

Not Just Talk: Crypto Activity, Equity Repricing, and Macro-Financial Transmission

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October 2026

Abstract

Aggregate spillovers from crypto returns into U.S. equities appear muted, but how crypto shocks reach traditional financial markets depends on which firms are exposed and how they are linked. Using large language models, I classify SEC Forms 10-K, 8-K, and 20-F covering 6,551 U.S. domestic and foreign private issuers, distinguishing crypto mentions from firms' actual crypto and stablecoin activities. In 7.05 million firm-day observations across 3,879 U.S. domestic issuers, Bitcoin-related equity repricing is concentrated in firms with substantive crypto activities: return sensitivity nearly triples from general disclosures to core activities, while mention-only firms show none. Repricing is strongest for proprietary holders, smaller firms, and financial firms, and Bitcoin returns also affect operating income and asset growth. Through industry links, Bitcoin movements also reprice firms without direct exposure, more strongly in business services and less in banking. Stablecoin activity, by contrast, is mostly reserve holding and service provision rather than payment settlement. These findings show that financial stability surveillance must look beyond aggregate market correlations to identify where crypto exposure is concentrated and how it spreads across industries.

1 Introduction

Crypto assets now form a sizable market, yet their measured link to U.S. equities is weak. The International Monetary Fund characterizes Bitcoin spillovers into the S&P 500 as “muted” ([International Monetary Fund, 2025](#), Chapter 1), and a muted aggregate correlation is often read as evidence that crypto prices have little bearing on traditional financial markets. That reading conflates two distinct questions. The first is how strongly the market as a whole moves with Bitcoin; the second is which firms carry crypto exposure, through which assets and businesses, and how a shock to those firms travels to others. An index can move little with Bitcoin even when a subset of its members is heavily exposed, provided that exposure is concentrated and offset elsewhere in the portfolio. Answering the second question requires knowing what individual firms actually do with crypto assets, and no available dataset records this for the population of listed firms. This paper constructs such a measure and uses it to show that crypto prices reach U.S. equities through the activities of a concentrated set of firms and through the industries in which those firms operate.

The measurement problem is that crypto vocabulary appears in corporate filings far more often than crypto activity. A risk factor that mentions Bitcoin, an accounting policy note, and a description of a mining operation contain the same keywords but describe different economic relationships to the crypto price. I use large language models to classify SEC Forms 10-K, 8-K and 20-F filed by 6,551 U.S. domestic and foreign private issuers between 2015 and 2025, assigning each relevant passage to the firm whose activity it describes and to the economic function it reports. The classification separates mentions from a firm’s own activity, and own activity from core activity tied directly to crypto prices, such as treasury holdings, mining, trading, custody and stablecoin provision. Each statement is dated by its public filing or acceptance time, so the daily indicators record only information that investors could have observed before a given return. Linked to CRSP and accounting data, the measures cover 7.05 million firm-days for 3,879 U.S. domestic issuers from July 2015 through December 2025.

Equity markets reprice crypto activity, not crypto talk. A firm’s stock return becomes more sensitive to Bitcoin as the measure moves from any crypto discussion to the firm’s own activity and then to core, price-linked activity: a 10 percent rise in Bitcoin is associated with an additional stock return of about 0.45 percentage points for firms with any crypto disclosure, 0.85 percentage points for firms with their own activity, and 1.28 percentage points for firms with core activity. When the three layers enter jointly, the response sits in core activity, and firms whose filings mention crypto without reporting

any activity of their own show none. The ordering survives controls for the Fama–French factors and momentum, comparisons within industry on the same trading day, and an event-time design in which sensitivity rises only after a firm first discloses its activity. Among exposed firms, the response is largest where crypto represents a larger share of firm value. Firms that report holding crypto on their balance sheets are about three times as sensitive as firms with crypto operations, sensitivity among core-exposed firms falls roughly fivefold from the smallest to the largest size quintile, and financial firms show the largest industry response. These are the patterns implied by a valuation framework in which crypto prices enter equity value through the revaluation of holdings and through crypto-linked business cash flows, both scaled by the size of the firm.

The repricing has a counterpart in corporate fundamentals. Among firms with disclosed activity, a 10 percent rise in Bitcoin raises quarterly operating income by about 0.1 percent of assets and asset growth by about 0.3 percentage points, while operating cash flow does not respond, consistent with revaluation entering reported income before it generates cash. The link between accounts and prices is systematic: across activity types, size groups and industries, groups whose operating income and assets move more with Bitcoin are also repriced more in the stock market. Holders’ reported income responds most strongly, and Tesla’s filings illustrate the mechanism directly, with the change in the reported fair value of an unchanged Bitcoin position matching the market-price change almost exactly. Reported holdings nevertheless explain only a small part of the overall repricing; most of it comes from firms whose businesses, rather than balance sheets, depend on crypto markets.

These firm-level results explain why the aggregate link appears muted. Firms with crypto activity account for 8.9 percent of the covered value of the S&P 500 but for 15.9 percent of its Bitcoin sensitivity, and after controlling for the market their positive sensitivity is offset by the rest of the index, leaving the index itself with essentially none. The collapse of FTX in November 2022 shows that this concentrated exposure is economically real. FTX was an offshore exchange whose failure originated inside the crypto market; between November 8 and 11, Bitcoin fell 17 percent while the S&P 500 rose 5 percent. Firms with core crypto activity underperformed firms without crypto disclosures by 3.7 percentage points, an abnormal loss of about \$57 billion in market value, close to the \$56 billion implied by their daily sensitivity, whereas firms that only mentioned crypto were unaffected. A crypto shock of this kind reprices a well-defined set of firms by an amount that their ordinary exposure predicts, even as the index moves in the opposite direction.

The direct loss is modest relative to the equity market: a 20 percent decline in Bitcoin

implies first-round repricing of about \$17–45 billion. The question for financial stability is whether the shock stops there. It does not. Comparing unexposed firms over time as the share of their industry peers with crypto activity changes, I find that business-services firms become more sensitive to Bitcoin as more of their peers engage in crypto, while unexposed banks become less sensitive. The business-services effect is concentrated among young firms, whose own exposure is hardest for investors to observe, consistent with investors inferring exposure from peers; the banking pattern is consistent with competition among rival institutions for customers and funding. Both patterns strengthen as the exposure measure moves toward core activity and on days when Bitcoin falls, and their magnitude is large relative to the direct effect. At end-2025 exposures, a 20 percent Bitcoin decline implies about \$22 billion of direct repricing among core business-services firms and a further \$140 billion among their unexposed peers, so that spillovers account for more than four-fifths of the industry’s repricing. Within the financial sector, tail risk concentrates in exposed institutions: on Bitcoin’s worst days, financial firms with core crypto activity earn 1.8 percentage points less per day than other financial firms, and banks’ returns on Bitcoin’s worst days in 2022 predict their losses during the banking stress of March 2023.

Stablecoin activity follows a different pattern from Bitcoin exposure. Listed firms report stablecoins mainly as reserve balances and as services they provide to customers, such as issuance, distribution and custody, while use of stablecoins to settle the firm’s own payments remains rare. Reported participation expanded sharply in fiscal 2025, when 59 firms reported stablecoin activity for the first time, 39 of them with no earlier crypto disclosure.

The paper contributes to four literatures. Studies of corporate factor exposure relate stock returns to the prices that affect firms’ assets and operations, from exchange rates (Adler and Dumas, 1984; Jorion, 1990) to oil prices and interest rates (Jones and Kaul, 1996; Flannery and James, 1984), and typically infer exposure from proxies such as foreign sales (He and Ng, 1998; Dominguez and Tesar, 2006; Bartram and Bodnar, 2007). I measure the underlying activities directly and show that crypto exposure is priced beyond the standard risk factors (Fama and French, 1993, 2015; Carhart, 1997), scales with the importance of the activity to the firm, and is reflected in fundamentals. Research on crypto asset pricing studies the returns of crypto assets themselves (Liu and Tsyvinski, 2021; Liu et al., 2022; Makarov and Schoar, 2020; Griffin and Shams, 2020), and research on spillovers studies their aggregate correlation with equity markets (Iyer, 2022; Iyer and Popescu, 2023; International Monetary Fund, 2025); I move from the market level to the

firms through which that correlation arises and explain why it appears muted. Studies of corporate crypto activity have examined hand-collected holdings (Anderson et al., 2026), blockchain announcements (Cheng et al., 2019), listed miners (Halaburda and Yermack, 2023) and individual firms such as MicroStrategy (Andrade et al., 2026); I provide a dated, population-wide measure that separates holdings, operations and intermediation from discussion, building on text-based measures of firm exposure (Hassan et al., 2019; Sautner et al., 2023; Gentzkow et al., 2019) and on validation methods for language-model measurement (Ludwig et al., 2025). Finally, I bring the intra-industry framework of Lang and Stulz (1992) to crypto shocks, showing that their transmission to unexposed firms depends on whether peers are valued as comparables or compete for the same customers and funding (Gatev and Strahan, 2006). The stablecoin results complement work on stablecoins as private money and payment infrastructure (Gorton and Zhang, 2023; Ahmed and Aldasoro, 2025; Auer et al., 2025; Ahmed et al., 2025) by identifying which corporate functions listed firms actually perform. Throughout, the estimates describe repricing associated with publicly disclosed activity, and the FTX collapse provides an external crypto shock against which the daily estimates can be evaluated.

The remainder of the paper is organized as follows. Section 2 presents the valuation framework and its predictions. Section 3 describes the filings, the classification and the return sample. Section 4 examines how disclosed activity is priced, and Section 5 turns to corporate fundamentals. Section 6 follows exposure from individual firms to the index, the FTX collapse, industry peers and financial institutions. Section 7 describes stablecoin activity, and Section 8 concludes.

2 Framework

2.1 Direct exposure

A firm can be exposed to crypto prices through what it owns and through what it does. Following the corporate exchange-rate exposure framework of Adler and Dumas (1984) and Jorion (1990), write the equity value of firm i as

$$V_i = A_i + H_i P + G_i(P) - L_i, \quad s_i \equiv \frac{\partial V_i}{\partial P} \frac{P}{V_i} = \underbrace{\frac{H_i P}{V_i}}_{\text{revaluation}} + \underbrace{\frac{G'_i(P) P}{V_i}}_{\text{business value}}, \quad (1)$$

where A_i is the value of other assets, H_i the firm's own Bitcoin units, P the Bitcoin price, $G_i(P)$ the value of crypto-linked businesses such as mining, trading or custody, and L_i

senior claims. The elasticity s_i is the equity response to a one percent change in the Bitcoin price, holding positions and other claims fixed. The first term is the mechanical revaluation of holdings; the second captures revenues, costs and fees that vary with the crypto market. For a firm whose only exposure is a fixed position, the equity return is

$$r_i^{\text{direct}} \simeq \frac{PH_i}{ME_i^-} r^{\text{BTC}}, \quad (2)$$

where ME_i^- is prior equity market value.

Equation (1) yields four predictions. *P1 (activity, not talk)*: a filing that mentions crypto without describing a position or business adds neither term, so mention-only firms should show no additional sensitivity. *P2 (price link)*: the sensitivity should be larger for core activity, whose assets and revenues depend directly on crypto prices, than for broader activity that includes blockchain technology work. *P3 (composition and scale)*: holders have a direct revaluation term, and a claim of given dollar size matters more at a smaller firm, so holders and small firms should be most sensitive. *P4 (fundamentals)*: revaluation and crypto business income should move reported operating income and assets with Bitcoin, revaluation need not move operating cash flow, and groups whose fundamentals move more with Bitcoin should be repriced more.

2.2 From exposed firms to the index and to industry peers

Aggregation explains how firm-level exposure can coexist with a weak market link. The Bitcoin sensitivity of an index is the value-weighted average of its members' sensitivities,

$$s_{\text{index}} = \sum_i w_i s_i, \quad (3)$$

so a large s_i at a small group of firms contributes little when their weight is small, and other members with negative conditional sensitivities can offset it entirely. A muted index sensitivity therefore says little about where exposure sits. The relevant objects are the exposed firms' share of index value and their share of index sensitivity.

Exposure can also reach firms that hold no crypto and run no crypto business. Consider a firm k without direct exposure in industry j , and let π_k be the share of its industry peers with exposure, each with sensitivity s . Its Bitcoin sensitivity is

$$\beta_k = \theta_j + (\rho_j - \kappa_j) s \pi_k, \quad (4)$$

where θ_j is the industry’s sensitivity without exposed peers. The term ρ_j captures information: when a firm’s own exposure is hard to observe, investors infer it from similar peers, so its price moves with theirs (Lang and Stulz, 1992). The term κ_j captures competition: when exposed peers are hit, customers and funding move to unexposed rivals, which gain relative to them (Lang and Stulz, 1992; Gatev and Strahan, 2006). The two forces are not measured separately; equation (4) instead yields three testable predictions. *S1*: the sign of the spillover can differ across industries, positive where information dominates and negative where competition does. *S2*: the spillover strengthens with the sensitivity of exposed peers, and hence as the exposure measure moves from mentions to own and core activity. *S3*: the information force, and therefore a positive spillover, is strongest for recipients whose own exposure is hardest to observe, such as young or small firms. Table 1 lists each prediction and the test that addresses it.

Table 1: Predictions and Tests

Prediction	(1) Test	(2) Where
P1: Activity, not talk	Joint core, technology-only and mention-only layers	Table 4
P2: Price link	Nested Any, own activity and core exposure	Table 4
P3: Composition and scale	Holder–operations contrast; size gradient	Table 5; Figure 13
P4: Fundamentals	Income and assets; group fundamental and return betas	Table 7; Figure 17
Aggregation	Exposed firms’ value and sensitivity shares	Table 9; Figure 19
S1: Industry-specific sign	Business services versus banking	Table 12
S2: Scaling with direct sensitivity	Spillovers under nested exposure definitions	Table 12; Figure 22
S3: Recipient opacity	Listing-history age and market-value splits	Table 13

Notes: The predictions distinguish directly exposed firms from industry recipients without direct exposure. Direct exposure depends on the activity and its share in equity value. The references identify the pricing, accounting, aggregation and spillover tests.

3 Data and Measurement

3.1 Filings and candidate passages

The filing census covers SEC Forms 10-K, 8-K with EX-99 exhibits, and 20-F from 2015 to 2025. The domestic annual frame contains 41,910 firm-years at 4,897 operating firms; adding current reports and foreign private issuers’ annual reports expands coverage to 51,426 firm-years at 6,551 firms. Pooled investment vehicles are excluded, because their returns follow the assets they hold by construction, and when a firm files an amended annual report for the same fiscal year the substantive version with the largest file size is retained, with the latest filing date breaking ties. Annual reports describe ongoing activities and financial positions, while current reports reveal new positions and businesses between annual filings, so combining the two shortens the delay between an activity and its first public record. Figure 3 summarizes the five steps that turn these filings into dated firm-level measures; the remainder of this section describes each step and the definitions it relies on.

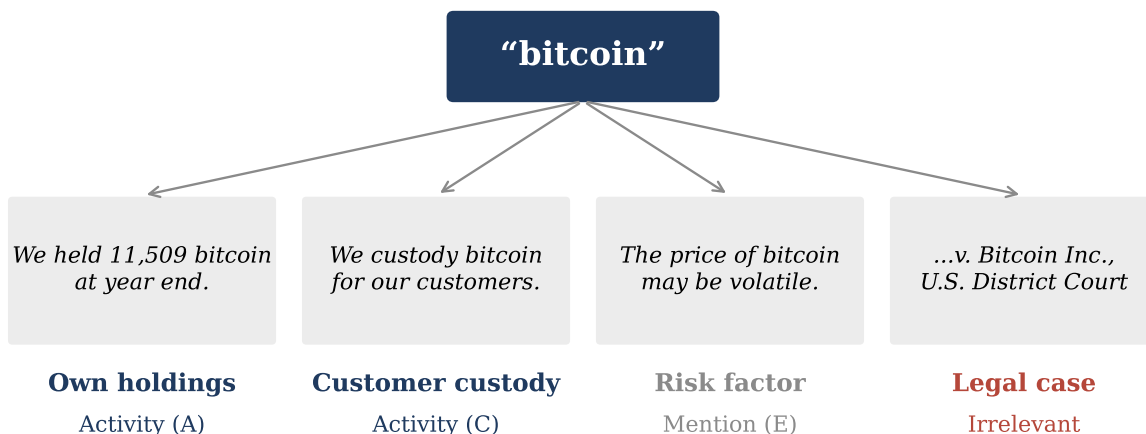


Figure 1: One Word, Four Meanings: Classified Passages Containing “bitcoin”

Notes: The examples illustrate how attribution and use distinguish own holdings, customer custody, a risk discussion, and an irrelevant legal reference.

The first step converts each filing into passages and retains those that could concern crypto. Each document is parsed from its source HTML into paragraphs, each paragraph is tagged with the recognized item heading, or marked unknown when no heading is recognized, and tables are written out row by row so that units, cost and fair value remain next to their headings. A passage is retained when it contains at least one term from a dictionary of 93 terms. The dictionary is built for recall rather than precision:

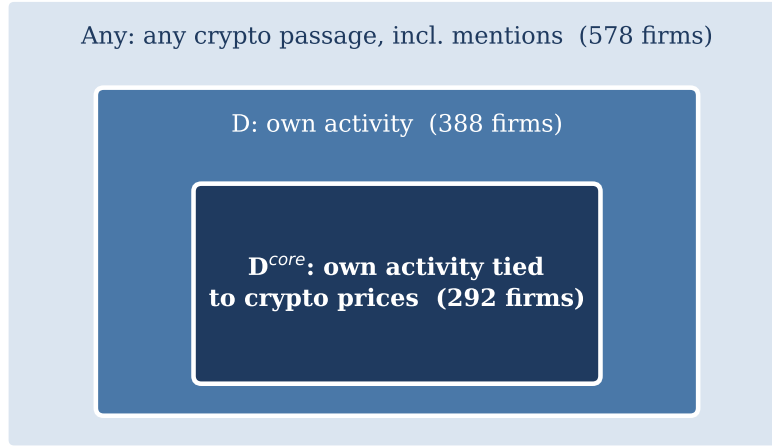


Figure 2: Nested Exposure Measures

Notes: The diagram shows the nested definitions and their exposed-firm counts in the daily return sample.

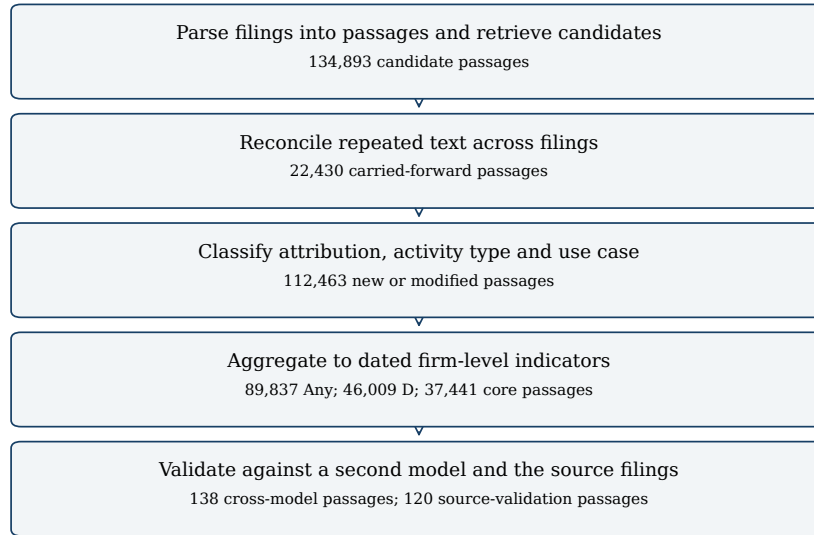


Figure 3: Construction of the Activity Measures

Notes: Counts refer to fiscal 2015–2025 after excluding pooled vehicles. The aggregate measures are nested, so their passage counts overlap. Cross-model agreement and source-filing validation use separate samples.

it contains unambiguous terms such as bitcoin, cryptocurrency, stablecoin and virtual currency, the wording that dominates early filings; ambiguous terms such as blockchain, digital assets, token, USDC and ether, which are retained deliberately and resolved in the classification step; and the names of crypto firms such as Coinbase, Circle Internet and Paxos, which capture relationships with crypto counterparties that asset names alone would miss. Terms are matched on word boundaries, so that “bitcoins” is retrieved while

“deficit” and “cryptographic” are not, and strings that collide with common words or legal abbreviations, such as ADA and “ripple”, are excluded. Retrieval yields 134,893 candidate passages in 17,282 filings. Only these passages are passed to the classification step; the rest of each filing is not.

