after the default, Monday, November 14. Interestingly, we find no evidence of significant post-failure cumulative abnormal returns over the period November 15-22. On November 23, information was released about other U.S. banks that were intertwined with the crypto sphere. Abnormal returns on that day are negative and statistically significant. The cumulative abnormal returns remain negative and significant thereafter. The results are robust to the use of the Fama-French 3-Factor model, albeit lower in magnitude, and tercile sorts. All untabulated results are available from the authors upon request.

In the second step we incorporate $\theta$ into the analysis. We split the sample into above- and below-median $\theta$ values to assess whether there are differences in market reactions between both groups. The results are shown in Panel B and C. Interestingly, over the days preceding the default, we find that stocks with low $\theta$'s performed better than stocks with high $\theta$'s. That is, investors seem to have been cautious with stocks that were known to have higher levels of crypto-related risk (high $\theta$). Firms with low $\theta$'s, i.e., more traditional, conservative banks, exhibit significantly positive abnormal returns relative to the market. We may interpret the results as an indication that investors perceive the competitive position of these banks relative to the crypto sphere to be stronger as uncertainty around FTX intensifies. On the day of the event itself, however, the more traditional banks fared worse, as the uncertainty precipitated by FTX's failure appears to have spread beyond the crypto sphere. We view this result as an indication that investors have previously priced in a premium for crypto-related risk in respective stocks, further supporting the legitimacy of $\theta$. Interestingly, cumulative abnormal returns over

Table 1: This table presents the average cumulative abnormal returns (CAR) of 219 US banks categorized based on their GCIS classification. The CAR values are computed using the market model. In the left section of the table are descriptive sample statistics. Columns (1)-(6) display CAR values for different time periods surrounding the collapse of FTX: before the collapse (1), on the collapse day (2), the day after (3), the week after (4), the day information about other banks that are interwined with the crypto sphere was published (5), and the period to end of November (6). Panel A shows the cumulative returns of bitcoin (BTC) and FTT during the same periods for comparison. Panel B reports cross-sectional CARs of the full sample. The cross-sectional descriptions and the sample split in panels C and D utilize $\theta$ calculated using Equation 1 as in Hanke et al. (2020). Significance testing is based on standardized abnormal returns following Boehmer et al. (1991). We use t-test and Wilcoxon signed rank test to test the hypotheses that mean and median, respectively, are different from zero.

| | | CAR | | | | | |
|---|---|---|---|---|---|---|---|
| Desc. Stats | Column Stats | (1) Nov. 02-10 | (2) Nov. 11 | (3) Nov. 14 | (4) Nov. 15-22 | (5) Nov. 23 | (6) Nov. 24-30 |
| Panel A: BTC and FTT returns | | | | | | | |
| | BTC | -0.129 | -0.031 | -0.024 | -0.024 | 0.026 | 0.034 |
| | FTT | -0.950 | -0.263 | -0.431 | -0.054 | -0.025 | 0.038 |
| Panel B: CAR full sample | | | | | | | |
| Avg. $\theta$: -0.0404 | Mean | 0.538** | -1.884*** | -0.248* | -0.196 | -0.750*** | -0.621*** |
| Avg. $\beta$: 0.73 | [t-stat] | [3.060] | [-17.351] | [-2.219] | [-0.145] | [-13.607] | [-4.811] |
| Avg. Size: 7720 | Median | 0.721*** | -2.017*** | -0.069 | -0.029 | -0.772*** | -0.455*** |
| No. of Firms: 219 | [z-score] | [15545] | [1243] | [10632] | [11603] | [2173] | [7784] |
| Panel C: Top median split (crypto-friendly banks) | | | | | | | |
| Avg. $\theta$: -0.0159 | Mean | 0.106 | -1.616*** | -0.524*** | -0.439 | -0.634*** | -0.863*** |
| Avg. $\beta$: 0.74 | [t-stat] | [1.195] | [-9.460] | [-3.470] | [-0.339] | [-7.939] | [-4.673] |
| Avg. Size: 8548 | Median | 0.625* | -1.553*** | -0.364*** | -0.123 | -0.745*** | -0.741*** |
| No. of Firms: 110 | [z-score] | [3781] | [570] | [1934] | [2777] | [733] | [1449] |
| Panel D: Bottom median split (conservative banks) | | | | | | | |
| Avg. $\theta$: -0.0651 | Mean | 0.973** | -2.154*** | 0.031 | 0.049 | -0.866*** | -0.378* |
| Avg. $\beta$: 0.71 | [t-stat] | [3.304] | [-16.528] | [1.043] | [0.214] | [-11.789] | [-2.035] |
| Avg. Size: 6884 | Median | 0.761** | -2.355*** | 0.176 | 0.107 | -0.915*** | -0.323 |
| No. of Firms: 109 | [z-score] | [4028] | [111] | [3536] | [3044] | [365] | [2465] |
| *Note:* | | | | | | | $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$ |

the period November 15-22 are on average negative for banks with high $\theta$'s, although statistical significance is missing. Strikingly, traditional, conservative banks fared worse on the day when information about other banks interwined with the crypto sphere became public. Conversely, traditional banks subsequently outperformed, while the returns of crypto-friendly banks remain significantly depressed.

