Media Coverage and the Cross-section of Cryptocurrency Returns

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Abstract

This paper studies the cross-sectional relation between media coverage and expected cryptocurrency returns. We find that a long-short portfolio, that longs cryptocurrencies with no media coverage and shorts cryptocurrencies with high media coverage, yields a statistically significant and positive expected return, even after controlling for well-known cryptocurrency risk factors. However, this expected return decreases significantly after accounting for transaction costs. The long leg of this portfolio continues to yield a significant and positive average net-of-costs return while the short leg does not. These results are strong among small cryptocurrencies and cryptocurrencies with high illiquidity, low beta, or high idiosyncratic volatility. We also find that the media effect is not subsumed by a host of anomalies documented in the literature, but it may be subsumed under the liquidity effect.

Keywords: Media coverage; Cryptocurrency; Investor attention; Liquidity; Transaction costs; Idiosyncratic volatility.
JEL classification: G12; G14; G17; G19; G40.

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1 Introduction

Investors' limited attention induces mispricing in financial assets [see, e.g., Barber, Huang, Odean, and Schwarz (2022); Hirshleifer, Lim, and Teoh (2011); Hirshleifer and Teoh (2003); Kahneman (1973); Peng and Xiong (2006)]. Media coverage is proven to be a good proxy for both individual and institutional investor attention [see, e.g., Barber and Odean (2008); Ben-Rephael, Da, and Israelsen (2017)]. There is a vast amount of literature studying the link between media coverage and asset prices [see, e.g., Barber and Odean (2008); Dougal, Engelberg, García, and Parsons (2012); Engelberg and Parsons (2011); Fang and Peress (2009); Goldman, Martel, and Schneemeier (2022); Haroon and Rizvi (2020); Hillert, Jacobs, and Müller (2014); Peress (2014); Schwenkler and Zheng (2021); Tetlock (2015)].

All the aforementioned papers find a strong empirical evidence of the media effect in stocks before accounting for transaction costs. This study represents the first attempt to provide empirical support for the media effect in the rapidly growing cryptocurrency market. We find a strong empirical evidence of the media effect in cryptocurrencies, even after adjusting for transaction costs. Specifically, we find that, before accounting for transaction costs, the average returns [in the holding week] of equally weighted portfolios of tokens with no-, low-, and high-media coverage [in the portfolio formation week] are 4.08%, 2.25%, and 1.46% per week, respectively; and the long-short portfolio [that longs no-coverage tokens and shorts high-coverage tokens] yields an average return of 2.61% per week (t-statistic = 3.90).[1] After deducting transaction costs, the tokens with no media coverage still achieve an average net-of-costs return of 3.15% per week (t-statistic = 2.96). In contrast, the tokens with high media coverage yield a negative average net-of-costs return of -2.27% per week, largely due to the considerably higher turnover associated with frequently rebalancing the portfolio of those tokens. As a result, the average net-of-costs return of the long-short media-based portfolio declines to -2.25% per week (t-statistic = -3.40) – it is thus difficult to implement profitable long-short strategies based on individual cryptocurrency characteristics, as suggested by Bianchi and Babiak (2022a).

Tokens with no media coverage also yield a statistically significant and positive abnormal return after

[1] Note that, since cryptocurrencies are digital tokens [that can be used as a medium of exchange or a method of payment, and they give the holders a set of rights, including access to a platform, or the right to vote, etc.] typically issued through Initial Coin Offerings [e.g., Li, Shin, and Wang (2019)], we shall write 'cryptocurrency' and 'token' interchangeably throughout the paper.

adjusting for transaction costs [defined by Novy-Marx and Velikov's (2016) generalized alpha in factor models for cryptocurrencies proposed by Liu, Tsyvinski, and Wu (2022)]. The average return on the equally weighted portfolio of no-coverage tokens is particularly large (even after accounting for transaction costs) among small tokens, tokens with high illiquidity, tokens with high idiosyncratic volatility, and tokens with low beta. In these subsamples, the average net-of-costs return [of the portfolio of no-coverage tokens] ranges from 3% to 5% per week, and the average net-of-costs abnormal return (*or* the generalized alpha in the three-factor model for cryptocurrencies) ranges from 2% to 4% per week. Those returns are also statistically significant. We also find that the transaction cost of short-selling tokens with high media coverage is roughly three times larger than that of longing tokens with no media coverage, as the former are turned over more frequently within the portfolio than the latter.

The existence of the premium of no-coverage tokens (*or* the no-coverage premium) is consistent with the hypothesis that limited attention delays the incorporation of information into prices, causing the prices to drift upward or downward, depending on the content of the information while a lot of attention accelerates the assimilation of information into prices, causing price reversal. Larger assets usually have a faster speed of information incorporating into their prices (as there is more attention focussing on those assets) while smaller assets can face a delay in the process of information incorporation [see, e.g., Hou and Moskowitz (2005)]. In stock markets, the buying decision of individual investors is more influenced by attention than their selling decision as they tend to sell only assets they already own, thus the current price of an attention-grabbing stock tends to be high, leading to low future returns [e.g., Barber et al. (2022); Barber and Odean (2008)]. This implies that, as attention towards a stock rises, its projected return could decline. We expect to observe the same phenomenon in the cryptocurrency market which is dominated by retail investors, largely due to the blockchain-based decentralized finance (which makes cryptocurrencies accessible to individual investors) [e.g., Harvey, Ramachandran, Santoro, Ehrsam, and Buterin (2021)]. Retail investors often incline toward smaller cryptocurrencies, due to their higher risk tolerance and limited attention. Therefore, we also expect that the media effect is strongest among small tokens.

Fang and Peress (2009) suggest two main explanations for the no-coverage premium in the cross-section: (1) the 'impediments-to-trade' hypothesis (if the no-coverage premium reflects a mispricing, in a frictionless market, investors will try to exploit, and thereby eliminate this mispricing. Therefore, a mispricing can only persist due to severe market frictions); (2) the 'investor recognition' hypothesis (investors are not aware of all assets traded in the market, and assets with lower investor recognition tend to be less traded/held. Thus, those assets need to offer higher returns as a compensation for imperfect diversification). Fang and Peress (2009) provide an empirical evidence supporting both the hypotheses for stocks.

Our empirical evidence also provides support for those hypotheses for cryptocurrencies. In particular, we find that the media effect is strong among small tokens, tokens with low trading volumes, tokens with high illiquidity, or tokens with low beta. These results are consistent with the 'impediments-to-trade' hypothesis. Using idiosyncratic volatility to proxy the cost of poor investor recognition (i.e., a token, that not every investor knows about, is often associated with high idiosyncratic risk while a token, that every investor knows about, largely fluctuates with the cryptocurrency market, leading to a lower idiosyncratic volatility), we find that the media effect is also strong among tokens with high idiosyncratic volatility. The long-short portfolio [that longs no-coverage tokens and shorts high-coverage tokens in the portfolio formation week] yields an average return of 4.77% per week (t-statistic = 3.01) in the subsample of tokens with highest idiosyncratic volatility while this portfolio has a statistically insignificant average return in the subsample of tokens with lowest idiosyncratic volatility. In addition, the alpha and generalized alpha of the portfolio [that borrows fund at the risk-free rate to finance an equally weighted long position in the tokens with no media coverage during the portfolio formation week] in Liu et al.'s (2022) three-factor model for cryptocurrencies monotonically increase with the level of idiosyncratic volatility.

We also find that the media effect is not driven by (a) negative return drift among high-coverage tokens with low past returns, and (b) return reversal of no-coverage tokens with low past returns. Moreover, the media effect is not subsumed by a host of anomalies (mostly for equity) documented in the literature, such as the size effect, the idiosyncratic volatility effect, the Value-at-Risk (VaR) effect, the momentum effect, and the beta effect. However, it may be subsumed under the liquidity effect. Indeed, Bianchi and Babiak (2022b) empirically show that liquidity (besides past performances and volatility) plays an important role in the price discovery of cryptocurrencies. Unlike traditional equity markets, cryptocurrency markets operate continuously through time. Turnover on centralized exchanges is significantly higher than technology stocks traded on the Nasdaq. Therefore, liquidity is an even more important factor in the cryptocurrency market. Our findings confirm a strong interaction between the media effect and the liquidity effect.

We also compare the media effect with other effects: size, liquidity, volatility, VaR, beta, and momentum. Before accounting for transaction costs, the long-short portfolio [that longs small tokens and short large tokens] yields an average return of 3.32% per week (t-statistic = 4.63) in the following week, confirming the presence of the size premium documented in the literature [e.g., Cong, Karolyi, Tang, and Zhao (2022); Liu et al. (2022)]; the long-short portfolio [that longs tokens with high illiquidity and shorts tokens with low illiquidity] yields an average return of 4.84% per week (t-statistic = 4.55) in the following week, confirming the presence of the liquidity effect documented in the literature [e.g., Bianchi and Babiak (2022b)]; the long-short portfolio [that longs tokens with high VaR and short tokens with low VaR] yields an average return of 3.28% per week (t-statistic = 4.05) in the following week; the long-short portfolio [that longs tokens with high beta and shorts tokens with low beta] yields an average return of 0.34% per week (t-statistic = 0.54) in the following week; the long-short portfolio [that longs tokens with high past performance and short tokens with low past performance] yields an average return ranging from -0.09% per week (t-statistic = -0.16) to 3.06% per week (t-statistic = 4.22) in the following week, confirming the presence of the momentum effect documented in the literature [e.g., Bianchi and Babiak (2022b); Cong et al. (2022); Liu and Tsyvinski (2021)]; and the long-short portfolio [that longs tokens with no media coverage and shorts tokens with high media coverage] yields an average return of 2.61% per week (t-statistic = 3.90) in the following week. Therefore, before deducting transaction costs the media effect seems quite comparable with the other effects. After accounting for transaction costs, all the long-short strategies become non-profitable. However, the long-only strategies may still yield positive average net-of-costs returns, largely due to a lower turnover from rebalancing these long-only portfolios. Therefore, in the cryptocurrency market, a long-only strategy may withstand transaction costs while a long-short strategy may not.

The rest of this paper is organized as follows. Section 2 discusses the literature related to this study. Section 3 describes data and summary statistics. Section 4 analyzes the relationship between media coverage and cryptocurrency returns in the cross section through a bivariate sorting procedure and regression analysis. Section 5 discusses possible explanations of the media effect: the 'impediments to trade' hypothesis and the investor recognition hypothesis, suggested in Fang and Peress (2009), as well as return continuation and reversals. Section 5.4 investigates if the media effect is subsumed under other anomalies related to size, past performance, idiosyncratic volatility, liquidity, VaR, and beta. Section 6 compares media coverage with other cross-sectional predictors based on cryptocurrency characteristics (such as size, liquidity, volatility, risk, and momentum). Section 7 concludes this paper. The description of the cryptocurrency characteristics and robustness check results are collected in a companion Supplemental Material (SM).

2 Related Literature

Cryptocurrencies are digital tokens that use cryptography for security and to control the creation of new units. These tokens are not only used as a method of payment for goods and services in absence of a centralized custodian, but they are also used as a speculative asset [see, e.g., Yermack (2015)]. As of January 2024, there are more than 20,000 cryptocurrencies traded on over 500 cryptocurrency trading platforms worldwide, out of which, about 60% are centralised and 40% are decentralised [see, e.g., Chen, Gurrola-Perez, and Lin (2023)]. The aggregate market capitalization of cryptocurrencies has reached above $2.3 trillion with about $50 billion in daily trading volume by the end of September 2024.[2] Cryptocurrencies are notoriously volatile (for example, by the end of 2018, Bitcoin lost 85% of its value from the peak and plunged to $3000 per coin). Maximum day-to-day losses from investing in a cryptocurrency can exceed 70% [see, e.g., Brauneis and Mestel (2018)]. Cryptocurrencies also have some features similar to lottery-type stocks often traded for the purpose of speculation and gambling [e.g., Dorn, Dorn, and Sengmueller (2015); Dorn and Sengmueller (2009); Sadik (2024)]. Moreover, cryptocurrency markets are quite segmented; and the price of a cryptocurrency may largely deviate across different exchanges, regions, or countries so that day traders can make a significant amount of arbitrage profits [e.g., Borri and Shakhnov (2022); Makarov and Schoar (2020)].

There is a burgeoning number of studies that attempt to explain the determinants of cryptocurrency returns in the cross section and over time. In the time dimension, the returns of major cryptocurrencies are

[2] Source: https://coinmarketcap.com/.

driven by stock market returns, macroeconomic factors, inflation, or gold and oil returns [e.g., Panagiotidis, Stengos, and Vravosinos (2018)], investor attention [e.g., Guindy (2021); Liu and Tsyvinski (2021); Philippas, Rjiba, Guesmi, and Goutte (2019)] as well as by their current adoption, expected future network growth, or peer linkages [see, e.g., Cong, Li, and Wang (2021); Liu and Tsyvinski (2021)]. Other studies find that cryptocurrency returns can vary independent of their fundamentals [e.g., Biais, Bisiere, Bouvard, Casamatta, and Menkveld (2023)]; these variations may be due to the cryptocurrency market sentiment [e.g., Canayaz, Cao, Nguyen, and Wang (2023)].

In the cross section, Liu et al. (2022) identify three main factors, namely the cryptocurrency market, size, and momentum, which can cross-sectionally predict expected cryptocurrency returns. There are also several recent studies of momentum effects in cryptocurrencies [e.g., Proelss, Schweizer, and Buchwalter (2024)]. Bianchi and Babiak (2022b) show that, through a latent factor model with time-varying factor loadings and alphas (which is estimated using Kelly, Pruitt, and Su's (2019) Instrumented Principal Component Analysis), the conditional expected cryptocurrency returns are mainly driven by liquidity, volatility, and past performance. Cong et al. (2022) find that the cross-section of expected cryptocurrency returns can be significantly explained by market, size, momentum, value, and network growth. John, Li, and Liu (2024) show that, besides market, size, and momentum, the sensitivities of cryptocurrencies to market sentiment can also cross-sectionally predict expected cryptocurrency returns. Schwenkler and Zheng (2023) document that the co-movement among peer cryptocurrencies, which are co-mentioned in online news, can also predict the cross-section of expected cryptocurrency returns, and that mispricing among peer cryptocurrencies is due to an overreaction to news reporting.

The existing studies focus on either (1) the influence of news outlets and social media on market sentiment (especially about Bitcoin) that can in turn predict cryptocurrency returns [e.g., Canayaz et al. (2023); John et al. (2024)], or (2) the role played by the proxies of investor attention [of the cryptocurrency market] derived from Twitter or Google Trends in shaping future cryptocurrency market returns [e.g., Liu and Tsyvinski (2021); Philippas et al. (2019)]. We study the extent to which media coverage [measured by the number of news articles mentioning about each cryptocurrency in our sample] can predict the cross-section of expected cryptocurrency returns. Our empirical analysis also accounts for transaction costs.

3 Data and Descriptive Statistics

We obtain daily data on opening, closing, high, and low prices, volume, and market capitalization (in USD) for both active and inactive cryptocurrencies from CoinMarketCap. The price of each token listed on CoinMarketCap is calculated by taking the volume-weighted average of all prices quoted on different exchanges. We end up with a total of 11,739 tokens (both active and inactive), thus this dataset is somewhat survivorship bias-free. We then removed any token whose name and symbol are identical, as searching for articles that mention this token may lead to a high false positive rate. We are then left with 8166 tokens. Next, we search for all articles that contain both the name and symbol of each token case-sensitively in their bodies using a large news corpus (Common Crawl).[3] We filtered out tokens that have zero closing prices at any point in time while appearing in less than 100 articles throughout the sample period. After this step, we are left with 1575 tokens. Our sample period is from 2017-06-05 to 2023-03-27. We then calculate weekly returns and weekly measures of the cryptocurrency characteristics listed in Table S.I.1 for each token. The weekly media coverage of a token is defined as the number of articles mentioning about this token in a week.

If we consider only active tokens, we have 1811 tokens left after removing any token whose name and symbol are identical. Among those tokens, there are only 1355 tokens that have positive closing prices at any point in time, and that are mentioned in at least 100 articles throughout the whole sample period. As suggested by Liu et al. (2022), to avoid the issue of low liquidity in cryptocurrency trading, we include in our final samples only cryptocurrencies that have information on price, volume, and market capitalization of more than $1,000,000 during the portfolio formation period. We tabulate the cryptocurrency characteristics used in this study and the references in Table S.I.1.

We start our analysis by calculating the fractions of cryptocurrencies [ever listed on CoinMarketCap] covered by all newspapers and each of the main newspapers across years in Table 1. Panel A shows that, for all the years, American Banking and Market News account for 70.81% of all covered tokens, followed by WKRB News (58.32%), Enterprise Leader (52.54%), and Community Financial News (52.08%) while

[3] We use a webscraping tool to collect all news articles from Common Crawl for the period from 2016-01-01 to 2023-04-01. Each news article in this sample has been cleaned by removing stop words, short words, and special characters. Words in each article are also lemmatized.

traditional news outlets (such as Yahoo News or Nasdaq) only account for less than 10% of the covered tokens. Note that a token can be covered by more than one newspaper. Panel B indicates that only 2% of all the tokens [ever listed on CoinMarketCap] are covered by at least a newspaper back in 2017, and this fraction continues to increase over the years. Overall, Common Crawl covers 56% of all the tokens ever listed on CoinMarketCap for all the years. Panel C shows that there are 353 newspapers that publish articles written about at least a cryptocurrency back in 2017, and this number increases to 2118 in 2022. In total, we have 3561 newspapers that publish articles about at least one cryptocurrency for all the years.

We also tabulate the fractions of active cryptocurrencies [currently listed on CoinMarketCap] covered by all newspapers and each of the main newspapers across years in Table S.II.2. Panel A shows that, for all the years, American Banking and Market News account for 92.65% of all the covered tokens, followed by WKRB News (92.22%), Community Financial News (90.92%), and Markets Daily (90.86%) while other traditional news outlets only account for less than 20% of the covered tokens. Panel B indicates that only 8% of the currently active tokens are covered by at least a newspaper in 2017, and this fraction increases to 83% in 2022. Overall, Common Crawl covers 89% of the active tokens currently listed on CoinMarketCap. Panel C shows that there are 272 newspapers that publish articles written about at least one cryptocurrency back in 2017, and this number increases to 1575 in 2022. We have a total of 2879 newspapers publish articles about at least a token for all the years.

We also tabulate the conditional coverage statistics of all the cryptocurrencies [ever listed on CoinMarketCap] in Table 2. Overall, Bitcoin (BTC) and Ethereum (ETH) receive the most newspaper coverage, which is quite obvious as those two cryptocurrencies account for over 90% of the entire cryptocurrency market capitalization. The number of articles mentioning about BTC increases to 143045 in 2022 from 860 in 2017 while the number of articles mentioning about ETH increases to 72298 in 2022 from 355 in 2017. The most covered tokens include Bitcoin, Ethereum, Global (GLOBE), Dogecoin (DOGE), Tether (USDT), and Shiba Inu (SHIB). The number of covered tokens increases to 3873 in 2022 from 181 in 2017. There is a total of 4636 tokens mentioned in at least one article in our entire sample. The average number of articles per covered token increases to its maximum level of 927.95 in 2021 from its minimum level of 24 in 2017. This number decreases to 495.86 in 2022 from its peak in 2021, because the fraction of tokens covered by newspapers increases to 48% in 2022 from 29% in 2021 while the number of newspapers that publish articles about at least a cryptocurrency only moderately increases to 2018 in 2022 from 1978 in 2021, as shown in Table 1. In the entire sample, there are 1128.81 articles per covered token on average. The median number of articles per covered token increases to its maximum level of 319.50 in 2021 from its minimum level of 3.00 in 2017, then decreases to 31.00 in 2022. In the entire sample, the median number of articles per covered token is 36 (which is much less than the average number of articles per covered token that is 1128.81). The difference between the mean and median numbers of articles per covered token suggests that the distribution of the number of articles per covered token is highly skewed, with certain tokens being mentioned very frequently while others being mentioned infrequently or not at all.

The conditional coverage statistics of active cryptocurrencies currently listed on CoinMarketCap are reported in Table S.II.3. The most covered cryptocurrencies over the entire sample include BTC, ETH, DOGE, USDT, and SHIB. Sorting the most covered tokens by year, we notice that in 2017, the top ranked tokens include BTC, Newton (NEW), ETH, and Litecoin (LTC). NEW is the token of the Newton Project first launched in 2018, and thus it is the most covered token in 2018. The popularity of NEW started fading in 2019. Throughout the years, BTC and ETH remain among the top four most covered cryptocurrencies. The number of active tokens mentioned in at least one article increases to 1500 in 2022 from 138 in 2017. There is a total of 1619 active tokens being covered in the entire sample. The mean (median) number of articles per covered token increases to 1577.66 (1327.00) in 2021 from 22.62 (3.00) in 2017, then decreases to 1077.41 (792.00) in 2022. These mean (median) numbers of articles per covered token are much greater than the numbers reported for all the tokens ever listed on CoinMarketCap, suggesting that active tokens are more likely to be covered in the media than inactive tokens. The grand mean and median numbers of articles per covered token are 3033.22 and 2357.00, respectively, suggesting that the distribution of the number of articles per covered token is still highly skewed for active cryptocurrencies.

Table 3 examines the determinants of media coverage in a panel regression setting. The dependent variable is the logarithm of one plus the number of news articles written about a cryptocurrency in a given week, and the independent variables are average market capitalization per week (AMCAP), log average daily volume times price scaled by market capitalization for each week (VOLSCALED), return volatility for each week (RETVOL), idiosyncratic volatility (IDIOVOL), maximum return in a week (MAXRET), illiquidity (DAMIHUD), Value-at-Risk (VaR), past returns ($r\ i, 0$, $i = 1, 2, 3, 4, 8, 16, 50, 100$, and $r\ 4, 1$), the negative of the past 52-week return (NPAST52), beta, and beta^2 (which are all defined in Table S.I.1). We employ the fixed-effect panel regression estimator. Because cryptocurrencies may be contemporaneously correlated or lagged cross-correlated, and the cryptocurrency characteristics may be persistent over time, we thus correct the standard errors for cross-sectional and serial correlation by using Driscoll and Kraay's (1998) procedure. In general, we find that market capitalization has a highly significant effect on media coverage – large tokens are more likely to be covered than small tokens. Indeed, the slope coefficient on AMCAP is statistically significant and positive under three different model specifications. VOLSCALED, RETVOL, IDIOVOL, MAXRET, or BETA has a significant effect on media coverage only when the past returns are included as control variables, thus the presence of this effect may be due to a model misspecification. Illiquidity has a strong negative effect on media coverage – illiquid tokens are much less likely to be covered than liquid tokens (as liquid tokens have a much higher trading volume than illiquid tokens). VaR has a strong positive effect on media coverage – tokens with lower 5% quantiles of their return distributions are more likely to be covered by the media. Past returns have a significant impact on media coverage (past one-week return has a positive effect on media coverage while past two-, three-, or 100-week returns have a negative effect on media coverage): tokens with a larger recent price increase (*or* recent winners) tend to receive a higher media coverage while tokens with a lower past two-, three-, or 100-week return (past losers) are also more likely to be covered. Therefore, in the cryptocurrency market, a price move often causes the news, possibly because the media tends to report about cryptocurrencies with extreme past price movements. However, this may not be the case in the equity market, as evidenced in Fang and Peress (2009). Table S.II.4 also confirms these effects on media coverage for active cryptocurrencies.

Table 1: Summary Statistics of Newspaper Coverage: Unconditional Coverage Statistics for All Cryptocurrencies ever listed on CoinMarketCap

This table presents summary statistics for the newspaper coverage of all cryptocurrencies in our sample. The top 30 newspapers that cover the highest fractions of tokens ($\times 100$) are reported for each year and for all the years.

Panel A: Unconditional coverage statistics (Fraction of covered tokens by newspaper for each year)														Fraction of covered tokens by newspaper for all years	
2017		2018		2019		2020		2021		2022		2023 (January - March)		All years	
techcrunch.com	0.97	macondaily.com	20.71	www.chaffeybreeze.com	22.46	www.wkrb13.com	22.44	www.americanbankingnews.com	32.02	www.americanbankingnews.com	67.21	www.wkrb13.com	10.2	www.americanbankingnews.com	70.81
www.finanznachrichten.de	0.88	www.chaffeybreeze.com	16.91	macondaily.com	19.12	www.com-unik.info	22.31	www.wkrb13.com	31.22	www.wkrb13.com	54.48	theenterpriseleader.com	9.84	www.wkrb13.com	58.32
www.huffingtonpost.com	0.63	www.prnewswire.com	2.16	www.americanbankingnews.com	14.95	www.themarketsdaily.com	22.16	www.tickerreport.com	31.02	theenterpriseleader.com	49.1	www.com-unik.info	9.82	theenterpriseleader.com	52.54
www.nigeriatoday.ng	0.58	www.finanznachrichten.de	2.01	www.wkrb13.com	12.32	www.americanbankingnews.com	20.6	www.themarketsdaily.com	31.0	www.com-unik.info	48.39	www.themarketsdaily.com	9.8	www.com-unik.info	52.08
www.businessinsider.com	0.37	markets.businessinsider.com	1.86	www.tickerreport.com	11.35	theenterpriseleader.com	19.5	theenterpriseleader.com	30.85	www.themarketsdaily.com	46.0	www.tickerreport.com	7.34	www.themarketsdaily.com	49.77
www.forbes.com	0.37	dminute.com	1.79	www.themarketsdaily.com	11.11	www.tickerreport.com	19.31	www.com-unik.info	29.92	www.tickerreport.com	36.89	www.americanbankingnews.com	5.46	www.tickerreport.com	41.47
seekingalpha.com	0.35	www.zerohedge.com	1.45	www.com-unik.info	8.41	www.prnewswire.com	2.93	www.newsbreak.com	24.03	www.etfdailynews.com	25.78	www.newsbreak.com	3.88	www.newsbreak.com	31.54
www.techmeme.com	0.28	www.forbes.com	1.4	theenterpriseleader.com	8.28	www.nasdaq.com	2.89	upnewsinfo.com	7.51	reporter.am	19.37	www.stl.news	2.52	www.etfdailynews.com	25.78
www.reuters.com	0.28	thenextweb.com	1.14	www.modernreaders.com	4.83	www.fxstreet.com	2.85	www.benzinga.com	7.27	www.newsbreak.com	15.06	u.today	2.37	macondaily.com	24.72
uk.reuters.com	0.26	www.marketscreener.com	1.04	www.prnewswire.com	2.63	www.somagnews.com	2.83	www.globenewswire.com	7.23	www.somagnews.com	14.15	www.einpresswire.com	2.14	www.chaffeybreeze.com	23.11
www.marketwatch.com	0.24	www.benzinga.com	0.84	www.finanznachrichten.de	2.18	www.coindesk.com	2.39	www.prnewswire.com	6.49	recentlyheard.com	9.73	www.fxstreet.com	2.03	reporter.am	19.37
thedailycoin.org	0.24	www.nigeriatoday.ng	0.78	nctynews.com	2.09	www.wfmz.com	2.09	www.einpresswire.com	6.34	www.benzinga.com	8.11	www.inferse.com	1.94	www.somagnews.com	16.05
in.reuters.com	0.24	techcrunch.com	0.71	www.marketscreener.com	2.07	hackernoon.com	2.05	bitcoinist.com	5.46	coinjournal.net	7.34	www.nasdaq.com	1.92	www.einpresswire.com	13.66
www.benzinga.com	0.24	bgr.com	0.71	www.prnewswire.co.uk	1.57	www.einpresswire.com	2.03	www.entrepreneur.com	5.11	www.globenewswire.com	7.08	www.benzinga.com	1.75	www.globenewswire.com	13.03
www.ibtimes.co.uk	0.24	seekingalpha.com	0.63	www.fxstreet.com	1.45	u.today	2.03	www.wfmz.com	5.11	www.einpresswire.com	6.73	www.prnewswire.com	1.73	www.benzinga.com	12.73
freedombunker.com	0.22	www.express.co.uk	0.63	www.sys-con.com	1.42	www.finanznachrichten.de	1.94	investorplace.com	4.92	www.mexc.com	6.69	finance.yahoo.com	1.64	www.prnewswire.com	12.25
www.dailymail.co.uk	0.22	venturebeat.com	0.63	www.forbes.com	1.38	www.cryptopolitan.com	1.75	hackernoon.com	4.85	www.prnewswire.com	5.67	news.yahoo.com	1.64	recentlyheard.com	11.46
forextv.com	0.19	www.4-traders.com	0.63	www.benzinga.com	1.12	www.reporter.am	1.73	www.somagnews.com	4.83	itbusinessnet.com	5.42	coinjournal.net	1.62	www.finanznachrichten.de	9.84
www.zdnet.com	0.19	www.dailymail.co.uk	0.6	dminute.com	1.06	www.thestreet.com	1.66	finance.yahoo.com	4.75	finance.yahoo.com	5.37	investorplace.com	1.55	coinjournal.net	9.8
www.cnbc.com	0.17	www.webnewswire.com	0.58	news.yahoo.com	1.04	www.marketscreener.com	1.64	u.today	4.7	www.inferse.com	5.31	247wallst.com	1.49	finance.yahoo.com	8.37
www.cryptoanalyst.co	0.17	www.nowindia.com	0.56	www.einpresswire.com	0.91	www.forbes.com	1.62	coinjournal.net	4.57	www.nasdaq.com	5.2	itbusinessnet.com	1.45	u.today	8.2
fortune.com	0.15	webnewswire.com	0.56	www.nasdaq.com	0.91	www.benzinga.com	1.55	www.nasdaq.com	4.47	www.thewhig.com	5.11	euroweeklynews.com	1.42	www.nasdaq.com	8.13
nakedsecurity.sophos.com	0.15	www.educationews.com	0.54	seekingalpha.com	0.8	www.prnewswire.co.uk	1.42	www.thestreet.com	4.19	investorplace.com	5.03	www.latestly.com	1.38	upnewsinfo.com	7.7
www.nextbigfuture.com	0.15	www.indiabynet.com	0.54	nbonews.com	0.6	www.globenewswire.com	1.19	www.explica.co	4.12	news.yahoo.com	4.88	www.rttnews.com	1.23	www.wfmz.com	7.66
www.theregister.co.uk	0.15	www.indiaeconomics.webnewswire.com	0.5	www.thesouthafrican.com	0.58	upnewsinfo.com	1.1	recentlyheard.com	3.88	www.stl.news	4.64	www.business2community.com	1.21	investorplace.com	7.55
mashable.com	0.15	business.financialpost.com	0.43	thenextweb.com	0.56	seekingalpha.com	1.08	www.fxstreet.com	3.82	u.today	4.64	www.marketbeat.com	1.19	www.fxstreet.com	7.55
www.foxbusiness.com	0.15	bizwatchnigeria.ng	0.43	business.financialpost.com	0.54	nairametrics.com	1.06	www.bullfrag.com	3.71	www.cryptopolitan.com	4.36	www.globenewswire.com	1.19	news.yahoo.com	7.23
www.moneycontrol.com	0.15	news.yahoo.com	0.41	www.newswire.ca	0.5	www.thebulletintime.com	0.97	www.finanznachrichten.de	3.65	www.outlookindia.com	4.29	forextv.com	1.14	www.thewhig.com	7.18
www.prweb.com	0.13	www.ibtimes.com	0.39	www.finyear.com	0.47	ca.sports.yahoo.com	0.91	www.marketscreener.com	3.5	themerkle.com	3.73	www.cryptopolitan.com	1.12	www.mexc.com	6.8
catallaxyfiles.com	0.13	www.businessinsider.sg	0.39	finance.yahoo.com	0.43	fusionscienceacademy.com	0.88	news.yahoo.com	3.39	www.marketbeat.com	3.56	seekingalpha.com	1.01	hackernoon.com	6.67
Panel B: Fraction of tokens covered by at least one newspaper for each year)														Fraction of tokens covered by at least one newspaper for all years	
0.02		0.14		0.15		0.16		0.29		0.48		0.11		0.56	
Panel C: Number of newspapers that publish articles written about at least a cryptocurrency															
353		555		562		875		1978		2118		853		3561	

Table 2: Summary Statistics of Newspaper Coverage: Conditional Coverage Statistics for All Cryptocurrencies ever listed on CoinMarketCap
This table presents summary statistics for the newspaper coverage of all cryptocurrencies in our sample. The top 30 cryptocurrencies that receive the most newspaper coverage are reported for each year and for all the years.

Conditional coverage statistics (Number of articles per covered token for each year)														Number of articles per covered token for all years	
2017		2018		2019		2020		2021		2022		2023 (January - March)		All years	
BTC	860	BCH	3395	LTC	4850	BTC	10846	BTC	122082	BTC	143045	BTC	42919	BTC	326135
ETH	355	DIS	2103	BCH	4467	ETH	8466	ETH	95951	ETH	72298	ETH	35536	ETH	216729
CTO	282	BTC	2075	BTC	4300	TRX	5039	DOGE	44139	USDT	39836	USDT	18496	GLOBE	109427
LTC	238	MIOTA	1140	DIS	4108	XLM	4854	ADA	41441	GLOBE	37080	DOGE	15997	DOGE	96240
DIS	231	LTC	1093	ETH	3097	CTO	4486	SHIB	21508	SHIB	34251	SHIB	15953	USDT	75767
LG	223	ETH	1026	TRX	2009	LTC	4332	SOL	14558	DOGE	34202	SOL	14647	SHIB	71712
BCH	209	CTO	985	XLM	1948	BSV	3472	LTC	13780	USDC	29624	LTC	13868	DIS	68041
GLOBE	117	ONT	940	CTO	1715	BCH	3409	USDT	13545	SOL	21730	GLOBE	13470	ADA	65752
CO2	95	CO2	764	CO2	1549	BAT	2780	LINK	11048	DIS	20927	USDC	6890	LTC	52558
XMR	66	MUSK	731	BSV	1284	USDT	2427	MATIC	10534	ADA	19190	MN	3675	SOL	51106
BITS	51	VET	693	XMR	1249	PLF	2205	CAKE	10460	LUNA	17026	OMNIA	3311	USDC	45113
CRM	47	XLM	665	KBC	1079	VET	2116	XLM	8597	MATIC	16925	KILT	3308	MATIC	28939
BNT	46	MN	620	LINK	943	LINK	2087	KFX	8586	LTC	14396	KITTY	3184	BCH	28865
BITCF	38	TRX	558	USDT	910	CO2	1999	KSM	8370	LINK	11972	ZOOT	3184	LINK	26903
BAT	36	USDT	533	AOA	873	XMR	1809	AVAX	8240	BUSD	9552	QANX	3179	CTO	25718
MEDIA	36	XMR	373	MN	748	RKT	1696	MKR	8038	NEW	9068	ADA	2984	NEW	23560
ZEC	32	XVG	369	VET	659	MIN	1593	BCH	7751	CTO	8981	LNR	2552	LUNA	22514
GNO	31	SYS	304	MUSK	639	ADA	1567	CTO	7717	BCH	8939	LEGO	2413	TRX	19979
KFC	26	ZIL	284	CAN	577	XTZ	1461	HOT	7386	AVAX	8710	DIS	2328	XLM	19882
SIE	25	KFC	270	BAT	481	ZEC	1367	USDC	7368	FTT	8679	CTO	1548	BSV	18395
MN	23	BSD	234	SOC	457	ATOM	1350	FIL	7344	MN	8002	MATIC	1480	AVAX	18238
TSL	23	MAN	227	MKR	455	BECN	1348	AXS	7283	ICP	7175	HBAR	1396	BUSD	18109
APO	22	CAN	223	ADVT	444	SLS	1340	BUSD	7278	BSV	6790	AGIX	1293	MN	16205
REP	21	XEM	202	ZEC	433	DOGE	1295	WBNB	6767	FIL	6383	AXS	1201	FTT	15304
USDT	20	ISL	199	XTZ	415	OMG	1256	OMG	6609	TRX	5790	777	1125	FIL	14455
B2X	19	DOGE	196	DOGE	404	COMP	1236	MANA	6479	WTRX	5616	AVAX	1115	AXS	14004
SSD	18	CWXT	191	HT	394	NEW	1162	NEW	6279	WADA	5533	CRO	1115	CO2	13823
HMQ	16	CREVA	190	COMP	385	XVG	1160	KLAY	6249	AXS	5482	T	1044	MANA	13046
TNT	16	LDOGE	185	ADA	381	WBTC	1082	BSV	6141	MANA	5333	ALGO	988	XMR	12877
UBI	15	FRWC	183	HPB	341	ONT	1073	HT	5978	FTM	5314	GT	929	ATOM	12761
No. of tokens[a]	181	1121		1216		1290		2398		3873		869		4636	
Mean No. of articles:	24.00	62.26		103.53		397.00		927.95		495.86		430.52		1128.81	
Median No. of articles:	3.00	23.00		57.50		294.00		319.50		31.00		197.00		36.00	

[a] *No. of tokens* is the number of tokens mentioned in at least one article. *Mean No. of articles* is the average number of articles per covered token. *Median No. of articles* is the median number of articles per covered token.

Table 3: Determinants of Media Coverage: All Cryptocurrencies ever listed on CoinMarketCap

This table reports the fixed-effect panel regression results on the determinants of media coverage. The dependent variable is the logarithm of one plus the number of news articles written about a cryptocurrency in a given week. The independent variables are defined in Table S.I.1. (Only cryptocurrencies mentioned in at least 100 news articles throughout the sample period are included.) t-statistics based on standard errors adjusted for weak contemporaneous, lagged cross-cryptocurrency, and temporal correlations using Driscoll and Kraay's (1998) HAC estimator are shown in parentheses. The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent variable: $\log(1 +$ number of articles per week$)$			
Constant	−3.3068***	−3.3030***	−3.0272***
	(−3.7126)	(−4.2920)	(−4.0453)
AMCAP	0.3638***	0.3379***	0.3327***
	(6.2613)	(6.6598)	(6.5382)
VOLSCALED	0.0507***	0.0213	0.0180
	(3.3299)	(1.2613)	(1.1015)
RETVOL	0.0641***	0.0008	0.0006
	(2.6512)	(0.9081)	(0.7141)
IDIOVOL	−0.0582**	−0.0005	−0.0006
	(−2.4536)	(−0.5534)	(−0.7402)
MAXRET	−0.0029***	−0.0002*	
	(−5.4905)	(−1.7761)	
DAMIHUD	−0.0000***	−0.0000**	−0.0000***
	(−7.1981)	(−2.5338)	(−2.9726)
VaR	1.3042***	1.4043***	
	(5.3021)	(4.8274)	
$r\ 1,0$	0.0018***		
	(6.1151)		
$r\ 2,0$	−0.0007***		
	(−5.3007)		
$r\ 3,0$	−0.0002***		
	(−2.9561)		
$r\ 4,0$	0.0002		
	(1.4029)		
$r\ 8,0$	−0.0000		
	(−0.2824)		
$r\ 16,0$	−0.0001		
	(−1.5499)		
$r\ 50,0$	−0.0000		
	(−1.3595)		
$r\ 100,0$	−0.0000***		
	(−4.4258)		
$r\ 4,1$	−0.0003		
	(−1.5369)		
NPAST52	0.0000		
	(0.3773)		
BETA	−0.0046***	−0.0001*	−0.0001
	(−4.8553)	(−1.6635)	(−1.5799)
BETA2	0.0000***	0.0000*	0.0000*
	(2.9719)	(1.8743)	(1.7636)
No. of tokens	1409	1409	1409
Sample size	128416	128416	128416
R^2	0.1014	0.0804	0.0727

4 Media Coverage and the Cross-section of Cryptocurrency Returns

This section explores the relation between media coverage and returns for cryptocurrencies by employing the same procedure used in Fang and Peress (2009). We use the following two samples of cryptocurrencies downloaded from CoinMarketCap: (a) a sample of all active and inactive tokens and (b) a sample of currently active tokens. Media coverage of token i in week t is measured by the number of news articles mentioning about this token during week t.

4.1 Bivariate Sorting Analysis

4.1.1 Returns before Transaction Costs

At the end of each week (also referred to as the portfolio formation week), we first sort the tokens into terciles by the cryptocurrency characteristics (such as market capitalization or past one-week return, etc.) listed in Table S.I.1 one at a time. (Note at this point that we use the following selection criterion to form portfolios throughout this paper: a token is included during the portfolio formation week if its average market capitalization is at least one million during this week while its name and symbol are mentioned in at least 100 articles throughout the sample period.) Next, we sort tokens in each of these characteristic-based terciles by their media coverage into three equally weighted portfolios: *no coverage*, *low coverage*, and *high coverage* (cryptocurrencies with no media coverage are first identified, then the remaining cryptocurrencies are sorted into low- and high-coverage groups by the median number of articles per covered token.) We also form a zero-investment portfolio that longs tokens with no media coverage and shorts tokens with high media coverage during the week. We then calculate the buy-and-hold returns of these three media-based portfolios and the long-short portfolio using individual cryptocurrency returns for the following week (which is also referred to as the holding week). As a result, we obtain a time series of weekly returns for each portfolio. We then compute the average weekly return and its t-statistics for each of those four portfolios. Note that, throughout this paper, we trim out 1% extremely low or high weekly returns before calculating the mean to reduce biases because certain cryptocurrencies may experience a huge day-to-day price increase/decrease within a week (e.g., the return of Shiba Inu on 1/30/2021 was over 580%), and these tokens can then dominate the entire equally weighted portfolio.

Table 4 reports the average portfolio returns before transaction costs, their *t*-statistics, and the average number of cryptocurrencies in each media-based portfolio constructed with the full sample of both active and inactive tokens. The first row shows that unconditionally, the average weekly returns for tokens with no-, low-, and high-media coverage are 4.08%, 2.25%, and 1.46%, respectively. The difference between the no- and high-coverage portfolio returns is a statistically significant and economically meaningful 2.61% per week (approximately 282% per year).[4] Therefore, sorting cryptocurrencies by media coverage generates a significant premium associated with no-coverage tokens. This finding is also consistent with Fang and Peress's (2009) finding that no-coverage stocks tend to yield a higher average return than high-coverage stocks. The double-sorts to control for cryptocurrency characteristics one at a time generally produce positive return differences between no-coverage tokens and high-coverage tokens across characteristic-based terciles. These positive return differentials are statistically significant in the following characteristic-based terciles: (a) the terciles of tokens with small or medium market capitalization (MCAP), which is somewhat consistent with the finding in Fang and Peress (2009); (b) the terciles of tokens with small or medium price volume (PRCVOL); (c) the terciles of tokens with small, medium, or large price volume scaled by market capitalization (VOLSCALED); (d) the terciles of tokens with low or high return volatility (RETVOL); (e) the terciles of tokens with high idiosyncratic volatility (IDIOVOL); (f) the terciles of tokens with small, medium, or large maximum daily return during the portfolio formation week (MAXRET); (g) the terciles of tokens with medium or high illiquidity (DAMIHUD); (h) the terciles of tokens with medium or high Value-at-Risk (VaR); (i) the terciles of tokens with low, medium, or high returns during the past one- to eight- weeks ($r\ 1,0$, $r\ 2,0$, $r\ 3,0$, $r\ 4,0$, $r\ 4,1$, or $r\ 8,0$); (j) the terciles of tokens with medium or high returns during the past 16- or 50- week ($r\ 16,0$ or $r\ 50,0$); (k) the terciles of tokens with low or high returns in the past 100-week ($r\ 100,0$); (l) the tercile of tokens with low negative past 52-week return (NPAST52); (m) the tercile of tokens with low beta (BETA); (n) terciles of tokens with low or medium squared beta (BETA2).

Therefore, the no-coverage premium seems to persist among cryptocurrencies sorted by various characteristics one at a time. This premium is statistically significant mostly in terciles of small tokens, or illiquid tokens, or tokens with high volatility, or tokens with low beta. The no-coverage premium de-

[4] We use the following formula: Annualized return $=$ (weekly return $+\ 1)^{52} - 1$ as there are about 52 weeks per year.

creases for large tokens, liquid tokens, tokens with low volatility, or tokens with high beta. Therefore, the media effect in the cross-section of cryptocurrency returns is, unlike stock returns, mainly driven by size, liquidity, and volatility. The no-coverage premium seems to be independent of the past performance of a cryptocurrency. This is consistent with the finding in Fang and Peress (2009) that stocks without news outperform stocks with news, regardless of their past month returns.