The second step reconciles text that firms repeat from one filing to the next, which is common in risk factors and accounting policies. Each candidate passage is compared with the passages in the same firm’s previous filing of the same form. A passage is treated as carried forward when its word sequences overlap with an earlier passage with a Jaccard similarity of at least 0.7, computed over sets of up to 24 hashed eight-word sequences after numbers are normalized, and when the numbers it reports are unchanged; it then inherits the label of the earlier passage. A passage that matches earlier text but reports different numbers, for example a larger holding, is treated as modified and is classified again, as is every new passage. Of the 134,893 candidate passages, 22,430 are carried forward and 112,463 are new or modified. The rule ensures that a repeated statement does not count as new information and that a changed quantity always does.

3.2 Classification and dated measures

The third step classifies each new or modified passage with a language model. The production run uses GPT-4o at temperature zero, one passage per call, under a fixed instruction set that contains the definition of every category with verbatim examples, rules for recurring ambiguities such as USDC as an abbreviation for a district court, mining of minerals, ether as a chemical and central bank digital currencies, and worked examples of the hardest boundaries. The model returns a structured record for each passage that is checked automatically for admissible codes and internal consistency; a record that fails the check is returned with the error, with up to four attempts in total, and a passage that still fails is recorded as a classification error and omitted from passage-label aggregation. Each passage receives separate attribution, activity-type and use-case codes. The activity-type code records the firm’s own holdings, its operations, its intermediation or custody for clients, or accounting, risk and regulatory discussion, with passages about other firms, about the market in general or unrelated to crypto coded separately. The use-case code records the use case, such as treasury reserves, mining, payments, retail offerings, custody, stablecoin provision, trading, staking, collateral, or blockchain technology work without crypto assets. Figure 1 shows four passages that contain the same word and receive four different labels, and Figure 2 shows how the labels map into the measures used below.

The fourth step aggregates the passage labels into dated firm-level indicators. *Any*

equals one when the firm has filed a passage about its own holdings, operations or intermediation, or an accounting, risk or regulatory passage regardless of attribution; other-firm and general-market activity passages and passages classified as unrelated to crypto do not count. D equals one when the firm reports its own holdings, operations or intermediation, that is, when at least one passage attributes such an activity to the firm itself. D^{core} retains own activity assigned to use cases U1–U9 and excludes blockchain technology work and unassigned use cases. Each indicator uses passages made public in the 365 calendar days before the return date, so a firm enters an exposure category when a qualifying statement becomes public and leaves it when the information expires. For annual reports the public date is the filing date; for current reports it is the acceptance timestamp, and the indicator begins on the following trading day. The nested indicators also define three mutually exclusive layers — core, technology-only and mention-only — which allow the paper to test which kind of statement carries the price response when all enter the same regression. The difference between counting words and reading passages is large. In domestic annual reports, keyword search flags 5,397 firm-years, but only 1,312 of them contain a passage that describes the firm’s own activity. Crypto mentions are therefore far more common than own activity (Figure 4), and first observed activity arrives through annual and current reports alike (Figure 5).

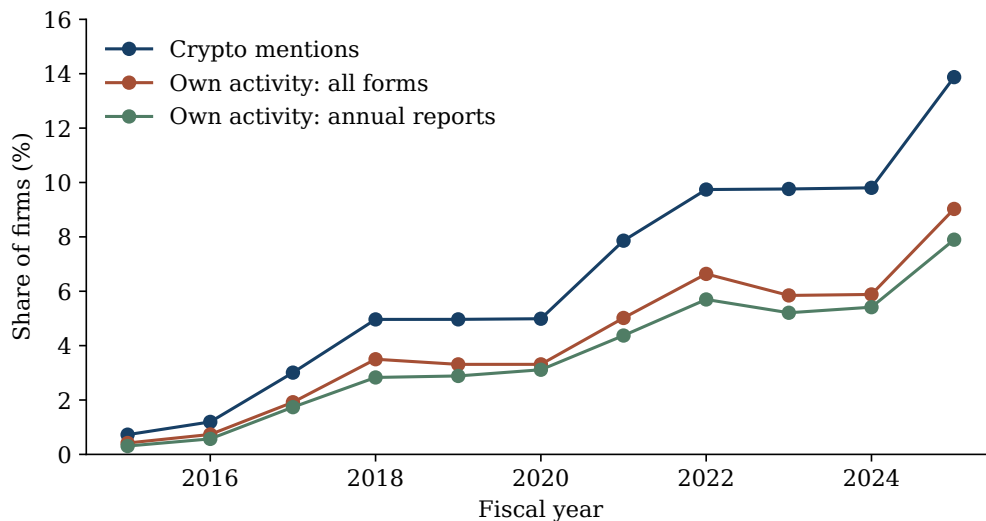


Figure 4: Crypto Mentions and Own Activity among SEC Filers

Notes: The series show the share of SEC filers with a relevant crypto passage, with own activity measured across Forms 10-K, 20-F, and 8-K, and with own activity measured from annual reports only. The definitions distinguish mentions from self-attributed corporate activity.

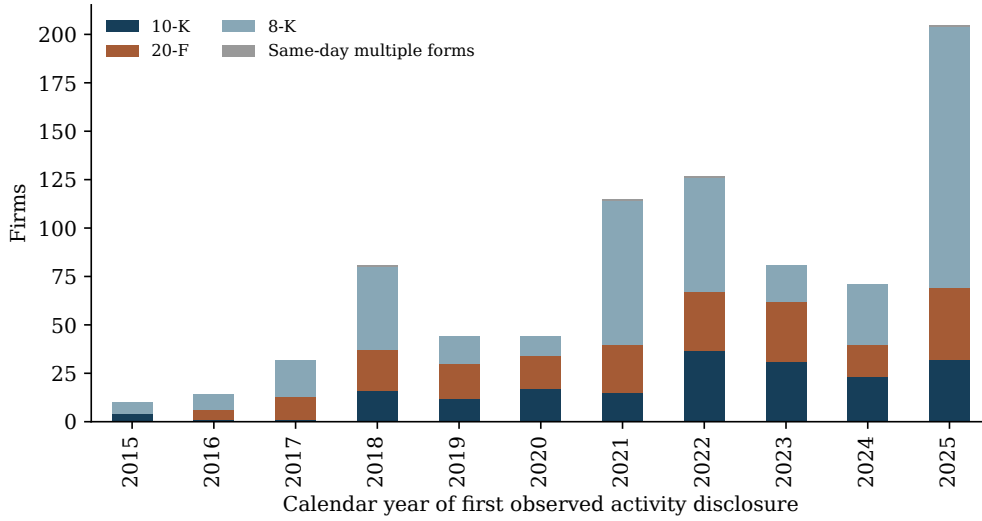


Figure 5: Filing Forms at First Observed Activity

Notes: SEC annual and current reports. The figure groups first observed own-activity statements by information year and filing form. Public dates determine information arrival; they need not date the start of the underlying business.

3.3 Validation

The fifth step checks the labels in three ways, and the statistics it reports have standard definitions. The first check measures agreement across model families. A model from a second provider, Claude Sonnet 5, independently classifies a validation sample of 138 payment-related passages under the same instructions. The agreement rate is the share of passages to which the two models assign the same payment-function code; they agree on 121 of the 138 passages, or 87.7 percent. Because two classifiers that assign labels at random would still agree on some passages, I also report Cohen’s kappa, $\kappa = (p_o - p_e) / (1 - p_e)$, where p_o is the observed agreement rate and $p_e = \sum_k p_k^A p_k^B$ is the agreement expected if each model assigned category k independently with its own observed frequency p_k^A or p_k^B . Kappa equals one under perfect agreement and zero when agreement is no better than chance. The estimate of 0.83 exceeds 0.8, the level conventionally required of reliable coding.

The second check compares the labels with a reading of the source filing. For a sample drawn before the production run, a separate model reading the full filing reads each passage in the context of the full filing and records the correct label. Precision is the share of passages assigned to a category that the audit confirms, and recall is the share of passages that belong to a category according to the audit and that the classifier assigns to it. For any stablecoin activity, precision is 46 of 48 and recall is 46 of 51, and a separate audit of a random draw of provider passages from the production run confirms 82 of 91

(Appendix A). The third check concerns attribution within a filing, which keyword counts cannot provide. Block’s fiscal 2023 annual report contains 8,038 bitcoin held for its own account and 24,570 bitcoin held in custody for customers; a keyword-based measure would combine the two, while the classification records them separately.

3.4 Who reports crypto activity

Crypto activity spans several corporate functions, and firms often report more than one. In the domestic annual frame, 1,310 firm-years at 454 firms report own activity (Figure 6). Operations are the most common role, appearing in three-quarters or more of activity-positive firm-years in each major sector, while holdings and intermediation are concentrated in finance. In finance, insurance and real estate, own holdings appear in 24.6 percent of activity-positive firm-years and intermediation in 54.6 percent, compared with 13.4 and 37.4 percent in business services and 14.4 and 23.1 percent in manufacturing. Activity is most prevalent in business services and finance, where roughly one in ten and one in sixteen firm-years report it, against about one percent in manufacturing (Figure 7). The mix also changes with size: operations appear in 85.8 percent of activity-positive firm-years in the smallest asset quartile and 64.3 percent in the largest, while intermediation rises from 33 to 51.5 percent. An industry label therefore does not identify the channel through which crypto prices reach a firm, which is why the pricing tests separate roles, size and industry. Foreign private issuers report activity more often than domestic filers, by about 4.5 percentage points within the same industry and year, which is one reason the census includes Form 20-F filers even though the return analysis uses domestic issuers (Appendix C).

Firms that report crypto activity differ from other listed firms in ways that could affect their returns independently of crypto. They are younger, with a median recorded age of 12 years against 20, and smaller, with median log assets of 6.39 against 7.31. They also hold more cash, with a median cash-to-assets ratio of 0.158 against 0.107, and carry less debt, with a median debt-to-assets ratio of 0.170 against 0.240 (Table 2; Figure 8). Smaller, younger and cash-rich firms may load differently on common risk factors, so all return regressions control for size, cash, leverage and profitability and their interactions with the Bitcoin return, and robustness tests add the Fama–French factors interacted with exposure.

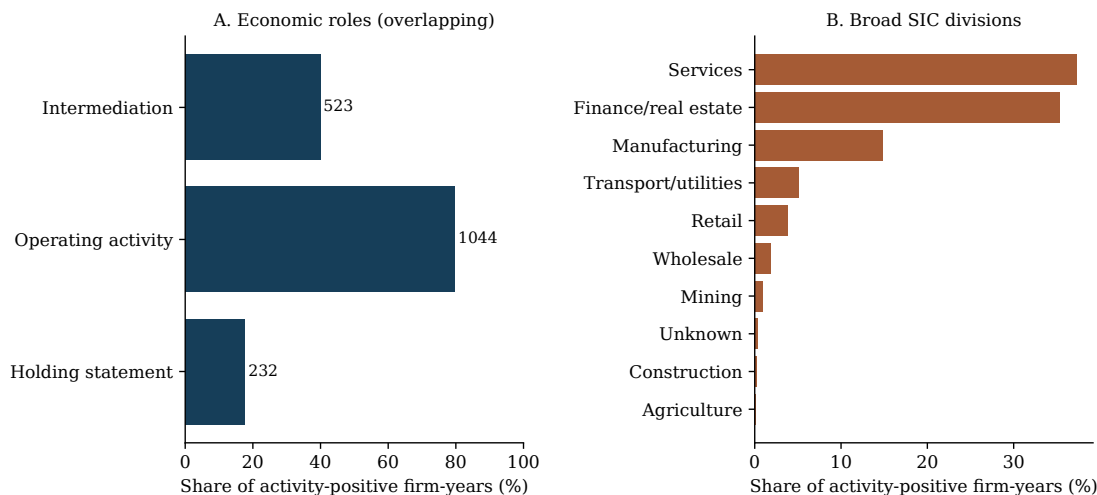


Figure 6: Corporate Crypto Activity by Role

Notes: Both panels condition on 1,310 observed activity-positive firm-years in the domestic 10-K reconstruction. Role shares overlap and need not sum to 100 percent; labels show counts. Industry shares use broad SIC divisions, with missing classifications retained as unknown.

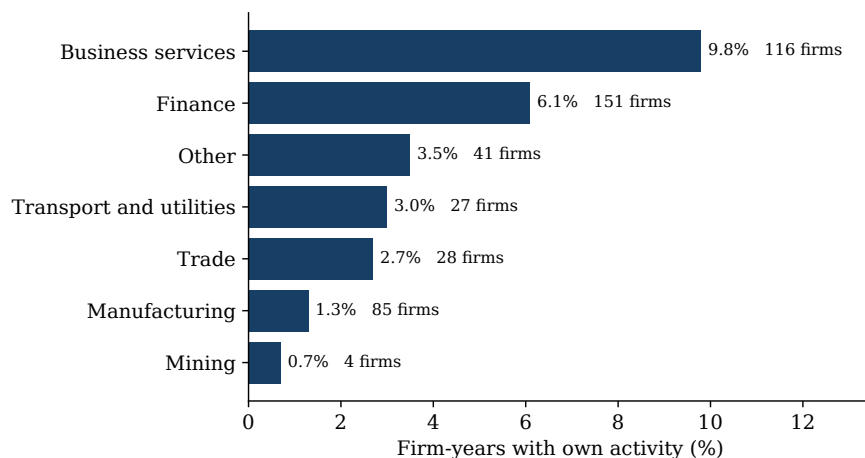


Figure 7: Own Crypto Activity by Industry

Notes: Bars report the share of firm-years with own crypto activity by broad industry over 2015–2025. Labels report the percentage and number of firms. Industry classification uses the static two-digit SEC SIC code.

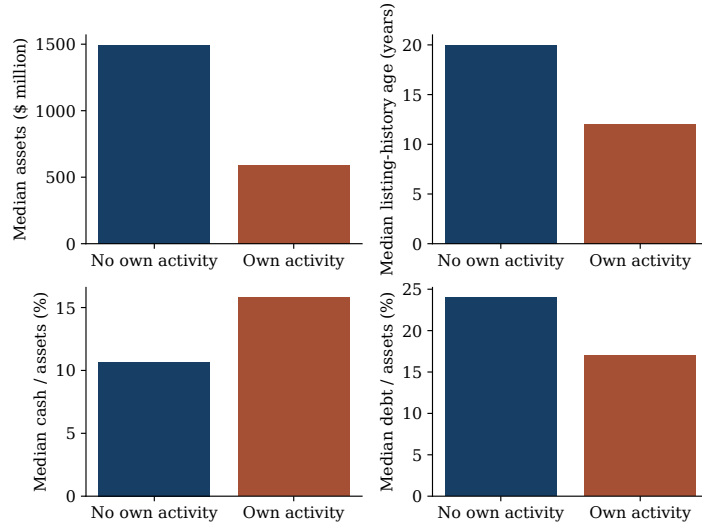
3.5 The return sample

The daily analysis uses domestic filers linked to their primary CRSP security. CRSP supplies daily stock and market returns; Compustat annual fundamentals, supplemented by SEC XBRL items, supply size, cash, leverage and profitability; and rolling regressions on past returns supply each firm's prior market and Bitcoin betas. Every control enters only after the filing or estimation date on which it became public. Bitcoin returns are measured between consecutive CRSP closing dates, so weekend price changes enter the

Table 2: Financial Characteristics by Prior Disclosed Activity

	(1)	(2)	(3)	(4)	(5)	(6)
	No prior recorded activity		Prior recorded activity			
	<i>N</i>	Median	Mean	<i>N</i>	Median	Mean
Log assets (USD millions)	26,936	7.310	7.049	756	6.387	6.511
Years since first financial record	26,962	20.000	24.157	756	12.000	17.664
Cash / current assets	26,936	0.107	0.222	756	0.158	0.227
Debt / current assets	26,857	0.240	0.324	756	0.170	0.339
Net stock flows / current assets	24,988	−0.000	0.077	720	0.000	0.144
CAPEX / current assets	26,773	0.013	0.027	754	0.007	0.052

Notes: Data: linked annual accounting data, before outcome-specific regression exclusions. Columns report nonmissing firm-year counts, medians and means. Asset levels are in USD millions before taking logs. Cash is reported cash; debt is long- plus short-term debt; net stock flows subtract repurchases from stock-sale proceeds; Ratios use positive current assets for this descriptive table; Missing components remain missing. Prior disclosure uses the pre-window activity dummy, not contemporaneous financial outcomes.

**Figure 8:** Financial Profiles by Disclosure Category

Notes: Panels compare total assets, years since first record, cash/assets, and debt/assets for crypto-active and other firms. Amounts are in USD millions; balance-sheet ratios are percentages.

next trading session. The final sample contains 7,050,425 firm-days at 3,879 firms over 2,642 trading days from July 2015 to December 2025 (Table 3). Of these firms, 578 enter the Any category on at least one day, 388 enter D, and 292 enter D^{core}. Eligibility depends only on information available before each return, not on later disclosure, so firms without activity remain in the comparison group and firms move in and out of exposure as statements enter and leave the information window.

Table 3: Regression Sample Construction

Restriction	(1) Firms	(2) Firm-days	(3) Dates	(4) $D+$	(5) $D0$	(6) Days lost
Domestic SEC population	4,897	–	–	–	–	–
Linked daily records	4,154	8,677,006	2,766	444	3,710	–
Valid dated security link	4,154	8,495,872	2,766	442	3,712	181,134
Prior annual filing / primary security	4,017	7,279,815	2,741	411	3,606	1,216,057
Observed return, financial controls and SIC	3,888	7,105,907	2,741	391	3,497	173,908
Prior betas: final daily sample	3,879	7,050,425	2,642	388	3,491	55,482

Notes: Counts are distinct firms and firm-days. Initial SEC records have no daily observation unit. $D+$ counts firms positive on at least one retained day; $D0$ counts the remainder and denotes no prior activity disclosure. Losses are firm-days removed since the previous reported daily stage; grouped stages include all intervening restrictions; the final sample uses dated primary-security links, prior annual reporting within 365 days, observed classification, financial controls, industry and prior betas. The detailed sequence and variable coverage appear in Appendix B.

4 Activity and Equity Repricing

4.1 Activity, not talk

Equity markets reprice firms' own crypto activity, not the appearance of crypto language in their filings. I estimate

$$r_{id} = \alpha_i + \lambda_d + \rho D_{i,d-} + \beta D_{i,d-} r_d^{BTC} + \Gamma'(X_{i,d-} r_d^{BTC}) + \zeta \hat{b}_{i,d-}^M r_d^M + \xi \hat{b}_{i,d-}^{BTC} r_d^{BTC} + \Phi' X_{i,d-} + \varepsilon_{id}, \quad (5)$$

where $D_{i,d-}$ is a disclosure indicator, X contains log assets, cash, leverage and profitability, and $\hat{b}^M$ and $\hat{b}^{BTC}$ are prior market and Bitcoin betas. Firm and date fixed effects absorb persistent return differences and common market movements, so β is identified from differences across firms in their response to the same Bitcoin return, and standard errors are clustered by firm and date. The coefficient measures the additional Bitcoin sensitivity associated with disclosure, beyond what a firm's past Bitcoin beta and balance sheet already predict.

