Crypto Shocks[☆]

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Abstract

Can fluctuations in cryptocurrency prices *cause* movements in traditional financial asset prices? To investigate this question, we construct a new series of crypto shocks—exogenous changes in cryptocurrency prices that are unrelated to developments in the real economy or traditional financial markets. We identify these shocks by combining narrative, high-frequency, and large language model (LLM) approaches: selecting cryptocurrency-specific events from Reuters news coverage, measuring Bitcoin price responses within a two-hour window, and using an LLM to validate each event's narrative classification. We estimate the effects of these shocks on firm-level stock prices using event study and local projection methods, exploiting variation across time and firms. To capture firms' exposure to cryptocurrency markets, we use text analysis of earnings call transcripts to build a quarterly crypto-exposure measure for 1,234 publicly listed firms across more than 50 countries. Our results show that crypto shocks significantly affect the stock prices of firms exposed to cryptocurrency markets, with more exposed firms experiencing stronger reactions. We explore the underlying mechanisms and find evidence of strong balance sheet effects.

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

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

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1 Introduction

The rapid adoption of cryptocurrencies over the past decade, together with their increasing comovement with traditional asset prices, has raised concerns about their potential implications for financial stability.[1] While these correlations are well documented, the direction of causality remains unclear. This raises a central question: do shocks originating in cryptocurrency markets spill over to traditional financial assets, or do these comovements simply reflect common macroeconomic and financial forces?

Answering this question is challenging because cryptocurrency prices respond to a wide range of global developments, including macroeconomic news, changes in risk sentiment, and shifts in monetary policy. As a result, simple correlations between crypto and traditional asset prices cannot be interpreted causally. To make progress, one needs to isolate variation in cryptocurrency prices that is plausibly exogenous to broader economic conditions.

We address this identification challenge by constructing a novel series of exogenous cryptocurrency shocks. Our approach combines narrative and high-frequency identification techniques. Building on Romer and Romer (2004), we use narrative evidence from Reuters news coverage to identify cryptocurrency-specific events that are plausibly unrelated to developments in the real economy and traditional financial markets. A key contribution of the paper is the construction of a new, systematically curated dataset of such events between 2017 and 2024.

The dataset is assembled using a structured two-stage procedure. We first identify candidate crypto-related events based on news coverage. We then validate each event by combining human assessment with a large language model, which evaluates whether observed intraday Bitcoin price movements are consistent with the narrative and not driven by confounding information. Only events that pass this validation are retained. This approach preserves the strengths of traditional narrative identification—careful economic judgment and exogeneity assessment—while introducing a scalable and replicable framework for event selection.

The resulting dataset documents a wide range of events, including exchange hacks, regulatory announcements, technological disruptions, and changes in corporate policies regarding cryptocurrencies. For each event, we measure the high-frequency response of Bitcoin prices—the largest and most liquid cryptocurrency—within a two-hour window surrounding the event, following Gürkaynak et al. (2005). We then aggregate these responses into

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

a daily measure of crypto surprises, which captures unexpected changes in cryptocurrency valuations.

We study the transmission of these shocks to equity markets using both time-series and cross-sectional variation. We estimate their effects on firm-level stock prices using event study and local projection methods. A key ingredient of our analysis is a novel measure of firms' exposure to cryptocurrency markets. To construct this measure, 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 cryptocurrency-related discussions, we build a quarterly measure of firm-level exposure that captures the extent to which firms are affected by developments in cryptocurrency markets. Our dataset covers 1,234 firms across more than 50 countries over the period 2017–2024.

To shed light on the underlying mechanisms, we complement this approach with a detailed firm-level narrative analysis of the most exposed firms. Focusing on the top 200 firms in the exposure distribution, we use a structured classification procedure to identify the specific channels through which cryptocurrency developments affect firm value, including direct balance sheet exposures, revenue linkages, and strategic involvement in crypto-related activities. This allows us to move beyond reduced-form evidence and provide direct insight into the economic mechanisms underlying the transmission of crypto shocks.

Our empirical analysis yields two main findings. First, crypto shocks have economically and statistically significant effects on the stock prices of firms exposed to cryptocurrency markets. Firms with higher exposure exhibit larger and more persistent responses, consistent with heterogeneous transmission of cryptocurrency shocks across firms. Second, these effects are primarily driven by firms with direct and economically meaningful links to cryptocurrency markets, in line with the mechanisms identified in the firm-level analysis. At the same time, we find limited evidence of spillovers to aggregate financial markets. Crypto shocks do not systematically affect broad equity indices, such as the S&P 500, nor do they significantly influence measures of financial volatility, corporate credit spreads, or government bond yields. These results suggest that while cryptocurrency fluctuations can have meaningful effects at the firm level, their aggregate impact on traditional financial markets remains limited.

Our paper contributes to a growing literature studying the interaction between cryptocurrency markets and traditional financial assets. Adrian et al. (2022) document increasing correlations between cryptocurrencies and equity markets, but do not establish causality. Several studies show that macroeconomic policies affect cryptocurrency prices (Che et al., 2023a; Divakaruni and Zimmerman, 2024; Karau, 2023), while others find limited responses

of crypto markets to macroeconomic news (Benigno and Rosa, 2023; Aldasoro et al., 2025). Somoza and Didisheim (2022) argue that comovement may be driven by investor behavior. Relative to this literature, our key contribution is to provide a new identification strategy that isolates plausibly exogenous shocks originating within cryptocurrency markets and allows us to trace their causal effects on traditional financial assets.

Methodologically, our paper relates to the literature combining narrative identification (Romer and Romer, 2004, 2010; Cloyne, 2013) with high-frequency approaches (**?**Känzig, 2021) to isolate exogenous shocks. Our contribution is to extend this framework along two dimensions. First, we introduce a structured two-stage validation procedure that combines human judgment with a large language model to systematically assess the consistency between news narratives and high-frequency price responses, and to rule out confounding events. This yields a scalable and transparent approach to constructing narrative shock series. Second, we integrate this identification strategy with text-based measures of firm exposure following Hassan et al. (2019); Bloom et al. (2021); Hassan et al. (2023a,c,b), allowing us to connect exogenous shocks to heterogeneous firm-level outcomes and to study the transmission of crypto shocks across firms.

Finally, our work relates to studies examining the real effects of cryptocurrency wealth. Aiello et al. (2023) and Weber et al. (2023) show that fluctuations in crypto wealth affect household consumption and durable purchases. We complement this literature by focusing on asset prices and by providing evidence on the transmission of crypto shocks to equity markets. Importantly, we go beyond reduced-form evidence by combining cross-sectional variation in exposure with firm-level narrative analysis of the most exposed firms, which allows us to shed light on the economic mechanisms underlying these effects. Our results show that cryptocurrency shocks transmit to the stock prices of exposed firms, primarily through firms with direct economic links to crypto markets, while having limited aggregate financial effects.

2 Identifying Crypto Shocks

Our empirical strategy is designed to identify exogenous fluctuations in cryptocurrency prices and to study their effects on traditional financial assets. The key challenge is to isolate variation in cryptocurrency prices that is orthogonal to developments in the real economy and broader financial markets.

To address this challenge, we construct a novel series of cryptocurrency shocks by com-

bining narrative and high-frequency identification techniques. We assemble a new dataset of cryptocurrency-related events and isolate those that are plausibly unrelated to macroeconomic and financial conditions. A key contribution of our approach is to make narrative identification feasible in an environment with no predefined event set, by combining disciplined human reading with a structured and reproducible validation procedure. This approach allows us to systematically identify economically meaningful events while preserving the economic judgment required to assess their exogeneity, thereby extending traditional narrative identification methods. For each event, we measure the high-frequency response of Bitcoin prices within a narrow time window around the event. These high-frequency price changes capture unexpected movements in cryptocurrency valuations and serve as a proxy for exogenous crypto shocks.

2.1 A Novel Approach to Narrative Analysis

A central challenge in applying narrative identification to cryptocurrency markets is that, unlike in standard macroeconomic applications, the universe of potential events is not predefined. In settings such as monetary policy, researchers can focus on a known and finite set of policy announcements. In contrast, the cryptocurrency sector generates a continuous and high-volume flow of heterogeneous news, spanning regulatory actions, technological developments, exchange incidents, and public statements. As a result, the identification of relevant events requires a systematic and scalable procedure to screen a large and evolving information set.

To address this challenge, we develop a structured approach to narrative analysis that combines human identification with algorithmic validation. Our procedure builds on the four principles for rigorous narrative identification emphasized by Romer and Romer (2004): the use of a reliable contemporaneous source, a clear definition of the target events, a dispassionate and consistent reading of the source, and detailed documentation of the evidence. We extend this framework by introducing a large language model (LLM) as a structured and reproducible second reader in the validation stage, thereby enhancing the scalability and transparency of the narrative approach.

We begin by constructing a comprehensive corpus of cryptocurrency-related news using the Reuters News Archive, which provides a real-time, timestamped, and globally consistent record of events. We restrict attention to English-language Reuters articles identified through the Refinitiv query reported below, to select the universe of the news concerning

the cryptocurrency markets released by Reuters in English:

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CRYCUR AND RTRS AND LEN NEWS2.0
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From this universe, we preselect candidate events through a systematic human screening procedure. Following the principles of narrative identification, each article is read individually and evaluated based on whether it contains new, economically meaningful, and unanticipated information specific to the cryptocurrency sector. We retain only events that plausibly correspond to discrete information arrivals and are orthogonal to contemporaneous macroeconomic and financial developments. In particular, we exclude articles that overlap with major macroeconomic announcements or broader policy measures that could confound the interpretation of price movements.

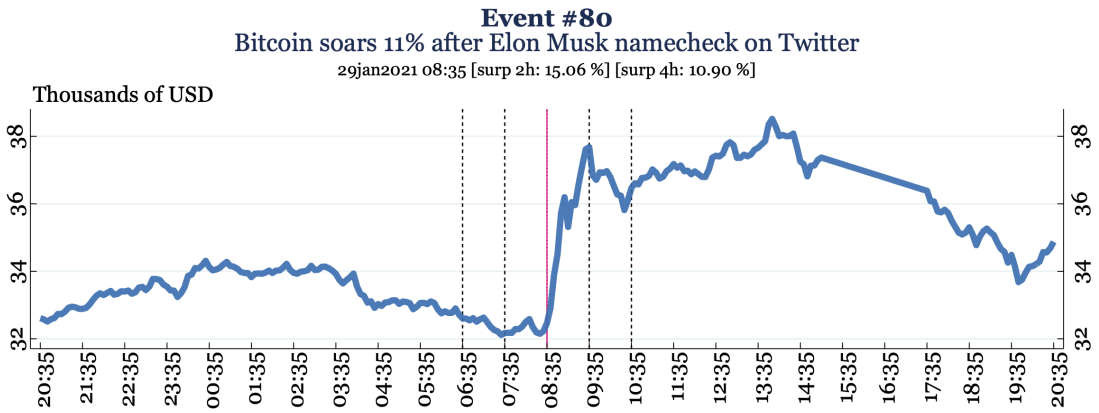
The screening is guided by a set of explicit and consistently applied criteria. We exclude events that are not economically significant for cryptocurrency markets, such as news related to central bank digital currencies, stablecoins, or the launch of new exchanges. We also remove events that are unlikely to be exogenous, including anticipated announcements and trading disruptions driven by endogenous market conditions. In addition, we discard events that are potentially contaminated by broader policy developments, such as cryptocurrency investment taxation measures or international sanctions announced jointly with other macroeconomic policies. Finally, we exclude enforcement actions targeting individual violations and other idiosyncratic developments that do not represent systematic shocks to the cryptocurrency sector.

After applying these filters, we retain a set of events that reflect significant and unanticipated developments in cryptocurrency markets. These events are then classified into economically meaningful categories—such as regulatory, adoption, and sentiment shocks—which are used in subsequent analysis. The resulting dataset provides a transparent and disciplined foundation for the identification of exogenous cryptocurrency shocks in an environment characterized by a large and unstructured flow of information.

To illustrate the type of events captured by our approach, we consider a prominent example. On January 29, 2021, at 08:21 (GMT), Elon Musk updated his Twitter profile to include the hashtag #bitcoin and posted the message “In retrospect, it was inevitable.” Although this action did not reflect any change in macroeconomic conditions or policy, it conveyed new information to market participants regarding the stance of a highly influential figure toward cryptocurrency markets.

Figure 1 shows the intraday evolution of Bitcoin prices around the event. Within minutes of the update, Bitcoin prices increased sharply, rising by approximately $5,000 within an hour. The timing and magnitude of the response indicate that the price movement was closely aligned with the arrival of this crypto-specific news.

Figure 1 An Example of a Crypto Surprise



Note. The figure shows the 5-minute evolution of Bitcoin prices in the three hours before and after Elon Musk's Twitter endorsement of Bitcoin on January 29, 2021, at 08:21 (GMT).

In a second stage, each candidate event is evaluated against high-frequency Bitcoin price data. This validation step serves to discipline the narrative identification by confronting each event with the market's contemporaneous reaction. Specifically, we match each event to intraday Bitcoin prices and examine price dynamics in a ±12-hour window around the event timestamp. The objective is to determine whether the observed price movement is temporally aligned with the news and consistent with its economic interpretation.

We implement this validation using two independent approaches. First, human researchers re-examine each event by jointly considering the original Reuters article and the corresponding intraday price chart. Using a structured classification framework, events are assigned to four categories: `Matched`, when the price response aligns with the news; `No Move`, when no meaningful price response is observed; `Mismatch`, when the direction of the price movement contradicts the narrative; and `Polluted`, when attribution is confounded by other contemporaneous developments.

Second, we conduct a parallel validation using a large language model (LLM), which is provided with event metadata and a standardized intraday price chart. The LLM follows a fully pre-specified and reproducible decision procedure to classify each event and conducts a structured search of contemporaneous news sources to identify potential confounding events. This allows for a systematic assessment of whether price movements are consistent with the

narrative interpretation.

