Crypto Shocks[☆]

Ambrogio Cesa-Bianchi[†] Bank of England CEPR and CfM

Marco Pinchetti[‡] Bank of England and CfM

March 20, 2025

[Preliminary and Incomplete - Do not circulate]

Abstract

This paper investigates whether fluctuations in cryptocurrency prices can *cause* movements in asset prices within the traditional financial sector. By combining narrative and high-frequency identification methods, we construct a new series of crypto shocks—exogenous fluctuations in cryptocurrency prices that are unrelated to developments in the real economy or traditional financial markets. We measure these shocks by computing the change in Bitcoin prices within a 2-hour window surrounding 107 significant cryptocurrency market events from 2017 to 2022. We then estimate the effects of these shocks on firm-level stock prices using event study and local projection techniques, leveraging both time-series and cross-sectional variation. Using text analysis of earnings call transcripts from publicly listed firms worldwide, we create a quarterly measure of firm-level exposure to cryptocurrency fluctuations spanning $1,234$ firms across over 50 countries from 2017 to 2022. Our findings show that crypto shocks significantly affect the stock prices of firms with exposure to cryptocurrency markets, with more exposed firms experiencing stronger effects. However, these shocks do not significantly impact aggregate asset prices, suggesting that their influence on traditional financial markets is (still) limited.

Keywords: Event-Study, Narrative Identification, High-Frequency Identification, Crypto, Bitcoin, Asset Pricing, Text Analysis

JEL Codes: C32, E44, G12, G14, G15

[☆]We would like to thank William Cunliffe, Angel Rai, and Emmanuel Sobakhin for excellent research assistance. We also thank Miguel Faria-e-Castro, Clodomiro Ferreira, Daniel Lewis, Igor Makarov, Giovanni Ricco, Harald Uhlig, and seminar and conference participants at the Bank of England, Bank of Spain, the IMF, and University of Pavia for useful comments. The views expressed in this paper are those of the authors, and not necessarily those of the Bank of England or its committees.

[†]Email: ambrogio.cesa-bianchi@bankofengland.co.uk Web: sites.google.com/site/ambropo

[‡]Email: marco.pinchetti@bankofengland.co.uk Web: sites.google.com/view/marcopinchetti

1 Introduction

The rapid adoption of cryptocurrencies over the past decade and their increasing correlation with traditional asset prices has raised the question of whether their volatile price fluctuations pose risks to macroeconomic and financial stability.[1] While these correlations are well-documented, the nature and strength of any causal relationship between cryptocurrencies and traditional asset prices remain unexplored. This gap raises a fundamental question: can shocks originating in cryptocurrency markets spill over to traditional financial assets, or are the observed correlations merely a reflection of broader macroeconomic and financial conditions?

We address this identification challenge in two steps. First, we identify unexpected and exogenous fluctuations in cryptocurrency prices—which we label *crypto shocks*—by combining narrative and high-frequency identification techniques borrowed from the monetary policy literature. Building on the approach of Romer and Romer (2004), we use narrative judgment to identify major cryptocurrency-related events unrelated to broader economic and financial developments. Between 2017 and 2022, we identify 151 such events, including cryptocurrency exchange hacks, endorsements by influential figures, and shifts in corporate policies regarding cryptocurrencies. For each event, we then measure the high-frequency market reaction by calculating changes in Bitcoin prices—the largest and most liquid cryptocurrency—within a 2-hour window surrounding the event, following the methodology pioneered by Gürkaynak et al. (2005). The resulting time series of high-frequency crypto surprises serves as a noisy proxy for exogenous crypto shocks.

Second, we estimate the effects of these shocks on firm-level stock prices using event study and local projection techniques, leveraging both time-series and cross-sectional variation. Specifically, we apply the text-analysis approach of Hassan et al. (2019) to earnings call transcripts of publicly listed firms worldwide. By analyzing the frequency and context of key terms associated with cryptocurrency discussions, we construct a quarterly measure of firm-level exposure to cryptocurrency fluctuations. This measure spans $1,234$ firms across more than 50 countries from 2017 to 2022, enabling us to examine the differential impact of crypto shocks across firms with varying levels of exposure.

Our empirical analysis yields two key findings. First, crypto shocks have statistically significant effects on the stock prices of firms with cryptocurrency exposure, with larger

[1] For instance, Adrian et al. (2022) document periods of significant positive correlation between Bitcoin and the S&P 500.

impacts observed for firms with higher levels of exposure. Second, we find no evidence that crypto shocks influence aggregate asset prices, such as major stock indices (e.g., the S&P 500), the VIX index, corporate bond spreads, or Treasury yields. These results indicate that while individual firms exposed to cryptocurrency fluctuations are vulnerable, the broader impact on traditional financial markets appears to be limited.

Related literature The growing integration of cryptocurrencies into mainstream finance has generated considerable interest regarding their impact on traditional asset markets. Adrian et al. (2022) document a rising correlation between Bitcoin and equity indices such as the S&P 500. However, the direction of causality remains ambiguous. On one hand, Che et al. (2023), Divakaruni and Zimmerman (2024), and Karau (2023) find that monetary and fiscal policy shocks affect crypto prices. On the other hand, Benigno and Rosa (2023) show that crypto markets do not respond to macro news, and Aldasoro et al. (2024) show that money market funds do not respond to crypto news. Finally, Somoza and Didisheim (2022) suggest that crypto-equity correlations might be driven by the behavior of cryptocurrency investors.

To address this identification challenge, this study constructs a series of crypto shocks by combining insights from narrative and high-frequency identification methods. On the narrative side, the paper builds on the works by Romer and Romer (2004), Romer and Romer (2010), and Cloyne (2013), who identify exogenous economic shocks by analyzing unanticipated events and policy actions. On the other hand, the paper relies on high-frequency identification techniques (see Gürkaynak et al., 2005 and Känzig, 2021) to quantitatively assess the importance of exogenous events based on market reactions[2]. To quantify cryptocurrency exposure at firm-level, we rely on the text-based analysis of earning calls following Hassan et al. (2019, 2023a,b,c) and Bloom et al. (2021), and develop a firm-level exposure metric that captures firms' concerns about cryptocurrency developments.

Our paper most closely relates to two studies which focus on the macroeconomic implications of cryptocurrency fluctuations. Aiello et al. (2023) investigate the effects of cryptocurrency wealth on household consumption and investment, finding that fluctuations in crypto wealth significantly influence spending behaviors and contribute to house price appreciation. Similarly, Weber et al. (2023) highlight that changes in Bitcoin prices can directly affect households' purchasing behavior for durable goods.

By combining narrative and high-frequency identification methods, we develop a unique

[2] Aldasoro et al. (2024) also develop a crypto shocks series, but their identification relies on the restrictive assumption that financial markets do not contemporaneously react to crypto news.

measure of cryptocurrency surprises and assess firm-level exposure through earnings call analysis. Unlike previous work by Aiello et al. (2023) and Weber et al. (2023), which examines household behavior in response to cryptocurrency wealth, our research focuses on asset prices at the firm and aggregate levels, and shows for the first time that cryptocurrency fluctuations can spill over to equity prices of crypto-exposed firms.

2 Identifying Crypto Shocks

We identify crypto shocks using a combination of narrative and high-frequency approaches to construct a series of exogenous cryptocurrency price shocks. First, in the spirit of the literature on the narrative approach to identification, we employ a narrative approach to isolate cryptocurrency-related events that are plausibly exogenous to broader macroeconomic and financial conditions. Second, after identifying these events, we apply high-frequency techniques to measure their impact on Bitcoin prices within a 2-hour event window. The combination of narrative and high-frequency techniques contributes to ensuring that each shock reflects a plausible, timely, and unanticipated shift in cryptocurrency prices.

2.1 Event Selection

To implement a narrative approach, we select significant events within the cryptocurrency market, isolating those expected to impact Bitcoin prices independently of broader economic developments.

We construct a list of cryptocurrency related events through a comprehensive search for Bitcoin-related articles in Google News, conducted on a week-by-week basis from January 2017 to December 2022, by targeting specific n-grams associated with cryptocurrencies.[3] For each event, we record the precise time stamp of the news, marked as day t at time k, based on details provided in the news article or, when unavailable, from the article's publication timestamp. This process results in a dataset comprising 151 crypto-specific events.

The resulting dataset includes three primary types of events: adoption, regulatory, and sentiment events. Adoption events involve news of institutional and corporate involvement into cryptocurrency markets, such as banks incorporating crypto services or firms adding Bitcoin to their treasuries. Regulatory events consist of legislative actions, enforcement

[3]The full list of n-grams is available in the Appendix.

measures, and regulatory guidance that affect market expectations. Sentiment events include sudden shifts in investor perception due to unexpected developments, such as security breaches or public statements by influential figures.

2.2 Construction of Crypto Surprises

Our high-frequency identification approach measures the high-frequency of each selected event on Bitcoin prices, constructing a series of crypto surprises that capture unanticipated price movements within a narrow time window around each event. This method allows us to isolate rapid market adjustments triggered by the identified cryptocurrency-specific events, mitigating potential confounding effects from broader financial market fluctuations.

To capture the impact of each event on Bitcoin prices, we define a 2-hour event window centered on the event timestamp. Specifically, the event window spans from 1 hour before to 1 hour after the event timestamp. This approach draws from high-frequency identification techniques, and is designed to isolate the price response of Bitcoin to crypto-specific news. The choice of a 2-hour window is motivated by the need to balance capturing timely price adjustments while minimizing exposure to unrelated market movements and potential measurement errors in the timing of the events.

We focus on the Bitcoin spot price for the following reasons. First, the Bitcoin price is the relevant benchmark for pricing Bitcoin internationally. Second, Bitcoin spot price contracts have the longest available history, as they were the first kind of contracts traded in Bitcoin.[4] They trade in a numerous amount of centralized and decentralized exchanges and are available at minute-level frequency. In particular, our analysis exploits data by Kraken, a US–based cryptocurrency exchange, founded in 2011, hence with a long history and very high trading volumes[5]. Kraken makes available minute-frequency data about the opening and the closing price, the highest and lowest trading price, the volume of trades, and the number of trades within each trading minute.

We construct our series of Bitcoin surprises by taking the log difference of Bitcoin spot prices one hour after the event and the price one hour before the event:

$$s_t = log(BTC_{t,k+60'}) - log(BTC_{t,k-60'}) \tag{1}$$

[4]While Bitcoin futures might be preferable to capture the role of expectations, these have only been introduced in December 2017.

[5]According to Reuters (2023), as of the 9th November 2022, Kraken is the 10th largest crypto exchange with a year-to-date trading volume of $237.48 billion, and the oldest among the top 10 exchanges.

where k and t indicate the time (measured based on 5-minute intervals) and day of the event, and $BTC_{t,k}$ is the natural logarithm of the average settlement price of Bitcoin spot transaction at minute k on day t.