The sensitivity rises as the measure moves from discussion toward a direct price channel. A 10 percent rise in Bitcoin is associated with an additional stock return of 0.45 percentage points for firms with any crypto disclosure, 0.85 percentage points for firms with their own activity, and 1.28 percentage points for firms with core activity (Table 4). The ordering is not a mechanical consequence of a narrower definition. When core activity, technology-only activity and mention-only disclosure enter the same regression, core activity carries the response, technology-only activity carries a small one, and mention-

only firms carry none. A firm that discusses Bitcoin in a risk factor is priced like a firm that never mentions it; a firm that holds Bitcoin, mines it or earns fees from it is not. The first comparison confirms prediction P1, and the gradient from own to core activity confirms P2.

Table 4: Bitcoin Sensitivity by Disclosure Measure

	(1) Any	(2) Own activity D	(3) Core activity D_{core}
<i>Panel A. Nested Definitions</i>			
Exposure $\times$ Bitcoin return	0.045*** (0.009)	0.085*** (0.014)	0.128*** (0.022)
Exposed firms	578	388	292
<i>Panel B. Mutually Exclusive Layers</i>			
	Mention only	Technology only	Core activity
Layer $\times$ Bitcoin return	−0.004 (0.005)	0.013* (0.007)	0.128*** (0.022)
Exposed firms	240	154	292
Firm fixed effects	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes
Baseline controls	Yes	Yes	Yes
Observations	7,050,425	7,050,425	7,050,425
Firms	3,879	3,879	3,879
Dates	2,642	2,642	2,642
<i>Equality Tests, p-values</i>			
Core = technology only		< 0.001	
Core = mention only		< 0.001	
Technology only = mention only		0.041	

Notes: The dependent variable is the daily stock return in the domestic-issuer sample. Panel A estimates the nested exposure measures separately, and Panel B enters mutually exclusive layers jointly. All specifications include firm and date fixed effects and baseline controls. Standard errors are two-way clustered by firm and date. Standard errors are in parentheses; * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$ denote raw two-sided probabilities.

The result is not driven by the familiar characteristics of crypto-active firms. Allowing exposed firms to load separately on each of the Fama–French five factors and momentum lowers the core-activity sensitivity only from 0.128 to 0.112 and preserves the ordering across measures (Figure 9). Comparing firms within the same two-digit industry on the same day yields a similar own-activity estimate, so industry-wide news does not account for the response. Part of the repricing arrives in the following sessions: adding one- and two-day lags of the Bitcoin return raises the cumulative core-activity sensitivity to 0.164,

and the cumulative own-activity sensitivity rises from 0.086 on the same day to 0.127 over five sessions without reversing (Figure 10; Appendix D). The estimates are also similar in an expanded comparison sample that matches disclosing firms to comparison firms on the full disclosure history (Appendix B). Reporting intensity also matters, since firms that describe their activity in more paragraphs are repriced more for the same activity status (Appendix D).

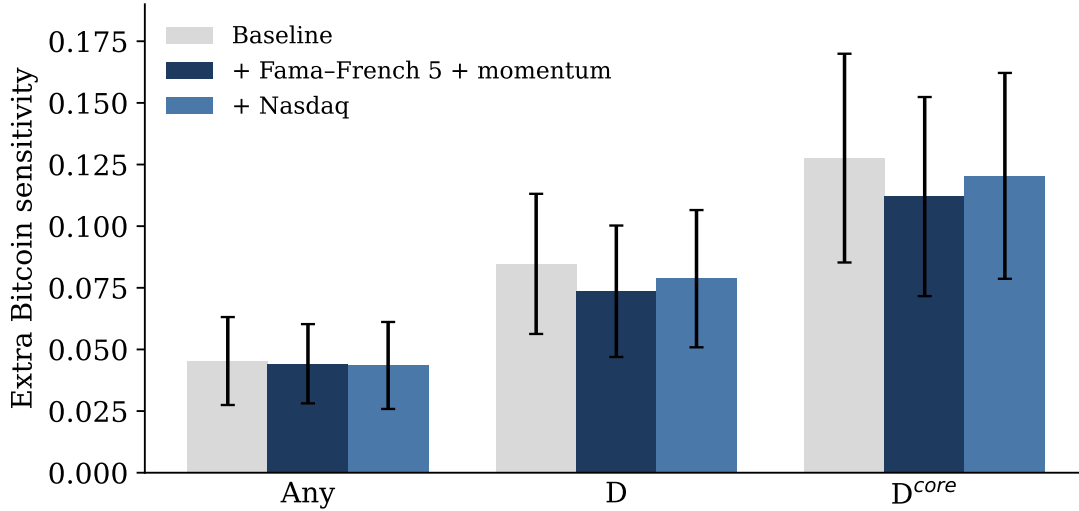


Figure 9: Bitcoin Sensitivity with Factor Controls

Notes: The specifications add crypto-interacted five-factor and momentum returns or the Nasdaq return. Bars show 95 percent confidence intervals.

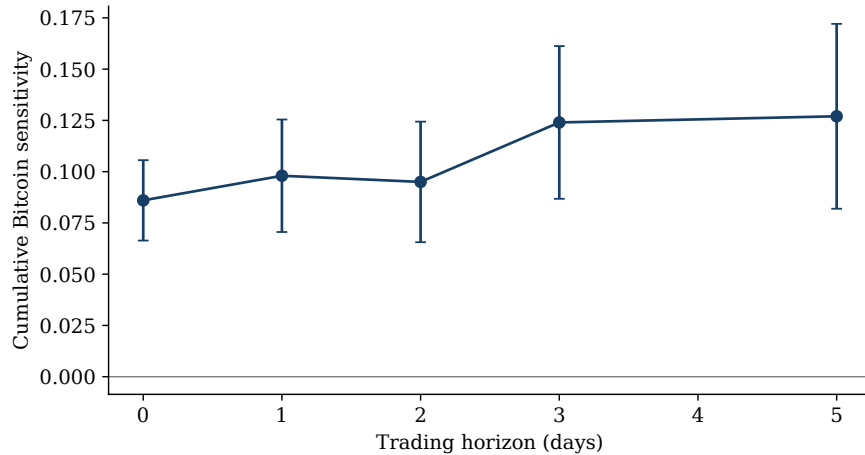


Figure 10: Cumulative Bitcoin Sensitivity by Trading Horizon

Notes: The points report cumulative return sensitivities; bars show 95 percent confidence intervals.

The timing of the response points to information arrival. Aligning firms on the date

their activity first appears in a public filing, I find no detectable change in Bitcoin sensitivity in the four quarters before disclosure and an increase of about 0.06 in the first quarter after it, which corresponds to roughly 0.6 percentage points of additional stock return for a 10 percent Bitcoin rise (Figure 11). Because the indicator uses only filings public before each return, the increase does not reflect dating the activity with hindsight. The same pattern appears in the full risk set, where the first-quarter increase is 0.060 (Appendix D). Investors reprice a firm once its filings reveal what it does with crypto. Among firms that do engage in crypto activity, the next question is which are repriced most.

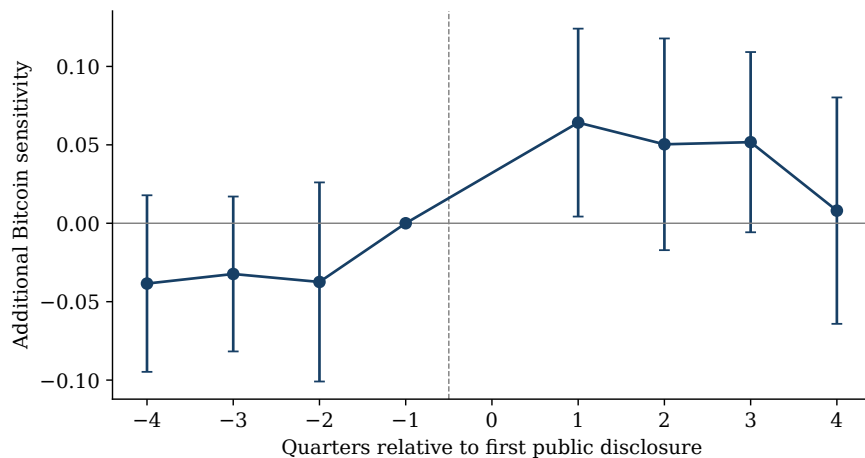


Figure 11: First-Disclosure Bitcoin Sensitivity in Quarterly Bins

Notes: Points report Bitcoin-sensitivity differences relative to the quarter immediately before first disclosure in the selected sample. Bars show 95 percent confidence intervals. The vertical line separates pre-disclosure and post-disclosure quarters.

4.2 Who is repriced most

The response is largest where the crypto claim is largest relative to the firm. Prediction P3 distinguishes the nature of the claim from its relative size, and the two are tested separately. To compare roles, I enter indicators for holdings, operations, intermediation and risk discussion jointly in equation (5), so that a firm reporting several roles contributes to each and every coefficient is conditional on the others. Holders are the most sensitive: controlling for prior Bitcoin beta, a holding statement adds about 2.2 percentage points of stock return for a 10 percent Bitcoin rise, roughly three times the response associated with operations and four times that associated with intermediation, while risk discussion

adds nothing (Table 5; Figure 12).¹ The holder premium survives industry-by-date effects and the exclusion of Strategy, the largest corporate holder. It narrows and is no longer statistically distinguishable once firms that also mine Bitcoin are excluded, which indicates that much of the premium comes from firms whose balance-sheet holdings accompany a crypto business.

Table 5: Bitcoin Sensitivity by Type of Crypto Activity

	(1)	(2)
Holding statement $\times$ BTC	0.266***	0.217***
	(0.078)	(0.060)
Operations $\times$ BTC	0.087***	0.069***
	(0.024)	(0.018)
Intermediation $\times$ BTC	0.067**	0.054**
	(0.029)	(0.023)
Risk discussion $\times$ BTC	0.015*	0.012
	(0.009)	(0.008)
Prior BTC beta $\times$ BTC	No	Yes
Firm effects	Yes	Yes
Time effects	Date	Date
Additional risk controls	Yes	Yes
Firm-days	7,050,425	7,050,425
Firms	3,879	3,879
Trading dates	2,642	2,642
Holding statement firms	42	42
Operations firms	184	184
Intermediation firms	101	101
Risk discussion firms	284	284

Notes: The dependent variable is daily equity return over July 2015–December 2025. Holdings, operations, intermediation and risk indicators enter jointly, and columns differ in the prior-Bitcoin-beta control. Models include firm and date effects, role–market interactions, prior financial characteristics and their Bitcoin interactions, and prior factor betas. Standard errors are clustered by firm and date. Standard errors are in parentheses; * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$ denote raw two-sided probabilities.

Size produces a steep gradient. Among firms with core activity, the Bitcoin sensitivity

¹Adjusting for multiple testing across the six pairwise role contrasts (Holm, 1979), the holding-versus-operations and holding-versus-intermediation differences remain significant at the 10 percent level, and both holding and operations differ from risk discussion at the 1 percent level.

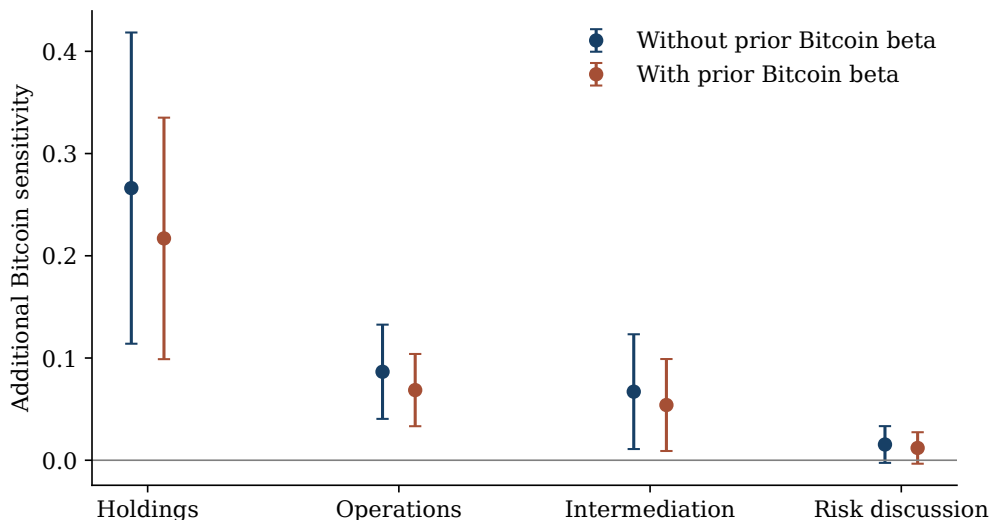


Figure 12: Bitcoin Sensitivity by Type of Crypto Activity

Notes: Points report role-specific Bitcoin sensitivities with and without the prior-Bitcoin-beta control. The roles enter jointly. Bars show 95 percent confidence intervals.

falls from 0.222 in the smallest asset quintile to 0.136 in the middle quintile and 0.044 in the largest (Figure 13). The same gradient appears when size enters as a continuous interaction and persists when cash, leverage and profitability are included jointly, so it is not a proxy for liquidity or profitability (Appendix D). Profitability has a separate negative interaction, whereas cash and leverage do not change the sensitivity.² A crypto position or business of a given dollar value represents a larger share of a small firm's equity, which is the relative-scale channel in equation (1).

Financial firms show the largest industry response. Allowing the disclosure sensitivity to differ by broad industry, with industry-by-date fixed effects, a 10 percent Bitcoin rise is associated with about 1.7 percentage points of additional return for financial firms with own activity, against about 0.3 percentage points in business services and 0.5 in manufacturing (Table 6).³ The finance premium is essentially unchanged when holding, operating and intermediation indicators are added, so it does not simply reflect the larger share of holders and intermediaries in finance. Financial firms combine proprietary positions, trading and client services, and the scale of these activities relative to firm value appears to differ from nominally similar activities in other sectors. Holders, small firms and financial firms are thus repriced most, which raises the question of whether their reported fundamentals respond in the same way.

²After a Holm adjustment across the four characteristic interactions, the size and profitability interactions remain significant at the 1 percent level.

³The finance–business-services contrast remains significant at the 1 percent level after a Holm adjustment across the 21 pairwise industry contrasts.

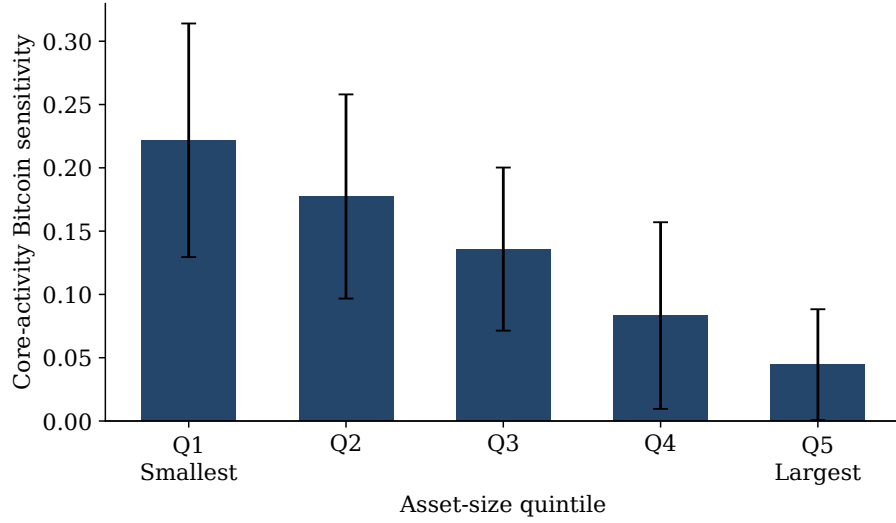


Figure 13: Core Bitcoin Sensitivity by Firm Size

Notes: Five core-exposure Bitcoin-return interactions enter jointly in the baseline specification. Quintile cutoffs use log assets among core-positive firm-days and remain fixed over the sample; firms can change bins as their reported assets change. Points and 95 percent intervals use the two-way firm/date CRV1 estimates. All 7,050,425 firm-days, 3,879 firms and 2,642 dates enter. The core-exposure level and market interaction and all other baseline controls enter. Intervals are pointwise.

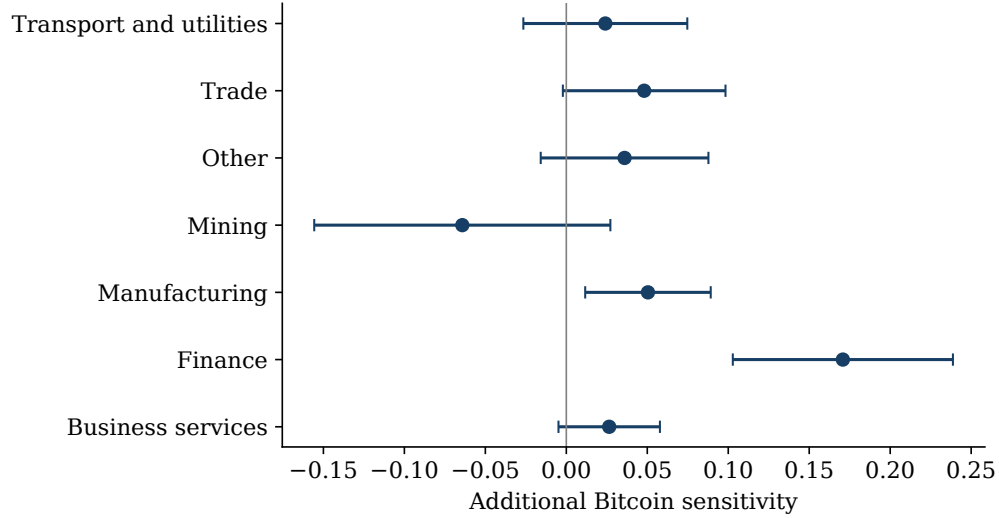


Figure 14: Bitcoin Sensitivity by Industry

Notes: Points are the industry coefficients in Table 6; bars show 95 percent confidence intervals.

5 Fundamentals and Repricing

5.1 Accounting evidence

Bitcoin returns move the reported operating income and assets of firms with disclosed crypto activity. I estimate the quarterly analogue of equation (5), regressing each ac-

Table 6: Industry-Specific Disclosure–Bitcoin Sensitivities

Sector	(1) Disclosure–BTC slope	(2) Effective exposed firms
Business services	0.026* (0.016)	44.750
Finance/insurance/RE	0.171*** (0.035)	62.670
Manufacturing	0.050** (0.020)	28.660
Mining	−0.064 (0.047)	3.480
Other sectors	0.036 (0.026)	17.900
Trade	0.048* (0.026)	9.230
Transport/utilities	0.024 (0.026)	16.150

Notes: Firm and broad-industry/date fixed effects with the full baseline equity controls, industry-specific disclosure levels and firm/date covariance. Intervals use t_{2641} . Effective firms equal the inverse Herfindahl of firm shares in the residual sum of squares of the focal interaction after projecting out the other regressors and fixed effects. This is an identification-support diagnostic, not a replacement cluster degrees of freedom; All seven industries are reported. Standard errors are in parentheses; * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$ denote raw two-sided probabilities.

counting outcome on prior disclosure interacted with the Bitcoin return over the firm’s own fiscal quarter, with firm and calendar-quarter fixed effects and public financial controls interacted with the Bitcoin return. Standard errors allow serial dependence across calendar quarters. The outcomes are operating income and operating cash flow scaled by lagged assets, sales growth, asset growth, debt and cash. A 10 percent rise in Bitcoin raises operating income by about 0.1 percent of assets and asset growth by about 0.3 percentage points among firms with disclosed activity, while operating cash flow does not respond (Table 7; Figure 15). Sales growth and cash holdings rise modestly, and leverage does not change.⁴

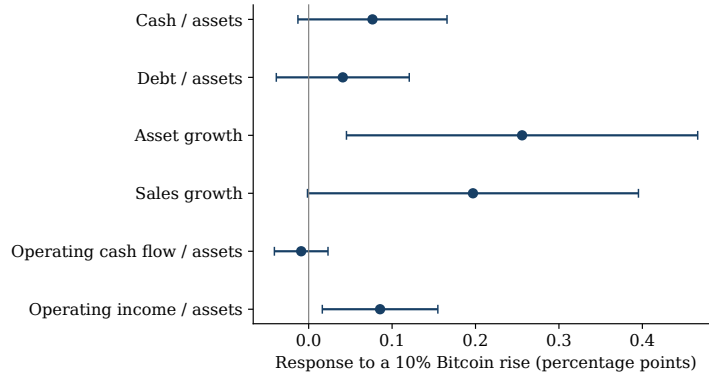
The contrast between income and cash flow follows prediction P4. Revaluation of a crypto position enters reported income and the balance sheet without producing a

⁴After a Holm adjustment across the six outcomes, the operating-income and asset-growth responses remain significant at the 10 percent level. Estimates on unwinsorized outcomes and alternative covariance choices are in Appendix F.