Only events classified as `Matched` are retained for the analysis. In the baseline specification, we focus on the intersection of the two validation procedures—that is, events classified as `Matched` by both human and LLM validators. This intersection sample provides a conservative set of shocks that satisfy both narrative and price-based criteria under two independent classification methods.

The dual-validation design serves two purposes. First, it strengthens identification by requiring consistency between the narrative and high-frequency price evidence. Even if an event appears economically relevant based on the narrative alone, it is discarded unless it generates a clear and timely market response. Second, it allows us to assess the extent to which narrative classification can be systematized. The use of an LLM as a second reader allows us to implement a fully specified and reproducible decision procedure for validating narrative events, reducing discretion in the classification of borderline cases and enabling systematic identification at scale.

From an identification perspective, the dual-validation framework plays a central role. By requiring consistency between the narrative evidence and high-frequency price responses, and by cross-validating events across two independent procedures, we substantially reduce the risk of including spurious or contaminated observations.

Overall, our methodology extends the narrative identification tradition by combining three elements: systematic event discovery from a large and unstructured information set, high-frequency validation based on market responses, and dual classification using both human judgment and a fully specified algorithmic procedure. This combination allows us to construct a shock series that is both economically interpretable and empirically disciplined, providing a credible basis for causal inference.

2.2 Construction of Crypto Surprises

Our high-frequency identification approach measures the high-frequency response of Bitcoin prices to each selected event, 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 cryptocurrency-specific news, 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.

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:

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

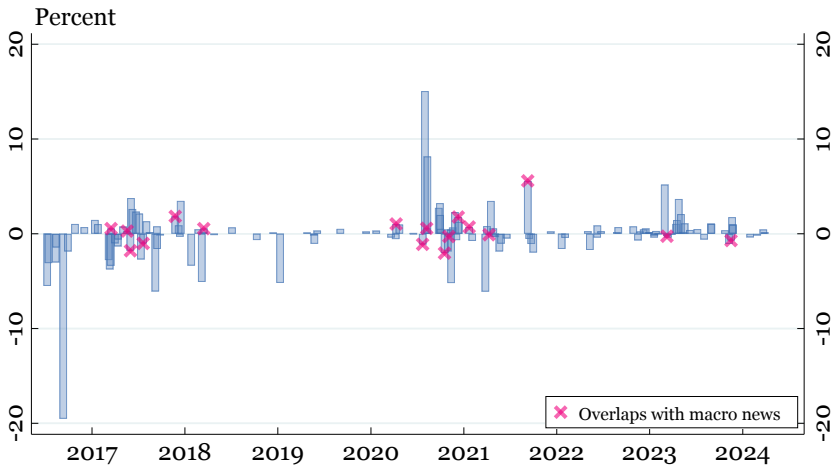
Our intraday surprises are aggregated to a daily series as follows. When there is only one announcement in a given day, the daily surprise is equal to the intraday one. When there are multiple announcements, the daily surprise is the sum of the intraday surprises. When there is no announcement, the daily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

2.3 The Crypto Surprise Series

We aggregate intraday Bitcoin price changes into a daily series of crypto surprises. This aggregation accounts for days with multiple events and provides a tractable measure of crypto shocks at the daily frequency.

Figure 2 displays the time series of these daily crypto surprises from 2017 to 2024. The figure highlights periods of large positive and negative surprises, reflecting substantial market reactions to cryptocurrency-specific news.

Figure 2 The Crypto Surprise Series



To ensure exogeneity, we exclude days that coincide with major macroeconomic announcements, as recorded in the Bloomberg global calendar. This filtering step reduces the

risk of contamination from broader financial developments.

This shock series forms the basis for our analysis of the transmission of cryptocurrency shocks to equity markets and for the investigation of the firm-level mechanisms through which these shocks affect asset prices.

3 Measuring Firm Exposure to Cryptocurrencies

In this section, we describe how we construct a firm-level measure of exposure to cryptocurrency markets using earnings-call transcripts. Our objective is to obtain a reduced-form proxy for the extent to which publicly listed firms are economically linked to cryptocurrencies, based on the intensity with which crypto-related topics are discussed in their earnings calls. This baseline text-based measure is used in the panel regressions below to study whether firms that are more exposed to cryptocurrency markets react more strongly to identified crypto shocks.

Our approach builds on the text-analysis framework of Hassan et al. (2019); Bloom et al. (2021); Hassan et al. (2023a,c,b) and uses standard natural-language-processing tools from NL Analytics, an automated text-analysis platform applied to large corpora of earnings-call transcripts. In addition to the baseline exposure measure, the same text infrastructure also allows us to construct related measures of crypto risk and crypto sentiment, which we use in descriptive and robustness exercises.

3.1 Data

To measure firm-level exposure to cryptocurrencies, we use earnings-call transcripts, which provide granular information on the topics discussed by firm executives and financial analysts. Earnings calls are especially useful in our setting because they capture how firms describe their business models, strategic priorities, risks, and opportunities in near real time, using language intended for investors and market participants.

The transcripts are sourced and processed through NL Analytics. The broader corpus contains more than 400,000 transcripts of quarterly earnings conference calls held by publicly listed firms worldwide since 2002. For the baseline analysis in this paper, we focus on the period from 2017Q1 to 2024Q4, which matches the period used to construct the crypto-shock event-study sample. The resulting baseline exposure sample contains 1,234 firms with non-zero average crypto exposure. Firms are identified by the location of their headquarters, and

the underlying transcript database has broad international coverage, including approximately 96% of market capitalization in the United States, 90% in the euro area, 90% in the United Kingdom, and 35% in China.

3.2 Measurement

The construction of the baseline crypto-exposure measure proceeds in two steps. First, we define a set of crypto-related n-grams, that is, words and short phrases whose meaning is directly associated with cryptocurrencies, related technologies, and crypto-market infrastructure. Second, we compute the share of sentences in each earnings call that mention at least one of these n-grams.

Table 1 reports the set of selected crypto-related n-grams. The expressions are grouped into four broad semantic fields: generic crypto terms, technology and applications, tokens, and stablecoins. The selection is based on the vocabulary most frequently used in sentences discussing cryptocurrencies and related topics in the earnings-call corpus, and is cross-checked through manual reading of sample transcripts to ensure that the selected expressions are used with the intended meaning.

For a given earnings call c of firm i in quarter t, we define crypto exposure as the share of sentences that contain at least one crypto-related n-gram:

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

where N_{cit} denotes the total number of sentences in the call, $\mathbb{C}$ is the set of crypto-related n-grams, and $\mathbb{1}[\cdot]$ is an indicator function equal to one when sentence n_{cit} contains at least one crypto-related expression.

Because some firms hold more than one earnings call in a given quarter, we aggregate call-level exposure to the quarterly firm level 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 held by firm i in quarter t.

Finally, for descriptive purposes, we define a firm-level average exposure measure by

Table 1 Selected Crypto-Related N-grams in Earnings Calls

N-gram(s)	Semantic Field
Crypto*	generic
Bitcoin(s)	cryptocurrency markets
BTC(s)	cryptocurrency markets
Ethereum / Ethereums	cryptocurrency markets
ETH(s)	cryptocurrency markets
Initial coin offering(s)	cryptocurrency markets
Blockchain(s) / Block-chain(s) / Block chain(s)	technology/applications
Distributed ledger	technology/applications
DLT(s)	technology/applications
DeFi	technology/applications
Smart contract(s)	technology/applications
NFT / NFTs	technology/applications
Tokenization	technology/applications
Stablecoin	stablecoins
USD Coin / USDC	stablecoins
Tether / USDT	stablecoins

Note. This table reports the set of crypto-related n-grams used to construct the earnings-call-based exposure measure. The expressions are grouped by semantic field and are selected to capture references to cryptocurrencies, related technologies, tokens, and stablecoins. Crypto* indicates any words starting with the n-gram "crypto".

aggregating quarterly exposure across time:

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

where T_i denotes the number of quarters observed for firm i.

This baseline measure is intentionally broad. It captures the intensity with which cryptocurrency-related topics enter firms' communications with investors, and therefore provides a reduced-form proxy for firm exposure to crypto markets. At the same time, it does not by itself identify the specific channel through which a firm is exposed. We return to this issue in the mechanism analysis below.

Using the same corpus and the same set of crypto-related n-grams, we also construct two related text-based measures. The first is *crypto risk*, defined as the share of sentences that jointly contain crypto-related language and risk-related terms. The second is *crypto sentiment*, defined as the tone of crypto-related sentences using the sentiment-classification

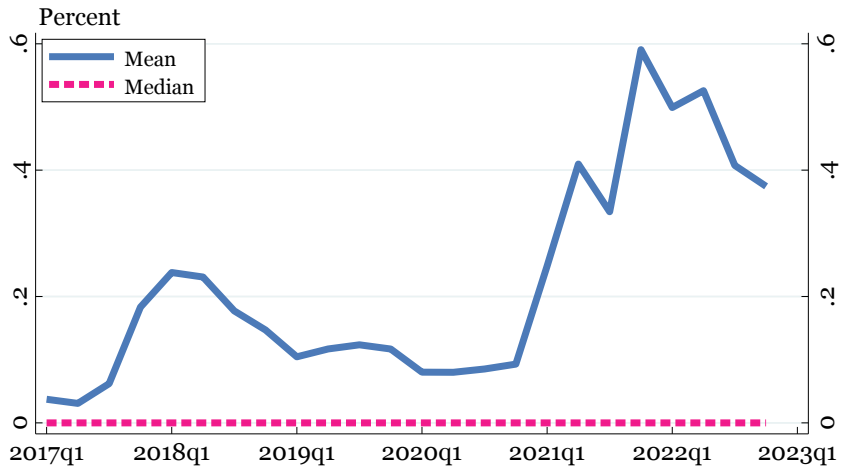
tools embedded in NL Analytics. These measures are useful for descriptive analysis and robustness, but our baseline exposure proxy remains CryptoExpo_{it}.

3.3 Crypto-Exposure Facts

We summarize the empirical properties of the exposure measure along three dimensions: its evolution over time, its sectoral distribution, and its geographic distribution.

Figure 3 plots the cross-sectional average of CryptoExpo_{it} across firms from 2017Q1 to 2024Q4. The figure shows that average exposure rises sharply during periods of heightened crypto-market activity, in particular around the 2017–2018 boom and again during the 2020–2021 phase of broader institutional and corporate adoption. The series then stabilizes at a higher level than in the early part of the sample, indicating that crypto-related discussion became a more persistent feature of firms' communication with investors.

Figure 3 Average Crypto Exposure Across Firms

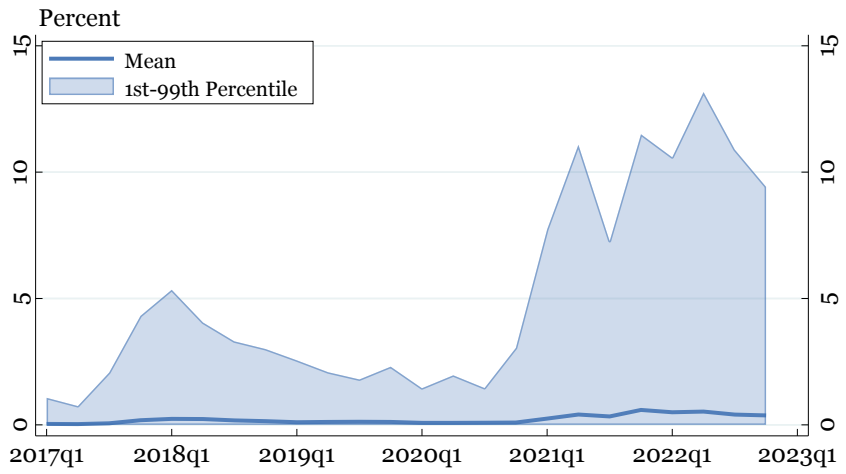


Note. Cross-sectional average of the crypto-exposure measure CryptoExpo_{it} (equal-weighted across firms). Sample period: 2017Q1 to 2024Q4.

Figure 4 reports the cross-sectional distribution of CryptoExpo_{it}, together with the 1st and 99th percentiles. The distribution is highly skewed: most firms exhibit little or no discussion of cryptocurrencies in their earnings calls, while a relatively small subset of firms displays persistent and sometimes very high exposure. This heterogeneity is important for our empirical analysis, since it provides the cross-sectional variation that allows us to study differential responses to crypto shocks.

Figure 5 shows the average exposure measure by sector. The highest levels of exposure are concentrated in Information Technology and Financials, which is consistent with the role

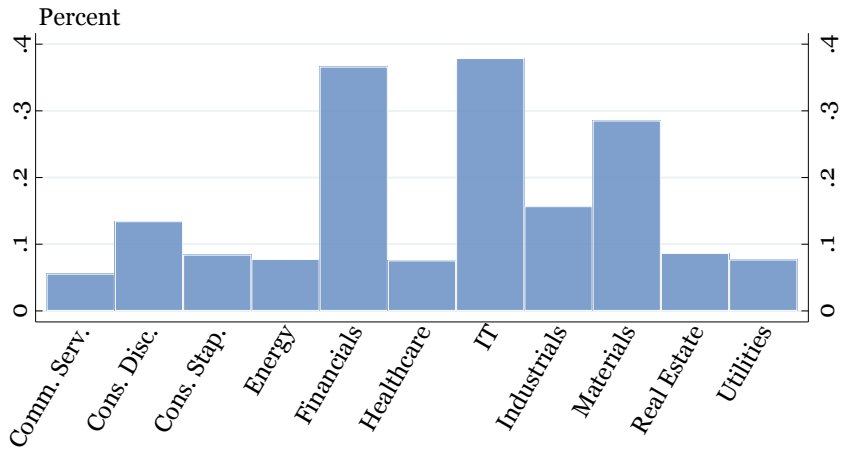
Figure 4 Cross-Sectional Distribution of Crypto Exposure



Note. Cross-sectional distribution of the crypto-exposure measure CryptoExpo_{it}. Shaded areas indicate the 1st and 99th percentiles. Sample period: 2017Q1 to 2024Q4.

of crypto exchanges, trading platforms, payment firms, software providers, and blockchain-related business models. Other sectors, such as Consumer Discretionary and Industrials, also show meaningful average exposure, reflecting the broader diffusion of crypto-related activities across the corporate sector.