We also repeat the same sorting exercise while skipping a week between the portfolio formation period and the holding period. As suggested in Jegadeesh and Titman (1993), by skipping a week, we can avoid some of the bid-ask spread, price pressure, and lagged reaction effects that may influence the predictability of returns. Table 5 confirms most of the evidence reported in Table 4. The first row in Table 5 shows that unconditionally, the average weekly returns on tokens with no-, low-, and high-media coverage are 4.65%, 2.21%, and 1.60%, respectively. The difference between the no- and high-coverage portfolio returns is a statistically significant and economically meaningful 3.06% per week (approximately 379% per year) on average. The double-sorts controlling for other cryptocurrency characteristics one at a time also generate statistically significant and positive average return differences between no-coverage tokens and high-coverage tokens in most cases. These results are quite similar to those reported in Table 4.

4.1.2 Returns after Transaction Costs

Table 6 reports the average weekly turnover and transaction cost (defined in Section A.II) of an equally weighted portfolio invested in no-coverage tokens, an equally weighted portfolio invested in high-coverage tokens, and the long-short portfolio [that longs no-coverage tokens and shorts high-coverage tokens] as well as the net-of-costs return of this long-short media-based portfolio. The first row shows that the average weekly turnovers of tokens with no- and high-media coverage are 19.67% and 79.27%, respectively. This result is interesting as the portfolio of no-coverage tokens requires less rebalancing than that of high-coverage tokens, although the average numbers of tokens in those two portfolios are roughly the same (there are 168.55 no-coverage tokens and 175.08 high-coverage tokens on average, as seen in the first row of Table 4). A possible explanation for this low rebalancing of the portfolio of no-coverage tokens is that these tokens, which are often small or less liquid, are more likely to remain uncovered in a week if they were uncovered in the week before so that rebalancing is minimum. High-coverage tokens tend to have a larger market capitalization and higher trading volume, thus their media coverage can vary week after week so that frequent rebalancing is needed. The long-short portfolio thus has a high turnover (103.22%) mostly coming from the short leg. The average weekly transaction costs of tokens with no- and high-media coverage are 93 and 373 basis points, respectively (the long-short media-based portfolio then incurs an average transaction cost of 487 basis points). Therefore, the cost to trade high-coverage tokens is over three times more than the cost to trade no-coverage tokens. Hence, the long-short media-based portfolio has a negative average net-of-costs return of -2.25% per week (approximately -69.3% per year, t-statistic = -3.40). However, the long-only media-based portfolio generates an average net-of-costs return of 3.15% per week (approximately $(0.0315 + 1)^{52} - 1 \approx 402\%$ per year, t-statistic = 2.96 [not tabulated])

We also find that it costs more to trade an equally weighted portfolio of high-coverage tokens than that of no-coverage tokens across characteristic-based terciles. Moreover, Table 6 shows that the long-short media-based portfolio has a highly negative average return net of transaction costs in the tercile of tokens with (a) large MCAP (because the average return of this portfolio is lower in this tercile as seen in Table 4); (b) medium or high PRCVOL; (c) low or medium RETVOL (or IDIOVOL); (d) low or medium past returns (e.g., low or medium MAXRET, $r\ 2,0$, $r\ 3,0$, $r\ 4,0$, $r\ 4,1$, $r\ 8,0$, $r\ 16,0$, $r\ 50,0$, $r\ 100,0$); (e) low or medium DAMIHUD; (f) low or medium VaR; or (g) medium or high BETA, largely due to the low average returns of the long-short media-based portfolio in those terciles.

Given the average returns reported in Table 4, we also find that the long-only media-based portfolio generates a statistically significant and positive average net-of-costs return [not reported] in the tercile of tokens with (a) small MCAP (3.63% per week, t-statistic = 2.75) or medium MCAP (3.12% per week, t-statistic = 2.10); (b) low PRCVOL (4.47% per week, t-statistic = 2.89); (c) high RETVOL (4.71% per week, t-statistic = 2.72) or IDIOVOL (4.24% per week, t-statistic = 2.27); (d) high past returns (for example, MAXRET: 4.16% per week, t-statistic = 2.57 or $r\ 2,0$: 3.41% per week, t-statistic = 2.55); (e) high DAMIHUD (4.84% per week, t-statistic = 3.04); (f) high VaR (3.95% per week, t-statistic = 2.96); or (g) low BETA (3.74% per week, t-statistic = 2.42). These results are interesting as transaction cost does not eliminate the mispricings due to trading small or less liquid tokens, or tokens with high risk/volatility. Another possibility is that Hasbrouck's (2009) Gibbs bid-ask spread estimator that we use to estimate the transaction cost for each cryptocurrency underestimates the true trading costs. In the cryptocurrency market, the bid-ask spread is generally negligible compared to the exchange fees [e.g., Aleti and Mizrach (2021)].

We also check for the robustness of the results reported in this section by performing the same sorting analysis using (i) all [active and inactive] cryptocurrencies with one week skipped in between the portfolio formation week and the holding week, and (ii) only currently active cryptocurrencies. The results of these robustness checks are reported in Section S.III.1.

Table 4: Newspaper Coverage and Cryptocurrency Returns before Transaction Costs: All Cryptocurrencies ever listed on CoinMarketCap

This table reports average weekly returns for tokens with no-, low-, and high-media coverage. At the end of each week, we divide our sample of cryptocurrencies into three media-based portfolios: no media coverage, low media coverage, and high media coverage. Media coverage of a token is measured by the number of newspaper articles written about that token, and the median is used to divide the covered tokens into low and high groups. We then compute the average returns of the three media-based portfolios and the difference between the *no coverage* portfolio return and the *high coverage* portfolio return using individual cryptocurrency returns during the holding week. All the portfolios are equally weighted. We also compute the return differentials for the subsamples of cryptocurrencies sorted by cryptocurrency characteristics defined in Table S.I.1 one at a time. Note that a cryptocurrency is included if its market capitalization is at least one million during the portfolio formation week while its name and symbol are mentioned in at least 100 articles throughout the sample period. All t-statistic values use the Newey-West standard error.

	Average weekly returns (%)				t-statistics for No - High	Average number of tokens		
	Media coverage					Media coverage		
	No	Low	High	No - High		No	Low	High
All tokens	4.08	2.25	1.46	2.61	3.90	168.55	190.99	175.08
Sort by MCAP								
0	4.82	2.96	1.49	3.33	3.08	56.31	66.98	59.92
1	4.29	1.31	1.57	2.72	1.71	63.78	94.35	85.43
2	1.09	0.52	0.97	0.12	0.51	32.54	77.92	72.88
Sort by AMCAP								
0	4.91	3.56	1.59	3.32	2.98	56.46	66.68	60.09
1	4.33	1.04	1.44	2.89	1.88	63.88	94.10	85.60
2	0.82	0.69	0.90	−0.08	−0.32	32.58	77.94	72.87
Sort by PRCVOL								
0	5.80	3.08	2.10	3.69	2.97	51.67	67.54	60.49
1	2.21	0.61	0.89	1.32	2.56	61.85	93.09	84.83
2	0.79	0.38	0.54	0.26	1.06	36.77	74.05	69.33

Continued on next page

Table 4 (continued): Newspaper Coverage and Cryptocurrency Returns before Transaction Costs: All Cryptocurrencies ever listed on CoinMarketCap

	Average weekly returns (%)				t-statistics for No - High	Average number of tokens		
	Media coverage					Media coverage		
	No	Low	High	No - High		No	Low	High
				Sort by VOLSCALED				
0	5.47	3.07	2.32	3.15	2.80	50.26	67.15	60.56
1	1.89	0.72	0.98	0.91	2.56	62.38	91.23	83.78
2	1.28	0.50	0.39	0.88	2.20	40.14	71.67	66.52
				Sort by RETVOL				
0	2.11	0.89	0.67	1.44	2.30	48.87	65.37	59.93
1	1.78	1.11	1.39	0.39	1.06	63.91	87.32	79.96
2	6.49	3.02	0.84	5.65	3.86	51.82	63.20	57.81
				Sort by IDIOVOL				
0	1.19	0.70	0.56	0.63	1.49	30.21	54.78	51.10
1	1.60	0.69	1.15	0.46	0.93	44.29	70.98	64.98
2	6.00	2.80	1.24	4.77	3.01	36.65	51.65	46.79
				Sort by MAXRET				
0	2.07	0.63	0.59	1.48	2.29	49.71	63.80	58.50
1	2.25	1.09	1.24	1.01	1.84	65.33	85.04	77.70
2	6.03	3.31	1.21	4.82	3.60	52.40	61.85	56.52
				Sort by DAMIHUD				
0	0.97	0.59	0.78	0.20	0.84	35.82	76.40	71.66
1	2.00	0.41	0.67	1.33	2.32	62.88	94.34	85.86
2	6.11	5.33	2.12	3.99	2.72	54.07	67.10	60.33
				Sort by VaR				
0	1.93	0.58	0.82	1.11	1.97	41.43	67.33	62.18
1	1.73	0.80	0.79	0.94	2.43	57.97	88.99	81.19
2	5.21	3.03	2.5	2.71	2.25	50.34	63.38	57.51
				Sort by r $1,0$				
0	2.73	1.11	0.35	2.38	3.34	51.33	63.77	57.78
1	2.75	1.22	0.74	2.01	3.23	64.82	86.07	78.50
2	4.09	2.44	1.44	2.65	2.49	50.49	63.64	57.71
				Sort by r $2,0$				
0	2.64	1.48	0.48	2.17	3.89	50.96	63.59	57.67
1	2.55	1.36	0.91	1.64	3.57	65.00	85.48	78.03
2	5.14	3.35	1.87	3.27	2.56	50.46	63.03	57.69

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Table 4 (continued): Newspaper Coverage and Cryptocurrency Returns before Transaction Costs: All Cryptocurrencies ever listed on CoinMarketCap

	Average weekly returns (%)				t-statistics for No - High	Average number of tokens		
	Media coverage					Media coverage		
	No	Low	High	No - High		No	Low	High
Sort by r $3,0$								
0	1.91	2.49	0.68	1.23	2.56	50.61	63.58	58.31
1	2.29	0.87	0.92	1.37	2.37	64.06	85.90	78.88
2	6.07	2.97	1.19	4.88	3.73	50.68	62.95	57.86
Sort by r $4,0$								
0	2.63	1.73	0.63	2.00	3.32	50.30	63.45	57.93
1	2.84	0.88	0.93	1.91	2.90	64.07	85.53	78.22
2	4.80	2.37	1.33	3.48	3.28	50.70	62.57	57.33
Sort by r $4,1$								
0	3.17	1.75	1.02	2.15	2.88	50.38	63.56	57.91
1	2.53	1.12	1.05	1.48	2.13	63.63	85.62	78.83
2	4.11	1.31	0.93	3.17	3.86	50.45	62.83	57.56
Sort by r $8,0$								
0	3.74	2.28	1.57	2.17	3.28	49.52	62.57	56.22
1	2.19	0.77	0.94	1.25	2.32	61.66	84.34	77.35
2	4.97	2.52	1.50	3.47	3.29	49.24	61.86	56.28
Sort by r $16,0$								
0	2.52	1.88	1.61	0.91	1.43	45.89	62.07	56.68
1	2.60	0.90	1.03	1.57	2.87	57.57	83.62	77.40
2	3.63	1.43	1.09	2.54	2.49	47.08	60.82	55.80
Sort by r $50,0$								
0	1.88	1.98	0.99	0.89	1.12	34.99	50.93	46.09
1	2.09	1.15	0.99	1.10	1.87	41.90	69.25	63.57
2	3.30	0.79	0.73	2.57	2.40	34.81	49.84	46.02
Sort by r $100,0$								
0	5.65	3.42	2.49	3.15	2.16	23.04	43.24	39.65
1	1.47	1.77	1.34	0.13	0.22	27.79	58.40	53.87
2	7.57	1.85	0.68	6.90	2.11	20.41	43.88	40.67
Sort by NPAST52								
0	3.57	1.03	0.82	2.74	1.74	34.38	49.98	46.57
1	1.57	0.72	0.82	0.75	1.42	41.11	69.14	63.43
2	1.83	2.05	1.10	0.72	0.86	34.17	50.56	45.53

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Table 4 (continued): Newspaper Coverage and Cryptocurrency Returns before Transaction Costs: All Cryptocurrencies ever listed on CoinMarketCap

	Average weekly returns (%)				t-statistics for No - High	Average number of tokens		
	Media coverage					Media coverage		
	No	Low	High	No - High		No	Low	High
Sort by BETA								
0	4.94	1.75	0.78	4.16	3.00	38.14	49.60	44.81
1	1.16	0.97	0.87	0.28	0.96	45.16	67.87	62.46
2	1.65	1.59	1.54	0.11	0.21	30.57	52.65	48.37
Sort by BETA2								
0	3.74	1.33	0.67	3.07	3.39	37.24	49.84	45.49
1	1.60	0.96	0.77	0.82	2.02	45.12	67.95	62.41
2	2.56	2.09	1.72	0.84	1.04	31.52	52.17	47.90

Table 5: Newspaper Coverage and Cryptocurrency Returns before Transaction Costs (Skipping a Week between the Portfolio Formation Week and the Holding Week): All Cryptocurrencies ever listed on CoinMarketCap

This table reports average weekly returns for tokens with no-, low-, and high-media coverage. At the end of each week, we divide our sample of cryptocurrencies into three media-based portfolios: no media coverage, low media coverage, and high media coverage. Media coverage of a token is measured by the number of newspaper articles written about that token, and the median is used to divide the covered tokens into low and high groups. We then compute the average returns of the three media-based portfolios and the difference between the *no coverage* portfolio return and the *high coverage* portfolio return using individual cryptocurrency returns during the holding week. All the portfolios are equally weighted. We also compute the return differentials for the subsamples of cryptocurrencies sorted by cryptocurrency characteristics defined in Table S.I.1 one at a time. Note that a cryptocurrency is included if its market capitalization is at least one million during the portfolio formation week while its name and symbol are mentioned in at least 100 articles throughout the sample period. All t-statistic values use the Newey-West standard error.

	Average weekly returns (%)				t-statistics for No - High	Average number of tokens		
	Media coverage					Media coverage		
	No	Low	High	No - High		No	Low	High
All tokens	4.65	2.21	1.60	3.06	3.66	167.42	191.07	175.13
Sort by MCAP								
0	6.89	3.51	1.73	5.16	3.01	55.56	67.20	60.13
1	4.20	1.31	1.43	2.77	2.21	63.09	94.54	85.60
2	1.06	0.84	1.27	–0.21	–0.48	32.57	77.75	72.79
Sort by AMCAP								
0	6.97	3.65	1.85	5.12	3.06	55.72	66.90	60.30
1	3.85	1.04	1.69	2.16	1.65	63.18	94.29	85.78
2	1.19	1.08	1.07	0.12	0.52	32.62	77.78	72.77
Sort by PRCVOL								
0	6.36	3.83	2.81	3.55	2.21	51.00	67.74	60.66
1	2.01	0.98	1.03	0.98	2.37	61.34	93.21	84.93
2	1.23	0.69	0.80	0.43	2.03	36.62	74.02	69.28

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Table 5 (continued): Newspaper Coverage and Cryptocurrency Returns before Transaction Costs (Skipping a Week between the Portfolio Formation Week and the Holding Week): All Cryptocurrencies ever listed on CoinMarketCap

	Average weekly returns (%)				t-statistics for No - High	Average number of tokens		
	Media coverage					Media coverage		
	No	Low	High	No - High		No	Low	High
Sort by VOLSCALED								
0	7.02	3.65	2.23	4.80	2.54	49.69	67.29	60.69
1	1.58	0.76	1.08	0.50	1.45	61.88	91.33	83.88
2	1.09	0.52	0.57	0.52	1.96	39.92	71.67	66.51
Sort by RETVOL								
0	2.23	0.99	0.93	1.30	2.50	48.48	65.43	59.99
1	2.52	1.43	1.05	1.47	2.17	63.49	87.36	79.99
2	5.86	3.63	1.61	4.25	3.50	51.37	63.26	57.88
Sort by IDIOVOL								
0	1.98	1.11	1.04	0.94	1.72	29.87	54.74	51.07
1	2.90	1.76	1.44	1.46	2.30	43.71	71.01	65.00
2	9.05	4.31	2.30	6.75	2.78	36.09	51.71	46.86
Sort by MAXRET								
0	2.32	0.94	0.82	1.50	2.21	49.34	63.85	58.55
1	2.01	1.38	1.33	0.67	0.95	64.93	85.05	77.74
2	5.78	2.91	1.07	4.71	3.95	51.95	61.92	56.58
Sort by DAMIHUD								
0	0.99	0.94	0.97	0.02	0.09	35.73	76.33	71.61
1	1.74	0.77	1.03	0.71	1.91	62.27	94.51	86.00
2	8.92	4.09	2.51	6.41	2.65	53.39	67.27	60.49
Sort by VaR								
0	1.64	0.42	0.77	0.87	1.75	41.08	67.37	62.22
1	1.61	0.90	0.74	0.87	2.75	57.55	89.02	81.22
2	6.07	3.44	1.88	4.19	3.02	49.75	63.50	57.63
Sort by r 1, 0								
0	2.25	1.59	0.69	1.55	2.49	50.94	63.82	57.83
1	4.07	1.17	1.13	2.93	3.31	64.40	86.11	78.54
2	3.83	2.74	2.08	1.76	2.05	50.08	63.71	57.75
Sort by r 2, 0								
0	2.28	2.18	0.64	1.64	3.00	50.53	63.67	57.72
1	3.22	0.76	0.81	2.41	3.19	64.60	85.51	78.05
2	6.24	1.97	1.89	4.35	2.99	50.06	63.08	57.74

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Table 5 (continued): Newspaper Coverage and Cryptocurrency Returns before Transaction Costs (Skipping a Week between the Portfolio Formation Week and the Holding Week): All Cryptocurrencies ever listed on CoinMarketCap

	Average weekly returns (%)				t-statistics for No - High	Average number of tokens		
	Media coverage					Media coverage		
	No	Low	High	No - High		No	Low	High
Sort by r 3, 0								
0	2.89	1.25	1.09	1.80	3.09	50.14	63.67	58.38
1	3.58	0.99	0.91	2.67	3.15	63.70	85.92	78.88
2	4.22	1.99	1.64	2.58	2.77	50.26	63.01	57.93
Sort by r 4, 0								
0	3.07	2.23	0.75	2.32	3.91	49.90	63.49	57.97
1	2.90	1.33	1.16	1.74	2.39	63.65	85.57	78.25
2	4.87	2.35	1.52	3.35	2.87	50.27	62.65	57.39
Sort by r 4, 1								
0	2.98	1.37	1.14	1.84	2.54	50.01	63.61	57.94
1	3.41	1.31	1.14	2.27	2.78	63.20	85.66	78.87
2	4.30	1.50	1.19	3.10	2.40	50.00	62.90	57.62
Sort by r 8, 0								
0	4.03	2.03	1.27	2.76	3.79	49.16	62.60	56.24
1	2.35	1.32	1.13	1.22	3.26	61.22	84.36	77.38
2	6.40	1.83	1.51	4.89	2.68	48.77	61.94	56.36
Sort by r 16, 0								
0	2.36	1.89	1.28	1.08	1.87	45.50	62.12	56.73
1	2.64	1.12	1.19	1.44	2.81	57.13	83.64	77.41
2	6.42	1.73	1.43	5.00	2.91	46.62	60.89	55.86
Sort by r 50, 0								
0	2.96	1.85	1.41	1.56	2.19	34.52	50.95	46.11
1	2.61	1.31	0.90	1.71	2.93	41.38	69.24	63.56
2	4.77	1.56	0.68	4.10	3.43	34.37	49.85	46.04
Sort by r 100, 0								
0	3.99	2.86	2.64	1.35	1.09	22.43	43.33	39.75
1	1.82	1.88	1.30	0.51	0.85	27.19	58.42	53.89
2	13.39	2.54	0.90	12.48	2.82	20.01	43.87	40.66
Sort by NPAST52								
0	3.64	1.63	0.68	2.96	3.17	33.93	49.97	46.59
1	2.67	1.17	0.79	1.88	3.16	40.60	69.14	63.42
2	4.50	1.74	1.65	2.85	1.39	33.66	50.59	45.57
Sort by BETA								
0	5.98	2.55	1.15	4.82	3.20	37.62	49.65	44.86
1	1.35	0.79	0.90	0.45	1.16	44.58	67.90	62.48
2	2.78	2.13	1.30	1.48	2.52	30.25	52.60	48.33
Sort by BETA2								
0	4.55	1.65	0.86	3.69	2.95	36.71	49.89	45.53
1	1.49	0.79	0.92	0.56	1.43	44.54	67.97	62.43
2	4.53	2.91	1.59	2.94	2.75	31.19	52.12	47.86

Table 6: Newspaper Coverage, Turnovers, Transaction Costs, and Long-short Cryptocurrency Returns Net of Transaction Costs: All Cryptocurrencies ever listed on CoinMarketCap

This table presents average weekly turnovers, transaction costs, and returns net of costs for tokens with no- and high-media coverage. At the end of each week, we divide our sample of cryptocurrencies into three media-based portfolios: no media coverage, low media coverage, and high media coverage. Media coverage of a token is measured by the number of newspaper articles written about this token, and the median is used to divide the covered tokens into low and high groups. All the portfolios are equally weighted. We then compute the average returns of the three media-based portfolios (and the turnover and transaction cost of the no- and high-coverage portfolios and their long-short portfolio) using individual cryptocurrency returns in the holding week. We also compute the average weekly turnovers, transaction costs, and returns net of costs for the subsamples of tokens sorted by cryptocurrency characteristics defined in Table S.I.1 one at a time. Note that a cryptocurrency is included if its market capitalization is at least one million during the portfolio formation week while its name and symbol are mentioned in at least 100 articles throughout the sample period. All t-statistic values use the Newey-West standard error.

	Average weekly turnover (%)			Average weekly transaction cost (%)			Average weekly returns net of transaction costs for No - High (%)	t-statistics of net-of-costs returns for No - High
	Media coverage			Media coverage				
	No	High	No - High	No	High	No-High		
All tokens	19.67	79.27	103.22	0.93	3.73	4.87	−2.25	−3.40
Sort by MCAP								
0	25.08	68.69	99.93	1.18	3.24	4.72	−1.39	−1.29
1	24.56	71.18	101.60	1.16	3.36	4.79	−2.07	−1.30
2	20.04	83.73	105.06	0.94	3.95	4.95	−4.83	−20.22
Sort by AMCAP								
0	25.09	69.42	100.87	1.18	3.28	4.76	−1.44	−1.29
1	24.46	71.64	101.80	1.15	3.38	4.80	−1.91	−1.24
2	19.89	83.69	104.88	0.94	3.95	4.94	−5.02	−20.27
Sort by PRCVOL								
0	27.99	68.82	104.24	1.32	3.25	4.92	−1.22	−0.99
1	24.35	71.18	100.50	1.15	3.36	4.74	−3.42	−6.61
2	20.60	82.10	104.26	0.97	3.87	4.92	−4.66	−18.68
Sort by VOLSCALED								
0	27.45	69.89	103.84	1.29	3.30	4.90	−1.75	−1.58
1	24.65	72.59	102.03	1.16	3.43	4.81	−3.90	−10.83
2	22.00	80.61	104.41	1.04	3.79	4.92	−4.04	−9.84
Sort by RETVOL								
0	34.52	68.63	104.17	1.63	3.23	4.92	−3.48	−5.50
1	36.41	62.63	100.91	1.72	2.95	4.76	−4.37	−11.57
2	37.61	61.67	102.45	1.77	2.90	4.83	0.82	0.56
Sort by IDIOVOL								
0	36.08	72.18	108.85	1.70	3.39	5.13	−4.50	−10.36
1	37.25	62.39	101.50	1.76	2.94	4.79	−4.33	−8.76
2	37.32	62.25	102.88	1.76	2.94	4.85	−0.09	−0.06
Sort by MAXRET								
0	37.27	65.68	103.95	1.76	3.09	4.90	−3.43	−5.33
1	36.38	61.62	100.03	1.72	2.91	4.72	−3.71	−6.71
2	39.44	59.94	102.28	1.86	2.83	4.83	−0.01	−0.01

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Table 6 (continued): Newspaper Coverage, Turnovers, Transaction Costs, and Long-short Cryptocurrency Returns Net of Transaction Costs: All Cryptocurrencies ever listed on CoinMarketCap

	Average weekly turnover (%)			Average weekly transaction cost (%)			Average weekly returns net of transaction costs for No - High (%)	t-statistics of net-of-costs returns for No - High
	Media coverage			Media coverage				
	No	High	No - High	No	High	No-High		
Sort by DAMIHUD								
0	22.43	82.21	105.92	1.06	3.88	4.99	–4.80	–18.85
1	26.29	69.68	101.02	1.24	3.29	4.76	–3.43	–6.05
2	26.84	69.39	102.25	1.27	3.28	4.82	–0.84	–0.57
Sort by VaR								
0	22.92	79.80	104.83	1.08	3.76	4.94	–3.83	–6.71
1	25.80	71.79	102.07	1.22	3.39	4.82	–3.89	–9.96
2	26.68	71.08	102.97	1.26	3.33	4.86	–2.15	–1.79
Sort by r 1, 0								
0	41.04	56.27	98.76	1.93	2.66	4.66	–2.28	–3.22
1	35.91	64.31	102.06	1.69	3.04	4.82	–2.81	–4.51
2	42.54	59.63	104.11	2.01	2.81	4.91	–2.26	–2.13
Sort by r 2, 0								
0	35.48	61.57	99.45	1.67	2.88	4.67	–2.51	–4.68
1	34.34	65.68	102.10	1.62	3.10	4.82	–3.18	–6.79
2	36.58	65.21	104.44	1.72	3.07	4.92	–1.65	–1.29
Sort by r 3, 0								
0	33.10	63.16	99.49	1.56	2.98	4.69	–3.46	–7.19
1	32.97	66.99	102.46	1.55	3.16	4.83	–3.46	–5.84
2	33.75	68.69	105.12	1.59	3.23	4.96	–0.08	–0.06
Sort by r 4, 0								
0	31.79	65.28	100.34	1.50	3.07	4.74	–2.74	–4.63
1	31.89	68.61	102.72	1.50	3.22	4.85	–2.94	–4.52
2	31.76	70.48	104.56	1.50	3.31	4.94	–1.46	–1.39
Sort by r 4, 1								
0	33.94	64.04	100.76	1.60	3.01	4.76	–2.60	–3.49
1	33.82	68.02	103.96	1.59	3.20	4.90	–3.42	–4.97
2	33.35	68.49	103.69	1.57	3.22	4.89	–1.72	–2.09

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Table 6 (continued): Newspaper Coverage, Turnovers, Transaction Costs, and Long-short Cryptocurrency Returns Net of Transaction Costs: All Cryptocurrencies ever listed on CoinMarketCap

	Average weekly turnover (%)			Average weekly transaction cost (%)			Average weekly returns net of transaction costs for No - High (%)	t-statistics of net-of-costs returns for No - High
	Media coverage			Media coverage				
	No	High	No - High	No	High	No-High		
				Sort by r 8, 0				
0	29.01	67.29	99.89	1.37	3.16	4.71	–2.54	–3.88
1	29.29	70.38	102.14	1.38	3.31	4.82	–3.57	–6.51
2	28.84	74.09	105.47	1.36	3.48	4.98	–1.51	–1.44
				Sort by r 16, 0				
0	27.70	69.26	101.01	1.31	3.25	4.77	–3.86	–6.04
1	27.81	72.66	103.16	1.31	3.42	4.86	–3.30	–6.02
2	26.60	75.72	105.32	1.25	3.57	4.96	–2.43	–2.43
				Sort by r 50, 0				
0	29.58	71.69	105.88	1.39	3.36	5.00	–4.11	–5.02
1	27.30	74.14	104.12	1.29	3.49	4.92	–3.82	–6.42
2	25.24	78.81	105.70	1.19	3.71	4.99	–2.42	–2.25
				Sort by r 100, 0				
0	33.73	71.26	107.97	1.59	3.37	5.10	–1.94	–1.31
1	27.74	74.42	104.06	1.31	3.51	4.91	–4.78	–7.83
2	26.37	81.56	108.81	1.24	3.84	5.13	1.77	0.54
				Sort by NPAST52				
0	25.35	79.32	106.14	1.20	3.74	5.02	–2.27	–1.44
1	27.07	74.07	103.60	1.28	3.48	4.88	–4.13	–7.63
2	29.76	71.42	105.65	1.40	3.36	4.99	–4.27	–4.97
				Sort by BETA				
0	25.31	76.72	105.24	1.19	3.60	4.97	–0.80	–0.58
1	24.42	77.60	105.15	1.15	3.65	4.96	–4.67	–14.74
2	24.67	77.58	105.68	1.16	3.64	4.99	–4.88	–8.86
				Sort by BETA2				
0	25.79	76.81	105.87	1.22	3.61	5.00	–1.93	–2.10
1	24.31	77.66	105.09	1.15	3.65	4.95	–4.13	–9.76
2	24.83	77.54	105.73	1.17	3.64	5.00	–4.16	–5.24

4.2 Regression Analysis

4.2.1 Abnormal Returns before Transaction Costs

We examine whether the returns of a portfolio, that longs the cryptocurrencies with no media coverage and shorts the cryptocurrencies with high media coverage, can be driven by common risk factors, and whether this long-short media-based portfolio can generate a positive alpha beyond the common risk factors. As described above, the long-short media-based portfolio is constructed as follows: at the end of each week, we divide a sample of cryptocurrencies into no-, low-, and high-media coverage groups. We then calculate the return [in the holding week] on a zero-investment portfolio that longs tokens with no media coverage and shorts tokens with high media coverage. Both the long and short positions are equally weighted. Repeating the same procedure every week, we obtain a time series of returns on this long-short portfolio. We then regress the time-series returns on risk factor returns to estimate the alpha and beta coefficients. If the return of a portfolio is fully explained by the known risk factors, then the estimated alpha should be statistically insignificant. Liu et al. (2022) identifies three risk factors – cryptocurrency market factor (Mkt-RF), size (CSMB), and momemtum (CMOM) – that drive most of the cross-section of expected cryptocurrency returns. (See Section A.III for details on the calculation of the returns and transaction costs of those risk factors.)

Table 7 reports the results obtained by regressing the return of the long-short media-based portfolio [formed using all cryptocurrencies ever listed on CoinMarketCap] on the returns of risk factors (note that Mkt-Rf denotes the cryptocurrency market return in excess of the risk-free rate). The table confirms the earlier finding from the bivariate sorting analysis that there is a before-costs no-coverage premium even after controlling for market, size, and momentum factors. Panel A suggests that the two- or three-factor models seem to explain a small portion of the no-coverage premium, as adding factors only reduces the alpha slightly. For example, the alpha in the three-factor model is 197 basis points, compared to 246 basis points in the market model. Thus, only about 20% of the alpha relative to the market model can be absorbed by CSMB and CMOM. The positive loadings on the risk factors suggest that the no-coverage premium has a positive exposure to all the three risk factors. However, the loading on the cryptocurrency market factor is clearly statistically insignificant in every factor model, suggesting that the no-coverage premium is barely correlated with the excess market return. A possible explanation for this phenomenon is that, as mentioned in Section 4.1, the no-coverage premium is strongest in the group of cryptocurrencies with small market capitalization while the value-weighted cryptocurrency market portfolio is dominated by the two largest tokens (Bitcoin and Ethereum), and many small tokens with no media coverage may not co-move much with Bitcoin and Ethereum. As documented in Section 6 at the end of this paper, the cross-section of cryptocurrencies is strongly driven by size and momentum effects. Therefore, it is not surprising to see that the loadings on CSMB and CMOM are positive and statistically significant. The long-short media-based portfolio thus has a statistically significant and positive exposure to the size and momentum factors.

Panels B and C of Table 7 report the results obtained by regressing the return of the long or short leg of the long-short media-based portfolio on the common risk factors. The findings here are aligned with the study of media effect for equity by Fang and Peress (2009). The no-coverage premium, after controlling for risk factors, is mainly driven by the long positions in the tokens with no media coverage while the tokens with high media coverage do not exhibit significant alphas except for the market model where the alpha is only 82 basis points (compared to 329 basis points in the market model for no-coverage tokens). This asymmetry suggests that neglected cryptocurrencies can yield a significant premium. Moreover, the media effect is unlikely to be caused by individual investors buying attention-grabbing cryptocurrencies as the short positions in the tokens with high media coverage should yield a statistically significant and positive alpha if this is the case. The large R^2 values (over 0.80 for the short leg and 0.49 for the long leg in the three-factor model) indicates that the tokens with high media coverage have a stronger exposure to the cryptocurrency market index, size and momentum factors than the tokens with no media coverage.

Table 8 examines the media effect in the subsamples of all cryptocurrencies [ever listed on CoinMarketCap] sorted by various characteristics listed in Table S.I.1 one at a time. At the end of each week, tokens are first sorted into terciles by the cryptocurrency characteristics one at a time. Then, tokens within each tercile are sorted into three media-based portfolios: no-, low-, and high-media coverage (i.e., the tokens with no media coverage are first identified, and the remaining tokens are divided into low- and high-coverage groups based on the median number of articles written about them). We then form a long-short portfolio by longing the tokens with no media coverage and shorting tokens with high media coverage, and hold this portfolio for the following week. The long and short legs of this portfolio invest equally in each underlying token. The portfolio weights are rebalanced weekly. We then obtain a time series of returns on the long-short media-based portfolio for each characteristic-based tercile. To calculate the alpha for this portfolio, we estimate the three factor models defined in Table 7. When sorting by MCAP, we can see that the media effect is concentrated among small and medium-sized tokens – in the first tercile (including tokens with small MCAP), the alphas for the one-factor, two-factor, and three-factor models are 0.0259, 0.0251, and 0.0262, respectively (and all of them are statistically significant at the 1% level); in the second tercile (including tokens with medium MCAP), the alphas for the one-factor, two-factor, and three-factor models are 0.0289, 0.0294, and 0.0294, respectively (and all of them are statistically significant at the 10% level). The same result holds for tokens sorted by AMCAP. When sorting by PRCVOL, we also see the strongest media effect among cryptocurrencies with low and medium PRCVOL. When sorting by VOLSCALED (which is PRCVOL/MCAP), the media effect still remains the strongest in the first tercile. When sorting by RETVOL, we can see that the media effect is concentrated among cryptocurrencies with high RETVOL – in the third tercile (including tokens with high RETVOL), the alphas for the one-factor, two-factor, and three-factor models are 0.0488, 0.497, and 0.0484, respectively (and all of them are statistically significant at the 1% level). The same phenomenon is also observed among tokens with high IDIOVOL or MAXRET (i.e., only the tokens with high idiosyncratic volatility or maximum daily return in the portfolio formation week receive no-coverage premium). When sorting by illiquidity (measured by DAMIHUD), we observe that the media effect is the strongest among highly illiquid tokens – in the third tercile (including cryptocurrencies with high DAMIHUD), the alphas for the one-factor, two-factor, and three-factor models are 0.0300, 0.0295, and 0.0298, respectively (and all of them are statistically significant at the 5% level). When sorting by VaR, we can see that the media effect seems to increase as VaR increases – in the last tercile (including tokens with the highest VaR), the alphas for the one-factor, two-factor, and three-factor models are 0.0260, 0.0234, and 0.0246, respectively (and all of them are statistically significant at the 10% level) while these alphas are 0.0066, 0.0063, and 0.0057, respectively in the second tercile. Therefore, we can conclude that the media effect is mostly concentrated among small tokens, tokens with high volatility, tokens with high illiquidity, or tokens with high risk/volatility.

When sorting by past returns, the media effect measured by the alpha is the strongest among tokens with high past returns (which is in contrast with Fang and Peress's (2009) finding that the media effect is strongest among tokens with low past returns). For example, when sorting by the past one-week return ($r\ 1, 0$), the alphas for the one-factor, two-factor, and three-factor models in the first tercile are 0.0156, 0.0150, and 0.0136, respectively while the alphas in the last tercile are 0.0233, 0.0229, and 0.0223, respectively. This result is consistent with the bivariate sorting results reported in Table 4, where the no-coverage premium is mostly likely to be strongest among tokens with high past returns. Therefore, the cryptocurrencies that have high returns in the past and receive no media coverage tend to have more upside potential than those that have high returns in the past and receive high media coverage. The media effect is also strongest among tokens with low beta. Since the value-weighted cryptocurrency market portfolio is largely driven by the prices of Bitcoin and Ethereum or other large tokens (which also receive most media coverage), the media effect is then strongest among tokens that are less correlated with those large tokens (and thus the cryptocurrency market index).

The empirical finding that the media effect is most noticeable among small tokens or tokens with high volatility or illiquidity raises two main concerns: (1) the media effect could be driven by bid-ask bounce among small tokens, and (2) the media effect could be subsumed by a size effect or any other effect. To address the first concern, we conduct two robustness checks by performing the same regression analysis using (i) the returns on the long-short media-based portfolio constructed using all cryptocurrencies with one week skipped in between the portfolio formation week and the holding week, (ii) the returns on the long-short media-based portfolio constructed using only active cryptocurrencies. The results of these robustness checks are reported in Section S.III.2.1. We have also obtained quite similar results reported here in those two robustness checks.

We also use the characteristic-based benchmark method proposed by Daniel, Grinblatt, Titman, and Wermers (1997) (DGTW) to verify our regression results. We calculate three DGTW measures: the Characteristic Selectivity (CS) measure, the Characteristic Timing (CT) measure, and the Average Style (AS) return measure for the three media-based portfolios [formed by (a) longing no-coverage tokens, (b) shorting high-coverage tokens, (c) simultaneously longing no-coverage tokens while shorting high-coverage tokens].

As detailed in Section A.IV, the DGTW method involves two main stages: (1) constructing passive benchmark portfolios by triple-sorting cryptocurrencies into terciles according to the last-day market capitalization (MCAP) in the portfolio formation week, the standard deviation of daily returns (RETVOL) in the portfolio formation week, and momentum measured by the past three-week return ($r\,3,0$) as suggested by Liu et al. (2022); (2) each token in a media-based portfolio is then assigned to a passive benchmark portfolio based on its MCAP, RETVOL, and $r\,3,0$. The excess return of this token at the end of the portfolio holding week can be calculated by subtracting the return on this passive benchmark portfolio from the return of this token; (3) the excess returns of the tokens in a media-based portfolio are then multiplied by their portfolio weights [calculated at the end of the portfolio formation week] to obtain the benchmark-adjusted return [on the media-based portfolio] for the holding week. This benchmark-adjusted return is called the CS measure.

We can also calculate the CT measure and the AS return measure. The CT measures how much a media-based portfolio can outperform the passive benchmark portfolios by varying its weights to exploit the time-varying expected returns of the passive benchmark portfolios. The AS measures how similar a strategy is to a passive investment strategy. Thus, a strategy which systematically mimics a passive investment strategy should exhibit a high AS return. Table 9 shows that the no-coverage tokens exhibit statistically significant and positive benchmark-adjusted returns: Panel A suggests that, in the entire sample period, the average weekly CS measure of these tokens is 123 basis points (t-statistic = 3.05), compared to 36 basis points (t-statistic = 1.85) for the high-coverage tokens; when splitting the sample by year (in Panels B - F), the average weekly CS measure of no-coverage tokens is still positive and statistically significant, and it is also higher than that of high-coverage tokens in every year. These results are indeed aligned with the sorting and regression results reported above.

Turning to the CT measure, all the three media-based portfolios [formed by (a) longing no-coverage tokens, (b) shorting high-coverage tokens, and (c) simultaneously longing no-coverage tokens while shorting high-coverage tokens] are not able to effectively time the three cryptocurrency characteristics (i.e., the weights of each of these portfolios do not seem to co-move with the time-varying expected returns of the passive benchmark portfolios as the average CT measure is statistically insignificant in the entire sample period, and it is not significantly positive in any subsample period). This finding is also consistent with the results reported for mutual funds in Daniel et al. (1997). In addition, the average AS measure of the long-only portfolio [which longs no-coverage tokens] or the long-short portfolio [which longs no-coverage tokens and shorts high-coverage tokens] is statistically significant and positive while that of the short-only portfolio [which shorts high-coverage tokens] is significantly negative in the entire sample period: Panel A of Table 9 shows that, in the entire sample period, the average AS measure of no-coverage tokens is 242 basis points (t-statistic = 3.17), compared to -185 basis points (t-statistic = -2.79) for high-coverage tokens, and the average AS measure of the long-short media-based portfolio is 64 basis points (t-statistic = 2.70); when splitting the sample by year (in Panels B - F), the average AS measure of no-coverage tokens is still significantly higher than that of high-coverage tokens. This finding suggests that the long-only media-based portfolio systematically holds small tokens, highly volatile tokens, or tokens with high momentum to boost its portfolio return and the return of the long-short media-based portfolio, which is consistent with the sorting and regression results reported earlier.

4.2.2 Abnormal Returns after Transaction Costs

We use Novy-Marx and Velikov's (2016) generalized alpha to examine if the long-short strategy [that longs tokens with no media coverage and shorts tokens with high media coverage] can generate abnormal returns beyond common risk factors after accounting for transaction costs. Let MVE_X represent the ex-post mean variance efficient portfolio of the assets X. The weights of MVE_X are based on the optimal portfolio of long and short versions of all the assets X, net of transaction costs, subject to a non-negativity constraint. Let $w_{y,MVE_{X,y}}$ denote the weight of the asset y in portfolio $\text{MVE}_{X,y}$. The generalized alpha α^* is defined as the intercept from the following regression:

$$\frac{\text{return of MVE}_{X,y}}{w_{y,MVE_{X,y}}} = \alpha^* + \beta^* \left(\text{return of MVE}_X\right) + \epsilon^*. \tag{4.1}$$

Novy-Marx and Velikov (2016) set $\alpha^* = 0$ if $w_{y,MVE_{X,y}} = 0$. In this case, the asset y does not improve the investment opportunity set.

Table 7 also reports the generalized alphas relative to three factor models: the Cryptocurrency CAPM, the CAPM augmented with CSMB, the CAPM augmented with CSMB and CMOM. Clearly, the long-short media-based portfolio does not improve the net-of-costs return of an investor who is already holding the market portfolio and the size portfolio. However, Panel B shows that the long-only media-based portfolio can generate an abnormal return after accounting for transaction costs (i.e., the generalized alpha of 0.0231 is statistically significant in this case). Panel C indicates that the short-only media-based portfolio generates a zero abnormal return after accounting for transaction costs. The reason that the long-short media-based portfolio yields the generalized alpha of zero is that the costs of trading high-coverage tokens cancel out the net-of-costs return obtained from the long leg of this long-short strategy. The positive generalized alphas from the long-only media-based portfolio are aligned with the positive net-of-costs returns reported in Section 4.1.2.

Table 8 also reports the generalized alphas of the long-short media-based strategy in the subsamples of all cryptocurrencies [ever listed on CoinMarketCap] sorted by various characteristics listed in Table S.I.1 one at a time. The generalized alphas across the characteristic-based terciles are either zeros or statistically insignificant. Therefore, the media effect [that is concentrated among (a) small tokens, (b) tokens with low trading volume, (c) tokens with high volatility, (d) tokens with high illiquidity, (e) tokens with high downside risk, (f) tokens with high past returns, and (g) tokens with low beta, as discussed in Section 4.2.1] completely disappears after accounting for transaction costs. This is due to the fact that rebalancing the weights for those types of tokens in the portfolio usually incurs high turnover and thus transaction costs which more than offset the spread obtained from the long-short strategy.