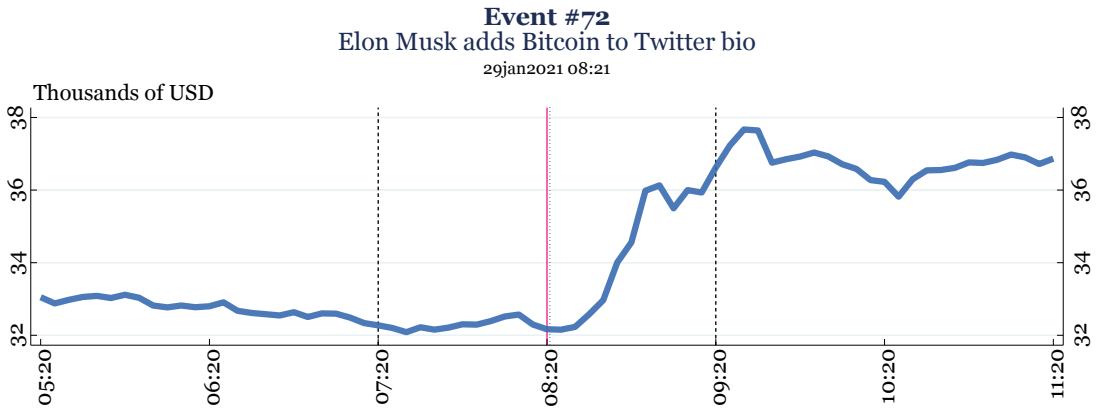
Our intraday surprises are aggregated to a daily series as follows. When there is only one announcement in a given day, the daily surprise is equal to the daily one. When there are multiple announcements, the daily surprise is the sum of the intraday surprises in the given day. When there is no announcement, the daily surprise equals zero.

2.3 An example: Elon Musk endorses Bitcoin via Twitter

To illustrate the nature and impact of a crypto shock, we examine the event on Friday, 29 January 2021, at 08:21 AM (GMT), when Elon Musk updated his Twitter profile by adding #bitcoin and posted a cryptic tweet: "In retrospect, it was inevitable." This event demonstrates how sudden, high-profile endorsements can trigger significant reactions in cryptocurrency markets, independent of macroeconomic factors.

As shown in Figure 1, the impact of Musk's tweet on Bitcoin prices was sharp and timely. At around 08:30, just minutes after the update, Bitcoin's price surged, adding $5,000 within an hour and trading at approximately $37,000. This rapid price movement exemplifies the type of crypto shock our analysis aims to capture, characterized by sudden and significant shifts prompted by crypto-specific news.

Figure 1 An Example of a Crypto Surprises



Note. This figure shows the 5-minute evolution of bitcoin prices in the three hours preceding and following Elon Musk's endorsement of Bitcoin via Twitter on Friday, 29 January 2021, at 08:21 AM (GMT).

This example underscores how narrative-driven, crypto-specific events can trigger abrupt

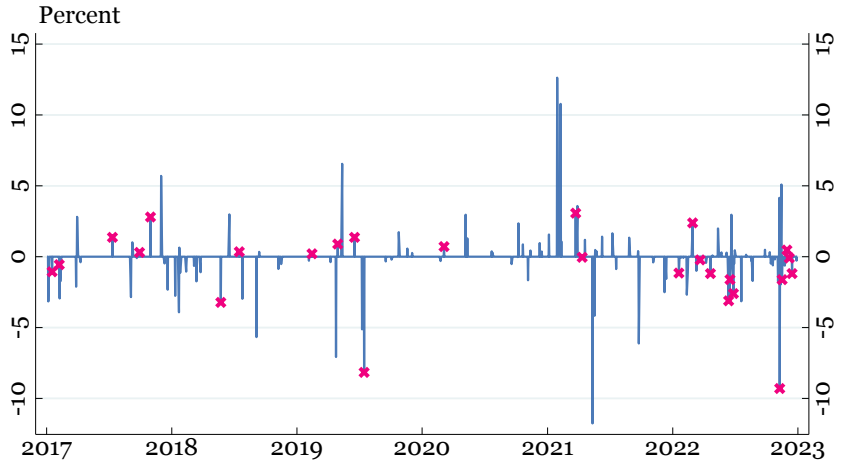
and significant price responses, isolated from broader macroeconomic factors. It serves as an illustration of the type of crypto shocks our study seeks to capture, combining narrative selection and high-frequency techniques to capture exogenous shocks within the cryptocurrency market.

2.4 The Crypto Surprise Series

To construct the crypto surprise series, we aggregate intraday Bitcoin price changes triggered by identified events into daily surprises. This approach helps manage cases where multiple crypto-related events occur within the same day. Starting with 151 identified intraday events, we derive 133 daily surprises by summing event-driven price changes and excluding weekends and holidays, which tend to have lower trading volumes and could introduce noise.

Figure 2 displays the time series of these daily crypto surprises from 2017 to 2022. Each data point represents the percentage change in Bitcoin prices attributable to specific crypto events on a given day. The plot illustrates notable spikes, reflecting days of significant market reaction, both positive and negative, to major news and developments within the cryptocurrency ecosystem.

Figure 2 The Crypto Surprise Series



Note. This figure shows the crypto surprise series. The events marked by a cross are those which overlap with global macro news and central bank releases in a 2h window.

To ensure the exogeneity of our crypto surprises, we further refine the series by removing days that coincide with global macroeconomic announcements, as recorded in the Bloomberg global calendar. Specifically, we exclude any day where a crypto event overlaps with central

bank releases or major macroeconomic news within a 2-hour window. This step reduces the risk of contamination from broader financial developments, isolating the price movements driven purely by crypto-specific factors. After this filtering process, the series comprises 107 daily surprises.

2.5 Key Events

To provide insight into the types of events included in our surprise series, we highlight the top 10 events with the largest Bitcoin price changes, as presented in Table 1. These examples illustrate the impact of various regulatory, corporate, and sentiment-driven events on Bitcoin prices. Details of these events are provided below, with links to relevant news sources.

Table 1 Top 10 Largest Crypto Surprises

Date	Event	ΔBTC (%)
01/12/17	CME gets regulatory approval to trade Bitcoin future contracts	+5.70
05/09/18	Goldman Sachs scraps project to open a crypto trading desk	-5.67
25/04/19	NY Attorney General announces court order against exchange Bitfinex	-7.08
13/05/19	Launch of network Flexa for crypto payments in mainstream stores	+6.55
10/07/19	Fed Governor Powell raises "serious concerns" over Facebook's Libra	-5.12
29/01/21	Elon Musk publicly endorses Bitcoin via his Twitter profile	+12.63
08/02/21	Tesla announces 1.5 billion USD Bitcoin purchase	+10.78
12/05/21	Tesla stops accepting Bitcoin as means of payment	-11.76
24/09/21	PBOC declares all crypto transactions illegal	-6.12
14/11/22	Binance announces creation of "crypto recovery fund"	+5.09

1. On 01/12/2017, the CME Group received regulatory approval to trade Bitcoin futures contracts, signaling increased institutional acceptance of cryptocurrency. This announcement led to a 5.70% increase in Bitcoin prices. The event was covered inter alia by CNBC.

2. On 05/09/2018, Goldman Sachs announced it would scrap its plans to open a cryptocurrency trading desk. This decision reflected a shift in institutional support and contributed to a 5.67% decline in Bitcoin prices. The event was reported by Business Insider and CNBC.

3. On 25/04/2019, the New York Attorney General announced a court order against the exchange Bitfinex, accusing it of using funds from affiliated stablecoin Tether to cover up an

$850 million loss. This event led to a 7.08% drop in Bitcoin prices and was covered by the Wall Street Journal.

4. On 13/05/2019, Flexa, a cryptocurrency payment network, launched support for crypto payments in major retailers, including GameStop and Whole Foods. This significant step towards mainstream adoption resulted in a 6.55% increase in Bitcoin prices. The event was covered by CBS News.

5. On 10/07/2019, Fed Chair Jerome Powell raised "serious concerns" over Facebook's planned Libra project during testimony to Congress. This regulatory signal dampened sentiment across cryptocurrency markets, leading to a 5.12% decline in Bitcoin prices. Coverage included Reuters, CNBC, and the New York Times.

6. On 29/01/2021, Elon Musk publicly endorsed Bitcoin by adding #bitcoin to his Twitter bio, resulting in a 12.63% surge in Bitcoin prices. This marked one of the most substantial sentiment-driven shocks and was reported by Reuters, while the timestamp is recovered from Twitter.

7. On 08/02/2021, Tesla announced its purchase of $1.5 billion in Bitcoin, boosting market confidence and driving Bitcoin prices up by 10.78%. This endorsement of cryptocurrency as a corporate investment was covered by Reuters and Bloomberg.

8. On 12/05/2021, Tesla announced it would stop accepting Bitcoin as a payment method, citing environmental concerns. This reversal led to an 11.76% decline in Bitcoin prices and was reported by the CNBC and the FT, while the timestamp is recovered from Twitter.

9. On 24/09/2021, the People's Bank of China (PBOC) declared all cryptocurrency-related transactions illegal, including buying, selling, and using cryptocurrencies for payments. This led to a sharp 6.21% drop in Bitcoin prices within two hours. The crackdown furthered the government's efforts to control the financial system and curbed cryptocurrency activity, triggering global market sell-offs. the event was covered by Reuters and Bloomberg.

10. On 14/11/2022, Binance announced plans to create a "crypto recovery fund" to support projects facing a liquidity crisis following the collapse of FTX. This announcement boosted market sentiment, leading to a 5.09% increase in Bitcoin prices. The timestamp is recovered from Binance's CEO's Twitter and the event was reported by Reuters.

These examples demonstrate how both regulatory actions and endorsements from influential figures can significantly impact Bitcoin prices. The magnitude and nature of these

events underscore the volatility of the cryptocurrency market and its sensitivity to sectoral developments.

2.6 Diagnostic Checks

To validate the robustness and reliability of the crypto surprise series, we conduct a series of diagnostic checks. The results of these diagnostics are summarized below and detailed in the Appendix.

First, we analyze the overall distribution of the daily crypto surprises to assess its shape and moments. Figure A.1 shows that the distribution is approximately symmetric, with a concentration around zero and a range that captures both substantial positive and negative price changes.

Second, we break down the distribution of surprises by year and quarter to evaluate consistency over time. Figures A.2 and A.3 display these distributions, indicating that crypto shocks occur with varying frequency across different periods but maintain a relatively stable range of magnitudes. This temporal breakdown confirms that the series is not overly dominated by a particular year or quarter, supporting the robustness of our analysis across multiple time frames.

Third, we examine the distribution of crypto surprises by hour to check for potential time-of-day effects. Figure A.4 shows that events are well-distributed throughout the trading day, without clustering in specific time slots. This observation suggests that the crypto surprise series is not biased toward certain hours, which could have implied market-specific operational artifacts.

