STORE OF VALUE OR SPECULATIVE INVESTMENT? MARKET REACTION TO CORPORATE ANNOUNCEMENTS OF CRYPTOCURRENCY ACQUISITION

Abstract: We evaluate the stock market reaction following publicly-traded companies' announcements of cryptocurrency acquisition, selling, or acceptance as a means of payment. Focusing on firms whose core business is unrelated to blockchain or cryptocurrency (i.e., traditional firms), we analyze 35 events associated with 32 companies listed on stock exchanges from 7 countries. At the aggregate level, market reaction around such events is slightly positive but statistically indistinguishable from zero for most event windows. However, heterogeneity analyses reveal remarkable differences in market reaction between high (larger CARs) and low cryptocurrency exposure events (lower CARs). Multivariate regressions confirm that the extent to which a firm is exposed to cryptocurrency ("skin in the game") is a critical factor underlying abnormal returns around the event. Further analyses reveal that such an effect stems from economically meaningful acquisitions of BTC or ETH (relative to firm's total assets). Our evidence is crucial to managers, investors, and analysts since it highlights how crypto adoption relates to firm value.

Keywords: Corporate cryptocurrency acquisition; bitcoin; Cryptocurrency; Blockchain; Market reaction.

JEL Codes: G31, G32, G14, G11.

1. Introduction

"In January 2021, we updated our investment policy to provide us with more flexibility to further diversify and maximize returns on our cash that is not required to maintain adequate operating liquidity. As part of the policy, we may invest a portion of such cash in certain specified alternative reserve assets. Thereafter, we invested an aggregate $1.50 billion in bitcoin under this policy."

Tesla, Inc. (2021) Form 10-K, Part II, Item 7, management's discussion and analysis of financial condition and results of operations.

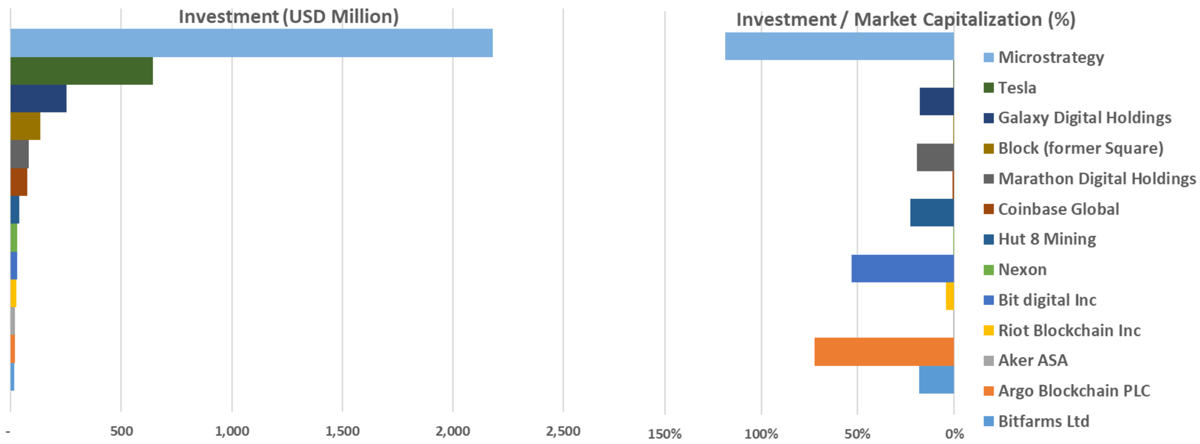
The emergence of disruptive technologies has always been associated with corporate value creation and wealth production. Recently, we have witnessed a wave of institutional adoption of cryptocurrency and other digital assets that shifted the crypto space closer to the mainstream (Hamlin, 2021). However, companies have only recently started acquiring cryptocurrency to manage excess cash and engage in digital investments. The net present value of such corporate decisions is ex-ante unclear: while such investments may hedge for inflationary risks (Dyhrberg, 2016; Blau et al., 2021; Choi and Shin, 2021) and provide more significant returns on excess cash than traditional fiat currencies (Umar et al., 2021), they are more volatile and subject to regulatory and cybernetic risks (Caporale et al., 2021). Thus, evaluating the market reaction to corporate announcements of investments and divestments in cryptocurrency is critical to understanding how crypto adoption relates to firm value.

Corporate investments in cryptocurrency are a recent trend in many countries, especially after Tesla announced in early 2021 an investment of $1.5 billion in bitcoin (BTC) as part of a new policy to manage excess cash.[1] Figure 1 shows the publicly traded companies with the most prominent bitcoin positions in December 2022. We show on the left side the amount invested, in Millions of Dollars, and the ratio between the investment's value and each company's market capitalization on the right side. We observe that MicroStrategy, the company with the most prominent BTC position, is also the most significant investment by market value. On the other hand, despite being the

[1] Source: https://www.wsj.com/articles/tesla-buys-1-5-billion-in-bitcoin-11612791688.

second largest company regarding announced investments in cryptocurrency, Tesla has a relatively low investment compared to its market value. Such a significant cross-sectional variability in the exposure to cryptocurrency is a feature we further explore in this paper.

Figure 1: Publicly traded companies with the most prominent positions in bitcoin



Source: Authors' elaboration, based on data from cryptotreasuries.org and Bloomberg (Dec./2022).

Several studies deal with companies' relationship with blockchain technology, examining the market reaction to announcements of investment projects related to these decentralized networks (Adhami, Giudici, and Martinazzi, 2018; Giudici and Rossi-Lamastra, 2018). Some papers, such as Autore, Clarcke, and Jiang (2021), separately classify companies whose investment plans are in early or advanced stages, verifying a positive market reaction around the event date. However, the effect is permanent only for credible, advanced-stage projects. Other works seek to quantify price fluctuations around corporate news related to changes in the name of the company, seeking an association with blockchain technology (Jain and Jain, 2019, Cahill, Baur, Liu, and Yang, 2020). Jain and Jain (2019), analyzing companies that added bitcoin or blockchain to their name, identify positive abnormal returns in a short time window and negative abnormal returns in longer time windows. Complementarily, Akyildirim, Corbet, Sensoy, and Yarovaya (2020) build on the event studies technique and find positive, persistent CARs for companies that changed their name to a blockchain-related denomination.

Specifically concerning cryptocurrencies, one of the multiple blockchain applications, the literature presents research evaluating the adoption of crypto assets by institutional (see, e.g., Bialkowski, 2020) and retail (see, e.g., Platanakis and Urquhart, 2020) investors. These studies broadly indicate substantial room for diversification benefits. The reason is that cryptocurrencies combine high average historical returns and low correlation with traditional assets (Bouri, Molnár, Azzi, Roubaud, Harfors, 2017; Zend et al., 2020; Aharon and Demir, 2021; Yousaf et al., 2022). Nonetheless, one should also note that cryptocurrencies' hedge and safe-haven properties have been questioned both before (Klein, Thu and Walther, 2018) and after the COVID-19 global pandemic (Conlon and McGee, 2020; Caferra and Vidal-Tomás, 2021). Because of such inconclusive findings, whether cryptocurrency acquisition is value-enhancing or value-decreasing to corporations is an empirical question.

In particular, while empirical evidence on crypto-asset adoption by retail and institutional investors is relatively extensive, we find no research that verifies such effects from the perspective of corporate investors. Several reasons potentially explain such a lack of studies on this area of research. First, corporate investment in cryptocurrency is a relatively new phenomenon. Second, publicly traded companies demonstrate a timid or reticent stance on investing in bitcoin and other cryptocurrencies, as they are subject to increased scrutiny by auditors and regulators. Regardless of the potential reasons, however, the adoption of cryptocurrencies by corporations is of practical importance, and there is still an avenue to be filled by academic research.

To address the abovementioned literature gap, we examine the response of publicly traded companies against cryptocurrency-related announcements using the event study approach. We use data from 35 events associated with 32 listed companies from major stock markets – New York, London, Toronto, Oslo, Hong Kong, Tokyo, and São Paulo, from 2014 to 2022. These corporate cryptocurrency announcements are classified into three groups: acquisition/investment, selling/divestment, and acceptance as means of payment. Our empirical approach goes as follows. First, we estimate the abnormal returns around each event using the market model approach. We then test the statistical significance of cumulative average abnormal returns

(CAARs) around the events and analyze whether firm, industry, and market-level factors are the determinants of the CARs (cumulative abnormal returns). Finally, we explore the cross-sectional variation in the degree of exposure to cryptocurrency to analyze heterogeneous market responses.

The results of our study reveal that the cumulative abnormal returns around crypto-related corporate events are slightly positive but statistically indistinguishable from zero in most cases. Thus, findings at the aggregate level suggest that corporate announcements of cryptocurrency adoption are neither value-increasing nor value-decreasing, on average. Using the CARs as dependent variables in linear regression models, we find that tech firms experience more significant abnormal returns than non-tech firms (mainly the financial or retail sectors).

We then analyze a potential heterogeneity in market reaction across different levels of cryptocurrency exposure. Using the USD amount of BTC or ETH acquisition/divestment relative to the Total Assets of the firm and a qualitative assessment of the news content for indirect crypto investments (e.g., acquisition of a crypto firm) and acceptance as means of payment (intention vs. effective acceptance of cryptocurrency), we classify events into low, medium, or high degree of exposure to cryptocurrency. We find a remarkable difference in CARs for high (3.63 to 7.97 p.p.) and low-cryptocurrency exposure events (ranging from -1.57 to -5.15 p.p.). Multivariate regressions confirm that the high (low) degree of cryptocurrency exposure dummy is a positive (negative) and statistically significant regressor that explains the CARs, and the robustness analyses reveal that such a result stems from the subset of events where we do have an objective, market-based metric of "skin in the game". Moreover, further analyses reveal that the results are not driven by extreme, tail CARs. Though limited by the sample size (N=35), our evidence suggests that the extent to which a given firm is exposed to cryptocurrency is critical to understand how the market reacts to the announcement. Such a pattern corroborates Autore et al. (2021) findings that market reaction differs significantly between credible and non-credible corporate blockchain investments.

This research expands the understanding of the role of cryptocurrencies for corporations and thus helps managers, analysts, and investors to comprehend the consequences of crypto-related corporate announcements. Furthermore, this study complements a growing literature that deals with corporate association with blockchain (Akyildirim et al., 2020; Jain & Jain, 2019; Autore et al., 2021, Chen, Lai, Liu and Wang, 2022, Ali, Jia, Lou, and Xie, 2023), a technology that may transform businesses (Cheg, Hu, Puschmann, and Zhao, 2021).

The rest of the paper is structured as follows: section 2 describes the data and methodology, section 3 presents the results, and section 4 concludes.

2. Data and Methodology

2.1. Data selection and event definition

We focus on cryptocurrency-related events associated with public domestic and foreign companies (i.e., firms listed on a stock exchange). To gauge the impact of crypto exposition on traditional firms, we delimit our analysis to firms whose core business is unrelated to the blockchain technology or management of cryptocurrencies/digital assets ("traditional companies"). We thus exclude digital asset management firms, crypto mining companies, and crypto exchanges from the sample since these crypto-related firms could bias our analysis.[2] We identify crypto-entry events in three categories of corporate announcements: investment (acquisition of currency or crypto-related companies), acceptance as a form of payment, and divestment (such as selling cryptos or tokens or discontinuing the endorsement as a means of payment).