Figure 5 Sectoral Breakdown: Average Crypto Exposure

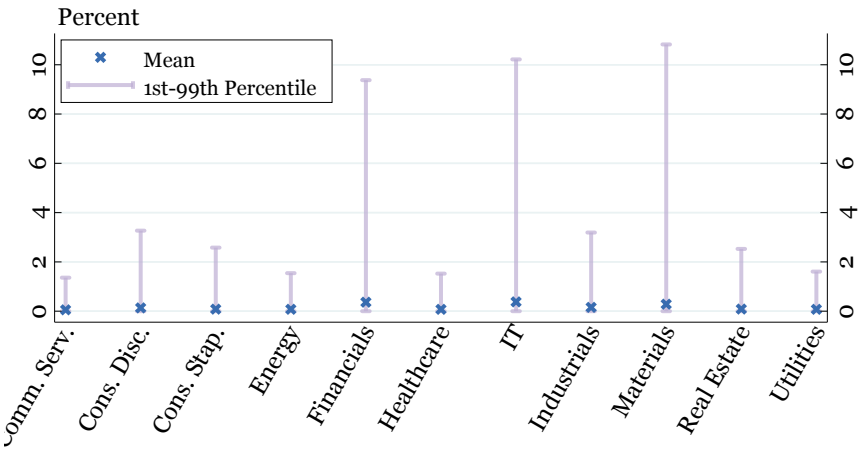


Note. Cross-sectional average of the crypto-exposure measure CryptoExpo_{it} across firms by sector. Sample period: 2017Q1 to 2024Q4.

Figure 6 provides additional detail on the within-sector distribution of exposure, reporting sectoral averages together with the 1st and 99th percentiles. The figure highlights substantial heterogeneity even within the most exposed sectors, indicating that a few firms account for

a disproportionate share of crypto-related discussion.

Figure 6 Sectoral Breakdown: Exposure Distribution



Note. Cross-sectional average of the crypto-exposure measure CryptoExpo_{it} across firms by sector. Whiskers indicate the 1st and 99th percentiles. Sample period: 2017Q1 to 2024Q4.

Figure C.2 illustrates the geographic distribution of average crypto exposure across firms. The map reveals that crypto-related discussion is concentrated in countries with deep financial markets and strong technology sectors, including the United States, Canada, Australia, Japan, and parts of Northern Europe. This cross-country heterogeneity suggests that the corporate relevance of crypto markets depends both on industrial composition and on the broader financial and technological environment.

3.4 Interpretation and Validation

A natural validation exercise is to examine whether firms with the highest values of $\overline{\text{CryptoExpo}}_i$ correspond to companies that are plausibly linked to cryptocurrency markets based on their business activities. In the Appendix, we report the firms with the highest average exposure and show that the ranking includes well-known cryptocurrency exchanges, mining firms, financial intermediaries, and technology companies that publicly discuss crypto-related business lines. This provides a first validation that the text-based measure identifies firms that are meaningfully connected to cryptocurrency markets.

At the same time, a high value of CryptoExpo_{it} does not by itself reveal the precise economic channel through which crypto shocks affect the firm. A mention of Bitcoin in an earnings call may reflect balance-sheet holdings, mining operations, transaction-based

financial services, customer demand, technology adoption, or infrastructure provision. For this reason, the baseline exposure measure should be interpreted as a broad proxy for crypto relevance rather than a direct measure of mechanism.

To investigate mechanisms more directly, we complement the baseline text-based exposure measure with a separate narrative classification exercise for the top 200 firms in the exposure distribution. For each of these firms, we combine evidence from earnings-call transcripts, corporate filings, and financial news to assign the firm to a business-model and transmission-mechanism bucket. The main categories are crypto holders, crypto miners, crypto financial services, crypto non-financial services, crypto clientele, crypto infrastructure providers, and an unclassified residual group. This second-stage firm-level narrative analysis allows us to move beyond reduced-form exposure and to study whether the transmission of crypto shocks differs systematically across underlying channels.

The two measures therefore play complementary roles in the paper. The baseline variable CryptoExpo_{it} provides a transparent and scalable measure of firm-level crypto exposure that can be used in panel regressions across a broad international sample. The top-200 narrative classification, by contrast, is designed to interpret the source of that exposure and to shed light on the economic mechanisms underlying firms' equity-price responses to crypto shocks.

4 High-Frequency Effects on Asset Prices

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

We conduct two main analyses. First, we estimate both the average and the heterogeneous effects of crypto shocks on firm-level equity prices, exploiting cross-sectional variation in firms' exposure to cryptocurrency markets. Second, we examine the response of aggregate asset prices to assess whether crypto shocks generate broader spillovers in financial markets.

4.1 Firm-Level Effects

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

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

where y_{it} denotes the 2-day log-change in the equity price of firm i on day t, α_i are firm fixed effects, and s_t is the daily crypto surprise constructed from validated events. The variable $CryptoExpo_{i,\tau-1}^{High}$ is an indicator equal to one if the firm's crypto exposure in the previous quarter is above the median.

The coefficient β captures the average response of equity prices to crypto shocks across firms, while γ measures the differential effect for firms with high crypto exposure. This specification allows us to test whether firms that are more exposed to cryptocurrency markets exhibit stronger responses to exogenous crypto shocks. Importantly, the exposure measure is a reduced-form proxy for crypto relevance and does not by itself identify the underlying transmission mechanism. We return to this issue below using firm-level narrative evidence.

Table 2 reports the results. In the baseline specification, the estimated average effect β is positive and statistically significant, indicating that crypto shocks are associated with an increase in equity prices on average. When we introduce the interaction term, the coefficient γ is positive and statistically significant, showing that firms with higher crypto exposure exhibit a stronger response to crypto shocks.

The magnitude of the estimates implies that a one-standard-deviation crypto shock generates a non-trivial movement in equity prices, particularly for highly exposed firms. This pattern is consistent with a heterogeneous transmission of crypto shocks across firms, with stronger effects among firms that are more economically linked to cryptocurrency markets.

To account for potential confounding factors, we augment the specification with time-by-sector and time-by-sector-by-country fixed effects. The estimated differential effect γ remains stable across specifications, indicating that the results are not driven by sectoral or geographic variation in equity returns.

We next examine the robustness of the results along several dimensions. First, including events that overlap with macroeconomic announcements reduces the magnitude and significance of the estimates, confirming the importance of isolating clean crypto-specific shocks. Second, splitting the sample reveals a strong time variation: in the pre-2020 period, the

Table 2 The Response of Firm-Level Equity Prices to Crypto Shocks

	(1)	(2)	(3)	(4)
Crypto surprise (β)	0.10**	0.10**		
	(0.05)	(0.05)		
Crypto surprise x High Exposure (γ)		0.07*	0.05**	0.06**
		(0.04)	(0.02)	(0.03)
High Exposure (δ)		-0.15	-0.05	-0.07
		(0.15)	(0.06)	(0.06)
Observations	113,006	108,085	108,085	98,458
R squared	0.02	0.02	0.20	0.32
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.

estimated effects are small and statistically insignificant, while in the post-2020 period they are substantially larger and highly significant. This pattern is consistent with the increasing integration of cryptocurrency markets into the broader financial system in recent years.

Third, excluding the largest shocks leaves the results qualitatively unchanged, indicating that they are not driven by extreme observations. Finally, an instrumental-variable specification using Bitcoin price changes yields similar estimates, providing additional robustness to the baseline results.

Overall, these findings indicate that crypto shocks have economically meaningful effects on equity prices, with stronger responses among firms with higher crypto exposure. This reduced-form heterogeneity is consistent with firms' differential exposure to cryptocurrency markets and motivates a deeper analysis of the underlying transmission mechanisms.

To shed light on these mechanisms, we complement the exposure-based analysis with a firm-level narrative classification of the most exposed firms. In particular, we classify the top 200 firms in the exposure distribution into categories such as crypto holders, miners, financial intermediaries, non-financial service providers, and infrastructure firms. This classification allows us to link the heterogeneous equity-price responses documented here to specific economic channels, such as balance sheet exposure, revenue linkages, and strategic involvement in crypto-related activities.

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:

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

where y_t denotes the 2-day log-change in an aggregate asset price, and s_t is the daily crypto surprise.

Table 3 reports the results for a range of aggregate financial variables, including the S&P 500, the VIX index, Treasury yields, exchange rates, gold prices, and corporate credit spreads.

Table 3 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 surprise (β)	0.10**	0.07	0.03	-0.46	0.01	0.02	0.05
	(0.04)	(0.04)	(0.07)	(0.31)	(0.02)	(0.04)	(0.09)
Observations	107	107	107	107	107	107	107
R squared	0.02	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.

The estimated responses of aggregate asset prices are generally small and not statistically significant. While there is some evidence of a positive response for indices of crypto-exposed firms, broader financial variables—such as equity indices, volatility measures, interest rates, exchange rates, and safe-haven assets—do not exhibit systematic reactions to crypto shocks.

Overall, these results indicate that the effects of crypto shocks are highly concentrated among firms with direct exposure to cryptocurrency markets, with limited transmission to aggregate financial variables. This pattern is consistent with a transmission mechanism operating primarily through firm-level balance sheet and business-model channels, rather than through broad macro-financial linkages.

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:

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

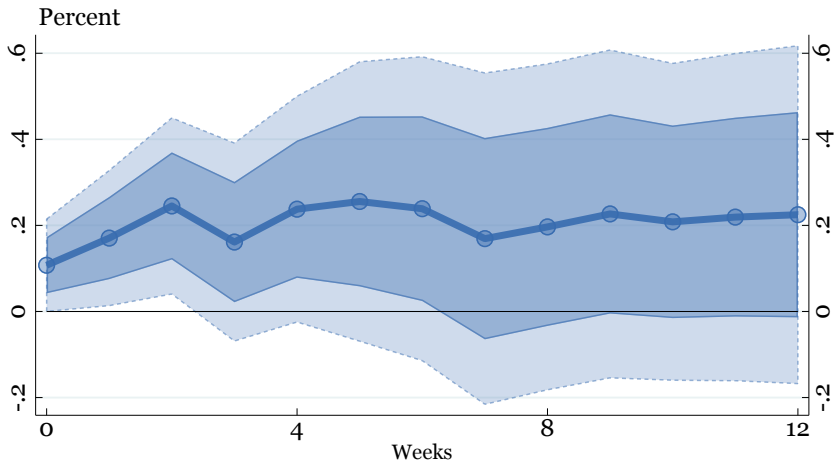
In this model, y_{it} represents the weekly equity price for firm i, α_i denotes firm fixed effects, which account for time-invariant characteristics of each firm, s_t is the weekly crypto surprise, aggregated as the sum of daily surprises within each week, and Z_t is a vector of control variables, including 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 7 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 7 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:

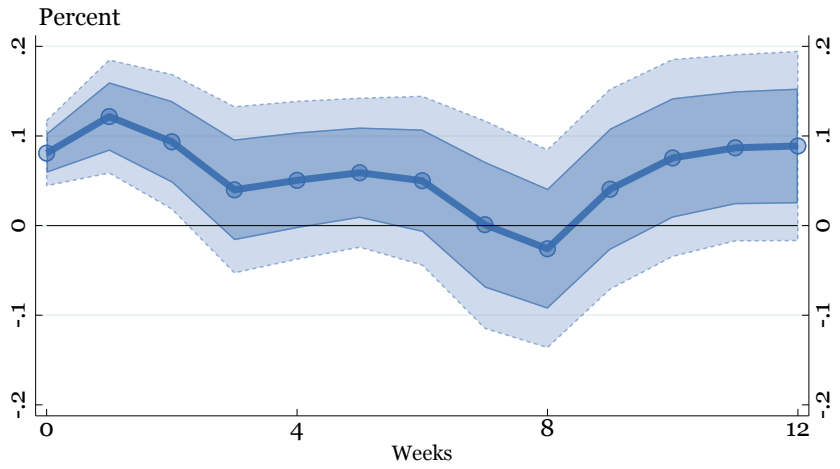
$$y_{it} = \alpha_i + \alpha_{sct,k,t} + \gamma \left(s_t \times CryptoExpo_{i,\tau-1}^{High} \right) + \sum_{p=0}^{4} \phi_p y_{i,t-1} + \varepsilon_{it}$$

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 8 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).

Figure 8 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.

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 Mechanism Analysis

The baseline results show that crypto shocks have economically and statistically significant effects on equity prices, with stronger responses for firms more exposed to crypto markets. While these findings establish the relevance of crypto shocks for the cross-section of equity returns, they do not by themselves identify the economic mechanisms through which these effects operate. In particular, our baseline exposure measure captures the intensity of a firm's link to crypto markets, but does not distinguish between the margins along which shocks are transmitted.

This distinction is central for economic interpretation. Firms with similar levels of crypto exposure may respond very differently to the same shock depending on the underlying transmission channel. Firms holding crypto assets on their balance sheets are directly affected through valuation effects, whereas firms engaged in crypto-related activities—such as mining, trading, payments, or infrastructure provision—may respond through changes in revenues, costs, or demand conditions. More indirectly, crypto shocks may also affect firms through the exposure of their customer base to crypto wealth or crypto adoption. Disentangling these channels is therefore key to understanding both the nature of the estimated effects and their broader macro-financial implications.