We have also calculated the net-of-costs CS measure, the net-of-costs CT measure, and the net-of-costs AS return measure [as defined in Section A.IV] to verify the generalized alphas obtained above. Table 9 shows that the average weekly CS and CT measures are not statistically significant and positive after accounting for transaction costs in the entire sample period nor in any subsample period. The after-costs performance (measured by the net-of-costs CS measure) of all the three media-based portfolios [formed by (a) longing the no-coverage tokens, (b) shorting the high-coverage tokens, (c) simultaneously longing the no-coverage tokens while shorting the high-coverage tokens] seems to fall behind that of a passive benchmark portfolio in the entire sample period and in each year. Therefore, our media-based strategies generate no abnormal return after factoring in transaction costs. A possible explanation for the insignificant net-of-costs CS measure of the long-only media-based portfolio is that the passive benchmark portfolios [formed by triple-sorting tokens by size, volatility, and momentum] have lower transaction costs. This result is not consistent with the positive generalized alpha obtained for the long-only media-based portfolio, because volatility is not included as a risk factor in the three-factor model. However, the result is consistent with the general idea that anomalies exists because of market frictions [see, e.g., Chen and Velikov (2023)].

Moreover, the AS measure of the long-only/long-short media-based portfolio still remains positive and statistically significant after accounting for transaction costs in the entire sample period and in several subsample periods. This is because the long-only portfolio tends to systematically hold small tokens, highly volatile tokens, or tokens with high momentum to boost its portfolio return and the long-short portfolio return even when trades involve transaction costs.

Table 7: Performance of Long-Short Media-Based Trading Strategies Relative to Cryptocurrency Risk Factors: All Cryptocurrencies ever listed on CoinMarketCap

This table examines the return [in excess of the common risk factors in cryptocurrency proposed by Liu et al. (2022)] of a trading strategy that longs tokens with no media coverage and shorts tokens with high media coverage. Each week, tokens are sorted according to the number of news articles written about them. A token is considered to have no media coverage if no article is written about this token in a given week. A token is considered to have high media coverage if the number of articles written about it exceeds the median in a given week. Both the long and short positions are equally weighted, and they are held for the entire holding week after the portfolio formation. Portfolios are then re-balanced weekly. The resulting time-series returns on the long-short media-based portfolio are then regressed on three risk factors (cryptocurrency market, size, and momentum). The *p*-values [using the Newey-West standard error] are in parentheses. The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. Novy-Marx and Velikov's (2016) generalized alphas that account for transaction costs [calculated using the Matlab function *calcGenAlpha* provided in the second author's Github repository] are also reported.

	One-factor model	Two-factor model	Three-factor model
Panel A: Long no-media coverage tokens and short high-media coverage tokens			
Mkt-RF	0.0240	0.0175	0.0032
	(0.7570)	(0.8120)	(0.9640)
CSMB	–	0.1566*	0.1658**
		(0.0770)	(0.0210)
CMOM	–	–	0.1599*
			(0.0690)
Intercept (α)	0.0246***	0.0207***	0.0197***
	(0.0002)	(0.0030)	(0.0055)
Generalized α	0.0000	0.0000	0.0000
Sample size	243	243	243
R^2	0.0000	0.0350	0.0510
Panel B: Alphas for no-media coverage tokens			
α	0.0329***	0.0244***	0.0234***
	(0.0000)	(0.0009)	(0.0017)
Generalized α			0.0231***
			(0.0006)
R^2	0.4060	0.4850	0.4950
Panel C: Alphas for high-media coverage tokens			
α	0.0082**	0.0037	0.0036
	(0.0410)	(0.2143)	(0.2077)
Generalized α			0.0000
R^2	0.7620	0.8060	0.8060

Table 8: Performance of Long-Short Media-Based Trading Strategies Relative to Cryptocurrency Risk Factors by Token Characteristics: All Cryptocurrencies ever listed on CoinMarketCap

This table examines the return [in excess of the common risk factors in cryptocurrency proposed by Liu et al. (2022)] of a trading strategy that longs tokens with no media coverage and shorts tokens with high media coverage in the subsamples of tokens sorted by cryptocurrency characteristics (defined in Table S.I.1) one at a time. Each week, tokens are sorted according to the number of newspaper articles written about them. A token is considered to have no media coverage if no article is written about this token in a given week. A token is considered to have high media coverage if the number of articles written about it exceeds the median in a given week. Both the long and short positions are equally weighted, and they are held for one week after the portfolio formation. Portfolios are then re-balanced weekly. Alphas from regressing the resulting time-series returns of the long-short media-based portfolio on three risk factors (cryptocurrency market, size, and momentum) are reported. p-values [using the Newey-West standard error] are in parentheses. The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. Novy-Marx and Velikov's (2016) generalized alphas that account for transaction costs [calculated using the Matlab function *calcGenAlpha* provided in the second author's Github repository] are also reported.

	One-factor model		Two-factor model		Three-factor model	
	α	generalized α	α	generalized α	α	generalized α
Sort by MCAP						
0	0.0259***	0.0000	0.0251***	0.0000	0.0262***	0.0000
	(0.0062)		(0.0074)		(0.0057)	
1	0.0289*	0.0000	0.0294*	0.0000	0.0294*	0.0000
	(0.0610)		(0.0598)		(0.0600)	
2	−0.0006	0.0000	−0.0004	0.0000	−0.0007	0.0000
	(0.7878)		(0.8900)		(0.7814)	
Sort by AMCAP						
0	0.0287***	0.0000	0.0284***	0.0000	0.0296***	0.0000
	(0.0029)		(0.0028)		(0.0022)	
1	0.0288**	0.0000	0.0304**	0.0000	0.0306**	0.0000
	(0.0504)		(0.0424)		(0.0412)	
2	−0.0020	0.0000	−0.0029	0.0000	−0.0034	0.0000
	(0.3794)		(0.1669)		(0.1042)	
Sort by PRCVOL						
0	0.0260**	0.0000	0.0281**	0.0000	0.0281**	0.0000
	(0.0230)		(0.0180)		(0.0179)	
1	0.0117**	0.0000	0.0121**	0.0000	0.0117**	0.0000
	(0.0125)		(0.0105)		(0.0130)	
2	0.0021	0.0000	0.0009	0.0000	0.0008	0.0000
	(0.4188)		(0.7026)		(0.7584)	

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Table 8 (continued): Performance of Long-Short Media-Based Trading Strategies Relative to Cryptocurrency Risk Factors by Token Characteristics: All Cryptocurrencies ever listed on CoinMarketCap

	One-factor model		Two-factor model		Three-factor model	
	α	generalized α	α	generalized α	α	generalized α
			Sort by VOLSCALED			
0	0.0194*	0.0000	0.0209**	0.0000	0.0205**	0.0000
	(0.0533)		(0.0441)		(0.0480)	
1	0.0072*	0.0000	0.0059	0.0000	0.0049	0.0000
	(0.0580)		(0.1112)		(0.1919)	
2	0.0085**	0.0000	0.0081*	0.0000	0.0083*	0.0000
	(0.0458)		(0.0584)		(0.0585)	
			Sort by RETVOL			
0	0.0100*	0.0000	0.0076	0.0000	0.0080	0.0000
	(0.0871)		(0.1703)		(0.1735)	
1	−0.0019	0.0000	−0.0027	0.0000	−0.0029	0.0000
	(0.5687)		(0.3964)		(0.3799)	
2	0.0488***	0.0018	0.0497***	0.0018	0.0484***	0.0018
	(0.0002)	(0.8548)	(0.0002)	(0.8548)	(0.0002)	(0.8548)
			Sort by IDIOVOL			
0	0.0012	0.0000	0.0012	0.0000	0.0012	0.0000
	(0.6890)		(0.6875)		(0.6999)	
1	0.0004	0.0000	0.0010	0.0000	0.0008	0.0000
	(0.9300)		(0.8407)		(0.8682)	
2	0.0400**	0.0000	0.0312*	0.0000	0.0302*	0.0000
	(0.0132)		(0.0554)		(0.0763)	
			Sort by MAXRET			
0	0.0101*	0.0000	0.0079	0.0000	0.0086	0.0000
	(0.0698)		(0.1644)		(0.1335)	
1	0.0042	0.0000	0.0041	0.0000	0.0037	0.0000
	(0.3209)		(0.3607)		(0.4072)	
2	0.0461***	0.0000	0.0389***	0.0000	0.0362***	0.0000
	(0.0002)		(0.0025)		(0.0057)	

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Table 8 (continued): Performance of Long-Short Media-Based Trading Strategies Relative to Cryptocurrency Risk Factors by Token Characteristics: All Cryptocurrencies ever listed on CoinMarketCap

	One-factor model		Two-factor model		Three-factor model	
	α	generalized α	α	generalized α	α	generalized α
			Sort by DAMIHUD			
0	0.0014	0.0000	–0.0004	0.0000	–0.0006	0.0000
	(0.5545)		(0.8342)		(0.7777)	
1	0.0102*	0.0000	0.0101*	0.0000	0.0102**	0.0000
	(0.0526)		(0.0520)		(0.0497)	
2	0.0300**	0.0000	0.0295**	0.0000	0.0298**	0.0000
	(0.0370)		(0.0321)		(0.0289)	
			Sort by VaR			
0	0.0118*	0.0000	0.0115	0.0000	0.0104	0.0000
	(0.0896)		(0.1131)		(0.1332)	
1	0.0066*	0.0000	0.0063*	0.0000	0.0057*	0.0000
	(0.0529)		(0.0658)		(0.0871)	
2	0.0260**	0.0000	0.0234*	0.0000	0.0246*	0.0000
	(0.0437)		(0.0607)		(0.0548)	
			Sort by r $1, 0$			
0	0.0156**	0.0000	0.0150**	0.0000	0.0136**	0.0000
	(0.0175)		(0.0173)		(0.0232)	
1	0.0170***	0.0000	0.0144**	0.0000	0.0144**	0.0000
	(0.0043)		(0.0134)		(0.0249)	
2	0.0233**	0.0000	0.0229**	0.0000	0.0223**	0.0000
	(0.0189)		(0.0175)		(0.0184)	
			Sort by r $2, 0$			
0	0.0143***	0.0000	0.0140***	0.0000	0.0128***	0.0000
	(0.0019)		(0.0017)		(0.0043)	
1	0.0105**	0.0000	0.0101**	0.0000	0.0099**	0.0000
	(0.0147)		(0.0235)		(0.0245)	
2	0.0246**	0.0000	0.0217*	0.0000	0.0233**	0.0000
	(0.0399)		(0.0573)		(0.0412)	

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Table 8 (continued): Performance of Long-Short Media-Based Trading Strategies Relative to Cryptocurrency Risk Factors by Token Characteristics: All Cryptocurrencies ever listed on CoinMarketCap

	One-factor model		Two-factor model		Three-factor model	
	α	generalized α	α	generalized α	α	generalized α
			Sort by r $3, 0$			
0	0.0118**	0.0000	0.0118**	0.0000	0.0118**	0.0000
	(0.0279)		(0.0243)		(0.0237)	
1	0.0079*	0.0000	0.0056	0.0000	0.0058	0.0000
	(0.0503)		(0.1259)		(0.1049)	
2	0.0547***	0.0063	0.0461***	0.0063	0.0423**	0.0063
	(0.0018)	(0.7023)	(0.0100)	(0.7023)	(0.0250)	(0.7023)
			Sort by r $4, 0$			
0	0.0172***	0.0000	0.0177***	0.0000	0.0188***	0.0000
	(0.0052)		(0.0042)		(0.0026)	
1	0.0146**	0.0000	0.0117**	0.0000	0.0120**	0.0000
	(0.0161)		(0.0430)		(0.0376)	
2	0.0392***	0.0000	0.0318**	0.0000	0.0292*	0.0000
	(0.0080)		(0.0320)		(0.0582)	
			Sort by r $4, 1$			
0	0.0151***	0.0000	0.0162***	0.0000	0.0164***	0.0000
	(0.0092)		(0.0071)		(0.0066)	
1	0.0096	0.0000	0.0076	0.0000	0.0082	0.0000
	(0.1215)		(0.2138)		(0.1785)	
2	0.0347***	0.0000	0.0278**	0.0000	0.0245*	0.0000
	(0.0057)		(0.0263)		(0.0607)	
			Sort by r $8, 0$			
0	0.0203***	0.0000	0.0198***	0.0000	0.0208***	0.0000
	(0.0053)		(0.0084)		(0.0056)	
1	0.0090*	0.0000	0.0060	0.0000	0.0063	0.0000
	(0.0785)		(0.1653)		(0.1384)	
2	0.0433***	0.0000	0.0369**	0.0000	0.0335**	0.0000
	(0.0056)		(0.0214)		(0.0419)	

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Table 8 (continued): Performance of Long-Short Media-Based Trading Strategies Relative to Cryptocurrency Risk Factors by Token Characteristics: All Cryptocurrencies ever listed on CoinMarketCap

	One-factor model		Two-factor model		Three-factor model	
	α	generalized α	α	generalized α	α	generalized α
			Sort by r $16, 0$			
0	0.0085	0.0000	0.0102	0.0000	0.0114*	0.0000
	(0.2352)		(0.1246)		(0.0911)	
1	0.0129**	0.0000	0.0122**	0.0000	0.0123**	0.0000
	(0.0106)		(0.0159)		(0.0176)	
2	0.0288**	0.0000	0.0276**	0.0000	0.0271**	0.0000
	(0.0329)		(0.0323)		(0.0337)	
			Sort by r $50, 0$			
0	0.0113	0.0000	0.0059	0.0000	0.0055	0.0000
	(0.2192)		(0.5226)		(0.5576)	
1	0.0077	0.0000	0.0073	0.0000	0.0071	0.0000
	(0.1526)		(0.1609)		(0.1765)	
2	0.0251**	0.0000	0.0186*	0.0000	0.0179	0.0000
	(0.0301)		(0.0933)		(0.1078)	
			Sort by r $100, 0$			
0	0.0465***	0.0000	0.0343*	0.0000	0.0331	0.0000
	(0.0089)		(0.0691)		(0.1148)	
1	−0.0020	0.0000	−0.0021	0.0000	−0.0031	0.0000
	(0.7073)		(0.6922)		(0.5499)	
2	0.0807**	0.0002	0.0772**	0.0002	0.0761**	0.0002
	(0.0101)	(0.2681)	(0.0171)	(0.2681)	(0.0195)	(0.2681)
			Sort by NPAST52			
0	0.0228	0.0000	0.0224	0.0000	0.0226	0.0000
	(0.1092)		(0.1212)		(0.1308)	
1	0.0062	0.0000	0.0052	0.0000	0.0049	0.0000
	(0.2616)		(0.3223)		(0.3591)	
2	0.0087	0.0000	0.0110	0.0000	0.0120	0.0000
	(0.3358)		(0.2176)		(0.1840)	
			Sort by BETA			
0	0.0412***	0.0000	0.0316**	0.0000	0.0315**	0.0000
	(0.0020)		(0.0211)		(0.0233)	
1	0.0021	0.0000	0.0009	0.0000	0.0008	0.0000
	(0.5391)		(0.7841)		(0.8053)	
2	−0.0000	0.0000	−0.0018	0.0000	−0.0019	0.0000
	(0.9936)		(0.7589)		(0.7365)	
			Sort by BETA2			
0	0.0310***	0.0000	0.0239**	0.0000	0.0239**	0.0000
	(0.0027)		(0.0302)		(0.0323)	
1	0.0029	0.0000	0.0015	0.0000	0.0015	0.0000
	(0.4000)		(0.6468)		(0.6620)	
2	0.0100	0.0000	0.0074	0.0000	0.0074	0.0000
	(0.3026)		(0.4312)		(0.4374)	

Table 9: Performance Attribution Analysis based on the DGTW Characteristic-based Benchmark Method: All Cryptocurrencies ever listed on CoinMarketCap

This table presents three average weekly performance attribution components for portfolios formed by (i) longing tokens with no media coverage, or (ii) shorting tokens with high media coverage, or (iii) simultaneously longing tokens with no media coverage while shorting tokens with high media coverage in the portfolio formation week (the portfolio-forming and rebalancing procedure is described in Table 4 above). These three components are calculated as follows. The Characteristic Selectivity (CS) measure is the difference between the time t return on each portfolio ("long", "short" or "long-short") held at time $t-1$ and the time t return of the time $t-1$ matching control portfolio, as defined by (A.1). The Characteristic Timing (CT) measure is computed, for each portfolio, by matching tokens held at week $t-13$ and at week $t-1$ with the proper control portfolios at week $t-13$ and week $t-1$, respectively. Next, the portfolio-weighted return of the week $t-13$ matching portfolio, at week t, is subtracted from the portfolio-weighted return of the week $t-1$ control portfolio, also at week t, as defined by (A.4). The Average Style (AS) measure is calculated, for week t, by matching each token held in a portfolio, at week $t-13$, with the proper control portfolio at week $t-13$. Then, the measure for a portfolio is computed by applying each token weight at $t-13$ to the matching control portfolio return at week t, as defined by (A.6). Note that a cryptocurrency is included if its market capitalization is at least one million during the portfolio formation week while its name and symbol are mentioned in at least 100 articles throughout the sample period. All t-statistic values (in parentheses) use the Newey-West standard error.

Portfolio	Average Weekly CS Attribute (%)		Average Weekly CT Attribute (%)		Average Weekly AS Attribute (%)	
	Before trans. cost	After trans. cost	Before trans. cost	After trans. cost	Before trans. cost	After trans. cost
			Panel A: All years			
long	1.23	−0.02	−0.25	−0.24	2.42	2.24
	(3.05)	(−0.04)	(−0.76)	(−0.77)	(3.17)	(2.99)
short	0.36	−4.41	−0.31	−0.31	−1.85	−1.84
	(1.85)	(−22.67)	(−1.00)	(−0.98)	(−2.79)	(−2.65)
long-short	1.55	−4.31	−0.23	−0.21	0.64	0.50
	(3.42)	(−9.95)	(−0.66)	(−0.65)	(2.70)	(2.47)
			Panel B: 2017-2018			
long	0.47	−0.33	−0.36	−0.36	0.91	0.77
	(2.61)	(−1.59)	(−1.51)	(−1.55)	(0.55)	(0.46)
short	0.16	−4.55	−0.96	−0.98	0.03	0.08
	(0.58)	(−16.53)	(−1.74)	(−1.73)	(0.02)	(0.06)
long-short	0.94	−4.49	−1.31	−1.34	1.03	0.98
	(3.58)	(−12.64)	(−2.17)	(−2.12)	(1.26)	(1.25)
			Panel C: 2019			
long	0.26	−1.16	−0.75	−0.73	1.32	1.16
	(2.31)	(−9.11)	(−4.08)	(−4.17)	(1.73)	(1.55)
short	-0.26	−5.03	0.23	0.24	−1.20	−1.17
	(-1.28)	(−22.84)	(1.00)	(1.05)	(−1.31)	(−1.22)
long-short	-0.02	−5.88	−0.37	−0.36	0.55	0.47
	(-0.08)	(−27.03)	(−1.23)	(−1.20)	(2.55)	(1.75)
			Panel D: 2020			
long	0.52	−1.34	−0.22	−0.21	2.91	2.74
	(2.16)	(−4.03)	(−0.71)	(−0.75)	(4.53)	(4.49)
short	-0.20	−4.99	0.23	0.26	−3.44	−3.49
	(-0.84)	(−21.3)	(1.09)	(1.21)	(−5.65)	(−5.45)
long-short	0.33	−5.86	0.04	0.08	0.04	−0.19
	(0.76)	(−14.26)	(0.13)	(0.27)	(0.30)	(−1.62)

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Table 9 (continued): Performance Attribution Analysis based on the DGTW Characteristic-based Benchmark Method: All Cryptocurrencies ever listed on CoinMarketCap

Portfolio	Average Weekly CS Attribute (%)		Average Weekly CT Attribute (%)		Average Weekly AS Attribute (%)	
	Before trans. cost	After trans. cost	Before trans. cost	After trans. cost	Before trans. cost	After trans. cost
Panel E: 2021						
long	2.59	1.47	−0.76	−0.67	6.63	6.35
	(2.82)	(1.66)	(−1.39)	(−1.23)	(3.87)	(3.80)
short	0.40	−4.43	−0.44	−0.45	−6.30	−6.45
	(1.56)	(−17.83)	(−0.64)	(−0.64)	(−4.36)	(−4.25)
long-short	2.91	−3.05	−0.68	−0.59	0.59	0.28
	(2.66)	(−2.99)	(−1.31)	(−1.11)	(1.91)	(1.16)
Panel F: 2022-2023						
long	1.56	0.36	−0.35	−0.33	0.27	0.15
	(1.45)	(0.35)	(−1.64)	(−1.61)	(0.42)	(0.24)
short	0.05	−4.74	0.19	0.19	−0.26	−0.17
	(0.33)	(−35.11)	(1.29)	(1.22)	(−0.35)	(−0.21)
long-short	1.74	−4.20	0.09	0.12	0.12	0.13
	(1.55)	(−3.89)	(0.40)	(0.50)	(0.56)	(0.62)

We also verify the above DGTW characteristic-based benchmark results for the above three media-based portfolios constructed using (i) all cryptocurrencies while skipping one week in between the portfolio formation week and the holding week, and (ii) only active cryptocurrencies. The results of these robustness checks are presented in Section S.III.3.

5 Explaining the Media Effect

In this section, we discuss the possible causes of the media effect: the ‘impediments to trade’ hypothesis and the investor recognition hypothesis, as suggested in Fang and Peress (2009).

5.1 The ‘Impediments to Trade’ Hypothesis

Under the rational agent framework, the no-coverage premium represents an arbitrage opportunity that still exists because (1) there are impediments that prevent traders from exploiting this effect, or (2) it is merely a fair compensation for risks not captured by risk factors. We shall examine these two explanations.

Fang and Peress (2009) found mixed evidence about whether impediments to trade explain the media effect for equity (such as, the media effect is most pronounced among stocks with a medium level of liquidity or trading volume). On the other hand, we have found a strong evidence that impediments to trade explain the media effect for cryptocurrency. Table 4 shows that the media effect is strongest among cryptocurrencies with small market capitalization, low trading volume, high volatility, high illiquidity, or high VaR. Sorting tokens by market capitalization (MCAP) at the end of the portfolio formation week generates a statistically significant and positive average return of 3.33% per week for the long-short portfolio [that longs tokens with no media coverage and shorts tokens with high media coverage] in the first tercile, and this return decreases over the terciles. Sorting tokens by log trading volume times price divided by market capitalization (VOLSCALED) at the end of the portfolio formation week also leads to a significant and positive average return of 3.15% per week for the long-short media-based portfolio in the first tercile (which is three times larger than the average returns in the other terciles). Sorting tokens by return volatility (RETVOL) generates a significant and positive average return of 5.65% per week for the long-short media-based portfolio in the last tercile (which is almost five times larger than the average returns in the other terciles). Sorting tokens by Amihud's (2002) illiquidity measure (DAMIHUD) [as deemed by Brauneis, Mestel, Riordan, and Theissen (2021) to be the best measure of liquidity for cryptocurrencies] generates a significant and positive average return of 3.99% per week for the long-short media-based portfolio in the last tercile (which is almost three times larger than the average returns in the other terciles). Sorting tokens by VaR leads to a significant and positive average return of 2.71% per week for the long-short media-based portfolio in the last tercile (which is at least twice larger than the average returns in the other terciles).

Table 8 shows that the alphas in the three factor models are the most statistically significant among cryptocurrencies with small market capitalization, low trading volume, high volatility, high illiquidity, or high VaR. Therefore, the no-coverage premium must represent a compensation for risk not captured by risk factors. All those alphas become statistically insignificant after accounting for transaction costs. This finding also confirms the 'impediments to trade' hypothesis.

As discussed in Section 4.1.2, the long leg of the long-short media-based portfolio may withstand transaction costs because an equally weighted portfolio of no-coverage tokens incurs a much lower turnover, and thus lower transaction costs, than that of high-coverage tokens. Moreover, trading no-coverage tokens requires less rebalancing in the portfolio than trading high-coverage tokens in the group of small/less liquid tokens, which can effectively lower the portfolio turnover and transaction costs (although it may be more costly to individually trade a small/less liquid token than a large/highly liquid token). Hence, we expect that the alphas and generalized alphas of a [self-financing] long-only media-based portfolio [that borrows fund at the risk-free rate to finance a long position in no-coverage tokens during the portfolio formation week] in factor models are larger or more statistically significant among small/illiquid tokens than large/liquid tokens. Table 10 suggests that this is indeed the case. Sorting tokens by market capitalization (MCAP) at the end of the portfolio formation week generates a statistically significant and positive alpha [in the three-factor model] of 3.29% per week (p-value = 0.0009) and a generalized alpha of 2.65% per week (p-value = 0.0004) for the self-financing long-only portfolio in the first tercile, and the p-values of the alpha and generalized alpha are also much larger in the other terciles. Sorting tokens by volume times price (PRCVOL) at the end of the portfolio formation week generates a significant and positive alpha of 3.87% per week (p-value = 0.0017) and a generalized alpha of 2.95% per week (p-value = 0.0009) in the first tercile. Sorting tokens by DAMIHUD at the end of the portfolio formation week leads to a significant and positive alpha of 4.01% per week (p-value = 0.0013) and a generalized alpha of 3.27% per week (p-value = 0.0022) in the last tercile. These numbers suggest that arbitrage trades seem possible in the group of small/less liquid tokens because no-coverage tokens have high average returns, and trading those tokens requires less rebalancing in the portfolio.

5.2 The Investor Recognition Hypothesis

Merton (1987) proposes a model of informationally incomplete markets in which investors only know about a subset of available stocks, and all informed traders in a security have the same information about that security. This model suggests that less well-known stocks with a smaller investor base tend to offer higher expected returns as a compensation for being imperfectly diversified. Since the media can improve investor recognition of a stock, we should expect that the media effect is stronger among stocks with a lower degree of investor recognition. Fang and Peress (2009) use analyst coverage or the fraction of individual ownership as a proxy for the degree of investor recognition, and idiosyncratic volatility as a proxy for the cost of poor investor recognition.[5]

[5] Merton's (1987) model suggests that idiosyncratic risk is priced because of the imperfect diversification caused by lack of

investor recognition.

As data for analyst coverage and the fraction of individual ownership is not available for most cryptocurrencies used in this study, we shall use idiosyncratic volatility to proxy the cost of poor investor recognition in tokens. Table 4 suggests that, when sorting tokens into terciles according to idiosyncratic volatility (IDIOVOL), the long-short portfolio [that longs no-coverage tokens and shorts high-coverage tokens in the portfolio formation week] yields an average weekly returns of 4.77% per week (t-statistic = 3.01) among the tokens with highest IDIOVOL, compared to the statistically insignificant returns among the tokens with a lower IDIOVOL. Table 8 shows that the alpha (and its level of significance) of this long-short media-based portfolio in factor models monotonically increase with idiosyncratic volatility. In addition, Table 10 suggests that both the alpha and generalized alpha (and their levels of significance) of the self-financing long-only portfolio [that borrows fund at the risk-free rate to finance a long position in the tokens with no media coverage in the portfolio formation week] in the three-factor model also monotonically increase with idiosyncratic volatility: the alphas in the first, second, and third IDIOVOL-based terciles are 0.1% (p-value = 0.7589), 0.45% (p-value = 0.4072), and 3.57% (p-value = 0.0334) per week, respectively while the generalized alphas are 0, 0, and 3.32% (p-value = 0.0051) per week, respectively. These results are thus consistent with the prediction of the Merton model.

5.3 Return Continuation and Reversals

We investigate whether the media effect is due to either (a) negative return drift among high-coverage tokens with low past returns or (b) return reversal of no-coverage tokens with low past returns. Possibility (a) can be ruled out because the alpha of the long-short media-based portfolio primarily comes from the long leg (as suggested in Table 7), and the self-financing long-only media-based strategy can generate statistically significant, positive alphas and generalized alphas in various subsamples of tokens sorted by cryptocurrency characteristics one at a time (as shown in Table 10). This finding is also consistent with the explanation in Fang and Peress (2009).

We now examine Possibility (b). If the media effect was caused by return reversal of the no-coverage tokens with low past returns, then the alpha and generalized alpha of the self-financing long-only media-based strategy should monotonically decrease from the group of tokens with lowest past returns to the group of tokens with highest past returns. Table 10 shows that this is not the case as the alpha and generalized alpha are either largest or most statistically significant in the group of tokens with higher past returns. For example, sorting tokens into terciles by their maximum daily returns (MAXRETs) during the portfolio formation week, the alphas of the self-financing long-only portfolio in the three-factor model for the first, second, and third MAXRET terciles are 0.86% (p-value = 0.1495), 0.76% (p-value = 0.1602), and 3.65% (p-value = 0.0044) per week, respectively while the generalized alphas are 0, 0, and 3.23% (p-value = 0.0030) per week, respectively. Sorting tokens into terciles by their past one-week returns (r $1, 0$), the alphas of the self-financing long-only portfolio in the three-factor model for the first, second, and third r $1, 0$ terciles are 1.28% (p-value = 0.0405), 1.48% (p-value = 0.0293), and 2.77% (p-value = 0.0029) per week, respectively while the generalized alphas are 0, 0.42% (p-value = 0.4314), and 1.42% (p-value = 0.0683) per week, respectively. Sorting tokens into terciles by their past 16-week returns (r $16, 0$), the alphas of the self-financing long-only portfolio in the three-factor model for the first, second, and third r $16, 0$ terciles are 1.82% (p-value = 0.0187), 1.17% (p-value = 0.016), and 2.83% (p-value = 0.0248) per week, respectively while the generalized alphas are 0.78% (p-value = 0.2546), 0.54% (p-value = 0.3306), and 2.29% (p-value = 0.0380) per week, respectively. Sorting tokens into terciles by their past 100-week returns (r $100, 0$), the alphas of the self-financing long-only portfolio in the three-factor model for the first, second, and third r $100, 0$ terciles are 4.65% (p-value = 0.0384), 0.19% (p-value = 0.7471), and 7.56% (p-value = 0.0188) per week, respectively while the generalized alphas are 5.13% (p-value = 0.0227), 0, and 6.99% (p-value = 0.0087) per week, respectively. Sorting tokens into terciles by their negatives of past 52-week returns (NPAST52), the alphas of the self-financing long-only portfolio in the three-factor model for the third, second, and first NPAST52 terciles are 1.49% (p-value = 0.1139), 0.42% (p-value = 0.4208), and 2.44% (p-value = 0.0971) per week, respectively while the generalized alphas are 0.28% (p-value = 0.7374), 0, and 1.64% (p-value = 0.1449) per week, respectively.

We also examine the horizon of the media effect (i.e, whether the media effect remains stable over a long holding period). We use the calendar-time overlapping approach of Jegadeesh and Titman (1993) to calculate the portfolio returns for the entire holding period: We form portfolios that long/short the tokens with no/high media coverage in the past K weeks (K = 1, 5, 10). These media-based portfolios are then held for next J weeks ($J = 1, 2, \ldots, 20$). Therefore, at the end of each week, we hold a composite portfolio consisting of the portfolio initiated K weeks prior to this week as well as the portfolios initiated in the previous $K-1$ weeks. The return on this composite portfolio at the end of each week is then calculated by averaging the returns [of the portfolios with overlapping holding periods] from the time those portfolios are initiated to the end of the week. The resulting weekly returns on the composite portfolio are then regressed on three common cryptocurrency risk factors (cryptocurrency market, size, and momentum). The alphas of the composite portfolio [that longs tokens with no media coverage and shorts tokens with high media coverage in the portfolio formation period], obtained from this regression using the entire sample of cryptocurrencies ever listed on CoinMarketCap, are reported in Table 11. Note that the factor models, used in this table, are defined in Table 7 above. This table suggests that the average weekly return on the composite long-short portfolio is statistically significant and positive for every holding period when the portfolio formation period is one week. This average return then behaves like a concave function of the holding period when the portfolio formation period is longer than a week. Therefore, the media effect can persist over many weeks before it eventually dies out. The alphas are also statistically significant and positive for every holding period when the portfolio formation period is one week. When the portfolio formation period is five weeks, the alphas intially increase with the holding horizon (up to 12 weeks), then decline to a small, or even negative, number. An explanation for the concavity of this effect is that the number of no-coverage tokens decreases with the portfolio formation period, and thus the media effect of the tokens, that receive no media coverage for several weeks, tends to be weaker than that of the tokens, that receive no media coverage for a week. Therefore, the media effect of the tokens with no media coverage for many weeks should decay much more quickly.

We also perform a robustness check of this finding by skipping a week between the portfolio formation period and the holding period, or by using the sample of active cryptocurrencies currently listed on CoinMarketCap. The robustness-check results reported in S.IV.3 confirm the empirical findings reported earlier.

Table 10: Performance of Long-Only Media-Related Trading Strategies Relative to Cryptocurrency Risk Factors: All Cryptocurrencies ever listed on CoinMarketCap

This table examines the return [in excess of the common risk factors in cryptocurrency proposed by Liu et al. (2022)] of a trading strategy that borrows fund at the risk-free rate to finance an equally weighted long position in tokens with no media coverage in the subsamples of tokens sorted by cryptocurrency characteristics (defined in Table S.I.1) one at a time. Each week, tokens are sorted according to the number of news articles written about them. A token is considered to have no media coverage if no article is written about this token in a given week. A token is considered to have a high media coverage if the number of articles written about it exceeds the median in a given week. Fund is then borrowed at the risk-free rate to finance an equally weighted long position in the no-coverage tokens. The portfolio is held for one week after the portfolio formation, and it is rebalanced weekly. Alphas obtained from regressing the resulting time-series returns of this self-financing media-based portfolio on three risk factors (cryptocurrency market, size, and momentum) and the p-values [using the Newey-West standard error] of those alphas are reported. The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. Novy-Marx and Velikov's (2016) generalized alphas that account for transaction costs [calculated using the Matlab function *calcGenAlpha* provided in the second author's Github repository] and their p-values are also reported.

	One-factor model		Two-factor model		Three-factor model			
	α	p-value	α	p-value	α	p-value	generalized α	p-value
				Sort by MCAP				
0	0.0386***	0.0002	0.0329***	0.0008	0.0329***	0.0009	0.0265***	0.0004
1	0.0409***	0.0065	0.0370**	0.0147	0.0363**	0.0175	0.0295*	0.0528
2	0.0046	0.2237	0.0022	0.5260	0.0022	0.5186	0.0000	
				Sort by AMCAP				
0	0.0413***	0.0001	0.0356***	0.0004	0.0356***	0.0006	0.0291***	0.0002
1	0.0411***	0.0040	0.0380***	0.0090	0.0374**	0.0110	0.0296**	0.0439
2	0.0033	0.4373	−0.0003	0.9414	−0.0003	0.9380	0.0000	
				Sort by PRCVOL				
0	0.0429***	0.0003	0.0399***	0.0011	0.0387***	0.0017	0.0295***	0.0009
1	0.0158***	0.0084	0.0128**	0.0212	0.0121**	0.0261	0.0043	0.4185
2	0.0045	0.2486	0.0019	0.5878	0.0020	0.5403	0.0000	
				Sort by VOLSCALED				
0	0.0375***	0.0004	0.0342***	0.0014	0.0331***	0.0020	0.0244***	0.0033
1	0.0111**	0.0297	0.0061	0.1358	0.0050	0.1923	0.0000	
2	0.0078	0.1051	0.0055	0.2480	0.0058	0.2182	0.0000	
				Sort by RETVOL				
0	0.0121*	0.0679	0.0070	0.2434	0.0074	0.2476	0.0000	
1	0.0073	0.1843	0.0013	0.7518	0.0004	0.9122	0.0000	
2	0.0531***	0.0001	0.0488***	0.0004	0.0468***	0.0006	0.0354***	0.0006
				Sort by IDIOVOL				
0	0.0025	0.4910	0.0006	0.8460	0.0010	0.7589	0.0000	
1	0.0077	0.1985	0.0043	0.4277	0.0045	0.4072	0.0000	
2	0.0509***	0.0019	0.0366**	0.0228	0.0357**	0.0334	0.0332***	0.0051

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Table 10 (continued): Performance of Long-Only Media-Related Trading Strategies Relative to Cryptocurrency Risk Factors: All Cryptocurrencies ever listed on CoinMarketCap

	One-factor model		Two-factor model		Three-factor model			
	α	p-value	α	p-value	α	p-value	generalized α	p-value
Sort by MAXRET								
0	0.0118*	0.0516	0.0077	0.1907	0.0086	0.1495	0.0000	
1	0.0110*	0.0555	0.0080	0.1567	0.0076	0.1602	0.0000	
2	0.0508***	0.0001	0.0393***	0.0022	0.0365***	0.0044	0.0323***	0.0030
Sort by DAMIHUD								
0	0.0041	0.3238	–0.0006	0.8599	–0.0005	0.8775	0.0000	
1	0.0134**	0.0382	0.0082	0.1078	0.0082	0.1039	0.0013	0.8097
2	0.0457***	0.0005	0.0400***	0.0012	0.0401***	0.0013	0.0327***	0.0022
Sort by VaR								
0	0.0163**	0.0331	0.0136*	0.0788	0.0121*	0.0956	0.0057	0.4585
1	0.0094*	0.0986	0.0051	0.3137	0.0043	0.3735	0.0000	
2	0.0462***	0.0002	0.0389***	0.0009	0.0398***	0.0010	0.0334***	0.0003
Sort by r 1, 0								
0	0.0167**	0.0128	0.0132**	0.0467	0.0128**	0.0405	0.0000	
1	0.0214***	0.0023	0.0150**	0.0185	0.0148**	0.0293	0.0042	0.4314
2	0.0346***	0.0006	0.0296***	0.0019	0.0277***	0.0029	0.0142*	0.0683
Sort by r 2, 0								
0	0.0130**	0.0224	0.0091*	0.0746	0.0090*	0.0718	0.0000	
1	0.0157**	0.0162	0.0110*	0.0652	0.0104*	0.0618	0.0000	
2	0.0410***	0.0005	0.0331***	0.0024	0.0326***	0.0038	0.0240***	0.0090
Sort by r 3, 0								
0	0.0145**	0.0108	0.0105*	0.0510	0.0116**	0.0293	0.0000	
1	0.0140**	0.0142	0.0075*	0.0713	0.0078*	0.0602	0.0000	
2	0.0645***	0.0004	0.0507***	0.0056	0.0459**	0.0167	0.0486***	0.0036
Sort by r 4, 0								
0	0.0208***	0.0024	0.0172***	0.0090	0.0186***	0.0045	0.0061	0.4077
1	0.0215***	0.0079	0.0144**	0.0305	0.0146**	0.0272	0.0065	0.2184
2	0.0486***	0.0011	0.0372**	0.0121	0.0338**	0.0281	0.0340**	0.0276
Sort by r 4, 1								
0	0.0197***	0.0029	0.0171***	0.0079	0.0178***	0.0053	0.0036	0.5632
1	0.0163**	0.0321	0.0105	0.1122	0.0109*	0.0989	0.0005	0.9295
2	0.0415***	0.0014	0.0313**	0.0136	0.0274**	0.0367	0.0256*	0.0584
Sort by r 8, 0								
0	0.0299***	0.0003	0.0247***	0.0028	0.0259***	0.0018	0.0158**	0.0284
1	0.0136**	0.0343	0.0065	0.1791	0.0066	0.1706	0.0000	
2	0.0497***	0.0014	0.0381**	0.0145	0.0342**	0.0329	0.0363**	0.0230
Sort by r 16, 0								
0	0.0208***	0.0059	0.0170**	0.0231	0.0182**	0.0187	0.0078	0.2546
1	0.0184***	0.0049	0.0120**	0.0124	0.0117**	0.016	0.0054	0.3306
2	0.0354***	0.0079	0.0295**	0.0195	0.0283**	0.0248	0.0229**	0.0380

Continued on next page

Table 10 (continued): Performance of Long-Only Media-Related Trading Strategies Relative to Cryptocurrency Risk Factors: All Cryptocurrencies ever listed on CoinMarketCap

	One-factor model		Two-factor model		Three-factor model			
	α	p-value	α	p-value	α	p-value	generalized α	p-value
				Sort by r 50, 0				
0	0.0196**	0.0318	0.0088	0.3201	0.0083	0.3546	0.0060	0.4969
1	0.0134*	0.0626	0.0085	0.1451	0.0085	0.1433	0.0007	0.8983
2	0.0280**	0.0152	0.0181*	0.0883	0.0177*	0.0982	0.0161	0.1511
				Sort by r 100, 0				
0	0.0666***	0.0007	0.0483**	0.0175	0.0465**	0.0384	0.0513**	0.0227
1	0.0071	0.3655	0.0031	0.628	0.0019	0.7471	0.0000	
2	0.0824***	0.0076	0.0766**	0.0167	0.0756**	0.0188	0.0699***	0.0087
				Sort by NPAST52				
0	0.0283**	0.0453	0.0240*	0.091	0.0244*	0.0971	0.0164	0.1449
1	0.0110*	0.0967	0.0047	0.3632	0.0042	0.4208	0.0000	
2	0.0166*	0.0703	0.0143	0.1225	0.0149	0.1139	0.0028	0.7374
				Sort by BETA				
0	0.0466***	0.0018	0.0339**	0.0190	0.0337**	0.0212	0.0347***	0.0016
1	0.0060	0.2086	0.0014	0.7088	0.0015	0.6999	0.0000	
2	0.0072	0.2292	0.0014	0.8029	0.0011	0.8411	0.0000	
				Sort by BETA2				
0	0.0336***	0.0033	0.0235**	0.0364	0.0234**	0.0390	0.0216**	0.0373
1	0.0052	0.2600	0.0007	0.8420	0.0008	0.8371	0.0000	
2	0.0203	0.0337	0.0137	0.1342	0.0137	0.1402	0.0088	0.2841

Figure 1 plots the alphas of the long and short legs of the long-short media-based strategies separately. This figure shows that the alphas of the long-short media-based strategy mostly stem from the long (no-coverage) leg, as we have noted above. In contrast with the results for equity reported in Fang and Peress (2009), we find that the alphas of the self-financing portfolios [that borrows funds at the risk-free rate to finance a long position in tokens with no/high media coverage] increase for the holding periods up to 15 weeks, then tend to decrease afterwards.[6] This finding holds for both the samples of cryptocurrencies – all cryptocurrencies ever listed on CoinMarketCap and active cryptocurrencies currently listed on CoinMarketCap, regardless of whether or not we skip a week in between the portfolio formation period and the holding period. Therefore, the media effect can last for many weeks before it eventually dies out.

[6] Fang and Peress (2009) find that the alphas of the long and short legs of the long-short strategy based on media coverage are stable over a long holding period for every portfolio formation period.

5.4 Media, Size, Idiosyncratic Volatility, Liquidity, Value-at-Risk, and Beta

We shall investigate if the media effect is subsumed under other anomalies related to size, idiosyncratic volatility, liquidity, VaR, and beta. The size effect [Banz (1981) and Fama and French (1993)] means that assets with small market capitalization should yield a higher average return than assets with large market capitalization. Ang, Hodrick, Xing, and Zhang (2006) find that assets with higher idiosyncratic volatility yield a lower average return than assets with lower idiosyncratic volatility. This idiosyncratic volatility effect seems to contradict the conventional risk-return trade-off. The liquidity effect suggests that less liquid assets or assets whose returns have a higher sensitivity to the aggregate market liquidity yield a higher expected return, because investors should be compensated for the opportunity costs of being precluded from using the funds invested in the illiquid assets to exploit other opportunities in a liquid market instead, or for high liquidation costs at times when liquidity is lower [see, e.g., Amihud (2002); Amihud and Mendelson (1986); Brennan and Subrahmanyam (1996); Korajczyk and Sadka (2008); Pástor and Stambaugh (2003)]. The VaR effect implies that there is a cross-sectional relation between VaR and expected returns. Bali and Cakici (2004) suggest that this relation can be positive, which is consistent with the conventional risk-return trade-off while Atilgan, Bali, Demirtas, and Gunaydin (2020) find that this relation is negative, and they provide a behavioural explanation for it.[7] Bi and Zhu (2020) find a negative cross-sectional relation between VaR and expected returns only in a high sentiment period and this may not be the case in a low sentiment period. Lastly, Frazzini and Pedersen (2014) suggest that low-beta assets yield a higher expected return than high-beta assets because some agents cannot use leverage on low-beta assets to achieve a better trade-off between risk and expected return, and they are then forced to overweight high-beta assets, causing those assets to offer lower returns.