Our dataset comes from Bloomberg (stock prices, volumes, and market capitalization), Thomson Reuters, and specialized websites (Cryptotreasuries.org, Cointelegraph.com, Bitcoinmagazine.com, among others, to search for corporate announcements related to cryptocurrency). We also search for Twitter's posts linked

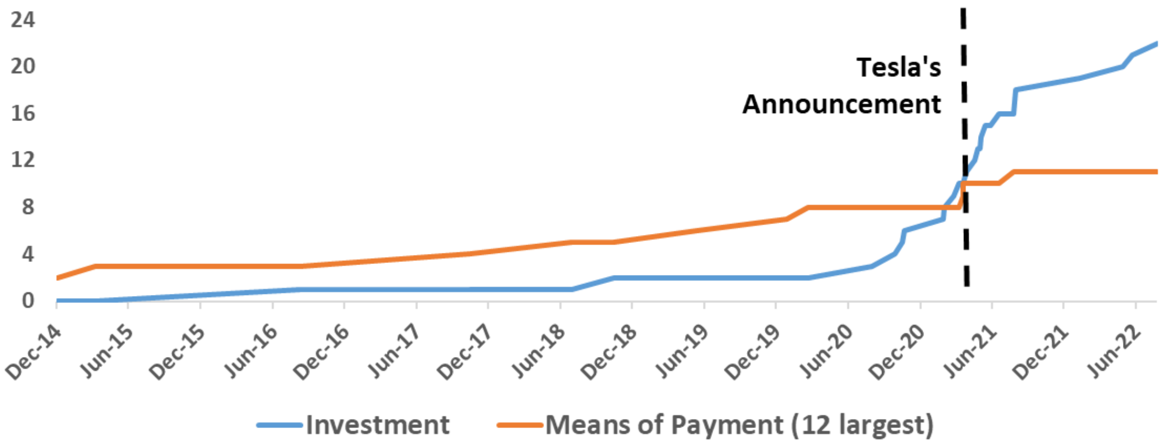
[2] For these firms, the impact on corporate value is fundamentally different from other companies because their core business is related to cryptocurrency.

to company announcements and official statements from investor relations sites. The sample period ranges from January 2014 to December 2022. The abovementioned procedure resulted in 35 events associated with 32 companies, negotiated in New York, London, Toronto, Oslo, Hong Kong, Tokyo, and São Paulo stock exchanges. Prices are collected in U.S. Dollars, and log returns are calculated for each stock and reference index – S&P 500, FTSE100, TSX, OSEBX, HSI, Nikkei225, and Ibovespa, respectively. In Appendix A, we disclose all the 35 events considered in this study.

An essential issue in our setting relates to the effective date of the event. In most cases, we found that the date on which the crypto expositions occurred was not revealed by the company through relevant facts (e.g. SEC *filings*), appearing only in its financial statement disclosures. Thus, we determine the event date as the first news published on that fact.

Figure 2 shows the number of publicly traded companies that have added cryptocurrency to their balance sheets, either by acquisitions or by adhering to it as means of payment. In the case of companies that started to accept cryptocurrency as a means of payment, the 12 largest corporations were considered. Those that converted into fiat currency when they received payments were excluded because they are not exposed to price fluctuations in crypto assets.

Figure 2: Publicly Traded Companies Investing in Cryptocurrencies

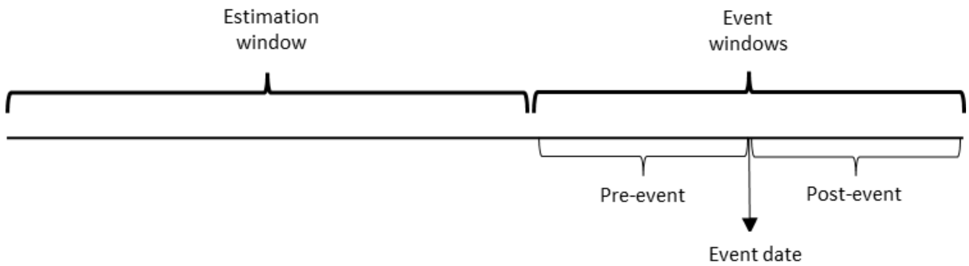


Note: This Figure shows the number of publicly traded companies adhering to cryptocurrencies over time. Such exposition is divided into investment throughout acquisitions (blue line) and acceptance as means of payment (orange line). The steeper slope, starting in early 2021, coincides with Tesla's announcement of investing USD 1.5 billion worth of bitcoin under the new policy of diversifying and maximizing returns on excess cash (the fraction of cash that is not required to maintain the company's operations).
Source: authors' elaboration.

2.2. Event windows and estimation of abnormal returns

We use the event study method to estimate the market reaction to corporate announcements of crypto-related expositions (see Mackinlay, 1997, and further references). First, we estimate expected returns using stock market information from 126 days before the beginning of the anticipation period (21 days before the event). Besides the estimating window, we also consider pre (-21 days to the day of the event) and post-event windows (from the day of the event to 21 days ahead). By doing that, we ensure that our windows do not overlap – see Figure 3 for details.

Figure 3 - Flow of the estimation period and observation period of abnormal returns



Note: the estimation, pre-, and post-event windows comprehend 126, 21, and 21 days, respectively.
Source: authors' elaboration.

To gauge potential abnormal market movements before, during, and after the announcement of each event, we estimate abnormal returns on the day of the event [0;0] and cumulative abnormal returns at different windows ([-1;1], [-2;2], [-5;5], [0;1], and [0;3]). We include other pre, during, and post-event windows in the analyses, but we focus on these six windows because the marginal benefit of adding other event windows proved to be very low.[3] Furthermore, these core event windows follow previous studies (e.g., Autore et al., 2021).

As already mentioned, we collect all stock prices in USD and calculate daily log returns. Then, we estimate "normal return" by projecting OLS regressions of the returns of each stock against the returns of the core stock index of the Stock Exchange where the stock is traded on a 126-working day window. In other words, we estimate each stock's

[3] A previous version of this paper analyzed CARs at nineteen-time windows. However, because the results are similar across these alternative event windows, we restrict the analysis to six of the most used time spams in event studies.

alpha (intercept) and beta (regression slope) parameters using the market model, as presented in Equation 1.

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it} \qquad (1)$$

Where:

R_{it}: Return of stock i in day t

R_{mt}: Return of the market portfolio index in day t

α_i: Alpha parameter of stock i

β_{i}: Beta parameter of stock i

ε_{it}: Random error term of stock i at day t, with E(ε_{it}it)=0 and $\sigma^2(\varepsilon_{it})$=$\sigma^2_{\varepsilon_i}$

We project the estimated parameters from Eq. (1) ($\hat{\alpha}_i$ and $\hat{\beta}_i$) to the event window together with the observed market index returns. By doing that, we obtain an estimator for each stock's expected, "normal" return. The next step is to compute the Abnormal Return (A.R.) of each stock as the disturbance term of the market model (Mackinlay, 1997):

$$AR_{it} = R_{it} - \hat{\alpha}_i - \hat{\beta}_i R_{mt} \qquad (2)$$

Where AR_{it} measures the difference between the observed and the expected return. Before aggregating A.R.s on the time dimension, we standardize these returns using the standard deviation of the estimation period, adjusted to the observation window (Equation 3).

$$SAR_{it} = \frac{AR_{it}}{\sigma_i \times \sqrt{n_i}} \qquad (3)$$

Where SAR_{it} refers to the Standardized (scaled) Abnormal Returns. After that, we estimate the Cumulative Abnormal Returns (CARs) by summing the SARs over time for each firm (see Equation 4). The date of the event is a particular case with a single day in the sample (n=1) and included as a window.

$$CAR_i(t1, tn) = \sum_{t=t1}^{tn} SAR_{it} \qquad (4)$$

Where:

$CAR_i(t1, tn)$: Cumulative Abnormal Return of stock i between t=1 and t=n.

t: t-th information in the event window

n: number of days in the event window

Finally, aside from the time dimension, we aggregate returns on the cross-section dimension. In particular, the Standardized Average Abnormal Return (SAAR) for period t is computed as follows:

$$SAAR_t = \frac{1}{N} \sum_{i=1}^{N} SAR_{it} \qquad (5)$$

Where N denotes the number of cross-sectional observations (i=1,…,N stocks), and standardization follows the approach shown in Eq. (3). Finally, we sum the SAAR for different days at the event window to get the Cumulative Average Abnormal Returns (CAARs):

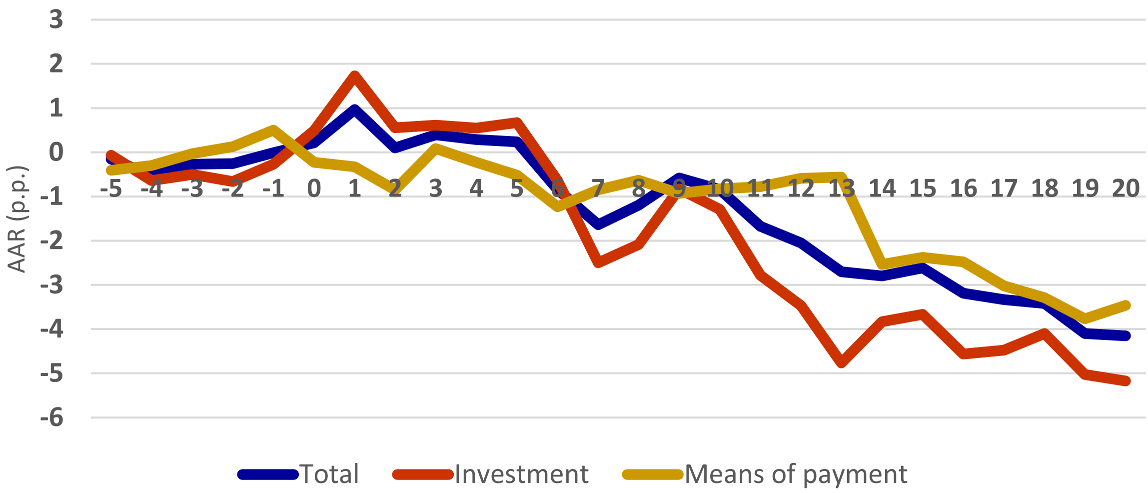
$$CAAR(t1, tn) = \sum_{t=t1}^{tn} SAAR_{it} \qquad (6)$$

Where t=t1,…,tn refers to the length of the event window used to calculate that particular CAAR.

To first look at the evolution of cumulative average abnormal returns stratified by event type, Figure 4 shows the evolution of CAARs starting five working days before the event. The data is stratified into three categories: *means of payment*, *divestment*, and *total* (summing up all events).[4] Based on this visual inspection, it is possible to observe near-zero abnormal returns among companies in all categories. However, on the day of the event and the following day, market reaction seems positive for the Investment and Total categories. Since this is just a first look at the data, we do not analyze t-stats and p-values to assess the results statistically.

[4] Divestments are excluded from the Figure because this category has only two events (Tesla and Ruffer). However, these events are part of the *Total* category.

Figure 4: Evolution of cumulative average abnormal returns (CAARs) for monitoring windows



Notes: Average cumulative daily returns for 5 days before each event up to 20 days after the event, stratified by the type of event.
Source: authors' elaboration, based on data from Bloomberg.

2.3. Hypothesis testing

Regarding statistical analyses, parametric tests of hypotheses assume normality of the distributions of observations, which is rejected for samples where N is low. Since we analyze a small sample of 35 events, in addition to the t-test, we apply several additional tests: the crude dependence adjustment test (CDA), the Patell test of standardized residuals, the adjusted Patell test of standardized residuals, the Corrado rank test, the Generalized Sign Test, and the Wilcoxon signed-ranks test (these tests are commonly used in event studies – see, for example, Agarwal, Jiang, Tang and Yang, 2013; and Kaspereit, 2021, for a review of the most common test statistics used in event studies in finance, accounting, and management).