Table 7: Corporate Fundamental Sensitivity to Bitcoin Market Returns

Dependent variable	(1) OI/A	(2) OCF/A	(3) $\Delta \ln Sales$	(4) $\Delta \ln Assets$	(5) Debt/A	(6) Cash/A
Prior disclosure $\times$ BTC	0.009** (0.003)	-0.001 (0.002)	0.020* (0.010)	0.026** (0.010)	0.004 (0.004)	0.008* (0.004)
Observations	58,335	67,400	69,789	74,918	69,639	72,641
Firms	2,435	2,954	2,893	2,985	3,108	2,941
Prior-disclosure firms	255	286	269	292	290	278
Calendar quarters	44	44	44	44	44	44
Firm and calendar-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Predetermined controls	Yes	Yes	Yes	Yes	Yes	Yes
Control $\times$ BTC interactions	Yes	Yes	Yes	Yes	Yes	Yes
Fiscal-window BTC main effect	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variables are quarterly operating income, operating cash flow, sales growth, asset growth, debt and cash, with ratios scaled by lagged assets. Samples contain domestic firms with the accounting outcome, prior financial controls and publicly dated own activity available. Outcomes are winsorized at the first and ninety-ninth percentiles; models include firm and calendar-quarter effects, fiscal-window Bitcoin returns and predetermined financial controls. Standard errors use quarterly-score HAC(4). Standard errors are in parentheses; * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$ denote raw two-sided probabilities.

**Figure 15:** Corporate Fundamental Sensitivity to Bitcoin

Notes: Points show the response to a 10 percent Bitcoin rise, in percentage points. Growth outcomes use 100 times log changes. Bars show 95 percent Student t_{43} intervals with quarterly-score HAC(4) standard errors.

cash receipt, whereas a crypto business transmits price changes through revenues and costs. The role estimates separate the two channels. Holders' operating income is the most sensitive outcome in the role model, with a coefficient about four times the pooled estimate, and it remains positive when Strategy is excluded, while holders' operating cash flow does not respond.⁵ Operating firms instead show a revenue-growth response. The

⁵Holders' operating-income response remains significant at the 1 percent level after a Holm adjustment

accounting data therefore reproduce the role ordering of the stock market: the firms whose equity responds most are the firms whose reported income responds most (Table 8).

Table 8: Equity and Accounting Sensitivities by Activity Type

	(1)	(2)	(3)	(4)	(5)
	Daily equity return		Quarterly fundamentals		
	Baseline	Past BTC beta control	Operating income/ lagged assets	Log asset growth	Operating cash flow/lagged assets
Holds crypto	0.266*** (0.078)	0.217*** (0.060)	0.0360*** (0.0077)	0.068** (0.027)	−0.001 (0.009)
Positive firms	42	42	31	33	32
Operations	0.087*** (0.024)	0.069*** (0.018)	0.0110* (0.0059)	0.031 (0.024)	−0.000 (0.003)
Positive firms	184	184	126	142	140
Intermediation	0.067** (0.029)	0.054** (0.023)	0.0023 (0.0050)	−0.010 (0.020)	0.004 (0.004)
Positive firms	101	101	69	81	79
Observations	7,050,425	7,050,425	55,462	71,032	65,013
All firms	3,879	3,879	2,421	2,969	2,940
Dates / quarters	2,642	2,642	42	42	41

Notes: Columns report daily equity-return sensitivity and quarterly accounting sensitivity by overlapping activity role. The daily sample and specifications match Table 5; quarterly outcomes are operating income and cash flow divided by lagged assets and log asset growth. Models include firm and time effects, predetermined financial controls, and all role indicators jointly. Daily standard errors are clustered by firm and date; quarterly standard errors use score HAC(4). Standard errors are in parentheses; * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$ denote raw two-sided probabilities.

Tesla’s filings show the revaluation channel at the level of a single position. The company reported 11,509 Bitcoin at both the end of 2024 and the end of 2025, and the reported fair value of that position fell from \$1,074 million to \$1,007 million. Applying the change in the Bitcoin price to the unchanged position implies a decline of \$68 million, within \$1 million of the reported change (Figure 16). With quantities fixed, the reported loss is a pure revaluation, recorded in income without any cash outflow.

5.2 Fundamentals line up with repricing

Groups whose fundamentals move more with Bitcoin are repriced more in the stock market. For each activity role, each core-exposure size quintile and each broad industry with sufficient accounting support, I pair the quarterly operating-income sensitivity with the

across the 18 role–outcome interactions.

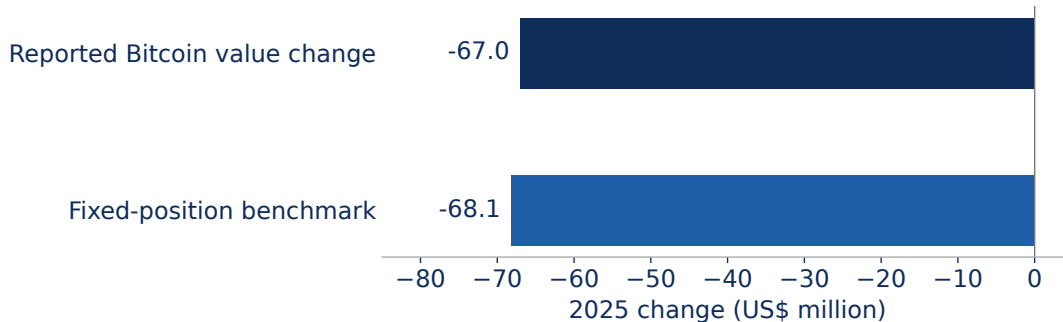


Figure 16: Tesla Bitcoin Valuation and a Fixed-Position Benchmark

Notes: Reported Bitcoin fair-value change and the fixed-position market-price comparison from the accounting bridge. Values are in millions of dollars. Data: Tesla’s annual filings and the market-price series.

daily stock-return sensitivity of the same group. Across these eleven groups, a group whose operating-income sensitivity is higher by 0.01 has a stock-return sensitivity higher by about 0.03, which corresponds to 0.3 percentage points of additional repricing for a 10 percent Bitcoin rise (Figure 17). The operating-income sensitivity accounts for about three-fifths of the variation in return sensitivity across groups, and asset-growth sensitivity accounts for nearly three-quarters. Because the groups overlap and both sensitivities are estimated, the relationship is descriptive; its value lies in showing that the role, size and industry patterns in returns have the same ranking in reported fundamentals.

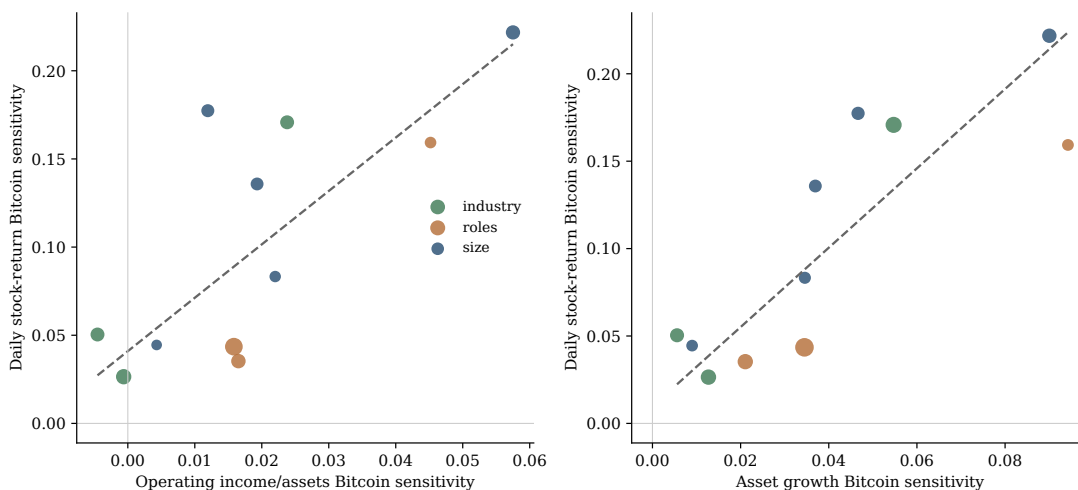


Figure 17: Fundamentals and Equity Repricing across Groups

Notes: Each point represents holders, operations or intermediation; a core-exposure size quintile; or a broad industry with sufficient quarterly support. The horizontal axes show quarterly operating-income/assets and asset-growth Bitcoin betas; the vertical axes show daily stock-returns Bitcoin betas. Lines use weights equal to the number of exposed firms with complete quarterly inputs in each group. Groups overlap.

Reported Bitcoin holdings explain only a small part of the repricing. Adding each

firm's holdings intensity — the value of its reported Bitcoin units relative to its equity value — to equation (5) lowers the core-activity coefficient by about 8 percent, and firms whose holdings are less than one percent of equity value are still repriced (Figure 18; Appendix G). The bulk of the response therefore comes from crypto-linked business value, the second term of equation (1). Nor does the repricing reflect institutional portfolio flows: firms whose institutional owners hold more crypto-active stocks are not more sensitive to Bitcoin, and managers with larger crypto-active positions do not sell their other holdings after Bitcoin falls (Appendix G). The repricing tracks what firms do and what it does to their accounts. The next section asks what this firm-level exposure implies for the market as a whole.

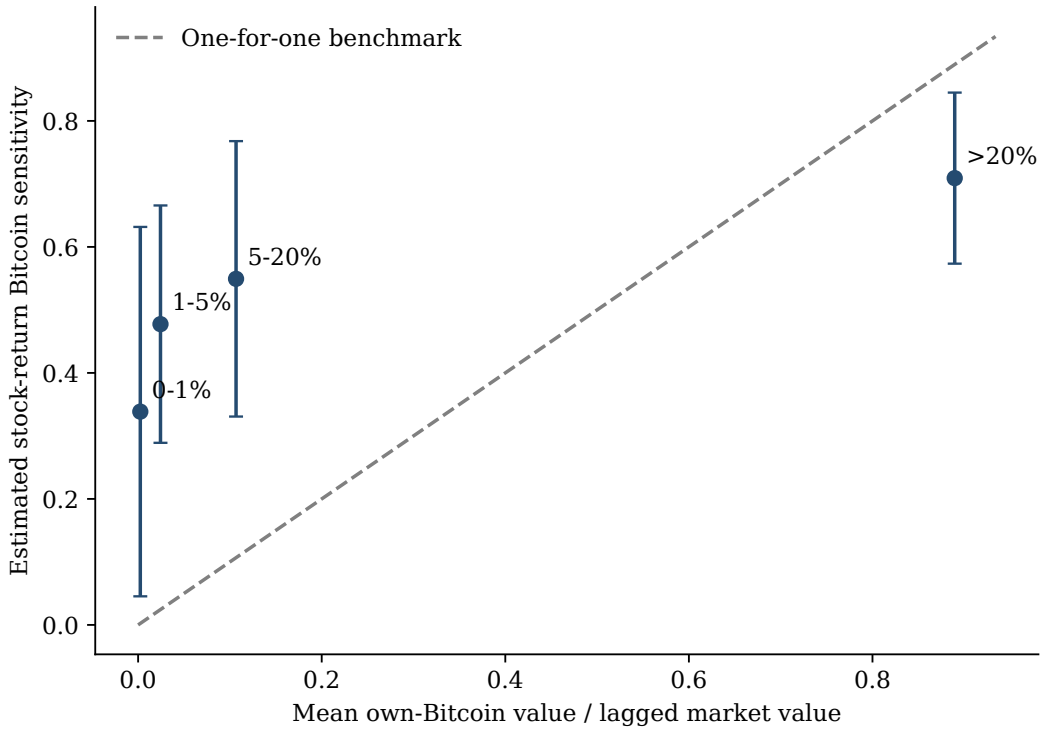


Figure 18: Holdings Intensity and Bitcoin Repricing

Notes: Points plot each positive-holdings bin's mean intensity against its Bitcoin return sensitivity relative to zero holdings, with marginal confidence intervals. The diagonal is the 45-degree line for one-for-one pass-through. The regression includes bin levels and Bitcoin interactions, firm and date effects, and two-way firm/date clustering.

6 From Exposed Firms to the Market

6.1 Concentration and the muted index

The aggregate Bitcoin link is muted because exposure is concentrated and offset, not because it is absent. I reconstruct the S&P 500 from its covered members, about 95 percent of index value, using prior-session market-value weights, and split it into members with disclosed crypto activity and other members. Firms with activity account for 8.9 percent of covered value in 2025 but for 15.9 percent of the index’s raw Bitcoin sensitivity, and a calculation that follows weights day by day assigns them 13.4 percent (Table 9; Figure 19). Their raw Bitcoin beta in 2025 is about twice that of other members. After controlling for the market return, their sensitivity remains positive at 0.070 while the index sensitivity is close to zero at -0.011 , because the remaining members carry a small negative conditional sensitivity that offsets the exposed group. This is equation (3) at work: a muted index can contain a group of members whose prices move strongly with Bitcoin.

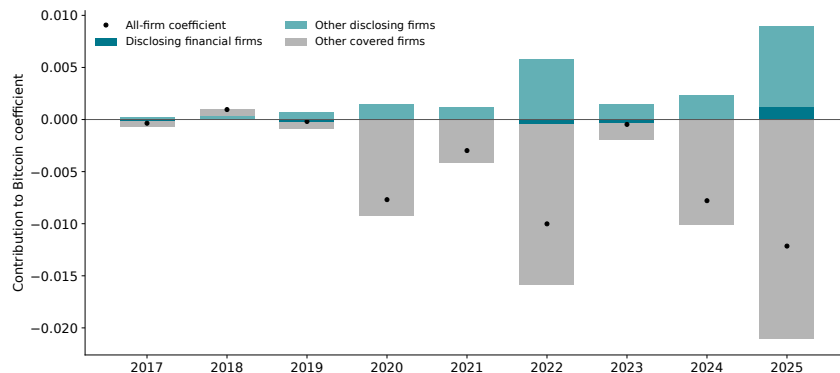


Figure 19: Components of Covered S&P Bitcoin Sensitivity

Notes: Coefficients from regressions of daily weighted return components. The three mutually exclusive components sum to the covered-basket sensitivity, indicated by black dots. The decomposition conditions on the CRSP market return. Signed component bars sum to the black point. Financial firms have SIC2 codes 60–67; negative components offset positive components. The covered basket uses full capitalization and the paper’s eligible primary securities.

6.2 The FTX collapse

The collapse of FTX provides a crypto shock that moved Bitcoin and U.S. stocks in opposite directions. FTX, then among the largest crypto exchanges, halted withdrawals on November 8, 2022 and filed for bankruptcy on November 11, after disclosures that its

Table 9: Portfolio Bitcoin Sensitivity in 2025

Portfolio	(1)	(2)
	Raw	Market-controlled
Covered US firms	0.212*** (0.050)	-0.005*** (0.001)
Covered S&P constituents	0.201*** (0.050)	-0.012*** (0.003)
Actual S&P price index	0.200*** (0.050)	-0.011*** (0.002)
Covered S&P disclosers	0.358*** (0.066)	0.070*** (0.027)
Covered S&P financial disclosers	0.175*** (0.039)	0.001 (0.029)
Daily observations per regression	250	250
CRSP market return	No	Yes
Intercept	Yes	Yes

Notes: Each portfolio row reports separate daily time-series regressions. Outcomes and factors are decimal returns. Covered portfolios use prior-session CRSP capitalization; disclosure is qualifying activity in the preceding 365 days, excluding the return date. Financial disclosers have SIC2 60–67; the actual S&P price index is separately observed through FRED. Newey–West (five-lag Bartlett) standard errors appear in parentheses, with the $n/(n - k)$ correction and t_{n-k} tests; Standard errors are in parentheses; * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$ denote raw two-sided probabilities.

affiliated trading firm had used customer funds. The shock originated inside the crypto market and unfolded within a few days. Between November 8 and 11, Bitcoin fell 17.3 percent, while the S&P 500 rose 4.9 percent and the Nasdaq Composite 7.2 percent, helped by a lower-than-expected inflation release on November 10. Because the macroeconomic news pushed stocks up, any underperformance of crypto-active firms reflects the crypto shock rather than a common decline.

Core activity identifies the abnormal loss. I compute cumulative abnormal returns from a Fama–French five-factor and momentum model estimated before the event, fix exposure on November 7, and regress the returns on the core, technology-only and mention-only layers with industry effects and controls for size and prior betas. Firms with core activity lost 3.65 percentage points more than firms without crypto paragraphs, while technology-only and mention-only firms show no abnormal difference (Table 10; Figure 20). Estimating the nested definitions separately reproduces the daily ordering, with abnormal losses of 1.8, 2.5 and 3.6 percentage points for Any, D and D^{core} . Market-

model abnormal returns, equal and value weights, and a window that begins with the first press reports on November 2 give the same ordering, and the Terra collapse of May 2022 provides a further comparison (Appendix I).

Table 10: Abnormal Returns during the FTX Collapse

	(1)	(2)	(3)
<i>Panel A. Mutually exclusive layers, one joint regression</i>			
	CAR difference from no crypto paragraph		
Core		−0.037***	
		(0.011)	
Technology-only		0.0040	
		(0.020)	
Mention-only		−0.0040	
		(0.0060)	
Core firms		95	
Technology-only firms		34	
Mention-only firms		75	
No-crypto-paragraph firms		2,908	
Observations / firms		3,112	
<i>Panel B. Nested definitions, separate regressions</i>			
	(1) Any	(2) D	(3) D_{core}
Own exposure	−0.018**	−0.025**	−0.036***
	(0.007)	(0.010)	(0.011)
Exposed firms	204	129	95
Firms without this exposure	2,908	2,983	3,017
Observations	3,112	3,112	3,112
Firms	3,112	3,112	3,112
Log market value and prior betas	Yes	Yes	Yes
SIC2 fixed effects	Yes	Yes	Yes
	(HC3)	(HC3)	(HC3)

Notes: November 8–11, 2022; factor-model CARs in decimal returns. Panel A is one joint regression; Panel B estimates the nested definitions separately. Both panels include SIC2 effects, log market value and prior Bitcoin and market betas. Singleton SIC2 cells are excluded. Standard errors are in parentheses; * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$ denote raw two-sided probabilities.