We first double-sort tokens by each of the aforementioned five characteristics as the first sorting variable and media coverage as the second sorting variable. We then calculate the excess return [using the DGTW CS measure] of each characteristic-based tercile. We also double-sort tokens by media coverage as the first sorting variable and a cryptocurrency characteristic as the second sorting variable, then calculate the excess return of each media coverage-based tercile. We then compare the return differential

[7] Investors may underestimate the persistence in left-tail risk and overprice stocks with large recent losses, which leads to low future returns.

(which is defined as the excess return of the long-short portfolio that longs tokens in the first tercile and shorts tokens in the last tercile based on the second sorting variable) along each dimension.

The results in this section are reported in Table 12. Double-sorting tokens by their average market capitalization (AMCAP) as the first sorting variable and media coverage as the second sorting variable reveals that, controlling for size, there is a statistically significant no-coverage premium before costs among small tokens (2.59% with t-statistic = 2.37) and an insignificant premium in the other two AMCAP-based terciles, which is similar to the results reported in Section 4. Double-sorting tokens by media coverage (as the first sorting variable) and AMCAP (as the second sorting variable) reveals that, controlling for media coverage, there is a significant large-market capitalization premium before costs among high-coverage tokens (1.71% with t-statistic = 2.56) – tokens with large (small) market capitalization yield high (low) average returns, which is quite similar to the phenomenon of attention-grabbing stocks suggested by Barber and Odean (2008) – and an insignificant small-market capitalization premium in the other two media coverage-based terciles. Therefore, the large-size effect exists only among high-coverage tokens. These results suggest that the media effect is not subsumed under the size effect.

Double-sorting tokens by idiosyncratic volatility (IDIOVOL) as the first sorting variable and media coverage as the second sorting variable reveals that, controlling for IDIOVOL, we find a statistically significant no-coverage premium before costs among tokens with high IDIOVOL (4.11% with t-statistic = 2.58) and an insignificant no-coverage premium in the other two IDIOVOL terciles. Double-sorting tokens by media coverage (as the first sorting variable) and IDIOVOL (as the second sorting variable) reveals that, controlling for media coverage, we find a significant high-IDIOVOL premium before costs among no-coverage tokens (3.28% with t-statistic = 2) – tokens with high (low) idiosyncratic volatility yield high (low) average returns, which is consistent with the conventional risk-return trade-off – and a low-IDIOVOL premium among high-coverage tokens (0.88% with t-statistic = 1.62) – tokens with high (low) idiosyncratic volatility yield low (high) average returns. This finding is also aligned with the results on media coverage for stocks reported by Fang and Peress (2009). The significance levels of these IDIOVOL premia are not very strong, thus the media effect is not subsumed under the idiosyncratic volatility effect.

Double-sorting tokens by illiquidity (DAMIHUD) as the first sorting variable and media coverage as the second sorting variable reveals that, controlling for illiquidity, there is a statistically significant no-coverage premium before costs among less liquid tokens (3.37% with t-statistic = 2.49), and the no-coverage premium decreases as liquidity increases. Double-sorting tokens by media coverage (as the first sorting variable) and DAMIHUD (as the second sorting variable) reveals that, controlling for media coverage, there is a significant high-illiquidity premium before costs among no- or low-coverage tokens (2.29% with t-statistic = 1.83 and 3.14% with t-statistic = 1.99, respectively) – tokens with high (low) illiquidity yield high (low) average returns, which is consistent with the conventional liquidity risk argument – and an insignificant illiquidity premium among high-coverage tokens as most high-coverage tokens are very liquid. Therefore, it seems that there is a strong correlation between media coverage and liquidity, and the media effect may be subsumed under the liquidity effect. To verify this result, we also use log average daily volume times price (PRCVOL) and the PRCVOL scaled by market capitalization (VOLSCALED) as other proxies for liquidity.

Double-sorting tokens by PRCVOL as the first sorting variable and media coverage as the second sorting variable reveals that, controlling for illiquidity, there is a statistically significant no-coverage premium before transaction costs only among tokens in the medium PRCVOL tercile (1.51% with t-statistic = 2.42). Double-sorting tokens by media coverage (as the first sorting variable) and PRCVOL (as the second sorting variable) suggests that, controlling for media coverage, there is a significant high-illiquidity premium before transaction costs only among no-coverage tokens. This result suggests that the media effect is not subsumed under the liquidity effect. In addition, double-sorting tokens by VOLSCALED as the first sorting variable and media coverage as the second sorting variable reveals that, controlling for illiquidity, there is a significant no-coverage premium before costs only among least liquid tokens (2.73% with t-statistic = 2.41). Double-sorting tokens by media coverage (as the first sorting variable) and VOLSCALED (as the second sorting variable) suggests that, controlling for media coverage, there is a significant high-illiquidity premium before costs only among no-coverage tokens (2.09% with t-statistic = 2.51), and thus the media effect is subsumed under the liquidity effect. Therefore, we found a mixed evidence that the media effect is subsumed under the liquidity effect.

Double-sorting tokens by VaR as the first sorting variable and media coverage as the second sorting variable reveals that, controlling for VaR, the largest, though not very highly significant, no-coverage premium before costs is found among tokens in the high VaR tercile (1.94% with t-statistic = 1.62). Double-sorting tokens by media coverage (as the first sorting variable) and VaR (as the second sorting variable) suggests that, controlling for media coverage, there is some high-VaR premium before transaction costs only among no-coverage tokens (2.24% with t-statistic = 1.79) – which is consistent with the conventional risk-return trade-off – and a significant low-VaR premium among high-coverage tokens (0.76% with t-statistic = 2.36) – this is possibly due to investors underestimating the persistence in the left-tail risk and thus overpricing tokens with large recent losses in a high-sentiment regime when these tokens are extensively covered in the media. This result suggests that the media effect is not subsumed under the VaR effect.

Double-sorting tokens by BETA as the first sorting variable and media coverage as the second sorting variable reveals that, controlling for BETA, there is a large and statistically significant no-coverage premium before costs only among tokens in the low BETA tercile (2.77% with t-statistic = 2.25). Double-sorting tokens by media coverage (as the first sorting variable) and BETA (as the second sorting variable) suggests that, controlling for media coverage, there is an insignificant beta premium before costs in every media coverage-based tercile. This result clearly suggests that the media effect cannot be subsumed under the BETA effect.

We also perform robustness checks using (i) all cryptocurrencies while skipping one week between the portfolio formation week and the holding week, and (ii) only active cryptocurrencies. The results [reported in Section S.IV.4] confirm the findings reported in this section: the media effect is not subsumed under other anomalies related to size, idiosyncratic volatility, VaR, and beta, but it may be subsumed under the liquidity effect.

6 Comparing the Media Effect with Other Characteristic-Based Effects

In this section, we shall compare the media effect with other effects based on cryptocurrency characteristics, such as size (proxied by AMCAP), liquidity (proxied by PRCVOL, VOLSCALED, or DAMIHUD), volatility (proxied by RETVOL or IDIOVOL), risk (proxied by VaR, BETA, or BETA2), and momentum (MAXRET, $r\ i, 0$ for $i = 1, 2, 3, 4, 8, 16, 50, 100$, $r\ 4, 1$, or NPAST52). (All the characteristics are defined in Table S.I.1.) Given a characteristic (other than media coverage), we first sort tokens into three groups (namely, 0, 1, and 2) based on the values of this characteristic. We then form an equally weighted portfolio of tokens in each group (tercile). These portfolios will then be held for a week after portfolio formation, and they are re-balanced weekly. Therefore, we obtain a time series of weekly returns for each of the portfolios. We can also calculate the turnovers and transaction costs of these portfolios over time by employing the procedure explained in Section A.II.

Table 11: Performance of Media-Related Trading Strategies Relative to Cryptocurrency Risk Factors for Different Portfolio Formation and Holding Periods: All Cryptocurrencies ever listed on CoinMarketCap

This table reports the average returns [in excess of the common risk factors in cryptocurrency proposed by Liu et al. (2022)] of a trading strategy that longs tokens with no media coverage over the past K weeks and shorts tokens with high media coverage over the past K weeks (K = 1, 5, 10). In each portfolio formation period, tokens are sorted according to the average number of news articles written about them per week in this period. A token is considered to have no media coverage if no article is written about this token. A token is considered to have a high media coverage if the average number of articles written about it per week exceeds the median during the period. Both the long and short positions are equally weighted, and they are held for the entire holding period of J weeks after portfolio formation ($J = 1, 2, \ldots, 20$). Therefore, in any given week, the strategy holds a composite portfolio consisting of the long/short/long-short portfolio initiated K weeks prior to this week as well as the portfolios initiated in the previous $K - 1$ weeks. These portfolios have overlapping holding periods at the end of each week if $J > 1$. The return of the composite portfolio in a week is then calculated by averaging the returns [of the portfolios with overlapping holding periods] from their initiation weeks to this week [as described in Jegadeesh and Titman (1993)]. The resulting time-series returns on the composite long-short portfolio are regressed on three risk factors (cryptocurrency market, size, and momentum). Alphas obtained from this regression are then reported, and p-values [using the Newey-West standard error] are in parentheses. The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. Note that a cryptocurrency is included if its market capitalization is at least one million during the portfolio formation week while its name and symbol are mentioned in at least 100 articles throughout the sample period.

Holding period [J week(s)]	Time-series mean	One-factor model	Two-factor model	Three-factor model	Average number of tokens		
					Media coverage		
					No	Low	High
Panel A: Formation period (K) = 1 week							
1	0.0123***	0.0088***	0.0089***	0.0088***	148.07	195.31	177.02
	(0.0000)	(0.0055)	(0.0047)	(0.0068)			
3	0.0163***	0.0142***	0.0144***	0.0146***			
	(0.0000)	(0.0000)	(0.0001)	(0.0001)			
6	0.0192***	0.0182***	0.0173***	0.0172***			
	(0.0000)	(0.0000)	(0.0000)	(0.0001)			
9	0.0221***	0.0203***	0.0201***	0.0200***			
	(0.0000)	(0.0000)	(0.0000)	(0.0000)			
12	0.0234***	0.0228***	0.0225***	0.0228***			
	(0.0000)	(0.0001)	(0.0000)	(0.0001)			
15	0.0222***	0.0218***	0.0221***	0.0224***			
	(0.0000)	(0.0002)	(0.0002)	(0.0002)			
18	0.0161***	0.0143***	0.0151***	0.0152***			
	(0.0000)	(0.0000)	(0.0001)	(0.0001)			
20	0.0153***	0.0132***	0.0139***	0.0140***			
	(0.0000)	(0.0000)	(0.0000)	(0.0000)			

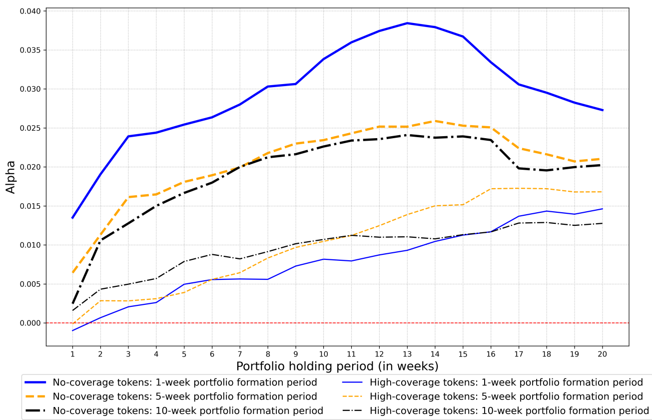
Continued on next page

Table 11 (continued): Performance of Media-Related Trading Strategies Relative to Cryptocurrency Risk Factors for Different Portfolio Formation and Holding Periods: All Cryptocurrencies ever listed on CoinMarketCap

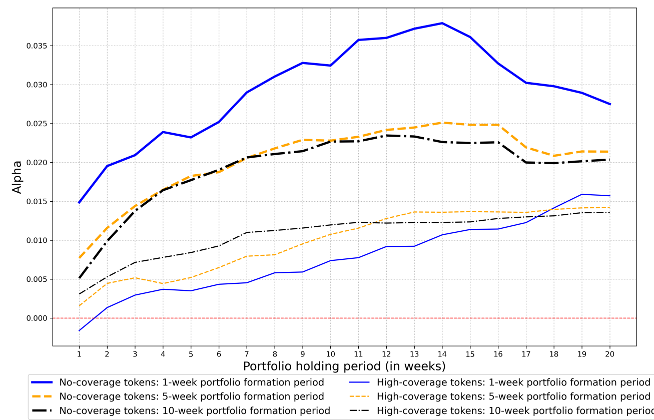
Holding period [J week(s)]	Time-series mean	One-factor model	Two-factor model	Three-factor model	Average number of tokens: Media coverage: No	Low	High
Panel B: Formation period (K) = 5 weeks							
1	0.0065***	0.0046**	0.0054**	0.0051**	74.63	230.69	219.09
	(0.0015)	(0.0164)	(0.0123)	(0.0161)			
3	0.0096***	0.0089***	0.0079***	0.0076***			
	(0.0001)	(0.0007)	(0.0028)	(0.0035)			
6	0.0090***	0.0098***	0.0093***	0.0092***			
	(0.0005)	(0.0012)	(0.0040)	(0.0046)			
9	0.0083***	0.0071**	0.0071**	0.0072**			
	(0.0026)	(0.0266)	(0.0286)	(0.0301)			
12	0.0061**	0.0046	0.0047	0.0049			
	(0.0477)	(0.2421)	(0.2404)	(0.2289)			
15	0.0044	0.0025	0.0031	0.0033			
	(0.1817)	(0.5732)	(0.4954)	(0.4690)			
18	−0.0003	−0.0017	−0.0014	−0.0014			
	(0.8942)	(0.5184)	(0.6029)	(0.5809)			
20	−0.0014	−0.0029	−0.0028	−0.0028			
	(0.5031)	(0.2173)	(0.2518)	(0.2362)			
Panel C: Formation period (K) = 10 weeks							
1	0.0038**	0.0029	0.0027	0.0025	48.85	238.54	229.67
	(0.0408)	(0.1463)	(0.2122)	(0.2522)			
3	0.0067***	0.0073***	0.0056***	0.0055**			
	(0.0023)	(0.0012)	(0.0068)	(0.0127)			
6	0.0078***	0.0085***	0.0075**	0.0075**			
	(0.0033)	(0.0060)	(0.0198)	(0.0223)			
9	0.0088***	0.0083***	0.0073**	0.0071**			
	(0.0018)	(0.0064)	(0.0166)	(0.0204)			
12	0.0096***	0.0078**	0.0067*	0.0065*			
	(0.0040)	(0.0279)	(0.0583)	(0.0691)			
15	0.0105***	0.0085**	0.0079*	0.0077*			
	(0.0041)	(0.0313)	(0.0592)	(0.0688)			
18	0.0053**	0.0045	0.0038	0.0035			
	(0.0437)	(0.1077)	(0.1784)	(0.2273)			
20	0.0057**	0.0051*	0.0047*	0.0044			
	(0.0307)	(0.0623)	(0.0911)	(0.1197)			

Figure 1: Horizon Analysis of the Media Effect

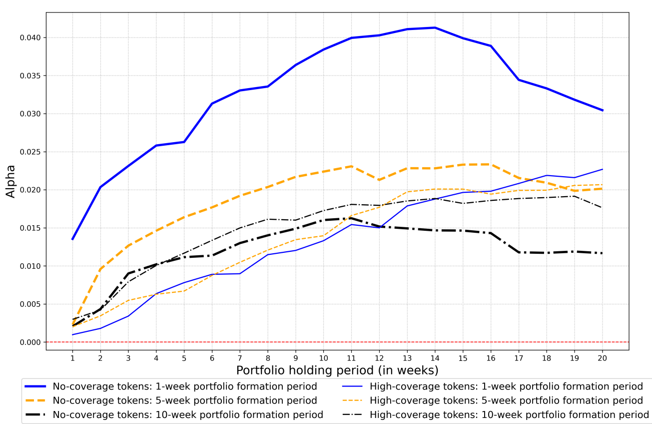
The alphas [adjusted for Liu et al.'s (2022) three common cryptocurrency risk factors] for no- and high-coverage tokens are displayed for various formation and holding periods. Tokens are assigned to a portfolio based on their coverage in the media over the past 1, 5, or 10 weeks. Given a portfolio formation period, the alphas are plotted across various holding horizons ranging from 1 week to 20 weeks.



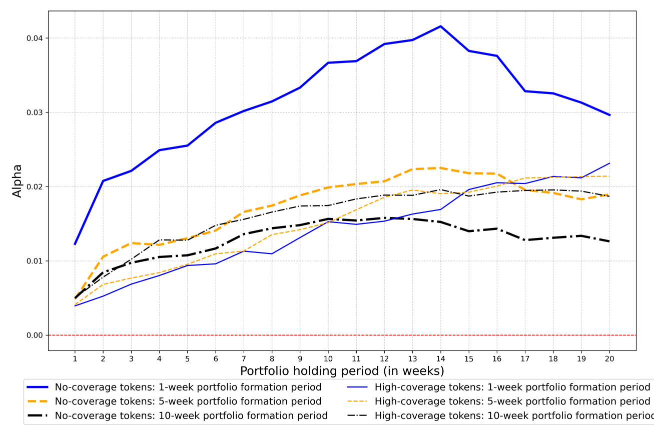
(a) All tokens[a]



(b) All tokens: skipping one week between the formation period and the holding period



(c) Active tokens[b]



(d) Active tokens: skipping one week between the formation period and the holding period

[a] All cryptocurrencies ever listed on CoinMarketCap are included.

[b] Only active cryptocurrencies currently listed on CoinMarketCap are included.

Table 12: Media Effect versus other Cryptocurrency Characteristics: All Cryptocurrencies ever listed on CoinMarketCap

This table examines whether the media effect is subsumed under another cryptocurrency characteristic effect. We double-sort tokens by two variables (media coverage and a cryptocurrency characteristic defined in Table S.I.1). We first sort tokens into terciles by the first sorting variable. In each of these terciles, we further sort tokens into three subsamples by the second sorting variable. We then form three sub-portfolios by (i) longing the tokens in the first subsample, or (ii) shorting the tokens in the third subsample, or (iii) simultaneously longing the tokens in the first subsample while shorting the tokens in the third subsample for every first sorting variable except VaR (in this case, the tokens in the first/third subsample are shorted/longed respectively) during the portfolio formation week (the portfolio-forming and rebalancing procedure is described in Table 4 above). All portfolios are equally weighted. Excess returns (in percentage) are computed using the DGTW characteristic-based benchmark methods. All *t*-statistic values (in parentheses) use the Newey-West standard error.

Second sorting var / First sorting var	Long		Short		Long-Short	
	Before trans. cost	After trans. cost	Before trans. cost	After trans. cost	Before trans. cost	After trans. cost
Double-sort by (AMCAP, Newspaper Coverage)						
0	1.15	−0.46	1.45	−3.31	2.59	−3.54
	(1.18)	(−0.47)	(2.06)	(−4.70)	(2.37)	(−3.29)
1	1.93	0.19	−0.46	−5.28	1.47	−4.86
	(2.72)	(0.28)	(−0.59)	(−6.75)	(1.32)	(−4.41)
2	0.21	−1.24	−0.41	−5.16	−0.18	−6.26
	(0.77)	(−4.18)	(−2.26)	(−28.61)	(−0.91)	(−29.06)
Double-sort by (Newspaper Coverage, AMCAP)						
0	1.34	−0.22	−0.07	−4.83	1.57	−4.75
	(1.48)	(−0.25)	(−0.32)	(−20.58)	(1.49)	(−4.62)
1	0.23	−2.65	0.21	−4.56	0.81	−6.85
	(0.42)	(−4.44)	(0.83)	(−18.20)	(1.32)	(−10.95)
2	-1.41	−4.44	−0.26	−5.01	−1.71	−9.47
	(-2.25)	(−7.13)	(−2.06)	(−39.03)	(−2.56)	(−14.31)
Double-sort by (IDIOVOL, Newspaper Coverage)						
0	0.15	−2.88	−0.08	−4.83	0.24	−7.47
	(0.42)	(−7.47)	(−0.57)	(−35.17)	(0.57)	(−17.41)
1	-0.04	−3.21	−0.13	−4.91	−0.02	−7.85
	(-0.10)	(−7.08)	(−0.60)	(−22.04)	(−0.04)	(−16.40)
2	2.23	−0.50	1.68	−3.20	4.11	−3.37
	(1.56)	(−0.35)	(2.39)	(−4.60)	(2.58)	(−2.10)
Double-sort by (Newspaper Coverage, IDIOVOL)						
0	-0.05	−2.95	−3.84	−8.68	−3.28	−10.72
	(-0.17)	(−9.75)	(−2.28)	(−5.13)	(−2.00)	(−6.54)
1	-0.05	−3.56	0.04	−4.81	−0.38	−8.55
	(-0.25)	(−17.24)	(0.07)	(−7.75)	(−0.48)	(−11.02)
2	-0.04	−2.87	1.08	−3.77	0.88	−6.57
	(-0.32)	(−19.90)	(1.86)	(−6.52)	(1.62)	(−12.23)
Double-sort by (DAMIHUD, Newspaper Coverage)						
0	0.27	−1.43	−0.25	−5.01	0.02	−6.33
	(1.05)	(−5.02)	(−1.86)	(−37.32)	(0.08)	(−27.62)
1	0.41	−1.50	0.95	−3.84	1.74	−4.77
	(0.88)	(−3.20)	(1.85)	(−7.51)	(2.17)	(−6.06)
2	2.31	0.53	1.37	−3.44	3.37	−3.00
	(1.78)	(0.41)	(1.47)	(−3.72)	(2.49)	(−2.22)
Double-sort by (Newspaper Coverage, DAMIHUD)						
0	0.37	−1.21	−3.01	−7.76	−2.29	−8.63
	(1.66)	(−5.12)	(−2.57)	(−6.63)	(−1.83)	(−6.75)
1	-0.01	−2.88	−2.15	−6.94	−3.14	−10.78
	(-0.06)	(−11.41)	(−1.90)	(−6.13)	(−1.99)	(−6.88)
2	0.14	−1.58	0.31	−4.49	0.48	−6.05
	(1.15)	(−13.16)	(0.67)	(−9.56)	(0.93)	(−11.24)

Continued on next page

Table 12 (continued): Media Effect versus other Cryptocurrency Characteristics: All Cryptocurrencies ever listed on CoinMarketCap

First sorting var \ Second sorting var	Long: Before trans. cost	Long: After trans. cost	Short: Before trans. cost	Short: After trans. cost	Long-Short: Before trans. cost	Long-Short: After trans. cost
			Double-sort by (PRCVOL, Newspaper Coverage)			
0	1.79	−0.04	1.03	−3.76	−0.63	−7.04
	(1.78)	(−0.04)	(1.46)	(−5.32)	(−0.17)	(−1.83)
1	0.54	−1.23	0.85	−3.95	1.51	−4.84
	(1.11)	(−2.56)	(2.05)	(−9.56)	(2.42)	(−8.02)
2	-0.15	−1.61	0.05	−4.71	−0.09	−6.20
	(-0.54)	(−5.72)	(0.37)	(−39.30)	(−0.32)	(−22.81)
			Double-sort by (Newspaper Coverage, PRCVOL)			
0	2.14	0.41	0.32	−4.43	2.75	−3.74
	(2.77)	(0.53)	(1.33)	(−18.49)	(3.15)	(−4.29)
1	0.29	−2.59	0.24	−4.52	0.91	−6.74
	(0.47)	(−4.07)	(1.05)	(−19.49)	(1.37)	(−9.90)
2	-0.78	−3.79	−0.06	−4.81	−0.88	−8.63
	(-1.53)	(−7.33)	(−0.49)	(−42.04)	(−1.71)	(−16.71)
			Double-sort by (VOLSCALED, Newspaper Coverage)			
0	2.34	0.50	0.42	−4.38	2.73	−3.70
	(2.79)	(0.61)	(0.86)	(−8.78)	(2.41)	(−3.32)
1	-0.00	−1.84	0.37	−4.42	0.75	−5.68
	(-0.0)	(−4.24)	(1.37)	(−16.48)	(1.42)	(−11.21)
2	-0.06	−1.61	0.35	−4.41	0.39	−5.81
	(-0.16)	(−4.45)	(2.02)	(−25.49)	(0.95)	(−14.53)
			Double-sort by (Newspaper Coverage, VOLSCALED)			
0	2.10	0.36	0.02	−4.69	2.09	−4.37
	(2.45)	(0.43)	(0.05)	(−11.93)	(2.51)	(−5.19)
1	0.61	−2.25	0.63	−4.12	1.69	−5.93
	(0.86)	(−3.12)	(2.08)	(−13.58)	(1.60)	(−5.64)
2	-0.41	−3.32	0.33	−4.42	−0.14	−7.79
	(-0.90)	(−7.65)	(2.21)	(−29.77)	(−0.31)	(−16.79)
			Double-sort by (VaR, Newspaper Coverage)			
0	0.21	−1.48	−0.04	−4.80	0.35	−5.98
	(0.46)	(−3.31)	(−0.28)	(−33.17)	(0.78)	(−13.91)
1	0.32	−1.60	0.51	−4.29	0.75	−5.78
	(0.84)	(−4.16)	(2.06)	(−17.28)	(1.83)	(−14.78)
2	1.90	0.15	0.02	−4.81	1.94	−4.45
	(1.62)	(0.13)	(0.05)	(−10.25)	(1.62)	(−3.78)
			Double-sort by (Newspaper Coverage, VaR)			
0	2.62	0.90	−0.42	−5.17	2.24	−4.22
	(2.45)	(0.86)	(−1.02)	(−12.63)	(1.79)	(−3.39)
1	-0.16	−3.06	0.79	−3.99	0.95	−6.71
	(-0.26)	(−4.92)	(2.44)	(−12.38)	(1.83)	(−12.38)
2	-0.82	−3.72	−0.22	−4.98	−0.76	−8.40
	(-2.47)	(−10.96)	(−1.61)	(−36.04)	(−2.36)	(−25.07)
			Double-sort by (BETA, Newspaper Coverage)			
0	1.97	0.30	0.78	−4.01	2.77	−3.50
	(1.61)	(0.25)	(1.92)	(−10.62)	(2.25)	(−2.89)
1	-0.40	−2.15	0.57	−4.21	0.28	−6.07
	(-1.07)	(−5.63)	(2.68)	(−19.83)	(0.77)	(−15.69)
2	-0.38	−2.10	0.16	−4.63	−0.07	−6.40
	(-0.83)	(−4.30)	(0.58)	(−16.98)	(−0.12)	(−10.55)
			Double-sort by (Newspaper Coverage, BETA)			
0	1.83	0.18	−0.49	−5.27	2.02	−4.41
	(1.30)	(0.13)	(−0.83)	(−8.86)	(1.39)	(−2.71)
1	-0.93	−3.63	0.44	−4.36	−2.38	−9.88
	(-1.25)	(−4.82)	(1.04)	(−10.34)	(−1.30)	(−5.43)
2	-0.71	−3.18	0.10	−4.69	−0.68	−7.92
	(-2.11)	(−9.35)	(0.34)	(−16.65)	(−1.74)	(−20.42)

Table 13 reports the average returns (and their t-statistics), the average turnovers, and the average transaction costs of the tercile portfolios and the long-short portfolio [that longs the tokens in the first/last group and shorts the tokens in the last/first group, as specified in the second column] as well as the average number of tokens per week in each group. While the average numbers of tokens per week in the first and last groups are quite similar for every sorting variable, the average returns on the first tercile portfolio are highest for AMCAP (4.43%), PRCVOL (4.65%), VOLSCALED (4.62%), No. of articles (4.08%), and $r\ 100, 0$ (3.78%), meaning that the tokens with smallest market capitalization, lowest trading volume, highest past 100-week return, or no-media coverage yield the highest expected returns. The first two empirical results are consistent with the results reported in Liu et al. (2022).

In addition, the average returns on the last tercile portfolio are highest for RETVOL (4.21%), MAXRET (4.29%), DAMIHUD (5.89%), and VaR (4.40%), meaning that the tokens with the highest volatility, highest maximum return in the portfolio formation week, highest illiquidity, or highest VaR yield the highest expected returns. The average returns on the long-short portfolios are highest and statistically significant for AMCAP (3.32% with t-statistic = 4.63), PRCVOL (3.84% with t-statistic = 4.77), VOLSCALED (3.87% with t-statistic = 4.63), RETVOL (2.94% with t-statistic = 4.32), IDIOVOL (2.76% with t-statistic = 3.22), MAXRET (3.06% with t-statistic = 4.22), DAMIHUD (4.84% with t-statistic = 4.55), VaR (3.28% with t-statistic = 4.05), and No. of articles (2.61% with t-statistic = 3.90). This suggests that, before accounting for transaction costs, the size effect, the volatility effect, the momentum effect, the liquidity effect, the VaR effect, and the media effect are the strongest for cryptocurrencies. Moreover, as suggested by Liu et al. (2022), market capitalization and past one-, two-, three-, and four-week returns are successful cross-sectional predictors while BETA, $BETA^2$, and DAMIHUD are not. Therefore, our findings are mostly in line with their findings, except we find that DAMIHUD can strongly predict the cross-section of cryptocurrencies.

We also observe that, for every sorting characteristic other than VaR, the average turnover (and thus the average transaction cost) in the first tercile portfolio is always much lower than in the last tercile portfolio, as the cryptocurrencies in the first tercile do not often migrate to the other terciles. Moreover, all the long-short strategies based on a given cryptocurrency characteristic (including the media-based strategy) are not profitable after accounting for transaction costs. However, the long-only strategies [that long tokens in the first tercile based on AMCAP, PRCVOL, VOLSCALED, No. of articles, or r 100, 0 or in the last tercile based on RETVOL, MAXRET, DAMIHUD, or VaR] may yield a positive average net-of-costs return. Therefore, in the cryptocurrency market, a long-only strategy [that longs tokens in the lowest/highest characteristic-based tercile] may withstand transaction costs while a long-short strategy may not.

7 Conclusion

A common wisdom in investing is that "buy the rumor, sell the news" (Peterson, 2006). This phrase suggests that the price of a risky asset is often high (as such, the expected return is low) when this asset is in the spotlight while the price tends to be low (as such, the expected return is high) when the asset is still not known to many investors. We find that cryptocurrencies with no media coverage, on average, outperform cryptocurrencies with high media coverage by over 2.61% per week, even after adjusting for well-known risk factors (cryptocurrency market, size, and momentum). Moreover, this average return spread is particularly large and statistically significant (ranging from 3% to 6% per week) for small tokens and tokens with high illiquidity, high volatility, high Value-at-Risk, or low beta. When accounting for transaction costs, the tokens with no media coverage still achieve a statistically significant average net-of-costs return of 3.15% per week while the tokens with high media coverage yield a negative net-of-costs return of -2.27% per week due to their much higher turnover and transaction costs. As a result, the net-of-costs return spread is reduced to -2.25% per week, due to the transaction costs incurred from the short leg. These results hold even after adjusting for common risk factors in cryptocurrency.

We show that the media effect is distinct from time-series patterns, such as negative return drift among high-coverage tokens with low past returns and return reversal of no-coverage tokens with low past returns. Instead, the return differential between no-coverage tokens and high-coverage tokens could be explained by either illiquidity, risk, or investor recognition, which is consistent with the explanation of the media effect for stocks, reported in Fang and Peress (2009). Moreover, the media effect is not subsumed by a host of anomalies documented in the literature, such as the size effect, the idiosyncratic volatility effect, the Value-at-Risk (VaR) effect, the momentum effect, and the beta effect. However, it may be subsumed by the liquidity effect. Thus, illiquidity and the media effect are highly related (i.e., illiquidity can explain the persistence of the media effect while it may also cause the media effect).

We also compare the magnitude of the media effect with that of other anamolies, such as size, liquidity, volatility, VaR, beta, and momentum. In particular, the long-short portfolio [that longs small tokens and short large tokens] yields an average return of 3.32% per week (t-statistic = 4.63) in the following week; the long-short portfolio [that longs tokens with high illiquidity and shorts tokens with low illiquidity] yields an average return of 4.84% per week (t-statistic = 4.55) in the following week; the long-short portfolio [that longs tokens with high VaR and short tokens with low VaR] yields an average return of 3.28% per week (t-statistic = 4.05) in the following week; the long-short portfolio [that longs tokens with high beta and shorts tokens with low beta] yields an average return of 0.34% per week (t-statistic = 0.54) in the following week; the long-short portfolio [that longs tokens with high past performance and short tokens with low past performance] yields an average return ranging from -0.09% per week (t-statistic = -0.16) to 3.06% per week (t-statistic = 4.22) in the following week; and the long-short portfolio [that longs tokens with no media coverage and shorts tokens with high media coverage] yields an average return of 2.61% per week (t-statistic = 3.90) in the following week. Therefore, the media effect seems quite comparable with the other effects before deducting transaction costs. After accounting for transaction costs, all the long-short strategies become non-profitable. However, the long-only strategies may still achieve a positive average net-of-costs returns. Therefore, in the cryptocurrency market, media coverage is positively correlated with size, liquidity, VaR, beta, and momentum. This correlation suggests that the effect of media coverage on pricing stems from its ability to influence individual investors' attention.

Table 13: Average Weekly Cryptocurrency Returns, Turnovers, and Transaction Costs across Terciles Formed by Sorting Tokens by a Cryptocurrency Characteristic: All Cryptocurrencies ever listed on CoinMarketCap

This table presents average weekly returns, turnovers, and transaction costs for tokens in each of the terciles formed by sorting tokens according to the cryptocurrency characteristics (listed in Table S.I.1) one at a time. For every sorting characteristic (*sort char*), we divide our sample of cryptocurrencies into terciles enumerated as 0, 1, and 2 at the end of the portfolio formation week (for the media coverage, the first tercile consists of tokens with no media coverage while the last tercile consists of tokens with high media coverage with the median being used to divide the covered tokens into low- and high-coverage groups, as described in Table 4). We then compute the average returns of the three tercile portfolios using individual cryptocurrency returns in the holding week. All the portfolios are equally weighted. We also report the average turnovers and transaction costs of the portfolios of tokens in the first (and last) terciles and their long-short (LS) portfolio as well as the average net-of-costs returns of the LS portfolio. Note that a cryptocurrency is included if its market capitalization is at least one million during the portfolio formation week while its name and symbol are mentioned in at least 100 articles throughout the sample period. All the t-statistic values use the Newey-West standard error.

Sort char	Long-short (LS)	Average returns (%)				t-statistics for LS portfolios	Average turnover (%)			Average transaction cost (%)			Average net-of-costs returns for LS portfolios (%)	t-statistics of net-of-costs returns for LS portfolios	Average number of tokens per week		
		0	1	2	LS		0	2	LS	0	2	LS			0	1	2
AMCAP	0-2	4.43	2.19	1.10	3.32	4.63	12.80	98.68	111.54	0.60	4.65	5.26	−1.99	−2.85	160.50	213.44	160.68
PRCVOL	0-2	4.65	1.43	0.81	3.84	4.77	13.33	96.91	110.25	0.63	4.57	5.20	−1.49	−1.90	158.70	211.74	159.10
VOLSCALED	0-2	4.62	1.54	0.75	3.87	4.63	13.11	95.44	108.40	0.62	4.50	5.11	−1.38	−1.69	158.80	211.68	159.06
RETVOL	2-0	1.27	1.79	4.21	2.94	4.32	26.67	76.35	104.87	1.26	3.60	4.94	−2.21	−3.28	160.98	213.54	159.63
IDIOVOL	2-0	0.89	1.44	3.65	2.76	3.22	25.02	78.33	105.06	1.18	3.69	4.95	−2.40	−2.82	126.00	166.77	124.99
MAXRET	2-0	1.23	1.76	4.29	3.06	4.22	30.50	73.86	106.92	1.44	3.48	5.04	−2.13	−2.98	160.97	213.32	159.71
DAMIHUD	2-0	1.05	1.21	5.89	4.84	4.55	8.94	92.89	101.82	0.42	4.38	4.80	−0.13	−0.13	161.57	213.38	159.20
VaR	2-0	1.12	1.68	4.40	3.28	4.05	94.80	15.50	110.39	4.47	0.73	5.20	−1.93	−2.45	154.77	206.11	154.43
r 1, 0	2-0	1.93	2.03	3.22	1.30	2.56	36.60	68.35	107.63	1.73	3.22	5.07	−3.88	−7.77	160.79	213.26	159.77
r 2, 0	2-0	2.00	1.85	3.64	1.65	2.55	27.73	78.19	107.91	1.31	3.69	5.09	−3.49	−5.49	160.48	212.82	159.44
r 3, 0	2-0	2.21	1.76	3.78	1.56	2.12	24.04	82.17	107.58	1.13	3.87	5.07	−3.72	−5.07	160.00	212.19	159.01
r 4, 0	2-0	2.29	1.64	3.57	1.28	1.75	21.72	84.48	107.39	1.02	3.98	5.06	−3.94	−5.45	159.84	212.10	158.82
r 4, 1	2-0	2.48	1.87	3.06	0.57	0.91	25.27	80.67	106.30	1.19	3.80	5.01	−4.60	−7.32	159.83	212.04	158.84
r 8, 0	2-0	2.77	1.49	3.17	0.39	0.46	17.77	88.74	107.25	0.84	4.18	5.06	−4.90	−5.80	157.54	208.96	156.62
r 16, 0	2-0	2.82	1.80	2.72	−0.09	−0.16	14.96	91.48	107.00	0.71	4.31	5.04	−5.38	−9.11	153.55	203.81	152.66
r 50, 0	0-2	2.57	1.26	1.63	0.94	1.62	12.33	94.52	107.19	0.58	4.46	5.05	−4.33	−7.49	126.30	167.08	124.99
r 100, 0	0-2	3.78	1.53	2.13	1.65	2.18	11.52	95.58	107.43	0.54	4.51	5.06	−3.92	−5.24	105.17	139.06	104.18
NPAST52	2-0	1.62	1.07	2.38	0.76	1.22	11.95	91.81	104.31	0.56	4.33	4.92	−4.36	−6.97	124.28	164.80	123.58
BETA	2-0	2.20	1.11	2.54	0.34	0.54	10.19	96.56	106.81	0.48	4.55	5.04	−5.12	−8.12	126.18	166.97	125.22
BETA2	2-0	1.64	1.11	3.13	1.49	2.41	9.76	96.48	106.39	0.46	4.55	5.02	−3.92	−6.38	126.18	166.97	125.22
No. of articles	0-2	4.08	2.25	1.46	2.61	3.90	19.67	79.27	103.22	0.93	3.73	4.87	−2.40	−3.62	168.55	190.99	175.08

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A.I Transaction Costs

A.I.1 Hasbrouck's (2009) Gibbs bid-ask spread estimator

Hasbrouck's (2009) estimator is based on a Bayesian Gibbs sampler assuming the following generalized Roll's (1984) dynamics of stock prices:

$$\begin{aligned} V_t &= V_{t-1} + \epsilon_t, \\ P_t &= V_t + cQ_t, \end{aligned} \tag{A.1}$$

where V_t is the 'efficient' (log) price, P_t is the transaction price, $Q_t = \begin{cases} 1 & \text{if it is a buy transaction} \\ -1 & \text{if it is a sell transaction} \end{cases}$, $\epsilon_t \overset{i.i.d.}{\sim} N(0, \sigma_\epsilon^2)$ is a random public shock to the 'efficient' price, and c is the effective one-way transaction cost. This model implies that

$$\Delta P_t = c\Delta Q_t + \epsilon_t. \tag{A.2}$$

Hasbrouck (2009) estimates c by applying a Gibbs sampler to an augmented version of (A.2):

$$\Delta P_t = c\Delta Q_t + \beta^{(m)} r_t^{(m)} + \epsilon_t, \tag{A.3}$$

where $r_t^{(m)}$ denotes the market return on day t.

The unknown parameters of the model defined by (A.3) are c, β, σ_ϵ^2, and the latent trade indicators $Q_1, \ldots, Q_T$. As suggested by Hasbrouck (2009), we assume that the prior distribution of c is a truncated normal distribution with mean equal to zero and variance equal to 0.05^2, restricted to nonnegative values. The prior distribution of $\beta^{(m)}$ is $N(1,1)$ and that of σ_ϵ^2 is an inverted gamma distribution, $IG\left(10^{-12}, 10^{-12}\right)$. The prior distribution of Q_t, $t = 1, \ldots, T$, is a Bernoulli distribution with equal probabilities.

The Gibbs sampler starts by initializing σ_ϵ^2 to $\sigma_\epsilon^{2[0]} = 0.0004$ and Q_t, $t = 1, \ldots, T$, to $Q_t^{[0]}$, $t = 1, \ldots, T$, with $Q_1^{[0]} = 1$ and $Q_t^{[0]} := \begin{cases} \text{sign}(\Delta P_t) & \text{if } \Delta P_t \neq 0, \\ Q_{t-1}^{[0]} & \text{if } \Delta P_t = 0. \end{cases}$

For the i-the sweep of the Gibbs sampler, based on the most recently simulated values $\sigma_\epsilon^{2[i-1]}$ and $Q_t^{[i-1]}$ for σ_ϵ^2 and Q_t, $t = 1, \ldots, T$, we draw values, $c^{[i]}$ and $\beta^{(m)[i]}$ for c and $\beta^{(m)}$ from their posterior distribution. To derive this posterior distribution, we define $\boldsymbol{y} := (\Delta P_1, \ldots, \Delta P_T)^\top$, $\boldsymbol{X} := \begin{pmatrix} \Delta Q_1 & r_1^{(m)} \\ \vdots & \vdots \\ \Delta Q_T & r_T^{(m)} \end{pmatrix}$,

$\boldsymbol{b} := \left(c, \beta^{(m)}\right)^{\top} \sim N\left(\boldsymbol{\mu}_b, \boldsymbol{\Omega}_b\right)$ restricted to $c > 0$ with $\boldsymbol{\mu}_b := (0,1)^{\top}$ and $\boldsymbol{\Omega}_b := \left(\begin{smallmatrix} 0.05^2 & 0 \\ 0 & 1 \end{smallmatrix}\right)$, and $\boldsymbol{e} = (\epsilon_1, \ldots, \epsilon_T)^{\top} \sim N\left(\mathbf{0}, \boldsymbol{\Omega}_e\right)$ with $\boldsymbol{\Omega}_e := \operatorname{diag}\left(\sigma_\epsilon^2\right)$. The posterior distribution of $\boldsymbol{b}$ is then $N\left(\boldsymbol{\mu}_b^*, \boldsymbol{\Omega}_b^*\right)$ restricted to $c > 0$, where $\boldsymbol{\mu}_b^* := \left(\boldsymbol{X}^{\top}\boldsymbol{\Omega}_e^{-1}\boldsymbol{X} + \boldsymbol{\Omega}_b^{-1}\right)^{-1}\left(\boldsymbol{X}^{\top}\boldsymbol{\Omega}_e^{-1}\boldsymbol{y} + \boldsymbol{\Omega}_b^{-1}\boldsymbol{\mu}_b\right)$ and $\boldsymbol{\Omega}_b^* := \left(\boldsymbol{X}^{\top}\boldsymbol{\Omega}_e^{-1}\boldsymbol{X} + \boldsymbol{\Omega}_b^{-1}\right)^{-1}$.

Given $c^{[i]}$, $\beta^{(m)[i]}$, and $Q_t^{[i-1]}$, $t = 1, \ldots, T$, we draw values, $\sigma_\epsilon^{2[i]}$, for σ_ϵ^2 from its posterior distribution, $IG\left(10^{-12} + T/2, (10^{12} + \sum e_t^2/2)^{-1}\right)$, where $e_t := \Delta P_t - \left(c^{[i]}\Delta Q_t^{[i-1]} + \beta^{(m)[i]} r_t^{(m)}\right)$.