We also evaluate the autocorrelation of the crypto surprise series to ensure that shocks are independent and not serially correlated. Figure A.5 plots the autocorrelation function, showing negligible correlations at all lags. This result supports the assumption that the series consists of discrete, exogenous events rather than a process influenced by persistent trends or patterns.

Lastly, we assess the correlation of our crypto surprises with other known financial and economic shocks to verify their exogeneity. Table A.2 reports the correlations between the crypto surprise series and various macroeconomic shocks, including oil price shocks (Känzig, 2021), monetary policy shocks (Gertler and Karadi, 2015), geopolitical risk (Caldara and Iacoviello, 2022), TFP shocks (Fernald, 2012), and global uncertainty (Ahir et al., 2022).

The low correlation coefficients across these comparisons indicate that our crypto shocks are distinct and exogenous to other macroeconomic shocks.

2.7 Effect of Crypto Surprises on Daily Bitcoin Prices

To assess the impact of crypto surprises on Bitcoin prices at a daily frequency, we estimate the following event study specification:

$$\Delta BTC_t = \alpha + \beta s_t + \varepsilon_t$$

where ΔBTC_t represents the daily change in Bitcoin prices, and s_t denotes the daily crypto surprises identified through our narrative and high-frequency approach. The estimation focuses on two high-frequency windows for capturing crypto shocks: a ±1-hour window around the event and a more precise ±30-minute window.

Table 2 presents the results of the estimation. Column (1) reports the estimated effect using the baseline ±1-hour window, while column (2) shows the results for the robust ±30-minute window. Both specifications indicate a significant positive relationship between crypto surprises and daily Bitcoin price changes. The coefficient estimates indicate that a one-unit increase in the crypto surprise index leads to an average daily increase in Bitcoin prices of approximately 0.97% when using the ±1-hour window and 1.38% for the ±30-minute window. These results are statistically significant at the 99% level, underscoring the robustness of the estimated effects across different windows. The higher coefficient in the ±30-minute window suggests that narrower windows may capture excessive price reactions to crypto events.

These findings validate the premise that our identified crypto surprises have a pronounced and impact on Bitcoin prices. The significant reactions observed in daily returns provide evidence of the effectiveness of our narrative and high-frequency identification strategy in capturing meaningful, market-moving events within the cryptocurrency space.

Table 2 The Effect of Crypto Surprises on Daily Bitcoin Prices

	(1)	(2)
Crypto shock (Baseline, ±1-hour window)	0.97***	
	(0.24)	
Crypto shock (Robust, ±30-min window)		1.38***
		(0.46)
Observations	107	107
R squared	0.274	0.203
F-Statistic	15.7	8.9

Note. Robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Coefficients corresponding to the constant not reported.

3 Measuring Firm Exposure to Cryptocurrencies

In this section, we illustrate how we exploit natural language processing tools to measure $CryptoExposure_{i,c,t}$ at the firm-call-quarter level. Our objective here is to measure (i) the exposure to cryptocurrencies for each listed firm i via measuring the number of times cryptocurrencies are mentioned in its earnings conference call c held in quarter t. To this end, we use standard natural language processing tools and training libraries from NL Analytics, an automated text-analysis tool based on the work by Hassan et al. (2019, 2023a,b,c) and Bloom et al. (2021).

3.1 Data

To measure firm-level exposure to cryptocurrencies, we utilize data from earnings call transcripts, a granular information resource that provides direct insights into the topics discussed by firm executives and analysts.

Earnings calls are key events for investors who want to understand how a company is performing financially. During these calls, the senior management team of a company presents insights and answers questions about their financial performance and future developments to its investors and analysts. The discussions held during the earning calls can concern the company's financial health, strategic plans, and any challenges or opportunities they face. Earnings calls allow financial analysts and market experts to closely examine a company's performance and compare it to their expectations. Their analysis helps investors to deepen

their understanding of a company's prospects and can influence the company's market valuation.

The transcripts are sourced from LSEG-Refinitiv, and encompass more than 400'000 transcripts of quarterly earning conference calls held by 8402 publicly listed firms from January 2002 to December 2022 in 73 countries. This dataset spans from 2017 to 2022, a period characterized by significant developments in cryptocurrency markets. The coverage of the dataset is comprehensive, capturing approximately 96% of market capitalization in the U.S., 90% in the Euro Area, 90% in the U.K., and 35% in China. Firms are identified based on their headquarters' location, ensuring a geographic breakdown that reflects global exposure to cryptocurrency discussions.

3.2 Measurement

The measurement of crypto exposure follows two separate steps. First, we select a set of relevant n-grams, i.e. combination of words composed of n keywords, whose meaning is associated with cryptocurrencies. Second, we count the number of times our n-grams appear in the earning calls, and normalize this quantity by the total number of words in each transcript.

The selection of the relevant n-grams is a key choice for the quantification of the exposure. We selected our n-grams, based on the expressions which are most frequently mentioned in sentences where a selected number of words associated with cryptocurrencies and their variations appear. Our selection of relevant n-grams is documented in Table 3. Our n-grams primarily pertain either to (i) cryptocurrencies, (ii) the crypto-ecosystem, (iii) technology and applications, (iv) tokens, (v) stablecoins. Additionally, we read a limited sample of earnings-call transcripts to verify that our n-grams are used with the intended meaning, and making sure that the n-grams are not used with alternative meanings within the transcripts.

In the second step, we compute the crypto exposure for a given earnings call c of firm i in quarter t by determining the ratio of sentences mentioning at least one of the defined crypto n-grams to the total number of sentences in the call. This measure is defined as:

$$\text{CryptoExpo}_{cit} = \frac{1}{N_{cit}} \sum_{n=1}^{N_{cit}} \mathbb{1} \left[n_{cit} \in \mathbb{C} \right] \tag{2}$$

where N_{cit} represents the total number of sentences in the call, and $\mathbb{1}$ is an indicator function

Table 3 Selected Crypto-Related N-grams in Earnings Calls

N-gram(s)	Number of ECs	Semantic Field
Crypto / Cryptos		crypto-currencies
Cryptocurrency / Cryptocurrencies		crypto-currencies
Crypto-currency / Crypto-currencies		crypto-currencies
Cryptoasset / Cryptoassets		crypto-currencies
Crypto-asset / Crypto-assets		crypto-currencies
Cryptospace / Crypto-space		crypto-ecosystem
Cryptomining / Crypto-mining		crypto-ecosystem
Cryptowallet / Crypto-wallet		crypto-ecosystem
Initial coin offering(s)		crypto-ecosystem
Blockchain(s) / Block-chain(s)		technology/applications
Distributed ledger		technology/applications
DLT / DLTs		technology/applications
DeFi		technology/applications
Smart contracts		technology/applications
NFT / NFTs		technology/applications
Tokenization		technology/applications
Bitcoin / Bitcoins		tokens
BTC		tokens
Ethereum / Ethereums		tokens
ETH		tokens
Stablecoin / Stablecoins		stablecoins
USD Coin / USDC		stablecoins
Tether / USDT		stablecoins

Note. This table lists the selected crypto-related n-grams identified in earnings calls. Column 2 shows the number of earnings calls mentioning each n-gram. Column 3 reports the semantic field associated with each n-gram.

that equals 1 if sentence n_{cit} contains an n-gram from $\mathbb{C}$ and 0 otherwise. To control for differences in transcript lengths, we normalize the measure by the total number of words in each call. As occasionally some firms have more than one call in the same quarter, we aggregate all the calls in each quarter to compute a quarterly crypto exposure measure for firm i is as:

$$\text{CryptoExpo}_{it} = \frac{1}{C_{it}} \sum_{c=1}^{C_{it}} \text{CryptoExpo}_{cit} \tag{3}$$

where C_{it} is the number of earnings calls for firm i in quarter t. Finally, we calculate a firm-level exposure CryptoExpo_i measure over multiple quarters by aggregating CryptoExpo_{it}

across time:

$$\text{CryptoExpo}_i = \frac{1}{T_i} \sum_{t=1}^{T_i} \text{CryptoExpo}_{it} \tag{4}$$

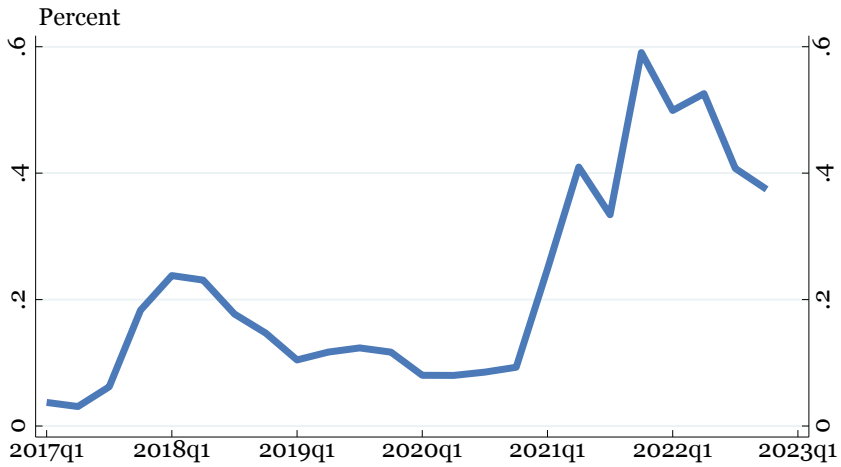
where T_i denotes the number of quarters for firm i.

3.3 Crypto-Exposure Facts

In this subsection, we document the empirical properties of our firm-level crypto-exposure measure in three dimensions: (i) the evolution of its firm-level distribution average during our sample period, (ii) its sectoral distribution, and (iii) its geographic distribution.

In Figure 3, we show how our crypto exposure measure evolves over time. This figure presents the cross-sectional average of the crypto-exposure measure, $CryptoExpo_{it}$, calculated with equal weights across all firms in our sample. The exposure measure covers the period from 2017q1 to 2022q4, exhibiting peaks and troughs that correspond to key market events within the crypto space, and broader cryptocurrency adoption trends.

Figure 3 Average crypto exposure across firms

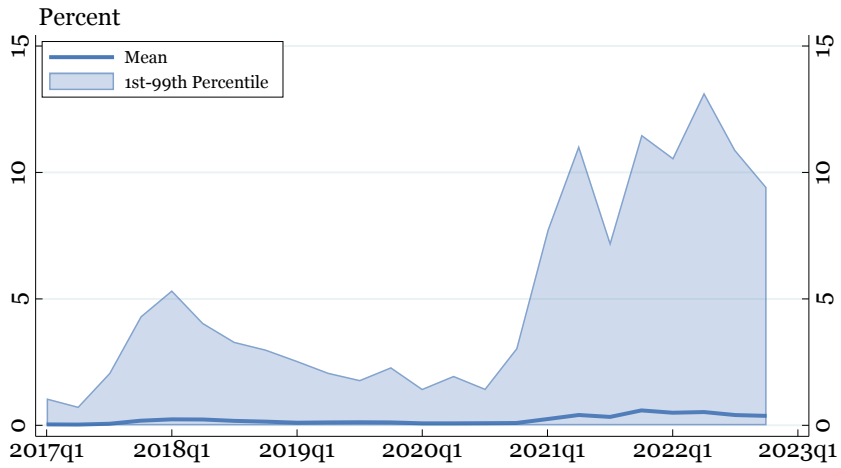


Note. Cross-sectional average of the crypto-currency exposure measure $CryptoExpo_{it}$ (with equal weights) across all firms in our sample. Sample period: 2017q1 to 2022q4.