2.4. Determinants of Cumulative Abnormal Returns (CARs)

After the parametric and non-parametric tests of hypotheses, we use a multivariate regression approach to address whether firm, industry, and market-level variables are associated with the abnormal returns calculated in different windows. To do that, we collect the following firm-level data immediately before the event: market capitalization (Ln(Market Capitalization)), cumulative log-returns on 21 days preceding the event (Ln(Prior Return), the ratio between Cash and Assets (Cash/Assets), and a proxy for investment opportunities (Price/Book). To account for market-specific fluctuations that may impact the CARs, we include the 6-week cumulative log-return of bitcoin on the pre-event period (Ln(Past BTC Return)) as a regressor. Following Autore et al. (2020) and Chen et al. (2022), we also include a binary indicator to identify firms in the tech sector, whose market reaction may differ from the other sample firms (Tech Firms Dummy).[5] We also add a dummy to control for financial firms (Financial Firms Dummy), so our baseline sectoral category comprises non-financial, non-tech firms.[6] Finally, we include country-fixed effects in the regression to account for potential systematic differences between stock market or jurisdictional levels that may affect abnormal returns.[7] Specifically, the regression we estimate is the following:

$$CAR(t1, tn)_{ijc} = \alpha_0 + \beta_1 Investment\_Dummy_{ijc} + \beta_2 Tech\_Firms\_Dummy_{ijc} + \beta_3 Financial\_Firms\_Dummy_{ijc} + X'\delta + \theta_C + \varepsilon_{ijc} \quad (7)$$

Where the dependent variable $CAR(t1, tn)_{ijc}$ indicates the cumulative abnormal return for the interval $(t1, tn)$ of firm i in the industry j in the country c. $Investment\_Dummy$ equals one if the type of event is investment/acquisition and zero otherwise (i.e., means of payments or divestment). Tech Firms Dummy and Financial Firms Dummy indicate sectoral characteristics. X is the vector of firm and market-level regressors, including Ln(Market Capitalization), Ln(Prior Return), Cash/Assets, Price/Book, and Ln(Past BTC Return). θ_C denotes country-fixed effects. To analyze whether market responses depend on the degree of exposure to cryptocurrency ("skin in the game"), we add to eq. (7) two dummy variables separately:

$$CAR(t1, tn)_{ijc} = \alpha_0 + \gamma_1 High\_Exposure\_Dummy_{ijc} + \beta_1 Investment\_Dummy_{ijc} + \beta_2 Tech\_Firms\_Dummy_{ijc} + \beta_3 Financial\_Firms\_Dummy_{ijc} + X'\delta + \theta_C + \varepsilon_{ijc} \quad (8)$$

$$CAR(t1, tn)_{ijc} = \alpha_0 + \gamma_2 Low\_Exposure\_Dummy_{ijc} + \beta_1 Investment\_Dummy_{ijc} + \beta_2 Tech\_Firms\_Dummy_{ijc} + \beta_3 Financial\_Firms\_Dummy_{ijc} + X'\delta + \theta_C + \varepsilon_{ijc} \quad (9)$$

[5] For example, tech firms have larger investment opportunities than retail firms, on average. Furthermore, the asset structure of tech firms is also likely to be different since they disproportionately rely on human capital. Thus, firm-level technological orientation may be relevant to explain the CARs in our sample.
[6] The baseline sectoral category comprises Consumer Cyclical (N = 11), Telecon Services (N = 6), and Industrials (N = 1).
[7] The country dummies absorb any systematic jurisdiction or market differences that are not reflected in the country market index and may affect CARs. We thank an anonymous referee for the suggestion.

Where $High\_Exposure\_Dummy_{ijc}$ and $Low\_Exposure\_Dummy_{ijc}$ are dummy variables equal to one if the event is classified as high or low exposure to cryptocurrency, respectively, and zero otherwise. We detail the systematic approach to classify events in high, medium, and low exposure to cryptocurrency in Section 3.4 — Heterogeneity Analysis.

3. Results and discussion

Before analyzing the market reaction to corporate announcements of investments, divestments, or acceptance of cryptocurrency for payments, we investigate whether firms try to "time" the market. Table 1 shows the 5-day cumulative bitcoin returns immediately before each investment announcement (N=21) or acceptance as a means of payment (N=12). As the Table shows, (20/33=)60.6% of the investment or acceptance announcements occur when the price of BTC fluctuates positively.[8] In other words, corporations are more likely to announce that they are exposed to cryptocurrency when the crypto ecosystem is performing well. Such suggestive evidence corroborates the hypothesis that managers try to time the market, a well-documented phenomenon in corporate debt and equity issuances (see, for example, Berk and DeMarzo, 2020).

[8] We have also made this analysis using the CCi30 (a rules-based index designed to objectively measure the overall growth, daily and long-term movement of the blockchain sector) as benchmark, and the conclusions remain. However, since the referred index starts in 2015, it is impossible to compare earlier events in our sample (like Microsoft and Newegg).

Table 1: Weekly return of bitcoin, verified 5 days before each investment or acceptance as means of payment event

Company	**Prior BTC return**	**Company**	**Prior BTC return**	**Company**	**Prior BTC return**
AT&T	24%	JP Morgan	4%	Mercado_Livre (2)	-1%
Xiaomi	21%	Tesla	4%	Visa	-2%
Mastercard	21%	BlackRock	3%	Metromile	-3%
Meitu	17%	Chipotle	3%	AMC	-3%
Rakuten	16%	Microstrategy	3%	Paypal	-4%
Overstock	15%	FRMO	2%	Newegg	-4%
Ruffer	13%	Mercado Livre	2%	Starbucks	-6%
Phunware	6%	RBI Inc	1%	Nexon	-12%
BMW	6%	Microsoft	0%	Aker ASA	-19%
Brook	5%	Oracle	-1%	Meliuz	-22%
Square	5%	Townsquare	-1%	Globant	-28%
Positive returns	20	**Negative returns**	13		

Note: sample excludes divestment announcements (N = 2).
Source: Authors' elaboration.

3.1. Individual Cumulative Abnormal Returns (CARs)

Table 2 shows the cumulative abnormal returns (CARs) for each stock in several windows around the event date: pre-event, post-event, and total period. We order the exposition according to the type of event – investment, acceptance as means of payment, and divestment (in this order). As a general result, one can see that the evidence is mixed, and no pattern emerges. Among the companies of the Investment group, we highlight the positive results obtained for MicroStrategy on the day of the event and in other event windows, especially [0;1] and [0;3]. Such a strong reaction may be related to the fact that this company made the most significant investments in cryptocurrency among all the corporations analyzed (in relative terms, as Figure 1 reveals), and the event brought much attention to the market. Also, in the Investment Group, while The Brooker Group had significantly positive returns, Metromile showed an adverse market reaction in several windows.

Regarding the group of firms that announced the acceptance of crypto as means of payment, no particular event stands out. The only statistically significant return occurred for BMW on the day of the event (+2.5 p.p.). Overall, this group presented slightly negative CAARs across all event windows.

Table 2: Cumulative abnormal returns for each event in different windows

Company		**Event Window**					
	Event Category	**[0,0]**	**[-1,1]**	**[-2,2]**	**[-5,5]**	**[0,1]**	**[0,3]**
FRMO Corporation		-5.3	3.5	3.5	3.2	3.2	-0.1
AMC Entertainment Holdings		-5.8	-3.1	-3.1	-0.8	-0.8	5.6
JPMorgan Chase & Co.		-2.5	-2.4	-2.4	-2.9	-2.9	6.4
Mastercard Incorporated		0.5	1.4	1.4	-1.0	-1.0	-1.7
Meitu		-4.5	2.0	2.0	-3.2	-3.2	-3.6
MercadoLibre		0.6	-6.4	-6.4	-4.4	-4.4	-13.1
MercadoLibre_2		4.1	0.7	0.7	-1.7	-1.7	-3.5
Metromile		-3.2	**-36.6**	**-36.6**	**-30.9**	-30.9	-42.5
MicroStrategy Incorporated		**10.4**	10.5	10.5	11.1	**11.1**	**11.8**
Méliuz S.A.		-1.9	-0.2	-0.2	3.2	3.2	-4.9
NEXON Co.	Investment (N = 21)	0.0	-0.5	-0.5	-0.2	-0.2	3.0
Oracle Corporation		0.5	2.9	2.9	3.5	3.5	6.7
Phunware		11.1	20.5	20.5	13.4	13.4	1.0
Ruffer Investment Company Limited		-1.3	0.0	0.0	1.9	1.9	3.3
Aker ASA		-1.5	-1.2	-1.2	-2.5	-2.5	-2.6
Tesla		0.4	-1.7	-1.7	-8.6	-8.6	-4.7
The Brooker Group Public Company Limited		**18.5**	**61.4**	**61.4**	**46.2**	**46.2**	**34.9**
Townsquare Media		-6.1	-3.3	-3.3	-0.4	-0.4	2.6
BlackRock		0.4	1.9	1.9	1.4	1.4	6.4
Block		1.3	2.8	2.8	-2.4	-2.4	10.1
Globant S.A.		0.2	-2.1	-2.1	-2.8	-2.8	-1.0
Avg. of "Investment"		0.76	2.39	2.39	1.05	1.05	0.67
Microsoft Corporation		0.1	1.0	1.0	0.7	0.7	-0.6
AT&T Inc.		1.2	1.5	1.5	1.1	1.1	5.2
Newegg Commerce		-5.9	-3.9	-3.9	-8.9	-8.9	-11.3
Overstock.com		-0.9	-0.6	-0.6	-4.8	-4.8	-5.1
PayPal Holdings		0.5	-0.1	-0.1	1.7	1.7	1.2
Rakuten Group	Acceptance as Means of Payment (N = 12)	-0.3	-0.8	-0.8	3.0	3.0	4.5
Restaurant Brands International Inc.		-2.6	-1.8	-1.8	-3.9	-3.9	-5.1
Starbucks Corporation		-1.6	-4.1	-4.1	-3.1	-3.1	0.9
Visa Inc.		1.1	1.4	1.4	-0.4	-0.4	2.1
Xiaomi Corporation		-1.2	1.8	1.8	3.8	3.8	0.7
BMW		**2.5**	2.0	2.0	0.7	0.7	-0.2
Chipotle Mexican Grill		-1.3	-1.9	-1.9	0.2	0.2	1.6
Avg. of "Acceptance as means of payment"		-0.73	-0.45	-0.45	-0.82	-0.82	-0.52
Tesla_Out	Divestment (N = 2)	0.4	-2.2	-2.2	0.7	0.7	2.6
Ruffer_Out		0.2	0.2	0.2	0.0	0.0	-2.1
Avg. of "Divestment"		0.32	-1.00	-1.00	0.35	0.35	0.26
Avg. of all categories		0.22	1.22	1.22	0.37	0.37	0.24

Note: **bold numbers** indicate statistical significance at least at the 10% level.

3.2. Parametric and non-parametric hypotheses tests on the Cumulative Average Abnormal Returns (CAARs)

To test the significance of returns, we apply the parametric and non-parametric tests discussed in section 2.3. Table 3 presents the results for the windows of the different periods analyzed (AAR[0] and several CAARs around the event date). Besides the entire sample (N=35), we perform the tests on the investment (N=21), divestment (N=2), and means of payment (N=12) groups individually.