The daily estimates predict the size of the loss. In aggregate, core firms lost about \$57 billion of market value in abnormal terms; multiplying their daily Bitcoin sensitivities by the event’s Bitcoin return and their pre-event market values gives \$56 billion (Figure 21). The sensitivities estimated from ordinary trading days thus describe the repricing in an external crypto crisis, which justifies using them to size other scenarios. Applied to all firms with core activity at end-2025 values, with sensitivities that vary by size quintile,

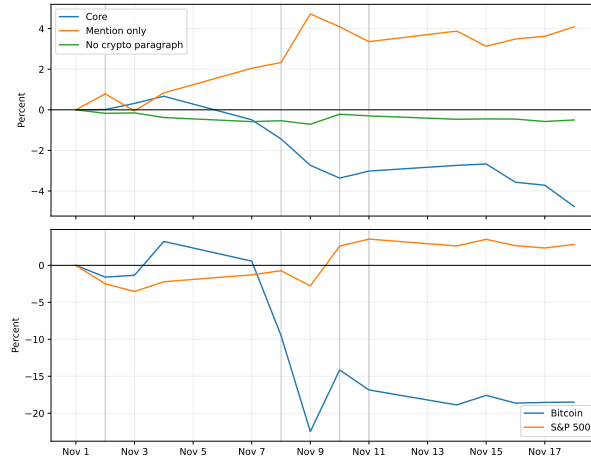


Figure 20: Equity Repricing during the FTX Collapse

Notes: Panel A uses factor-model CARs (five factors plus momentum) with fixed November 1 groups and market-value weights, normalized to zero at that day's close. Firms need complete November 1–18 histories. Panel B shows cumulative Bitcoin and S&P 500 returns. Vertical lines mark November 2, 8, 10 and 11.

a 20 percent Bitcoin decline implies about \$17–45 billion of first-round repricing. The amount is modest relative to the U.S. equity market, so the question for financial stability is whether repricing extends beyond the exposed firms.

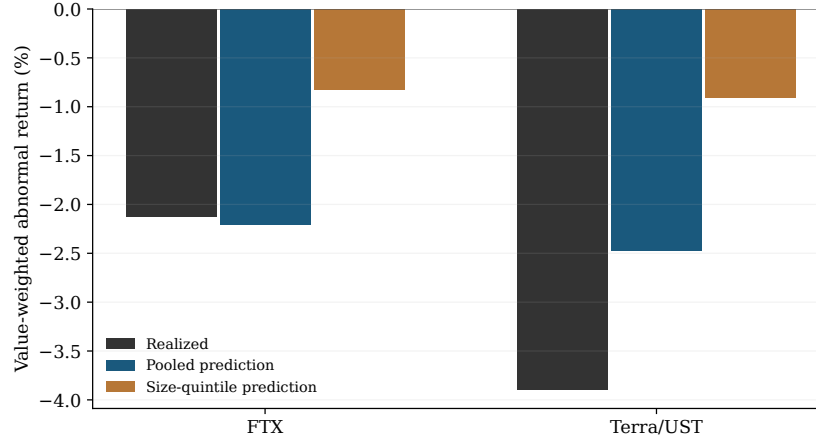


Figure 21: Realized and Predicted Repricing during FTX and Terra

Notes: Value-weighted market-model abnormal returns of core-exposed firms, in percent. Predictions multiply the pooled or firm-size-quintile Bitcoin sensitivity by the event's compounded Bitcoin return. Realized CAR includes other firm and industry news as well as crypto-related repricing.

6.3 Industry spillovers

Repricing reaches firms without direct exposure through their industries, with a sign that depends on the industry. Following equation (4), I restrict the sample to firm-days

without exposure and interact the Bitcoin return with the share of the firm’s industry peers that have exposure, measured on the previous trading day and excluding the firm itself. The regression includes firm and date fixed effects, industry-specific Bitcoin slopes, the baseline controls and prior betas, so the peer coefficient is identified from changes over time in an industry’s exposure, holding fixed the industry’s own link to Bitcoin. Industry-specific peer coefficients are estimated jointly. Averaged across all industries, the spillover is close to zero (Table 11); the average conceals responses of opposite sign.

Business-services firms become more sensitive to Bitcoin as more of their peers engage in crypto, and banks become less sensitive. Under core exposure, moving the peer share from its median to its 90th percentile raises an unexposed business-services firm’s sensitivity by 6.9 percent of the direct core sensitivity and lowers an unexposed bank’s by 32.1 percent (Table 12; Figure 22). Non-bank lenders and brokers, the industries in which Coinbase and Strategy are classified, show no spillover, consistent with prediction S1’s implication that peers matter only when they resemble or compete with the recipient. Both effects strengthen as the measure moves from Any to D to D^{core} , as prediction S2 implies, and both are larger on days when Bitcoin falls.⁶ With value-weighted peer shares, the business-services spillover is larger, while the bank spillover keeps its negative sign but loses precision, which indicates that the number of crypto-linked banks rather than their size carries the bank pattern. Spillovers in other industries and in broader linkage groups are reported in Appendix J. The business-services effect survives finer industry and size-specific Bitcoin slopes, the exclusion of small recipients, a post-2020 sample and the removal of each influential peer in turn. The bank effect holds outside March 2023, among both small and large recipient banks, and when exposure is measured by the number of crypto-linked peer banks; during the FTX collapse, banks with more crypto-linked peers also lost less (Table J1).

The positive spillover in business services is concentrated among young firms, consistent with investors inferring exposure from peers. Splitting recipients by listing age, the spillover among young firms exceeds that among older firms by about 1.4 per unit of peer share, and older firms show none; a split by market value points in the same direction but is less precise (Table 13). Young firms have short public histories, so investors have less information about their own exposure and rely more on their peers, as prediction S3 implies. Recipients’ operating income, cash flow and asset growth do not move with peer exposure, and only their sales growth responds, so the spillover operates mainly through

⁶After a Holm adjustment across the eight industry terms, the business-services and bank spillovers remain significant at the 1 percent level, as does a positive spillover in electronic equipment; no other industry term reaches 10 percent.

Table 11: Pooled Spillovers to Firms Without Crypto Exposure

	(1) Any	(2) D	(3) D _{core}
<i>Panel A. Equal-weighted peers</i>			
Peer exposure share $\times$ Bitcoin return:			
SIC2 peers	−0.051 (0.042)	0.002 (0.041)	0.035 (0.046)
SIC3 peers	−0.015 (0.015)	−0.009 (0.014)	−0.011 (0.015)
Firm fixed effects	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes
Industry-specific Bitcoin slopes	Yes	Yes	Yes
Observations (SIC2 peers)	6,692,412	6,844,571	6,904,923
Firms (SIC2 peers)	3,800	3,817	3,828
Observations (SIC3 peers)	6,588,420	6,740,328	6,800,477
Firms (SIC3 peers)	3,767	3,784	3,795
<i>Panel B. Value-weighted peers</i>			
Peer exposure share $\times$ Bitcoin return:			
SIC2 peers	−0.003 (0.011)	−0.015 (0.016)	0.033** (0.016)
SIC3 peers	−0.003 (0.007)	−0.015 (0.011)	−0.003 (0.009)
Firm fixed effects	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes
Industry-specific Bitcoin slopes	Yes	Yes	Yes
Observations (SIC2 peers)	6,676,737	6,828,153	6,888,323
Firms (SIC2 peers)	3,800	3,817	3,828
Observations (SIC3 peers)	6,579,597	6,731,201	6,791,271
Firms (SIC3 peers)	3,767	3,784	3,795

Notes: The dependent variable is daily stock return for firms without the column's exposure. Columns use Any, D and core activity; panels use equal- and value-weighted leave-one-out industry peer shares from the previous trading day. Regressions include firm and date effects and industry-specific Bitcoin slopes. Standard errors are clustered by firm and date and appear in parentheses. Standard errors are in parentheses; * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$ denote raw two-sided probabilities.

valuation rather than through a common change in fundamentals (Appendix J). The negative bank spillover is consistent with competition among rival institutions for customers and funding (Lang and Stulz, 1992; Gatev and Strahan, 2006): when crypto-linked banks are hit, unexposed rivals move less with Bitcoin and, during FTX, lost less.

The spillovers are large in dollar terms. At end-2025 exposures and market values, a 20 percent Bitcoin decline implies \$22 billion of direct repricing among the 38 core

Table 12: Spillovers to Firms Without Crypto Exposure, by Industry

	(1) Any	(2) D	(3) D_{core}
<i>Equal-Weighted Peers</i>			
Peer exposure share $\times$ Bitcoin return:			
Business services (SIC 73)	0.301*** (0.080)	0.316*** (0.102)	0.684*** (0.155)
Banks (SIC 60)	-0.148* (0.079)	-1.322** (0.524)	-1.738*** (0.503)
Non-bank credit (SIC 61)	-0.017 (0.066)	-0.021 (0.066)	-0.001 (0.069)
Brokerage (SIC 62)	0.011 (0.027)	-0.007 (0.050)	-0.004 (0.058)
Other industries	-0.023 (0.045)	-0.005 (0.050)	0.063 (0.061)
Firm fixed effects	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes
Industry-specific Bitcoin slopes	Yes	Yes	Yes
Peer weighting	EW	EW	EW
Peer industry level	SIC2	SIC2	SIC2
Observations	6,692,412	6,844,571	6,904,923
Firms	3,800	3,817	3,828

Notes: The dependent variable is the daily return of firms without direct exposure. Columns use Any, own activity, and core activity, with equal-weighted peer shares; all eight industry interactions enter jointly. Regressions include firm and date fixed effects, industry-specific Bitcoin slopes, and baseline controls. Standard errors are two-way clustered by firm and date. Standard errors are in parentheses; * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$ denote raw two-sided probabilities.

business-services firms and a further \$140 billion among the 380 unexposed firms in the industry, for a total of \$162 billion, or 1.2 percent of the industry's equity value. Spillovers account for 86 percent of the total. The estimate is \$175 billion with value-weighted peer shares and remains \$59 billion, still more than twice the direct amount, after excluding the four largest unexposed firms (Table 14). In business services, monitoring only the firms that disclose crypto activity would miss most of the repricing.

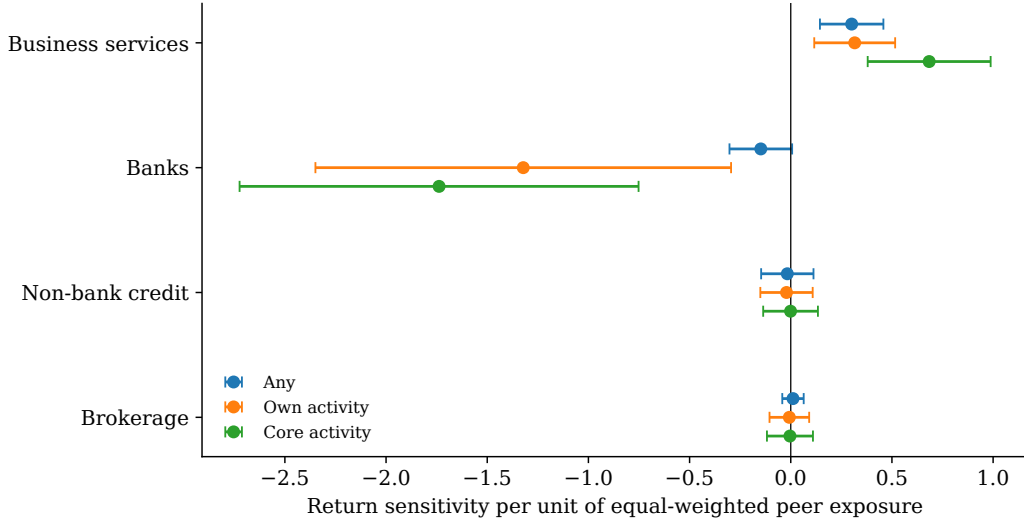


Figure 22: Industry Spillovers with Equal-Weighted Peers

Notes: Points report the interaction between peer exposure and Bitcoin returns for firms without direct exposure. Peer exposure is equal-weighted. Bars are 1.96 standard errors in each direction; all eight industry interactions enter jointly, as in Table 12.

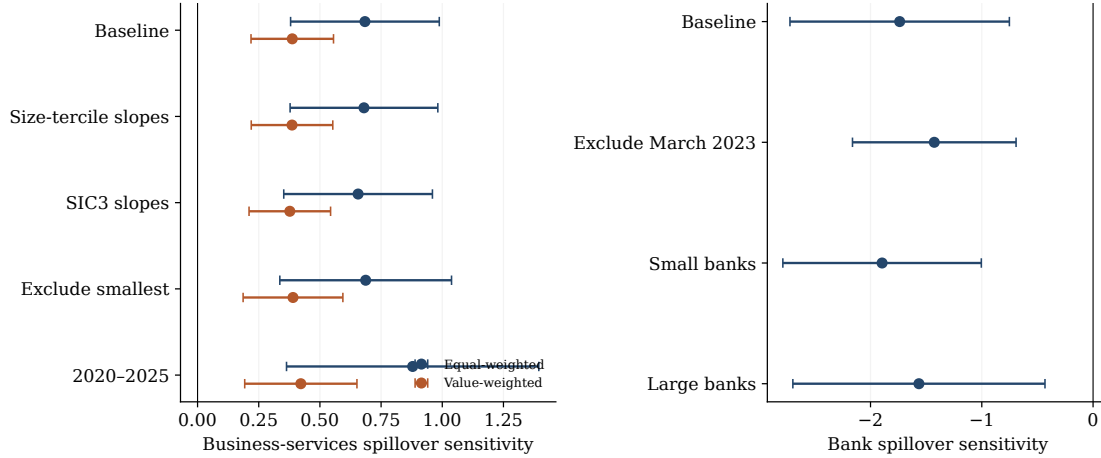


Figure 23: Business-Services and Bank Spillover Robustness

Notes: Points are the coefficients in Table J1; bars are 1.96 standard errors in each direction. The influential-peer ranges and count-based bank specification appear in that table.

6.4 Tail losses in exposed financial institutions

Within the financial sector, losses concentrate in exposed institutions when the crypto market is under stress. Following [Acharya et al. \(2017\)](#), I define a financial firm's crypto marginal expected shortfall (Crypto-MES) as its average daily stock return on the worst 5 percent of Bitcoin return days in each year, and regress it on core exposure at the start of the year, controlling for prior-year market value and year fixed effects. Across 4,560 firm-years at 627 financial firms, 60 of them with core exposure, exposed institutions

Table 13: Business-Services Spillovers by Recipient Opacity

	(1) Any	(2) D	(3) D_{core}
<i>Panel A: Listing-history age</i>			
Comparison-group γ	-0.025 (0.071)	-0.085 (0.091)	0.030 (0.136)
Opaque minus comparison	0.684*** (0.114)	0.841*** (0.145)	1.363*** (0.211)
Opaque-group total γ	0.659*** (0.119)	0.756*** (0.150)	1.393*** (0.225)
N	6,692,412	6,844,571	6,904,923
Firms	3,800	3,817	3,828
Days	2,641	2,641	2,641
FE	Firm + date	Firm + date	Firm + date
Clustering	Firm/date	Firm/date	Firm/date
<i>Panel B: Prior-year market value</i>			
Comparison-group γ	0.164 (0.107)	0.104 (0.134)	0.441** (0.212)
Opaque minus comparison	0.214 (0.136)	0.345** (0.166)	0.353 (0.259)
Opaque-group total γ	0.378*** (0.107)	0.448*** (0.131)	0.794*** (0.189)
N	6,625,059	6,774,967	6,833,622
Firms	3,780	3,798	3,811
Days	2,641	2,641	2,641
FE	Firm + date	Firm + date	Firm + date
Clustering	Firm/date	Firm/date	Firm/date

Notes: The dependent variable is daily equity return for unexposed business-services firms. Columns use Any, own activity and core activity; panels split recipients by listing-history age or prior-year market value. The comparison-group coefficient and opaque-group increment enter jointly with firm and date effects, industry-specific Bitcoin slopes and predetermined controls. Standard errors are clustered by firm and date. Standard errors are in parentheses; * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$ denote raw two-sided probabilities.

earn 1.8 percentage points less per day than other financial firms on Bitcoin's worst days (Table 15; Figure 25).

The measure identifies vulnerable banks in advance. Banks with lower Crypto-MES in 2022 had lower abnormal returns during the banking stress of March 2023, across 239 banks. The episode included the liquidation of Silvergate and the failure of Signature, both of which held large deposits from crypto firms. A bank's performance on Bitcoin's worst days thus contains information about its vulnerability in a later stress event (Ap-

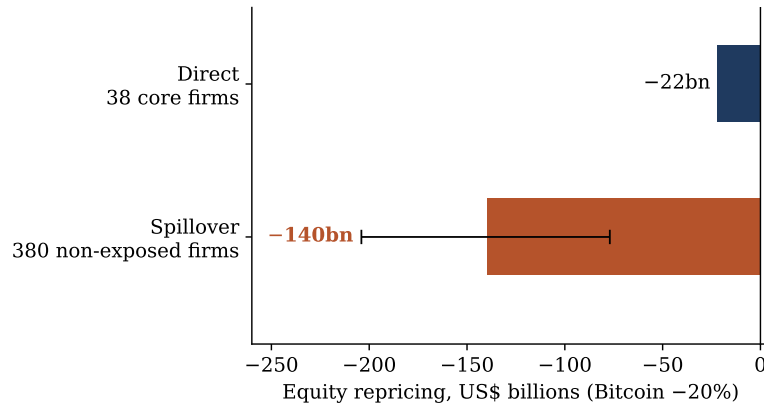


Figure 24: Business-Services Repricing in Dollars

Notes: The scenario applies a 20 percent Bitcoin decline to December 2025 exposures and market values. The 95 percent interval runs from -204 to -77 billion and reflects uncertainty in the spillover coefficient only.

Table 14: Business-Services Dollar Scenario

Quantity	(1) Value
Direct repricing	-22.0
Spillover repricing, equal-weighted peers	-140.0
Total repricing	-162.0
Share of industry equity value (percent)	1.2
Spillover share of total (percent)	86.4
Spillover repricing, value-weighted peers	-175.0
Spillover repricing, excluding four largest recipients	-59.0

Notes: Bitcoin declines by 20 percent at December 2025 exposures and market values. Dollar amounts are in billions. The baseline uses equal-weighted peer shares; direct repricing uses the size-quintile sensitivities. The exclusion removes four unexposed recipients above \$500 billion, holding peer exposure fixed.

pendix K). Together with the spillover results, this evidence locates crypto-related losses in identifiable places: exposed firms, their unexposed industry peers, and exposed financial institutions in the tail.

7 Stablecoin Activity

Listed firms engage with stablecoins mainly by holding them as reserves and providing stablecoin services, not by using them to settle their own payments. The classification distinguishes proprietary stablecoin balances, issuance and distribution, custody and in-

Table 15: Core Exposure and Financial Firms' Bitcoin-Tail Returns

	(1) Crypto-MES
Core exposure at year start	−0.018*** (0.004)
Log prior-year-end market value	0.000 (0.000)
Year fixed effects	Yes
Firm-years	4,560
Firms	627
Ever core-exposed firms	60

Notes: The outcome is mean daily stock return on each year's worst 5 percent of Bitcoin days. Exposure is measured at January 1; market value is measured at the previous year end. Year effects enter; standard errors are clustered by firm, with t_{626} inference. Standard errors are in parentheses; * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$ denote raw two-sided probabilities.