Given $c^{[i]}$, $\beta^{(m)[i]}$, and $\sigma_\epsilon^{2[i]}$, we draw new values, $Q_t^{[i]}$, for Q_t, $t = 1, \ldots, T$. To draw $Q_1^{[i]}$, we use the posterior odds ratio of a buy versus a sell:

$$\frac{Prob\left(Q_1^{[i]} = +1 | Q_2^{[i-1]}, \ldots, Q_T^{[i-1]}\right)}{Prob\left(Q_1^{[i]} = -1 | Q_2^{[i-1]}, \ldots, Q_T^{[i-1]}\right)} = \frac{f\left(e_2(Q_1^{[i]} = +1)\right)}{f\left(e_2(Q_1^{[i]} = -1)\right)},$$

where $f(\cdot)$ is the normal probability density function with mean zero and variance $\sigma_\epsilon^{2[i]}$; and $e_2(Q_1) := \Delta P_2 - c^{[i]}Q_2^{[i-1]} + c^{[i]}Q_1 - \beta^{(m)[i]} r_2^{(m)}$. To draw $Q_t^{[i]}$, $t = 2, \ldots, T-1$, we use the posterior odds ratio of a buy versus a sell:

$$\frac{Prob\left(Q_t^{[i]} = +1 | Q_1^{[i]}, \ldots, Q_{t-1}^{[i]}, Q_{t+1}^{[i-1]}, \ldots, Q_T^{[i-1]}\right)}{Prob\left(Q_t^{[i]} = +1 | Q_1^{[i]}, \ldots, Q_{t-1}^{[i]}, Q_{t+1}^{[i-1]}, \ldots, Q_T^{[i-1]}\right)} = \frac{f\left(e_t(Q_t^{[i]} = +1)\right) f\left(e_{t+1}(Q_t^{[i]} = +1)\right)}{f\left(e_t(Q_t^{[i]} = -1)\right) f\left(e_{t+1}(Q_t^{[i]} = -1)\right)},$$

where $e_t(Q_t) := \Delta P_t - c^{[i]}Q_t + c^{[i]}Q_{t-1}^{[i]} - \beta^{(m)[i]} r_t^{(m)}$ and $e_{t+1}(Q_t) := \Delta P_{t+1} - c^{[i]}Q_{t+1}^{[i-1]} + c^{[i]}Q_t - \beta^{(m)[i]} r_{t+1}^{(m)}$. To draw the last trade indicator $Q_T^{[i]}$, we use

$$\frac{Prob\left(Q_T^{[i]} = +1 | Q_1^{[i]}, \ldots, Q_{T-1}^{[i]}\right)}{Prob\left(Q_T^{[i]} = +1 | Q_1^{[i]}, \ldots, Q_{T-1}^{[i]}\right)} = \frac{f\left(e_T(Q_T^{[i]} = +1)\right)}{f\left(e_T(Q_T^{[i]} = -1)\right)},$$

where $e_T(Q_T) := \Delta P_T - c^{[i]}Q_T + c^{[i]}Q_{T-1}^{[i]} - \beta^{(m)[i]} r_T^{(m)}$.

As suggested in Hasbrouck (2009), this sampler is run for 1,000 sweeps which generate 1,000 draws for each parameter (of which, the first 200 draws are discarded to remove the effect of starting values). The average of the remaining 800 draws serves as the point estimate of the parameter in our analysis.

A.II Returns Net of Transaction Costs

Let $R_{i,t}$ ($c_{i,t}$) denote the simple return (one-way transaction cost) of asset i at time t. We can compute the turnover (TO) and transaction costs (TC) of a portfolio by using the same procedure as Novy-Marx and Velikov (2016) or Detzel, Novy-Marx, and Velikov (2023):

$$TO_t := \frac{1}{2} \sum_{i=1}^{N_t} \left| w_{i,t} - w_{i,t-} \right|, \tag{A.1}$$

$$TC_t := \sum_{i=1}^{N_t} \left| w_{i,t} - w_{i,t-} \right| c_{i,t}, \tag{A.2}$$

where N_t is the number of assets in the portfolio at time t, $w_{i,t}$ is the weight of asset i (defined as the value of this asset in the portfolio divided by the total value of the portfolio) at time t after rebalancing, and $w_{i,t-} := \frac{w_{i,t-1}(1+R_{i,t})}{\sum_{k=1}^{N_t} w_{k,t-1}\left(1+R_{k,t}\right)}$ is the weight of asset i in the portfolio at time t before rebalancing. The weight $w_{i,t}$ is positive (negative) if there is a long (short) position in asset i. The net-of-costs return on the portfolio is then defined as

$$R_t^{(net)} := R_t^{(gross)} - TC_t,$$

where $R_t^{(gross)}$ represents the gross return before transaction costs.

A.III Common Cryptocurrency Risk Factors

We follow the procedure in Liu et al. (2022) to construct the cryptocurrency market (Mkt), size (CSMB), and momentum (CMOM) factors. The return of the cryptocurrency market portfolio at week t is defined as

$$R_t^{(Mkt)} := \sum_{i=1}^{N_t} w_{i,t-1} R_{i,t}, \tag{A.1}$$

where N_t is the number of tokens in the portfolio at week t (note that only cryptocurrencies with the market capitalization of at least one million are included); $w_{i,t-1} := \frac{\text{market\_cap}_{i,t-1}}{\sum_{i=1}^{N_t} \text{market\_cap}_{i,t-1}}$ with $\text{market\_cap}_{i,t-1}$ representing the market capitalization of token i at the end of week $t-1$; and $R_{i,t}$ is the simple return of token i at the end of week t.

To form the size portfolio, at the end of each week, we first sort cryptocurrencies into terciles according to their market capitalizations. We then long tokens in the first tercile and short tokens in the last tercile. Next, we calculate the return of the value-weighted portfolio of the longed tokens and that of the shorted tokens using the cryptocurrency returns in the portfolio holding week and the market capitalizations in the portfolio formation week. The CSMB factor return is the difference between the return of the long valued-weighted portfolio and the return of the short value-weighted portfolio. By repeating this procedure for every week, we obtain a time series of the CSMB factor returns.

To form the momentum portfolio, at the end of each week, we first double-sort cryptocurrencies by their market capitalizations and their past three-week returns into 2×3 equal groups (i.e., we use the median market capitalization to sort tokens into two groups by market capitalization, and we then sort tokens in each of those two groups into terciles by the past three-week return). Next, we calculate the return of the value-weighted portfolio of tokens using the returns in the portfolio holding week and the market capitalizations in the portfolio formation week for each of the six groups. Let $R_t^{(k,h)}$ denote the portfolio return for group $k \times h$. The return of the CMOM factor at week t is then defined as

$$R_t^{(CMOM)} := \frac{1}{2}\left(R_t^{(1,3)} + R_t^{(2,3)}\right) - \frac{1}{2}\left(R_t^{(1,1)} + R_t^{(2,1)}\right). \tag{A.2}$$

Since this procedure produces a time series of portfolio weights for each factor portfolio, we can immediately calculate the turnover and transaction cost of each risk factor by using Eqs. (A.1) and (A.2), respectively.

A.IV Daniel et al.'s (1997) (DGTW) Characteristic-based Benchmark Method

At the end of each week, we form media-based portfolios by first identifying cryptocurrencies with no media coverage, then sorting the remaining cryptocurrencies into low- and high-media coverage groups with the median as the cut-off point. Next, we form equally weighted portfolios by (a) longing no-coverage tokens, (b) shorting high-coverage tokens, and (c) simultaneously longing no-coverage tokens while shorting high-coverage tokens. These portfolios are then held for a week. We re-balance the portfolios every week to ensure that the asset weights are maintained.

Given a time series of the returns of a media-based portfolio as described above, the DGTW procedure can be summarized as follows: (1) at the end of each week, we form benchmark portfolios by triple-sorting tokens into terciles based on the last-day market capitalization in the week (MCAP), the standard deviation of daily returns in the week (RETVOL), and momentum measured by the past three-week return ($r\ 3, 0$) as suggested by Liu et al. (2022). This triple-sort gives 27 passive benchmark portfolios. Note that Daniel et al. (1997) uses quintile triple-sorts as they worked with equity data. We have a small number of cryptocurrencies to sort each week (i.e., a minimum of 100 tokens during each portfolio formation week). Due to this constraint, we use tercile triple-sorts instead; (2) each token in the media-based portfolio is then assigned to a passive benchmark portfolio based on its MCAP, RETVOL, and $r\ 3, 0$. The excess return of this token at the end of the portfolio holding week can be calculated by subtracting the return on this passive benchmark portfolio from the return on this token; (3) the excess returns of tokens in the media-based portfolio are then multiplied by their portfolio weights [calculated at the end of the portfolio formation week] to obtain the benchmark-adjusted return for the holding week. This benchmark-adjusted return is called the Characteristic Selectivity (CS) measure. A CS measure of zero tells us that the performance of a strategy could have been replicated, on average, by simply purchasing cryptocurrencies with the same size, volatility, and momentum characteristics as the tokens that this strategy invests in. A statistically significant and positive CS measure indicates that the investor using this strategy has additional selectivity ability.

The week t component of the CS measure is defined as

$$CS_t \coloneqq \sum_{i=1}^{N_t} \widetilde{w}_{i,t-1} \left(R_{i,t} - R_t^{(b_{i,t-1})} \right), \tag{A.1}$$

where N_t is the number of tokens in the media-based portfolio at the end of week t; $\widetilde{w}_{i,t-1}$ is the portfolio weight on token i at the end of week $t-1$; $R_{i,t}$ is the week t return of token i; and $R_t^{(b_{i,t-1})}$ is the week t return of the characteristic-based passive benchmark portfolio that is matched to token i during week $t-1$.

Using the approach proposed in Detzel et al. (2023), we can also define the week t component of the net-of-costs CS measure of a long-short portfolio as: $CS_t^{(net)} := CS_t^{(long,net)} + CS_t^{(short,net)}$, where

$$CS_t^{(long,net)} := \sum_{i=1}^{N_t} \widetilde{w}_{i,t-1} I\left(\widetilde{w}_{i,t-1} > 0\right) \left(R_{i,t} - R_t^{(net,b_{i,t-1})}\right) - TC_{t-1}^{(long)} \tag{A.2}$$

is the long portion of $CS_t^{(net)}$, where $I(A)$ is an indicator function that take on a value of one if A is true and zero otherwise; and the transaction cost of the long leg [of the long-short portfolio] is defined as $TC_t^{(long)} := \sum_{i=1}^{N_t} \left|\widetilde{w}_{i,t} - \widetilde{w}_{i,t-}\right| I\left(\widetilde{w}_{i,t} > 0\right) c_{i,t}$, where $\widetilde{w}_{i,t-} := \frac{\widetilde{w}_{i,t-1}(1+R_{i,t})}{\sum_{k=1}^{N_t} \widetilde{w}_{k,t-1} I\left(\widetilde{w}_{i,t-1}\widetilde{w}_{k,t-1}>0\right)(1+R_{k,t})}$ is the weight of token i in the long or short leg of the long-short portfolio at week t before re-balancing, and $c_{i,t}$ is the one-way transaction cost of token i at week t; and $R_t^{(net,b_{i,t-1})}$ is the week t net-of-costs return of the characteristic-based passive benchmark portfolio that is matched to token i at the end of week $t-1$ (see Section A.II); and

$$CS_t^{(short,net)} := \sum_{i=1}^{N_t} \widetilde{w}_{i,t-1} I\left(\widetilde{w}_{i,t-1} < 0\right) \left(R_{i,t} - R_t^{(net,b_{i,t-1})}\right) - TC_{t-1}^{(short)} \tag{A.3}$$

is the short portion of $CS_t^{(net)}$, where $TC_t^{(short)} := \sum_{i=1}^{N_t} \left|\widetilde{w}_{i,t} - \widetilde{w}_{i,t-}\right| I\left(\widetilde{w}_{i,t} < 0\right) c_{i,t}$ is the transaction cost of the short leg [of the long-short portfolio].

The week t component of the Characteristic Timing (CT) measure is defined as

$$CT_t := \sum_{i=1}^{N_t} \left(\widetilde{w}_{i,t-1} R_t^{(b_{i,t-1})} - \widetilde{w}_{i,t-13} R_t^{(b_{i,t-13})}\right), \tag{A.4}$$

where $R_t^{(b_{i,t-13})}$ is the week t return of the characteristic-based passive benchmark portfolio that is matched to token i during week $t-13$.

Similarly, the week t component of the net-of-costs CT measure is defined as

$$CT_t^{(net)} := \sum_{i=1}^{N_t} \left(\left(\widetilde{w}_{i,t-1} - TC_{i,t-1}\right) R_t^{(net,b_{i,t-1})} - \left(\widetilde{w}_{i,t-13} - TC_{i,t-13}\right) R_t^{(net,b_{i,t-13})}\right), \tag{A.5}$$

where $R_t^{(net,b_{i,t-13})}$ is the week t net-of-costs return of the characteristic-based passive benchmark portfolio that is matched to token i during week $t-13$, and $TC_{i,t} := \left|\widetilde{w}_{i,t} - \widetilde{w}_{i,t-}\right| c_{i,t}$ is the cost of transacting token

i at week t.

If the weights of an investment portfolio can vary in order to exploit the time-varying expected returns of the characteristic-based passive benchmark portfolios, the CT measure must then be positive.

The week t component of the Average Style (AS) return measure is defined as

$$AS_t := \sum_{i=1}^{N_t} \widetilde{w}_{i,t-13} R_t^{(b_{i,t-13})}. \tag{A.6}$$

The week t component of the net-of-costs AS return measure is defined as

$$AS_t^{(net)} := \sum_{i=1}^{N_t} \left(\widetilde{w}_{i,t-13} - TC_{i,t-13}\right) R_t^{(net,b_{i,t-13})}. \tag{A.7}$$

If our strategy systematically mimics the passive investment strategy, the AS measure will be very high.

Media Coverage and the Cross-section of Cryptocurrency Returns
– Supplemental Material –

Ba Chu*

January 11, 2025

Abstract

This Supplemental Material (SM) appendix contains the following sections: (I) Section S.I – a table tabulating the cryptocurrency characteristics mentioned in the main text and their definitions; (II) Section S.II – the descriptive statistics of media coverage and its determinants using active cryptocurrencies currently listed on CoinMarketCap; (III) Section S.III – a robustness check of the empirical findings reported in Section 4 (in the main text) by replicating the same analysis for the sample of active cryptocurrencies currently listed on CoinMarketCap; (IV) Section S.IV – a robustness check of the empirical findings reported in Section 5 by replicating the same analysis for (i) all cryptocurrencies while skipping one week in between the portfolio formation week and the holding week, and (ii) for only active cryptocurrencies; and (V) Section S.V – a robustness check of the empirical findings reported in Section 6 by replicating the same analysis for (i) all cryptocurrencies while skipping one week in between the portfolio formation week and the holding week, and (ii) for only active cryptocurrencies.

Keywords: Media coverage; Cryptocurrency; Investor attention; Liquidity; Transaction costs; Idiosyncratic volatility.
JEL classification: G12; G14; G17; G19; G40.

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S.I Cryptocurrency Characteristics

Table S.I.1: Cryptocurrency characteristics

Category	Characteristic	Definition	Reference
Size	MCAP	Log last-day market capitalization (in U.S. dollars) in the portfolio formation week	Banz (1981)
Size	AMCAP	Log average market capitalization (in U.S. dollars) in the portfolio formation week	Banz (1981)
Momentum	$r\ 1,0$	Past one-week return	Jegadeesh and Titman (1993)
Momentum	$r\ 2,0$	Past two-week return	Jegadeesh and Titman (1993)
Momentum	$r\ 3,0$	Past three-week return	Jegadeesh and Titman (1993)
Momentum	$r\ 4,0$	Past four-week return	Jegadeesh and Titman (1993)
Momentum	$r\ 4,1$	Past one-to-four-week return	Jegadeesh and Titman (1993)
Momentum	$r\ 8,0$	Past eight-week return	Jegadeesh and Titman (1993)
Momentum	$r\ 16,0$	Past 16-week return	Jegadeesh and Titman (1993)
Momentum	$r\ 50,0$	Past 50-week return	Bondt and Thaler (1985)
Momentum	$r\ 100,0$	Past 100-week return	Bondt and Thaler (1985)
Value	NPAST52	The negative of the past 52-week return (a reversal effect)	Asness, Moskowitz, and Pedersen (2013)
Volume	PRCVOL	Log average daily volume times price in the portfolio formation week	Chordia, Subrahmanyam, and Anshuman (2001)
Volume	VOLSCALED	Log average daily volume times price scaled by market capitalization in the portfolio formation week	Chordia et al. (2001)
Volatility	BETA	The regression coefficient $\beta_i^{(CMKT)}$ in $R_i - R_f = \alpha_i + \beta_i^{(CMKT)} CMKT + \epsilon_i$, where *CMKT* is the cryptocurrency market factor [see Liu, Tsyvinski, and Wu (2022)]. The model is estimated using daily returns of the previous 365 days before the portfolio formation week	Fama and MacBeth (1973)
Volatility	BETA2	BETA^2	Fama and MacBeth (1973)
Volatility	IDIOVOL	Idiosyncratic volatility, measured as the standard deviation of the residuals from the regression: $R_i - R_f = \alpha_i + \beta_i^{(CMKT)} CMKT + \epsilon_i$. This model is estimated using daily returns of the previous 365 days before the portfolio formation week	Ang, Hodrick, Xing, and Zhang (2006)
Volatility	RETVOL	Standard deviation of daily returns in the portfolio formation week	Ang et al. (2006)
Volatility	MAXRET	Maximum daily return in the portfolio formation week	Bali, Cakici, and Whitelaw (2011)
Volatility	DAMIHUD	Average absolute daily return divided by daily trading volume in the portfolio formation week	Amihud (2002)
Volatility	VaR	Measure of the downside risk in the cryptocurrency market (as the negative of the 5% percentile of the past 90 days daily returns)	Atilgan, Bali, Demirtas, and Gunaydin (2020)

S.II Data and Descriptive Statistics

This section tabulates the descriptive statistics of media coverage and its determinants for active cryptocurrencies currently listed on CoinMarketCap.

Table S.II.2: Summary Statistics of Newspaper Coverage: Unconditional Coverage Statistics for Active Cryptocurrencies currently listed on CoinMarketCap

This table presents summary statistics for the newspaper coverage of active cryptocurrencies in our sample. The top 30 newspapers that cover the highest fractions of tokens ($\times 100$) are reported for each year and for all the years.

Panel A: Unconditional coverage statistics (Fraction of covered tokens by newspaper for each year)														Fraction of covered tokens by newspaper for all years	
2017		2018		2019		2020		2021		2022		2023 (January - March)		All years	
techcrunch.com	3.21	macondaily.com	40.27	www.chaffeybreeze.com	53.92	www.com-unik.info	73.07	www.americanbankingnews.com	82.52	www.americanbankingnews.com	88.26	www.wkrb13.com	18.47	www.americanbankingnews.com	92.65
www.finanznachrichten.de	1.98	www.chaffeybreeze.com	35.76	macondaily.com	53.37	www.themarketsdaily.com	72.88	www.themarketsdaily.com	82.03	www.wkrb13.com	86.78	theenterpriseleader.com	18.1	www.wkrb13.com	92.22
www.huffingtonpost.com	1.61	dminute.com	5.06	www.americanbankingnews.com	50.15	www.wkrb13.com	72.88	www.tickerreport.com	81.66	www.com-unik.info	85.55	www.themarketsdaily.com	18.04	www.com-unik.info	90.92
www.nigeriatoday.ng	1.54	www.finanznachrichten.de	5.0	www.wkrb13.com	41.51	www.americanbankingnews.com	68.0	www.wkrb13.com	81.66	www.themarketsdaily.com	85.11	www.com-unik.info	17.97	www.themarketsdaily.com	90.86
www.forbes.com	1.17	www.prnewswire.com	4.82	www.tickerreport.com	38.42	theenterpriseleader.com	64.55	theenterpriseleader.com	81.16	theenterpriseleader.com	84.68	www.tickerreport.com	13.84	theenterpriseleader.com	90.3
www.businessinsider.com	1.11	markets.businessinsider.com	4.2	www.themarketsdaily.com	36.44	www.tickerreport.com	64.11	www.com-unik.info	79.56	www.tickerreport.com	80.11	www.americanbankingnews.com	10.38	www.tickerreport.com	87.58
seekingalpha.com	0.99	www.zerohedge.com	3.89	www.com-unik.info	28.47	www.fxstreet.com	8.89	www.newsbreak.com	50.65	www.etfdailynews.com	67.08	www.newsbreak.com	6.92	www.etfdailynews.com	67.08
freedombunker.com	0.68	thenextweb.com	3.4	theenterpriseleader.com	26.44	www.somagnews.com	8.71	upnewsinfo.com	12.35	reporter.am	48.61	www.stl.news	5.87	macondaily.com	54.6
uk.reuters.com	0.68	www.forbes.com	3.21	www.modernreaders.com	15.81	www.prnewswire.com	7.29	www.benzinga.com	11.61	www.newsbreak.com	19.21	u.today	4.63	www.newsbreak.com	54.48
www.reuters.com	0.68	techcrunch.com	2.04	nctynews.com	7.04	www.coindesk.com	6.92	hackernoon.com	10.75	www.somagnews.com	17.73	www.fxstreet.com	4.45	www.chaffeybreeze.com	54.42
in.reuters.com	0.62	www.nigeriatoday.ng	1.98	www.prnewswire.com	6.42	www.nasdaq.com	6.67	investorplace.com	10.25	recentlyheard.com	12.29	investorplace.com	4.08	reporter.am	48.61
www.ibtimes.co.uk	0.62	venturebeat.com	1.91	www.finanznachrichten.de	6.24	hackernoon.com	6.24	www.prnewswire.com	10.25	coinjournal.net	11.61	247wallst.com	4.01	www.somagnews.com	21.99
www.dailymail.co.uk	0.56	webnewswire.com	1.73	www.fxstreet.com	4.69	www.wfmz.com	6.18	www.entrepreneur.com	10.13	www.benzinga.com	11.55	www.nasdaq.com	3.89	www.prnewswire.com	20.57
www.zdnet.com	0.56	www.webnewswire.com	1.73	www.marketscreener.com	4.08	u.today	6.11	coinjournal.net	9.57	www.stl.news	10.13	www.benzinga.com	3.64	www.finanznachrichten.de	17.67
www.benzinga.com	0.49	www.benzinga.com	1.67	www.prnewswire.co.uk	3.95	www.finanznachrichten.de	5.56	www.somagnews.com	9.51	investorplace.com	9.26	www.inferse.com	3.52	www.benzinga.com	17.54
www.marketwatch.com	0.49	www.educationews.com	1.67	www.sys-con.com	3.09	www.einpresswire.com	5.25	u.today	9.02	www.nasdaq.com	8.65	euroweeklynews.com	3.52	www.modernreaders.com	15.81
fortune.com	0.43	www.indiabynet.com	1.67	news.yahoo.com	3.03	www.reporter.am	4.94	www.globenewswire.com	8.59	www.marketbeat.com	8.34	news.yahoo.com	3.34	www.fxstreet.com	15.63
www.theeventchronicle.com	0.43	www.nowindia.com	1.61	www.forbes.com	2.96	www.cryptopolitan.com	4.88	www.wfmz.com	8.52	www.inferse.com	8.15	coinjournal.net	3.27	coinjournal.net	15.50
nakedsecurity.sophos.com	0.43	www.marketscreener.com	1.61	dminute.com	2.96	www.thestreet.com	4.76	www.nasdaq.com	8.52	www.cryptopolitan.com	7.35	www.marketbeat.com	3.15	www.einpresswire.com	15.07
mashable.com	0.43	www.express.co.uk	1.54	www.einpresswire.com	2.22	www.prnewswire.co.uk	3.58	www.explica.co	8.21	finance.yahoo.com	7.35	www.prnewswire.com	2.9	hackernoon.com	14.89
www.cryptoanalyst.co	0.43	www.indiaeconomics.webnewswire.com	1.42	www.benzinga.com	2.22	nairametrics.com	3.21	finance.yahoo.com	8.15	techstory.in	7.29	www.rttnews.com	2.9	investorplace.com	14.45
www.techmeme.com	0.43	seekingalpha.com	1.36	www.nasdaq.com	2.1	www.benzinga.com	3.15	www.fxstreet.com	8.03	u.today	7.16	seekingalpha.com	2.84	recentlyheard.com	14.21
www.prweb.com	0.37	bizwatchnigeria.ng	1.24	www.thesouthafrican.com	1.73	upnewsinfo.com	3.15	www.jagranjosh.com	7.97	www.globenewswire.com	6.98	www.cryptopolitan.com	2.59	www.nasdaq.com	14.14
www.nextbigfuture.com	0.37	news.yahoo.com	1.24	seekingalpha.com	1.67	www.forbes.com	3.15	www.einpresswire.com	7.97	news.yahoo.com	6.92	www.latestly.com	2.59	u.today	13.71
thedailycoin.org	0.37	www.ibtimes.com	1.17	thenextweb.com	1.61	www.marketscreener.com	2.84	playcrazygame.com	7.29	www.prnewswire.com	6.79	www.investopedia.com	2.59	upnewsinfo.com	12.97
www.cellular-news.com	0.37	bgr.com	1.17	www.finyear.com	1.48	www.globenewswire.com	2.72	www.bullfrag.com	6.86	www.einpresswire.com	6.61	www.business2community.com	2.47	www.wfmz.com	12.72
forextv.com	0.31	www.dailymail.co.uk	1.05	business.financialpost.com	1.3	www.cryptoninjas.net	2.59	www.thestreet.com	6.73	www.fxstreet.com	6.55	finance.yahoo.com	2.41	www.stl.news	12.42
tomluongo.me	0.31	www.foxbusiness.com	1.05	finance.yahoo.com	1.11	www.thebulletintime.com	2.53	recentlyheard.com	6.73	www.mexc.com	6.18	www.deccanherald.com	2.1	www.globenewswire.com	12.29
wolfstreet.com	0.31	www.4-traders.com	1.05	forextv.com	1.11	ca.sports.yahoo.com	2.41	news.yahoo.com	6.49	thegoaspotlight.com	6.18	www.einpresswire.com	2.04	www.entrepreneur.com	11.98
www.cnbc.com	0.31	www.zdnet.com	0.99	www.zdnet.com	1.05	news.yahoo.com	2.16	marketrealist.com	6.36	www.financialexpress.com	6.05	cyprus-mail.com	2.04	finance.yahoo.com	11.92
Panel B: Fraction of tokens covered by at least one newspaper for each year)														Fraction of tokens covered by at least one newspaper for all years	
0.08		0.40		0.53		0.72		0.79		0.83		0.25		0.89	
Panel C: Number of newspapers that publish articles written about at least a cryptocurrency															
272		424		391		673		1686		1575		702		2879	

Table S.II.3: Summary Statistics of Newspaper Coverage: Conditional Coverage Statistics for Active Cryptocurrencies currently listed on CoinMarketCap

This table presents summary statistics for the newspaper coverage of active cryptocurrencies in our sample. The top 30 cryptocurrencies that receive the most newspaper coverage are reported for each year and for all the years.

Conditional coverage statistics (Number of articles per covered token for each year)														Number of articles per covered token for all years	
2017		2018		2019		2020		2021		2022		2023 (January - March)		All years	
BTC	860	NEW	3662	LTC	4850	BTC	10846	BTC	122082	BTC	143045	BTC	42919	BTC	326135
NEW	620	BCH	3395	BCH	4467	ETH	8467	ETH	95935	ETH	72296	ETH	35533	ETH	216709
ETH	355	BTC	2075	BTC	4300	TRX	5039	DOGE	44139	USDT	39836	USDT	18496	DOGE	96240
LTC	238	MIOTA	1140	ETH	3097	XLM	4854	ADA	41441	SHIB	34251	DOGE	15997	USDT	75767
BCH	209	LTC	1093	SPY	2684	SPY	4761	DOT	21518	DOGE	34202	SHIB	15953	SHIB	71712
XMR	66	ETH	1026	NEW	2069	LTC	4332	SHIB	21508	USDC	29623	SOL	14647	ADA	65752
CRM	47	ONT	940	TRX	2009	BSV	3472	SOL	14559	SOL	21703	LTC	13868	DOT	54566
BNT	46	VET	693	XLM	1948	BCH	3410	LTC	13780	DOT	19278	DOT	13263	LTC	52558
ETC	43	XLM	665	BSV	1284	BAT	2780	USDT	13545	ADA	19190	USDC	6890	SOL	51080
SPY	43	TRX	558	XMR	1249	USDT	2427	SPY	12965	MATIC	16925	ADA	2984	USDC	45110
BAT	36	USDT	533	ETC	1104	PLF	2205	LINK	11048	LTC	14396	MATIC	1480	SPY	30353
ZEC	32	SPY	434	KBC	1079	VET	2116	MATIC	10534	LINK	11972	HBAR	1396	MATIC	28939
GNO	31	XMR	373	LINK	943	ETC	2099	CAKE	10460	BUSD	9552	AGIX	1293	BCH	28864
KFC	26	XVG	369	USDT	910	LINK	2087	ETC	9210	NEW	9068	AXS	1201	LINK	26903
TSL	23	SYS	304	AOA	873	XMR	1809	XLM	8597	BCH	8937	SPY	1129	NEW	23560
REP	21	ZIL	284	VET	659	MIN	1593	KSM	8370	AVAX	8710	AVAX	1115	TRX	19979
USDT	20	KFC	270	BAT	481	ADA	1567	AVAX	8240	FTT	8679	CRO	1115	XLM	19882
HMQ	16	ETC	235	SOC	457	XTZ	1461	MKR	8038	SPY	8337	ALGO	988	ETC	19667
XLM	14	BSD	234	MKR	455	HEDG	1385	BCH	7751	BSV	6790	GT	929	BSV	18395
XEM	13	MAN	227	ZEC	433	ZEC	1367	USDC	7366	FIL	6383	BUSD	905	AVAX	18238
BTS	10	XEM	202	XTZ	415	ATOM	1350	FIL	7344	ETC	6281	LINK	846	BUSD	18109
FUEL	10	DOGE	196	DOGE	404	BECN	1348	AXS	7283	TRX	5790	ATOM	828	FTT	15304
MIOTA	10	POLY	192	HT	394	SLS	1340	BUSD	7278	AXS	5482	XCM	776	FIL	14455
ADA	9	CREVA	190	COMP	385	DOGE	1295	WBNB	6767	MANA	5333	NEAR	748	AXS	14004
NEU	9	MED	189	ADA	381	OMG	1256	OMG	6609	FTM	5314	SAND	731	MANA	13046
STX	9	BTM	187	POLY	349	COMP	1236	MANA	6479	ATOM	5228	TRX	696	XMR	12877
TRX	9	LDOGE	185	HPB	341	LEO	1215	NEW	6279	SAND	4989	BCH	695	ATOM	12761
NMC	8	CS	183	CNX	337	NEW	1162	KLAY	6249	ALGO	4781	ETC	695	CAKE	12330
VERI	8	ADA	180	SYS	337	XVG	1160	BSV	6141	YOUC	4470	NEW	693	MKR	11513
XVG	8	POST	175	LEO	332	BTM	1100	HT	5978	KLAY	4467	BSV	688	ALGO	11311
No. of tokens[a]	138	730		966		1301		1427		1500		445		1619	
Mean No. of articles:	22.62	62.69		124.90		448.50		1577.66		1077.41		652.26		3033.22	
Median No. of articles:	3.00	23.00		86.00		471.00		1327.00		792.00		297.00		2357.00	

[a] *No. of tokens* is the number of tokens mentioned in at least one article. *Mean No. of articles* is the average number of articles per covered token. *Median No. of articles* is the median number of articles per covered token.

Table S.II.4: Determinants of Media Coverage: All Active Cryptocurrencies currently listed on CoinMarketCap

This table reports the fixed-effect panel regression results on the determinants of media coverage. The dependent variable is the logarithm of one plus the number of news articles written about a cryptocurrency in a given week. The independent variables are defined in Table S.I.1. (Only cryptocurrencies mentioned in at least 100 news articles throughout the sample period are included.) t-statistics based on standard errors adjusted for weak contemporaneous, lagged cross-cryptocurrency, and temporal correlations using Driscoll and Kraay's (1998) HAC estimator are shown in parentheses. The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent variable: $\log(1 + \text{number of articles per week})$			
Constant	−2.8919***	−2.7921***	−2.5326***
	(−3.1409)	(−3.5108)	(−3.2935)
AMCAP	0.3439***	0.3068***	0.3021***
	(5.6807)	(5.7560)	(5.6550)
VOLSCALED	0.0471***	0.0116	0.0088
	(3.5682)	(0.8238)	(0.6449)
RETVOL	−0.0006	0.0004	0.0001
	(−0.2293)	(0.8180)	(0.5132)
IDIOVOL	0.0014	−0.0003	−0.0001
	(0.5044)	(−0.7344)	(−0.5871)
MAXRET	−0.0004***	−0.0001	
	(−3.7967)	(−1.0443)	
DAMIHUD	−0.0000***	−0.0000***	−0.0000***
	(−5.5287)	(−2.9872)	(−3.3699)
VaR	1.2579***	1.2875***	
	(5.4002)	(4.5793)	
r 1, 0	0.0002		
	(1.4441)		
r 2, 0	0.0001***		
	(2.5958)		
r 3, 0	0.0000		
	(0.8078)		
r 4, 0	−0.0002		
	(−1.2628)		
r 8, 0	0.0000		
	(0.0077)		
r 16, 0	−0.0001		
	(−1.1510)		
r 50, 0	−0.0000		
	(−1.1622)		
r 100, 0	−0.0000***		
	(−4.5516)		
r 4, 1	0.0003		
	(1.2652)		
NPAST52	0.0000		
	(0.7958)		
BETA	−0.0010***	−0.0000	−0.0000
	(−3.5366)	(−1.0334)	(−1.3693)
BETA2	0.0000***	0.0000	0.0000
	(3.2436)	(0.1426)	(0.8162)
No. of tokens	1355	1355	1355
Sample size	153582	153582	153582
R^2	0.0920	0.0662	0.0592

S.III Media Coverage and the Cross-section of Cryptocurrency Returns: A Robustness Check

This section confirms that the empirical findings, which are obtained using the sample of all active and inactive cryptocurrencies (reported in Section 4), can also be verified for the sample of only active cryptocurrencies currently listed on CoinMarketCap.

S.III.1 Bivariate Sorting Analysis

S.III.1.1 Returns before Transaction Costs

Table S.III.5 reports the average portfolio returns before transaction costs, their t-statistics, and the average number of tokens in each media-based portfolio constructed using the method described in the main text. The first row shows that unconditionally, the average weekly returns for tokens with no-, low-, and high-media coverage are 4.79%, 2.47%, and 1.83%, respectively. The difference between the no- and high-coverage portfolio returns is a statistically significant and economically meaningful 2.95% per week (approximately 353% per year) with t-statistic = 3.82. Therefore, sorting tokens by media coverage generates a significant premium associated with the no-coverage tokens. Double-sorting tokens by cryptocurrency characteristics one at a time and media coverage reveals that the no-coverage premium still remains strong among tokens with small or medium market capitalization (MCAP), or tokens with small or medium scaled price volume (VOLSCALED), tokens with medium/high volatility (RETVOL), or tokens with high illiquidity (DAMIHUD), or tokens with low beta (BETA or BETA2). This premium also seems independent of the past performances of cryptocurrencies.

Table 4 shows that the no-coverage premium is statistically significant in the group of tokens with high idiosyncratic volatility. However, this may not the case for active tokens. Interestingly, Table S.III.5 shows that the no-coverage premium in the group of tokens with high idiosyncratic volatility is about ten times larger that in the group of tokens with low idiosyncratic volatility, but these premia are not statistically significant.

We repeat the same analysis while skipping a week between the portfolio formation period and the holding period. The first row of Table S.III.6 shows that unconditionally, the average weekly returns for tokens with no-, low-, and high-media coverage are 5.15%, 2.59%, and 2.01%, respectively. The difference between the no- and high-coverage portfolio returns is a statistically significant and economically meaningful 3.15% per week (approximately 401% per year). The double-sorts to control for cryptocurrency characteristics one at a time also confirm that there is a positive no-coverage premium in most groups of tokens. This corroborates the findings reported in Table 5.

Table S.III.5: Newspaper Coverage and Cryptocurrency Returns before Transaction Costs: All Active Cryptocurrencies currently listed on CoinMarketCap

This table reports average weekly returns for tokens with no-, low-, and high-media coverage. At the end of each week, we divide our sample of cryptocurrencies into three media-based portfolios: no media coverage, low media coverage, and high media coverage. Media coverage of a token is measured by the number of newspaper articles written about that token, and the median is used to divide the covered tokens into low- and high-coverage groups. We then compute the average returns of the three media-based portfolios and the difference between the *no coverage* portfolio return and the *high coverage* portfolio return using individual cryptocurrency returns in the holding week. All the portfolios are equally weighted. We also compute the return differentials for the subsamples of cryptocurrencies sorted by cryptocurrency characteristics defined in Table S.I.1 one at a time. Note that a cryptocurrency is included if its market capitalization is at least one million during the portfolio formation week while its name and symbol are mentioned in at least 100 articles throughout the sample period. All t-statistic values use the Newey-West standard error.

	Average weekly returns (%)				t-statistics for No - High	Average number of tokens		
	Media coverage					Media coverage		
	No	Low	High	No - High		No	Low	High
All tokens	4.79	2.47	1.83	2.95	3.82	185.63	193.65	177.88
				Sort by MCAP				
0	4.55	2.80	1.86	2.69	2.99	59.69	68.48	61.94
1	6.84	1.51	1.39	5.44	1.81	67.41	97.40	88.25
2	1.01	0.63	0.79	0.22	0.76	36.12	79.85	74.26
				Sort by AMCAP				
0	4.71	3.41	1.82	2.88	3.02	59.61	69.0	61.52
1	6.50	1.31	1.23	5.27	2.54	67.58	97.17	88.26
2	0.77	0.71	0.81	−0.04	−0.16	36.02	79.9	74.32
				Sort by PRCVOL				
0	6.21	3.21	2.35	3.86	1.27	55.71	68.79	62.16
1	1.96	0.62	1.08	0.88	1.92	65.44	96.05	87.04
2	0.55	0.53	0.39	0.16	0.52	39.24	76.52	71.21
				Sort by VOLSCALED				
0	6.73	2.94	2.50	4.22	2.93	55.71	67.65	60.94
1	1.91	1.01	1.12	0.79	1.96	65.99	93.94	85.51
2	0.90	0.56	0.51	0.38	1.12	43.00	73.54	68.11
				Sort by RETVOL				
0	1.90	0.87	0.84	1.06	1.74	53.52	66.08	60.72
1	2.49	1.25	1.28	1.21	2.32	70.42	88.39	80.36
2	6.80	3.20	1.19	5.62	3.46	56.48	64.29	57.92
				Sort by IDIOVOL				
0	1.16	0.81	0.82	0.34	0.72	33.18	61.79	57.10
1	1.78	0.86	1.18	0.61	1.62	47.64	80.42	73.41
2	6.74	3.06	1.49	5.25	0.76	39.20	58.71	53.18

Continued on next page

Table S.III.5 (continued): Newspaper Coverage and Cryptocurrency Returns before Transaction Costs: All Active Cryptocurrencies currently listed on CoinMarketCap

	Average weekly returns (%)				t-statistics for No - High	Average number of tokens		
	Media coverage					Media coverage		
	No	Low	High	No - High		No	Low	High
Sort by MAXRET								
0	2.14	1.01	0.71	1.42	2.34	54.11	65.76	59.82
1	2.69	1.42	1.47	1.22	2.44	71.71	87.04	79.39
2	6.45	3.80	2.36	4.08	2.42	56.92	63.74	57.61
Sort by DAMIHUD								
0	1.09	0.80	0.91	0.18	0.62	40.55	77.23	72.03
1	1.85	0.74	0.91	0.94	2.00	67.69	96.30	87.31
2	7.45	5.30	1.83	5.61	2.98	59.43	67.66	60.23
Sort by VaR								
0	1.51	0.70	0.81	0.70	1.49	46.05	69.23	63.99
1	1.47	0.97	0.89	0.58	1.96	64.39	90.76	83.70
2	6.57	3.26	2.50	4.07	3.25	54.55	65.49	59.22
Sort by r 1, 0								
0	2.32	1.47	0.75	1.57	2.57	55.29	65.44	59.21
1	2.89	1.36	0.79	2.10	3.79	71.45	87.39	80.00
2	3.97	1.94	2.16	1.81	1.77	54.86	65.04	59.01
Sort by r 2, 0								
0	2.75	1.59	0.29	2.47	3.99	55.06	65.61	59.79
1	2.80	1.27	0.92	1.87	3.19	71.83	87.56	80.11
2	5.04	2.96	1.99	3.05	2.35	55.10	65.31	59.04
Sort by r 3, 0								
0	2.12	2.17	0.75	1.37	2.79	54.97	66.00	59.49
1	2.29	0.63	0.84	1.44	2.61	71.22	87.97	80.43
2	5.71	1.93	1.46	4.26	2.99	55.03	65.18	59.39
Sort by r 4, 0								
0	3.37	2.26	1.04	2.33	3.47	54.39	65.20	59.44
1	2.94	1.08	1.06	1.88	2.62	70.28	87.00	80.23
2	5.12	2.21	1.61	3.51	2.89	54.95	64.52	58.65

Continued on next page

Table S.III.5 (continued): Newspaper Coverage and Cryptocurrency Returns before Transaction Costs: All Active Cryptocurrencies currently listed on CoinMarketCap

	Average weekly returns (%)				t-statistics for No - High	Average number of tokens		
	Media coverage					Media coverage		
	No	Low	High	No - High		No	Low	High
				Sort by r 4, 1				
0	4.08	2.32	1.57	2.51	3.28	54.63	65.07	59.77
1	2.54	1.24	1.03	1.51	2.19	70.69	87.61	80.03
2	4.01	1.28	1.05	2.96	3.82	54.75	64.59	59.25
				Sort by r 8, 0				
0	3.57	2.50	1.77	1.80	2.79	54.22	64.72	58.23
1	2.73	0.92	0.96	1.78	2.64	69.16	87.03	79.15
2	5.16	2.55	1.67	3.49	2.52	54.32	63.82	58.23
				Sort by r 16, 0				
0	3.97	2.15	1.76	2.21	2.53	49.74	64.50	58.56
1	2.91	1.40	1.28	1.63	2.69	64.32	86.22	79.21
2	4.31	1.73	1.46	2.85	2.33	51.72	63.04	57.31
				Sort by r 50, 0				
0	3.29	2.23	1.82	1.48	1.53	37.24	58.94	53.35
1	2.36	0.82	0.88	1.48	2.38	46.79	78.95	72.20
2	3.27	1.02	0.77	2.51	2.26	39.29	56.35	52.45
				Sort by r 100, 0				
0	6.15	2.91	2.45	3.70	2.25	26.65	50.45	45.92
1	1.27	1.61	1.38	−0.11	−0.17	32.76	67.53	62.49
2	5.98	1.19	0.55	5.43	2.54	24.25	50.74	47.06
				Sort by NPAST52				
0	3.88	0.75	0.86	3.02	2.37	38.66	55.95	52.09
1	2.26	1.08	1.17	1.09	1.91	45.83	77.68	71.11
2	3.75	2.39	1.63	2.12	2.00	36.18	57.89	52.06
				Sort by BETA				
0	5.23	1.70	1.17	4.06	3.17	41.04	56.35	51.26
1	1.75	1.02	1.37	0.38	0.95	49.14	77.00	70.85
2	1.92	1.66	1.43	0.49	0.93	33.57	59.33	54.81
				Sort by BETA2				
0	3.96	1.13	1.09	2.87	3.37	40.13	56.92	51.61
1	2.03	1.07	1.31	0.72	1.69	49.07	77.02	70.90
2	2.94	2.14	1.58	1.35	1.95	34.55	58.90	54.25

Table S.III.6: Newspaper Coverage and Cryptocurrency Returns before Transaction Costs (Skipping a Week between the Portfolio Formation Week and the Holding Week): All Active Cryptocurrencies currently listed on CoinMarketCap

This table reports average weekly returns for tokens with no-, low-, and high-media coverage. At the end of each week, we divide our sample of cryptocurrencies into three media-based portfolios: no media coverage, low media coverage, and high media coverage. Media coverage of a token is measured by the number of newspaper articles written about that token, and the median is used to divide the covered tokens into low- and high-coverage groups. We then compute the average returns of the three media-based portfolios and the difference between the *no coverage* portfolio return and the *high coverage* portfolio return using individual cryptocurrency returns in the holding week. All the portfolios are equally weighted. We also compute the return differentials for the subsamples of cryptocurrencies sorted by cryptocurrency characteristics defined in Table S.I.1 one at a time. Note that a cryptocurrency is included if its market capitalization is at least one million during the portfolio formation week while its name and symbol are mentioned in at least 100 articles throughout the sample period. All t-statistic values use the Newey-West standard error.