Table 3: hypothesis tests applied to different event windows, full sample and stratification by type of event

Event Group	Event Window	CAAR	Test						
			t-test	*CDA*	*Patell*	*PatellADJ*	*Corrado-Cowan*	*GenSign*	*Wilcox*
All events (N = 35)	AAR[0]	0.223	0.78	0.77	0.26	0.23	0.51	0.51	0.49
	[-1;1]	1.222	0.37	0.36	**0.01**	**0.00**	0.53	0.98	0.69
	[-2;2]	0.37	0.83	0.83	0.13	0.11	0.77	0.98	0.75
	[-5;5]	0.24	0.93	0.92	0.10	**0.08**	0.75	0.51	0.98
	[0;1]	0.978	0.38	0.37	**0.03**	**0.02**	0.88	0.49	0.90
	[0;3]	0.407	0.80	0.79	0.13	0.11	0.61	0.72	0.70
Investment/Acquisition (N = 21)	AAR[0]	0.758	0.54	0.54	0.13	0.12	0.79	0.42	0.88
	[-1;1]	2.39	0.27	0.26	**0.00**	**0.00**	0.35	0.71	0.46
	[-2;2]	1.053	0.70	0.70	**0.07**	**0.06**	0.79	0.35	0.84
	[-5;5]	0.671	0.87	0.87	0.11	**0.10**	0.74	0.71	0.94
	[0;1]	1.997	0.25	0.25	**0.00**	**0.00**	0.40	0.95	0.54
	[0;3]	0.881	0.72	0.72	**0.02**	**0.01**	0.90	0.62	0.83
Means of Payment (N = 12)	AAR[0]	-0.729	0.34	0.33	0.88	0.88	0.41	0.61	0.27
	[-1;1]	-0.453	0.73	0.72	0.78	0.79	0.93	0.61	0.74
	[-2;2]	-0.823	0.63	0.62	0.90	0.91	0.81	0.52	0.62
	[-5;5]	-0.517	0.84	0.83	0.42	0.44	0.88	0.52	0.88
	[0;1]	-0.827	0.45	0.43	0.61	0.63	0.35	0.28	0.30
	[0;3]	-0.417	0.79	0.78	0.49	0.51	0.60	0.94	0.65
Divestment (N = 2)	AAR[0]	0.316	0.88	0.85	0.82	0.83	0.74	0.18	0.18
	[-1;1]	-0.996	0.78	0.74	0.60	0.61	0.94	0.95	0.60
	[-2;2]	0.349	0.94	0.93	0.95	0.95	0.78	0.18	0.33
	[-5;5]	0.258	0.97	0.96	0.76	0.77	0.90	0.95	0.94
	[0;1]	1.111	0.71	0.65	0.68	0.70	0.68	0.95	0.27
	[0;3]	0.38	0.93	0.91	0.92	0.93	0.89	0.95	0.78

Notes: The Table shows the p-values of each hypothesis test – t-test, Crude Dependence Adjustment test (CDA), Patell test, Adjusted Pattel test, Corrado rank test, Generalized Sign test, and Wilcoxon signed-ranks test for different groups of events based on its type: all events (full sample), investment/acquisition of cryptocurrencies, acceptance as means of payment, and divestment. We highlight in **bold** the p-values lower or equal to 0.10.
Source: authors' elaboration.

From Table 3, we infer that the average market reaction is slightly positive for the entire sample events – CAARs ranging from 0.22 percentage points (p.p.) on the day of the event to a maximum of 1.22 p.p. at the window [-1,1]. However, the CAARs are almost always statistically insignificant (exceptions being the Patell and Adjusted Patell tests at very tight windows around the event – [-1, 1] and [0,1]). Thus, the aggregate evidence suggests a near "neutral" market reaction. However, for inference purposes, one important caveat applies: the sample size is small (N=35 in the whole sample), and the small sample size increases the probability of a Type II error (that occurs when one fails to reject a false null hypothesis).

The average market responses seem to hide significant differences among event groups. In particular, Table 3 suggests that the positive abnormal returns are concentrated in the investment/acquisition group (N=21). CAARs for this particular group range from +0.67 to 2.39 p.p.. Furthermore, we find that responses within this group are more prominent when the investment/acquisition is a direct acquisition of BTC or ETH – we report this Analysis in Appendix B – Table B1.[9] Thus, market reactions seem stronger for events related to cryptocurrency's direct acquisition than other events.[10]

3.3. Multivariate analysis: determinants of cumulative abnormal returns (CARs)

In Table 4, we present the results of the OLS estimations using the cumulative abnormal returns (CARs) on different windows as dependent variables. We run this analysis for the entire sample (Panel A: all events, N = 35) and the subsample without divestment events (Panel B: excluding divestment events, N = 33). In addition, we include as regressors the following company-specific data: Market Capitalization (Ln_Market Capitalization), price return in the previous period (Ln_Prior Return), Cash/Assets, and Price/Book. We also include past bitcoin returns to account for the crypto-market fluctuations that may impact the CARs (Ln(Past BTC Return)), a dummy for niche technological (Tech Firms Dummy, as in Autore et al., 2021) and financial (Financial Firms Dummy) companies, and country-fixed effects. Descriptive statistics (mean, S.D., etc.) for each variable used in the cross-sectional regressions are presented in Appendix B – Table B2.

A particular result from Table 4 is worth a deeper discussion. Tech firms show larger CARs than their counterparts belonging to other sectors in almost all windows (except [-5,5]), suggesting that market reactions are stronger for tech firms. Specifically,

[9] In our sample, only Meitu, Inc. directly acquired ETH – a mix of USD 22 million in ETH and USD 17.9 million in BTC, announced in 08/03/2021. All the other 14 firms in our sample acquired only BTC.

[10] Consistent with non-significant or even negative market reactions to divestment announcements, Gerritsen, Lugtigheid, and Walther (2022) show that bitcoin investors react to bearish predictions but not to buy recommendations of crypto experts.

relative to non-tech and non-financial peers, market reactions are between 5.17 and 9.44 p.p. larger for tech companies, ceteris paribus. Table B3 in Appendix B shows that the CAARs for the Tech sector are indeed superior to CAARs from the Financial, Consumer Cyclical, and Other (Communication and Industrial) sectors. These findings corroborate Chen et al. (2022), who find that high-tech firms earn more significant abnormal returns on blockchain announcements. The authors rationalize the findings by suggesting the presence of a credibility channel – high-tech firms with more technological attributes could be seen as more credible and trigger more significant stock returns than non-high-tech firms. The referred channel may be a plausible explanation for our results too.

Overall, at the aggregate level, only tech firm status is strongly associated with CARs.[11] We find limited evidence that CARs are positively (negatively) related to past BTC returns (firm size). However, across all regressions, the coefficients are not statistically significant. We again emphasize that, given the small sample size, our findings should be interpreted carefully.

[11] We also test for a dummy variable that reflects a broader definition of tech companies – including technology-based firms that operate outside the tech sector, such as Tesla, Inc., Meitu, Inc., Mercado Libre, Inc., Méliuz, S/A, and NEXON Co., Ltd., and we find very similar results.

Table 4: Multivariate Regression: determinants of the CARs

Window	Panel A: All events						Panel B: Excluding divestment events					
	[0]	*[-1,1]*	*[-2,2]*	*[-5,5]*	*[0,1]*	*[0,3]*	*[0]*	*[-1,1]*	*[-2,2]*	*[-5,5]*	*[0,1]*	*[0,3]*
Tech Firms Dummy	5.4432**	7.3108	8.2274*	5.1743	5.4608	6.0838	5.4950*	7.8939	9.4356**	6.5195	6.2283	6.8269
	(2.45)	(5.34)	(4.21)	(5.14)	(3.71)	(3.90)	(2.58)	(5.71)	(4.33)	(5.14)	(3.85)	(3.91)
Financial Firms Dummy	0.2661	-1.2891	0.8367	-2.2872	-0.0670	-0.4414	0.2961	-0.6335	2.3205	-0.6410	0.8325	0.4596
	(1.84)	(4.98)	(4.56)	(5.76)	(2.53)	(2.90)	(2.12)	(4.75)	(4.14)	(5.34)	(2.47)	(2.60)
Type of Event: Investments	-1.3314	1.5361	-0.3135	5.4576	0.1950	0.2910	-1.0262	2.5202	0.7611	6.6993	1.2095	1.0422
	(1.36)	(3.41)	(3.01)	(3.67)	(2.11)	(1.93)	(1.64)	(4.41)	(3.83)	(4.61)	(2.42)	(2.13)
Ln(Market Capitalization)	0.1349	-0.4383	-0.4213	0.3496	-0.2054	-0.0785	0.1439	-0.5100	-0.6379	0.1116	-0.3196	-0.2054
	(0.34)	(0.79)	(0.61)	(0.75)	(0.48)	(0.36)	(0.38)	(0.88)	(0.60)	(0.73)	(0.48)	(0.36)
Ln(Prior Return)	0.3818	9.5889	0.1468	8.9169	-0.1071	0.8850	0.0576	9.0843	0.3388	9.0725	-0.4109	0.8873
	(4.54)	(16.27)	(13.85)	(16.59)	(9.84)	(7.32)	(4.81)	(16.64)	(13.95)	(16.54)	(9.74)	(6.94)
Ln(Past BTC Return)	9.8480	11.5291	14.5057	6.2154	9.5042	7.3177	11.3451	13.9614	13.8706	5.7748	11.0532	7.4580
	(7.27)	(16.04)	(10.55)	(11.13)	(10.08)	(8.37)	(8.02)	(17.82)	(12.29)	(13.57)	(11.43)	(9.92)
Cash/Assets	7.9078	-16.7218	-14.9491	-32.2203	-1.0675	-7.6145	7.5469	-19.5978	-20.4432	-38.3591	-4.7178	-11.0376
	(6.55)	(26.23)	(22.69)	(26.08)	(11.04)	(13.61)	(7.47)	(29.52)	(24.36)	(28.23)	(11.26)	(14.50)
Price/Book	0.0462	0.1554	0.0705	0.4398	0.1889	0.0520	0.0252	0.0780	-0.0275	0.3279	0.1052	-0.0140
	(0.32)	(0.69)	(0.62)	(0.86)	(0.51)	(0.53)	(0.35)	(0.73)	(0.69)	(0.94)	(0.54)	(0.55)
Obs.	35	35	35	35	35	35	33	33	33	33	33	33
Adj. R-Sq.	.467	.503	.429	.23	.513	.432	.438	.478	.426	.219	.514	.421
Country F.E.s	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Sectoral dummies follow Yahoo Finance's sectoral classification – Tech Firms Dummy equals one for the MicroStrategy, Block, Inc. (former Square), Globant, Microsoft, Oracle, Phunware, Inc., and Xiaomi Corporation. Financial Firms Dummy equals one for Blackrock, Inc., FROM Corporation, JPMorgan Chase & Co., Mastercard Incorporated, Metromile, Inc., PayPal Holdings, Inc., Ruffer Investment Company Limited, The Brooker Group Public Company Limited, and Visa, Inc. All firm-level accounting and market information are collected at the date of the Financial Statements disclosed right before the crypto-related event – Market capitalization (Ln(Market Capitalization)), cumulative log-returns on 21 days preceding the event (Ln(Prior Return), the ratio between Cash and Assets (Cash/Assets), and a proxy for investment opportunities (Price/Book). To account for market-specific fluctuations that may impact the CARs, we include the 6-week cumulative log-return of bitcoin on the pre-event period (Ln(Past BTC Return)) as a regressor. Finally, we include country-fixed effects in the regression to account for potential systematic differences between stock market or jurisdictional levels that may affect abnormal returns. Robust standard errors are reported in parentheses. ***, **, and * represent statistical significance at the 10%, 5% and 1% levels, respectively.

3.4. Heterogeneity analysis

One critical dimension so far neglected is how much exposure the announcing company effectively has to cryptocurrency. Treating equally small and substantial corporate cryptocurrency investments may hide the genuine underlying market reactions to cryptocurrency-related corporate announcements. Moreover, our sample effectively has a significant variation in the size of cryptocurrency acquisitions. As Table 5 shows, within direct cryptocurrency acquisition (BTC or ETH), the ratio between the USD volume of crypto acquisition and total assets of the firm varies from 0.0% (Globant S.A. announced the acquisition of USD1 Million in BTC relative to USD1,289 Million in Total Assets) to 27.3% (MicroStrategy Incorporated announced the acquisition of USD250 Million in BTC relative to USD917 Million in Total Assets). We exploit this market-based measure of how much skin in the game the firm has in cryptocurrency to separate events into three groups: high (top), medium, and low (bottom tercile) cryptocurrency exposure.