To shed light on these mechanisms, we exploit cross-sectional heterogeneity in the *type* of firms' crypto exposure. Our analysis focuses on the 200 firms with the highest average crypto exposure over the sample period. Restricting attention to this subset allows us to concentrate on firms for which crypto-related activities are economically meaningful, while limiting attenuation from firms with only negligible or incidental links to crypto markets.

We then classify these firms according to their primary economic linkage to crypto markets and compare their sensitivity to identified crypto shocks across groups. Under the maintained assumption that the shocks we identify are exogenous to firm-level fundamentals, systematic differences in responses across groups can be interpreted as evidence on the relative importance of alternative transmission channels.

A key challenge in implementing this strategy is that the relevant transmission mechanism is not directly observable and must be inferred from qualitative firm-level information. To address this challenge, we develop a narrative classification framework that combines structured economic reasoning with large-scale textual analysis. Specifically, we draw on firm-level disclosures—including earnings call transcripts, annual reports and 10-K filings, other regulatory filings, and external business descriptions from financial news and company coverage—and use a large language model (LLM) to apply a pre-specified set of decision rules that map each firm to a transmission mechanism. This approach allows us to operationalize narrative identification at scale while preserving transparency and economic interpretability.

6.1 Narrative Classification Methodology

The key empirical challenge in our setting is that transmission mechanisms are not directly observable and must instead be inferred from qualitative information on firms' activities. To address this challenge, we adopt a narrative classification approach that maps firms into exposure types based on their underlying economic linkages to crypto markets.

Our methodology builds on the narrative identification approach pioneered by Romer and Romer (2004) and Romer and Romer (2010). A defining feature of this tradition is that identification relies on a structured reading of qualitative evidence, guided by explicit economic criteria, rather than on purely statistical comovement. We adapt this logic to the firm level. Instead of classifying policy actions or macroeconomic shocks, we classify firms according to the dominant mechanism through which crypto shocks are likely to affect their equity values.

Implementing this approach in a large cross-section of firms requires a procedure that

is both systematic and scalable. To this end, we combine narrative analysis with a large language model (LLM), which allows us to process firm-level textual information and apply a pre-specified classification protocol in a consistent and reproducible way. The LLM is not used to generate unconstrained labels. Rather, it operates within a structured decision framework that encodes our economic criteria for assigning firms to mechanism categories. In this sense, the LLM scales up a narrative methodology that would otherwise require extensive manual reading and coding.

For each firm, the classification is based on publicly available disclosures, including earnings call transcripts, annual reports and 10-K filings, other regulatory filings, and external business descriptions from financial news and company materials. These sources provide detailed information on firms' business models, sources of revenue, balance-sheet positions, and involvement in crypto-related activities. More broadly, our use of earnings call transcripts follows a growing literature that extracts firm-level economic information from managerial discussions and corporate disclosures, including Hassan et al. (2019), Hassan et al. (2023a), Hassan et al. (2023c), and Hassan et al. (2023b). Relative to this literature, however, our objective is different: rather than constructing a continuous text-based measure of exposure, we use these materials to identify the dominant *mechanism* linking crypto shocks to firm outcomes.

We implement the classification on the subset of the 200 firms with the highest average crypto exposure over the sample period. For each firm, the LLM is provided with firm-specific textual inputs and a set of explicit instructions describing the classification task, the admissible categories, the underlying economic definitions, and the decision rules governing assignment. The model is required to evaluate the evidence, apply the decision criteria, and return a structured output.

The underlying classification framework allows firms to load on more than one business-model category when the evidence points to multiple relevant channels. This is useful because some firms are active along several crypto-related margins. At the same time, for the main empirical analysis we assign each firm to a *dominant* mechanism, defined as the category with the highest weight. This dominant-category representation provides a transparent partition of the sample for regression analysis, while the underlying weights are used descriptively to show that mixed cases are limited and that the dominant assignment captures the data well.

Our classification protocol distinguishes six categories: crypto holders, crypto miners, crypto financial services, crypto non-financial services, crypto infrastructure providers, and unclassified. The first five categories correspond to economically distinct transmission chan-

nels, while the final category captures firms for which the available evidence does not support a sufficiently precise attribution to a dominant mechanism. The instructions used to perform the firm-level narrative analysis, as well as the output of the classification exercise, are included in the supplementary material.

Crucially, the procedure is designed to avoid forced classification. If the available evidence does not support a sufficiently clear allocation, the firm is assigned to the *Unclassified* category. This conservative treatment mirrors the discipline of traditional narrative methods and reduces the risk of spurious precision in ambiguous cases. Because both the information set and the classification protocol are fully specified ex ante, the procedure remains transparent, economically interpretable, and replicable.

6.2 Classification of Firms by Transmission Mechanism

We next apply the narrative classification procedure to the 200 firms with the highest average crypto exposure in our sample. For each firm, the objective is to identify the dominant economic mechanism through which crypto shocks are likely to affect firm value. The resulting classification partitions the sample into six categories, summarized in Table 4.

The first category, *Crypto Holders*, comprises firms whose exposure arises primarily from crypto assets held on the balance sheet. For these firms, the dominant channel is a valuation effect, since changes in crypto prices directly affect the marked-to-market value of firm assets.

The second category, *Crypto Miners*, includes firms whose exposure reflects mining activity. For these firms, crypto shocks operate mainly through revenues and operating margins, amplified by the high operating leverage of mining business models.

The third category, *Crypto Financial Services*, captures firms whose exposure arises from financial intermediation linked to crypto markets, including trading, brokerage, custody, and payments. For these firms, the primary transmission channel is through trading volumes, transaction activity, and user participation.

The fourth category, *Crypto Non-Financial Services*, includes firms that provide crypto-related goods or services without directly intermediating financial transactions or holding crypto as a core asset. These firms are exposed through technology adoption, platform integration, software provision, or demand for crypto-related applications.

The fifth category, *Crypto Infrastructure*, comprises firms supplying critical inputs to the crypto ecosystem, such as hardware, semiconductors, cloud services, or other foundational infrastructure. For these firms, crypto shocks primarily affect demand for infrastructure

Table 4 Classification of Firms by Dominant Transmission Mechanism

Category	Economic Channel	Representative Firms
Crypto Holders	Balance-sheet valuation effects from marked-to-market crypto holdings	MicroStrategy; Tesla
Crypto Miners	Mining revenues and operating leverage tied to crypto prices	Marathon Digital; Hut 8
Crypto Financial Services	Trading volumes, intermediation activity, and user participation	Coinbase; Robinhood
Crypto Non-Financial Services	Technology adoption, platform integration, and demand for crypto-related applications	Block; PayPal
Crypto Infrastructure	Demand for hardware, software, and cloud inputs supporting the crypto ecosystem	NVIDIA; AMD
Unclassified	No dominant mechanism identified based on available information	–

NOTE. Each firm is assigned to the category corresponding to its dominant economic linkage to cryptocurrency markets, based on the narrative classification procedure described in Section 6.1. While the underlying framework allows firms to load on multiple categories, the dominant-category assignment is used in the main regressions. The *Unclassified* category includes firms for which the available evidence does not support a sufficiently precise attribution to a dominant mechanism.

products and services.

The sixth category, *Unclassified*, is reserved for firms for which the available evidence does not allow a sufficiently precise attribution to a dominant mechanism. This category plays a deliberate role in the design of the classification. It ensures that firms are not forced into ill-fitting groups when the underlying evidence is limited, mixed, or economically ambiguous, and should therefore be interpreted as a disciplined acknowledgement of classification uncertainty rather than as a separate economic channel.

Two features of the classification are worth emphasizing. First, the taxonomy is organized around economic mechanisms rather than traditional industry classifications. Firms within the same sector may therefore be assigned to different categories depending on how their crypto exposure arises. Second, although the underlying procedure allows for multiple mechanism weights, the main empirical analysis uses the dominant mechanism only. As we show below, this simplification entails little loss of information because most firms load overwhelmingly on a single category.

The next subsection provides descriptive evidence on the distribution of firms across categories and on how measured crypto exposure varies across mechanisms.

6.3 Descriptive Evidence Across Mechanism Groups

Before turning to the estimation of mechanism-specific responses, we provide descriptive evidence on the distribution of firms across categories and on how measured crypto exposure varies across mechanisms.

Figure 9 reports the distribution of firms across mechanism groups within the sample of the 200 most crypto-exposed firms. For each category, the figure reports both the *primary count*, defined as the number of firms assigned to that group under the dominant-mechanism classification, and the *weighted count*, defined as the sum of firm-level mechanism weights within the group. The two series are very similar across categories. This pattern indicates that the classification is close to binary for most firms: although the underlying procedure allows for mixed cases, firms typically load overwhelmingly on a single mechanism.

The figure also shows that the distribution of firms across mechanisms is uneven. Crypto financial services and infrastructure providers account for a substantial share of the sample, while crypto holders and miners represent smaller but economically salient groups. The unclassified category remains non-trivial, consistent with the conservative design of the classification procedure.

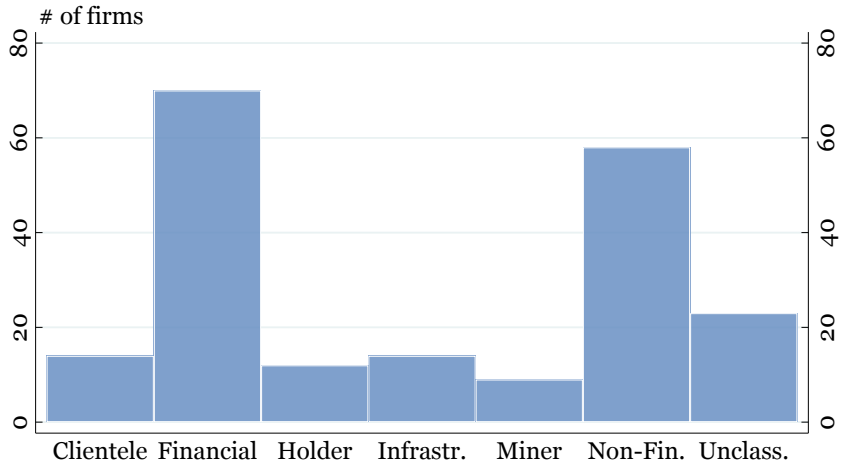


Figure 9 Number of Firms by Transmission Mechanism

NOTE. Number of firms by business-model group among the 200 most crypto-exposed firms. Each group shows two bars: the primary count, based on dominant-category assignment, and the weighted count, computed as the sum of firm-level category weights. The similarity of the two series indicates that the dominant-category classification captures the underlying weighted classification well. Sample period: 2017Q1–2024Q4.

Figure 10 complements this evidence by reporting the average crypto exposure by mechanism group. As in the previous figure, we report both the *primary average*, computed over firms assigned to a given dominant mechanism, and the *weighted average*, computed using the full set of mechanism weights. The two measures are again very similar, indicating that the classification is not sensitive to the use of dominant assignments.

More importantly, the figure reveals systematic differences in exposure intensity across mechanisms. Crypto holders and miners exhibit the highest average exposure, consistent with direct balance-sheet and operating-revenue channels. By contrast, financial services and infrastructure firms display lower, though still substantial, exposure, consistent with more indirect transmission through trading volumes, user activity, or demand for inputs and services.

These patterns provide a useful validation of the classification while also highlighting an important identification issue. Differences in estimated responses across mechanism groups may reflect differences in exposure intensity, differences in transmission mechanisms, or both. Disentangling these two dimensions is therefore central to the analysis that follows.

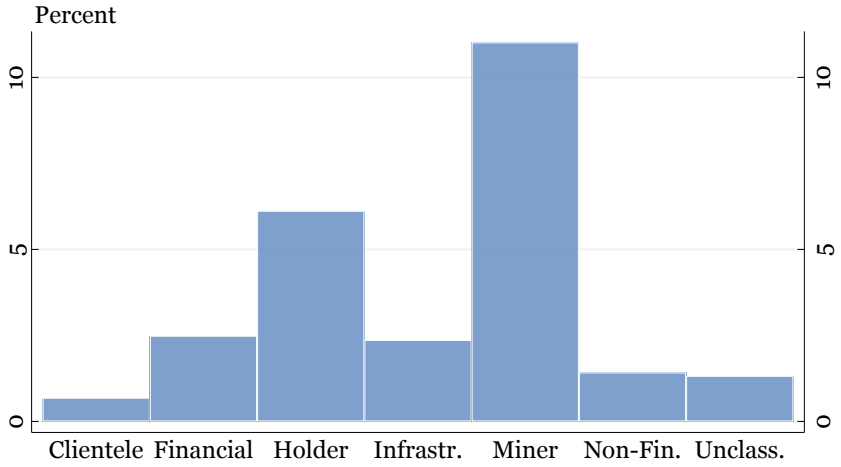


Figure 10 Average Crypto Exposure by Transmission Mechanism

NOTE. Average crypto exposure ($\overline{\text{CryptoExpo}}_i$) by business-model group among the 200 most crypto-exposed firms. Each group shows two bars: the primary average, computed using dominant-category assignment, and the weighted average, computed using the full set of category weights. The similarity between the two measures indicates that the classification is robust to the use of dominant assignments. Sample period: 2017Q1–2024Q4.

The evidence in Figures 9 and 10 shows that the narrative classification delivers economically meaningful and empirically sharp partitions of the sample. In the next subsection, we further characterize these firms using accounting information.

6.4 Firm Characteristics by Transmission Mechanism

To further characterize the firms underlying each transmission mechanism, we merge the narrative classification with firm-level accounting data from Worldscope. This allows us to document how firms differ across mechanism groups in terms of size, balance-sheet composition, profitability, and leverage.

Table 5 reports summary statistics by business-model category. Each observation corresponds to a firm, assigned to the category associated with its dominant mechanism. Several patterns emerge.