The results of this exercise are interpreted as follows. Investors are well aware of which banks are intertwined with the crypto sphere and therefore demand risk compensation. Conversely, contagion effects that impact the market values of more traditional banks are only present on the particular event days and are therefore of limited economic impact and longevity.

As a sort of robustness check, we analyze the returns in our sample and the impact of $\theta$ while controlling for standard firm-level control variables in multivariate regressions. The results, summarized in Table 2, echo our earlier findings. For the sake of brevity, we spare verbatim elaboration. We repeat the multivariate regressions for cumulative abnormal returns and find similar results. We also test the results for the pre-default period including our battery of control variables for operational risk, which are explained in the following section. The results remain robust. $\theta$ effectively explains the stock returns of U.S. financial institutions in the context of FTX's default.

Table 2: This table presents the results of OLS regressions examining the relationship between cumulated raw returns and the variable $\theta$, along with standard firm-level control variables, i.e., book-to-market ratio, natural logarithm of market capitalization, and leverage. The results substantiate the robustness of the finding that $\theta$ carries explanatory power for stock returns in the context of FTX's default and is thus likely to capture crypto-related risk in financial institutions. T-statistics are reported in squared brackets. The coefficients of control variables are omitted due to space limitations.

| | Dependent Variable: CRR | | | | | |
|---|---|---|---|---|---|---|
| | (1) Nov. 02-10 | (2) Nov. 11 | (3) Nov. 14 | (4) Nov. 15-22 | (5) Nov. 23 | (6) Nov. 24-30 |
| $\theta$ | -0.521$^{***}$ | 0.116$^{***}$ | -0.331$^{***}$ | 0.143$^{***}$ | -0.018 | -0.421$^{***}$ |
| | [-9.314] | [5.064] | [-8.940] | [10.146] | [-0.712] | [-6.469] |
| Constant | -0.014 | -0.022$^{*}$ | 0.007 | -0.011 | -0.035$^{**}$ | -0.020 |
| | [-0.443] | [-1.725] | [0.357] | [-1.406] | [-2.550] | [-0.563] |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 218 | 218 | 218 | 218 | 218 | 218 |
| $R^2$ | 0.297 | 0.113 | 0.274 | 0.345 | 0.044 | 0.182 |
| Adjusted $R^2$ | 0.284 | 0.096 | 0.261 | 0.332 | 0.026 | 0.167 |

*Note:* $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

### 4.3. Cross-Sectional Results

Thus far, it can be concluded that $\theta$ effectively captures the relationship between bitcoin returns and the market valuation of financial institutions. It thus constitutes a valuable tool for assessing the crypto-related risk associated with a financial institution. Moving forward, our focus shifts to the analysis of $\theta$ itself. Specifically, we aim to investigate whether there exists any relationship between variables previously identified as determinants of operational risk in the literature and the propensity of banks to engage in crypto-related activities. The results are provided in Table 3. We see that neither governance scores nor non-interest income ratios load significantly on $\theta$. However, banks liquidity, measured as the Tier 1 capital adequacy ratio, shows a significant and positive relation to $\theta$. Not only does the coefficient reach statistical significance, it also adds substantially to the explanatory power of the overall model. The (adjusted) sum of squared residuals increases from close to zero to almost 0.2. It seems that it is the banks that have sufficient liquidity reserves which are positively attuned to the crypto sphere.

## 5. Conclusion

We propose a market-implied sensitivity measure that effectively captures crypto-related risk in financial institutions. To validate its effectiveness, we conducted out-of-sample portfolio tests and examined its explanatory power using abnormal stock returns around the failure of FTX. The results are robust to both univariate sorts and multivariate regressions, controlling for firm-level variables.

Our research holds significant implications for policy makers and regulators. Operational risk stemming from crypto-related assets and services has been extensively discussed in Peters et al. (2016). Furthermore, existing shortcomings in monitoring and oversight practices under Basel III, particularly concerning the (self-reported) assessment of operational risk, have been noted by Amorello (2016). We argue that market-implied risk measures offers an ideal complementary approach for effectively monitoring and overseeing risks that may have previously been overlooked within existing frameworks. Consulting financial markets can considerably facilitate investigations and the identification of ties between banks and the crypto sphere.