The figure highlights a notable upward trend in average exposure over the initial years, coinciding with the rapid adoption and increasing interest in cryptocurrencies during 2017 and 2018. Following this period, there is a period of relative stability followed by a rapid increase in early 2021. Towards the final part of the sample (between late 2021 and 2022), the crypto exposure measure stabilizes.

Figure 4 presents the cross-sectional distribution of the crypto exposure measure across firms, along with the 1st and 99th percentiles, highlighting the distribution's spread over the sample period from 2017q1 to 2022q4. The shaded areas in the figure represent these percentiles, illustrating the range of exposure among firms. The distribution highlights a substantial degree of heterogeneity in firms' engagement with cryptocurrencies, revealing that while the vast majority of firms maintains very limited levels of exposure, a subset exhibits significant exposure that can shift in response to market and regulatory developments.

Figure 4 Cross-sectional distribution of crypto exposure



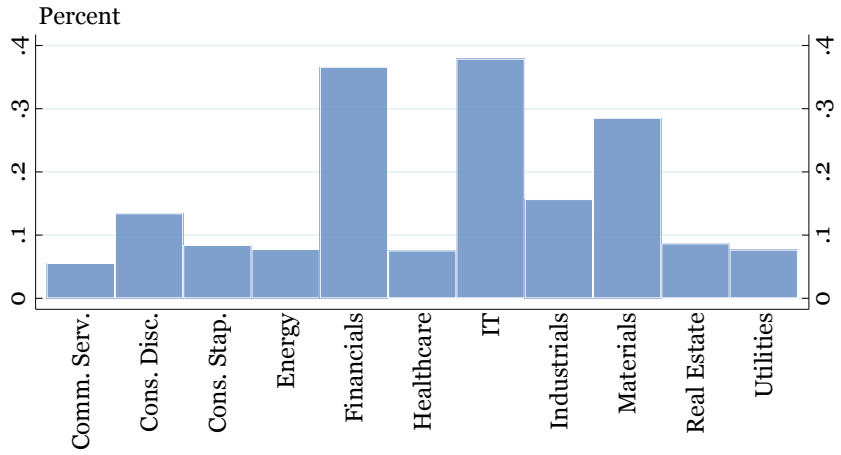
Note. Cross-sectional average of the crypto-currency exposure measure $CryptoExpo_{it}$ (with equal weights) across all firms in our sample. Shaded areas are 1st and 99th percentiles. Sample period: 2017q1 to 2022q4.

Figure 5 presents the sectoral breakdown of the average crypto exposure measure, $CryptoExpo_{it}$, across firms from 2017q1 to 2022q4. The figure illustrates that exposure to cryptocurrencies is not uniform across sectors, highlighting key differences in engagement levels. Notably, sectors such as Information Technology and Financials show higher average exposure compared to other industries, reflecting their greater engagement with emerging technologies and digital assets.

Other sectors, such as Consumer Discretionary, Industrials, and Materials, also display moderate levels of exposure, reflecting instances where companies have incorporated cryptocurrency strategies or shown interest in blockchain applications. In contrast, traditionally less tech-focused sectors like Utilities and Consumer Staples demonstrate minimal exposure, indicating that cryptocurrencies remain on the periphery of their strategic interests during the sample period.

Figure 6 provides a more detailed look at the sectoral distribution of the crypto exposure

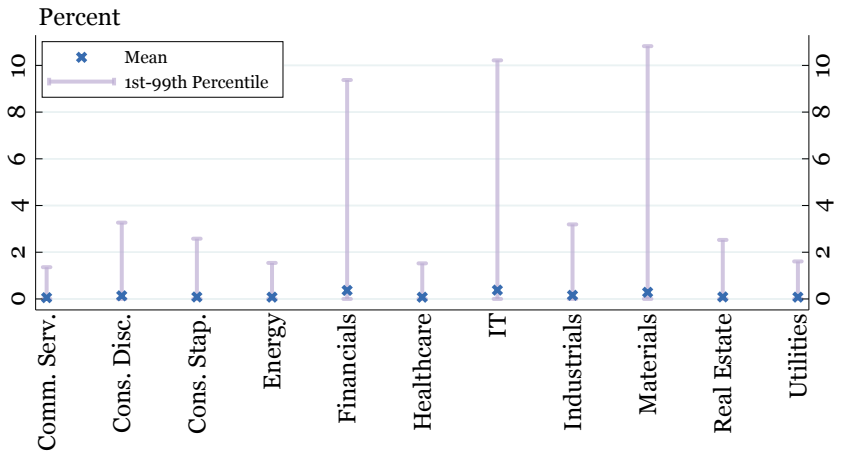
Figure 5 Sectoral breakdown: Average crypto exposure



Note. Cross-sectional average of the crypto-currency exposure measure $CryptoExpo_{it}$ (with equal weights) across firms by sector. Sample period: 2017q1 to 2022q4.

measure, $CryptoExpo_{it}$, showing the cross-sectional averages along with the 1st and 99th percentiles, outlined in the chart by the whiskers. The chart emphasizes not only the central tendencies within each sector but also the range of exposure, which reveals substantial intra-sector variation and skewness. The Information Technology and Financials sectors continue to exhibit higher average exposure, while the whiskers indicate that some firms within these sectors have exceptionally high exposure levels.

Figure 6 Sectoral breakdown: Exposure distribution

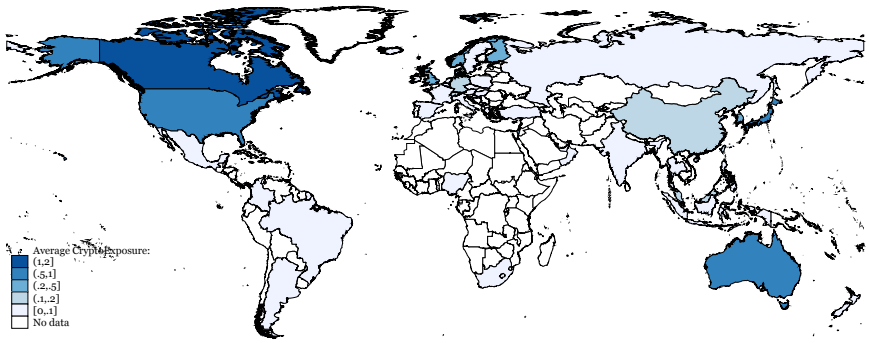


Note. Cross-sectional average of the crypto-currency exposure measure $CryptoExpo_{it}$ (with equal weights) across firms by sector. Whiskers are 1st and 99th percentiles. Sample period: 2017q1 to 2022q4.

The presence of wide percentiles in sectors such as Information Technology highlights that while the average exposure is significant, there is considerable heterogeneity among firms. This dispersion suggests varying degrees of strategic engagement with cryptocurrency-related initiatives. In contrast, sectors like Utilities and Consumer Staples display narrower whiskers, indicating that most firms in these industries maintain consistently low levels of exposure, with few outliers.

Figure 7 illustrates the geographic distribution of average crypto exposure across firms, with color intensity representing the level of exposure in each country. The figure reveals that firms headquartered in Australia, Canada, Japan, the United States and Northern European countries generally show higher average exposure, aligning with these regions' greater participation in global financial and technological markets. Notable concentrations of exposure can also be observed in countries with established or rapidly growing tech sectors, suggesting a link between technological development and engagement with cryptocurrencies.

Figure 7 Geographic breakdown of Crypto-Exposure



Note. The colour intensity indicates the average crypto exposure of crypto-exposed firms in each country.

In contrast, emerging markets, including China, exhibit lower average exposure, which may reflect differing regulatory landscapes or the relative maturity of cryptocurrency integration within these markets. In the Appendix, Figure B.1 shows the geographic distribution of the number of firms characterized by non-zero crypto exposure, which highlights a similar pattern. This geographic heterogeneity underscores the varying degrees of adoption of cryptocurrencies across the globe.

3.4 Validation

To validate our firm-level crypto exposure measure, we analyze the firms identified as having the highest average exposure align with expectations based on their business activities and sectors. Table **??** provides a list of the top 50 firms by average exposure over the sample period, measured by the frequency of mentions of crypto-related keywords in their earnings calls. The table includes the company's name, business sector, country of headquarters, and the average exposure value.

The firms shown in Table **??** include well-known cryptocurrency exchanges, mining companies, and financial institutions that have publicly demonstrated significant interest in or exposure to cryptocurrencies. For example, firms such as Coinbase Global and Galaxy Digital Holdings are leading entities in cryptocurrency trading and investment, while mining-focused firms like HUT 8 Mining and Marathon Digital Holdings also feature prominently due to their core business operations in crypto mining.

The presence of mainstream firms such as PayPal and NVIDIA suggests broader technological and payment integration with cryptocurrencies, reflecting their participation in or facilitation of crypto-related services. Overall, the table confirms that our measure effectively identifies firms with expected high exposure to cryptocurrencies, thus validating its relevance and robustness.

4 High-Frequency Effects on Asset Prices

In this section, we estimate the high-frequency effects of crypto shocks on asset prices using an event-study framework. Our objective is to analyze how unexpected changes in cryptocurrency prices impact both firm-level equity prices and aggregate asset prices. To this purpose, we use an event-study version of our dataset, where t indexes days with identified crypto events.

We conduct two main analyses: first, we estimate the average and the relative effects of crypto shocks on the equity prices of firms with varying levels of exposure to cryptocurrencies. Second, we examine how these shocks influence broader aggregate asset prices to understand the potential spillover effects in the financial markets.

4.1 Firm-Level Effects

To assess the impact of crypto shocks on firm-level equity prices, we estimate a panel event-study regression, using the following specification:

$$y_{it} = \alpha_i + \beta s_t + \gamma \left(s_t \times CryptoExpo_{i,\tau-1}^{High} \right) + \delta CryptoExpo_{i,\tau-1}^{High} + \varepsilon_{it}$$

In this model, y_{it} represents the 2-day log-change in the equity price of firm i on day t, α_i denotes firm fixed effects, controlling for unobserved, time-invariant firm characteristics, and s_t is the daily crypto surprise, capturing the exogenous component of price changes in the cryptocurrency market. $CryptoExpo_{i,\tau-1}^{High}$ is an indicator variable equal to 1 if the firm's crypto exposure in the previous quarter (τ) is above the median level.