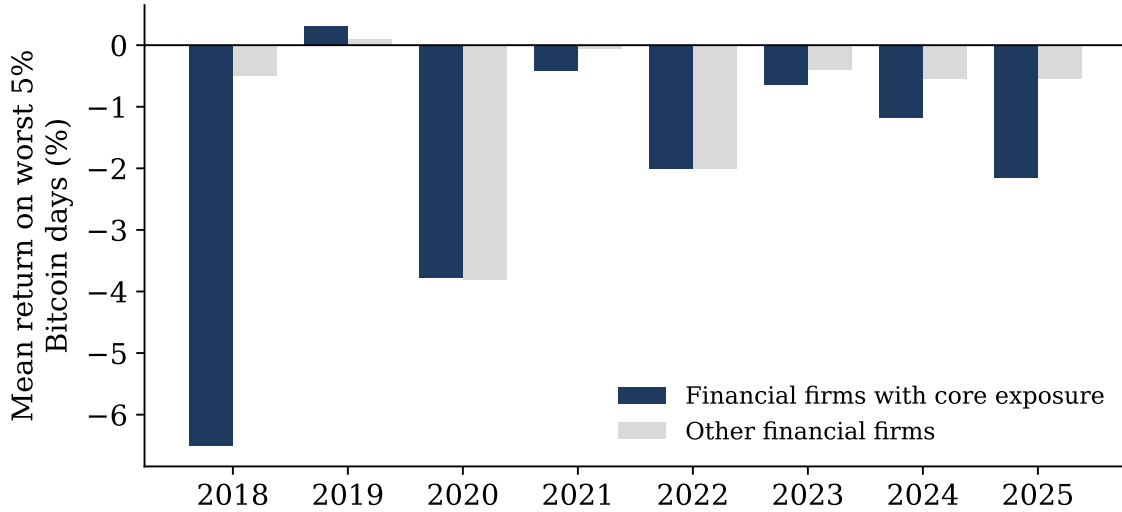


Figure 25: Financial Firms' Returns On Bitcoin's Worst Days

Notes: Value-weighted firm-year Crypto-MES, using prior-year-end market values. Only years with at least three core-exposed firms with valid weights are shown. Their counts are 2018: 3; 2019: 9; 2020: 10; 2021: 11; 2022: 23; 2023: 39; 2024: 40; 2025: 42. The figure shows weighted group means; the regression additionally controls for size and year.

termediation, payments and settlement, financing denominated in stablecoins, and announced plans, and a firm can report several roles. A balance gives the firm a claim on an issuer and exposes it to the peg and to redemption; a service generates fees and obligations

even when the firm holds little for its own account; settlement is the use of the instrument as a means of payment. Reported activity is dominated by balances and provision, while settlement of the firm’s own transactions is rare (Figure 26). Passage audits support the provider classification and show that settlement candidates require careful review, since many describe services offered to customers rather than the firm’s own use (Appendix L).

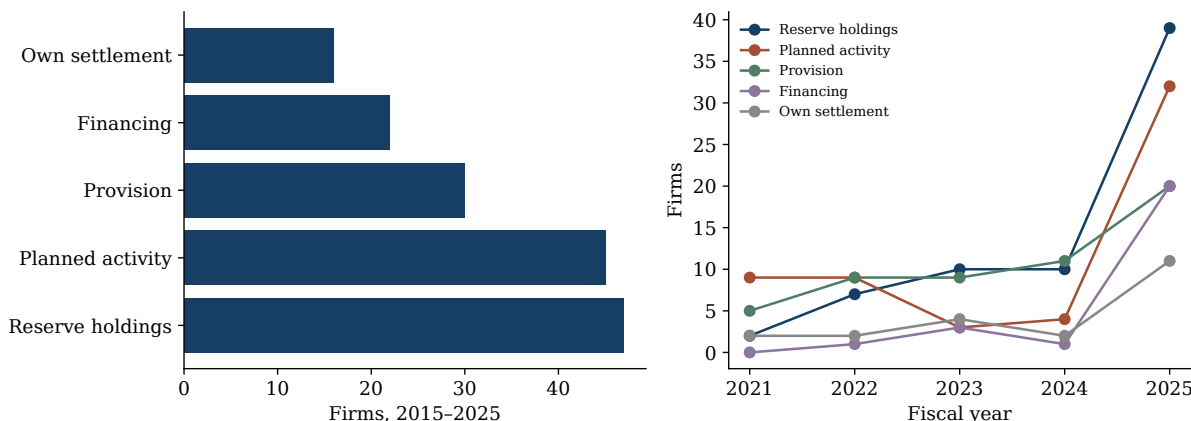


Figure 26: Stablecoin Activity by Corporate Function

Notes: The left panel reports the number of firms by stablecoin role; the right panel reports annual firm-year counts. Roles can overlap. Reserve holding and service provision are distinct from own-transaction settlement.

Participation expanded sharply in fiscal 2025, the year the GENIUS Act was signed. In that year 59 firms reported stablecoin activity for the first time, 39 of them with no earlier crypto disclosure (Figure 27). Entrants include payment incumbents, banks, other financial firms and non-financial firms, and in several cases the filing describes a plan rather than live activity (Appendix L). The growth in participation therefore reflects new providers and holders entering the market rather than a shift of listed firms toward stablecoin payments. For monitoring, the relevant distinction is the same as for Bitcoin exposure: the label “stablecoin activity” becomes informative only when it identifies whether the firm holds a claim, provides a service or uses the instrument to pay.

8 Conclusion

Crypto prices reach U.S. equities through what firms do, not through what they say. Using language models to read corporate filings, I separate firms that mention crypto from firms that hold crypto assets, run crypto businesses or serve crypto clients, and date each statement by when it became public. Bitcoin sensitivity rises from 0.045 for any disclosure to 0.085 for own activity and 0.128 for core activity, while firms that only

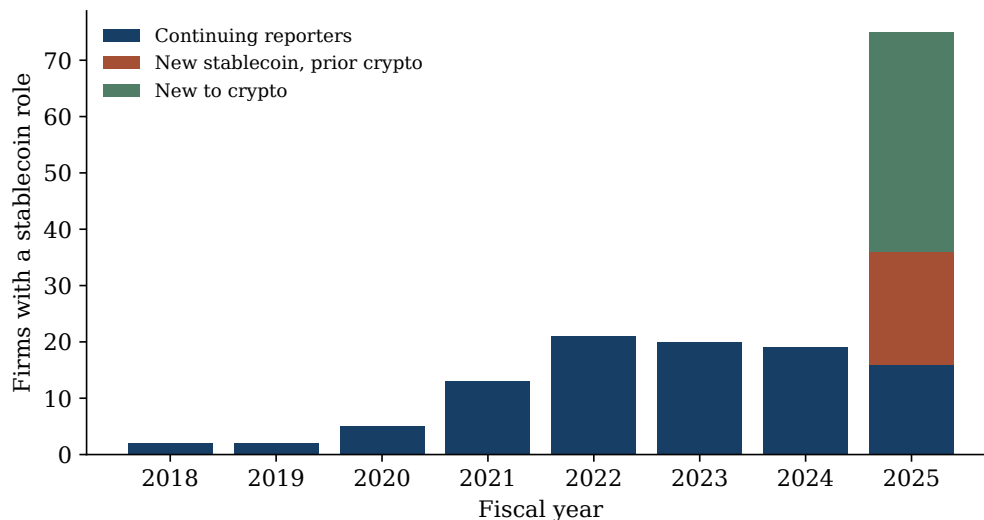


Figure 27: Firms with a Stablecoin Role by Fiscal Year

Notes: Bars report annual numbers of firms with a stablecoin role. The latest-year bar separates continuing firms from new entrants with and without prior crypto activity. The latest-year components distinguish continuing reporters, entrants with prior crypto activity, and entrants without prior crypto activity.

mention crypto are not repriced. The response is largest for holders, small firms and financial firms, and it rises after a firm first discloses its activity.

The repricing is grounded in fundamentals. Operating income and assets move with Bitcoin among firms with disclosed activity, holders' income responds most, and groups whose fundamentals move more are repriced more. Reported holdings account for a small part of the response; most of it reflects the value of crypto-linked businesses.

Concentration explains why the aggregate link appears muted. Firms with crypto activity carry a disproportionate share of the index's Bitcoin sensitivity, and the rest of the index offsets it. When FTX collapsed, core-activity firms lost about \$57 billion in abnormal value, close to what their daily sensitivity predicts, while the market rose. The direct exposure is modest in size, but it spreads. In business services, unexposed firms are repriced with their exposed peers, especially young firms whose own exposure is hard to observe, and these spillovers are about six times the direct repricing. Unexposed banks instead move less with Bitcoin as their peers become crypto-linked, and within finance, institutions with crypto activity bear the largest losses on Bitcoin's worst days.

For financial-stability surveillance, market-wide correlations are the wrong summary statistic. The relevant information is which firms hold crypto claims or run crypto businesses, how large those claims are relative to firm value, which firms share an industry with them, and which financial institutions are exposed in the tail. Stablecoin participa-

tion calls for the same discipline: counting participants says little until reserve holding, service provision and payment use are distinguished. The filing-based measure shows where to look.

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A Measurement and Validation

The classification evidence supports the activity measures in Section 3.1. The passage examples distinguish own activity from references to other firms, while the validation exercises compare the classifications with independently checked information.

Tables A1–A4 define the codes, report the passage counts, and assess classification accuracy. Figures 28 and 29 illustrate attribution and repeated text.

Table A1: Classification Categories

Code	Definition	Measure eligibility
<i>Attribution</i>		
self	Activity of the filing firm	Required for own activity
counterparty	Activity of another firm	Discussion categories only
generic	Market-wide statement	Discussion categories only
<i>Activity type</i>		
A	Proprietary holdings	Any, D; core if U1–U9
B	Operations and business revenue	Any, D; core if U1–U9
C	Intermediation and custody	Any, D; core if U1–U9
D	Accounting policy	Any
E1	General risk discussion	Any
E2	Firm-specific risk discussion	Any
F	Regulation	Any
IRRELEVANT	Unrelated to crypto	None
<i>Use case</i>		
U1	Treasury reserves	Any, D, core
U2	Mining and validation	Any, D, core
U3	Payments and transfers	Any, D, core
U4	Retail offerings	Any, D, core
U5	Custody	Any, D, core
U6	Stablecoin issuance and distribution	Any, D, core
U7	Trading and market making	Any, D, core
U8	Staking and yield	Any, D, core
U9	Collateral and financing	Any, D, core
U10	Blockchain technology without asset exposure	Any, D
NA	Unassigned use case	Any, D

Notes: Codes describe attribution, activity type and use case separately. Any includes self-attributed A/B/C activity and D/E1/E2/F discussion regardless of attribution. D requires self-attribution and activity type A, B or C; core activity additionally requires U1–U9. Use-case eligibility in the last panel is conditional on this own-activity requirement; unrelated passages enter no measure.

Table A2: Passage Counts by Step

Step	(1) 10-K	(2) 8-K	(3) 20-F	(4) Total
Filings	41,910	460,148	9,136	511,194
Filings with candidates	5,418	9,054	2,810	17,282
Candidate passages	54,921	40,585	39,387	134,893
Carried forward	8,788	3,247	10,395	22,430
New or modified: classified	46,133	37,338	28,992	112,463
Coded unrelated	12,754	16,730	12,122	41,606
Missing after retry	0	0	0	0
Unresolved inherited labels	0	75	0	75
Passages entering Any	41,243	21,946	26,648	89,837
Passages entering D	18,187	16,157	11,665	46,009
Passages entering core activity	14,680	13,473	9,288	37,441

Notes: The census covers fiscal 2015–2025 and excludes pooled investment vehicles. Columns distinguish filing forms; current reports use the fiscal-year assignments in the integrated panel. Counts refer to distinct passage identifiers in the raw extraction files, and the nested indicators use the category rules in Table A1. The new-or-modified count excludes 628 carried-forward passages that also received direct labels; 75 carried-forward current-report passages have unresolved inherited labels.

Table A3: Cross-Model Agreement

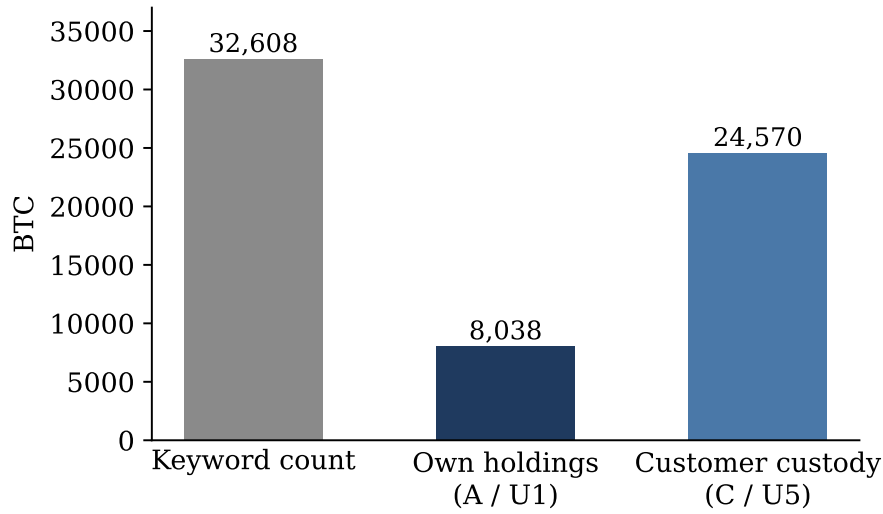
Production model	Second model: Claude Sonnet 5					
	S1	S2	S3	S4	S5	S6
S1	27	0	1	1	0	3
S2	0	2	0	0	0	0
S3	0	0	36	3	0	0
S4	2	0	3	44	0	1
S5	0	0	0	0	7	0
S6	0	0	2	1	0	5
Passages	138					
Observed agreement	0.876812 (121/138)					
Chance agreement	0.269954					
Cohen's kappa	0.831259					

Notes: The sample contains 138 payment-related passages with valid codes from both GPT-4o and Claude Sonnet 5. The S1–S6 categories denote own settlement, reserve management, customer products, general or risk discussion, negative statements, and other or unclear uses. Observed agreement is the diagonal share; chance agreement is the sum of products of row and column marginal shares. Kappa equals observed agreement minus chance agreement, divided by one minus chance agreement.

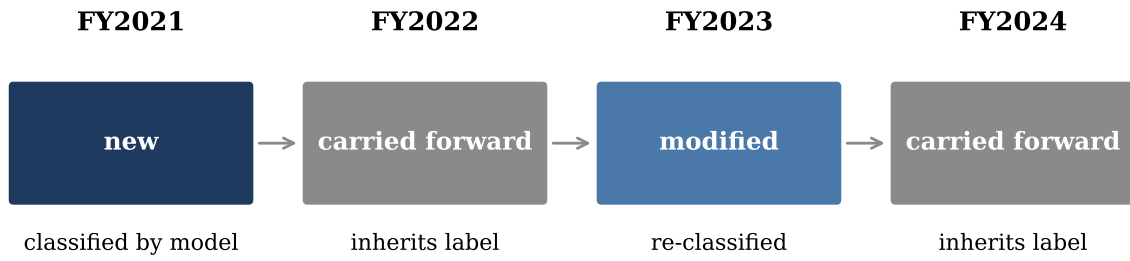
Table A4: Stablecoin Passage Classification: Sample Size and Accuracy

Activity	(1) Firm-years	(2) Firms	(3) Precision (%)	(4) Recall (%)
Provision	56	30	90.9 (10/11)	55.6 (10/18)
Reserve holdings	68	47	100.0 (10/10)	76.9 (10/13)
Planned activity	66	45	64.3 (9/14)	81.8 (9/11)
Financing	25	22	80.0 (4/5)	100.0 (4/4)
Own settlement	21	16	50.0 (4/8)	80.0 (4/5)
Any stablecoin activity	157	101	95.8 (46/48)	90.2 (46/51)

Notes: The firm-year census excludes pooled investment vehicles and separates the listed stablecoin functions. The validation sample contains 120 candidate passages reviewed in the full source filing by a separate model. Precision is the fraction of assigned positives confirmed by the audit; recall is the fraction of audit positives recovered by the classifier. Parentheses give the corresponding numerators and denominators.

**Figure 28:** Attribution Within a Corporate Filing

Notes: The bars distinguish Block’s own Bitcoin holdings from Bitcoin held in customer custody. A keyword total combines the two categories; the classification attributes them separately.



Same firm, same passage, compared across filings

Figure 29: Public Dates and Deduplication

Notes: The timeline illustrates how repeated disclosure is dated and deduplicated.

B Sample Construction and Variable Definitions

The variable definitions support the return sample in Section 3.5. Public filing dates determine when information enters the daily panel; accounting controls use information available before the return observation.

Table B1 provides the supporting evidence.

Table B1: Variable Definitions

Variable	Definition and source
Equity return	Daily stock total return from CRSP.
Market return	Daily value-weighted market total return from CRSP.
Bitcoin return	Bitcoin USD price change between consecutive CRSP closing dates, from Yahoo Finance.
Disclosure and frequency	Self-attributed A/B/C passages in SEC Forms 10-K, 8-K and 20-F made public in $[d - 365, d)$ define D and the log of one plus the passage count.
Size	Log total assets from the latest public Compustat annual report, with SEC XBRL fallback.
Cash ratio	Cash and equivalents divided by assets, bounded to $[0, 1]$, from the same annual sources.
Leverage	Total debt divided by assets, bounded to $[0, 2]$, from the same annual sources.
Profitability	Net income divided by assets, bounded to $[-2, 1]$, from the same annual sources.
Prior factor betas	Market and Bitcoin coefficients from a joint rolling regression of 250 returns, requiring 150, available at the preceding quarterly estimate.
Industry and links	Static SEC two-digit SIC and dated CRSP/Compustat security links identify industries and the primary security.
Fama–French factors	Daily market, size, value, profitability, investment and momentum factors from the Kenneth French Data Library.

Notes: The sample is the domestic daily return panel described in Section 3.5. Accounting controls enter after their public filing date, and exposure excludes same-day filings. Factor controls are used in Figure 9 and in the FTX abnormal-return models.

C Foreign Private Issuers

The foreign-issuer evidence complements the population description in Section 3.4. The comparison separates reporting-category differences from the equity-return estimates for domestic issuers.

Tables C1 and Figure 30 provide the supporting evidence.

Table C1: Annual Activity Reporting: Foreign Private Issuers Versus Domestic Filers

Reporting category	(1) Adjusted gap (pp)
Broad activity	4.543 (0.755)
Named non-stablecoin candidate	1.203 (0.458)
Named stablecoin candidate	0.982 (0.260)
Proprietary/treasury	0.658 (0.345)
Operations	4.335 (0.709)
Intermediation	1.033 (0.397)
Payment/transfer	0.549 (0.239)
Issuance/distribution	0.097 (0.103)
Collateral/financing	0.315 (0.160)
Observations	42,018
Firm clusters	5,726
Industry-year effects	Yes

Notes: Raw gaps use the same common sample as the adjusted regressions. Adjusted gaps are percentage points, with two-digit SIC-year effects and issuer-clustered inference. All nine outcomes share 42,018 observations, 5,726 issuers and 482 comparison cells. Holm probabilities cover the nine issuer-status coefficients; Named-asset and current-function categories are classified as reported activity; the broad activity variable retains its definition; Standard errors are in parentheses.

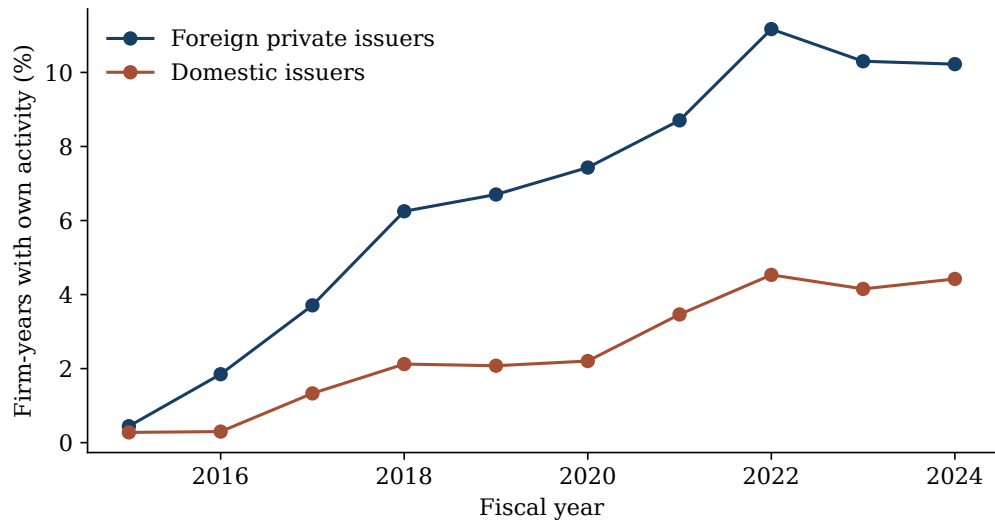


Figure 30: Crypto Activity among Foreign and Domestic Issuers

Notes: The annual-report comparison uses Forms 20-F and 10-K over the period plotted.