Table 5: the market-based measure of the degree of cryptocurrency exposure

Company	Announcement date	Degree of Cryptocurrency Exposure	Crypto Acquisition (USD Million)	Assets (USD Million)	Ratio
MicroStrategy Incorporated	11/Aug./2020	High	250	917	27.3%
NEXON Co., Ltd.	27/Apr./2021	High	100	862	11.6%
The Brooker Group Public Company	11/May/2021	High	7	82	8.0%
Ruffer_Out	07/Jun./2021	High	1,840	27,300	6.7%
Phunware, Inc.	06/Apr./2021	High	2	32	4.7%
Tesla, Inc.	08/Feb./2021	Medium	1,500	52,148	2.9%
Ruffer Investment Company Limited	15/Dec./2020	Medium	744	27,300	2.7%
Tesla_Out	20/Jul./2022	Medium	936	52,148	1.8%
Block, Inc.	08/Oct./2020	Medium	50	4,551	1.1%
Meitu, Inc.	08/Mar./2021	Medium	40	4,507	0.9%
Aker ASA	08/Mar./2021	Low	50	6,779	0.7%
Townsquare Media, Inc.	10/May/2022	Low	5	726	0.7%
Metromile, Inc.	11/Aug./2021	Low	1	202	0.5%
MercadoLibre, Inc.	05/May/2021	Low	8	6,526	0.1%
Globant S.A.	24/May/2021	Low	1	1,289	0.0%

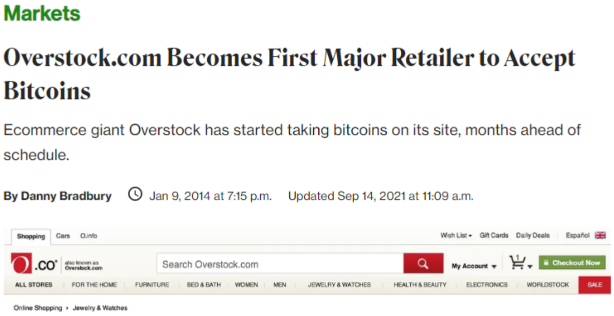
Note: This Table reports all the corporate announcements of direct acquisition or divestment of cryptocurrency (N = 15). All events refer to BTC, except for Meitu, Inc., which announced the addition of BTC and ETH. The total USD value of cryptocurrency is obtained from regulatory fillings (e.g., 10-Q, 8-K), firms' announcements, or media posts. The USD value of total assets is obtained from the Financial Statements right before the cryptocurrency announcement. The data is sorted by the ratio of Crypto Acquisition / Total Assets of the firm. Degree of Cryptocurrency Exposure is a categorical variable that equals 3 (High) if the ratio of crypto acquisition over total assets is in the top tercile, 2 (Medium) if it is in the middle tercile, and 1 (Low) if in the bottom tercile.

One drawback of this analysis is that cryptocurrencies' direct acquisition/sale is tiny (N=15 events: 13 acquisitions and two divestments). Thus, to cover the entire sample, we must also rely on a qualitative assessment to assign a "high", "medium", or "low" cryptocurrency exposure to indirect investment events and acceptance as means of payments. We do that by manually analyzing the content of the news announcement and the regulatory filing (10-Q, 8-K, etc.) and adopting the following systematic sorting strategy that resembles the classification of corporate blockchain investments proposed by Autore et al. (2021). First, we classify as Low exposure the following type of announcements: i) plans to accept cryptocurrency, not actual acceptance (AMC Entertainment Holdings, Mastercard), ii) global companies that started accepting cryptocurrency only in a single country or store (BMW, Xiaomi Corporation), and iii) only indirect or partial acceptance of crypto as means of payment, such as gift cards (Starbucks). Conversely, we classify as High exposure announcements of i) effective, direct acceptance of cryptocurrency as means of payment by industry pioneers (Telecom Services, AT&T Inc.; Diversified Banks, JPMorgan Chase & Co.; Software-Infrastructure, Microsoft; Internet Retail, Overstock.com, Inc.; and Credit Services, Visa Inc.[12]) and ii) worldwide, economically relevant M&A or partnerships (Blackrock, Inc., MercadoLibre). Finally, we categorize as medium exposure the remaining events – the effective acceptance by non-industry pioneers (i.e., a non-prime mover in its industry) and M&A or partnerships not worldwide noticed (FRMO Corporation and Méliuz). While Figure 5 provides concrete examples of the systematic approach to classify indirect investments and acceptance as means of payment events, Appendix C shows the cryptocurrency exposure assessment of each of these events.

[12] Visa Inc. announced cryptocurrency integration into its network one month later than Mastercard Incorporated. However, while Visa's announcement disclosed an already-launched pilot program, Mastercard mentioned that the firm would start supporting selected cryptocurrencies later that year. Because of that, we classify Visa, Inc. as the prime-mover.

Figure 5: Examples of the systematic approach to classifying the corporate degree of cryptocurrency exposure.

Subfigure A: High Exposure



Subfigure B: High Exposure

Subfigure C: Medium Exposure

Subfigure D: Medium Exposure

Subfigure E: Low Exposure

Subfigure F: Low Exposure

Note: This Figure shows examples of the systematic approach to classifying corporate announcements where we do not have an objective, market-based criterion (i.e., not a direct market acquisition of BTC or ETH) into High, Medium, or Low cryptocurrency exposure. Each example refers to the following assorting rule:
High exposure (Subfigures A and B): effective acceptance of cryptocurrency by an industry pioneer (Online Retail and Restaurants, respectively).
Medium Exposure (Subfigures C and D): effective acceptance of cryptocurrency by a non-prime mover in its industry – i.e., following an industry pioneer (Rakuten operates in the Online Retail industry and started accepting bitcoin after Overstock.com, and Chipotle operates in the Restaurants industry and started to accept cryptocurrency after Restaurant Brands International [Burger King]).
Low Exposure (Subfigure E): AMC announced *plans* to accept cryptocurrency, not actual acceptance.
Low Exposure (Subfigure F): Starbucks announced cryptocurrency could now be applied to gift cards saved in the Starbucks app, but not directly accepting cryptocurrency for payments.

We then use this cross-sectional variation in the degree of corporate exposure to cryptocurrency to analyze the abnormal returns for each categorical value (high, medium, and low exposure) and their role in explaining the CARs. Table 6 shows that the CAAR for high-exposure events (N=12) is positive and significantly more extensive (between 3.6 and 8.0 p.p., N = 13) than for medium (from -1.5 to 0.0) and low-exposure events (ranging from -1.6 to -5.2 p.p., N = 10). Furthermore, the CAARs for high-exposure events are statistically significant for most tests. On the contrary, the CAARs of low-exposure events are negative and, in some cases, statistically distinguishable from zero. Graphical visualization of the remarkable differences in market reactions according to the degree of exposure to cryptocurrency is shown in Appendix B – see Subfigure B1a of Figure B1.

Table 6: CAARs stratified by the degree of cryptocurrency exposure

Event Group	**Event Window**	**CAAR**	**Test**						
			t-test	*CDA*	*Patell*	*PatellADJ*	*Corrado-Cowan*	*GenSign*	*Wilcox*
High Exposure (N = 12)	AAR[0]	3.632	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.01**	**0.04**
	[-1;1]	7.966	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.06**	**0.02**
	[-2;2]	5.327	**0.02**	**0.00**	**0.00**	**0.00**	0.37	0.45	0.55
	[-5;5]	4.958	0.14	**0.08**	**0.00**	**0.00**	0.24	0.18	0.65
	[0;1]	5.091	**0.00**	**0.00**	**0.00**	**0.00**	**0.02**	0.45	**0.09**
	[0;3]	4.825	**0.02**	**0.00**	**0.00**	**0.00**	0.16	0.45	0.37
Medium Exposure (N = 13)	AAR[0]	-1.547	0.13	**0.10**	**0.09**	**0.08**	**0.04**	0.41	0.10
	[-1;1]	-0.1	0.95	0.95	0.94	0.94	0.90	0.41	0.82
	[-2;2]	-0.74	0.74	0.72	0.47	0.45	1.00	0.40	0.96
	[-5;5]	0.009	1.00	1.00	0.43	0.41	0.60	0.78	0.53
	[0;1]	-0.236	0.87	0.86	0.47	0.45	0.72	0.41	0.97
	[0;3]	-1.358	0.50	0.47	0.22	0.20	0.41	0.41	0.53
Low Exposure (N = 10)	AAR[0]	-1.567	0.48	0.47	0.57	0.57	0.21	0.58	0.14
	[-1;1]	-5.151	0.18	0.17	**0.00**	**0.00**	**0.06**	0.23	**0.07**
	[-2;2]	-4.136	0.41	0.39	**0.02**	**0.02**	0.18	**0.07**	0.29
	[-5;5]	-5.12	0.49	0.47	0.16	0.16	0.25	0.58	0.28
	[0;1]	-2.378	0.45	0.44	0.35	0.35	0.18	0.23	0.14
	[0;3]	-2.599	0.56	0.55	0.19	0.19	0.23	0.58	0.33

Note: This Table shows the p-values of each hypothesis test – t-test, Crude Dependence Adjustment test (CDA), Patell test, Adjusted Pattel test, Corrado rank test, Generalized Sign test, and Wilcoxon signed-ranks test for different groups of cryptocurrency exposure. We highlight in **bold** the p-values lower or equal to 0.10. The degree of cryptocurrency exposure is assessed using data from regulatory fillings (e.g., 10-Q, 8-K), firms' announcements, and media posts. For cryptocurrency direct acquisitions (BTC or ETH), we assign high (low) exposure to events at the top (bottom) tercile of the ratio between the USD value of cryptocurrency acquisitions and the USD value of total assets. For indirect acquisitions/investments and acceptance as means of payment, we qualitatively analyze the information content of each event and use the following sorting criteria. Plans to accept cryptocurrency (not actual acceptance) and indirect acceptance of crypto as means of payment (e.g., only through gift cards) are classified as *low* cryptocurrency exposure events. Conversely, effective acceptance of cryptocurrency by a firm pioneer in its industry and worldwide, economically relevant M&A or partnerships are classified as *high* exposure. Finally, we categorize *medium* exposure as the effective acceptance of crypto by a non-pioneer firm in its industry and M&A or partnerships not worldwide noticed.

Though suggestive that the degree of exposure is a critical factor in mediating market returns to corporate announcements of cryptocurrency adoption, the previous analysis does not control for factors that may correlate to the degree of corporate exposure and the CARs. To overcome this limitation, we estimate the determinants of the 35 CARs just as in the previous regression analysis, but now we add the dummy for low and high cryptocurrency exposure (see eq. 8 and 9, respectively). Table 7 presents the results.

Table 7: CARs and the heterogeneity among high and low cryptocurrency-exposure events

Window	High Exposure to Cryptocurrency						Low Exposure to Cryptocurrency					
	[0]	*[-1,1]*	*[-2,2]*	*[-5,5]*	*[0,1]*	*[0,3]*	*[0]*	*[-1,1]*	*[-2,2]*	*[-5,5]*	*[0,1]*	*[0,3]*
High Exposure Dum	3.94***	4.80	3.25	2.47	3.79*	3.81*						
	(1.14)	(3.61)	(3.16)	(4.01)	(1.94)	(2.10)						
Low Exposure Dum							-2.77*	-9.02**	-5.90*	-6.28	-5.10**	-3.87
							(1.48)	(3.57)	(3.29)	(4.20)	(2.01)	(2.34)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	35	35	35	35	35	35	35	35	35	35	35	35
Adj. R-Sq.	.686	.569	.489	.225	.62	.546	.563	.651	.541	.296	.661	.534
Country F.E.s	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This Table shows the results of OLS regressions considering the Abnormal Returns (A.R.s) on the day of the event [0] and Cumulative Abnormal Returns (CARs) estimated at different event windows ([-1,1], [-2,2], [-5,5], [0,1], [0,3]) as dependent variables. High Exposure Dum (Low Exposure Dum) is a dummy that equals one if the event is classified as High Exposure (Low Exposure) to Cryptocurrency and zero otherwise. All regressions include country-fixed effects and firm, industry, and market-level controls as reported in Table 4. Robust standard errors are reported in parentheses. ***, **, and * represent statistical significance at the 10%, 5% and 1% levels, respectively.

The results shown in Table 7 confirm that the CARs are indeed closely related to the degree of corporate exposure to cryptocurrency. After controlling for firm size, cash/assets, investment opportunities, prior stock return, prior BTC return, and sectoral and country characteristics, the Table shows a considerable difference in CARs for high and low-cryptocurrency exposure events. Specifically, the High (Low) Exposure Dummy shows positive (negative) and statistically significant coefficients in most event windows. Moreover, the effects are also economically relevant: high exposure events show a larger CAR ranging from 2.5 to 4.8 p.p. relative to medium and low exposure events, on average. Conversely, on average, low exposure events are associated with lower CARs ranging from 2.8 to 9.0 p.p.. Such a pattern suggests that the degree of exposure is a vital factor underlying market reactions to corporate cryptocurrency announcements. A potential interpretation for that phenomenon is that, on average, investors value corporate cryptocurrency adoption as long as such events are economically meaningful (i.e., have enough "skin in the game").