Table 5 Firm Characteristics by Transmission Mechanism

	Total Assets		Employment		Liquid		Sales	
Business model	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Financial	13560.0	8.0	4.9	1.1	0.34	0.31	0.34	0.31
Holder	1.2	0.0	0.6	0.1	0.41	0.45	0.41	0.45
Infrastr.	1129.7	5.8	5.6	1.0	0.30	0.33	0.30	0.33
Miner	0.4	0.3	0.3	0.0	0.35	0.36	0.35	0.36
Non-Fin.	235.4	0.6	51.2	1.1	0.24	0.20	0.24	0.20
	EBITDA		Debt		Leverage		Exposure	
Business model	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Financial	-0.05	0.02	0.15	0.10	0.15	0.10	2.99	1.00
Holder	-0.06	-0.12	0.11	0.01	0.11	0.01	3.43	1.16
Infrastr.	0.14	0.08	0.30	0.15	0.30	0.15	1.64	0.74
Miner	-0.05	-0.01	0.14	0.10	0.14	0.10	9.98	9.75
Non-Fin.	-0.05	0.06	0.17	0.13	0.17	0.13	1.44	0.49

NOTE. Each observation is a firm. Firms are assigned to the business-model bucket with the largest classification weight. The unclassified bucket is omitted. Variables report the mean and median within bucket. Total assets are reported in millions, and employment is reported in thousands. Liquid, sales, EBITDA, and debt are reported as shares of total assets. Exposure is the firm-level mean of crypto exposure, and leverage is total debt divided by total assets using those firm-level means. Sources: NLA exposure data, Worldscope Datastream.

NOTE. This table reports firm characteristics by dominant transmission mechanism for the 200 most crypto-exposed firms. Accounting variables are drawn from Worldscope.

First, there is substantial heterogeneity in firm size across categories. Firms in the financial services and infrastructure groups tend to be significantly larger, both in terms of total assets and employment, while crypto holders and miners are considerably smaller on average. This difference reflects the fact that many firms with direct exposure to crypto markets are relatively specialized entities, whereas infrastructure and financial-service providers often

operate at a much larger scale.

Second, balance-sheet composition varies systematically across groups. Crypto holders exhibit relatively high liquidity ratios, consistent with the presence of liquid balance-sheet positions linked to crypto assets. Infrastructure firms tend to display higher leverage and capital intensity, reflecting the hardware- and investment-heavy nature of their activities. Financial firms occupy an intermediate position.

Third, profitability differs markedly across categories. Infrastructure firms display positive EBITDA on average, while miners and holders tend to exhibit lower or more volatile profitability, consistent with the cyclical and often highly levered nature of their business models. Non-financial service firms also show substantial dispersion, reflecting the heterogeneity of activities captured in this category.

Finally, the table confirms the patterns observed in the previous subsection regarding exposure intensity. Firms classified as miners and holders exhibit the highest average crypto exposure, while financial services and infrastructure firms show lower but still meaningful exposure.

6.5 Heterogeneous Responses by Transmission Mechanism

We now turn to the central test of the mechanism classification by estimating how the response of equity prices to identified crypto shocks varies across business-model groups.

For each transmission mechanism g, we estimate group-specific responses to crypto surprises using firm-level event-study regressions of the form:

$$R_{it} = \beta_g \cdot \text{CryptoShock}_t + \alpha_i + \varepsilon_{it}, \tag{5}$$

where R_{it} denotes the return of firm i around event t, CryptoShock_t is the identified crypto surprise, and α_i are firm fixed effects. The coefficient β_g captures the average sensitivity of firms in group g to crypto shocks.

Table 6 reports the estimated coefficients by transmission mechanism.

Three main results emerge.

First, firms with the most direct exposure to crypto markets exhibit the strongest responses. Crypto holders show large and statistically significant responses, consistent with a balance-sheet valuation channel through which changes in crypto prices directly affect the marked-to-market value of firm assets. Crypto miners also display strong sensitivity, consis-

Table 6 Effect of Crypto Surprises by Transmission Mechanism

	(1) Client.	(2) Fin.	(3) Hold.	(4) Infra.	(5) Min.	(6) Non-Fin.	(7) Uncl.
Crypto surprise (β_g)	0.05	0.24***	0.54***	0.19**	0.77***	0.18***	0.20**
	(0.10)	(0.09)	(0.12)	(0.10)	(0.21)	(0.06)	(0.08)
Observations	1,166	5,779	1,112	1,185	619	4,493	1,931
R squared	0.01	0.03	0.07	0.01	0.06	0.02	0.01
# of Firms	14	70	12	14	9	58	23
Firm FE	yes	yes	yes	yes	yes	yes	yes
Time x Sector FE	no	no	no	no	no	no	no
Time x Sector x Country FE	no	no	no	no	no	no	no

NOTE. Columns correspond to business-model groups: Client. = Clientele; Fin. = Financial; Hold. = Crypto holders; Infra. = Infrastructure providers; Min. = Miners; Non-Fin. = Non-financial firms; Uncl. = Unclassified. Robust standard errors (clustered two-way, by firm and day) are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

NOTE. This table reports event-study estimates of the effect of crypto surprises on firm-level equity prices by dominant transmission mechanism. The sample consists of the 200 firms with the highest average crypto exposure.

tent with a revenue and operating-leverage channel whereby crypto price fluctuations affect expected profitability through mining rewards and margins.

Second, firms providing financial and infrastructure services to crypto markets also respond positively and significantly, but with smaller magnitudes. For financial intermediaries, the relevant channel runs through trading volumes, transaction activity, and user engagement. For infrastructure providers, the main channel runs through demand for hardware, software, and related inputs into the crypto ecosystem.

Third, firms in the crypto non-financial services and unclassified categories display more muted responses on average. This pattern is consistent with weaker, more diffuse, or less immediate links to crypto-market conditions.

Overall, the ranking of coefficients aligns closely with the economic interpretation of the classification. Transmission mechanisms associated with direct balance-sheet exposure and strong cash-flow sensitivity generate the largest responses, while more indirect channels operate with attenuated effects. These results provide strong support for the view that crypto shocks propagate to equity markets through economically distinct and measurable firm-level channels.

6.6 Controlling for Exposure Levels

The differences in sensitivity documented above may reflect not only distinct transmission mechanisms, but also systematic differences in the *level* of crypto exposure across business-model groups. In particular, firms such as miners and holders tend to exhibit substantially higher exposure, raising the concern that the observed heterogeneity in responses may be driven by exposure intensity rather than by the underlying economic channel.

To address this concern, we construct a sample in which exposure is approximately comparable across groups. Specifically, we conduct a grid search over intervals of the form $\text{CryptoExpo}_i \in [a, b] \subset [0.25, 2]$ and select the range that minimizes cross-group differences in average exposure. This procedure identifies the interval $\text{CryptoExpo}_i \in [0.5, 1.5]$ as the range over which exposure levels are most similar across business-model groups.

We then restrict the sample to firms within this interval and re-estimate the event-study regressions by transmission mechanism. Table 7 reports the resulting coefficients.

Table 7 Effect of Crypto Surprises by Transmission Mechanism with Comparable Levels of Exposure

	(1) Client.	(2) Fin.	(3) Hold.	(4) Infra.	(5) Min.	(6) Non-Fin.	(7) Uncl.
Crypto surprise (β_g)	0.05	0.24***	0.54***	0.19**	0.77***	0.18***	0.20**
	(0.10)	(0.09)	(0.12)	(0.10)	(0.21)	(0.06)	(0.08)
Observations	1,166	5,779	1,112	1,185	619	4,493	1,931
R squared	0.01	0.03	0.07	0.01	0.06	0.02	0.01
# of Firms	14	70	12	14	9	58	23
Firm FE	yes	yes	yes	yes	yes	yes	yes
Time x Sector FE	no	no	no	no	no	no	no
Time x Sector x Country FE	no	no	no	no	no	no	no

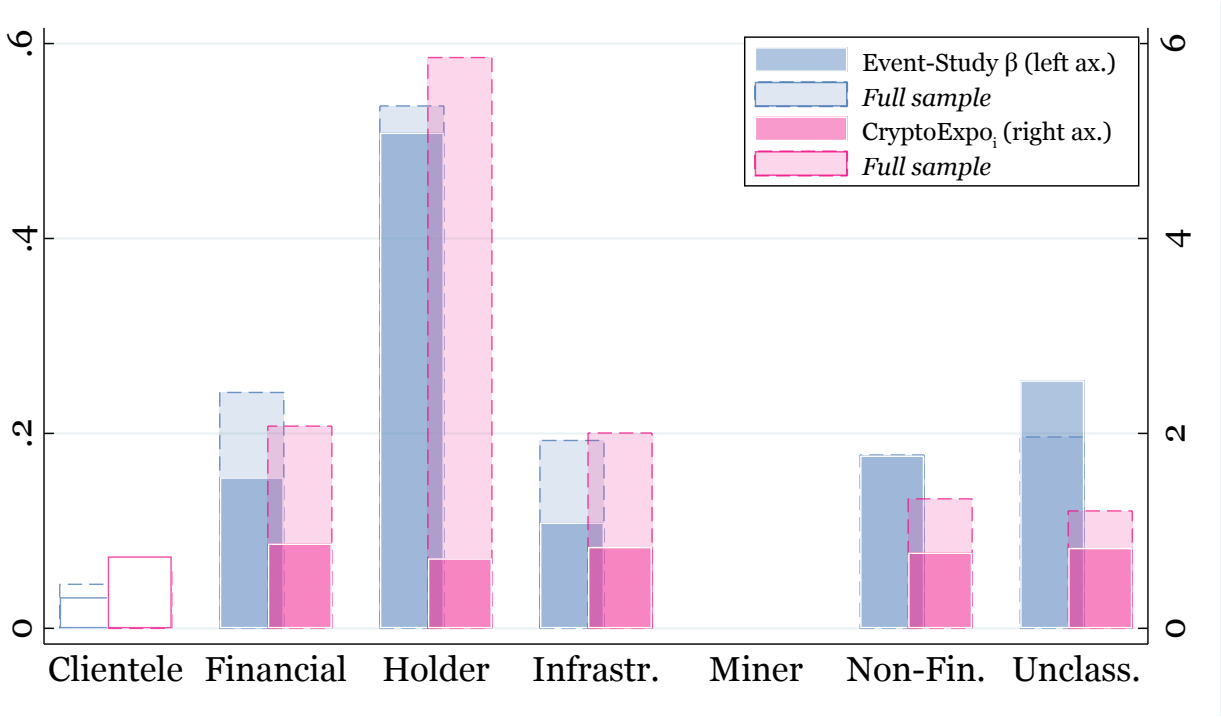
NOTE. Columns correspond to business-model groups: Client. = Clientele; Fin. = Financial; Hold. = Crypto holders; Infra. = Infrastructure providers; Min. = Miners; Non-Fin. = Non-financial firms; Uncl. = Unclassified. Robust standard errors (clustered two-way, by firm and day) are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

NOTE. This table reports event-study estimates by dominant transmission mechanism in the subsample of firms whose crypto exposure lies in the interval $[0.5, 1.5]$, chosen to reduce cross-group differences in exposure intensity.

Despite the substantial compression in cross-sectional variation in exposure, the pattern of responses remains largely unchanged. Firms with direct exposure—particularly holders and miners—continue to exhibit the strongest sensitivity to crypto shocks, while financial and

infrastructure firms display intermediate responses, and non-financial-service and unclassified firms show more muted effects.

To further illustrate this result, Figure 11 plots the estimated group-specific responses against the average exposure within each group in the restricted sample.



NOTE. Estimated response of equity prices to crypto surprises by business-model group plotted against the corresponding average exposure within the restricted sample. Sample period: 2017Q1–2024Q4.

Figure 11 Exposure versus Transmission Mechanism

Consistent with the visual evidence, there is no strong monotonic relationship between exposure and sensitivity across groups in the restricted sample. Instead, firms with similar levels of exposure display markedly different responses depending on their business model. This pattern reinforces the conclusion that the nature of the transmission mechanism—rather than exposure intensity alone—plays a central role in shaping firm-level responses to crypto shocks.

6.7 Economic Interpretation

The evidence in this section yields three main economic conclusions.

First, the transmission of crypto shocks to equity prices appears to operate primarily through *direct* firm-level channels. The largest responses are concentrated among firms

whose exposure arises through balance-sheet holdings or mining activity. In both cases, the link between crypto prices and firm value is immediate and economically transparent: for holders, crypto price movements directly affect the marked-to-market value of assets; for miners, they affect expected revenues and profitability through a high-operating-leverage business model. By contrast, firms exposed through financial intermediation, infrastructure provision, or broader business adoption respond less strongly, and firms whose exposure is more diffuse respond least. This ranking strongly suggests that the cross-sectional propagation of crypto shocks is driven first and foremost by firms with direct claims on, or direct cash-flow dependence on, crypto markets.

Second, these findings help clarify what rising crypto-equity comovement does, and does not, imply at the aggregate level. Recent work documents that crypto prices have become increasingly synchronized with equity markets, particularly since 2020 (Adrian et al., 2022; Che et al., 2023b; Karau, 2023). Our results suggest that part of this comovement reflects a concrete transmission mechanism running through publicly listed firms with identifiable crypto exposure. At the same time, the magnitude and distribution of the mechanism-specific coefficients indicate that this transmission remains concentrated in a relatively narrow set of firms and business models. In this sense, our results are more consistent with selective cross-sectional propagation than with a broad-based market factor operating uniformly across equities.

Third, the mechanism evidence has implications for how one should think about the macro-financial relevance of crypto markets. The strongest channels identified here are balance-sheet and operating-leverage channels, both of which are familiar from the broader asset-pricing and macro-finance literature. More specifically, our findings fit naturally with a view in which asset price movements matter for firms when they change net worth, collateral values, or expected cash flows, rather than only through generalized sentiment. In our setting, crypto shocks appear to operate similarly, but through a new underlying asset class.