The coefficient β measures the average effect of crypto shocks on the equity prices of firms in the cross-section, while γ quantifies the differential impact on firms with high crypto exposure. This interaction term allows us to test whether firms more engaged with cryptocurrencies experience stronger reactions to crypto shocks. The term δ controls for the baseline effect of being a highly exposed firm on equity price changes.

Table 4 presents the results from various specifications of the event-study regression analyzing the impact of crypto shocks on firm-level equity prices. Specification (1) estimates the average effect of a crypto shock (β) without accounting for heterogeneous firm exposure. The coefficient on s_t is positive and statistically significant at the 5% level, with a value of 0.13, indicating that, on average, crypto shocks are associated with a modest increase in equity prices across firms.

In specification (2), we introduce the interaction term $s_t \times CryptoExpo_{i,\tau-1}^{High}$ to capture the differential effect on highly exposed firms. The coefficient γ is positive and significant at the 10% level, suggesting that firms with higher-than-median crypto exposure experience an amplified response to crypto shocks. The estimate for γ is 0.08, indicating that these firms see an additional equity price increase compared to the average firm response.

Specification (3) adds time-by-sector fixed effects to control for potential sector-specific time trends that could influence equity prices. The inclusion of these controls slightly reduces the size of γ to 0.07, now significant at the 5% level, while the estimate for the average effect (β) is omitted due to the interaction-focused model. This suggests that sector-level variations do not eliminate the significant differential impact on highly exposed firms.

Specification (4) extends the controls further by incorporating time-by-sector-by-country

Table 4 The Response of Firm-Level Equity Prices to Crypto Shocks

	(1)	(2)	(3)	(4)
Crypto shock (β)	0.13**	0.13**		
	(0.05)	(0.05)		
Crypto shock x High Exposure (γ)		0.08*	0.07**	0.07*
		(0.04)	(0.03)	(0.04)
High Exposure (δ)		-0.24	-0.07	-0.06
		(0.16)	(0.07)	(0.09)
Observations	114,047	109,079	109,079	99,463
R squared	0.02	0.02	0.14	0.22
Firm FE	yes	yes	yes	yes
Time x Sector FE	no	no	yes	no
Time x Sector x Country FE	no	no	no	yes

Note. Robust standard errors (clustered two-way, by firm and day) are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Coefficients corresponding to the constant and fixed effects not reported.

fixed effects, which aim to account for more granular market conditions and cross-country variations. The coefficient γ remains stable at 0.07, significant at the 10% level, reinforcing the interpretation that firms with high crypto exposure are more responsive to crypto shocks even after stringent controls.

The results across these specifications indicate that while the average effect of crypto shocks on equity prices is positive, firms with greater crypto exposure exhibit stronger reactions. This pattern suggests that these firms' equity prices are more sensitive to developments in the cryptocurrency market, highlighting their strategic alignment or financial stake in crypto-related activities.

Table 5 presents a series of robustness checks on the average effect of crypto shocks on firm-level equity prices, using the baseline specification from the previous analysis as a reference. Specification (1) reiterates the baseline result, where the coefficient on the crypto shock (β) is 0.13 and significant at the 5% level.

In specification (2), we include events that overlap with macroeconomic news to test whether the exclusion of such events in the baseline biases the results. The coefficient on β decreases to 0.10 and loses statistical significance, suggesting that including overlapping events might dilute the estimated effect of pure crypto shocks due to potential confounding factors.

Table 5 Average Response of Firm-Level Equity Prices: Robustness

	(1) Baseline	(2) With Over-lap	(3) Pre 2020	(4) Post 2020	(5) Drop top 10 shocks	(6) IV
Crypto shock (β)	0.13**	0.10	-0.07	0.20***	0.20*	
	(0.06)	(0.07)	(0.06)	(0.07)	(0.11)	
Bitcoin price log-change (β)						0.14**
						(0.06)
Observations	114,047	142,155	37,593	76,451	103,290	114,047
R squared	0.02	0.01	0.05	0.05	0.01	0.00
Firm FE	yes	yes	yes	yes	yes	yes
Time x Sector FE	no	no	no	no	no	no
Time x Sector x Country FE	no	no	no	no	no	no

Note. Robust standard errors (clustered two-way, by firm and day) are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Coefficients corresponding to the constant and fixed effects not reported.

Specification (3) restricts the sample to the period before 2020, which captures an earlier phase of cryptocurrency adoption and regulatory landscape. Here, the coefficient becomes negative at -0.07, indicating that in the earlier period, crypto shocks did not lead to positive average effects on firm equity prices. This contrast highlights the evolving relationship between crypto markets and traditional equity markets over time.

In specification (4), we analyze the period post-2020, a time marked by increased institutional adoption and mainstream integration of cryptocurrencies. The coefficient on β increases to 0.20 and is significant at the 1% level, demonstrating that the impact of crypto shocks on firm equity prices has strengthened in more recent years, likely due to higher exposure and engagement by firms in the cryptocurrency space.

Specification (5) tests the robustness of the results by excluding the top 10 largest shocks from the sample. The estimated coefficient remains positive at 0.20, though only significant at the 10% level, indicating that the baseline result is not solely driven by extreme events.

Lastly, specification (6) employs an instrumental variable (IV) approach using the Bitcoin price log-change to instrument for crypto shocks. The coefficient on β is 0.14 and significant at the 5% level, reinforcing the causal interpretation of the crypto shock variable.

Overall, the robustness checks confirm the main finding that crypto shocks have a mean-

ingful average effect on equity prices, particularly in the period post-2020, while highlighting some variation based on sample restrictions and methodologies.

Table 6 provides robustness checks for the relative effect of crypto shocks on firms with high exposure, building upon the baseline results from the main analysis. In the baseline specification (Column 1), the interaction term γ capturing the differential effect on highly exposed firms shows a significant positive coefficient of 0.08 (at the 10% level), indicating that these firms experience an additional positive response in equity prices following a crypto shock.

In Column (2), we include events that overlap with macroeconomic news to test whether the baseline results are affected by potential overlaps. The coefficient on γ remains positive, albeit reduced to 0.07 and becomes statistically insignificant, suggesting that overlapping macroeconomic events might dilute the effect observed in highly exposed firms.

Table 6 Relative Response of Firm-Level Equity Prices: Robustness

	(1) Baseline	(2) With Over-lap	(3) Pre 2020	(4) Post 2020	(5) Drop top 10 shocks	(6) IV
Crypto shock x High Exposure (γ)	0.07*	0.06	-0.02	0.10**	0.09*	
	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	
High Exposure (δ)	-0.06	-0.07	0.20	-0.13	-0.08	-0.09
	(0.09)	(0.08)	(0.16)	(0.10)	(0.09)	(0.10)
Bitcoin price x High Exposure (γ)						0.09*
						(0.05)
Observations	99,463	123,413	29,677	69,783	89,699	99,463
R squared	0.22	0.25	0.20	0.28	0.24	-0.00
Firm FE	yes	yes	yes	yes	yes	yes
Time x Sector FE	no	no	no	no	no	no
Time x Sector x Country FE	yes	yes	yes	yes	yes	yes

Note. Robust standard errors (clustered two-way, by firm and day) are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Coefficients corresponding to the constant and fixed effects not reported.

Column (3) restricts the sample to pre-2020 data, a period marked by less institutional and mainstream engagement in cryptocurrencies. Here, the coefficient for γ turns negative at -0.05 and loses significance, indicating that prior to 2020, highly exposed firms did not exhibit stronger equity price reactions to crypto shocks compared to less exposed peers.

Post-2020 data are analyzed in Column (4), reflecting a time of increased mainstream and institutional cryptocurrency involvement. The coefficient on γ in this specification increases to 0.12 and achieves significance at the 5% level. This reinforces the idea that the financial landscape changed post-2020, with highly exposed firms reacting more strongly to crypto market developments.

In Column (5), we exclude the top 10 largest shocks from the sample to check if the results are driven by outliers. The interaction term γ remains significant at 0.11 (10% level), indicating that the relative effect is not unduly influenced by extreme events.

Lastly, Column (6) employs an IV approach, using Bitcoin price log-changes as an instrument for the crypto shocks. The coefficient for γ remains positive at 0.09 and is statistically significant at the 5% level, supporting the robustness of the findings and the causal interpretation of the relative effect.

Overall, the robustness checks indicate that the stronger equity price response of highly exposed firms is particularly evident in the post-2020 period and remains consistent across different methodological adjustments.

4.2 Effects on Aggregate Asset Prices

To analyze the impact of crypto shocks on aggregate asset prices, we estimate the following event-study regression:

$$y_t = \alpha + \beta s_t + \varepsilon_t$$

In this specification, y_t represents the 2-day log-change in an aggregate asset price, such as the S&P500, VIX Index, or gold price, α is a constant term, and s_t denotes the daily crypto surprise, capturing exogenous changes in the cryptocurrency market. The coefficient β measures the effect of crypto shocks on the asset price y_t, allowing us to assess whether and how broader asset markets respond to unexpected developments in the cryptocurrency sector.

Table 7 summarizes the estimated effects of crypto shocks on various aggregate asset prices. Column (1) reports the results for an index of crypto-exposed firms, where the coefficient β is 0.12 and significant at the 5% level. This suggests that, on average, crypto shocks lead to a positive 2-day log-change in the equity prices of firms heavily engaged with

the cryptocurrency market. The statistically significant response implies that such firms are notably sensitive to changes within the crypto ecosystem.

Table 7 The Effect of Crypto Shocks on Aggregate Asset Prices

	(1) Crypto-firms Index	(2) S&P500 Index	(3) Vix Index	(4) 10-year Treasury Yield	(5) Dollar Exch. Rate	(6) Gold Price	(7) Corporate Bond Spread
Crypto shock (β)	0.12**	0.07	0.03	-0.46	0.01	0.02	0.05
	(0.05)	(0.04)	(0.07)	(0.31)	(0.02)	(0.04)	(0.09)
Observations	107	107	107	107	107	107	107
R squared	0.03	0.01	0.00	0.02	0.00	0.00	0.00

Note. Robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Coefficients corresponding to the constant and fixed effects not reported.

Columns (2) through (7) present results for broader financial markets. Column (2) shows the response of the S&P500 Index, with an estimated β of 0.07, which is positive but not statistically significant. This indicates that while there may be a weak association between crypto shocks and overall equity market movements, it is not robust enough to draw firm conclusions.

Column (3) assesses the impact on the VIX Index, a measure of market volatility. The coefficient of 0.03 is positive but not significant, suggesting that crypto shocks do not substantially contribute to shifts in market risk perceptions. Column (4) presents the results for the 10-year Treasury yield, with a coefficient of -0.46 that is not statistically significant. This implies that crypto shocks do not have a discernible effect on longer-term interest rates.