3.5. Robustness analyses on heterogeneous market reactions

3.5.1. Subsample of market-based measures of the degree of corporate exposure

One disadvantage of the heterogeneity analysis conducted previously= is that most events (22 out of 35) do not have an objective measure of corporate skin in the game (like, for example, the ratio between the market value of acquired cryptocurrency and firm's assets). Although we use a systematic approach to classify high, medium, and low exposure events, the sorting criteria is subjective by definition. Thus, one could argue that what drives the findings is the subjective criterion used to sort events into high, medium, and low corporate exposure.

To deal with such a concern, we constrain our analysis on the subsample of events (13 out of 35) where we have an objective, monetary-based metric of skin in the game – Cryptocurrency announced acquisition (USD Million) over Total Assets (USD Million) (see Table 5 for details on all the 13 events). Such events refer to the direct corporate acquisition of cryptocurrency that reflects in the company's balance sheet. Table 8 shows the abnormal returns for the high, medium, and low USD Crypto / USD Total Assets groups: the CAARs for high-exposure events are positive and significantly larger (between 10.01 and 22.96 p.p.) than for medium (from -3.06 to 1.26) and low-exposure events (ranging from -11.30 to -1.99 p.p.). Furthermore, the CAARs for high-exposure and low-exposure events are statistically significant in most tests. A graphical representation of such differences is shown in Appendix B – Subfigure B1b of Figure B1.

Thus, the robustness analysis reveals that the results are not driven by the subjective classification of events. On the contrary: the difference between high and low exposure CAARs on the constrained sample of objective, market-based events are actually larger than in the previous analysis that includes acceptance as means of payments and indirect investments and partnerships events. Thus, our core findings that market reaction increases as skin in the game increases is robust to considering only events where we have an objective, market-based metric to define high, medium, and low corporate exposure to cryptocurrency.

Table 8: CAARs stratified by the degree of cryptocurrency exposure – only market-based events (direct acquisition of BTH or ETH)

Event Group	Event Window	CAAR	Test						
			t-test	*CDA*	*Patell*	*PatellADJ*	*Corrado-Cowan*	*GenSign*	*Wilcox*
High Exposure (N = 4)	AAR[0]	10.008	**0.00**	**0.00**	**0.00**	**0.00**	**0.01**	**0.03**	**0.07**
	[-1;1]	22.959	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	0.23	**0.02**
	[-2;2]	17.609	**0.00**	**0.00**	**0.00**	**0.00**	**0.09**	0.23	0.16
	[-5;5]	12.666	0.16	0.12	**0.00**	**0.00**	0.58	**0.03**	0.89
	[0;1]	15.335	**0.00**	**0.00**	**0.00**	**0.00**	**0.01**	0.23	**0.07**
	[0;3]	14.447	**0.01**	**0.00**	**0.00**	**0.00**	**0.03**	**0.03**	0.18
Medium Exposure (N = 4)	AAR[0]	-1.036	0.60	0.56	0.45	0.49	0.26	0.99	0.72
	[-1;1]	0.78	0.82	0.80	0.71	0.73	0.89	0.31	0.53
	[-2;2]	-3.06	0.48	0.45	0.58	0.61	0.27	0.32	0.30
	[-5;5]	1.263	0.85	0.83	0.49	0.52	0.92	0.99	0.57
	[0;1]	0.27	0.92	0.92	0.82	0.83	0.71	0.99	0.89
	[0;3]	-2.009	0.61	0.58	0.41	0.44	0.31	0.32	0.53
Low Exposure (N = 5)	AAR[0]	-1.995	0.20	0.16	0.13	0.12	0.17	0.66	0.22
	[-1;1]	-9.907	**0.00**	**0.00**	**0.00**	**0.00**	**0.01**	**0.03**	**0.04**
	[-2;2]	-8.179	**0.02**	**0.01**	**0.00**	**0.00**	0.13	**0.03**	0.22
	[-5;5]	-11.299	**0.03**	**0.02**	**0.03**	**0.03**	0.16	0.18	0.11
	[0;1]	-3.848	**0.08**	**0.05**	**0.03**	**0.03**	**0.07**	0.18	0.17
	[0;3]	-5.809	**0.06**	**0.04**	**0.01**	**0.01**	**0.06**	**0.03**	0.10

Note: This Table shows the p-values of each hypothesis test – t-test, Crude Dependence Adjustment test (CDA), Patell test, Adjusted Pattel test, Corrado rank test, Generalized Sign test, and Wilcoxon signed-ranks test for different groups of cryptocurrency exposure – subsample of thirteen Balance Sheet events (i.e., only direct acquisition of BTC or ETH). The top, medium and bottom tercile of the variable USD Crypto Acquisition / USD Total Assets of the firm define High, Medium and Low exposure, respective. We highlight in **bold** the p-values lower or equal to 0.10.

3.5.2. Influence of outliers

In this subsection, we perform several additional tests to assess whether our findings on heterogeneous market responses are biased because of extreme values in CARs that may influence estimated OLS coefficients. First, we exclude tail events[13] (p1 and p99) of each CAR and run the OLS regressions on that new subset of events. Second, departing from the original cross-sectional regressions, we use Median Linear Regression (MLR) instead of OLS to estimate the parameters.[14] By doing both exercises, we can check to which extent extreme events may bias the empirical findings.

Table 9 shows the results of the estimation of eq. 9. For the sake of brevity, we present just the coefficients of the variable of interest (High Exposure Dummy). We can infer

[13] For example, The Brooker Group Public Company (an event assigned as high exposure since the Crypto Acquisition / Total Assets equaled 8% and is in the top tercile of this ratio) earned the most substantial abnormal returns at the day of the event and in all CARs surrounding the event (See Table 2 for details). Such an outlier is excluded in this robustness analysis.
[14] Unlike in usual regression method, the the median regression or the least absolute deviations (LAD) minimizes the sum of absolute value of the prediction error, and is less sensitive to outliers than OLS estimates.

that both the Median Regression and the OLS regression excluding observations at both tails of abnormal returns (p1 and p99) yield the same result as before: the larger the skin in the game, the more significant the abnormal market reaction around the event. Moreover, most coefficients are statistically significant, especially for the High Exposure Dummy. Thus, we conclude that the core findings are not driven by extreme CARs.

Table 9: Robustness analysis to mitigate the influence of outliers

Window	OLS Excluding p1 and p99						Median Linear Regression (MLR)					
	[0]	*[-1,1]*	*[-2,2]*	*[-5,5]*	*[0,1]*	*[0,3]*	*[0]*	*[-1,1]*	*[-2,2]*	*[-5,5]*	*[0,1]*	*[0,3]*
	Panel A. High Exposure to Cryptocurrecy											
High Exposure Dummy	4.2529**	4.8908**	3.0610*	2.9734	3.8717*	4.1334*	2.3242*	3.5163	2.3471	1.4863	4.5306**	4.6807**
	(1.50)	(1.69)	(1.57)	(4.62)	(1.82)	(2.20)	(1.11)	(2.27)	(2.80)	(3.79)	(2.08)	(1.65)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	31	31	31	31	31	31	33	33	33	33	33	33
Adj. R-Sq.	.324	.57	.473	-.254	.133	.117	-	-	-	-	-	-
Country F.E.s	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Panel B. Low Exposure to Cryptocurrency											
Low Exposure Dummy	-2.7781	-4.8753**	-1.7896	-7.0344	-3.7929	-1.9693	-1.5908	-3.4063	-3.3819	-3.9626	-4.1328**	-2.2714
	(1.84)	(1.91)	(2.33)	(5.92)	(2.29)	(2.10)	(1.41)	(2.80)	(2.90)	(3.60)	(1.71)	(1.53)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	31	31	31	31	31	31	33	33	33	33	33	33
Adj. R-Sq.	.0277	.495	.352	-.105	.0614	-.167	-	-	-	-	-	-
Country F.E.s	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This Table shows the results of the robustness analysis that deals with the influence of outliers. OLS regressions are reported on a subsample after dropping extreme events (p1 and p99 of each CAR). Alternatively, on the right-hand side of the Table, we estimate each equation using Median Linear Regression (MLR). The dependent variables are the CARs associated with each event window – [-1,1], [-2,2], [-5,5], [0,1], and [0,3]. High Exposure Dum (Low Exposure Dum) is a dummy that equals one if the event is classified as High Exposure (Low Exposure) to Cryptocurrency and zero otherwise. All regressions include country-fixed effects and firm, industry, and market-level controls, as reported in Table 4. Robust standard errors are reported in parentheses. ***, **, and * represent statistical significance at the 10%, 5% and 1% levels, respectively.

3.5.3. Dissecting High and Low Cryptocurrency Exposure status

A final sensitivity analysis breaks down the High Exposure Dummy and the Low Exposure Dummy into their components and tests the influence of each one individually on the CARs. By doing that, we can dissect the role of each underlying sorting factor in explaining abnormal returns. Notably, one may be concerned that the findings are biased because of subjective assessments of "high skin in the game".

Specifically, High Exposure events (N = 12) are broken into its components: Top Tercile Acquisitions (direct acquisition of BTC or ETH, N = 4), Industry Pioneer Acceptance (prime mover in its industry in accepting crypto for payments, N = 6), and Worldwide Noticed Partnerships or M&A (N = 2). Likewise, Low Exposure events (N = 10) are separated into Bottom Tercile Acquisitions (N = 5), Only Partial Acceptance of Cryptocurrency for Payments (N = 2), and Plans to Accept (N = 3).

Table 10 shows the results of the cross-sectional regressions estimated by OLS using each component of the High (Panel A) and Low Exposure (Panel B) Dummies. All regressions include firm, industry, and country-level controls, as eq. 8 and 9 indicate. As one can see, the only statistically significant and robust component of High Exposure (Panel A) is the top tercile of BTC or ETH acquisitions – coefficients range from 10.6 to 22.7 (i.e., are economically meaningful). Put differently, what drives the influence of the High Exposure Dummy in explaining CARs are precisely those economically meaningful direct acquisitions of cryptocurrencies rather than any subjective definition of High Exposure. Conversely, Panel B shows that the same rationale applies to the Low Exposure dummy: the underlying mechanism that systematically explains CARs is the economic relevance of the direct acquisition of cryptocurrency. Scatterplots shown in Appendix B - Figure B2 indicate intuitively the positive relationship between CARs and Value of Crypto Acquisitions/Value of Total Assets. Thus, we can infer that economically meaningful direct acquisitions of cryptocurrencies are value-increasing in the short run, while insignificant corporate investments in cryptocurrencies are associated with adverse market reactions.

Table 10: Breaking down High Exposure and Low Exposure to Cryptocurrency into its components.