	Average weekly returns (%)				t-statistics for No - High	Average number of tokens		
	Media coverage					Media coverage		
	No	Low	High	No - High		No	Low	High
All tokens	5.15	2.59	2.01	3.15	3.36	184.88	193.82	178.01
Sort by MCAP								
0	6.19	3.58	2.25	3.94	2.95	59.15	68.71	62.15
1	5.54	2.12	1.80	3.74	1.39	66.88	97.64	88.47
2	1.00	0.96	1.19	–0.19	–0.49	36.21	79.79	74.20
Sort by AMCAP								
0	6.30	4.05	2.13	4.16	3.08	59.08	69.23	61.73
1	5.21	1.80	1.99	3.22	1.22	67.05	97.41	88.50
2	0.95	1.20	1.04	–0.09	–0.33	36.10	79.85	74.25
Sort by PRCVOL								
0	7.99	5.25	3.06	4.93	2.48	55.22	69.01	62.36
1	1.76	1.08	0.87	0.89	1.82	65.11	96.21	87.19
2	0.75	0.64	0.78	–0.03	–0.10	39.20	76.55	71.21
Sort by VOLSCALED								
0	7.81	4.58	2.69	5.12	2.94	55.27	67.84	61.11
1	1.43	1.10	1.22	0.21	0.63	65.69	94.10	85.62
2	1.00	0.74	0.90	0.10	0.37	42.90	73.59	68.14
Sort by RETVOL								
0	1.69	1.36	1.16	0.53	0.97	53.26	66.17	60.81
1	2.49	1.32	0.66	1.83	2.07	70.19	88.46	80.42
2	6.77	4.07	1.95	4.82	3.42	56.13	64.40	58.02
Sort by IDIOVOL								
0	1.66	1.21	0.97	0.69	1.42	32.93	61.81	57.13
1	2.91	1.59	1.28	1.63	2.29	47.24	80.50	73.50
2	8.81	4.47	2.70	6.11	2.35	38.75	58.83	53.29

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Table S.III.6 (continued): Newspaper Coverage and Cryptocurrency Returns before Transaction Costs (Skipping a Week between the Portfolio Formation Week and the Holding Week): All Active Cryptocurrencies currently listed on CoinMarketCap

	Average weekly returns (%)				t-statistics for No - High	Average number of tokens		
	Media coverage					Media coverage		
	No	Low	High	No - High		No	Low	High
Sort by MAXRET								
0	2.26	1.37	1.22	1.03	1.82	53.86	65.83	59.90
1	1.89	1.76	1.32	0.57	0.83	71.45	87.12	79.47
2	6.92	3.38	1.74	5.18	3.81	56.61	63.84	57.69
Sort by DAMIHUD								
0	0.70	1.05	0.76	–0.06	–0.27	40.55	77.22	72.02
1	2.18	1.02	1.10	1.09	2.52	67.27	96.50	87.49
2	8.49	4.79	3.06	5.43	1.80	58.92	67.87	60.40
Sort by VaR								
0	1.51	0.74	0.92	0.59	1.16	45.78	69.32	64.08
1	1.67	1.10	0.83	0.84	1.55	64.16	90.83	83.77
2	7.82	4.35	2.46	5.36	3.05	54.14	65.64	59.34
Sort by r 1, 0								
0	3.11	1.75	1.12	1.99	2.44	55.04	65.53	59.28
1	3.91	1.37	1.36	2.55	2.42	71.17	87.49	80.07
2	4.40	2.62	2.46	1.93	2.27	54.58	65.14	59.10
Sort by r 2, 0								
0	2.84	2.83	1.17	1.67	2.37	54.77	65.70	59.87
1	2.85	0.91	0.77	2.08	3.11	71.58	87.64	80.18
2	5.64	1.88	1.71	3.93	3.24	54.80	65.40	59.13
Sort by r 3, 0								
0	3.02	2.19	1.52	1.50	2.17	54.64	66.11	59.60
1	3.92	1.43	1.11	2.81	2.17	71.01	88.01	80.49
2	4.14	1.84	1.74	2.40	2.78	54.73	65.28	59.49
Sort by r 4, 0								
0	2.98	2.68	1.37	1.61	1.90	54.13	65.29	59.50
1	4.27	1.69	1.07	3.2	2.89	70.03	87.08	80.29
2	3.85	1.97	1.43	2.42	2.61	54.61	64.63	58.75

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Table S.III.6 (continued): Newspaper Coverage and Cryptocurrency Returns before Transaction Costs (Skipping a Week between the Portfolio Formation Week and the Holding Week): All Active Cryptocurrencies currently listed on CoinMarketCap

	Average weekly returns (%)				t-statistics for No - High	Average number of tokens		
	Media coverage					Media coverage		
	No	Low	High	No - High		No	Low	High
				Sort by r 4, 1				
0	2.88	2.26	1.63	1.25	1.45	54.38	65.15	59.85
1	4.91	1.86	1.36	3.55	2.69	70.44	87.70	80.10
2	3.53	1.67	1.60	1.93	1.94	54.43	64.70	59.34
				Sort by r 8, 0				
0	4.15	2.55	2.12	2.03	2.58	53.96	64.81	58.29
1	3.02	1.88	1.15	1.87	2.95	68.90	87.10	79.21
2	6.40	1.94	1.58	4.82	2.82	54.00	63.92	58.32
				Sort by r 16, 0				
0	3.35	3.13	2.06	1.29	1.75	49.46	64.60	58.65
1	3.12	1.78	1.43	1.69	2.77	64.02	86.30	79.29
2	6.07	1.93	1.49	4.58	2.93	51.42	63.13	57.39
				Sort by r 50, 0				
0	3.38	3.41	1.46	1.92	2.52	36.91	59.01	53.41
1	2.75	1.42	1.23	1.53	2.64	46.43	79.01	72.24
2	4.47	1.75	0.91	3.56	3.39	38.93	56.42	52.53
				Sort by r 100, 0				
0	5.90	3.73	2.68	3.22	1.82	26.14	50.53	45.99
1	1.36	1.71	1.52	−0.15	−0.26	32.21	67.57	62.53
2	9.65	2.25	1.28	8.37	2.49	23.87	50.75	47.07
				Sort by NPAST52				
0	3.50	1.80	0.79	2.71	3.00	38.30	56.02	52.15
1	2.82	1.20	1.08	1.74	2.54	45.48	77.74	71.14
2	3.41	3.35	1.61	1.81	1.97	35.83	57.96	52.12
				Sort by BETA				
0	5.79	2.58	1.35	4.44	2.86	40.62	56.46	51.35
1	1.93	1.16	1.11	0.83	2.15	48.71	77.10	70.91
2	2.62	2.37	1.36	1.27	2.37	33.38	59.32	54.81
				Sort by BETA2				
0	3.93	1.68	0.89	3.04	2.67	39.71	57.02	51.70
1	2.09	1.35	1.21	0.88	2.18	48.64	77.12	70.97
2	4.44	3.26	1.70	2.73	2.47	34.37	58.90	54.25

S.III.1.2 Returns after Transaction Costs

We replicate the same analysis in Section 4.1.2 to verify the baseline results by using (i) all [active and inactive] cryptocurrencies with one week skipped between the portfolio formation week and the holding week, and (ii) only active cryptocurrencies.

Robustness Check (i):

Table S.III.7 reports the average weekly turnover and transaction cost (defined in Section A.II) of an equally weighted portfolio invested in no-coverage tokens, an equally weighted portfolio invested in high-coverage tokens, and the long-short portfolio [that longs the no-coverage tokens and shorts the high-coverage tokens] as well as the net-of-costs return of this long-short portfolio. The average weekly turnovers and transaction costs are pretty similar to those reported in Table 6, because we use the same strategy of forming and rebalancing portfolios as before except that we skip one week in between the portfolio formation week and the holding week. The long-short media-based portfolio then has a statistically significant and negative average net-of-costs return of -1.81% per week (approximately -61.3% per year, t-statistic = -2.17). This return is slightly larger than that obtained without the one-week skipping. Given the average weekly returns reported in Table 5, we can easily calculate the average net-of-costs return on the long-only media-based portfolio, which is 3.72% per week (approximately 568% per year, t-statistic = 3.26 [not tabulated]).

The results reported here also confirm the findings reported in Table 6: the net-of-costs return of the long-short media-based portfolio is highly [statistically] significant and negative in the tercile of tokens with (a) medium or large MCAP (because the return of this portfolio is lower in this tercile, as seen in Table 5); (b) medium or high PRCVOL; (c) low or medium RETVOL (or IDIOVOL); (d) low or medium past returns (e.g., low or medium MAXRET, $r\ 2,0$, $r\ 3,0$, $r\ 4,0$, $r\ 4,1$, $r\ 8,0$, $r\ 16,0$, $r\ 50,0$, and $r\ 100,0$); (e) low or medium DAMIHUD; (f) low or medium VaR; or (g) medium or high BETA.

Given the average weekly returns reported in Table 5, we can also see that the net-of-costs return of the long-only media-based portfolio is statistically significant and positive in the tercile of tokens with (a) small MCAP (5.70% per week, t-statistic = 2.75); (b) low PRCVOL (5.04% per week, t-statistic = 2.84); (c) high RETVOL (4.08% per week, t-statistic = 2.95) or IDIOVOL (7.28% per week, t-statistic = 2.80); (d) high past returns (for example, MAXRET: 3.91% per week, t-statistic = 2.93 or $r\ 2,0$: 4.51% per week, t-statistic = 2.60); (e) high DAMIHUD (7.65% per week, t-statistic = 3.12); (f) high VaR (4.81% per week, t-statistic = 3.40); or (g) low BETA (4.77% per week, t-statistic = 2.79).

Robustness Check (ii):

Tables S.III.8 and S.III.9 report the average weekly turnover and transaction cost (defined in Section A.II) of an equally weighted portfolio invested in no-coverage tokens, an equally weighted portfolio invested in high-coverage tokens, and the long-short portfolio [that longs the no-coverage tokens and shorts the high-coverage tokens] as well as the net-of-costs return of this long-short portfolio, using only active cryptocurrencies with/without one week skipped between the portfolio formation week and the holding week. The average weekly turnovers and transaction costs to trade an equally weighted portfolio of no-coverage tokens are much lower than those to trade an equally weighted portfolio of high-coverage tokens in the entire sample as well as in every characteristic-based tercile: The first row of these tables shows that the average weekly transaction costs are 0.94% for no-coverage tokens and 3.73% for high-coverage tokens. The long-short media-based portfolio then yields a statistically significant and negative average net-of-costs return of -1.95% per week (approximately -64% per year, t-statistic = -2.53). This return is quite similar (-1.76% per week with t-statistic = -1.88) when skipping a week between the portfolio formation week and the holding week. Given the average returns reported in Tables S.III.5 and S.III.6, we can also see that the long-only media-based portfolio yields an average net-of-costs return of 3.85% per week (approximately 613% per year, t-statistic = 3.34 [not tabulated]). This return is 4.21% per week (approximately 754% per year, t-statistic = 3.55) when skipping one week between the portfolio formation week and the holding week.

The net-of-costs return on the long-short media-based portfolio is highly [statistically] significant and negative in the tercile of tokens with (a) large MCAP (because the return of this portfolio is lower in this tercile, as seen in Table S.III.5); (b) medium or high PRCVOL; (c) low or medium RETVOL (or IDIOVOL); (d) low or medium past returns (e.g., low or medium MAXRET, $r\ 2,0$, $r\ 3,0$, $r\ 4,0$, $r\ 4,1$, $r\ 8,0$, $r\ 16,0$, $r\ 50,0$, and $r\ 100,0$); (e) low or medium DAMIHUD; (f) low or medium VaR; or (g) medium or high BETA.

Given the average weekly returns reported in Tables S.III.5 and S.III.6, we can also see that the net-of-costs return on the long-only media-based portfolio is also statistically significant and positive in the tercile of tokens with

(a) small MCAP [3.36% per week (t-statistic = 2.65) without the one-week skipping and 5% per week (t-statistic = 2.83) with the one-week skipping] or medium MCAP [5.57% per week (t-statistic = 2.30) without the one-week skipping and 4.27% per week (t-statistic = 1.86) with the one-week skipping];
(b) low PRCVOL [4.83% per week (t-statistic = 2.68) without the one-week skipping and 6.61% per week (t-statistic = 3.24) with the one-week skipping];
(c) high RETVOL [4.98% per week (t-statistic = 2.70) without the one-week skipping and 4.95% per week (t-statistic = 3.16) with the one-week skipping] or IDIOVOL [4.98% per week (t-statistic = 2.49) without the one-week skipping and 7.05% (t-statistic = 2.62) with the one-week skipping];
(d) high past returns [for example, MAXRET: 4.56% per week (t-statistic = 2.51) without the one-week skipping and 5.03% per week (t-statistic = 3.26) with the one-week skipping, or $r\ 2,0$: 3.30% per week (t-statistic = 2.41) without the one-week skipping and 3.90% per week (t-statistic = 2.55) with the one-week skipping];
(e) high DAMIHUD [6.20% per week (t-statistic 3.36) without the one-week skipping and 7.24% per week (t-statistic = 2.68) with the one-week skipping];
(f) high VaR [5.26% per week (t-statistic = 3.49) without the one-week skipping and 6.50% per week (t-statistic = 3.56) with the one-week skipping]; or
(g) low BETA [4.04% per week (t-statistic = 2.55) without the one-week skipping and 4.60% per week (t-statistic = 2.70) with the one-week skipping].

These results are all consistent with those reported in Section 4.1.2.

Table S.III.7: Newspaper Coverage, Turnovers, Transaction Costs, and Long-short Cryptocurrency Returns Net of Transaction Costs (Skipping a Week between the Portfolio Formation Week and the Holding Week): All Cryptocurrencies ever listed on CoinMarketCap

This table presents average weekly turnovers, transaction costs, and returns net of costs for tokens with no- and high-media coverage. At the end of each week, we divide our sample of cryptocurrencies into three media-based portfolios: no media coverage, low media coverage, and high media coverage. Media coverage of a token is measured by the number of newspaper articles written about this token, and the median is used to divide the covered tokens into low- and high-coverage groups. All the portfolios are equally weighted. We then compute the average returns of the three media-based portfolios (and the turnover and transaction cost of the no- and high-coverage portfolios and their long-short portfolio) using individual cryptocurrency returns in the holding week. We also compute the average weekly turnovers, transaction costs, and returns net of costs for the subsamples of tokens sorted by cryptocurrency characteristics defined in Table S.I.1 one at a time. Note that a cryptocurrency is included if its market capitalization is at least one million during the portfolio formation week while its name and symbol are mentioned in at least 100 articles throughout the sample period. All t-statistic values use the Newey-West standard error.

	Average weekly turnover (%)			Average weekly transaction cost (%)			Average weekly returns net of transaction costs for No - High (%)	t-statistics of net-of-costs returns for No - High
	Media coverage			Media coverage				
	No	High	No - High	No	High	No-High		
All tokens	19.67	79.26	103.23	0.93	3.73	4.87	−1.81	−2.17
Sort by MCAP								
0	25.11	68.65	99.96	1.18	3.24	4.72	0.44	0.26
1	24.64	71.16	101.68	1.16	3.35	4.79	−2.02	−1.60
2	20.09	83.74	105.13	0.95	3.95	4.96	−5.17	−11.25
Sort by AMCAP								
0	25.13	69.38	100.90	1.18	3.27	4.76	0.36	0.21
1	24.53	71.62	101.88	1.16	3.38	4.80	−2.65	−2.01
2	19.95	83.70	104.95	0.94	3.95	4.95	−4.82	−19.66
Sort by PRCVOL								
0	27.99	68.79	104.27	1.32	3.25	4.92	−1.37	−0.86
1	24.42	71.15	100.55	1.15	3.35	4.74	−3.76	−9.12
2	20.66	82.10	104.33	0.97	3.87	4.92	−4.49	−21.16
Sort by VOLSCALED								
0	27.53	70.11	104.10	1.30	3.30	4.91	−0.12	−0.06
1	24.76	72.69	102.05	1.17	3.43	4.82	−4.31	−12.46
2	22.13	80.51	104.51	1.04	3.79	4.93	−4.41	−17.47
Sort by RETVOL								
0	34.56	68.65	104.24	1.63	3.23	4.92	−3.62	−6.81
1	36.44	62.61	100.92	1.72	2.95	4.76	−3.29	−4.77
2	37.63	61.61	102.47	1.77	2.90	4.83	−0.58	−0.48
Sort by IDIOVOL								
0	36.14	72.20	108.94	1.70	3.39	5.14	−4.20	−7.73
1	37.27	62.41	101.56	1.76	2.94	4.79	−3.33	−5.27
2	37.39	62.26	102.96	1.76	2.94	4.86	1.90	0.78
Sort by MAXRET								
0	37.30	65.69	104.00	1.76	3.09	4.91	−3.41	−4.97
1	36.40	61.61	100.06	1.72	2.91	4.72	−4.05	−5.70
2	39.47	59.93	102.31	1.86	2.83	4.83	−0.12	−0.10

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Table S.III.7 (continued): Newspaper Coverage, Turnovers, Transaction Costs, and Long-short Cryptocurrency Returns Net of Transaction Costs (Skipping a Week between the Portfolio Formation Week and the Holding Week): All Cryptocurrencies ever listed on CoinMarketCap

	Average weekly turnover (%)			Average weekly transaction cost (%)			Average weekly returns net of transaction costs for No - High (%)	t-statistics of net-of-costs returns for No - High
	Media coverage			Media coverage				
	No	High	No - High	No	High	No-High		
				Sort by DAMIHUD				
0	22.47	82.22	105.98	1.06	3.88	5.00	–4.97	–19.41
1	26.36	69.67	101.10	1.24	3.28	4.77	–4.06	–11.21
2	26.92	69.36	102.32	1.27	3.27	4.83	1.58	0.65
				Sort by VaR				
0	23.02	79.79	104.93	1.09	3.76	4.95	–4.08	–8.13
1	25.86	71.78	102.13	1.22	3.39	4.82	–3.96	–12.56
2	26.68	71.07	102.97	1.26	3.33	4.86	–0.67	–0.49
				Sort by r $1,0$				
0	41.02	56.28	98.76	1.93	2.66	4.66	–3.10	–5.04
1	35.92	64.70	102.08	1.69	3.04	4.82	–1.89	–2.11
2	42.56	59.63	104.13	2.01	2.81	4.91	–3.16	–3.66
				Sort by r $2,0$				
0	35.48	61.55	99.44	1.67	2.88	4.67	–3.03	–5.48
1	34.35	65.65	102.09	1.62	3.10	4.82	–2.41	–3.17
2	36.64	65.21	104.50	1.73	3.07	4.92	–0.57	–0.39
				Sort by r $3,0$				
0	33.05	63.17	99.47	1.56	2.98	4.69	–2.89	–4.99
1	33.01	67.33	102.59	1.56	3.16	4.83	–2.16	–2.51
2	33.79	68.67	105.15	1.59	3.23	4.96	–2.39	–2.57
				Sort by r $4,0$				
0	31.76	65.27	100.32	1.50	3.06	4.74	–2.41	–4.17
1	31.94	68.59	102.76	1.51	3.22	4.85	–3.11	–4.29
2	31.81	70.48	104.61	1.50	3.31	4.94	–1.59	–1.36
				Sort by r $4,1$				
0	33.96	64.04	100.80	1.60	3.01	4.76	–2.92	–4.05
1	33.84	68.02	103.99	1.60	3.20	4.90	–2.63	–3.24
2	33.31	68.50	103.66	1.57	3.22	4.89	–1.79	–1.39

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Table S.III.7 (continued): Newspaper Coverage, Turnovers, Transaction Costs, and Long-short Cryptocurrency Returns Net of Transaction Costs (Skipping a Week between the Portfolio Formation Week and the Holding Week): All Cryptocurrencies ever listed on CoinMarketCap

	Average weekly turnover (%)			Average weekly transaction cost (%)			Average weekly returns net of transaction costs for No - High (%)	t-statistics of net-of-costs returns for No - High
	Media coverage			Media coverage				
	No	High	No - High	No	High	No-High		
Sort by r 8, 0								
0	28.96	67.28	99.85	1.37	3.15	4.71	−1.95	−2.69
1	29.33	70.38	102.19	1.38	3.31	4.82	−3.60	−9.54
2	28.89	74.10	105.54	1.36	3.48	4.98	−0.09	−0.05
Sort by r 16, 0								
0	27.76	69.26	101.07	1.31	3.25	4.77	−3.69	−6.45
1	27.86	72.54	103.21	1.31	3.42	4.87	−3.42	−6.67
2	26.67	75.71	105.38	1.26	3.57	4.97	0.03	0.02
Sort by r 50, 0								
0	29.63	71.67	105.93	1.40	3.36	5.00	−3.44	−4.93
1	27.33	74.12	104.14	1.29	3.48	4.92	−3.21	−5.50
2	25.31	78.79	105.77	1.19	3.71	4.99	−0.90	−0.74
Sort by r 100, 0								
0	33.96	71.25	108.20	1.60	3.36	5.11	−3.76	−3.06
1	27.85	74.41	104.16	1.31	3.51	4.91	−4.40	−7.69
2	26.46	81.53	108.88	1.25	3.84	5.13	7.35	1.67
Sort by NPAST52								
0	25.44	79.30	106.22	1.20	3.74	5.02	−2.06	−2.19
1	27.13	74.05	103.66	1.28	3.48	4.89	−3.00	−5.00
2	29.97	71.40	105.70	1.41	3.36	4.99	−2.14	−1.04
Sort by BETA								
0	25.42	76.71	105.35	1.20	3.60	4.97	−0.15	−0.10
1	24.49	77.58	105.20	1.15	3.65	4.96	−4.51	−11.24
2	24.74	77.57	105.75	1.17	3.64	5.00	−3.52	−6.04
Sort by BETA2								
0	25.94	76.79	106.01	1.22	3.61	5.00	−1.31	−1.06
1	24.41	77.64	105.17	1.15	3.65	4.96	−4.39	−10.90
2	24.90	77.54	105.81	1.17	3.64	5.00	−2.06	−1.90

Table S.III.8: Newspaper Coverage, Turnovers, Transaction Costs, and Long-short Cryptocurrency Returns Net of Transaction Costs: All Active Cryptocurrencies currently listed on CoinMarketCap

This table presents average weekly turnovers, transaction costs, and returns net of costs for tokens with no- and high-media coverage. At the end of each week, we divide our sample of cryptocurrencies into three media-based portfolios: no media coverage, low media coverage, and high media coverage. Media coverage of a token is measured by the number of newspaper articles written about this token, and the median is used to divide the covered tokens into low- and high-coverage groups. All the portfolios are equally weighted. We then compute the average returns of the three media-based portfolios (and the turnover and transaction cost of the no- and high-coverage portfolios and their long-short portfolio) using individual cryptocurrency returns in the holding week. We also compute the average weekly turnovers, transaction costs, and returns net of costs for the subsamples of tokens sorted by cryptocurrency characteristics defined in Table S.I.1 one at a time. Note that a cryptocurrency is included if its market capitalization is at least one million during the portfolio formation week while its name and symbol are mentioned in at least 100 articles throughout the sample period. All t-statistic values use the Newey-West standard error.

	Average weekly turnover (%)			Average weekly transaction cost (%)			Average weekly returns net of transaction costs for No - High (%)	t-statistics of net-of-costs returns for No - High
	Media coverage			Media coverage				
	No	High	No - High	No	High	No-High		
All tokens	19.97	79.43	104.07	0.94	3.73	4.91	−1.95	−2.53
Sort by MCAP								
0	25.19	68.85	100.74	1.19	3.25	4.75	−2.07	−2.31
1	26.80	71.53	104.73	1.26	3.37	4.94	0.51	0.17
2	19.69	83.75	104.84	0.93	3.95	4.94	−4.72	−15.96
Sort by AMCAP								
0	25.43	68.94	101.34	1.20	3.25	4.78	−1.90	−2.00
1	26.65	71.83	104.97	1.26	3.39	4.95	0.32	0.15
2	19.43	83.81	104.60	0.92	3.95	4.93	−4.97	−18.43
Sort by PRCVOL								
0	29.24	69.11	106.30	1.38	3.26	5.02	−1.15	−0.38
1	26.49	71.14	103.26	1.25	3.36	4.87	−3.99	−8.59
2	20.60	82.29	104.60	0.97	3.88	4.93	−4.77	−14.29
Sort by VOLSCALED								
0	29.44	70.05	106.32	1.39	3.29	5.02	−0.80	−0.56
1	26.08	72.47	103.90	1.23	3.43	4.90	−4.11	−9.88
2	22.10	80.72	104.78	1.04	3.79	4.94	−4.56	−12.43
Sort by RETVOL								
0	34.63	68.70	104.52	1.63	3.23	4.93	−3.87	−6.32
1	36.10	62.78	100.95	1.70	2.96	4.76	−3.55	−6.59
2	38.53	61.25	103.17	1.82	2.89	4.87	0.75	0.46
Sort by IDIOVOL								
0	36.21	71.49	108.52	1.71	3.36	5.12	−4.78	−9.79
1	36.54	62.68	100.90	1.72	2.94	4.76	−4.15	−10.80
2	37.18	61.96	102.52	1.75	2.92	4.84	0.42	0.06
Sort by MAXRET								
0	37.41	65.54	104.17	1.76	3.07	4.90	−3.48	−5.68
1	36.05	62.04	100.30	1.70	2.93	4.73	−3.51	−6.95
2	39.98	61.10	104.15	1.88	2.88	4.91	−0.83	−0.49

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Table S.III.8 (continued): Newspaper Coverage, Turnovers, Transaction Costs, and Long-short Cryptocurrency Returns Net of Transaction Costs: All Active Cryptocurrencies currently listed on CoinMarketCap

	Average weekly turnover (%)			Average weekly transaction cost (%)			Average weekly returns net of transaction costs for No - High (%)	t-statistics of net-of-costs returns for No - High
	Media coverage			Media coverage				
	No	High	No - High	No	High	No-High		
Sort by DAMIHUD								
0	22.16	82.02	105.95	1.04	3.87	4.99	–4.82	–15.98
1	29.04	69.64	104.74	1.37	3.28	4.94	–4.00	–8.25
2	26.29	69.20	101.99	1.24	3.27	4.81	0.80	0.43
Sort by VaR								
0	22.86	79.51	104.66	1.08	3.75	4.93	–4.23	–8.80
1	24.91	71.92	101.66	1.17	3.39	4.80	–4.22	–13.99
2	27.71	71.12	104.71	1.31	3.34	4.95	–0.87	–0.70
Sort by r 1, 0								
0	42.05	56.24	100.17	1.98	2.65	4.72	–3.15	–5.16
1	35.50	64.73	101.88	1.67	3.04	4.81	–2.71	–4.80
2	42.55	59.33	103.93	2.01	2.80	4.90	–3.09	–3.01
Sort by r 2, 0								
0	36.57	60.79	100.22	1.72	2.87	4.73	–2.26	–3.61
1	33.87	66.17	101.86	1.60	3.11	4.80	–2.93	–4.86
2	36.70	65.94	104.58	1.73	3.09	4.93	–1.89	–1.45
Sort by r 3, 0								
0	34.27	63.01	100.78	1.62	2.97	4.76	–3.39	–6.79
1	32.48	66.82	101.71	1.53	3.15	4.80	–3.36	–6.06
2	34.22	68.66	105.76	1.61	3.23	4.99	–0.74	–0.52
Sort by r 4, 0								
0	33.40	64.61	101.89	1.57	3.05	4.81	–2.48	–3.81
1	31.79	68.45	102.53	1.50	3.22	4.84	–2.96	–4.11
2	32.27	70.05	105.05	1.52	3.29	4.96	–1.45	–1.20
Sort by r 4, 1								
0	35.12	64.14	102.26	1.66	3.01	4.83	–2.31	–3.04
1	33.43	67.46	103.22	1.58	3.17	4.87	–3.35	–4.88
2	33.71	68.15	104.26	1.59	3.20	4.91	–1.95	–2.52

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Table S.III.8 (continued): Newspaper Coverage, Turnovers, Transaction Costs, and Long-short Cryptocurrency Returns Net of Transaction Costs: All Active Cryptocurrencies currently listed on CoinMarketCap

	Average weekly turnover (%)			Average weekly transaction cost (%)			Average weekly returns net of transaction costs for No - High (%)	t-statistics of net-of-costs returns for No - High
	Media coverage			Media coverage				
	No	High	No - High	No	High	No-High		
Sort by r 8, 0								
0	30.08	67.86	101.64	1.42	3.19	4.80	−3.00	−4.65
1	29.22	70.20	102.24	1.38	3.29	4.83	−3.05	−4.82
2	28.83	74.00	105.56	1.36	3.48	4.99	−1.49	−1.08
Sort by r 16, 0								
0	28.90	69.14	102.67	1.36	3.25	4.85	−2.64	−2.99
1	27.93	72.26	103.09	1.32	3.40	4.87	−3.24	−5.36
2	26.93	75.43	105.23	1.27	3.55	4.97	−2.12	−1.74
Sort by r 50, 0								
0	29.54	70.79	105.11	1.39	3.32	4.96	−3.49	−3.62
1	26.77	74.08	103.65	1.26	3.48	4.89	−3.40	−5.40
2	24.68	79.14	105.93	1.16	3.74	4.99	−2.49	−2.24
Sort by r 100, 0								
0	29.95	70.71	104.92	1.41	3.33	4.95	−1.24	−0.76
1	27.81	73.78	104.24	1.31	3.48	4.91	−5.02	−7.62
2	26.06	80.85	108.05	1.23	3.81	5.09	0.33	0.16
Sort by NPAST52								
0	25.29	78.74	105.93	1.19	3.71	5.00	−1.98	−1.55
1	26.38	73.57	102.66	1.24	3.46	4.85	−3.76	−6.40
2	29.39	71.14	105.18	1.39	3.34	4.97	−2.85	−2.69
Sort by BETA								
0	25.03	76.73	105.32	1.18	3.60	4.97	−0.91	−0.71
1	23.59	76.98	103.84	1.11	3.62	4.90	−4.51	−10.97
2	23.89	77.38	104.66	1.13	3.65	4.94	−4.45	−8.18
Sort by BETA2								
0	25.69	76.75	106.10	1.21	3.61	5.00	−2.13	−2.49
1	23.40	77.08	103.75	1.10	3.63	4.89	−4.17	−9.54
2	24.12	77.26	104.70	1.14	3.64	4.95	−3.60	−5.09

Table S.III.9: Newspaper Coverage, Turnovers, Transaction Costs, and Long-short Cryptocurrency Returns Net of Transaction Costs (Skipping a Week between the Portfolio Formation Week and the Holding Week): All Active Cryptocurrencies currently listed on CoinMarketCap

This table presents average weekly turnovers, transaction costs, and returns net of costs for tokens with no- and high-media coverage. At the end of each week, we divide our sample of cryptocurrencies into three media-based portfolios: no media coverage, low media coverage, and high media coverage. Media coverage of a token is measured by the number of newspaper articles written about this token, and the median is used to divide the covered tokens into low- and high-coverage groups. All the portfolios are equally weighted. We then compute the average returns of the three media-based portfolios (and the turnover and transaction cost of the no- and high-coverage portfolios and their long-short portfolio) using individual cryptocurrency returns in the holding week. We also compute the average weekly turnovers, transaction costs, and returns net of costs for the subsamples of tokens sorted by cryptocurrency characteristics defined in Table S.I.1 one at a time. Note that a cryptocurrency is included if its market capitalization is at least one million during the portfolio formation week while its name and symbol are mentioned in at least 100 articles throughout the sample period. All t-statistic values use the Newey-West standard error.

	Average weekly turnover (%)			Average weekly transaction cost (%)			Average weekly returns net of transaction costs for No - High (%)	t-statistics of net-of-costs returns for No - High
	Media coverage			Media coverage				
	No	High	No - High	No	High	No-High		
All tokens	19.98	79.35	104.08	0.94	3.73	4.91	−1.76	−1.88
Sort by MCAP								
0	25.27	68.84	100.83	1.19	3.25	4.76	−0.82	−0.61
1	26.89	71.51	104.83	1.27	3.37	4.94	−1.20	−0.44
2	19.74	83.75	104.90	0.93	3.95	4.95	−5.14	−12.71
Sort by AMCAP								
0	25.52	68.92	101.43	1.20	3.25	4.79	−0.62	−0.46
1	26.73	71.82	105.07	1.26	3.39	4.95	−1.73	−0.65
2	19.45	83.80	104.63	0.92	3.95	4.93	−5.02	−18.62
Sort by PRCVOL								
0	29.32	69.10	106.41	1.38	3.26	5.02	−0.09	−0.05
1	26.56	71.11	103.32	1.25	3.36	4.88	−3.99	−8.01
2	20.66	82.29	104.67	0.97	3.88	4.93	−4.96	−16.79
Sort by VOLSCALED								
0	29.52	70.03	106.40	1.39	3.29	5.03	0.10	0.06
1	26.15	72.45	103.97	1.23	3.42	4.90	−4.69	−13.44
2	22.17	80.71	104.85	1.05	3.79	4.94	−4.85	−17.56
Sort by RETVOL								
0	34.68	68.71	104.59	1.64	3.23	4.94	−4.41	−7.93
1	36.12	62.75	100.96	1.70	2.96	4.76	−2.93	−3.24
2	38.55	61.24	103.19	1.82	2.89	4.87	−0.05	−0.04
Sort by IDIOVOL								
0	36.28	71.50	108.61	1.71	3.36	5.12	−4.43	−9.00
1	36.58	62.69	100.95	1.72	2.94	4.76	−3.13	−4.42
2	37.24	61.96	102.60	1.76	2.92	4.84	1.27	0.49
Sort by MAXRET								
0	37.45	65.55	104.23	1.77	3.07	4.90	−3.87	−6.69
1	36.10	62.03	100.36	1.70	2.93	4.74	−4.17	−6.02
2	40.01	61.09	104.18	1.89	2.88	4.91	0.27	0.20

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Table S.III.9 (continued): Newspaper Coverage, Turnovers, Transaction Costs, and Long-short Cryptocurrency Returns Net of Transaction Costs (Skipping a Week between the Portfolio Formation Week and the Holding Week): All Active Cryptocurrencies currently listed on CoinMarketCap

	Average weekly turnover (%)			Average weekly transaction cost (%)			Average weekly returns net of transaction costs for No - High (%)	t-statistics of net-of-costs returns for No - High
	Media coverage			Media coverage				
	No	High	No - High	No	High	No-High		
Sort by DAMIHUD								
0	22.19	82.02	105.99	1.05	3.87	5.00	−5.06	−20.07
1	29.12	69.63	104.83	1.37	3.28	4.95	−3.86	−8.85
2	26.29	69.16	102.02	1.24	3.26	4.81	0.61	0.20
Sort by VaR								
0	22.98	79.50	104.77	1.08	3.75	4.94	−4.35	−8.36
1	24.97	71.89	101.72	1.18	3.39	4.80	−3.96	−7.21
2	27.81	71.09	104.78	1.31	3.34	4.95	0.41	0.23
Sort by r 1, 0								
0	42.03	56.25	100.17	1.98	2.65	4.72	−2.74	−3.40
1	35.51	64.72	101.89	1.67	3.04	4.81	−2.26	−2.12
2	42.56	59.33	103.95	2.01	2.80	4.90	−2.97	−3.47
Sort by r 2, 0								
0	36.56	60.78	100.23	1.72	2.87	4.73	−3.06	−4.27
1	33.87	66.16	101.86	1.60	3.11	4.80	−2.72	−3.92
2	36.75	65.94	104.63	1.73	3.09	4.94	−1.00	−0.83
Sort by r 3, 0								
0	34.24	63.01	100.81	1.61	2.97	4.76	−3.26	−4.71
1	32.53	66.78	101.71	1.53	3.15	4.80	−1.99	−1.52
2	34.27	68.65	105.80	1.62	3.23	5.00	−2.59	−2.99
Sort by r 4, 0								
0	33.40	64.60	101.89	1.57	3.05	4.81	−3.20	−3.96
1	31.83	68.42	102.54	1.50	3.22	4.84	−1.64	−1.48
2	32.31	70.06	105.10	1.52	3.29	4.96	−2.54	−2.73
Sort by r 4, 1								
0	35.16	64.15	102.34	1.66	3.01	4.83	−3.58	−4.17
1	33.44	67.44	103.22	1.58	3.17	4.87	−1.31	−1.00
2	33.68	68.15	104.23	1.59	3.20	4.91	−2.98	−2.97

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Table S.III.9 (continued): Newspaper Coverage, Turnovers, Transaction Costs, and Long-short Cryptocurrency Returns Net of Transaction Costs (Skipping a Week between the Portfolio Formation Week and the Holding Week): All Active Cryptocurrencies currently listed on CoinMarketCap

	Average weekly turnover (%)			Average weekly transaction cost (%)			Average weekly returns net of transaction costs for No - High (%)	t-statistics of net-of-costs returns for No - High
	Media coverage			Media coverage				
	No	High	No - High	No	High	No-High		
Sort by r 8, 0								
0	30.18	67.85	101.74	1.42	3.18	4.80	−2.77	−3.55
1	29.26	70.20	102.27	1.38	3.29	4.83	−2.96	−4.60
2	28.89	73.99	105.62	1.36	3.48	4.99	−0.16	−0.10
Sort by r 16, 0								
0	28.88	69.11	102.69	1.36	3.24	4.85	−3.56	−4.87
1	28.00	72.23	103.15	1.32	3.39	4.87	−3.18	−5.15
2	27.00	75.43	105.32	1.27	3.55	4.97	−0.40	−0.25
Sort by r 50, 0								
0	29.56	70.75	105.10	1.39	3.32	4.96	−3.04	−4.10
1	26.83	74.08	103.69	1.26	3.48	4.89	−3.36	−5.81
2	24.75	79.14	106.00	1.17	3.74	5.00	−1.43	−1.35
Sort by r 100, 0								
0	30.25	70.68	105.22	1.43	3.33	4.96	−1.74	−0.99
1	27.90	73.77	104.33	1.32	3.48	4.92	−5.07	−8.55
2	26.17	80.83	108.14	1.23	3.81	5.10	3.27	0.97
Sort by NPAST52								
0	25.36	78.72	105.98	1.20	3.70	5.00	−2.29	−2.48
1	26.45	73.57	102.72	1.25	3.46	4.85	−3.12	−4.50
2	29.29	71.09	105.11	1.38	3.34	4.96	−3.16	−3.51
Sort by BETA								
0	25.09	76.71	105.38	1.18	3.60	4.97	−0.53	−0.34
1	23.67	76.97	103.90	1.12	3.62	4.90	−4.07	−9.58
2	23.96	77.36	104.72	1.13	3.64	4.95	−3.68	−6.94
Sort by BETA2								
0	25.78	76.73	106.18	1.22	3.60	5.01	−1.97	−1.73
1	23.47	77.07	103.80	1.11	3.62	4.89	−4.01	−9.76
2	24.18	77.24	104.76	1.14	3.64	4.95	−2.22	−1.98

S.III.2 Regression Analysis

In this section, we replicate the analysis [explained in Section 4.2] to verify the baseline results by (i) using the returns on the long-short media-based portfolio of all [both active and inactive] cryptocurrencies constructed with one week skipped between the portfolio formation week and the holding week, and (ii) using the returns on the long-short media-based portfolio of only active cryptocurrencies. We shall report the results obtained from robustness checks (i) and (ii) both before and after accounting for transaction costs.

S.III.2.1 Abnormal Returns before Transaction Costs

Robustness Check (i):

Table S.III.10 reports the results obtained by regressing the return of the long-short portfolio [that longs tokens with no media coverage and shorts tokens with high media coverage while skipping one week between the portfolio formation week and the holding week] in the holding week on the returns of risk factors. This table confirms the finding reported in Table 7 that there is a strong evidence of the no-coverage premium before transaction costs even after controlling for risk factors, and the factor models can only explain a small portion of the no-coverage premium. Panel A of Table S.III.10 shows that the alpha in the three-factor model is 309 basis points, compared to 359 basis points in the market model. Therefore, about 14% of the alpha relative to the market model can be absorbed by CSMB and CMOM.

The statistically significant and positive coefficient on the size factor (CSMB) suggests that the long-short strategy [that longs no-coverage tokens and shorts high-coverage tokens] has a statistically significant and positive exposure to small tokens. This is quite similar to the result obtained without the one-week skipping. However, this long-short media-based strategy has an insignificant and negative exposure to the cryptocurrency market index and momentum cryptocurrencies (which is somewhat different from the result, reported in Table 7, that the long-short media-based strategy has a zero exposure to the cryptocurrency market index and it has a significant and positive exposure to momentum tokens). This finding is interesting because it must be the case that either the long or short leg of this media-based strategy does not co-move much with the cryptocurrency market and momentum tokens. The non-comovement of the long-short media-based strategy and momentum tokens can be explained by the fact that the no-coverage premium seems to be statistically significant and positive across all the terciles of past week returns as seen in Table 4 or 5.

Panels B and C of Table S.III.10 report the results obtained by regressing the return of the long/short leg of the long-short media-based portfolio in the holding week on the returns of common risk factors. This result confirms the finding, reported in Table 7, that the no-coverage premium after controlling for risk factors is mainly driven by the long positions in the tokens with no media coverage while the tokens with high media coverage do not exhibit significant alphas. In the three-factor model, the alpha for no-coverage tokens is 334 basis points (compared to 24 basis points for high-coverage tokens).

Table S.III.11 examines the media effect of the long-short portfolio [that longs no-coverage tokens and shorts high-coverage tokens while skipping one week in between the portfolio formation week and the holding week] in the subsamples of all cryptocurrencies [ever listed on CoinMarketCap] sorted by various characteristics listed in Table S.I.1 one at a time. Similar to the analysis described in Section 4.2.1, within each characteristic-based tercile, we control for risk factors by using a time-series regression. The results in this table confirm those reported earlier in Table 8. The media effect is indeed concentrated among: (a) small tokens (for example, when sorting tokens by AMCAP, the alpha of the three-factor model in the first tercile is highly positive and statistically significant with 453 basis points, compared to the insignificant alpha of 15 basis points in the last tercile); (b) tokens with low trading volume (for example, when sorting tokens by VOLSCALED, the alpha of the three-factor model in the first tercile is statistically significant and positive with 367 basis points, compared to 59 basis points in the last tercile); (c) tokens with high volatility (for example, when sorting tokens by RETVOL, the alpha of the three-factor model in the first tercile is 132 basis points while the alpha is about three times larger in the last tercile with 365 basis points); (d) highly illiquid tokens (when sorting tokens by DAMIHUD, the alpha of the three-factor model in the first tercile is statistically insignificant with -10 basis point, compared to the highly significant alpha of 568 basis points in the last tercile); (e) tokens with high downside risk (when sorting tokens by VaR, the alpha of the three-factor model in the last tercile is 361 basis points, compared to the insignificant alpha of 73 basis points in the first tercile); (f) tokens with high past returns (for example, when sorting tokens by MAXRET, the alpha of the three-factor model in the first tercile is 185 basis points, compared to 416 basis points in the last tercile; or when sorting tokens by the past two-week return (r $2, 0$), the alpha of the three-factor model in the first tercile is 142 basis points, compared to 476 basis points in the last tercile); (g) tokens with low beta (when sorting tokens by BETA, the alpha of the three-factor model in the first tercile is highly significant at 585 basis points, compared to 176 basis points in the last tercile).

Robustness Check (ii):

Table S.III.12 reports the results obtained from regressing the return of a long-short media-based portfolio on the returns of risk factors. Panel A confirms the findings, reported in the main text, that the no-coverage premium before transaction costs is statistically significant and positive after controlling for risk factors. The factor models can explain a relatively small portion of the premium in this case as the alpha only decreases slightly when factors are added (e.g., the alpha in the one-factor model is 246 basis points while the alpha in the three-factor model is 198 basis points, indicating that about 20% of the alpha relative to the market model is absorbed by the other risk factors). The statistically significant and positive loadings on the size and momentum factors in the three-factor model suggest that the long-short media-based strategy has a positive exposure to small tokens and momentum tokens.