Our empirical study is, however, subject to some limitations. We focus only on crypto-related risk in banks within the context of operational risk. However, contagion effects could have affected companies other than banks, e.g., fintech companies. Further investigation could explore contagion effects beyond banks. It is also possible encompass different crypto assets to drive $\theta$, and evaluate impacts on outstanding

Table 3: This table presents the results of OLS regressions examining the relationship between $\theta$ and variables that explain operational risk in the previous literature, namely governance score (GOV), complexity, proxied by non-interest income as a percentage of total income (NII), and liquidity, proxied by the Tier 1 capital adequacy ratio (Tier 1). T-statistics are reported in squared brackets. We control for return on equity, natural logarithm of total assets and book-to-market ratios. The selection of variables is based on Chernobai et al. (2021). The coefficients of control variables are omitted due to space limitations.

| | Dependent variable: $\theta$ | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| GOV | | -0.0001 | | | -0.0001 | -0.00001 |
| | | [-0.567] | | | [-0.675] | [-0.065] |
| NII | | | -0.0003 | | -0.0003 | -0.001$^{***}$ |
| | | | [-1.112] | | [-1.155] | [-3.020] |
| Tier 1 | | | | 0.006$^{***}$ | | 0.006$^{***}$ |
| | | | | [8.297] | | [8.977] |
| Constant | -0.045 | -0.062 | -0.054 | -0.159$^{***}$ | -0.074$^{*}$ | -0.226$^{***}$ |
| | [-1.197] | [-1.470] | [-1.415] | [-4.434] | [-1.703] | [-5.526] |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 218 | 215 | 218 | 212 | 215 | 209 |
| $R^2$ | 0.048 | 0.050 | 0.040 | 0.191 | 0.054 | 0.258 |
| Adjusted $R^2$ | 0.032 | 0.035 | 0.025 | 0.174 | 0.040 | 0.237 |
| *Note:* | $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$ | | | | | |

bonds and CDS spreads to provide further robustness.

In conclusion, our model streamlines the process for individuals to estimate a sensitivity measure that proxies the level of crypto-related risk over the cross-section of banks statistically, bypassing the tedious and costly task of collecting and analyzing data for each individual bank.

## References


Altman, E. I. (1984). A Further Empirical Investigation of the Bankruptcy Cost Question. *The Journal of Finance*, *39*(4), 1067–1089. https://doi.org/https://doi.org/10.1111/j.1540-6261.1984.tb03893.x

Amorello, L. (2016). Beyond the horizon of banking regulation: What to expect from Basel IV? *Harvard International Law Journal*, *58*, Fall. https://doi.org/10.2139/ssrn.2888960

Ba, S. (2001). Establishing online trust through a community responsibility system. *Decision Support Systems*, *31*, 323–336. https://doi.org/10.1016/S0167-9236(00)00144-5

BCBS. (2006). Basel ii: International convergence of capital measurement and capital standards: A revised framework—comprehensive version [[Online]. Available: http://www.bis.org/publ/bcbs128.htm (accessed on 09 June 2023)].

Boehmer, E., Masumeci, J., & Poulsen, A. B. (1991). Event-study methodology under conditions of event-induced variance. *Journal of Financial Economics*, *30*(2), 253–272. https://doi.org/10.1016/0304-405X(91)90032-F

Chakrabarty, B., & Zhang, G. (2012). Credit contagion channels: Market microstructure evidence from lehman brothers' bankruptcy. *Financial Management*, *41*(2), 320–343. https://doi.org/10.1111/j.1755-053X.2012.01194.x

Chen, Y., & Bellavitis, C. (2020). Blockchain disruption and decentralized finance: The rise of decentralized business models. *Journal of Business Venturing Insights*, *13*, e00151. https://doi.org/https://doi.org/10.1016/j.jbvi.2019.e00151

Chernobai, A., Jorion, P., & Yu, F. (2011). The determinants of operational risk in u.s. financial institutions. *Journal of Financial and Quantitative Analysis*, *46*(6), 1683–1725.