Window	CARs					
	[0]	*[-1,1]*	*[-2,2]*	*[-5,5]*	*[0,1]*	*[0,3]*
	Panel A. High Exposure to Cryptocurrency					
Top Tercile Acquisitions (BTC or ETH)	10.604***	22.742*	18.555*	16.453	14.999***	16.228**
	(1.82)	(12.05)	(9.89)	(13.59)	(3.85)	(5.60)
Industry Pioneer in Accepting for Payments	-0.820	-5.612	-5.656	-4.476	-3.519	-3.921
	(1.36)	(5.83)	(4.89)	(7.01)	(2.41)	(2.50)
Worldwide Noticed M&As or Partnerships	3.781***	-2.347	-4.300	-3.777	0.722	0.822
	(0.99)	(8.45)	(6.24)	(8.82)	(3.52)	(3.73)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	33	33	33	33	33	33
Adj. R-Sq.	.876	.633	.574	.237	.797	.758
Country F.E.s	Yes	Yes	Yes	Yes	Yes	Yes
	Panel B. Low Exposure to Cryptocurrency					
Bottom Tercile Acquisitions (BTC or ETH)	-3.793	-17.195**	-12.632*	-15.500**	-7.676**	-8.711**
	(2.52)	(7.38)	(6.73)	(7.09)	(3.28)	(3.28)
Only Partial Acceptance for Payments	-1.161	0.336	1.768	2.857	-1.040	2.182
	(2.32)	(3.66)	(3.44)	(4.88)	(3.66)	(1.76)
Plans to Accept Cryptocurrency for Payments	-2.802	-4.777	0.730	1.182	-6.981	-0.840
	(3.98)	(7.42)	(6.32)	(9.16)	(5.18)	(6.12)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	33	33	33	33	33	33
Adj. R-Sq.	.44	.708	.582	.457	.646	.581
Country F.E.s	Yes	Yes	Yes	Yes	Yes	Yes

Note: This Table shows the results of OLS regressions considering the Abnormal Returns (A.R.s) on the day of the event [0] and Cumulative Abnormal Returns (CARs) estimated at different event windows ([-1,1], [-2,2], [-5,5], [0,1], [0,3]) as dependent variables. The High Exposure Dummy (Panel A) is collapsed into Top Tercile Acquisitions (BTC or ETH), Industry Pioneer in Accepting Cryptocurrency for Payments, and Worldwide Noticed M&As or Partnerships. Similarly, the Low Exposure Dummy (Panel B) is separated into Bottom Tercile Acquisitions (BTC or ETH), Only Partial Acceptance for Payments, and Plans to Accept Cryptocurrency for Payments. regressions include country-fixed effects and firm, industry, and market-level controls, as reported in Table 4. Robust standard errors are reported in parentheses. ***, **, and * represent statistical significance at the 10%, 5% and 1% levels, respectively.

Overall, the sensitivity analyses corroborate that market returns are indeed heterogeneous on the dimension of degree of exposure/news content, which brings crucial implications for corporate managers, analysts, and investors – not all events are treated equally, and skin in the game matters for investors.

4. Conclusions

Building on a sample of 35 corporate events related to the acquisition, acceptance as means of payment, or divestment of cryptocurrencies, we find that the cumulative average abnormal returns around these events are slightly positive but statistically non-significant, on average. However, our findings reveal that abnormal returns are primarily explained by how much "skin in the game" a firm gets into crypto. High (low) exposure to cryptocurrency events presents positive (negative) and statistically significant cumulative average abnormal returns (CAARs). Furthermore, the extent to which a firm gets exposure to cryptocurrency is a critical determinant of CARs – in particular, economically meaningful acquisition of BTC or ETH (relative to the total assets of the firm) predicts CARs. Importantly, to gauge the effect of cryptocurrency adoption on corporate value, we focus on firms whose core business is unrelated to blockchain technology or digital assets (i.e., we exclude from the sample crypto mining companies, digital asset management firms, and cryptocurrency exchanges).

To our knowledge, this is the first research to analyze the stock market reaction to cryptocurrency-related corporate events. And this is undoubtedly a research topic of great practical importance. Despite being a recent trend, we are observing the movement of companies from traditional sectors of the economy, migrating part of their investments to cryptocurrencies. Additionally, on theoretical grounds, the net present value of cryptocurrency adoption is ex-ante unclear. On the one hand, past returns of crypto assets are high and almost uncorrelated with the returns of fiat currencies and other traditional investments. Nevertheless, on the other hand, the lack of uniform and international regulation, legal uncertainty, cyber risks, and high volatility of these assets may impose high present value costs.

By providing evidence that the perceived present value of these costs and benefits are of similar magnitude at the aggregate level (i.e., stock market reactions are close to zero, on average) but varies widely according to the degree of exposure to cryptocurrency, our study helps corporate managers, analysts, and investors to understand how crypto adoption relates to firm value. In addition, we contribute to two strands of the literature: the one that analyzes the impacts of cryptocurrency on portfolios of different investors (e.g., Bialkowski, 2020 and Platanakis and Urquhart, 2020) and the one that examines the corporate implications of blockchain-related projects (Adhami et al., 2018; Jain & Jain, 2019; Akyildirim et al., 2020; and Autore et al., 2021; Ali et al., 2023).

Finally, it is essential to highlight that our study has several limitations. One is the reduced number of events (N=35), which directly affect the occurrence of type II errors in our hypotheses testing (accepting a null hypothesis that is actually false). Another limitation is that the announcements are sometimes clustered in time and markets. Since corporate cryptocurrency adoption is an ongoing phenomenon, further studies may analyze a larger sample of events and stratify samples by sectors or regions, among other groupings.

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APPENDIX

Appendix A: Table of corporate cryptocurrency-related events

Table A1 – List, description, and date of all 35 events analyzed in the study.

Company name	Industry	Category	Event Date	Reference Index
Newegg	E-commerce	Means of Payment	01/Jul./14	Nasdaq (U.S.)
Microsoft	Operational systems	Means of Payment	11/Dec./14	Nasdaq (U.S.)
Rakuten	E-commerce	Means of Payment	17/Mar./15	Nikey 225 (J.P.)
FRMO	Holding	Investment	18/Aug./16	Nasdaq (U.S.)
Overstock	Outlet	Means of Payment	25/Oct./17	Nasdaq (U.S.)
BMW	Auto Manufacturers	Means of Payment	09/Jul./18	DAX (D.E.)
AT&T	Telecom	Means of Payment	23/May/19	Nasdaq (U.S.)
RBI Inc	Restaurant	Means of Payment	06/Jan./20	Nasdaq (U.S.)
Starbucks	Restaurant	Means of Payment	01/Mar./20	Nasdaq (U.S.)
Microstrategy	B.I.	Investment	11/Aug./20	Nasdaq (U.S.)
Square	Payment Solutions	Investment	07/Oct./20	Nasdaq (U.S.)
JP Morgan	Financial institution	Investment	27/Oct./20	Nasdaq (U.S.)
Ruffer	Investment company	Investment	01/Nov./20	FTSE100 (U.K.)
Tesla	Auto Manufacturers	Investment	08/Feb./21	Nasdaq (U.S.)
Mastercard	Payment Solutions	Investment	10/Feb./21	Nasdaq (U.S.)
Aker ASA	Holding	Investment	07/Mar./21	OSE (NO)
Meitu	Smartphones	Investment	18/Mar./21	HSI (H.K.)
Visa	Payment Solutions	Means of Payment	29/Mar./21	Nasdaq (U.S.)
Paypal	Payment Solutions	Means of Payment	30/Mar./21	Nasdaq (U.S.)
Phunware	Cloud platform	Investment	06/Apr./21	Nasdaq (U.S.)
Nexon	Online games	Investment	27/Apr./21	Nikey 225 (J.P.)
Mercado Livre	E-commerce	Investment	05/May/21	Nasdaq (U.S.)
Tesla	Auto Manufacturers	Divestment	12/May/21	Nasdaq (U.S.)
The Brooker Group	Financial Advisory and Consultancy	Investment	13/May/21	MAI (T.H.)
Ruffer	Investment company	Divestment	06/Jun./21	FTSE100 (U.K.)
Meliuz	Cashback services	Investment	29/Jun./21	Ibovespa (B.Z.)
Xiaomi	Cell Phones	Means of Payment	05/Aug./21	HSI (H.K.)
Metromile	Digital Insurance Platform	Investment	10/Aug./21	Nasdaq (U.S.)
AMC Entertainment Holdings, Inc.	Entertainment	Investment	10/Aug./21	Nasdaq (U.S.)
MercadoLibre, Inc.	Internet Retail	Investment	20/Jan./22	Nasdaq (U.S.)
Townsquare Media, Inc.	Advertising Agencies	Investment	10/May/22	Nasdaq (U.S.)
Chipotle Mexican Grill, Inc.	Restaurants	Means of Payment	01/Jun./22	Nasdaq (U.S.)
BlackRock, Inc.	Asset Management	Investment	04/Aug./22	Nasdaq (U.S.)

Appendix B: Additional Tables and Figures

Table B1: hypotheses tests on the subsample of firms that directly acquired cryptocurrency (BTC or ETH).

Event Group	Event Window	CAAR	Test						
			t-test	*CDA*	*Patell*	*PatellADJ*	*Corrado-Cowan*	*GenSign*	*Wilcox*
Investment - Treasury BTC or ETH acquisition (N = 13)	AAR[0]	1.993	**0.07**	**0.06**	**0.05**	**0.04**	0.88	0.34	0.65
	[-1;1]	3.494	**0.07**	**0.06**	**0.00**	**0.00**	0.92	0.88	0.63
	[-2;2]	1.331	0.59	0.57	**0.07**	**0.06**	0.43	0.21	0.68
	[-5;5]	-0.06	0.99	0.99	0.26	0.25	0.55	0.69	0.54
	[0;1]	3.321	**0.04**	**0.03**	**0.00**	**0.00**	0.97	0.88	0.57
	[0;3]	1.593	0.47	0.45	**0.01**	**0.01**	0.50	0.48	0.76

Notes: The Table shows the p-values of each hypothesis test – t-test, Crude Dependence Adjustment test (CDA), Patell test, Adjusted Pattel test, Corrado rank test, Generalized Sign test, and Wilcoxon signed-ranks test treasury cryptocurrency acquisition events (i.e., incorporation of BTC or ETH into the Balance Sheet). We highlight in **bold** the p-values lower or equal to 0.10.
Source: authors' elaboration.

Table B2: Descriptive statistics of CARs and explanatory variables used in the regression analysis.

Variable	Mean	P50	SD	p1	p99
AR[0]	0.223	0.06	4.829	-6.093	18.499
CAR[-1,1]	1.222	-0.072	13.009	-36.588	61.352
CAR[-2,2]	0.37	-0.229	10.454	-30.889	46.192
CAR[-5,5]	0.24	0.929	10.776	-42.466	34.855
CAR[0,1]	0.978	-0.166	7.44	-11.553	35.399
CAR[0,3]	0.407	-0.351	7.387	-16.508	32.085
Tech Firms Dummy	0.2	0	0.406	0	1
Financial Firms Dummy	0.286	0	0.458	0	1
Type of Event: Investment	0.6	1	0.497	0	1
Ln(Market Capitalization)	9.716	10.287	2.731	4.651	13.643
Ln(Prior Return)	-0.026	-0.017	0.155	-0.436	0.316
Ln(Past BTC Return)	0.024	0.017	0.102	-0.218	0.245
Cash/Assets	0.256	0.233	0.183	0.01	0.675
Price/Book	2.562	1.784	2.169	0	6.957

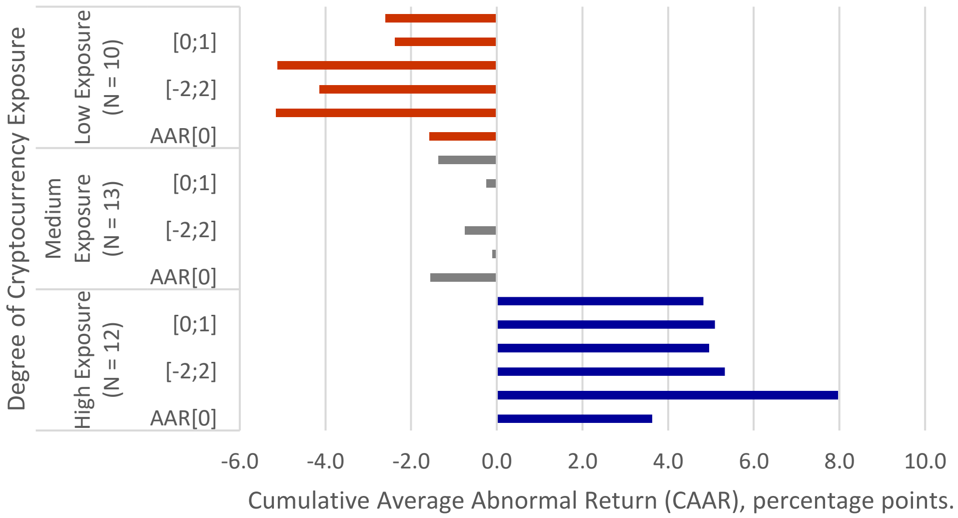
Table B3: hypotheses tests on subsamples stratified by sectors