Panels B and C of Table S.III.12 examine the long and short legs of the long-short media-based portfolio separately. The results reported here confirm the finding reported earlier that the no-coverage premium, after controlling for risk factors, is primarily driven by the long positions in the tokens with no media coverage. In the three-factor model, the alpha for the no-coverage tokens is 255 basis points, which is statistically significant at the 1% level while the alpha for the high-coverage tokens is only 56 basis points, which is only significant at the 10% level (which is about 20% of the alpha for the no-coverage tokens). Therefore, the tokens neglected by the media yield a statistically significant premium while the tokens extensively covered by the media are usually large and momentum tokens, which may yield a much less premium.

Table S.III.13 examines the media effect of the long-short media-based portfolio in the subsamples of active cryptocurrencies [currently listed on CoinMarketCap] sorted by various characteristics listed in Table S.I.1 one at a time. The results in this table confirm those reported earlier in Tables 8 and S.III.11. The media effect is indeed concentrated among: (a) small tokens (for example, when sorting tokens by AMCAP, the alpha of the three-factor model in the first tercile is statistically significant and highly positive with 272 basis points, compared to the insignificant alpha of -18 basis points in the last tercile); (b) tokens with low trading volume (for example, when sorting tokens by VOLSCALED, the alpha of the three-factor model in the first tercile is statistically significant and positive with 367 basis points, compared to 16 basis points in the last tercile); (c) tokens with high volatility (for example, when sorting tokens by RETVOL, the alpha of the three-factor model in the first tercile is 56 basis points while the alpha is about nine times larger in the last tercile at 540 basis points); (d) highly illiquid tokens (when sorting tokens by DAMIHUD, the alpha of the three-factor model in the first tercile is statistically insignificant with 16 basis points, compared to the highly significant alpha of 405 basis points in the last tercile); (e) tokens with high downside risk (when sorting tokens by VaR, the alpha of the three-factor model in the last tercile is 368 basis points, compared to the insignificant alpha of 122 basis points in the first tercile); (f) tokens with high past returns (for example, when sorting tokens by MAXRET, the alpha of the three-factor model in the first tercile is statistically insignificant with 97 basis points, compared to the 10% significant alpha of 286 basis points in the last tercile; or when sorting tokens by the past two-week return (r $2, 0$), the alpha of the three-factor model in the first tercile is 167 basis points, compared to 234 basis points in the last tercile); (g) tokens with low beta (when sorting tokens by BETA, the alpha of the three-factor model in the first tercile is highly significant with 435 basis points, compared to the insignificant alpha of 68 basis points in the last tercile).

We also conduct the same analysis using active cryptocurrencies while skipping one week between the portfolio formation week and the holding week. Table S.III.14 reports the results obtained from regressing the return of a long-short media-based portfolio on the returns of risk factors. The results confirm the findings reported earlier. Panel A of Table S.III.14 shows that the alpha of the three-factor model is 278 basis points, compared to 375 basis points in the market model. Therefore, about 25% of the alpha relative to the market model can be absorbed by CSMB and CMOM. The statistically significant and positive loading on the size factor in the three-factor model suggests that the long-short media-based strategy yields a positive exposure to small tokens. The loadings on the market index and the momentum factor in the three-factor model are not statistically significant, suggesting that the long-short media-based strategy may have a very little exposure to the market index and momentum tokens. This is consistent with the results reported in Panel A of Table S.III.10.

The alphas for the long and short legs of the long-short media-based portfolio are reported in Panels B and C of Table S.III.14. In the three-factor model, the alpha for the no-coverage tokens is statistically significant with 359 basis points while the alpha for the high-coverage tokens is only 81 basis points. This reiterates the earlier finding that the no-coverage premium is mainly driven by the long positions in the tokens with no media coverage. The no-coverage tokens tend to co-move less with the risk factors than the high-coverage tokens (i.e., the R^2 for no-coverage tokens in the three-factor model is 28.80% while the R^2 for high-coverage tokens is 71.80%).

Table S.III.15 examines the media effect of the long-short media-based portfolio (while skipping one week in between the portfolio formation week and the holding week) in the subsamples of active cryptocurrencies [currently listed on CoinMarketCap] sorted by various characteristics listed in Table S.I.1 one at a time. The results reported here also confirm those reported earlier. To be specific, we also find that the media effect is concentrated among: (a) small tokens (for example, when sorting tokens by AMCAP, the alpha of the three-factor model in the first tercile is statistically significant and highly positive with 369 basis points, compared to the insignificant alpha of 19 basis points in the last tercile); (b) tokens with low trading volume (for example, when sorting tokens by VOLSCALED, the alpha of the three-factor model in the first tercile is statistically significant and positive with 610 basis points, compared to 29 basis points in the last tercile); (c) tokens with high volatility (for example, when sorting tokens by RETVOL, the alpha of the three-factor model in the first tercile is 45 basis points while the alpha is about nine times larger in the last tercile at 420 basis points); (d) highly illiquid tokens (when sorting tokens by DAMIHUD, the alpha of the three-factor model in the first tercile is statistically insignificant with 1 basis point, compared to the 5%-level significant alpha of 89 basis points in the second tercile and the 10%-level significant alpha of 440 in the last tercile); (e) tokens with high downside risk (when sorting tokens by VaR, the alpha of the three-factor model in the last tercile is statistically significant with 363 basis points, compared to the insignificant alpha of 32 basis points in the first tercile); (f) tokens with high past returns (for example, when sorting tokens by MAXRET, the alpha of the three-factor model in the first tercile is 105 basis points, compared to the 1% significant alpha of 394 basis points in the last tercile; or when sorting tokens by the past two-week return (r $2, 0$), the alpha of the three-factor model in the first tercile is 100 basis points, compared to 209 basis points in the last tercile); (g) tokens with low beta (when sorting tokens by BETA, the alpha of the three-factor model in the first tercile is highly significant with 523 basis points, compared to the insignificant alpha of 37 basis points in the last tercile).

S.III.2.2 Abnormal Returns after Transaction Costs

Robustness Check (i):

As mentioned in Section 4.2.2, we use Novy-Marx and Velikov's (2016) generalized alpha to examine if the long-short strategy [that longs tokens with no media coverage and shorts tokens with high media coverage] can generate abnormal returns beyond common risk factors after accounting for transaction costs.

Table S.III.10 reports the generalized alphas [of the long-short media-based portfolio, the long-only media-based portfolio, and the short-only media-based portfolio, with one week skipped in between the portfolio formation week and the holding week] relative to three factor models: the Cryptocurrency CAPM, the CAPM augmented with CSMB, the CAPM augmented with CSMB and CMOM. The generalized alphas reported in this table are consistent with those reported in Table 7. We can also conclude that the long-short media-based portfolio does not improve the average net-of-costs return of an investor who already holds the market portfolio and the size/momentum portfolio. However, Panel B of the table shows that the long-only media-based portfolio can generate an abnormal return after accounting for transaction costs. Panel C shows that the short-only media-based portfolio does not generate any abnormal return after accounting for transaction costs. Therefore, after factoring in the transaction costs associated with both the long and short positions, the long-short media-based portfolio ultimately yields a zero average excess return.

Table S.III.11 also reports the generalized alphas of the long-short media-based strategy [that skips one week in between the portfolio formation week and the holding week] in the subsamples of all cryptocurrencies [ever listed on CoinMarketCap] sorted by various characteristics listed in Table S.I.1 one at a time. The generalized alphas reported here are aligned with those reported in Table 8 (i.e., in every factor model, most of the generalized alphas across the terciles formed by sorting tokens according to a characteristic are either zeros or statistically insignificant; the only time when the generalized alpha is statistically significant is when tokens are sorted by the past 100-week return – the generalized alpha in the last tercile is significant at the 10% level with 12 basis points, which is about 145 times less than the corresponding alpha). Therefore, the net-of-costs no-coverage premium may only exist among the tokens with a good past performance over a long period of time.

Robustness Check (ii):

Tables S.III.12 and S.III.14 report the generalized alphas of [the long-short media-base portfolio, the long-only media-based portfolio, and the short-only media-based portfolio, with or without skipping one week between the portfolio formation week and the holding week] in factor models. These results are also consistent with those reported in Tables 7 and S.III.10: The long-short media-based portfolio does not yield statistically significant abnormal returns net of costs beyond the cryptocurrency market index and the size/momentum portfolio, although the long-only media-based portfolio can yield a highly significant and positive generalized alpha.

Tables S.III.13 and S.III.15 report the generalized alphas of the long-short media-based strategy [with or without skipping one week in between the portfolio formation week and the holding week] in the subsamples of active cryptocurrencies [currently listed on CoinMarketCap] sorted by various characteristics listed in Table S.I.1 one at a time. The generalized alphas reported here are also aligned with those reported earlier in Tables 8 and S.III.11: The generalized alphas across the terciles formed by sorting tokens according to each characteristic are either zeros or statistically insignificant (i.e., the long-short media-based strategy does not improve the net-of-costs return of an investor who already holds the market portfolio and the size/momentum portfolio).

Table S.III.10: Performance of Long-Short Media-Based Trading Strategies Relative to Cryptocurrency Risk Factors (Skipping a Week between the Portfolio Formation Week and the Holding Week): All Cryptocurrencies ever listed on CoinMarketCap

This table examines the return [in excess of the common risk factors in cryptocurrency proposed by Liu et al. (2022)] of a trading strategy that longs tokens with no media coverage and shorts tokens with high media coverage. Each week, tokens are sorted according to the number of news articles written about them. A token is considered to have no media coverage if no article is written about this token in a given week. A token is considered to have high media coverage if the number of articles written about it exceeds the median in a given week. Both the long and short positions are equally weighted, and they are held for the entire holding week after the portfolio formation. Portfolios are then re-balanced weekly. The resulting time-series returns on the long-short media-based portfolio are then regressed on three risk factors (cryptocurrency market, size, and momentum). The *p*-values [using the Newey-West standard error] are in parentheses. The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. Novy-Marx and Velikov's (2016) generalized alphas that account for transaction costs [calculated using the Matlab function *calcGenAlpha* provided in the second author's Github repository] are also reported.

	One-factor model	Two-factor model	Three-factor model
Panel A: Long no-media coverage tokens and short high-media coverage tokens			
Mkt-RF	–0.0717	–0.0825	–0.0815
	(0.4440)	(0.3810)	(0.3900)
CSMB	–	0.2605	0.2673*
		(0.1030)	(0.0890)
CMOM	–	–	–0.0407
			(0.6290)
Intercept (α)	0.0359***	0.0309***	0.0309***
	(0.0006)	(0.0029)	(0.0028)
Generalized α	0.0000	0.0000	0.0000
Sample size	249	249	249
R^2	0.0020	0.0270	0.0280
Panel B: Alphas for no-media coverage tokens			
α	0.0427***	0.0334***	0.0334***
	(0.0001)	(0.0014)	(0.0011)
Generalized α			0.0332***
			(0.0004)
R^2	0.2260	0.2890	0.2940
Panel C: Alphas for high-media coverage tokens			
α	0.0067	0.0024	0.0024
	(0.1032)	(0.4341)	(0.4052)
Generalized α			0.0000
R^2	0.7600	0.7990	0.8080

Table S.III.11: Performance of Long-Short Media-Based Trading Strategies Relative to Cryptocurrency Risk Factors by Token Characteristics (Skipping a Week between the Portfolio Formation Week and the Holding Week): All Cryptocurrencies ever listed on CoinMarketCap

This table examines the return [in excess of the common risk factors in cryptocurrency proposed by Liu et al. (2022)] of a trading strategy that longs tokens with no media coverage and shorts tokens with high media coverage in the subsamples of tokens sorted by cryptocurrency characteristics (defined in Table S.I.1) one at a time. Each week, tokens are sorted according to the number of newspaper articles written about them. A token is considered to have no media coverage if no article is written about this token in a given week. A token is considered to have high media coverage if the number of articles written about it exceeds the median in a given week. Both the long and short positions are equally weighted, and they are held for one week after the portfolio formation. Portfolios are then re-balanced weekly. Alphas from regressing the resulting time-series returns of the long-short media-based portfolio on three risk factors (cryptocurrency market, size, and momentum) are reported. *p*-values [using the Newey-West standard error] are in parentheses. The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. Novy-Marx and Velikov's (2016) generalized alphas that account for transaction costs [calculated using the Matlab function *calcGenAlpha* provided in the second author's Github repository] are also reported.

	One-factor model		Two-factor model		Three-factor model	
	α	generalized α	α	generalized α	α	generalized α
			Sort by MCAP			
0	0.0460**	0.0016	0.0457***	0.0016	0.0455***	0.0016
	(0.0114)	(0.9032)	(0.0043)	(0.9032)	(0.0044)	(0.9032)
1	0.0273**	0.0000	0.0271**	0.0000	0.0272**	0.0000
	(0.0410)		(0.0407)		(0.0422)	
2	0.0001	0.0000	−0.0005	0.0000	−0.0006	0.0000
	(0.9827)		(0.8238)		(0.8188)	
			Sort by AMCAP			
0	0.0473***	0.0028	0.0454***	0.0028	0.0453***	0.0028
	(0.0068)	(0.8329)	(0.0035)	(0.8329)	(0.0036)	(0.8329)
1	0.0200	0.0000	0.0224	0.0000	0.0227	0.0000
	(0.1608)		(0.1036)		(0.1043)	
2	0.0020	0.0000	0.0015	0.0000	0.0015	0.0000
	(0.4306)		(0.5548)		(0.5601)	
			Sort by PRCVOL			
0	0.0318**	0.0000	0.0358***	0.0000	0.0358***	0.0000
	(0.0197)		(0.0053)		(0.0054)	
1	0.0085**	0.0000	0.0086*	0.0000	0.0086*	0.0000
	(0.0456)		(0.0508)		(0.0526)	
2	0.0048**	0.0000	0.0034	0.0000	0.0034	0.0000
	(0.0288)		(0.1206)		(0.1248)	

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Table S.III.11 (continued): Performance of Long-Short Media-Based Trading Strategies Relative to Cryptocurrency Risk Factors by Token Characteristics (Skipping a Week between the Portfolio Formation Week and the Holding Week): All Cryptocurrencies ever listed on CoinMarketCap

	One-factor model		Two-factor model		Three-factor model	
	α	generalized α	α	generalized α	α	generalized α
			Sort by VOLSCALED			
0	0.0334***	0.0000	0.0368***	0.0000	0.0367***	0.0000
	(0.0067)		(0.0033)		(0.0036)	
1	0.0027	0.0000	0.0012	0.0000	0.0012	0.0000
	(0.4287)		(0.7384)		(0.7295)	
2	0.0068**	0.0000	0.0058**	0.0000	0.0059**	0.0000
	(0.0148)		(0.0323)		(0.0288)	
			Sort by RETVOL			
0	0.0145**	0.0000	0.0131**	0.0000	0.0132**	0.0000
	(0.0289)		(0.0464)		(0.0469)	
1	0.0143*	0.0000	0.0106	0.0000	0.0107	0.0000
	(0.0597)		(0.1110)		(0.1106)	
2	0.0389***	0.0000	0.0365***	0.0000	0.0365***	0.0000
	(0.0006)		(0.0016)		(0.0016)	
			Sort by IDIOVOL			
0	0.0083	0.0000	0.0089	0.0000	0.0093	0.0000
	(0.1296)		(0.1054)		(0.1030)	
1	0.0101	0.0000	0.0082	0.0000	0.0081	0.0000
	(0.1024)		(0.1177)		(0.1122)	
2	0.0635**	0.0016	0.0667**	0.0016	0.0669**	0.0016
	(0.0131)	(0.4735)	(0.0105)	(0.4735)	(0.0112)	(0.4735)
			Sort by MAXRET			
0	0.0191**	0.0000	0.0185**	0.0000	0.0185**	0.0000
	(0.0191)		(0.0274)		(0.0285)	
1	0.0067	0.0000	0.0032	0.0000	0.0032	0.0000
	(0.3210)		(0.5896)		(0.5809)	
2	0.0442***	0.0000	0.0417***	0.0000	0.0416***	0.0000
	(0.0000)		(0.0001)		(0.0001)	

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Table S.III.11 (continued): Performance of Long-Short Media-Based Trading Strategies Relative to Cryptocurrency Risk Factors by Token Characteristics (Skipping a Week between the Portfolio Formation Week and the Holding Week): All Cryptocurrencies ever listed on CoinMarketCap

	One-factor model		Two-factor model		Three-factor model	
	α	generalized α	α	generalized α	α	generalized α
			Sort by DAMIHUD			
0	0.0003	0.0000	–0.0010	0.0000	–0.0010	0.0000
	(0.9054)		(0.6667)		(0.6677)	
1	0.0060	0.0000	0.0055	0.0000	0.0055	0.0000
	(0.1467)		(0.1672)		(0.1681)	
2	0.0641***	0.0018	0.0568***	0.0018	0.0568***	0.0018
	(0.0066)	(0.3915)	(0.0091)	(0.3915)	(0.0094)	(0.3915)
			Sort by VaR			
0	0.0086	0.0000	0.0072	0.0000	0.0073	0.0000
	(0.1340)		(0.2222)		(0.2277)	
1	0.0091*	0.0000	0.0079*	0.0000	0.0079*	0.0000
	(0.0636)		(0.0961)		(0.0967)	
2	0.0436***	0.0000	0.0361***	0.0000	0.0361***	0.0000
	(0.0007)		(0.0051)		(0.0052)	
			Sort by r $1,0$			
0	0.0144**	0.0000	0.0142**	0.0000	0.0141**	0.0000
	(0.0165)		(0.0181)		(0.0179)	
1	0.0345***	0.0000	0.0283***	0.0000	0.0283***	0.0000
	(0.0069)		(0.0088)		(0.0085)	
2	0.0183**	0.0000	0.0151*	0.0000	0.0151*	0.0000
	(0.0311)		(0.0642)		(0.0659)	
			Sort by r $2,0$			
0	0.0154***	0.0000	0.0144**	0.0000	0.0142**	0.0000
	(0.0055)		(0.0101)		(0.0110)	
1	0.0241***	0.0000	0.0218***	0.0000	0.0216***	0.0000
	(0.0023)		(0.0070)		(0.0067)	
2	0.0487**	0.0003	0.0468*	0.0003	0.0476**	0.0003
	(0.0369)	(0.9869)	(0.0514)	(0.9869)	(0.0492)	(0.9869)

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Table S.III.11 (continued): Performance of Long-Short Media-Based Trading Strategies Relative to Cryptocurrency Risk Factors by Token Characteristics (Skipping a Week between the Portfolio Formation Week and the Holding Week): All Cryptocurrencies ever listed on CoinMarketCap

	One-factor model		Two-factor model		Three-factor model	
	α	generalized α	α	generalized α	α	generalized α
			Sort by r $3, 0$			
0	0.0206***	0.0000	0.0185***	0.0000	0.0184***	0.0000
	(0.0009)		(0.0019)		(0.0020)	
1	0.0325**	0.0000	0.0239**	0.0000	0.0239**	0.0000
	(0.0183)		(0.0374)		(0.0384)	
2	0.0343***	0.0000	0.0303**	0.0000	0.0304**	0.0000
	(0.0085)		(0.0237)		(0.0250)	
			Sort by r $4, 0$			
0	0.0204***	0.0000	0.0197***	0.0000	0.0196***	0.0000
	(0.0006)		(0.0011)		(0.0009)	
1	0.0217***	0.0000	0.0151**	0.0000	0.0151**	0.0000
	(0.0075)		(0.0171)		(0.0165)	
2	0.0465***	0.0000	0.0417***	0.0000	0.0417**	0.0000
	(0.0047)		(0.0097)		(0.0102)	
			Sort by r $4, 1$			
0	0.0199***	0.0000	0.0168***	0.0000	0.0168***	0.0000
	(0.0046)		(0.0071)		(0.0068)	
1	0.0216**	0.0000	0.0145**	0.0000	0.0144**	0.0000
	(0.0127)		(0.0151)		(0.0147)	
2	0.0379**	0.0000	0.0333**	0.0000	0.0336*	0.0000
	(0.0274)		(0.0481)		(0.0510)	
			Sort by r $8, 0$			
0	0.0284***	0.0000	0.0296***	0.0000	0.0296***	0.0000
	(0.0013)		(0.0015)		(0.0015)	
1	0.0106***	0.0000	0.0091**	0.0000	0.0090**	0.0000
	(0.0033)		(0.0102)		(0.0127)	
2	0.0505**	0.0019	0.0441**	0.0019	0.0440**	0.0019
	(0.0102)	(0.9101)	(0.0167)	(0.9101)	(0.0172)	(0.9101)

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Table S.III.11 (continued): Performance of Long-Short Media-Based Trading Strategies Relative to Cryptocurrency Risk Factors by Token Characteristics (Skipping a Week between the Portfolio Formation Week and the Holding Week): All Cryptocurrencies ever listed on CoinMarketCap

	One-factor model		Two-factor model		Three-factor model	
	α	generalized α	α	generalized α	α	generalized α
			Sort by r $16, 0$			
0	0.0111*	0.0000	0.0140**	0.0000	0.0140**	0.0000
	(0.0667)		(0.0164)		(0.0166)	
1	0.0132***	0.0000	0.0114**	0.0000	0.0114**	0.0000
	(0.0089)		(0.0199)		(0.0197)	
2	0.0539***	0.0056	0.0493***	0.0056	0.0494***	0.0056
	(0.0041)	(0.7625)	(0.0075)	(0.7625)	(0.0083)	(0.7625)
			Sort by r $50, 0$			
0	0.0163*	0.0000	0.0167**	0.0000	0.0166**	0.0000
	(0.0541)		(0.0332)		(0.0331)	
1	0.0127*	0.0000	0.0126*	0.0000	0.0128*	0.0000
	(0.0621)		(0.0707)		(0.0643)	
2	0.0404***	0.0000	0.0406***	0.0000	0.0408***	0.0000
	(0.0017)		(0.0019)		(0.0021)	
			Sort by r $100, 0$			
0	0.0263	0.0000	0.0224*	0.0000	0.0217*	0.0000
	(0.1084)		(0.0767)		(0.0977)	
1	0.0077	0.0000	0.0020	0.0000	0.0024	0.0000
	(0.2697)		(0.7501)		(0.6854)	
2	0.1753**	0.0012*	0.1712***	0.0012*	0.1720**	0.0012*
	(0.0139)	(0.0507)	(0.0095)	(0.0507)	(0.0104)	(0.0507)
			Sort by NPAST52			
0	0.0315***	0.0000	0.0319***	0.0000	0.0317***	0.0000
	(0.0044)		(0.0053)		(0.0055)	
1	0.0154***	0.0000	0.0120**	0.0000	0.0119**	0.0000
	(0.0055)		(0.0257)		(0.0271)	
2	0.0581*	0.0010	0.0300	0.0010	0.0301	0.0010
	(0.0590)	(0.7623)	(0.2373)	(0.7623)	(0.2313)	(0.7623)

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Table S.III.11 (continued): Performance of Long-Short Media-Based Trading Strategies Relative to Cryptocurrency Risk Factors by Token Characteristics (Skipping a Week between the Portfolio Formation Week and the Holding Week): All Cryptocurrencies ever listed on CoinMarketCap

	One-factor model		Two-factor model		Three-factor model	
	α	generalized α	α	generalized α	α	generalized α
			Sort by BETA			
0	0.0593***	0.0011	0.0588***	0.0011	0.0585***	0.0011
	(0.0020)	(0.5392)	(0.0021)	(0.5392)	(0.0022)	(0.5392)
1	0.0018	0.0000	0.0014	0.0000	0.0016	0.0000
	(0.6341)		(0.6961)		(0.6594)	
2	0.0162*	0.0000	0.0172*	0.0000	0.0176*	0.0000
	(0.0668)		(0.0603)		(0.0594)	
			Sort by BETA2			
0	0.0411***	0.0000	0.0411***	0.0000	0.0410***	0.0000
	(0.0037)		(0.0039)		(0.0041)	
1	0.0037	0.0000	0.0026	0.0000	0.0028	0.0000
	(0.3577)		(0.4841)		(0.4434)	
2	0.0321**	0.0000	0.0262**	0.0000	0.0265**	0.0000
	(0.0148)		(0.0208)		(0.0196)	

Table S.III.12: Performance of Long-Short Media-Based Trading Strategies Relative to Cryptocurrency Risk Factors: All Active Cryptocurrencies currently listed on CoinMarketCap

This table examines the return [in excess of the common risk factors in cryptocurrency proposed by Liu et al. (2022)] of a trading strategy that longs tokens with no media coverage and shorts tokens with high media coverage. Each week, tokens are sorted according to the number of news articles written about them. A token is considered to have no media coverage if no article is written about this token in a given week. A token is considered to have high media coverage if the number of articles written about it exceeds the median in a given week. Both the long and short positions are equally weighted, and they are held for the entire holding week after the portfolio formation. Portfolios are then re-balanced weekly. The resulting time-series returns on the long-short media-based portfolio are then regressed on three risk factors (cryptocurrency market, size, and momentum). The *p*-values [using the Newey-West standard error] are in parentheses. The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. Novy-Marx and Velikov's (2016) generalized alphas that account for transaction costs [calculated using the Matlab function *calcGenAlpha* provided in the second author's Github repository] are also reported.

	One-factor model	Two-factor model	Three-factor model
Panel A: Long no-media coverage tokens and short high-media coverage tokens			
Mkt-RF	−0.0031	0.0029	−0.0062
	(0.9660)	(0.9690)	(0.9300)
CSMB	–	0.1822	0.1793***
		(0.1240)	(0.0100)
CMOM	–	–	0.2275***
			(0.0030)
Intercept (α)	0.0246***	0.0209***	0.0198***
	(0.0016)	(0.0050)	(0.0085)
Generalized α	0.0000	0.0000	0.0000
Sample size	273	273	273
R^2	0.0000	0.0300	0.0630
Panel B: Alphas for no-media coverage tokens			
α	0.0356***	0.0265***	0.0255***
	(0.0000)	(0.0005)	(0.0009)
Generalized α			0.0257***
			(0.0001)
R^2	0.3750	0.4710	0.4880
Panel C: Alphas for high-media coverage tokens			
α	0.0109**	0.0056*	0.0056*
	(0.0126)	(0.0845)	(0.0806)
Generalized α			0.0000
R^2	0.6960	0.7580	0.7580

Table S.III.13: Performance of Long-Short Media-Based Trading Strategies Relative to Cryptocurrency Risk Factors by Token Characteristics: All Active Cryptocurrencies currently listed on CoinMarketCap

This table examines the return [in excess of the common risk factors in cryptocurrency proposed by Liu et al. (2022)] of a trading strategy that longs tokens with no media coverage and shorts tokens with high media coverage in the subsamples of tokens sorted by cryptocurrency characteristics (defined in Table S.I.1) one at a time. Each week, tokens are sorted according to the number of newspaper articles written about them. A token is considered to have no media coverage if no article is written about this token in a given week. A token is considered to have high media coverage if the number of articles written about it exceeds the median in a given week. Both the long and short positions are equally weighted, and they are held for one week after the portfolio formation. Portfolios are then re-balanced weekly. Alphas from regressing the resulting time-series returns of the long-short media-based portfolio on three risk factors (cryptocurrency market, size, and momentum) are reported. *p*-values [using the Newey-West standard error] are in parentheses. The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. Novy-Marx and Velikov's (2016) generalized alphas that account for transaction costs [calculated using the Matlab function *calcGenAlpha* provided in the second author's Github repository] are also reported.

	One-factor model		Two-factor model		Three-factor model	
	α	generalized α	α	generalized α	α	generalized α
			Sort by MCAP			
0	0.0251***	0.0000	0.0244***	0.0000	0.0241***	0.0000
	(0.0012)		(0.0014)		(0.0017)	
1	0.0527**	0.0064	0.0514**	0.0064	0.0514**	0.0064
	(0.0187)	(0.7961)	(0.0200)	(0.7961)	(0.0204)	(0.7961)
2	0.0013	0.0000	0.0013	0.0000	0.0013	0.0000
	(0.6671)		(0.6798)		(0.6791)	
			Sort by AMCAP			
0	0.0292***	0.0000	0.0275***	0.0000	0.0272***	0.0000
	(0.0011)		(0.0011)		(0.0015)	
1	0.0572**	0.0108	0.0558**	0.0108	0.0558**	0.0108
	(0.0110)	(0.6645)	(0.0117)	(0.6645)	(0.0122)	(0.6645)
2	−0.0016	0.0000	−0.0019	0.0000	−0.0018	0.0000
	(0.5467)		(0.4873)		(0.4914)	
			Sort by PRCVOL			
0	0.0377**	0.0000	0.0378**	0.0000	0.0370**	0.0000
	(0.0159)		(0.0191)		(0.0208)	
1	0.0081*	0.0000	0.006	0.0000	0.0058	0.0000
	(0.0776)		(0.1919)		(0.2181)	
2	0.0019	0.0000	0.0009	0.0000	0.0010	0.0000
	(0.4857)		(0.7148)		(0.6871)	

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Table S.III.13 (continued): Performance of Long-Short Media-Based Trading Strategies Relative to Cryptocurrency Risk Factors by Token Characteristics: All Active Cryptocurrencies currently listed on CoinMarketCap

	One-factor model		Two-factor model		Three-factor model	
	α	generalized α	α	generalized α	α	generalized α
			Sort by VOLSCALED			
0	0.0392**	0.0000	0.0385**	0.0000	0.0367**	0.0000
	(0.0217)		(0.0325)		(0.0393)	
1	0.0067*	0.0000	0.0041	0.0000	0.0037	0.0000
	(0.0654)		(0.1807)		(0.2331)	
2	0.0032	0.0000	0.0015	0.0000	0.0016	0.0000
	(0.4028)		(0.7027)		(0.6803)	
			Sort by RETVOL			
0	0.0086	0.0000	0.0060	0.0000	0.0056	0.0000
	(0.1528)		(0.2935)		(0.3324)	
1	0.0084*	0.0000	0.0050	0.0000	0.0031	0.0000
	(0.0747)		(0.1627)		(0.3720)	
2	0.0559***	0.0083	0.0560***	0.0083	0.0540***	0.0083
	(0.0031)	(0.5459)	(0.0031)	(0.5459)	(0.0045)	(0.5459)
			Sort by IDIOVOL			
0	0.0020	0.0000	0.0009	0.0000	0.0008	0.0000
	(0.5764)		(0.8131)		(0.8325)	
1	0.0024	0.0000	0.0011	0.0000	0.0007	0.0000
	(0.5717)		(0.8004)		(0.8754)	
2	0.0492***	0.0021	0.0475***	0.0021	0.0476***	0.0021
	(0.0039)	(0.8683)	(0.0046)	(0.8683)	(0.0057)	(0.8683)
			Sort by MAXRET			
0	0.0126**	0.0000	0.0095	0.0000	0.0097	0.0000
	(0.0340)		(0.1024)		(0.1034)	
1	0.0103**	0.0000	0.0084*	0.0000	0.0077	0.0000
	(0.0527)		(0.0911)		(0.1335)	
2	0.0288*	0.0000	0.0301*	0.0000	0.0286*	0.0000
	(0.0966)		(0.0781)		(0.0945)	

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Table S.III.13 (continued): Performance of Long-Short Media-Based Trading Strategies Relative to Cryptocurrency Risk Factors by Token Characteristics: All Active Cryptocurrencies currently listed on CoinMarketCap

	One-factor model		Two-factor model		Three-factor model	
	α	generalized α	α	generalized α	α	generalized α
			Sort by DAMIHUD			
0	0.0028	0.0000	0.0018	0.0000	0.0016	0.0000
	(0.3147)		(0.4875)		(0.5429)	
1	0.0083*	0.0000	0.0097*	0.0000	0.0096*	0.0000
	(0.0863)		(0.0594)		(0.0577)	
2	0.0416***	0.0000	0.0404***	0.0000	0.0405***	0.0000
	(0.0069)		(0.0075)		(0.0073)	
			Sort by VaR			
0	0.0146	0.0000	0.0130	0.0000	0.0122	0.0000
	(0.1176)		(0.1468)		(0.1699)	
1	0.0059*	0.0000	0.0056	0.0000	0.0056	0.0000
	(0.0866)		(0.1091)		(0.1156)	
2	0.0386***	0.0000	0.0372***	0.0000	0.0368**	0.0000
	(0.0089)		(0.0088)		(0.0109)	
			Sort by r $1,0$			
0	0.0167**	0.0000	0.0137**	0.0000	0.0125**	0.0000
	(0.0118)		(0.0303)		(0.0493)	
1	0.0203**	0.0000	0.0165**	0.0000	0.0162**	0.0000
	(0.0077)		(0.0274)		(0.0386)	
2	0.0236**	0.0000	0.0219**	0.0000	0.0205*	0.0000
	(0.0338)		(0.0417)		(0.0585)	
			Sort by r $2,0$			
0	0.0204***	0.0000	0.0188***	0.0000	0.0167***	0.0000
	(0.0002)		(0.0004)		(0.0030)	
1	0.0150***	0.0000	0.0130**	0.0000	0.0117**	0.0000
	(0.0061)		(0.0268)		(0.0450)	
2	0.0274**	0.0000	0.0227*	0.0000	0.0234*	0.0000
	(0.0365)		(0.0632)		(0.0545)	

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Table S.III.13 (continued): Performance of Long-Short Media-Based Trading Strategies Relative to Cryptocurrency Risk Factors by Token Characteristics: All Active Cryptocurrencies currently listed on CoinMarketCap

	One-factor model		Two-factor model		Three-factor model	
	α	generalized α	α	generalized α	α	generalized α
			Sort by r $3, 0$			
0	0.0165***	0.0000	0.0144***	0.0000	0.0133***	0.0000
	(0.0018)		(0.0055)		(0.0094)	
1	0.0140**	0.0000	0.0100*	0.0000	0.0089	0.0000
	(0.0178)		(0.0652)		(0.1120)	
2	0.0407**	0.0000	0.0393**	0.0000	0.0388**	0.0000
	(0.0111)		(0.0152)		(0.0167)	
			Sort by r $4, 0$			
0	0.0231***	0.0000	0.0206***	0.0000	0.0196***	0.0000
	(0.0015)		(0.0029)		(0.0047)	
1	0.0157**	0.0000	0.0116*	0.0000	0.0107*	0.0000
	(0.0144)		(0.0551)		(0.0827)	
2	0.0323**	0.0000	0.0317**	0.0000	0.0303**	0.0000
	(0.0169)		(0.0180)		(0.0230)	
			Sort by r $4, 1$			
0	0.0321***	0.0000	0.0289***	0.0000	0.0279***	0.0000
	(0.0011)		(0.0037)		(0.0069)	
1	0.0150*	0.0000	0.0113	0.0000	0.0109	0.0000
	(0.0855)		(0.1820)		(0.2057)	
2	0.0306***	0.0000	0.0286**	0.0000	0.0265**	0.0000
	(0.0089)		(0.0162)		(0.0245)	
			Sort by r $8, 0$			
0	0.0191**	0.0000	0.0175**	0.0000	0.0172**	0.0000
	(0.0141)		(0.0249)		(0.0298)	
1	0.0159**	0.0000	0.0122**	0.0000	0.0108*	0.0000
	(0.0185)		(0.0362)		(0.0526)	
2	0.0388**	0.0000	0.0351*	0.0000	0.0337*	0.0000
	(0.0440)		(0.0688)		(0.0801)	

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Table S.III.13 (continued): Performance of Long-Short Media-Based Trading Strategies Relative to Cryptocurrency Risk Factors by Token Characteristics: All Active Cryptocurrencies currently listed on CoinMarketCap

	One-factor model		Two-factor model		Three-factor model	
	α	generalized α	α	generalized α	α	generalized α
			Sort by r 16, 0			
0	0.0206***	0.0000	0.0213**	0.0000	0.0214***	0.0000
	(0.0099)		(0.0105)		(0.0099)	
1	0.0136**	0.0000	0.0061	0.0000	0.0048	0.0000
	(0.0196)		(0.1417)		(0.2427)	
2	0.0341**	0.0000	0.0284*	0.0000	0.0265*	0.0000
	(0.0238)		(0.0519)		(0.0694)	
			Sort by r 50, 0			
0	0.0199*	0.0000	0.0219*	0.0000	0.0220*	0.0000
	(0.0825)		(0.0676)		(0.0655)	
1	0.0147***	0.0000	0.0105**	0.0000	0.0100*	0.0000
	(0.0091)		(0.0424)		(0.0614)	
2	0.0327**	0.0000	0.0278*	0.0000	0.0274*	0.0000
	(0.0239)		(0.0503)		(0.0555)	
			Sort by r 100, 0			
0	0.0313*	0.0000	0.0247	0.0000	0.0239	0.0000
	(0.0684)		(0.1323)		(0.1723)	
1	−0.0023	0.0000	−0.0022	0.0000	−0.0031	0.0000
	(0.7086)		(0.7149)		(0.6027)	
2	0.0563**	0.0051	0.0552**	0.0051	0.0546**	0.0051
	(0.0138)	(0.7686)	(0.0181)	(0.7686)	(0.0185)	(0.7686)
			Sort by NPAST52			
0	0.0332**	0.0000	0.0279*	0.0000	0.0274*	0.0000
	(0.0328)		(0.0695)		(0.0780)	
1	0.0102*	0.0000	0.0076	0.0000	0.0067	0.0000
	(0.0641)		(0.1568)		(0.2116)	
2	0.0289**	0.0000	0.0306**	0.0000	0.0299**	0.0000
	(0.0163)		(0.0171)		(0.0215)	

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Table S.III.13 (continued): Performance of Long-Short Media-Based Trading Strategies Relative to Cryptocurrency Risk Factors by Token Characteristics: All Active Cryptocurrencies currently listed on CoinMarketCap

	One-factor model		Two-factor model		Three-factor model	
	α	generalized α	α	generalized α	α	generalized α
			Sort by BETA			
0	0.0470***	0.0000	0.0440***	0.0000	0.0435***	0.0000
	(0.0046)		(0.0064)		(0.0079)	
1	0.0064	0.0000	0.0047	0.0000	0.0042	0.0000
	(0.1384)		(0.2465)		(0.3206)	
2	0.0055	0.0000	0.0068	0.0000	0.0068	0.0000
	(0.3319)		(0.2054)		(0.2088)	
			Sort by BETA2			
0	0.0310***	0.0000	0.0295***	0.0000	0.0295***	0.0000
	(0.0012)		(0.0019)		(0.0021)	
1	0.0066	0.0000	0.0050	0.0000	0.0047	0.0000
	(0.1079)		(0.1812)		(0.2398)	
2	0.0156	0.0000	0.0150*	0.0000	0.0149*	0.0000
	(0.1077)		(0.0777)		(0.0785)	

Table S.III.14: Performance of Long-Short Media-Based Trading Strategies Relative to Cryptocurrency Risk Factors (Skipping a Week between the Portfolio Formation Week and the Holding Week): All Active Cryptocurrencies currently listed on CoinMarketCap

This table examines the return [in excess of the common risk factors in cryptocurrency proposed by Liu et al. (2022)] of a trading strategy that longs tokens with no media coverage and shorts tokens with high media coverage. Each week, tokens are sorted according to the number of news articles written about them. A token is considered to have no media coverage if no article is written about this token in a given week. A token is considered to have high media coverage if the number of articles written about it exceeds the median in a given week. Both the long and short positions are equally weighted, and they are held for the entire holding week after the portfolio formation. Portfolios are then re-balanced weekly. The resulting time-series returns on the long-short media-based portfolio are then regressed on three risk factors (cryptocurrency market, size, and momentum). The *p*-values [using the Newey-West standard error] are in parentheses. The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. Novy-Marx and Velikov's (2016) generalized alphas that account for transaction costs [calculated using the Matlab function *calcGenAlpha* provided in the second author's Github repository] are also reported.

	One-factor model	Two-factor model	Three-factor model
Panel A: Long no-media coverage tokens and short high-media coverage tokens			
Mkt-RF	–0.0100	–0.0357	–0.0293
	(0.9300)	(0.7430)	(0.7870)
CSMB	–	0.4744***	0.4515***
		(0.0000)	(0.0000)
CMOM	–	–	0.1042
			(0.1840)
Intercept (α)	0.0375***	0.0276***	0.0278**
	(0.0021)	(0.0099)	(0.0101)
Generalized α	0.0000	0.0000	0.0000
Sample size	273	273	273
R^2	0.0000	0.0820	0.0830
Panel B: Alphas for no-media coverage tokens			
α	0.0487***	0.0361***	0.0359***
	(0.0001)	(0.0006)	(0.0006)
Generalized α			0.0391***
			(0.0002)
R^2	0.1810	0.2860	0.2880
Panel C: Alphas for high-media coverage tokens			
α	0.0111***	0.0085***	0.0081***
	(0.0055)	(0.0090)	(0.0065)
Generalized α			0.0000
R^2	0.6790	0.6960	0.7180

Table S.III.15: Performance of Long-Short Media-Based Trading Strategies Relative to Cryptocurrency Risk Factors by Token Characteristics (Skipping a Week between the Portfolio Formation Week and the Holding Week): All Active Cryptocurrencies currently listed on CoinMarketCap

This table examines the return [in excess of the common risk factors in cryptocurrency proposed by Liu et al. (2022)] of a trading strategy that longs tokens with no media coverage and shorts tokens with high media coverage in the subsamples of tokens sorted by cryptocurrency characteristics (defined in Table S.I.1) one at a time. Each week, tokens are sorted according to the number of newspaper articles written about them. A token is considered to have no media coverage if no article is written about this token in a given week. A token is considered to have high media coverage if the number of articles written about it exceeds the median in a given week. Both the long and short positions are equally weighted, and they are held for one week after the portfolio formation. Portfolios are then re-balanced weekly. Alphas from regressing the resulting time-series returns of the long-short media-based portfolio on three risk factors (cryptocurrency market, size, and momentum) are reported. p-values [using the Newey-West standard error] are in parentheses. The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. Novy-Marx and Velikov's (2016) generalized alphas that account for transaction costs [calculated using the Matlab function *calcGenAlpha* provided in the second author's Github repository] are also reported.