Additional supporting results are in Online Appendix Table OA.73.

D Pricing Robustness

These specifications support the activity-versus-talk comparison in Section 4.1. They vary reporting intensity, factor controls, the timing of returns, and the comparison sample while retaining the dated activity measures.

Tables D1, D2, D3, D4, D5 and Figures 9, 10 provide the supporting evidence.

Table D1: Disclosure-Based Bitcoin Equity Sensitivity

	(1) Expanded comparison	(2) Full baseline	(3) Added risk controls	(4) Industry by date	(5) Frequency alternative
Disclosure $\times$ BTC	0.090*** (0.020)	0.086*** (0.015)	0.085*** (0.014)	0.077*** (0.013)	0.063*** (0.009)
Disclosure	Dummy	Dummy	Dummy	Dummy	Frequency
Firm-days	6,535,300	7,050,425	7,050,425	7,036,831	7,050,425
Firms	3,615	3,879	3,879	3,875	3,879
Disclosure-positive firms	162	388	388	387	388
Comparison firms	3,453	3,491	3,491	3,488	3,491
Trading dates	2,642	2,642	2,642	2,642	2,642
Firm effects	Yes	Yes	Yes	Yes	Yes
Date effects	Yes	Yes	Yes	Absorbed	Yes
SIC2 $\times$ date effects	No	No	No	Yes	No
$X \times$ BTC; prior loadings	Yes	Yes	Yes	Yes	Yes
Levels of X and betas	No	No	Yes	Yes	Yes
Disclosure $\times$ market	No	No	Yes	Yes	Yes
Clustering	Firm/date	Firm/date	Firm/date	Firm/date	Firm/date

Notes: Outcome: decimal daily stock return. Coefficients and standard errors in parentheses are reported. Column (1) uses the expanded-comparison sample; (2)–(5) use the full eligible risk set, with industry-cell singleton exclusions in (4). X contains prior log assets, cash/assets, leverage and profitability; all columns include disclosure levels, $X \times$ BTC, prior market beta $\times$ market return, and prior BTC beta $\times$ Bitcoin return; Inference uses two-way firm/date clustering and $t_{\min(G_i, G_d)-1}$; Added market-risk controls use CRSP returns. Standard errors are in parentheses; * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$ denote raw two-sided probabilities.

Table D2: Disclosed Activity, Intensity and Mention-Only Comparisons

	(1)	(2)
	Two margins	Activity/mention
Disclosed activity $D \times \text{BTC}$	0.099*** (0.014)	
Centered intensity $D(F - \bar{F}) \times \text{BTC}$	0.103*** (0.015)	
ActivityAny $\times \text{BTC}$		0.085*** (0.015)
MentionOnly $\times \text{BTC}$		-0.002 (0.005)
Firm and date effects	Yes	Yes
Additional controls	Yes	Yes
Firm-days	7,050,425	7,050,425
Firms	3,879	3,879
Trading dates	2,642	2,642

Notes: The dependent variable is daily equity return in the sample of Table D1, column (3). Columns distinguish passage intensity from mutually exclusive activity and mention-only indicators. Public information enters over the preceding 365 calendar days, and models include firm and date effects, prior factor betas, market interactions and financial controls. Standard errors are clustered by firm and date. Standard errors are in parentheses; $*p < 0.10$, $**p < 0.05$, and $***p < 0.01$ denote raw two-sided probabilities.

Table D3: Robustness of the Bitcoin Sensitivity

	(1) Any	(2) D	(3) D_{core}
Baseline	0.045*** (0.009)	0.085*** (0.014)	0.128*** (0.022)
Five factors and momentum	0.044*** (0.008)	0.074*** (0.014)	0.112*** (0.021)
Nasdaq Composite	0.043*** (0.009)	0.079*** (0.014)	0.120*** (0.021)
Lag model: same day	0.046*** (0.009)	0.085*** (0.015)	0.129*** (0.022)
Lag model: one trading day	0.009* (0.005)	0.025*** (0.008)	0.032*** (0.011)
Lag model: two trading days	−0.000 (0.004)	0.000 (0.006)	0.003 (0.008)
Lag model: sum	0.055*** (0.012)	0.110*** (0.019)	0.164*** (0.028)
Up-day Bitcoin sensitivity	0.053*** (0.014)	0.092*** (0.020)	0.150*** (0.030)
Down-day Bitcoin sensitivity	0.035*** (0.010)	0.076*** (0.016)	0.100*** (0.022)
Up = down: raw p	0.268	0.483	0.121
Firm fixed effects	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes
Baseline controls and prior betas	Yes	Yes	Yes
Observations	7,050,425	7,050,425	7,050,425
Firms	3,879	3,879	3,879
Ever-exposed firms	578	388	292

Notes: The dependent variable is daily equity return in the domestic return sample. Columns use Any, own activity and core activity; rows vary factor controls, lag structure and Bitcoin-return signs. Models retain firm and date effects, prior factor betas and predetermined financial controls, and the lag sum uses the full coefficient covariance. Standard errors are clustered by firm and date. Standard errors are in parentheses; * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$ denote raw two-sided probabilities.

Table D4: Characteristic Interactions

	(1)
Characteristic	Triple interaction
Log assets	−0.039*** (0.009)
Cash/assets	0.008 (0.012)
Debt/assets	−0.000 (0.012)
Profitability	−0.035*** (0.010)

Notes: The dependent variable is daily equity return for 7,050,425 firm-days at 3,879 firms. Each column adds one interaction between disclosed activity and a financial characteristic, scaled by its reference-distribution standard deviation. Regressions retain firm and date effects, baseline financial controls and lower-order interactions. Standard errors are clustered by firm and date. Standard errors are in parentheses; $*p < 0.10$, $**p < 0.05$, and $***p < 0.01$ denote raw two-sided probabilities.

Table D5: First-Disclosure Sensitivity in Quarterly Bins

	(1)	(2)	(3)	(4)	(5)	(6)
	Selected sample			Full-risk-set extension		
Quarter	Coefficient	Firms	Firm-days	Coefficient	Firms	Firm-days
4 before	−0.038 (0.029)	156	9,658	−0.035 (0.023)	261	16,039
3 before	−0.032 (0.025)	159	9,875	−0.039* (0.020)	268	16,297
2 before	−0.037 (0.032)	162	10,094	−0.046** (0.023)	277	16,796
1 before	Reference	161	9,949	Reference	283	17,102
1 after	0.064** (0.031)	162	10,173	0.060** (0.023)	305	18,110
2 after	0.050 (0.034)	162	9,856	0.036 (0.027)	294	16,779
3 after	0.052* (0.029)	148	8,666	0.027 (0.022)	262	15,192
4 after	0.008 (0.037)	134	7,928	0.008 (0.025)	257	14,840
Pre-bin joint p	0.566			0.206		
Post-equality p	0.389			0.214		
Firm-days		425,342			6,549,482	
Event / comparison firms		162 / 187			338 / 3,453	

Notes: The dependent variable is daily equity return, and coefficients are Bitcoin-sensitivity differences relative to days −91 through −1 before first disclosure. Columns distinguish the baseline event specification from the extension with financial-characteristic and prior-beta levels and the disclosure–market interaction. Both models include firm and date effects, event-time indicators, event-firm Bitcoin exposure and predetermined financial controls. Standard errors are clustered by firm and date. Standard errors are in parentheses; * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$ denote raw two-sided probabilities.

Additional supporting results are in Online Appendix Table OA.74.

E Roles, Size, and Industry Details

These comparisons support the role, size, and industry results in Section 4.2. The role specifications distinguish proprietary holdings, operations, and intermediation, and the industry specifications hold the comparison sample fixed.

Tables E1, E2 and Figure 14 provide the supporting evidence.

Table E1: Full-Risk-Set Role Estimates and Robustness

	(1)	(2)	(3)	(4)	(5)
Holding statement $\times$ BTC	0.266***	0.217***	0.194***	0.184***	0.067**
	(0.078)	(0.060)	(0.053)	(0.053)	(0.032)
Operations $\times$ BTC	0.087***	0.069***	0.062***	0.070***	0.016*
	(0.024)	(0.018)	(0.017)	(0.018)	(0.009)
Intermediation $\times$ BTC	0.067**	0.054**	0.048**	0.048**	0.041***
	(0.029)	(0.023)	(0.022)	(0.023)	(0.013)
Risk discussion $\times$ BTC	0.015*	0.012	0.016***	0.012	−0.005
	(0.009)	(0.008)	(0.006)	(0.008)	(0.006)
Prior BTC beta $\times$ BTC	No	Yes	Yes	Yes	Yes
Firm effects	Yes	Yes	Yes	Yes	Yes
Time effects	Date	Date	SIC2/date	Date	Date
Additional risk controls	Yes	Yes	Yes	Yes	Yes
Firm-days	7,050,425	7,050,425	7,036,831	7,047,961	6,950,722
Firms	3,879	3,879	3,875	3,878	3,798
Trading dates	2,642	2,642	2,642	2,642	2,642
Holding statement firms	42	42	42	41	18
Operations firms	184	184	183	183	127
Intermediation firms	101	101	101	100	71
Risk discussion firms	284	284	284	283	240

Notes: Decimal daily equity returns. (A) omits prior BTC beta $\times$ BTC; (B) includes it; (C) adds SIC2/date effects; (D) excludes Strategy; (E) excludes ever-miners. All columns retain the role levels, role-market interactions and financial controls described above. Standard errors are firm/date, with the regressor-count, nonnested fixed-effect and cluster corrections. Marginal tests use t_{2641} ; All recorded covariance matrices pass positive-semidefiniteness checks. Standard errors are in parentheses; * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$ denote raw two-sided probabilities.

Table E2: Industry Sensitivity and Dated Economic-Role Adjustment

Industry	(1) Full sample	(2) Common sample	(3) With roles
Business services	0.026* (0.016)	0.022 (0.017)	−0.013 (0.022)
Finance/insurance/RE	0.171*** (0.035)	0.162*** (0.033)	0.130*** (0.032)
Manufacturing	0.050** (0.020)	0.022 (0.017)	−0.006 (0.021)
Mining	−0.064 (0.047)	−0.084* (0.045)	−0.101** (0.047)
Other sectors	0.036 (0.026)	0.006 (0.023)	−0.028 (0.032)
Trade	0.048* (0.026)	0.070** (0.030)	−0.002 (0.030)
Transport/utilities	0.024 (0.026)	0.020 (0.030)	−0.020 (0.039)

Notes: Entries are BTC interaction coefficients with standard errors beneath. Original: full Plan B industry model, 7,050,425 firm-days and 3,879 firms, t_{2641} . Common and With roles: identical 792,139 firm-days at 492 firms, 2,642 dates and 18,340 broad-industry/date cells, t_{491} . All use firm and broad-industry/date effects, industry-specific disclosure levels and Chapter 6 risk controls; With roles adds H/O/F levels and their BTC interactions; role slopes are common across industries; The sample uses the role-panel selection; The mining row has four positive firms and zero holding-statement firms, with particularly sparse support. Standard errors are in parentheses; * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$ denote raw two-sided probabilities.

Additional supporting results are in Online Appendix Table OA.75.

F Accounting Robustness

The accounting specifications support Section 5.1 and the cross-group comparison in Section 5.2. Common-sample estimates separate changes in the comparison population from differences across accounting outcomes.

Tables F1, F2, F3 provide the supporting evidence.

Table F1: Common-Sample Fundamental Sensitivity

	(1)	(2)	(3)	(4)	(5)	(6)
	OI/A	OCF/A	$\Delta \ln Sales$	$\Delta \ln Assets$	Debt/A	Cash/A
Prior disclosure $\times$ BTC	0.007*** (0.002)	−0.003 (0.002)	0.031*** (0.010)	0.031** (0.012)	−0.000 (0.003)	0.006 (0.005)
Observations	42,169	42,169	42,169	42,169	42,169	42,169
Firms	2,076	2,076	2,076	2,076	2,076	2,076
Prior-disclosure firms	212	212	212	212	212	212
Calendar quarters	44	44	44	44	44	44
Firm / quarter FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variables are the indicated quarterly accounting outcomes. The columns use a common complete-case sample of firms across outcomes, with own-activity exposure dated by public filings. Firm and calendar-quarter effects and predetermined financial controls enter each regression; quarterly-score HAC(4) standard errors account for serial dependence. Standard errors are in parentheses; * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$ denote raw two-sided probabilities.

Table F2: Economic Roles and Fundamental Sensitivity

	(1)	(2)	(3)	(4)	(5)	(6)
	OI/A	OCF/A	$\Delta \ln Sales$	$\Delta \ln Assets$	Debt/A	Cash/A
Holding statements $\times$ BTC	0.036*** (0.008)	-0.001 (0.009)	0.052 (0.034)	0.068** (0.027)	0.033* (0.018)	0.023 (0.019)
Positive firms	31	32	31	33	33	31
Operations $\times$ BTC	0.011* (0.006)	-0.000 (0.003)	0.052*** (0.017)	0.031 (0.024)	0.006 (0.010)	0.007 (0.009)
Positive firms	126	140	139	142	142	137
Intermediation $\times$ BTC	0.002 (0.005)	0.004 (0.004)	-0.000 (0.026)	-0.010 (0.020)	-0.017** (0.008)	0.020*** (0.007)
Positive firms	69	79	81	81	82	78
Observations	55,462	65,013	66,009	71,032	65,980	68,792
Firms	2,421	2,940	2,880	2,969	3,092	2,928
Prior-disclosure firms	254	286	269	291	289	275
Calendar quarters	42	41	42	42	42	42
Firm / quarter FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variables are the indicated quarterly accounting outcomes for domestic firms with publicly dated activity roles and accounting data. Holdings, operations and intermediation enter jointly with their Bitcoin interactions and fiscal-period Bitcoin returns. Models include firm and calendar-quarter effects and predetermined financial controls; standard errors use quarterly-score HAC(4). Standard errors are in parentheses; * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$ denote raw two-sided probabilities.

Table F3: Across-Group Fundamentals and Repricing

	(1)	(2)
	Operating income/assets	Asset growth
Across-group slope	3.0280 (0.3370)	2.270 (0.353)
R^2	0.5790	0.730
Groups	11	11

Notes: The dependent variable is the group's daily stock-return Bitcoin beta. Regressors are quarterly operating-income/assets or asset-growth Bitcoin betas. Weights count exposed firms with complete quarterly inputs. HC1 standard errors treat group estimates as data and ignore overlap and first-stage uncertainty.

Additional supporting results are in Online Appendix Table OA.76.

G Holdings Intensity and Institutional Ownership

These tests support the distinction between proprietary holdings and business activity in Section 5.2. Holdings intensity measures the direct balance-sheet price link, while common ownership and institutional trading measure transmission through portfolio investors.

Tables G1, G2 and Figure 18 provide the supporting evidence.

Holdings intensity h is the firm's publicly reported own Bitcoin units times the preceding calendar-day Bitcoin close, divided by equity market value from the preceding baseline trading session. Custody and produced quantities are excluded. The maximum eligible quantity within a filing date enters on the next trading day and expires after 365 calendar days. A missing preceding-session market value is not replaced by a stale value. The retained positive-intensity sample contains 26 firms and 11,491 firm-days.^a

Table G1: Holdings Intensity and Equity Repricing

	(1) Any	(2) D	(3) D_{core}
Crypto $\times$ BTC before h	0.041*** (0.009)	0.077*** (0.014)	0.116*** (0.022)
Crypto $\times$ BTC after h	0.037*** (0.008)	0.071*** (0.013)	0.106*** (0.020)
$h \times$ BTC	0.447*** (0.132)	0.429*** (0.126)	0.407*** (0.118)
N	7,042,908	7,042,908	7,042,908
Firms	3,872	3,872	3,872
Days	2,642	2,642	2,642
FE	Firm + date	Firm + date	Firm + date
Clustering	Firm/date	Firm/date	Firm/date

Notes: The before and after estimates use the same screened sample. The model includes the baseline daily controls, Crypto, Crypto interacted with the market, and h ; common Bitcoin and market returns are absorbed by date effects. Standard errors are in parentheses; * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$ denote raw two-sided probabilities.

^aThe small number of holders and measurement error in reported quantities limit the interpretation of the holdings slope as asset-value pass-through.

Table G1 compares identical complete-case samples. The holdings slope is about 0.4, below one-for-one pass-through. Adding holdings intensity lowers the core coefficient by about 8 percent. Firms with holdings at most 1 percent of equity are still repriced: their bin coefficient is 0.34. Figure 18 compares the bins with one-for-one pass-through.

Additional holdings screens are reported in Online Appendix Table OA.77.

The firm-level regression of stock-return betas on operating-income/assets betas has slope 0.286 ($p = 0.176$), with rank correlation 0.009 across 311 firms. Daily betas control for the market; quarterly betas relate operating income/assets to fiscal-period Bitcoin returns. The cross section uses heteroskedasticity-robust standard errors. Error in estimated fundamental

betas can attenuate this slope.

SEC Form 13F holdings from 2015Q1 through 2025Q4 are matched to CRSP securities. In 2025Q4, 80 percent of managers hold crypto-active stocks; the median positive portfolio weight is 3.7 percent.⁷

The common-owner test measures a non-crypto firm’s indirect exposure by weighting each institutional owner’s crypto-active portfolio share by its ownership of the target. The index excludes all share classes of the target issuer from both the source numerator and portfolio denominator. Table G2 reports the broad-disclosure and verified-Bitcoin-source estimates. Neither identifies positive indirect repricing through common ownership.

Table G2: Indirect Bitcoin Exposure Through Institutional Owners

	(1)	(2)
	Broad disclosure	Verified BTC source
Indirect exposure $\times$ BTC	−0.001 (0.002)	−0.025 (0.027)
N	6,017,328	6,017,328
Firms	3,508	3,508
Days	2,642	2,642

Notes: Coefficients are additional Bitcoin-return beta per percentage point of indirect exposure. Targets have prior SEC coverage and no observed prior crypto involvement. The specification includes firm and industry-date effects, predetermined risk controls, ownership and source-concentration levels and Bitcoin interactions. Inference clusters by firm and date. Standard errors are in parentheses; * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$ denote raw two-sided probabilities.

The rebalancing test regresses manager net trading in non-crypto stocks, valued at prior prices and divided by the prior reporting portfolio, on crypto-active portfolio weight interacted with the Bitcoin downturn. The combined reporting-quality screen removes reporting-scale and portfolio-continuity flags, requires a prior reporting portfolio of at least \$100 million, and restricts prior target coverage to at most 100 percent. For broad sources, the screened coefficient is −0.001277, with a 95 percent interval [−0.002988, 0.000435]. A one-percentage-point higher source weight and a 10 percent Bitcoin decline imply −1.28 basis points of net trading relative to the prior reporting portfolio. The screen leaves 114,535 manager-quarters, 7,096 managers and 42 quarters. The regression includes manager and calendar-quarter effects, predetermined portfolio controls, and two-way manager/quarter clustering. Unscreened estimates have invalid two-way covariance and are reported in the replication files. These ownership and rebalancing tests do not explain the repricing.

⁷Form 13F is quarterly and excludes retail investors.

H Index Decomposition Details

The portfolio decompositions support Section 6.1. The daily component returns add to the covered portfolio return and distinguish directly exposed firms from the remaining constituents.

Tables H1 and Figures 31, 32 provide the supporting evidence.