Event Group	Event Window	CAAR	Test						
			t-test	*CDA*	*Patell*	*PatellADJ*	*Corrado-Cowan*	*GenSign*	*Wilcox*
Financial sector (N = 10)	AAR[0]	0.876	0.33	0.29	0.13	**0.10**	0.88	0.42	0.80
	[-1;1]	3.069	**0.05**	**0.03**	**0.00**	**0.00**	0.17	0.15	0.52
	[-2;2]	1.925	0.34	0.30	**0.01**	**0.00**	0.59	0.42	0.77
	[-5;5]	0.784	0.80	0.78	0.20	0.15	0.37	0.42	0.80
	[0;1]	2.47	**0.05**	**0.04**	**0.00**	**0.00**	0.31	0.65	0.55
	[0;3]	1.441	0.42	0.39	**0.01**	**0.00**	0.55	0.86	0.69
Consumer Cyclical (N = 11)	AAR[0]	-0.434	0.66	0.65	0.94	0.94	0.37	0.78	0.59
	[-1;1]	-1.876	0.27	0.26	0.14	0.17	**0.10**	**0.04**	0.12
	[-2;2]	-2.806	0.20	0.19	0.26	0.30	0.11	0.37	**0.10**
	[-5;5]	-3.034	0.35	0.34	0.52	0.55	0.26	0.37	0.21
	[0;1]	-1.274	0.35	0.34	0.32	0.36	**0.09**	0.14	0.22
	[0;3]	-1.789	0.36	0.35	0.14	0.17	0.11	0.37	0.23
Technology sector (N = 7)	AAR[0]	3.197	**0.04**	**0.03**	**0.03**	**0.02**	0.12	**0.05**	**0.09**
	[-1;1]	5.363	**0.05**	**0.03**	**0.00**	**0.00**	**0.01**	**0.05**	**0.01**
	[-2;2]	3.903	0.26	0.23	**0.05**	**0.04**	**0.10**	0.22	0.11
	[-5;5]	4.094	0.43	0.40	**0.02**	**0.02**	0.24	0.22	0.38
	[0;1]	4.282	**0.05**	**0.04**	**0.00**	**0.00**	**0.04**	0.22	**0.04**
	[0;3]	4.145	0.18	0.15	**0.00**	**0.00**	0.10	0.22	0.14
Other sectors (N = 7)	AAR[0]	-2.652	0.42	0.39	0.12	0.13	**0.08**	0.26	**0.06**
	[-1;1]	-0.688	0.90	0.90	0.64	0.65	0.64	0.26	0.85
	[-2;2]	-0.394	0.96	0.95	0.75	0.76	0.50	0.26	0.73
	[-5;5]	0.756	0.94	0.94	0.50	0.52	0.98	0.71	0.66
	[0;1]	-0.917	0.84	0.83	0.60	0.61	0.57	0.71	0.55
	[0;3]	-1.356	0.83	0.83	0.34	0.36	0.27	0.26	0.27

Note: Notes: The Table shows the p-values of each hypothesis test – t-test, Crude Dependence Adjustment test (CDA), Patell test, Adjusted Pattel test, Corrado rank test, Generalized Sign test, and Wilcoxon signed-ranks test for different groups of events based on sectoral classification: Financial Sector (N = 10), Consumer Cyclical (N = 11), Technology Sector (N = 7), and Other Sectors (N = 7, composed of Communication Services [N = 6] and Industrials [N = 1]). We highlight in **bold** the p-values lower or equal to 0.10.
Source: authors' elaboration.

Figure B1: Graphical visualization of market reactions according to the degree of cryptocurrency exposure, full sample (N=35) and subsample comprising only direct acquisitions (N=13)

Subfigure B1a: Full sample (N=35), which includes objective (N=13) and subjective (N=22) classification of cryptocurrency exposure



Subfigure B1b: Direct acquisitions of BTC or ETH (N=13), which includes only objective classification of cryptocurrency exposure

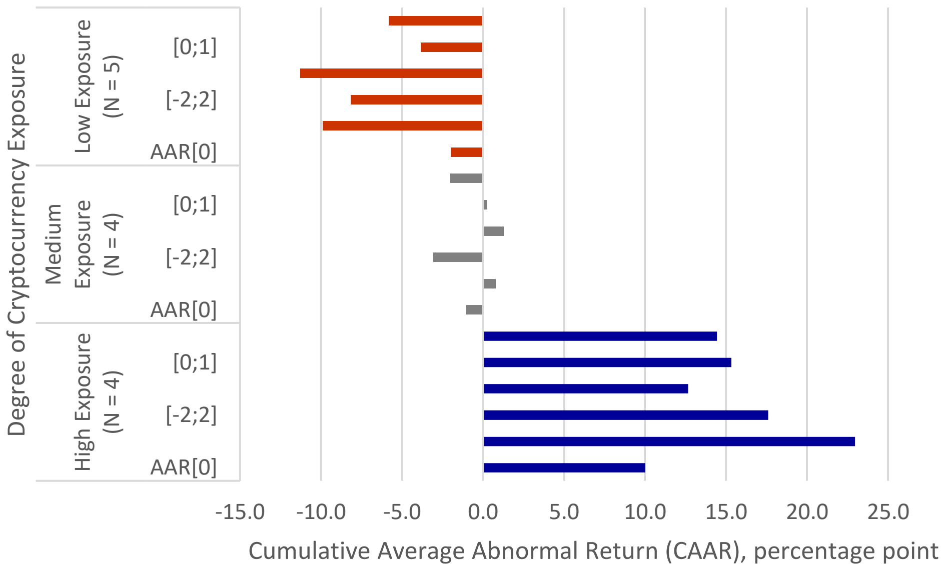
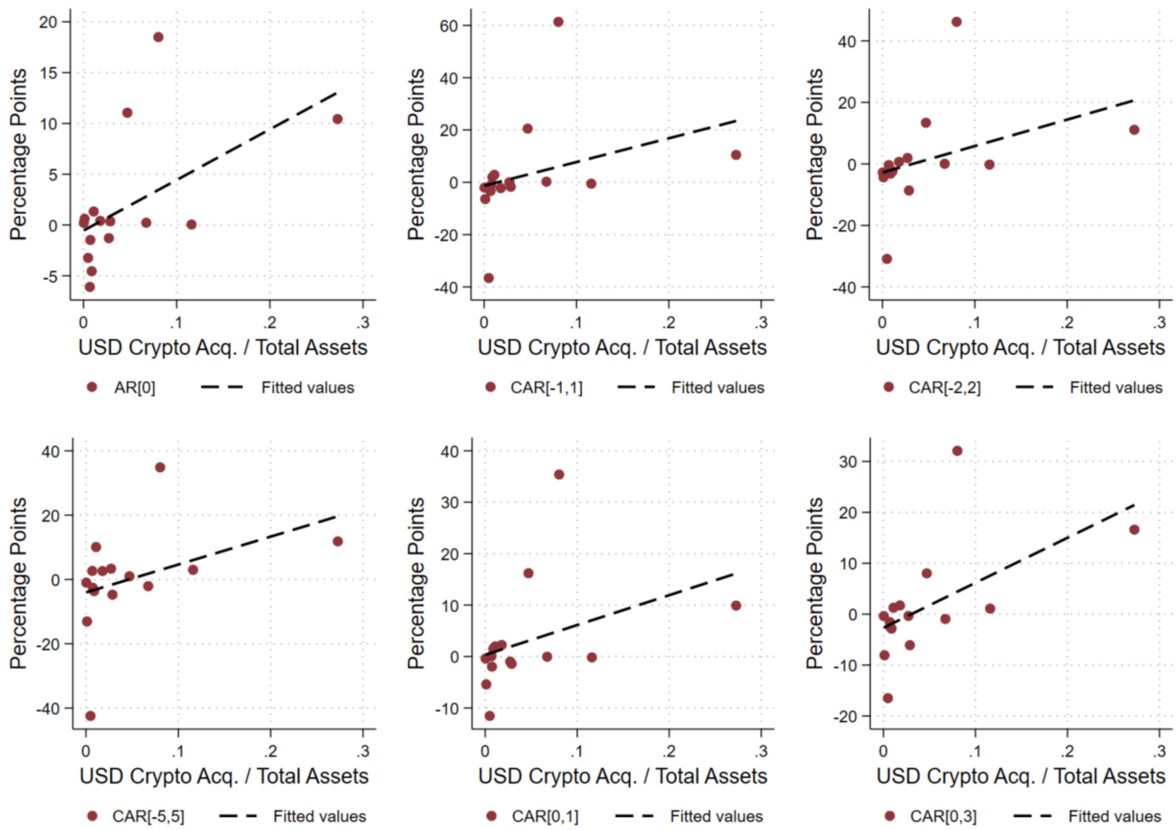


Figure B2: Scatterplots of cumulative abnormal returns (Y axis) and the ratio between Cryptocurrency Acquisition (USD) and Total Assets (USD)



Appendix C: Qualitative assessment of cryptocurrency corporate exposure for announcements of indirect investments and acceptance as means of payment

Company	Announcement date	Degree of Cryptocurrency Exposure	News' Headline
BlackRock, Inc.	04/aug./2022	3	BlackRock partners with Coinbase to expand into crypto
Overstock.com, Inc.	09/jan./2014	3	Overstock.com First Online Retailer to Accept Bitcoin
Visa Inc.	29/mar./2021	3	EXCLUSIVE Visa moves to allow payment settlements using cryptocurrency
AT&T Inc.	23/may/2019	3	U.S. Telecoms Giant AT&T Now Accepting Crypto Payments via BitPay
Microsoft Corporation	11/dec./2014	3	Microsoft begins accepting Bitcoin
JPMorgan Chase & Co.	27/oct./2020	3	JPMorgan Chase (JPM) has started using its digital currency for commercial transactions
MercadoLibre_2	20/jan./2022	3	MercadoLibre Doubles Down on Crypto With Two Purchases
PayPal Holdings, Inc.	30/mar./2021	2	PayPal Launches "Checkout with Crypto"
Newegg Commerce, Inc.	01/jul./2014	2	Newegg is Now Accepting Bitcoin
Rakuten Group, Inc.	16/mar./2015	2	Rakuten Starts Accepting Bitcoin
Chipotle Mexican Grill, Inc.	01/jun./2022	2	Chipotle Now Accepts Cryptocurrency as Payment
FRMO Corporation	18/aug./2016	2	Investment in grayscale
Méliuz S.A.	30/jul./2021	2	Méliuz anuncia contrato para compra da negociadora de criptomoedas Alter Pagamentos por R$ 25
Oracle Corporation	23/oct./2018	2	Oracle Unveils Business-Ready Blockchain Applications
Restaurant Brands International Inc.	06/jan./2020	2	Burger King starts accepting Bitcoin payments
Xiaomi Corporation	05/aug./2021	1	Xiaomi's Portuguese outlet now accepts Bitcoin
Starbucks Corporation	01/apr./2021	1	Starbucks Now Accepts Bitcoin as Payment (Kind of...)
BMW (Bayerische Motoren Werke Aktiengesellschaft)	05/jul./2018	1	Stephen James is now accepting Bitcoin for the purchase of your new BMW!
Mastercard Incorporated	10/feb./2021	1	Why Mastercard is bringing crypto onto its network
AMC Entertainment Holdings, Inc.	10/aug./2021	1	Memestock AMC now plans to accept Bitcoin

Note: This Table reports the assessment of corporate cryptocurrency exposure for indirect cryptocurrency investments (e.g., crypto-related partnerships and acquisitions) and announcements of cryptocurrency acceptance as means of payment. Degree of Cryptocurrency Exposure is a categorical variable that equals 3 if the qualitative assessment of the news' content indicates a high exposure (effective, direct acceptance of cryptocurrency as means of payment by industry pioneers and worldwide, economically relevant M&A or partnerships), 2 for medium exposure, and 1 for low exposure (just plans to accept cryptocurrency, not actual acceptance; global companies that started accepting cryptocurrency only in a single country or store; and indirect or partial acceptance of crypto as means of payment, such as gift cards.