In Column (5), the effect on the dollar exchange rate is negligible, with an estimated β of 0.01, while Column (6) shows a similarly small and insignificant response in the gold price ($\beta = 0.02$). These results imply that crypto shocks do not trigger significant adjustments in safe-haven assets or currency markets.

Lastly, Column (7) examines the corporate bond spread, with an estimated coefficient of 0.05, which is also not significant. This indicates that corporate credit risk, as reflected in bond spreads, remains largely unaffected by crypto market shocks.

Overall, while crypto shocks have a significant impact on firms within the crypto sector,

their influence on broader financial markets and traditional asset prices appears limited. This highlights the sector-specific nature of crypto shocks and their relatively contained effect on global financial stability.

5 The Persistence of Crypto Shocks

In this section, we analyze the dynamic propagation of crypto shocks on asset prices using a local projections framework. The objective is to estimate the impact of crypto shocks over a longer time horizon and assess how these effects evolve beyond the immediate aftermath captured in our event-study regressions. By understanding the persistence and timing of these responses, we can gauge the extent to which crypto shocks influence asset prices in the medium term.

To conduct this analysis, we aggregate our data at a weekly frequency. This involves summing the daily crypto shocks within each week and calculating the average of daily asset prices to form a consistent time series. This approach allows us to move beyond high-frequency responses and examine how shocks propagate over the subsequent weeks, shedding light on the potential lagged effects on both firm-level and aggregate asset prices.

5.1 Average Effect

To assess the dynamic effects of crypto shocks on asset prices, we estimate the following panel local projection specification:

$$y_{it} = \alpha_i + \beta s_t + \sum_{p=0}^{4} \phi_p y_{i,t-p} + \sum_{p=0}^{4} \Gamma_p Z_{t-p} + \varepsilon_{it}$$

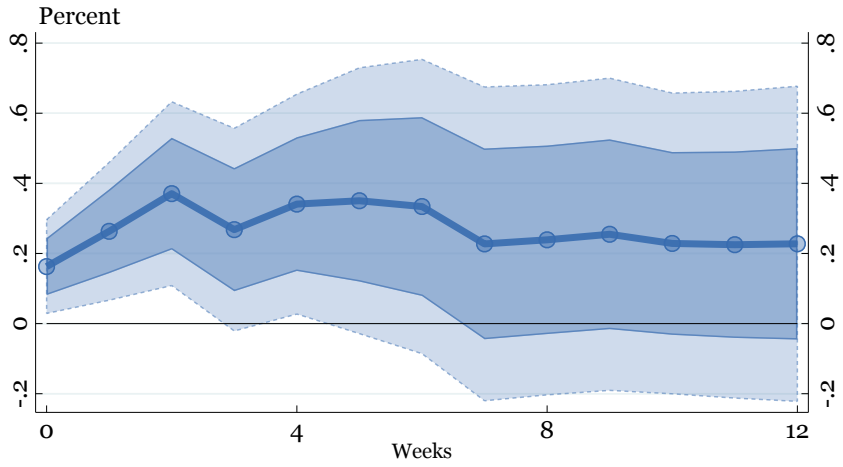
In this model, y_{it} represents the weekly equity price for firm i, α_i denotes firm fixed effects, which account for time-invariant characteristics of each firm, s_t is the weekly crypto surprise, aggregated as the sum of daily surprises within each week, and Z_t is a vector of control variables, including the global economic surprise index, the VIX index, the BTC price, the gold price, and a time trend, which helps isolate the specific impact of crypto shocks.

The specification includes lags of both the dependent variable ($\sum_{p=0}^{4} \phi_p y_{i,t-p}$) and control variables ($\sum_{p=0}^{4} \Gamma_p Z_{t-p}$) to account for potential autocorrelation and delayed responses in equity prices. Standard errors are clustered two-way by firm and week to ensure robust

inference. The coefficient β captures the average effect of crypto shocks on equity prices across the cross-section of firms, providing insight into the propagation of these shocks over the studied period.

Figure 8 illustrates the average effect of crypto shocks on the equity prices of firms with varying degrees of exposure. The estimation is based on the panel local projection specification described earlier, with crypto shocks scaled to reflect a 1% increase in Bitcoin prices at a daily frequency. This approach allows us to observe how firm-level equity prices evolve in response to a standardized crypto shock over several weeks.

Figure 8 Average Response of Equity Prices



Note. Average effect of a crypto shock (scaled to lead to a 1% increase in Bitcoin prices at daily frequency) on firm-level equity prices. Shaded areas show 68% and 90% confidence intervals based on robust standard errors clustered two-way (at the sector-week level).

The estimated impact shows an immediate positive response in equity prices of about 0.15% following a crypto shock, with the effect peaking within the first week. The confidence intervals, represented by shaded areas at the 68% and 90% levels, indicate the statistical reliability of these effects. While the positive impact remains discernible over the subsequent weeks, it gradually diminishes, suggesting a mean-reverting behavior in equity prices after the initial shock.

These findings highlight the short-term responsiveness of crypto-exposed firms' equity prices to shocks in the cryptocurrency market, followed by a stabilization phase. This pattern underscores the initial sensitivity and subsequent adjustment of firm valuations to crypto-driven developments.

5.2 Heterogeneous Effects

To capture the heterogeneous impact of crypto shocks on equity prices, we extend our local projection framework by incorporating sectoral and exposure-level differences. Specifically, we estimate the following specification:

$$y_{it} = \alpha_i + \alpha_{sct,k,t} + \gamma \left(s_t \times CryptoExpo_{i,\tau-1}^{High} \right) + \sum_{p=0}^{4} \phi_p y_{i,t-1} + \varepsilon_{it}$$

In this setup, y_{it} represents the weekly equity price for firm i, while α_i denotes firm fixed effects that control for time-invariant characteristics specific to each firm. The inclusion of $\alpha_{sct,k,t}$, which are time-by-sector-by-country fixed effects, allows us to account for macroeconomic and sector-specific conditions that may vary over time and across regions.

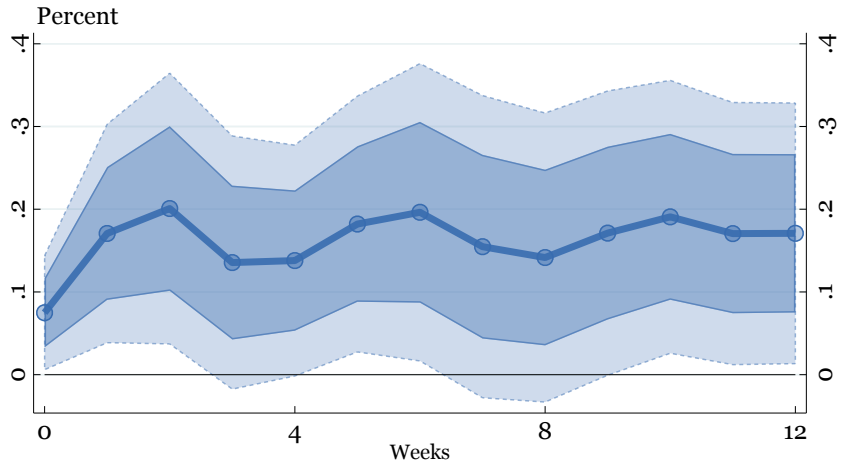
The variable s_t is the weekly crypto surprise, aggregated from the sum of daily surprises within each week, and $CryptoExpo_{i,\tau-1}^{High}$ is a binary indicator equal to 1 if the firm's exposure in the previous quarter (τ) is above the median. The interaction term $s_t \times CryptoExpo_{i,\tau-1}^{High}$ enables the estimation of γ, which captures the relative effect of crypto shocks on the equity prices of highly exposed firms.

The model also includes lags of the dependent variable, $\sum_{p=0}^{4} \phi_p y_{i,t-1}$, to control for potential autocorrelation in equity price changes. Standard errors are clustered two-way by firm and week to ensure robust statistical inference. This specification thus provides a framework for understanding the differentiated responses to crypto shocks across various sectors and firms with high levels of exposure.

Figure 9 presents the results of the local projections estimation, focusing on the relative effect of crypto shocks on firms with high crypto exposure. The estimated response captures the additional impact of crypto shocks on equity prices for firms with above-median crypto exposure, scaled to represent a 1% increase in Bitcoin prices at a daily frequency.

The chart indicates that firms with high exposure to cryptocurrencies exhibit a notably larger and persistently positive response to crypto shocks compared to their less-exposed counterparts. This relative effect is most pronounced within the first week following the shock, with the response peaking at 0.2%shortly after the initial event. The shaded areas, representing the 68% and 90% confidence intervals, suggest that the effect is statistically significant during the initial days and gradually persists over time, pointing to a diminishing impact as market conditions stabilize.

Figure 9 Relative Response: Highly Exposed Firms



Note. Relative effect of a crypto shock (scaled to lead to a 1% increase in Bitcoin prices at daily frequency) on firm-level equity prices for firms with high crypto exposure. Shaded areas show 68% and 90% confidence intervals based on robust standard errors clustered two-way (at the sector-week level).

The results underscore the heightened sensitivity of crypto-exposed firms to shocks in the cryptocurrency market, highlighting how firms' equity valuations adjust in the wake of significant crypto-related developments. This finding aligns with the hypothesis that firms with greater involvement or investment in cryptocurrency activities react more strongly to shifts in crypto market sentiment.

6 Conclusion

This paper investigates the impact of crypto shocks on both firm-level and aggregate asset prices, using a novel approach that combines narrative identification with high-frequency event study techniques. Our study moves a first step towards understanding how cryptocurrency market dynamics can influence traditional financial markets. While the direct implications of crypto shocks on aggregate asset prices, such as the S&P 500 or corporate bond spreads, appear limited, the effects on firms with significant crypto exposure are pronounced and immediate.

One key takeaway from our analysis is that, although the influence of crypto shocks on broad financial stability is currently restrained by the relatively limited exposure of most traditional firms and financial institutions, these shocks still pose potential risks. The fact

that equity prices of crypto-exposed firms exhibit significant responses to such shocks highlights the importance of monitoring risks from cryptocurrency markets. As adoption and integration of cryptocurrencies expand, the transmission channels of crypto shocks may become more significant, suggesting that policymakers should keep monitoring the integration of cryptocurrencies into the traditional financial system.

From a regulatory perspective, adapting frameworks to address the unique characteristics and potential systemic implications of cryptocurrencies will be critical. This is especially pertinent as technological adoption advances and more firms engage with crypto assets either directly or indirectly. A deeper understanding of the transmission mechanisms of crypto shocks—whether through balance sheet exposures or operational dependencies—will help refine policy responses and risk management strategies.

Our findings lay the groundwork for future research into the real effects of crypto exposure at the firm level, including whether such exposure translates into shifts in investment, employment, or broader operational decisions. Further investigation into these aspects will enhance our comprehension of the crypto market's role within the larger financial system and help inform more robust regulatory and oversight practices.