Table H1: Annual Portfolio Bitcoin Sensitivities

	(1) Covered US		(3) Covered S&P		(5) Actual S&P	
Year	Raw	Adjusted	Raw	Adjusted	Raw	Adjusted
2017	0.005 (0.004)	−0.000 (0.001)	0.005 (0.004)	−0.000 (0.001)	0.005 (0.004)	−0.000 (0.001)
2018	0.015 (0.020)	0.000 (0.001)	0.016 (0.020)	0.001 (0.001)	0.016 (0.020)	0.001 (0.001)
2019	−0.021 (0.017)	−0.000 (0.001)	−0.021 (0.016)	−0.000 (0.001)	−0.021 (0.016)	−0.001 (0.001)
2020	0.210*** (0.057)	−0.004* (0.002)	0.203*** (0.056)	−0.008 (0.005)	0.204*** (0.056)	−0.008* (0.004)
2021	0.049*** (0.011)	−0.001 (0.001)	0.043*** (0.010)	−0.003 (0.002)	0.044*** (0.010)	−0.003 (0.002)
2022	0.227*** (0.023)	−0.003** (0.002)	0.214*** (0.023)	−0.010*** (0.004)	0.214*** (0.022)	−0.010*** (0.003)
2023	0.045*** (0.017)	0.000 (0.001)	0.042*** (0.016)	−0.001 (0.003)	0.042*** (0.016)	−0.001 (0.003)
2024	0.090*** (0.021)	−0.001 (0.001)	0.081*** (0.021)	−0.008*** (0.002)	0.080*** (0.021)	−0.007*** (0.002)
2025	0.212*** (0.050)	−0.005*** (0.001)	0.201*** (0.050)	−0.012*** (0.003)	0.200*** (0.050)	−0.011*** (0.002)

Notes: Annual daily regressions include an intercept; adjusted specifications also include the CRSP value-weighted market return. Standard errors are Newey–West (five lags), with the $n/(n - k)$ correction and t_{n-k} inference. There are 250–253 daily observations per year. The S&P index is a price–return series; covered baskets retain the paper’s CRSP return definition and unadjusted capitalization weights; Standard errors are in parentheses; * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$ denote raw two-sided probabilities.

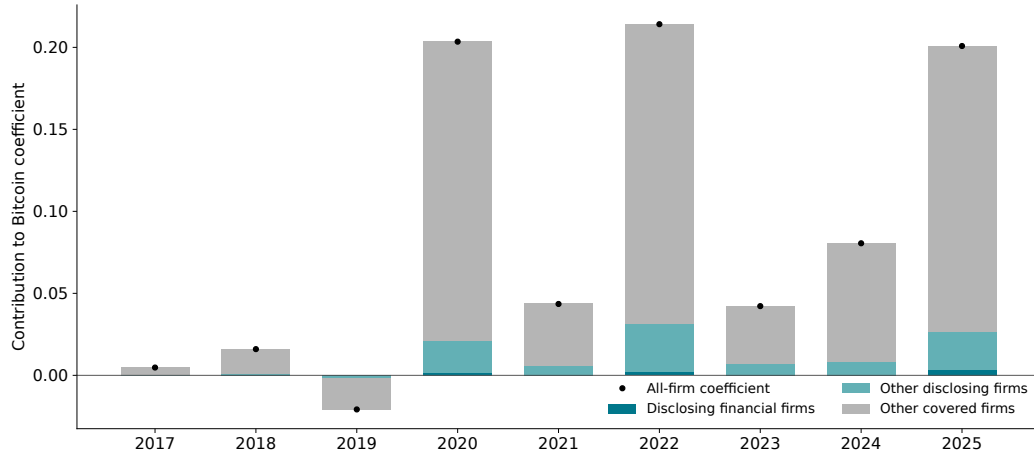


Figure 31: Raw Covered-Index Decomposition

Notes: The components sum to the covered-portfolio sensitivity before controlling for the market return.

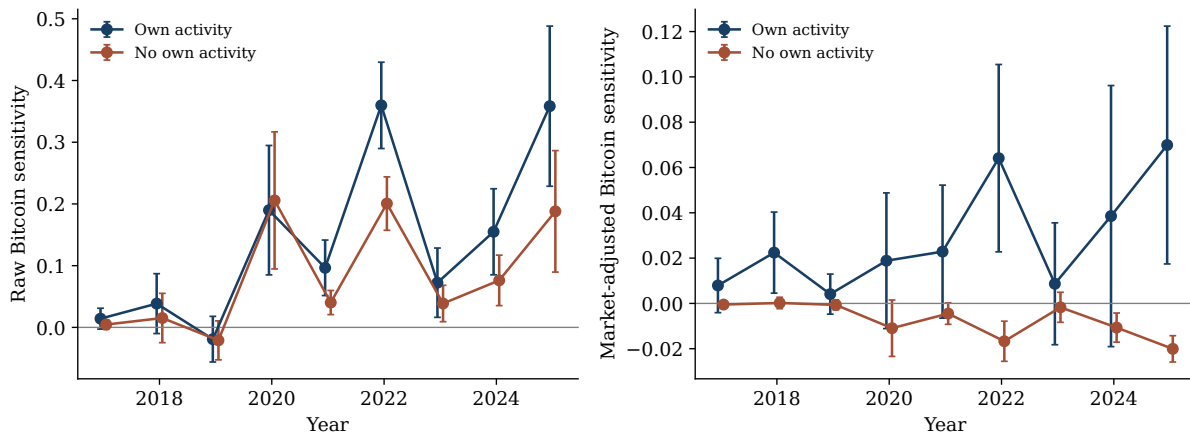


Figure 32: Bitcoin Sensitivity of Covered Index Members

Notes: The panels distinguish raw and market-controlled sensitivities. Bars show 95 percent confidence intervals.

Additional supporting results are in Online Appendix Table OA.78.

I FTX and Terra

The event comparisons support Section 6.2. Alternative event windows and return benchmarks assess the same first-round repricing comparison, and Terra provides a second crypto-market event.

Tables I1, I2 and Figure 21 provide the supporting evidence.

Table I1: FTX: Factor-Model Abnormal Returns Over November 2–11

	(1)	(2)	(3)
<i>Panel A. Mutually exclusive layers, one joint regression</i>			
	CAR difference from no crypto paragraph		
Core		−0.031**	
		(0.015)	
Technology-only		0.030	
		(0.018)	
Mention-only		0.0040	
		(0.0090)	
Core firms		82	
Technology-only firms		32	
Mention-only firms		74	
No-crypto-paragraph firms		2,797	
Observations / firms		2,985	
<i>Panel B. Nested definitions, separate regressions</i>			
	(1) Any	(2) D	(3) D_{core}
Own exposure	−0.006	−0.013	−0.032**
	(0.009)	(0.012)	(0.014)
Exposed firms	188	114	82
Firms without this exposure	2,797	2,871	2,903
Observations	2,985	2,985	2,985
Firms	2,985	2,985	2,985
Log market value and prior betas	Yes	Yes	Yes
SIC2 fixed effects	Yes	Yes	Yes
	(HC3)	(HC3)	(HC3)

Notes: Five factors plus momentum; the alternative event window. Cross-sectional controls and HC3 inference match Table 10. Standard errors are in parentheses; * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$ denote raw two-sided probabilities.

Table I2: Realized and Predicted Repricing of Core-Exposed Firms

	(1)	(2)
	FTX	Terra/UST
Bitcoin return (%)	−17.320	−19.400
Exposed firms	95	68
Realized VW abnormal return (%)	−2.120	−3.890
Predicted VW return: pooled (%)	−2.210	−2.480
Realized abnormal repricing (\$bn)	−53.7	−100.4
Predicted repricing: pooled (\$bn)	−56.0	−63.9
Predicted VW return: size quintiles (%)	−0.820	−0.910
Predicted repricing: size quintiles (\$bn)	−20.9	−23.4

Notes: VW denotes value-weighted returns. The pooled sensitivity is 0.1276; size predictions use the recorded five quintile sensitivities. Negative dollar amounts denote declines. The same firms enter the realized and predicted quantities within each event; Sensitivities and quintile cutoffs use the full recorded sample, so the event comparison uses the estimated daily sensitivities.

Additional supporting results are in Online Appendix Table OA.79.

J Spillover Details

These specifications support the industry spillovers in Section 6.3. They examine peer weighting, linkage groups, recipient fundamentals, and the identity of the crypto-linked peer banks.

Tables J1, J2, J3 and Figures 23, 24 provide the supporting evidence.

Table J1: Robustness of Industry Spillovers

	(1) EW	(2) VW
<i>Panel A. Business services (SIC 73)</i>		
Baseline	0.684*** (0.155)	0.387*** (0.086)
Size-tercile $\times$ Bitcoin slopes	0.680*** (0.154)	0.386*** (0.085)
SIC3 $\times$ Bitcoin slopes	0.656*** (0.155)	0.377*** (0.085)
Excluding smallest recipients	0.687*** (0.179)	0.390*** (0.104)
2020–2025 only	0.879*** (0.263)	0.422*** (0.117)
Drop influential peers, one at a time: range	0.641*** to 0.713***	0.360*** to 0.454***
Standard-error range	(0.151–0.160)	(0.086–0.103)
<i>Panel B. Banks (SIC 60), equal-weighted peers</i>		
Baseline	–1.738*** (0.503)	
Excluding March 2023	–1.427*** (0.375)	
Small recipient banks	–1.896*** (0.455)	
Large recipient banks	–1.565*** (0.578)	
Number of crypto-linked peer banks	–0.007*** (0.002)	
Firm and date fixed effects	Yes	Yes
Industry-specific Bitcoin slopes	Yes	Yes
Peer industry level	SIC2	SIC2

Notes: Core-negative firm-days; dependent variable: daily stock return; lagged leave-one-out core peers. Effects divide by 0.1276; the count row replaces the share; exact samples are in Table OA.37. Value-weighted bank results appear in Appendix Table OA.41. Standard errors are in parentheses; * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$ denote raw two-sided probabilities.

Table J2: Spillovers by Economic Linkage Group

	(1) Any	(2) D	(3) D_{core}
<i>Panel A. Equal-weighted peers</i>			
Peer exposure share $\times$ Bitcoin return:			
Financial intermediation (G1)	-0.055* (0.029)	-0.060** (0.026)	-0.068** (0.027)
Business services (G2)	0.279*** (0.079)	0.331*** (0.101)	0.662*** (0.151)
Other industries (G3)	0.037 (0.041)	0.066 (0.045)	0.157*** (0.057)
Joint equality of G1, G2 and G3: p	< 0.001	< 0.001	< 0.001
G1 = G3: p	0.044	0.014	< 0.001
Firm fixed effects	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes
Industry-specific Bitcoin slopes	Yes	Yes	Yes
Peer weighting	EW	EW	EW
Peer industry level	SIC3 G1; SIC2 G2/G3	SIC3 G1; SIC2 G2/G3	SIC3 G1; SIC2 G2/G3
Observations	6,684,539	6,836,698	6,897,050
Firms	3,797	3,814	3,825
<i>Panel B. Value-weighted peers</i>			
Peer exposure share $\times$ Bitcoin return:			
Financial intermediation (G1)	-0.027** (0.013)	-0.069** (0.031)	-0.050** (0.020)
Business services (G2)	0.009 (0.028)	0.053 (0.055)	0.354*** (0.085)
Other industries (G3)	0.034*** (0.012)	0.008 (0.012)	0.034* (0.018)
Joint equality of G1, G2 and G3: p	0.005	0.042	< 0.001
G1 = G3: p	0.001	0.021	0.003
Firm fixed effects	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes
Industry-specific Bitcoin slopes	Yes	Yes	Yes
Peer weighting	VW	VW	VW
Peer industry level	SIC3 G1; SIC2 G2/G3	SIC3 G1; SIC2 G2/G3	SIC3 G1; SIC2 G2/G3
Observations	6,670,141	6,821,874	6,882,055
Firms	3,797	3,814	3,825

Notes: Sample: firm-days without the column's exposure; dependent variable: daily stock return. Peers: leave-one-out exposed-industry share on the previous trading day. SIC is static SEC SIC. Effects use direct sensitivity 0.1276; confidence intervals and multiplicity checks are in the appendix. Standard errors are in parentheses; * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$ denote raw two-sided probabilities.

Table J3: Business-Services Recipients' Fundamentals

	(1) Any	(2) D	(3) D_{core}
Operating income/assets	0.023 (0.036)	0.004 (0.041)	0.022 (0.081)
N	50,798	51,457	51,992
Firms	2,280	2,295	2,310
Quarters	41	41	41
Operating cash flow/assets	-0.005 (0.036)	-0.034 (0.042)	-0.023 (0.064)
N	58,699	60,108	60,748
Firms	2,736	2,761	2,779
Quarters	41	41	41
Sales growth	0.035 (0.124)	0.070 (0.141)	0.391** (0.167)
N	59,860	61,316	61,974
Firms	2,701	2,717	2,732
Quarters	41	41	41
Asset growth	0.139 (0.100)	0.137 (0.100)	-0.043 (0.159)
N	64,352	65,815	66,484
Firms	2,775	2,792	2,808
Quarters	41	41	41
FE	Firm + quarter	Firm + quarter	Firm + quarter
Inference	HAC(4)	HAC(4)	HAC(4)

Notes: Each outcome panel reports the SIC 73 interaction between peer exposure and fiscal-period Bitcoin returns. Samples differ by outcome and exposure definition. Firm and calendar-quarter effects, publicly available financial controls and their Bitcoin interactions follow the main accounting design. Inference uses quarterly-score Bartlett HAC(4). Standard errors are in parentheses; * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$ denote raw two-sided probabilities.

Table J4 reports value-weighted peer estimates.

Table J4: Industry Spillovers with Value-Weighted Peers

	(1)	(2)	(3)
	Any	D	D_{core}
<i>Value-Weighted Peers</i>			
Peer exposure share $\times$ Bitcoin return:			
Business services (SIC 73)	0.023 (0.029)	0.059 (0.055)	0.387*** (0.086)
Banks (SIC 60)	-0.055** (0.024)	-0.102* (0.058)	-0.051 (0.046)
Non-bank credit (SIC 61)	0.006 (0.016)	-0.037 (0.065)	-0.017 (0.065)
Brokerage (SIC 62)	-0.001 (0.016)	-0.015 (0.029)	-0.020 (0.033)
Other industries	-0.016 (0.014)	-0.007 (0.014)	0.043 (0.027)
Firm fixed effects	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes
Industry-specific Bitcoin slopes	Yes	Yes	Yes
Peer weighting	VW	VW	VW
Peer industry level	SIC2	SIC2	SIC2
Observations	6,676,737	6,828,153	6,888,323
Firms	3,800	3,817	3,828

Notes: The dependent variable is the daily return of firms without direct exposure. Columns use Any, own activity, and core activity; all eight industry interactions enter jointly. The regressions include firm and date fixed effects, industry-specific Bitcoin slopes, and baseline controls. Standard errors are two-way clustered by firm and date. Standard errors are in parentheses; * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$ denote raw two-sided probabilities.

Additional supporting results are in Online Appendix Table OA.80.

K Financial Institutions and March 2023

The bank regressions support the financial-institution comparison in Section 6.4. The March event specification relates bank abnormal returns to prior exposure and bank characteristics.

Table K1 provides the supporting evidence.

Table K1: March 2023 Abnormal Bank Returns and Crypto-Linked Activity

	(1) March 2023 CAR
Own crypto-linked exposure	−0.236* (0.121)
Number of exposed SIC3 peer banks	0.005** (0.003)
Uninsured-deposit share, 2022Q4	−0.184*** (0.045)
Log assets, 2022Q4	−0.000 (0.008)
Constant	−0.071 (0.125)
Banks	193
Exposed banks with complete returns	6 (HC3)
<i>Panel B. Prior Crypto-MES and FTX CAR</i>	
2021 Crypto-MES	1.131 (1.271)
Firms (core exposed)	497 (29)
Log market value; SIC3 effects	Yes
<i>Panel C. Prior Crypto-MES and March CAR</i>	
2022 Crypto-MES	4.729*** (1.555)
Banks (core exposed)	239 (9)
Log market value; SIC3 effects	Yes

Notes: Panel A: cumulative abnormal stock return, March 8–13, 2023. HC3 standard errors appear below coefficients; Panel A tests use t_{188} . The inherited holding-company link and subsidiary aggregation are not fully point-in-time. The exposed-peer count is based on the preceding trading-date bank universe; panels B and C add prior Crypto-MES predictive regressions with log pre-event market value and SIC3 effects; their HC3 tests use the recorded regression degrees of freedom; Their exposed counts refer to core exposure. Standard errors are in parentheses; * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$ denote raw two-sided probabilities.

L Stablecoins

These exhibits support the stablecoin description in Section 7. The role classification separates reserve holdings, service provision, plans, financing, and transaction settlement, and the entry comparison describes the latest reporting year.

Tables L1 and Figure 33 provide the supporting evidence.

Table L1: Stablecoin Activity by Role: a Census of 10-K Filers

	(1) Provider	(2) Reserve	(3) Plan	(4) Financing	(5) Settlement	(6) Any
<i>Panel A. Firm-years by fiscal year</i>						
2018	1	0	2	0	0	2
2019	0	0	2	0	0	2
2020	1	0	5	0	0	5
2021	5	2	9	0	2	13
2022	9	7	9	1	2	21
2023	9	10	3	3	4	20
2024	11	10	4	1	2	19
2025	20	39	32	20	11	75
Firm-years, FY2015–2025	56	68	66	25	21	157
Firms	30	47	45	22	16	101
of which confirmed on audit					9 (7 firms)	
<i>Panel B. Firms by SIC division (a firm counted once per role)</i>						
Finance, insurance, real estate	15	26	18	15	10	50
Services	12	10	20	2	3	32
Manufacturing	1	7	3	4	3	12
Wholesale and retail trade	1	3	2	1	0	4
Transportation, communications, utilities	1	1	2	0	0	3

Notes: Rebuilt stage-2 margins (primary role only; intermediary, tokenized-deposit and discontinued-activity rules applied), fiscal years 2015–2025, pooled vehicles excluded. Fiscal years 2015–2017 are zero on every margin. A firm-year can carry several roles, so role columns do not sum to Any. Provider pools issuers, distributors and custodians (Table OA.68); Settlement is before audit: every settlement paragraph was read (36 paragraphs); 9 of the 21 settlement firm-years (7 firms) contain at least one correctly labelled paragraph. Population: 41,910 non-vehicle firm-years, 1,312 of them crypto-active.

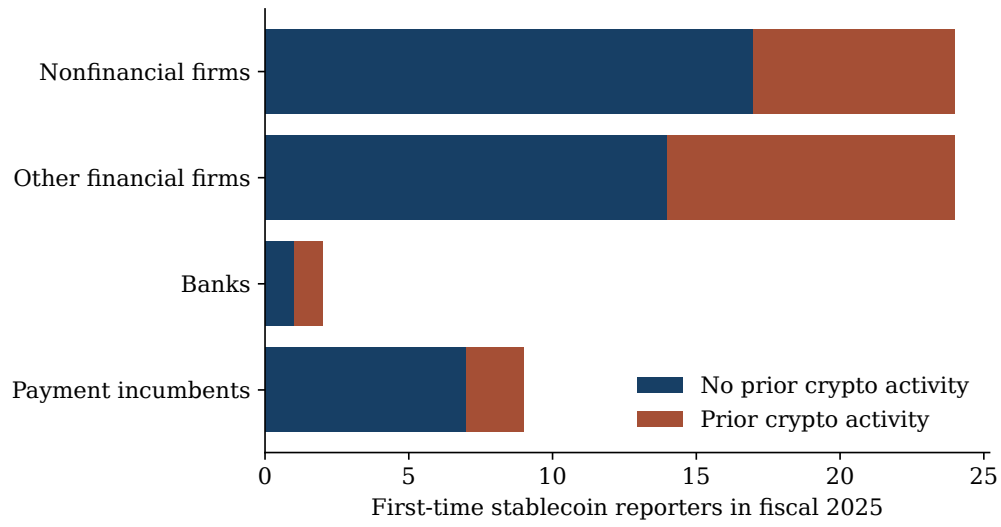


Figure 33: Stablecoin Entrants by Business Type

Notes: The fiscal-year entrant census and named-list business classifications. Bars distinguish prior crypto activity among first-time stablecoin reporters.

Additional supporting results are in Online Appendix Table OA.81.