The same logic also disciplines the policy interpretation. Our evidence does not imply that crypto markets currently pose a first-order aggregate risk. The firms with the strongest responses are precisely those with the most direct and concentrated crypto exposure, and they represent a limited subset of the listed-firm universe. However, the results do imply that the economic relevance of crypto shocks should be expected to grow endogenously with the scale and breadth of these exposures. To the extent that more firms begin to hold crypto on balance sheet, intermediate crypto transactions, or supply critical inputs to the sector, the channels documented here would become more quantitatively important. In that sense,

the mechanism estimates provide a set of building blocks for thinking about how further integration of crypto markets into the corporate and financial system may translate into broader macro-financial spillovers.

More broadly, the evidence helps distinguish between alternative views of crypto's economic role. A literature emphasizing the crypto-macro disconnect argues that crypto price fluctuations remain only weakly connected to broader macroeconomic outcomes (Benigno and Rosa, 2023). By contrast, other work points to increasing spillovers through institutional participation, household wealth effects, and policy transmission (Aiello et al., 2023; Weber et al., 2023; Che et al., 2023b). Our findings speak to this debate by identifying a concrete intermediate layer: publicly listed firms. Even if crypto shocks do not yet operate as economy-wide factors, they already affect equity prices through specific and interpretable firm-level channels. This does not overturn the view that aggregate spillovers remain limited at present, but it shows that the relevant transmission architecture is already in place and operates through economically meaningful corporate exposures.

7 Conclusion

This paper studies how shocks originating in cryptocurrency markets transmit to publicly listed firms. We construct a novel event-level dataset linking crypto-related news to high-frequency equity price responses, and combine it with a detailed classification of firm-level crypto exposure. This allows us to move beyond aggregate comovement and identify the economic channels through which crypto shocks affect equity valuations.

Our main finding is that the transmission of crypto shocks to equities is economically meaningful but highly heterogeneous. Firms with direct exposure—through balance-sheet holdings or mining activity—exhibit the largest and most systematic responses. Firms exposed through intermediation, infrastructure, or broader business adoption respond more modestly, while firms with diffuse exposure show little to no reaction. This cross-sectional pattern provides strong evidence that crypto-equity spillovers operate primarily through direct cash-flow and valuation channels, rather than through a broad-based sentiment or market-wide factor.

The mechanism results help reconcile two strands of the emerging literature. On the one hand, recent work documents increasing comovement between crypto assets and traditional financial markets. On the other hand, a growing body of evidence suggests that crypto markets remain only weakly connected to macroeconomic fundamentals. Our findings bridge

these views by identifying a concrete transmission layer—publicly listed firms with heterogeneous crypto exposure—through which crypto shocks affect equity prices without necessarily operating as a broad economy-wide factor.

From a macro-financial perspective, our results suggest that the aggregate importance of crypto markets remains limited, but is no longer negligible. The firms most strongly affected are those with concentrated and transparent exposure, representing a relatively small subset of the equity market. At the same time, the economic channels we identify—balance-sheet valuation effects and operating leverage—are standard mechanisms through which asset price fluctuations propagate in the broader economy. As the scale and breadth of corporate exposure to crypto assets expand, these channels are likely to become more quantitatively important, potentially amplifying the macro-financial relevance of crypto shocks.

These findings also have implications for monitoring financial stability. While crypto markets do not currently appear to generate large aggregate spillovers, the presence of clearly identifiable transmission channels suggests that risks could grow endogenously with further integration. In this sense, understanding not only the level but also the *distribution* of crypto exposure across firms is key for assessing potential vulnerabilities.

More broadly, the paper contributes to understanding how new asset classes become integrated into the financial system. Rather than operating as isolated speculative markets, cryptocurrencies already influence equity valuations through identifiable and economically interpretable firm-level linkages. This suggests that the key question is not whether crypto markets are connected to the real economy, but how the structure and distribution of these connections evolve over time.

Several directions for future research follow naturally. First, quantifying the equilibrium implications of these firm-level channels—particularly their potential to generate aggregate spillovers—remains an open question. Second, understanding how institutional adoption and regulatory developments shape the distribution of crypto exposure across firms may be critical for assessing future systemic relevance. Finally, extending the analysis to other asset classes and international settings would help establish the generality of the mechanisms documented here.

Our results show that crypto shocks already propagate to traditional financial markets through well-defined economic channels, while also highlighting that their broader macro-financial consequences depend on the evolving integration of crypto assets into the corporate and financial landscape.

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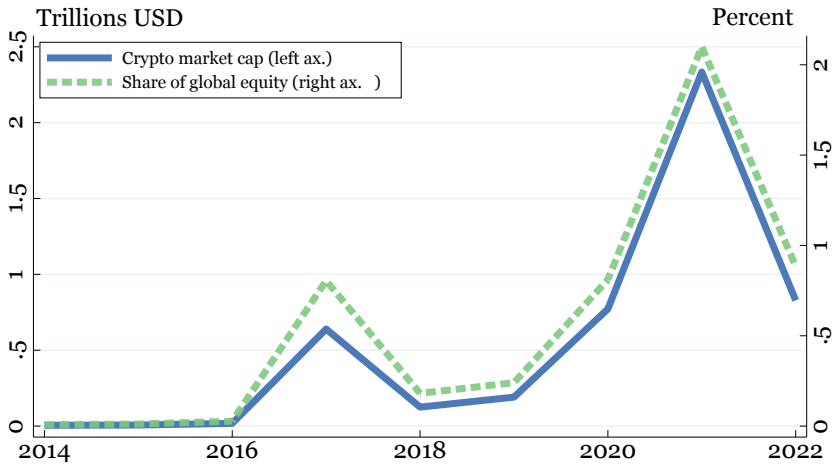
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Appendix

A Crypto Facts

Figure A.1 Global Equity versus Crypto Market Capitalization



Note. The figure compares the evolution of global crypto market capitalization with that of the global equity market over the sample period. It is intended to illustrate the rapid expansion of crypto markets relative to traditional asset classes, while also showing that crypto remains small in aggregate market-cap terms.

Table A.1 Overlap Between Crypto and U.S. Equity Markets: Market Capitalization

Year	Crypto MktCap / S&P500 MktCap	Crypto MktCap / Total U.S. MktCap
2017	34.05%	25.65%
2018	35.17%	25.49%
2019	36.88%	30.60%
2020	41.75%	34.22%
2021	41.96%	34.01%
2022	33.87%	28.24%

Note. The table reports the ratio of crypto market capitalization to the market capitalization of the S&P 500 and of the total U.S. equity market, by year. The figures are intended to provide a benchmark for the aggregate scale of crypto markets relative to listed equity markets in the United States.

Table A.2 Overlap Between Crypto and U.S. Equity Markets: Number of Firms

Year	# Crypto Firms / # S&P500 Firms	# Crypto Firms / # Total U.S. Market
2017	23.09%	24.80%
2018	26.14%	25.00%
2019	27.70%	25.20%
2020	27.27%	25.20%
2021	24.59%	25.20%
2022	25.05%	25.40%

Note. The table reports the number of firms identified as crypto-exposed relative to the number of firms in the S&P 500 and in the total U.S. equity market, by year. The objective is to illustrate the extensive-margin footprint of crypto-related firms within U.S. listed equities.

B Crypto Shocks

Table B.1 Top 10 Largest Crypto Surprises

Date	**Event**	ΔBTC (%)
10/03/2017	U.S. SEC rejects application to list Bitcoin ETF	-19.52
29/01/2021	Elon Musk publicly endorses Bitcoin via Twitter	+15.06
08/02/2021	Tesla announces large Bitcoin investment	+8.16
24/09/2021	PBOC declares all crypto transactions illegal	-6.11
07/03/2018	U.S. regulator urges crypto exchanges to register	-6.09
09/03/2022	Bitcoin jumps after apparent Yellen statement release	+5.59
06/01/2017	China central bank warns on Bitcoin speculation	-5.51
12/05/2021	Tesla suspends Bitcoin payments	-5.21
10/07/2019	Powell raises concerns over Facebook's Libra	-5.19
29/08/2023	Court ruling on Grayscale ETF boosts Bitcoin	+5.18

Note. The table reports the ten largest crypto surprise events in the baseline sample, ranked by the absolute two-hour change in Bitcoin prices around the event timestamp. These examples illustrate the range of regulatory, adoption, and sentiment-driven events captured by our identification strategy.

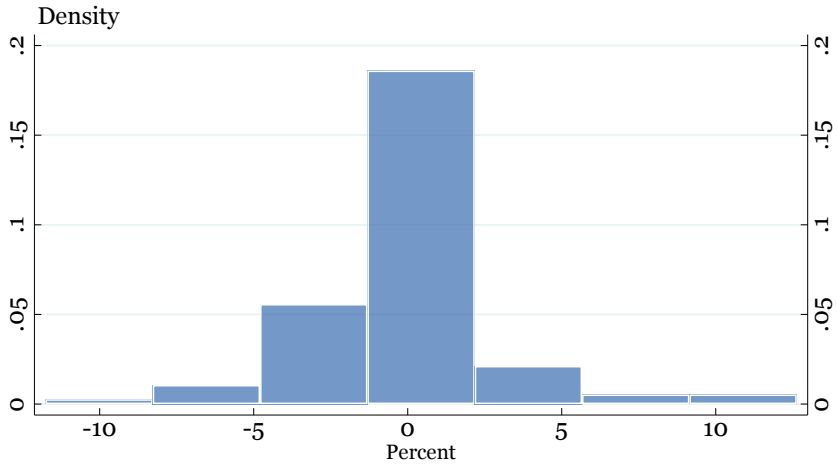
Table B.2 Summary Statistics of Crypto Surprise Events

	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.

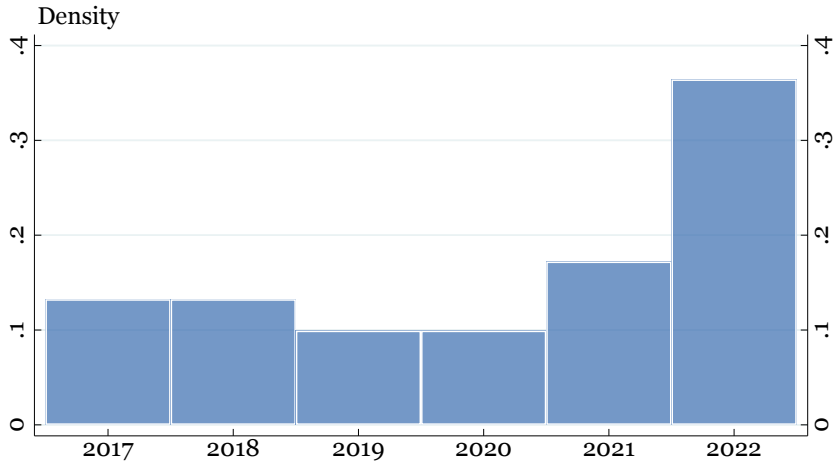
Note. Summary statistics for the daily crypto surprise series. The shocks are constructed from intraday Bitcoin price movements in a two-hour window around identified crypto-specific events. The sample covers the period from 2017 to 2024.

Figure B.1 Distribution of Crypto Surprises



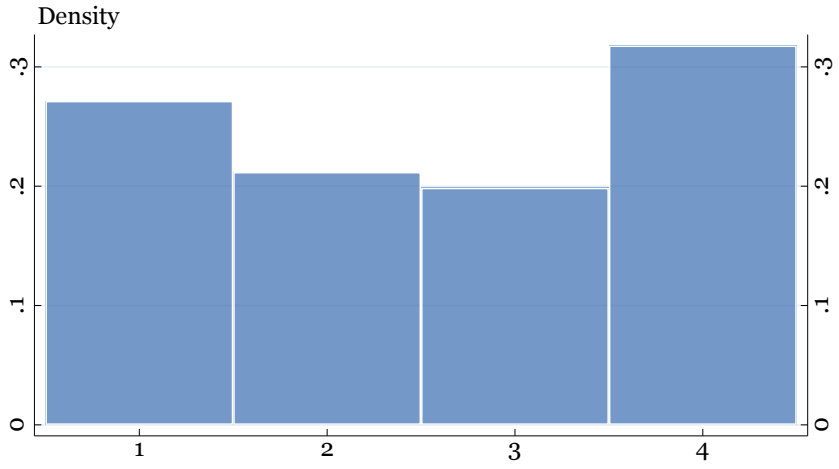
Note. The figure shows the empirical distribution of the daily crypto surprise series. It highlights the asymmetry and fat-tailed nature of event-driven Bitcoin price changes in the sample.

Figure B.2 Distribution of Crypto Surprises by Year



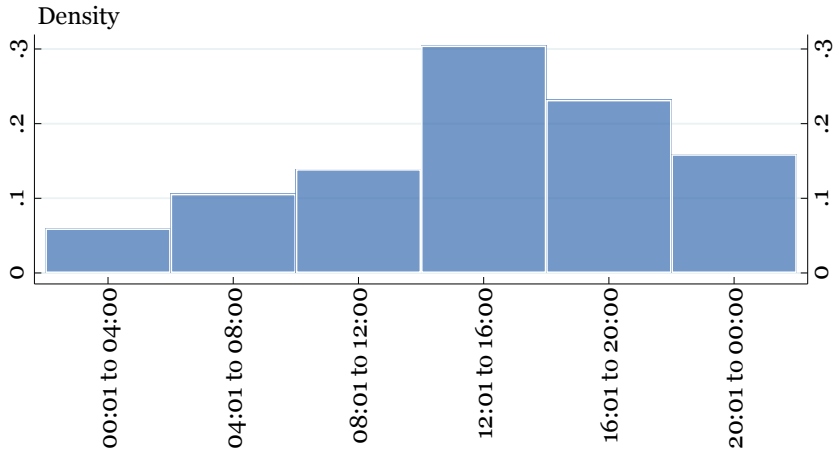
Note. The figure reports the distribution of crypto surprise events by calendar year. It illustrates how the frequency and magnitude of event-driven crypto price movements vary over time.