In summary, while crypto is not the most pressing risk for financial stability at present, it holds the potential for significant influence as exposure grows. The evolution of this sector should be watched closely, with proactive measures taken to ensure that emerging risks can be managed effectively.

References

Adrian, T., T. Iyer, and M. S. Qureshi (2022): "Crypto prices move more in sync with stocks, posing new risks," *IMF Blog*.

Ahir, H., N. Bloom, and D. Furceri (2022): "The World Uncertainty Index," *NBER Working Papers, 29763*.

Aiello, D., S. R. Baker, T. Balyuk, M. DiMaggio, M. J. Johnson, and J. D. Kotter (2023): "The Effects of Cryptocurrency Wealth on Household Consumption and Investment," *NBER Working Papers, 31445*.

Aldasoro, I., M. Ferrari Minesso, L. Gambacorta, M. M. Habib, and G. Cornelli (2024): "Stablecoins, money market funds and monetary policy," *ECB Working Paper No. 2024/2987*.

Benigno, G. and C. Rosa (2023): "The Bitcoin–Macro Disconnect," *FRB of New York Staff Report*.

Bloom, N., T. A. Hassan, A. Kalyani, J. Lerner, and A. Tahoun (2021): "The Diffusion of Disruptive Technologies," *NBER Working Paper Series, 26609*.

Caldara, D. and M. Iacoviello (2022): "Measuring Geopolitical Risk," *American Economic Review*, 112, 1194–1225.

Che, M. N. X., A. Copestake, D. Furceri, and T. Terracciano (2023): "The Crypto Cycle and US Monetary Policy," *IMF Working Papers, 2023/163*.

Cloyne, J. (2013): "Discretionary Tax Changes and the Macroeconomy: New Narrative Evidence from the United Kingdom," *American Economic Review*, 103, 1507–1528.

Divakaruni, A. and P. Zimmerman (2024): "Uncovering Retail Trading in Bitcoin: The Impact of COVID-19 Stimulus Checks," *Management Science*, 70, 2066–2085.

Fernald, J. G. (2012): "A quarterly, utilization-adjusted series on total factor productivity," *Federal Reserve Bank of San Francisco Working Paper Series, 2012-19*.

Gertler, M. and P. Karadi (2015): "Monetary Policy Surprises, Credit Costs, and Economic Activity," *American Economic Journal: Macroeconomics*, 7, 44–76.

Gürkaynak, R. S., B. Sack, and E. Swanson (2005): "Do Actions Speak Louder Than Words? The Response of Asset Prices to Monetary Policy Actions and Statements," *International Journal of Central Banking*.

Hassan, T. A., S. Hollander, L. van Lent, M. Schwedeler, and A. Tahoun (2023a): "Firm-Level Exposure to Epidemic Diseases: COVID-19, SARS, and H1N1," *The Review of Financial Studies*.

Hassan, T. A., S. Hollander, L. van Lent, and A. Tahoun (2019): "Firm-Level Political Risk: Measurement and Effects," *The Quarterly Journal of Economics*, 134, 2135–2202.

——— (2023b): "The Global Impact of Brexit Uncertainty," *The Journal of Finance*.

Hassan, T. A., J. Schreger, M. Schwedeler, and A. Tahoun (2023c): "Sources and Transmission of Country Risk," *The Review of Economic Studies*.

Karau, S. (2023): "Monetary policy and Bitcoin," *Journal of International Money and Finance*, 137.

Känzig, D. R. (2021): "The Macroeconomic Effects of Oil Supply News: Evidence from OPEC Announcements," *American Economic Review*, 111, 1092–1125.

Romer, C. D. and D. H. Romer (2004): "A New Measure of Monetary Shocks: Derivation and Implications," *American Economic Review*, 94, 1055–1084.

——— (2010): "The Macroeconomic Effects of Tax Changes: Estimates Based on a New Measure of Fiscal Shocks," *American Economic Review*, 100, 763–801.

Somoza, L. and A. Didisheim (2022): "The End of the Crypto-Diversification Myth," *Swiss Finance Institute Research Paper Series*.

Weber, M., B. Candia, O. Coibion, and Y. Gorodnichenko (2023): "Do You Even Crypto, Bro? Cryptocurrencies in Household Finance," *NBER Working Paper Series, 31284*.

Appendix

A Crypto Surprises

Table A.1 Summary Statistics of Crypto Surprise Events

	Shock (1 hour)	Shock (2 hour)	Shock (4 hour)
Mean	0.01	-0.01	-0.02
Median	0.00	0.00	0.00
Standard Dev.	0.47	0.77	0.80
Minimum	-3.42	-11.76	-9.32
Maximum	8.32	12.63	10.07
Observations	1539	1539	1539

Note. Summary statistics for the daily crypto surprises. The sample covers the period between Jan 2017 and 31 Dec 2022.