Chernobai, A., Ozdagli, A., & Wang, J. (2021). Business complexity and risk management: Evidence from operational risk events in U.S. bank holding companies. *Journal of Monetary*

*Economics*, *117*(100), 418–440. https://doi.org/10.1016/j.jmoneco.2020.02

Clay, K., & Strauss, R. P. (2000). Trust, risk and electronic commerce: Nineteenth century lessons for the twenty-first century [Publisher: National Tax Association]. *Annual Conference on Taxation and Minutes of the Annual Meeting of the National Tax Association*, *93*, 53–63. Retrieved January 31, 2023, from http://www.jstor.org/stable/41950586

Dumontaux, N., & Pop, A. (2013). Understanding the market reaction to shockwaves: Evidence from the failure of Lehman Brothers. *Journal of Financial Stability*, *9*(3), 269–286. https://doi.org/https://doi.org/10.1016/j.jfs.2013.04.001 Central banking 2.0

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The Journal of Finance*, *25*(2), 383–417. https://doi.org/10.2307/2325486

Ferris, S. P., Jayaraman, N., & Makhija, A. K. (1997). The response of competitors to announcements of bankruptcy: An empirical examination of contagion and competitive effects. *Journal of Corporate Finance*, *3*(4), 367–395. https://doi.org/https://doi.org/10.1016/S0929-1199(97)00006-0

Glaser, F. (2017). Pervasive Decentralisation of Digital Infrastructures: A Framework for Blockchain enabled System and Use Case Analysis. *Proceedings of the 50th Hawaii International Conference on System Sciences*.

Haensly, P. J., Theis, J., & Swanson, Z. (2001). Reassessment of contagion and competitive intra-industry effects of bankruptcy announcements. *Quarterly Journal of Business and Economics*, *40*(3/4), 45–63.

Hanke, M., Stöckl, S., & Weissensteiner, A. (2020). Political event portfolios. *Journal of Banking & Finance*, *118*, 1–18. https://doi.org/10.1016/j.jbankfin.2020.105883

Hanke, M., Stöckl, S., & Weissensteiner, A. (2022). Recovering election winner probabilities from stock prices. *Finance Research Letters*, *45*, 102122. https://doi.org/10.1016/j.frl.2021.102122

Jarvenpaa, S., & Teigland, R. (2017). Trust in digital environments: From the sharing economy to decentralized autonomous organizations. *Proceedings of the 50th Hawaii International Conference on System Sciences*, 5812–5816.

Kaiser, L., & Stöckl, S. (2020). Cryptocurrencies: Herding and the transfer currency. *Finance Research Letters*, *33*, 101214. https://doi.org/10.1016/j.frl.2019.06.012

Lang, L. H. P., & Stulz, R. (1992). Contagion and competitive intra-industry effects of bankruptcy announcements: An empirical analysis. *Journal of Financial Economics*, *32*(1), 45–60. https://doi.org/https://doi.org/10.1016/0304-405X(92)90024-R

MacKinlay, A. C. (1997). Event studies in economics and finance. *Journal of Economic Literature*, *35*(1), 13–39. http://www.jstor.org/stable/2729691

Marella, V., Upreti, B., Merikivi, J., & Tuunainen, V. K. (2020). Understanding the creation of trust in cryptocurrencies: The case of Bitcoin. *Electronic Markets*, *30*(2), 259–271. https://doi.org/10.1007/s12525-019-00392-5

Mukherjee, A., & Nath, P. (2003). A model of trust in online relationship banking [Publisher: MCB UP Ltd]. *International Journal of Bank Marketing*, *21*(1), 5–15. https://doi.org/10.1108/02652320310457767

Peters, G. W., Chapelle, A., & Panayi, E. (2016). Opening discussion on banking sector risk exposures and vulnerabilities from virtual currencies: An operational risk perspective. *Journal of Banking Regulation*, *17*, 239–272.

Schiereck, D., Kiesel, F., & Kolaric, S. (2016). Brexit: (Not) another Lehman moment for banks? *Finance Research Letters*, *19*, 291–297. https://doi.org/https://doi.org/10.1016/j.frl.2016.09.003

Underwood, S. (2016). Blockchain beyond bitcoin. *Communications of the ACM*, *59*(11), 15–17. https://doi.org/10.1145/2994581

Wagner, A. F., Zeckhauser, R. J., & Ziegler, A. (2018). Company stock price reactions to the 2016 election shock: Trump, taxes, and trade. *Journal of Financial Economics*, *130*(2), 428–451. https://doi.org/https://doi.org/10.1016/j.jfineco.2018.06.013

Wang, Y., & Kogan, A. (2018). Designing confidentiality-preserving blockchain-based transaction processing systems. *International Journal of Accounting Information Systems*, *30*, 1–18.

Weking, J., Mandalenakis, M., Hein, A., Hermes, S., Böhm, M., & Krcmar, H. (2020). The impact of blockchain technology on business models – a taxonomy and archetypal patterns. *Electronic Markets*, *30*(2), 285–305. https://doi.org/10.1007/s12525-019-00386-3