Figure B.3 Distribution of Crypto Surprises by Quarter



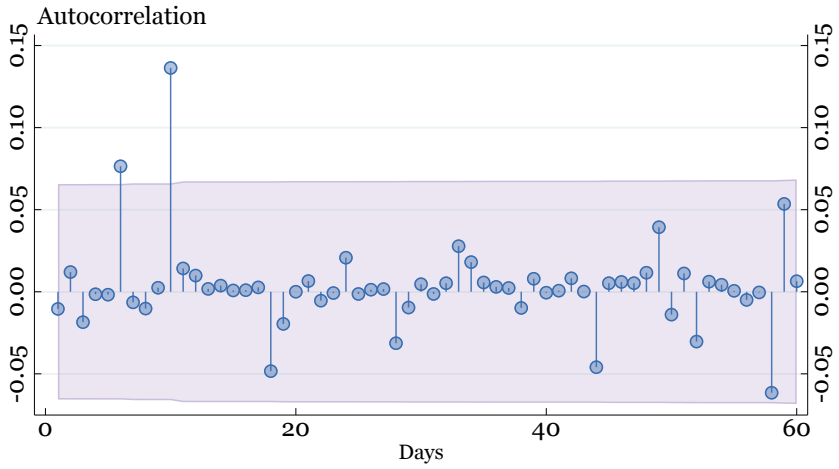
Note. The figure reports the distribution of crypto surprise events by calendar quarter. It is intended to show whether identified shocks are concentrated in particular parts of the year.

Figure B.4 Distribution of Crypto Surprises by Hour



Note. The figure reports the distribution of crypto surprise events across six four-hour time buckets within the day. It documents the intraday timing of identified crypto-specific news.

Figure B.5 Autocorrelation of Crypto Surprises



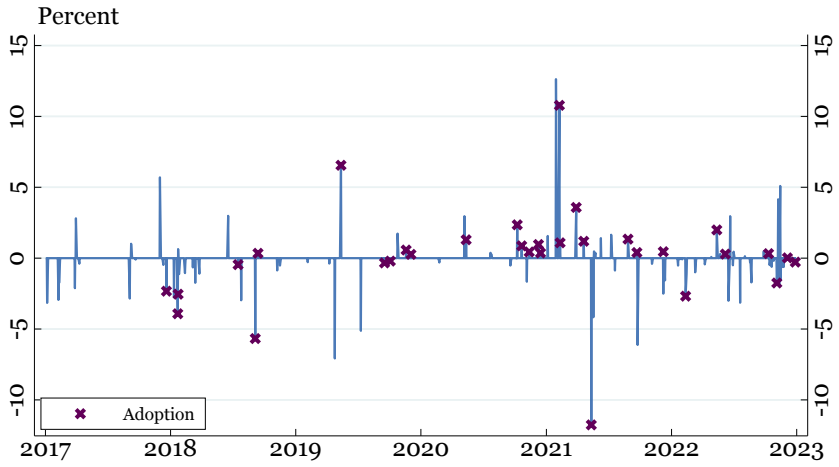
Note. The figure shows the autocorrelation function of the daily crypto surprise series. The absence of strong serial dependence is consistent with the interpretation of the shocks as discrete event-driven innovations.

Table B.3 Classification of Crypto Surprises

Category	Definition
Adoption	Company announcements signaling the adoption of crypto into mainstream finance, including banks offering custody services, public companies adding Bitcoin to their balance sheets, and payment platforms enabling crypto transactions.
Regulation	Policy news about the legal or institutional framework of crypto markets, including SEC enforcement actions, taxation changes, or mining bans.
Confidence	Changes in investor perceptions or confidence in the future of cryptocurrency markets, including exchange hacks, protocol failures, or public statements by influential figures.

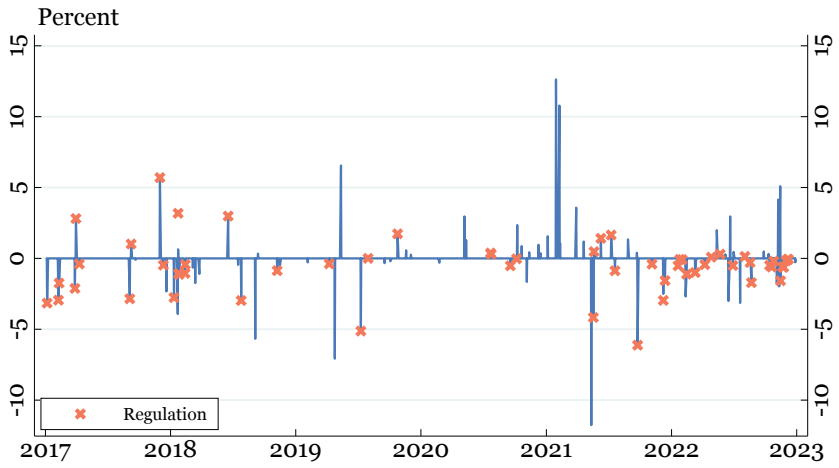
Note. The table summarizes the classification of identified crypto surprise events into adoption, regulation, and confidence shocks. The purpose of the classification is descriptive and is used to characterize the economic content of the underlying news events.

Figure B.6 Crypto Surprise Series: Adoption Shocks



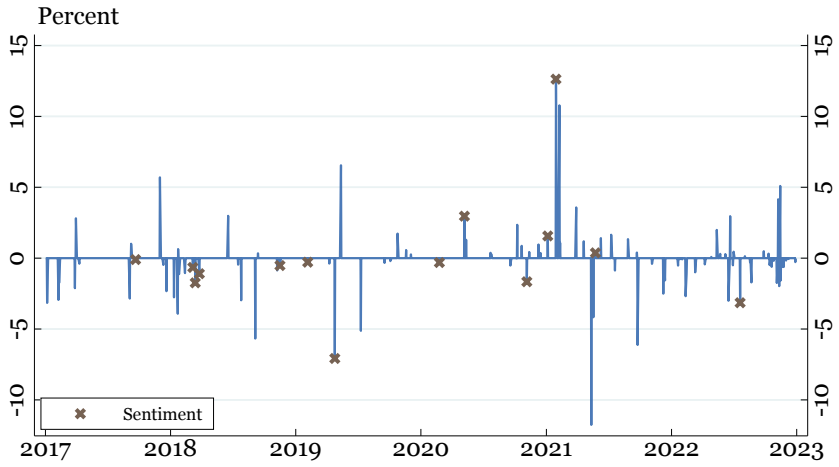
Note. The figure plots the subset of crypto surprises classified as adoption shocks. These correspond to events signaling greater integration of crypto into mainstream finance, payments, or corporate balance sheets.

Figure B.7 Crypto Surprise Series: Regulation Shocks



Note. The figure plots the subset of crypto surprises classified as regulation shocks. These capture news affecting the legal or institutional framework governing cryptocurrency markets.

Figure B.8 Crypto Surprise Series: Confidence Shocks



Note. The figure plots the subset of crypto surprises classified as confidence shocks. These events reflect shifts in investor sentiment or confidence in the future of cryptocurrency markets.

Table B.4 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

Note. The table reports pairwise correlations between the crypto surprise series and standard macroeconomic and financial shock measures. The low correlations support the view that the identified crypto shocks capture variation that is distinct from broader macro-financial disturbances.

C Crypto Exposure

Table C.1 Selected Crypto-Related N-grams in Earnings Calls

Semantic Field	Selected N-grams
Generic	crypto, cryptos, cryptocurrency, crypto-currency, cryptocurrencies, crypto-currencies, cryptoasset, crypto-asset, cryptoassets, crypto-assets, cryptospace, crypto-space, cryptomining, crypto-mining, cryptowallet, crypto-wallet, initial coin offering, initial coin offerings
Technology / Applications	blockchain, block-chain, block chain, blockchains, block-chains, block chains, distributed ledger, DLT, DLTs, DeFi, smart contracts, NFT, NFTs, tokenization
Tokens	Bitcoin, Bitcoins, BTC, BTCs, Ethereum, Ethereums, ETH, ETHs
Stablecoins	stablecoin, stablecoins, USD Coin, USDC, Tether, USDT

Note. The table reports the set of crypto-related n-grams used to construct the earnings-call-based exposure measure. The expressions are grouped by semantic field and are selected to capture references to cryptocurrencies, related technologies, tokens, and stablecoins.

Table C.2 Additional Text-Based Measures

Crypto Risk. For a given earnings call c, define

$$\text{CryptoRisk}_{cit} = \frac{1}{N_{cit}} \sum_{n=1}^{N_{cit}} \left\{ \mathbb{1}[n_{cit} \in \mathbb{C}] \times \mathbb{1}[n_{cit} \in \mathbb{R}] \right\}, \tag{C.1}$$

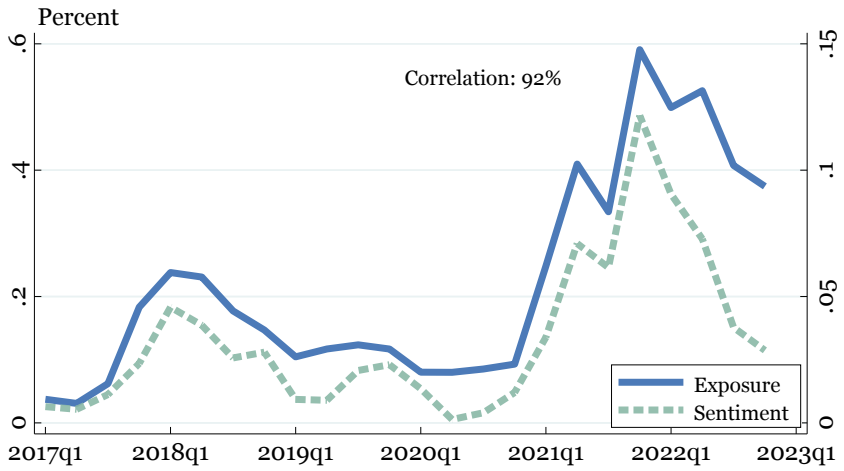
where N_{cit} is the number of sentences in the call, $\mathbb{C}$ is the set of crypto-related n-grams, and $\mathbb{R}$ is the set of risk-related expressions.

Crypto Sentiment. For a given earnings call c, define

$$\text{CryptoSent}_{cit} = \frac{1}{N_{cit}} \sum_{n=1}^{N_{cit}} \left\{ \mathbb{1}[n_{cit} \in \mathbb{C}] \times \text{Tone}(n) \right\}. \tag{C.2}$$

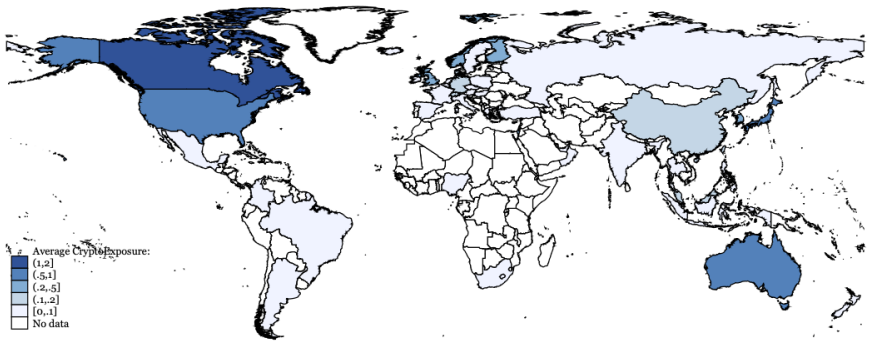
Note. The table reports the definitions of the additional text-based measures of crypto risk and crypto sentiment. Both measures are constructed using the same earnings-call corpus as the baseline exposure measure and are used for descriptive and robustness purposes.

Figure C.1 Crypto Exposure versus Crypto Sentiment



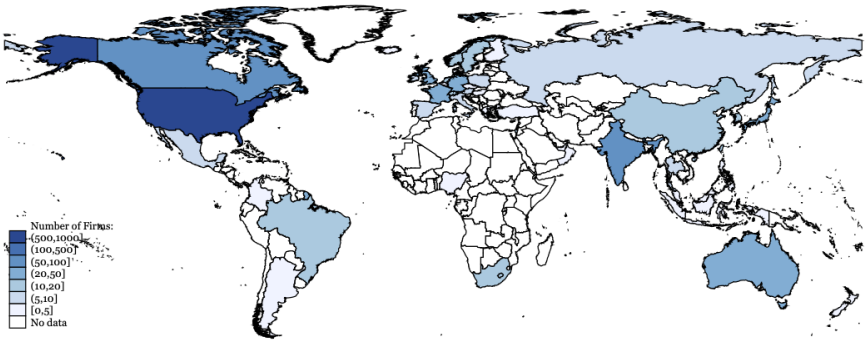
Note. The figure plots the cross-sectional average of the crypto exposure and crypto sentiment measures across firms over time. It provides a comparison between the intensity of crypto-related discussion and the tone of those discussions in earnings calls.

Figure C.2 Geographic Breakdown of Crypto Exposure



Note. The color intensity indicates the average crypto exposure of crypto-exposed firms in each country. The figure highlights the geographic distribution of firm-level engagement with crypto-related topics in earnings calls.

Figure C.3 Geographic Distribution of Crypto-Exposed Firms



Note. The color intensity indicates the number of firms with non-zero crypto exposure in each country. The figure complements the previous map by documenting the cross-country extensive margin of crypto-related firm exposure.