Figure A.1 Distribution of Crypto Surprises

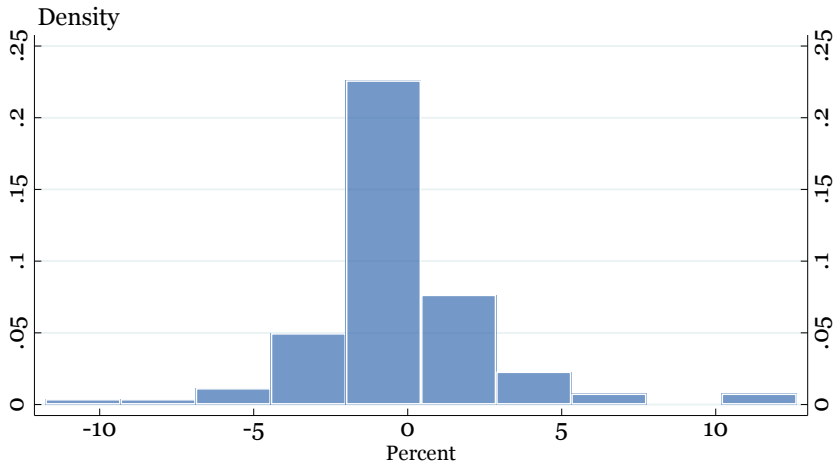


Figure A.2 Distribution of Crypto Surprises by Year

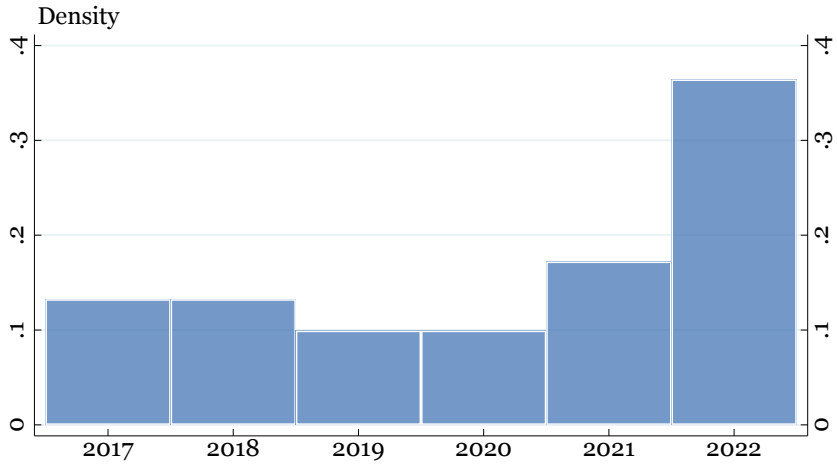


Figure A.3 Distribution of Crypto Surprises by Quarter

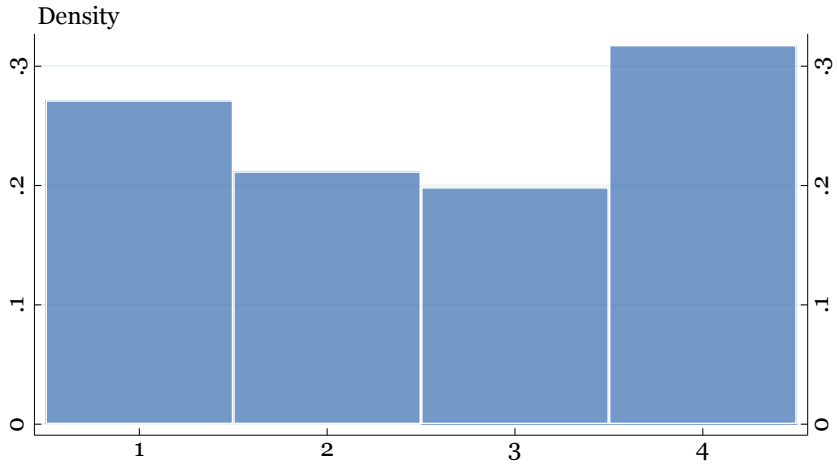


Figure A.4 Distribution of Crypto Surprises by Hour

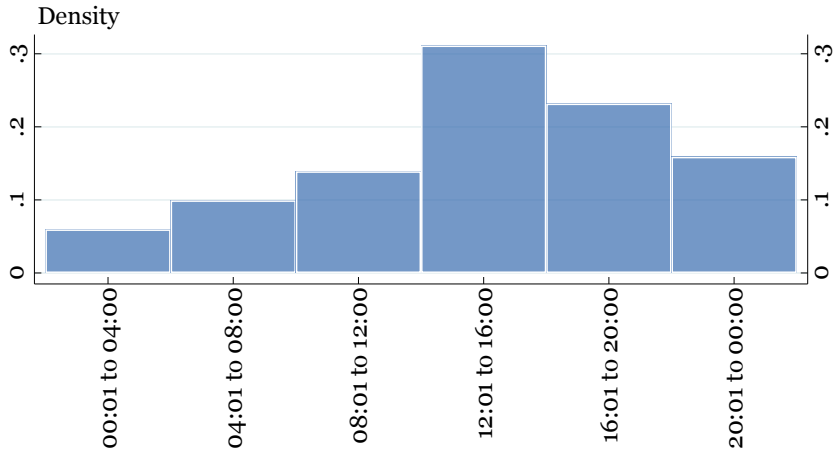


Figure A.5 Autocorrelation of Crypto Surprises

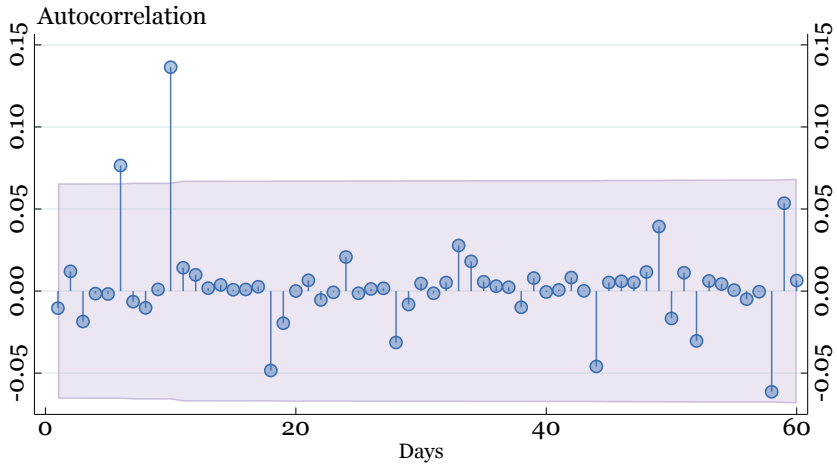
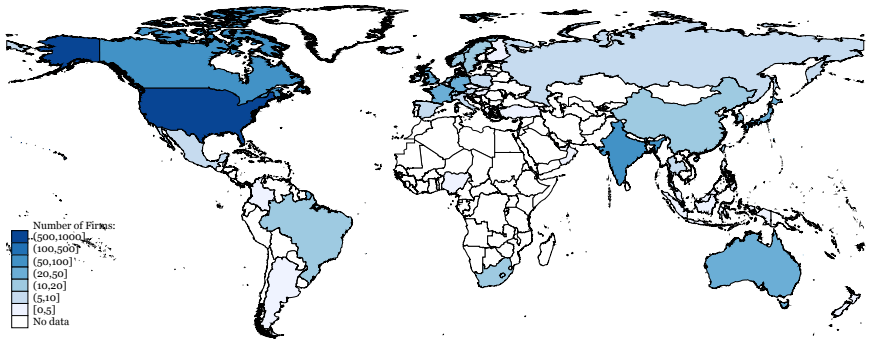


Table A.2 Correlation of Crypto Surprises with Other Shocks

Shock/Index	**Source**	ρ
Oil	Känzig (2021)	0.21
Monetary	Gertler and Karadi (2015)	-0.12
Geopolitical Risk	Caldara and Iacoviello (2022)	-0.14
TFP	Fernald (2012)	0.07
World Uncertainty	Ahir et al. (2022)	-0.08

B Crypto Exposure

Figure B.1 Geographic breakdown of Crypto-Exposure



Note. The colour intensity indicates the average crypto exposure of crypto-exposed firms in each country.

Table B.1 Top 50 firms by average crypto-exposure

Company	Sector	Country	Avg Exposure
BAKKT HOLDINGS A	Financials	US	19.58
GALAXY DIGITAL HOLDINGS	Financials	KY	16.06
COINBASE GLOBAL A	Financials	US	15.11
HUT 8 MINING	IT	CA	13.03
HALO COLLECTIVE DEAD - DELIST.15/08/23	Materials	CA	12.35
MAWSON INFRASTRUCTURE GROUP	IT	US	11.79
CLEANSPARK	IT	US	10.72
MONEX GROUP	Financials	JP	10.01
SILVERGATE CAPITAL A	Materials	US	9.67
WISDOMTREE	Financials	US	9.18
MICROSTRATEGY	IT	US	8.43
FRMO	Financials	US	7.28
COMPOSECURE A	Industrials	US	7.05
ARGO BLOCKCHAIN	IT	GB	7.02
ROBINHOOD MARKETS A	Financials	US	6.78
PAYSAFE	Industrials	BM	6.23
GMO INTERNET GROUP	IT	JP	6.18
MARATHON DIGITAL HOLDINGS	Financials	US	5.96
US GLOBAL INVRS.	Financials	US	4.73
NUVEI SUBORDINATE VOTING	Industrials	CA	2.59
SBI HDG.	Financials	JP	2.18
SOFI TECHNOLOGIES	Financials	US	2.01
BLOCK A	Industrials	US	1.67
FLOW TRADERS	Financials	BM	1.56
YEAHKA	Industrials	KY	1.51
MONEYGRAM INTL. DEAD - DELIST.02/06/23	Financials	US	1.44
FLATEXDEGIRO N	Financials	DE	1.44
METROPOLITAN BANK HDG.	Financials	US	1.40
PAYPAL HOLDINGS	Industrials	US	1.35
TASKUS A	Industrials	US	1.20
OVERSTOCK COM	ConsumerDisc	US	1.18
USIO	Industrials	US	1.10
VIRTU FINANCIAL CL.A	Financials	US	1.09
NVIDIA	IT	US	1.06
ALKAMI TECHNOLOGY	IT	US	1.06
GAMESTOP 'A'	ConsumerDisc	US	1.05
VERSABANK	Financials	CA	1.01
IG GROUP HOLDINGS	Financials	GB	1.00
CME GROUP	Financials	US	0.97
TAIWAN SEMICON.MNFG.	IT	TW	0.96
LEONTEQ	Financials	CH	0.95
MASTERCARD	Industrials	US	0.93
CBOE GLOBAL MARKETS(BTS)	Financials	US	0.89
VISA 'A'	Industrials	US	0.86
GOLD ROYALTY	Materials	CA	0.85
SIGNATURE BANK	Financials	US	0.84
DATA COMMS.MAN.	Industrials	CA	0.76
SHIFT4 PAYMENTS A	Industrials	US	0.68
NASDAQ	Financials	US	0.68
ASUSTEK COMPUTER	IT	TW	0.67

Note. This table lists the 50 companies associated with the highest average exposure across the sample as measured by the number of mentions of crypto-related keywords in their earning calls. *Legend:* BM = Bermuda, CA = Canada, CH = Switzerland, DE = Germany, GB = Great Britain, JP = Japan, KY = Cayman Islands, TW = Taiwan, US = United States.

C Event Study - Additional Results

Table C.1 The Response of Firm-Level Equity Prices: Linear interaction

	(1)	(2)	(3)	(4)
Crypto shock (β)	0.13**	0.14***		
	(0.05)	(0.05)		
Crypto shock x Exposure (γ)		0.03	0.03	0.03
		(0.03)	(0.02)	(0.03)
Exposure (δ)		-0.22**	-0.18***	-0.18***
		(0.09)	(0.07)	(0.06)
Observations	114,047	109,079	109,079	99,463
R squared	0.02	0.02	0.14	0.23
Firm FE	yes	yes	yes	yes
Time x Sector FE	no	no	yes	no
Time x Sector x Country FE	no	no	no	yes

Note. Robust standard errors (clustered two-way, by firm and day) are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Coefficients corresponding to the constant and fixed effects not reported.

D Local Projections - Additional Results

Figure D.1 Weekly crypto surprises

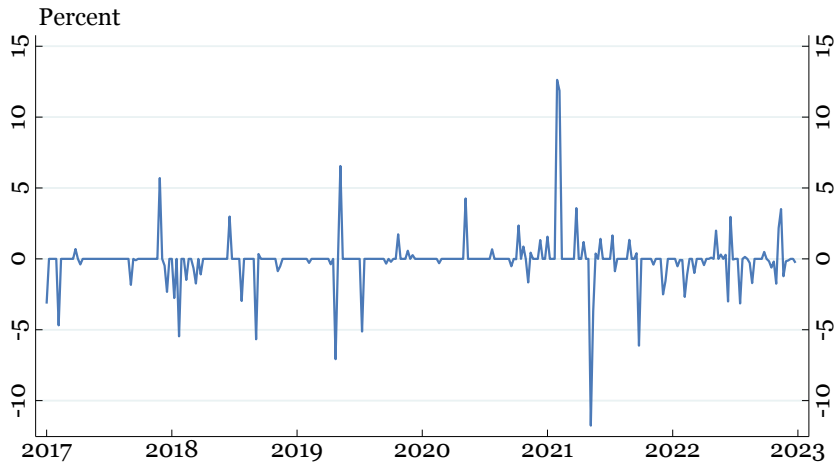


Figure D.2 Weekly crypto surprises: Distribution

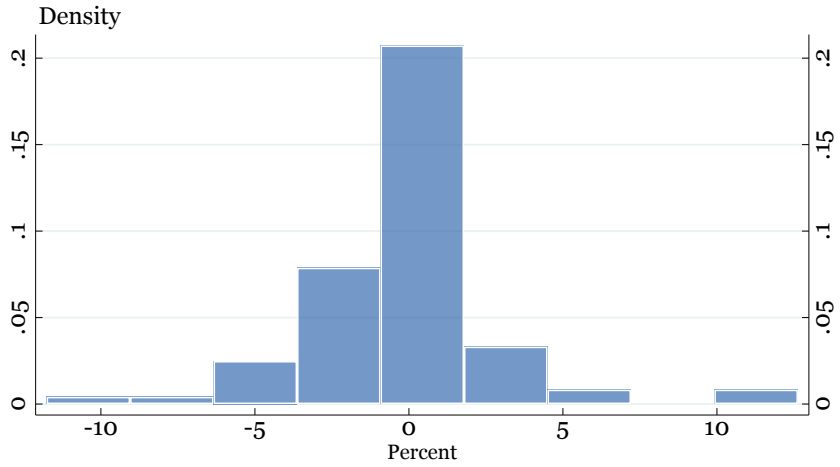


Figure D.3 Weekly crypto surprises: Autocorrelation

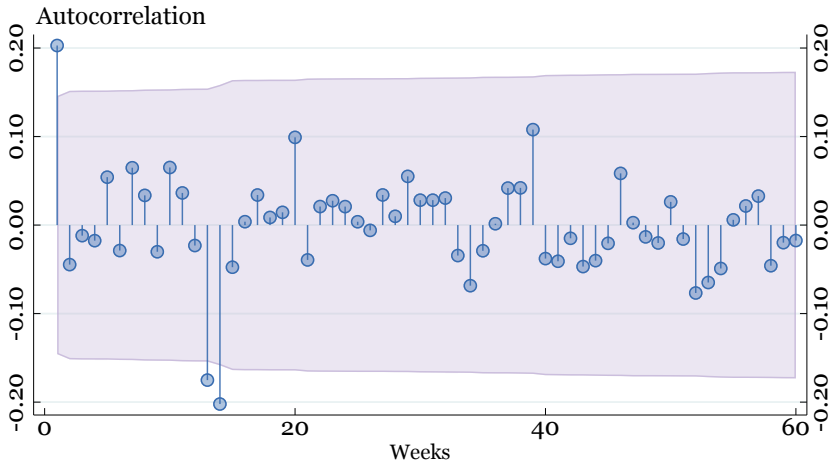


Table D.1 Weekly crypto surprises: Summary statistics

	Shock (1 hour)	Shock (2 hour)	Shock (4 hour)
Mean	0.04	-0.07	-0.09
Median	0.00	0.00	0.00
Standard Dev.	1.02	1.71	1.74
Minimum	-4.39	-11.76	-8.87
Maximum	9.60	12.63	9.94
Observations	312	312	312

Note. Summary statistics for the weekly surprises (sum of daily surprises over each week). The sample covers the period between 2017w1 and 2022w52.