Table C.3 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 firms with the highest average crypto exposure in the sample, measured using the frequency of crypto-related mentions in earnings calls. The table provides a simple validation check that the exposure measure identifies firms plausibly connected to cryptocurrency markets. *Legend:* BM = Bermuda, CA = Canada, CH = Switzerland, DE = Germany, GB = Great Britain, JP = Japan, KY = Cayman Islands, TW = Taiwan, US = United States.

D Event Study – Additional Results

Table D.1 Response of Firm-Level Equity Prices: Linear Interaction

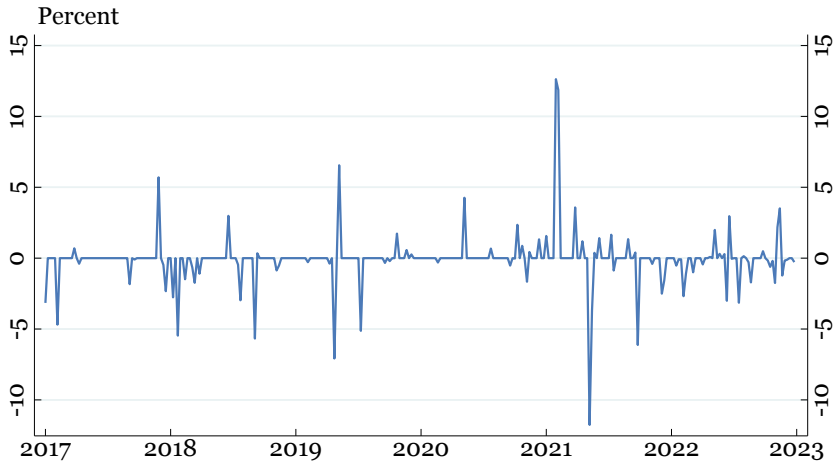
	(1)	(2)	(3)	(4)
Crypto surprise (β)	0.10**	0.11**		
	(0.05)	(0.05)		
Crypto surprise x Exposure (γ)		0.04*	0.03*	0.03*
		(0.02)	(0.02)	(0.02)
Exposure (δ)		-0.13**	-0.11***	-0.12***
		(0.06)	(0.04)	(0.04)
Observations	113,006	108,085	108,085	98,458
R squared	0.02	0.02	0.20	0.32
Firm FE	yes	yes	yes	yes
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.

Note. The table reports event-study regressions in which firm-level crypto exposure enters linearly and is interacted with the crypto surprise series. 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 are not reported.

E Local Projections – Additional Results

Figure E.1 Weekly Crypto Surprises



Note. The figure plots the weekly crypto surprise series, constructed by aggregating daily surprises within each calendar week. The sample spans 2017w1 to 2024w52.

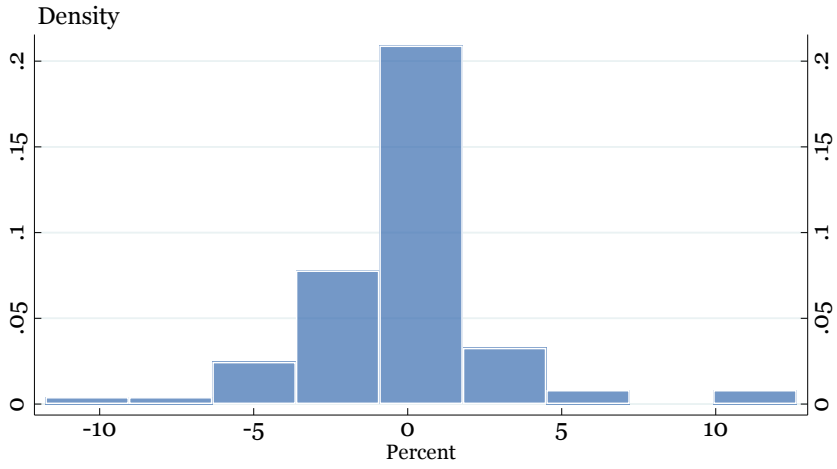
Table E.1 Weekly Crypto Surprises: Summary Statistics

	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.

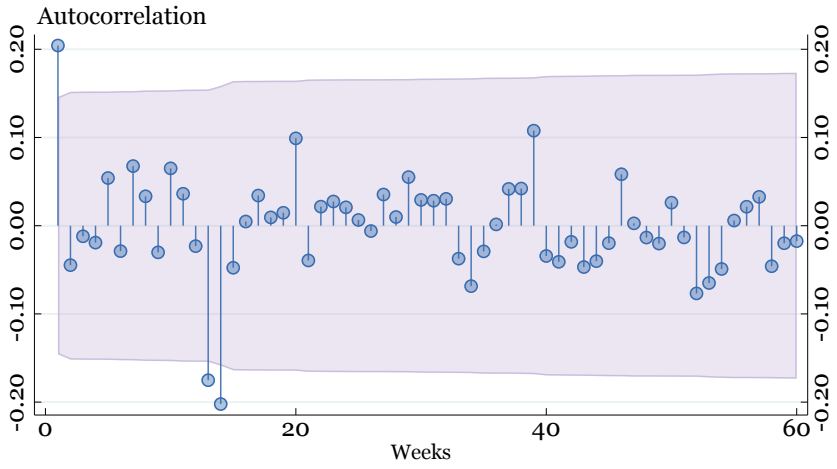
Note. Summary statistics for the weekly crypto surprise series, computed as the sum of daily crypto surprises within each week. The table provides the main moments of the shock distribution at the weekly frequency used in the local projection analysis.

Figure E.2 Weekly Crypto Surprises: Distribution



Note. The figure shows the empirical distribution of weekly crypto surprises. It is intended to describe the dispersion and skewness of the shock series used in the dynamic analysis.

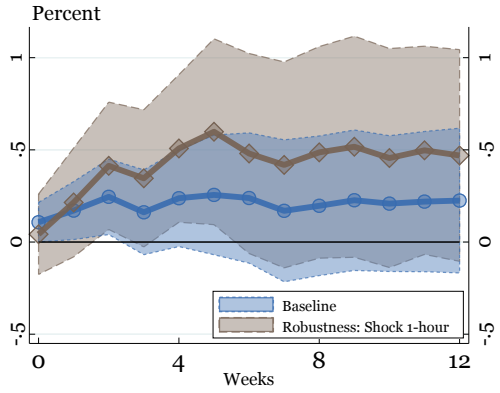
Figure E.3 Weekly Crypto Surprises: Autocorrelation



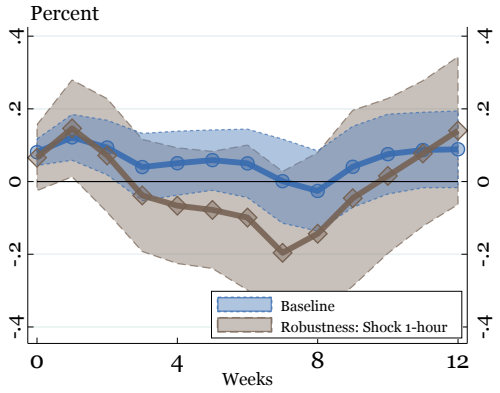
Note. The figure reports the autocorrelation function of the weekly crypto surprise series. Limited serial dependence supports the interpretation of the weekly series as a sequence of discrete innovations.

Figure E.4 Local Projections: Shock Based on 1-Hour Window

Panel A: Average effect (β)



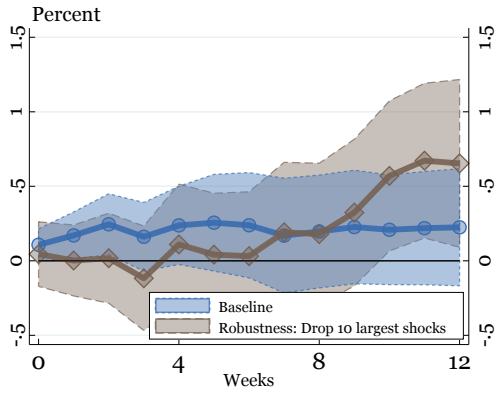
Panel B: Relative effect (γ)



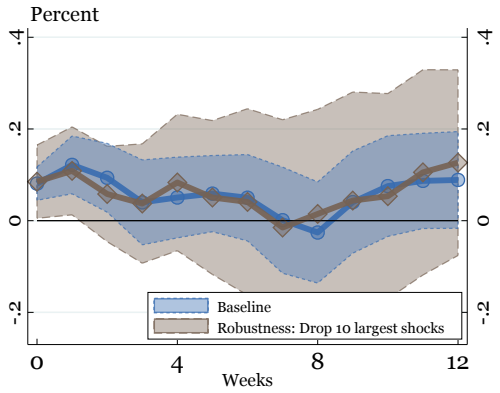
Note. The figure reports local projection estimates using an alternative shock measure constructed from a one-hour event window around each crypto event. Panel A shows the average effect, and Panel B the differential effect for highly exposed firms. Shaded areas represent 68% and 90% confidence intervals based on robust standard errors clustered two-way.

Figure E.5 Local Projections: Drop 10 Largest Shocks

Panel A: Average effect (β)

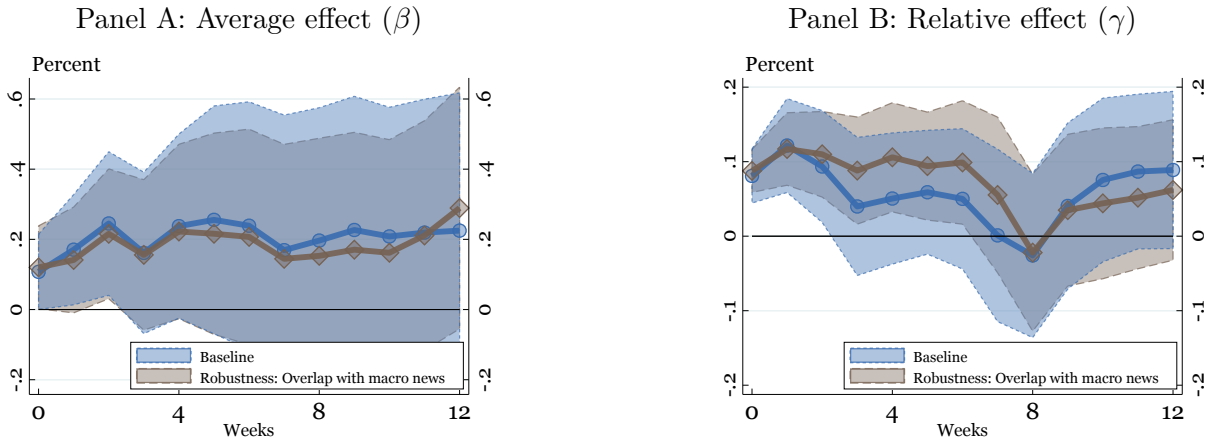


Panel B: Relative effect (γ)



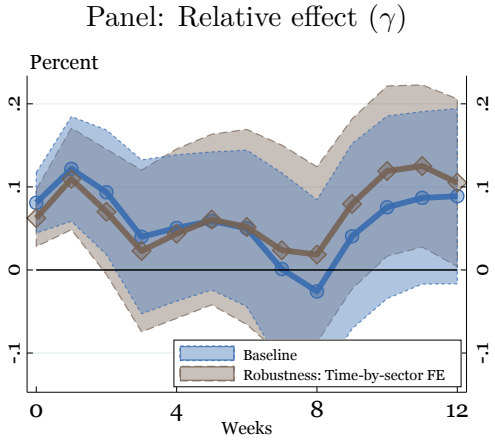
Note. The figure reports local projection estimates obtained after excluding the ten largest crypto shocks from the sample. Panel A shows the average effect, and Panel B the differential effect for highly exposed firms. This exercise assesses whether the baseline results are driven by extreme events.

Figure E.6 Local Projections: Overlap with Macro News



Note. The figure reports local projection estimates when events overlapping with major macroeconomic announcements are retained in the sample. Panel A shows the average effect, and Panel B the differential effect for highly exposed firms. The exercise evaluates the role of the overlap filter in the baseline specification.

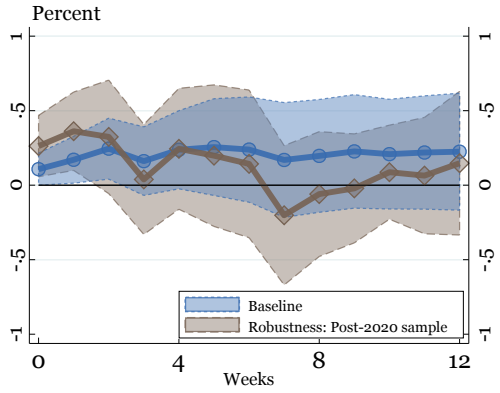
Figure E.7 Local Projections: Time-by-Sector Fixed Effects



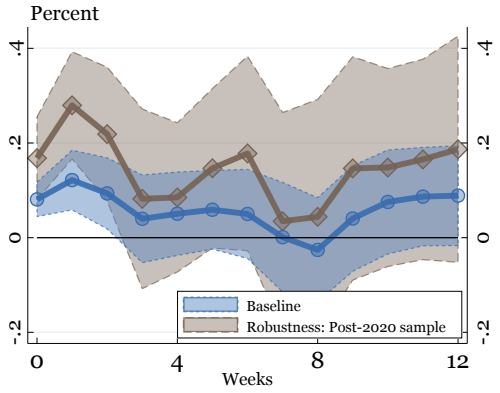
Note. The figure reports local projection estimates of the differential effect for highly exposed firms when time-by-sector fixed effects are included. The specification provides a robustness check for sector-specific time variation in equity prices.

Figure E.8 Local Projections: Post-2020 Sample

Panel A: Average effect (β)



Panel B: Relative effect (γ)



Note. The figure reports local projection estimates using only the post-2020 sample. Panel A shows the average effect, and Panel B the differential effect for highly exposed firms. The exercise evaluates whether crypto transmission has strengthened in the period of greater institutional adoption.