	One-factor model		Two-factor model		Three-factor model	
	α	generalized α	α	generalized α	α	generalized α
			Sort by MCAP			
0	0.0347***	0.0000	0.0351***	0.0000	0.0350***	0.0000
	(0.0047)		(0.0044)		(0.0045)	
1	0.0443*	0.0000	0.0413*	0.0000	0.0412*	0.0000
	(0.0598)		(0.0500)		(0.0507)	
2	0.0015	0.0000	0.0006	0.0000	0.0006	0.0000
	(0.6150)		(0.8579)		(0.8529)	
			Sort by AMCAP			
0	0.0359***	0.0000	0.0369***	0.0000	0.0369***	0.0000
	(0.0038)		(0.0032)		(0.0032)	
1	0.0362	0.0000	0.0338	0.0000	0.0338	0.0000
	(0.1234)		(0.1009)		(0.1026)	
2	0.0020	0.0000	0.0019	0.0000	0.0019	0.0000
	(0.3624)		(0.3835)		(0.3827)	
			Sort by PRCVOL			
0	0.0484**	0.0021	0.0528**	0.0021	0.0522**	0.0021
	(0.0149)	(0.8848)	(0.0106)	(0.8848)	(0.0109)	(0.8848)
1	0.0070	0.0000	0.0059	0.0000	0.0059	0.0000
	(0.1102)		(0.1702)		(0.1714)	
2	0.0031	0.0000	0.0012	0.0000	0.0011	0.0000
	(0.2673)		(0.6356)		(0.6733)	

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Table S.III.15 (continued): Performance of Long-Short Media-Based Trading Strategies Relative to Cryptocurrency Risk Factors by Token Characteristics (Skipping a Week between the Portfolio Formation Week and the Holding Week): All Active Cryptocurrencies currently listed on CoinMarketCap

	One-factor model		Two-factor model		Three-factor model	
	α	generalized α	α	generalized α	α	generalized α
			Sort by VOLSCALED			
0	0.0572**	0.0103	0.0616**	0.0103	0.0610**	0.0103
	(0.0363)	(0.6167)	(0.0410)	(0.6167)	(0.0415)	(0.6167)
1	0.0034	0.0000	0.0036	0.0000	0.0036	0.0000
	(0.3320)		(0.2973)		(0.2960)	
2	0.0047	0.0000	0.0029	0.0000	0.0029	0.0000
	(0.1888)		(0.3911)		(0.3932)	
			Sort by RETVOL			
0	0.0090	0.0000	0.0044	0.0000	0.0045	0.0000
	(0.1194)		(0.4053)		(0.4014)	
1	0.0219**	0.0000	0.0141*	0.0000	0.0143*	0.0000
	(0.0375)		(0.0951)		(0.0978)	
2	0.0503***	0.0030	0.0419***	0.0030	0.0420***	0.0030
	(0.0008)	(0.7828)	(0.0064)	(0.7828)	(0.0064)	(0.7828)
			Sort by IDIOVOL			
0	0.0062	0.0000	0.0054	0.0000	0.0056	0.0000
	(0.2120)		(0.2703)		(0.2651)	
1	0.0121*	0.0000	0.0061	0.0000	0.0061	0.0000
	(0.0802)		(0.3456)		(0.3416)	
2	0.0647**	0.0017	0.0562**	0.0017	0.0568**	0.0017
	(0.0167)	(0.4513)	(0.0349)	(0.4513)	(0.0340)	(0.4513)
			Sort by MAXRET			
0	0.0192**	0.0000	0.0105**	0.0000	0.0105**	0.0000
	(0.0228)		(0.0497)		(0.0496)	
1	0.0079	0.0000	0.0012	0.0000	0.0013	0.0000
	(0.3514)		(0.8508)		(0.8401)	
2	0.0509***	0.0033	0.0389***	0.0033	0.0394***	0.0033
	(0.0006)	(0.7831)	(0.0086)	(0.7831)	(0.0076)	(0.7831)

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Table S.III.15 (continued): Performance of Long-Short Media-Based Trading Strategies Relative to Cryptocurrency Risk Factors by Token Characteristics (Skipping a Week between the Portfolio Formation Week and the Holding Week): All Active Cryptocurrencies currently listed on CoinMarketCap

	One-factor model		Two-factor model		Three-factor model	
	α	generalized α	α	generalized α	α	generalized α
			Sort by DAMIHUD			
0	0.0016	0.0000	0.0001	0.0000	0.0001	0.0000
	(0.4871)		(0.9616)		(0.9711)	
1	0.0091**	0.0000	0.0090**	0.0000	0.0089**	0.0000
	(0.0419)		(0.0389)		(0.0380)	
2	0.0605**	0.0015	0.0441*	0.0015	0.0440*	0.0015
	(0.0261)	(0.5159)	(0.0575)	(0.5159)	(0.0595)	(0.5159)
			Sort by VaR			
0	0.0062	0.0000	0.0030	0.0000	0.0032	0.0000
	(0.1617)		(0.4664)		(0.4524)	
1	0.0148*	0.0000	0.0124	0.0000	0.0126	0.0000
	(0.0922)		(0.1496)		(0.1492)	
2	0.0464***	0.0001	0.0359***	0.0001	0.0363***	0.0001
	(0.0084)	(0.9925)	(0.0242)	(0.9925)	(0.0217)	(0.9925)
			Sort by r $1, 0$			
0	0.0193**	0.0000	0.0147*	0.0000	0.0148*	0.0000
	(0.0186)		(0.0610)		(0.0577)	
1	0.0326***	0.0000	0.0246**	0.0000	0.0246**	0.0000
	(0.0063)		(0.0133)		(0.0137)	
2	0.0232**	0.0000	0.0133	0.0000	0.0135	0.0000
	(0.0271)		(0.1663)		(0.1642)	
			Sort by r $2, 0$			
0	0.0155**	0.0000	0.0098*	0.0000	0.0100*	0.0000
	(0.0203)		(0.0816)		(0.0767)	
1	0.0209***	0.0000	0.0144**	0.0000	0.0144**	0.0000
	(0.0041)		(0.0215)		(0.0217)	
2	0.0277***	0.0000	0.0204*	0.0000	0.0209*	0.0000
	(0.0099)		(0.0626)		(0.0587)	

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Table S.III.15 (continued): Performance of Long-Short Media-Based Trading Strategies Relative to Cryptocurrency Risk Factors by Token Characteristics (Skipping a Week between the Portfolio Formation Week and the Holding Week): All Active Cryptocurrencies currently listed on CoinMarketCap

	One-factor model		Two-factor model		Three-factor model	
	α	generalized α	α	generalized α	α	generalized α
			Sort by r $3,0$			
0	0.0141**	0.0000	0.0079	0.0000	0.0081	0.0000
	(0.0439)		(0.2095)		(0.1986)	
1	0.0385**	0.0000	0.0301**	0.0000	0.0302**	0.0000
	(0.0198)		(0.0468)		(0.0471)	
2	0.0312***	0.0000	0.0238**	0.0000	0.0239**	0.0000
	(0.0067)		(0.0341)		(0.0359)	
			Sort by r $4,0$			
0	0.0164***	0.0000	0.0107*	0.0000	0.0109*	0.0000
	(0.0059)		(0.0842)		(0.0761)	
1	0.0434**	0.0000	0.0310**	0.0000	0.0312**	0.0000
	(0.0128)		(0.0379)		(0.0384)	
2	0.0337***	0.0000	0.0270**	0.0000	0.0270**	0.0000
	(0.0067)		(0.0249)		(0.0257)	
			Sort by r $4,1$			
0	0.0146**	0.0000	0.0109	0.0000	0.0109	0.0000
	(0.0268)		(0.1208)		(0.1196)	
1	0.0390**	0.0000	0.0292*	0.0000	0.0291*	0.0000
	(0.0332)		(0.0548)		(0.0574)	
2	0.0242*	0.0000	0.0202	0.0000	0.0202	0.0000
	(0.0520)		(0.1073)		(0.1073)	
			Sort by r $8,0$			
0	0.0206**	0.0000	0.0154*	0.0000	0.0154*	0.0000
	(0.0150)		(0.0793)		(0.0747)	
1	0.0204***	0.0000	0.0151**	0.0000	0.0151**	0.0000
	(0.0077)		(0.0208)		(0.0222)	
2	0.0542**	0.0055	0.0445**	0.0055	0.0445**	0.0055
	(0.0103)	(0.7856)	(0.0234)	(0.7856)	(0.0237)	(0.7856)

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Table S.III.15 (continued): Performance of Long-Short Media-Based Trading Strategies Relative to Cryptocurrency Risk Factors by Token Characteristics (Skipping a Week between the Portfolio Formation Week and the Holding Week): All Active Cryptocurrencies currently listed on CoinMarketCap

	One-factor model		Two-factor model		Three-factor model	
	α	generalized α	α	generalized α	α	generalized α
			Sort by r 16, 0			
0	0.0122	0.0000	0.0092	0.0000	0.0094	0.0000
	(0.1229)		(0.2708)		(0.2550)	
1	0.0199***	0.0000	0.0131**	0.0000	0.0132**	0.0000
	(0.0075)		(0.0469)		(0.0429)	
2	0.0492***	0.0009	0.0413**	0.0009	0.0420**	0.0009
	(0.0037)	(0.9559)	(0.0108)	(0.9559)	(0.0115)	(0.9559)
			Sort by r 50, 0			
0	0.0212**	0.0000	0.0175*	0.0000	0.0176*	0.0000
	(0.0198)		(0.0669)		(0.0631)	
1	0.0128**	0.0000	0.0084	0.0000	0.0088	0.0000
	(0.0425)		(0.1871)		(0.1681)	
2	0.0404***	0.0000	0.0341***	0.0000	0.0346***	0.0000
	(0.0013)		(0.0060)		(0.0063)	
			Sort by r 100, 0			
0	0.0362**	0.0000	0.0301**	0.0000	0.0309**	0.0000
	(0.0453)		(0.0426)		(0.0473)	
1	0.0008	0.0000	0.0009	0.0000	0.0006	0.0000
	(0.8855)		(0.8631)		(0.9164)	
2	0.0944**	0.0043	0.0869**	0.0043	0.0826**	0.0043
	(0.0202)	(0.2072)	(0.0140)	(0.2072)	(0.0146)	(0.2072)
			Sort by NPAST52			
0	0.0349***	0.0000	0.0264**	0.0000	0.0270**	0.0000
	(0.0051)		(0.0265)		(0.0266)	
1	0.0154**	0.0000	0.0108	0.0000	0.0110*	0.0000
	(0.0234)		(0.1010)		(0.0939)	
2	0.0315*	0.0000	0.0315*	0.0000	0.0316*	0.0000
	(0.0902)		(0.0849)		(0.0857)	

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Table S.III.15 (continued): Performance of Long-Short Media-Based Trading Strategies Relative to Cryptocurrency Risk Factors by Token Characteristics (Skipping a Week between the Portfolio Formation Week and the Holding Week): All Active Cryptocurrencies currently listed on CoinMarketCap

	One-factor model		Two-factor model		Three-factor model	
	α	generalized α	α	generalized α	α	generalized α
			Sort by BETA			
0	0.0543***	0.0064	0.0524***	0.0064	0.0523***	0.0064
	(0.0032)	(0.7081)	(0.0044)	(0.7081)	(0.0045)	(0.7081)
1	0.0079*	0.0000	0.0075	0.0000	0.0074	0.0000
	(0.0677)		(0.1226)		(0.1254)	
2	0.0191**	0.0000	0.0038	0.0000	0.0037	0.0000
	(0.0328)		(0.6431)		(0.6498)	
			Sort by BETA2			
0	0.0420***	0.0000	0.0404**	0.0000	0.0404***	0.0000
	(0.0080)		(0.0107)		(0.0099)	
1	0.0087*	0.0000	0.0075	0.0000	0.0075	0.0000
	(0.0508)		(0.1105)		(0.1122)	
2	0.0311**	0.0000	0.0167	0.0000	0.0166	0.0000
	(0.0196)		(0.1739)		(0.1750)	

S.III.3 Daniel, Grinblatt, Titman, and Wermers's (1997) (DGTW) Characteristic-based Benchmark Approach: A Robustness Check

In this section, we replicate the DGTW characteristic-based benchmark results [reported in Section 4.2] to verify the baseline results for the three media-based portfolios [formed by (a) longing no-coverage tokens, (b) shorting high-coverage tokens, and (c) simultaneously longing no-coverage tokens while shorting high--coverage tokens] using (i) all cryptocurrencies while skipping one week between the portfolio formation week and the holding week, and (ii) only active cryptocurrencies. We shall report the results of robustness checks (i) and (ii) both before and after accounting for transaction costs.

S.III.3.1 DGTW Characteristic-based Measures before Transaction Costs

Robustness Check (i):

Panel A of Table S.III.16 shows that, in the entire sample period, the average weekly CS measure of the long-only portfolio [of no-coverage tokens] is 138 basis points (t-statistic = 2.39), compared to 27 basis points (t-statistic = 0.86) for the short-only portfolio [of high-coverage tokens] (the average weekly CS measure of the long-short media-based portfolio is 194 basis points (t-statistic = 2.47). When splitting the sample by year (in Panels B - F), the average weekly CS measure of no-coverage tokens is still positive and statistically significant, and it is also larger than that of high-coverage tokens for most of the subsample periods. This result is thus consistent with the finding reported in Table 9 that the no-coverage tokens exhibit significant and positive benchmark-adjusted returns, which is also aligned with the sorting and regression results reported in the main text.

The average weekly CT measures are mostly negative or statistically insignificant for every media-based portfolio. This result suggests that the media-based strategy is not able to effectively time the cryptocurrency characteristics (size, volatility, and momentum), which is consistent with the results reported in Table 9. The average AS return measure of the long-only media-based portfolio is 248 basis points (t-statistic = 3.04), compared to -204 basis points (t-statistic = -3.09) for the short-only media-based portfolio in the entire sample period. Therefore, on average, the long-only media-based portfolio systematically holds small tokens, highly volatile tokens, or tokens with high momentum to boost its portfolio return, and this is not the case for the short-only media-based portfolio. This finding holds only in the subsample periods 2020 and 2021. The fact that the long-only media-based portfolio does not consistently tilt towards small tokens, highly volatile tokens, or momentum tokens suggests that this portfolio may generate a positive alpha relative to size, volatility, and momentum factors.

Robustness Check (ii):

Tables S.III.17 and S.III.18 (skipping one week between the portfolio formation week and the holding week) both suggest that

(a) no-coverage tokens exhibit a statistically significant and positive benchmark-adjusted return and this return is significantly greater than that of high-coverage tokens in the entire sample period: Panel A of Table S.III.17 shows that the average CS measure of the long-only media-based portfolio is 134 basis points (t-statistic = 2.72), compared to 21 basis points (t-statistic = 1.02) for the short-only media-based portfolio; Panel A of Table S.III.18 (skipping one week between the portfolio formation week and the holding week) shows that this measure is 132 basis points (t-statistic = 1.74), compared to 9 basis points (t-statistic = 0.25) for the short-only media-based portfolio; the same phenomenon is also observed for most of the subsample periods (Panels B - F);

(b) none of the media-based portfolios is able to effectively time the three cryptocurrency characteristics (size, volatility, and momentum): Panel A of Table S.III.17 and S.III.18 shows that the average CT measures for the long-only media-based portfolio are either negative or statistically insignificant in the entire sample period or in any subsample period;

(c) the average AS measure of the long-only media-based portfolio or the long-short media-based portfolio is statistically significant and positive while that of the short-only media-based portfolio is significantly negative in the entire sample period: Panel A of Table S.III.17 shows that the average AS measure of no-coverage tokens is 309 basis points (t-statistic = 3.87), compared to -241 basis points (t-statistic = -3.20) for high-coverage tokens, and the average AS measure of the long-short media-based portfolio is 84 basis points (t-statistic = 3.34) in the entire sample period; and Panel A of Table S.III.18 shows that the average AS measure of no-coverage tokens is 311 basis points (t-statistic = 3.69), compared to -255 basis points (t-statistic = -3.47) for high-coverage tokens, and the average AS measure of the long-short media-based portfolio is 47 basis points (t-statistic = 1.46) in the entire sample period; we also observe the same phenomenon in several subsample periods (Panels C - F of Table S.III.17, Panels D and E of Table S.III.18).

The above findings are aligned with those reported in Section 4.2.1.

S.III.3.2 DGTW Characteristic-based Measures after Transaction Costs

Robustness Check (i):

Table S.III.16 shows that the average weekly net-of-costs CS measure of each media-based portfolio is no longer statistically significant and positive either in the entire sample period or in any subsample period (for example, Panel A shows that the average CS measure of the long-only media-based portfolio decreases to 14 basis points (t-statistic = 0.24) from 138 basis points (t-statistic = 2.39) after accounting for transaction costs). The CT measure remains statistically insignificant before or after accounting for transaction costs. Therefore, the media-based portfolios do not outperform the passive benchmark portfolios after accounting for transaction costs, and they are not able to time the cryptocurrency characteristics (size, volatility, and momentum) before/after accounting for transaction costs.

The average net-of-costs AS measure of the long-only media-based portfolio is statistically significant and positive in the entire sample period and in several subsample periods [Panel A shows that the average AS measure of the long-only media-based portfolio decreases slightly to 231 basis points (t-statistic = 2.87) from 248 basis points (t-statistic = 3.04) after accounting for transaction costs]. This is because the long-only media-based portfolio tends to systematically hold small tokens, highly volatile tokens, or tokens with high momentum to boost its portfolio return. Moreover, the average net-of-costs AS measure of the short-only media-based portfolio is statistically significant and negative in the entire sample or in several subsample periods [Panel A shows that the average AS measure of the short-only media-based portfolio increases slightly to -203 basis points (t-statistic = -2.97) from -204 basis points (t-statistic = -3.09) after accounting for transaction costs]. Therefore, the short-only portfolio does not tend to systematically hold small tokens, highly volatile tokens, or tokens with high momentum. All these results are consistent with those reported in Section 4.2.2.

Robustness Check (ii):

Tables S.III.17 and S.III.18 (skipping one week between the portfolio formation week and the holding week) both suggest that

(a) the media-based portfolios do not outperform the passive benchmark portfolios once transaction costs are taken into account in the entire sample period as well as in subsample periods (for example, Panel A of Table S.III.17 shows that the average net-of-costs CS measure of the long-only media-based portfolio is 7 basis points (t-statistic = 0.14) while this measure is 5 basis points (t-statistic = 0.07) in Panel A of Table S.III.18);

(b) the media-based portfolios are not able to time the three cryptocurrency characteristics (the average net-of-costs CT measure is either insignificant or negative in the entire sample period or in the subsample periods);

(c) the long-only media-based portfolio tends to systematically hold small tokens, highly volatile tokens, or tokens with high momentum to boost its portfolio return while the short-only media-based portfolio does not in the entire sample period and in several subsample periods (for example, Panel A of Table S.III.17 shows that the average net-of-costs AS measure of the long-only portfolio is 290 basis points (t-statistic = 3.69), compared to -243 basis points (t-statistic = - 3.08) for the short-only portfolio; Panel A of Table S.III.18 shows that the average net-of-costs AS measure of the long-only portfolio is 292 basis points (t-statistic = 3.52), compared to -257 basis points (t-statistic = -3.35) for the short-only portfolio).

Table S.III.16: Performance Attribution Analysis based on the DGTW Characteristic-based Benchmark Method (Skipping a Week between the Portfolio Formation Week and the Holding Week): All Cryptocurrencies ever listed on CoinMarketCap

This table presents three average weekly performance attribution components for portfolios formed by (i) longing tokens with no media coverage, or (ii) shorting tokens with high media coverage, or (iii) simultaneously longing tokens with no media coverage while shorting tokens with high media coverage in the portfolio formation week (the portfolio-forming and rebalancing procedure is described in Table 4 above). These three components are calculated as follows. The Characteristic Selectivity (CS) measure is the difference between the time t return on each portfolio ("long", "short" or "long-short") held at time $t-1$ and the time t return of the time $t-1$ matching control portfolio, as defined by (A.1). The Characteristic Timing (CT) measure is computed, for each portfolio, by matching tokens held at week $t-13$ and at week $t-1$ with the proper control portfolios at week $t-13$ and week $t-1$, respectively. Next, the portfolio-weighted return of the week $t-13$ matching portfolio, at week t, is subtracted from the portfolio-weighted return of the week $t-1$ control portfolio, also at week t, as defined by (A.4). The Average Style (AS) measure is calculated, for week t, by matching each token held in a portfolio, at week $t-13$, with the proper control portfolio at week $t-13$. Then, the measure for a portfolio is computed by applying each token weight at $t-13$ to the matching control portfolio return at week t, as defined by (A.6). Note that a cryptocurrency is included if its market capitalization is at least one million during the portfolio formation week while its name and symbol are mentioned in at least 100 articles throughout the sample period. All t-statistic values (in parentheses) use the Newey-West standard error.

Portfolio	Average Weekly CS Attribute (%)		Average Weekly CT Attribute (%)		Average Weekly AS Attribute (%)	
	Before trans. cost	After trans. cost	Before trans. cost	After trans. cost	Before trans. cost	After trans. cost
			Panel A: All years			
long	1.38	0.14	0.03	0.01	2.48	2.31
	(2.39)	(0.24)	(0.12)	(0.05)	(3.04)	(2.87)
short	0.27	−4.50	−0.16	−0.16	−2.04	−2.03
	(0.86)	(−14.16)	(−0.51)	(−0.52)	(−3.09)	(−2.95)
long-short	1.94	−3.91	0.04	0.02	0.33	0.16
	(2.47)	(−5.02)	(0.16)	(0.07)	(1.28)	(0.66)
			Panel B: 2017-2018			
long	0.35	−0.43	−0.16	−0.16	0.95	0.79
	(2.12)	(−2.04)	(−0.58)	(−0.61)	(0.56)	(0.47)
short	-0.38	−5.09	0.28	0.26	−0.41	−0.38
	(-1.27)	(−17.7)	(1.27)	(1.19)	(−0.32)	(−0.28)
long-short	0.10	−5.32	0.09	0.10	0.81	0.72
	(0.25)	(−14.94)	(0.25)	(0.28)	(1.10)	(1.03)
			Panel C: 2019			
long	0.21	−1.22	−0.07	−0.07	0.83	0.69
	(1.53)	(−6.05)	(−0.32)	(−0.34)	(0.97)	(0.82)
short	0.24	−4.53	0.03	0.04	−1.20	−1.18
	(0.72)	(−13.70)	(0.09)	(0.14)	(−1.39)	(−1.29)
long-short	0.47	−5.40	0.28	0.28	0.02	−0.04
	(1.20)	(−13.75)	(1.26)	(1.29)	(0.08)	(−0.18)
			Panel D: 2020			
long	0.99	−0.82	−0.22	−0.21	3.81	3.62
	(3.93)	(−3.44)	(−1.41)	(−1.33)	(5.24)	(5.06)
short	0.12	−4.67	0.01	0.04	−3.48	−3.53
	(0.62)	(−23.46)	(0.07)	(0.20)	(−5.28)	(−5.09)
long-short	1.03	−5.14	−0.28	−0.27	0.29	0.13
	(2.91)	(−18.91)	(−0.80)	(−0.80)	(2.11)	(0.95)

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Table S.III.16 (continued): Performance Attribution Analysis based on the DGTW Characteristic-based Benchmark Method (Skipping a Week between the Portfolio Formation Week and the Holding Week): All Cryptocurrencies ever listed on CoinMarketCap

Portfolio	Average Weekly CS Attribute (%)		Average Weekly CT Attribute (%)		Average Weekly AS Attribute (%)	
	Before trans. cost	After trans. cost	Before trans. cost	After trans. cost	Before trans. cost	After trans. cost
Panel E: 2021						
long	1.89	0.74	−0.26	−0.24	6.18	5.89
	(1.76)	(0.67)	(−0.42)	(−0.42)	(4.04)	(3.94)
short	1.22	−3.61	−1.09	−1.13	−6.39	−6.53
	(1.60)	(−4.76)	(−1.33)	(−1.34)	(−4.59)	(−4.47)
long-short	3.56	−2.39	−0.93	−0.90	0.28	−0.02
	(3.34)	(−2.31)	(−3.53)	(−1.96)	(1.34)	(−0.10)
Panel F: 2022-2023						
long	2.05	0.77	0.20	0.21	−0.28	−0.39
	(2.15)	(0.80)	(0.68)	(0.73)	(−0.34)	(−0.48)
short	0.10	−4.69	−0.04	−0.05	−0.42	−0.34
	(0.50)	(−24.75)	(−0.23)	(−0.28)	(−0.64)	(−0.49)
long-short	2.08	−3.93	0.39	0.38	−0.10	−0.08
	(1.90)	(−3.58)	(1.62)	(1.63)	(−0.55)	(−0.41)

Table S.III.17: Performance Attribution Analysis based on the DGTW Characteristic-based Benchmark Method: All Active Cryptocurrencies currently listed on CoinMarketCap

This table presents three average weekly performance attribution components for portfolios formed by (i) longing tokens with no media coverage, or (ii) shorting tokens with high media coverage, or (iii) simultaneously longing tokens with no media coverage while shorting tokens with high media coverage in the portfolio formation week (the portfolio-forming and rebalancing procedure is described in Table 4 above). These three components are calculated as follows. The Characteristic Selectivity (CS) measure is the difference between the time t return on each portfolio ("long", "short" or "long-short") held at time $t-1$ and the time t return of the time $t-1$ matching control portfolio, as defined by (A.1). The Characteristic Timing (CT) measure is computed, for each portfolio, by matching tokens held at week $t-13$ and at week $t-1$ with the proper control portfolios at week $t-13$ and week $t-1$, respectively. Next, the portfolio-weighted return of the week $t-13$ matching portfolio, at week t, is subtracted from the portfolio-weighted return of the week $t-1$ control portfolio, also at week t, as defined by (A.4). The Average Style (AS) measure is calculated, for week t, by matching each token held in a portfolio, at week $t-13$, with the proper control portfolio at week $t-13$. Then, the measure for a portfolio is computed by applying each token weight at $t-13$ to the matching control portfolio return at week t, as defined by (A.6). Note that a cryptocurrency is included if its market capitalization is at least one million during the portfolio formation week while its name and symbol are mentioned in at least 100 articles throughout the sample period. All t-statistic values (in parentheses) use the Newey-West standard error.

Portfolio	Average Weekly CS Attribute (%)		Average Weekly CT Attribute (%)		Average Weekly AS Attribute (%)	
	Before trans. cost	After trans. cost	Before trans. cost	After trans. cost	Before trans. cost	After trans. cost
Panel A: All years						
long	1.34	0.07	−0.50	−0.48	3.09	2.90
	(2.72)	(0.14)	(−1.57)	(−1.58)	(3.87)	(3.69)
short	0.21	−4.56	−0.50	−0.51	−2.41	−2.43
	(1.02)	(−21.56)	(−1.22)	(−1.20)	(−3.20)	(−3.08)
long-short	1.74	−4.14	−0.65	−0.64	0.84	0.67
	(3.30)	(−7.92)	(−1.91)	(−1.88)	(3.34)	(2.73)
Panel B: 2017-2018						
long	0.31	−0.47	−0.10	−0.11	1.00	0.85
	(1.80)	(−2.46)	(−0.54)	(−0.57)	(0.61)	(0.52)
short	0.52	−4.20	−0.63	−0.64	−0.23	−0.19
	(1.82)	(−14.25)	(−2.43)	(−2.31)	(−0.17)	(−0.14)
long-short	1.12	−4.27	−0.86	−0.88	0.70	0.63
	(2.81)	(−10.71)	(−2.38)	(−2.31)	(1.41)	(1.37)
Panel C: 2019						
long	0.20	−1.20	−0.99	−0.97	1.56	1.41
	(2.10)	(−10.80)	(−3.84)	(−3.84)	(1.80)	(1.65)
short	-0.19	−4.96	0.20	0.21	−1.26	−1.23
	(-0.82)	(−20.39)	(0.99)	(1.07)	(−1.46)	(−1.35)
long-short	0.12	−5.72	−0.59	−0.56	0.64	0.58
	(0.40)	(−18.65)	(−2.64)	(−2.59)	(3.14)	(2.99)
Panel D: 2020						
long	0.52	−1.38	−0.09	−0.08	3.15	2.96
	(1.98)	(−3.59)	(−0.33)	(−0.30)	(4.28)	(4.09)
short	-0.37	−5.16	0.31	0.35	−4.25	−4.34
	(-1.64)	(−22.79)	(1.98)	(2.13)	(−7.56)	(−7.33)
long-short	0.03	−6.18	0.26	0.30	−0.09	−0.26
	(0.11)	(−19.19)	(1.08)	(1.41)	(−0.87)	(−2.03)

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Table S.III.17 (continued): Performance Attribution Analysis based on the DGTW Characteristic-based Benchmark Method: All Active Cryptocurrencies currently listed on CoinMarketCap

Portfolio	Average Weekly CS Attribute (%)		Average Weekly CT Attribute (%)		Average Weekly AS Attribute (%)	
	Before trans. cost	After trans. cost	Before trans. cost	After trans. cost	Before trans. cost	After trans. cost
Panel E: 2021						
long	3.16	2.09	−1.21	−1.10	7.00	6.71
	(3.83)	(2.50)	(−1.70)	(−1.59)	(4.00)	(3.91)
short	-0.45	−5.30	−1.72	−1.80	−6.76	−6.91
	(-1.90)	(−22.35)	(−0.97)	(−0.98)	(−3.82)	(−3.72)
long-short	3.00	−2.99	−1.59	−1.47	0.72	0.40
	(2.77)	(−2.88)	(−3.78)	(−3.40)	(2.25)	(1.53)
Panel F: 2022-2023						
long	2.01	0.68	−1.00	−0.98	1.12	0.99
	(1.49)	(0.50)	(−2.34)	(−2.33)	(1.46)	(1.31)
short	-0.17	−4.95	0.51	0.53	−0.74	−0.68
	(-1.57)	(−47.48)	(5.22)	(5.04)	(−1.03)	(−0.89)
long-short	2.08	−3.98	−0.50	−0.46	0.72	0.68
	(1.32)	(−2.56)	(−1.08)	(−1.00)	(2.67)	(2.62)

Table S.III.18: Performance Attribution Analysis based on the DGTW Characteristic-based Benchmark Method (Skipping a Week between the Portfolio Formation Week and the Holding Week): All Active Cryptocurrencies currently listed on CoinMarketCap

This table presents three average weekly performance attribution components for portfolios formed by (i) longing tokens with no media coverage, or (ii) shorting tokens with high media coverage, or (iii) simultaneously longing tokens with no media coverage while shorting tokens with high media coverage in the portfolio formation week (the portfolio-forming and rebalancing procedure is described in Table 4 above). These three components are calculated as follows. The Characteristic Selectivity (CS) measure is the difference between the time t return on each portfolio ("long", "short" or "long-short") held at time $t-1$ and the time t return of the time $t-1$ matching control portfolio, as defined by (A.1). The Characteristic Timing (CT) measure is computed, for each portfolio, by matching tokens held at week $t-13$ and at week $t-1$ with the proper control portfolios at week $t-13$ and week $t-1$, respectively. Next, the portfolio-weighted return of the week $t-13$ matching portfolio, at week t, is subtracted from the portfolio-weighted return of the week $t-1$ control portfolio, also at week t, as defined by (A.4). The Average Style (AS) measure is calculated, for week t, by matching each token held in a portfolio, at week $t-13$, with the proper control portfolio at week $t-13$. Then, the measure for a portfolio is computed by applying each token weight at $t-13$ to the matching control portfolio return at week t, as defined by (A.6). Note that a cryptocurrency is included if its market capitalization is at least one million during the portfolio formation week while its name and symbol are mentioned in at least 100 articles throughout the sample period. All t-statistic values (in parentheses) use the Newey-West standard error.

Portfolio	Average Weekly CS Attribute (%)		Average Weekly CT Attribute (%)		Average Weekly AS Attribute (%)	
	Before trans. cost	After trans. cost	Before trans. cost	After trans. cost	Before trans. cost	After trans. cost
Panel A: All years						
long	1.32	0.05	–0.28	–0.29	3.11	2.92
	(1.74)	(0.07)	(–0.71)	(–0.75)	(3.69)	(3.52)
short	0.09	–4.69	0.18	0.19	–2.55	–2.57
	(0.25)	(–13.65)	(0.74)	(0.75)	(–3.47)	(–3.35)
long-short	1.29	–4.59	0.16	0.15	0.47	0.29
	(1.55)	(–5.58)	(0.43)	(0.42)	(1.46)	(0.85)
Panel B: 2017-2018						
long	0.29	–0.45	–0.18	–0.19	0.59	0.44
	(2.21)	(–2.66)	(–0.87)	(–0.90)	(0.38)	(0.29)
short	-0.30	–5.02	0.30	0.31	–0.20	–0.14
	(-1.31)	(–21.82)	(1.44)	(1.42)	(–0.15)	(–0.10)
long-short	0.13	–5.25	0.17	0.13	0.47	0.40
	(0.45)	(–16.77)	(0.62)	(0.43)	(0.79)	(0.70)
Panel C: 2019						
long	0.08	–1.34	–0.19	–0.19	1.02	0.88
	(0.80)	(–7.63)	(–0.89)	(–0.89)	(1.05)	(0.92)
short	-0.07	–4.84	0.13	0.15	–1.36	–1.34
	(-0.27)	(–18.22)	(0.70)	(0.78)	(–1.64)	(–1.54)
long-short	-0.11	–5.97	0.07	0.06	0.09	0.03
	(-0.38)	(–16.15)	(0.42)	(0.35)	(0.31)	(0.09)
Panel D: 2020						
long	0.52	–1.30	–0.11	–0.12	3.54	3.35
	(1.78)	(–5.89)	(–0.68)	(–0.78)	(5.53)	(5.32)
short	0.07	–4.72	–0.01	0.01	–3.99	–4.06
	(0.33)	(–21.1)	(–0.08)	(0.05)	(–5.37)	(–5.22)
long-short	0.57	–5.65	0.00	0.01	0.01	–0.17
	(1.43)	(–19.48)	(0.00)	(0.10)	(0.06)	(–1.33)

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Table S.III.18 (continued): Performance Attribution Analysis based on the DGTW Characteristic-based Benchmark Method (Skipping a Week between the Portfolio Formation Week and the Holding Week): All Active Cryptocurrencies currently listed on CoinMarketCap

Portfolio	Average Weekly CS Attribute (%)		Average Weekly CT Attribute (%)		Average Weekly AS Attribute (%)	
	Before trans. cost	After trans. cost	Before trans. cost	After trans. cost	Before trans. cost	After trans. cost
Panel E: 2021						
long	1.30	0.16	−0.33	−0.29	6.02	5.73
	(0.80)	(0.09)	(−0.94)	(−0.87)	(3.08)	(3.00)
short	1.11	−3.73	−0.29	−0.31	−6.84	−6.99
	(1.45)	(−4.84)	(−0.57)	(−0.59)	(−3.78)	(−3.68)
long-short	2.55	−3.42	0.63	0.56	−0.28	−0.60
	(2.26)	(−3.01)	(0.92)	(0.88)	(−1.25)	(−2.51)
Panel F: 2022-2023						
long	2.57	1.17	−0.64	−0.62	1.00	0.87
	(2.17)	(0.95)	(−1.23)	(−1.22)	(1.22)	(1.08)
short	-0.02	−4.80	−0.21	−0.22	−0.68	−0.61
	(-0.07)	(−19.97)	(−0.53)	(−0.55)	(−0.95)	(−0.80)
long-short	2.89	−3.25	−1.44	−1.42	0.62	0.63
	(1.83)	(−2.03)	(−2.44)	(−2.46)	(2.21)	(2.29)

S.IV Explaining the Media Effect: A Robustness Check

In this section, we replicate the analysis [presented in Section 5] to verify the baseline findings that (1) the media effect is caused by the 'impediments to trade' hypothesis and the investor recognition hypothesis, as suggested in Fang and Peress (2009) and (2) the media effect is not subsumed under other anomalies related to size, idiosyncratic volatility, VaR, and beta, but it may be subsumed under the liquidity effect. We conduct this robustness check using (i) all cryptocurrencies while skipping one week between the portfolio formation week and the holding week, and (ii) only active cryptocurrencies.

S.IV.1 The 'Impediments to Trade' Hypothesis

Robustness Check (i):

Table 5 (skipping one week between the portfolio formation week and the holding week) shows that the media effect is strongest among cryptocurrencies with small market capitalization, low trading volume, high volatility, high illiquidity, or high VaR. The results reported in this table are even stronger than those reported in Table 4. Specifically, sorting tokens by market capitalization (MCAP) at the end of the portfolio formation week generates a statistically significant and positive average return of 5.16% per week for the long-short media-based portfolio in the first tercile, and this return decreases over the terciles. Sorting tokens by log trading volume times price divided by market capitalization (VOLSCALED) at the end of the portfolio formation week also generates a statistically significant and positive average return of 4.80% per week for the long-short media-based portfolio in the first tercile (which is over nine times larger than the average returns in the other terciles). Sorting tokens by return volatility (RETVOL) leads to a significant and positive average return of 4.25% per week for the long-short media-based portfolio in the last tercile (which is over three times larger than the returns in the other terciles). Sorting tokens by

Amihud's (2002) illiquidity measure (DAMIHUD) yields a statistically significant and positive average return of 6.41% per week for the long-short media-based portfolio in the last tercile (which is over six times larger than the average returns in the other terciles). Sorting tokens by VaR generates a significant and positive average return of 4.19% per week for the long-short media-based portfolio in the last tercile (which is over four times larger than the average returns in the other terciles).

Table S.III.11 suggests that the alphas in the three factor models are the most [statistically] significant and largest among tokens with small market capitalization, low trading volume, high volatility, high illiquidity, or high VaR. Therefore, the no-coverage premium must represent a compensation for risk not explained by the risk factors. All those alphas also disappear after accounting for transaction costs. This result is indeed consistent with those reported in Section 5.1.

Table S.IV.19 suggests that the alphas and generalized alphas of a self-financing long-only portfolio [that borrows fund at the risk-free rate to finance a long position in tokens with no media coverage during the portfolio formation week] in factor models are larger or more significant among small/less liquid tokens than large/liquid tokens. Sorting tokens by market capitalization (MCAP) at the end of the portfolio formation week generates a statistically significant and positive alpha of 4.86% per week (p-value = 0.0018) and a generalized alpha of 4.44% per week (p-value = 0.0017), using the three-factor model for the self-financing long-only portfolio in the first tercile, and the p-values of the alpha and the generalized alpha are much larger in the other terciles. Sorting tokens by volume times price (PRCVOL) at the end of the portfolio formation week generates a significant and positive alpha of 4.22% per week (p-value = 0.0008) and a generalized alpha of 3.70% per week (p-value = 0.0010) in the first tercile. Sorting tokens by DAMIHUD at the end of the portfolio formation week leads to a statistically significant and positive alpha of 6.73% per week (p-value = 0.0015) and a generalized alpha of 6.93% per week (p-value = 0.0014) in the last tercile. These numbers suggest that arbitrage trades seem possible in the group of small/less liquid tokens because no-coverage tokens yield high average returns, and trading those tokens in the portfolio also requires less rebalancing. This result is also consistent with those reported in Section 5.1.

Robustness Check (ii):

Table S.III.5 suggests that, in the subset of currently active cryptocurrencies, the media effect is still strongest among tokens with small market capitalization, low trading volume, high volatility, high illiquidity, or high VaR. Sorting tokens by market capitalization (MCAP) at the end of the portfolio formation week generates a statistically significant and positive average return of 2.69% per week for the long-short media-based portfolio in the first tercile, and the average return of the long-short portfolio is statistically insignificant in the other MCAP terciles. Sorting tokens by log trading volume times price divided by market capitalization (VOLSCALED) at the end of the portfolio formation week also generates a significant and positive average return of 4.22% per week for the long-short media-based portfolio in the first tercile (which is about five times larger than the average returns in the other terciles). Sorting tokens by return volatility (RETVOL) leads to a significant and positive average return of 5.62% per week for the long-short media-based portfolio in the last tercile (which is about five times larger than the average returns in the other terciles). Sorting tokens by Amihud's (2002) illiquidity measure (DAMIHUD) generates a statistically significant and positive average return of 5.61% per week for the long-short media-based portfolio in the last tercile (which is over five times larger than the average returns in the other terciles). Sorting tokens by VaR generates a significant and positive average return of 4.07% per week for the long-short media-based portfolio in the last tercile (which is over four times larger than the average returns in the other terciles).

This result remains valid if one skips a week in between the portfolio formation week and the holding week. Table S.III.6 suggests that: Sorting tokens by market capitalization (MCAP) at the end of the portfolio formation week generates a statistically significant and positive average return of 3.93% per week for the long-short media-based portfolio in the first tercile, and this average return decreases over the terciles. Sorting tokens by log trading volume times price divided by market capitalization (VOLSCALED) at the end of the portfolio formation week also generates a significant and positive average return of 5.12% per week for the long-short media-based portfolio in the first tercile (which is about 24 times larger than the average returns in the other terciles). Sorting tokens by return volatility (RETVOL) leads to a statistically significant and positive average return of 4.82% per week for the long-short media-based portfolio in the last tercile (which is about four times larger than the average returns in the other terciles). Sorting tokens by Amihud's (2002) illiquidity measure (DAMIHUD) generates a significant and positive average return of 5.43% per week for the long-short media-based portfolio in the last tercile (which is over five times larger than the average returns in the other terciles). Sorting tokens by VaR generates a significant and positive average return of 5.36% per week for the long-short media-based portfolio in the last tercile (which is over five times larger than the average returns in the other terciles).

Tables S.III.13 and S.III.15 (skipping one week between the portfolio formation week and the holding week) show that the alphas in three factor models are the most [statistically] significant and largest among the tokens with small market capitalization, low trading volume, high volatility, high illiquidity, or high VaR. This is consistent with the results reported in Section 5.1.

Tables S.IV.20 and S.IV.21 (skipping one week between the portfolio formation week and the holding week) suggest that the alphas and generalized alphas of a self-financing long-only portfolio [that borrows fund at the risk-free rate to finance a long position in no-coverage tokens during the portfolio formation week] in factor models are larger or more statistically significant among small/less liquid tokens than large/liquid tokens. This confirms the baseline finding that arbitrage trades seem possible in the group of small/less liquid tokens because no-coverage tokens yield a high average return, and trading those tokens in the portfolio requires less rebalancing.

S.IV.2 The Investor Recognition Hypothesis

Robustness Check (i):

Table 5 (skipping one week between the portfolio formation week and the holding week) shows that, when sorting tokens into terciles by idiosyncratic volatility (IDIOVOL), the long-short media-based portfolio yields an average weekly returns of 6.75% per week (t-statistic = 2.78), compared to 4.77% per week (t-statistic = 3.01) obtained without the one-week skipping, among the tokens with the highest idiosyncratic volatility. This average return in the high IDIOVOL tercile is over five times larger than the average returns in the lower IDIOVOL terciles. Table S.III.11 suggests that the alpha (and its level of significance) of this long-short portfolio in factor models monotonically increase with IDIOVOL. In addition, Table S.IV.19 suggests that both the alpha and generalized alpha (and their levels of significance) of the self-financing long-only portfolio in the three-factor model also monotonically increase with IDIOVOL: the alphas in the first, second, and third terciles are 0.64% (p-value = 0.2548), 0.96% (p-value = 0.0812), and 7.43% (p-value = 0.0051) per week, respectively while the generalized alphas are 0, 0, and 5.77% (p-value = 0.0091) per week, respectively. These results are thus consistent with those reported in Section 5.2.

Robustness Check (ii):

Table S.III.5 (using currently active cryptocurrencies) shows that, when sorting tokens into terciles by IDIOVOL, the long-short media-based portfolio yields an average weekly returns of 5.25% per week (t-statistic = 0.76) among the tokens with the highest idiosyncratic volatility. However, this average return is statistically insignificant, thus the investor recognition hypothesis is not strongly supported by our data in this case. A possible explanation is that there are much less no-coverage tokens than high-coverage tokens in every IDIOVOL tercile [for example, in the high IDIOVOL tercile, the average number of no-coverage tokens is 39.20 while the average number of low (high)-coverage tokens is 58.71 (53.18)]. Table S.III.13 suggests that the alpha (and its level of significance) of this long-short portfolio in factor models monotonically increase with IDIOVOL (for example, the alphas of the long-short media-based portfolio in the three-factor model for the first, second, and third IDIOVOL terciles are 0.08% (p-value = 0.8325), 0.07% (p-value = 0.8754), and 4.76% (p-value = 0.0057) per week, respectively. Moreover, Table S.IV.20 shows that both the alpha and generalized alpha (and their levels of significance) of the self-financing long-only portfolio [that borrows fund at the risk-free rate to finance a long position in the no-coverage tokens during the portfolio formation week] in the three-factor model also monotonically increase with IDIOVOL: The alphas in the first, second, and third terciles are 0.23% (p-value = 0.5353), 0.29% (p-value = 0.4616), and 5.19% (p-value = 0.0033) per week, respectively while the generalized alphas are 0, 0, and 4.21% (p-value = 0.001) per week, respectively. This result supports the investor recognition hypothesis.

Table S.III.6 (skipping one week between the portfolio formation week and the holding week) shows that, when sorting tokens into terciles by IDIOVOL, the long-short media-based portfolio yields an average weekly returns of 6.11% per week (t-statistic = 2.35) among the tokens with the highest idiosyncratic volatility. Table S.III.15 suggests that the alpha (and its level of significance) of this long-short portfolio in factor models monotonically increase with IDIOVOL (for example, the alphas of the long-short portfolio in the three-factor model for the first, second, and third IDIOVOL terciles are 0.56% (p-value = 0.2651), 0.61% (p-value = 0.3416), and 5.68% (p-value = 0.0340) per week, respectively. Also, Table S.IV.21 shows that both the alpha and generalized alpha (and their levels of significance) of the self-financing long-only media-based portfolio in the three-factor model also monotonically increase with IDIOVOL: The alphas in the first, second, and third terciles are 0.56% (p-value = 0.2994), 0.98% (p-value = 0.1330), and 6.96% (p-value = 0.0065) per week, respectively while the generalized alphas are 0, 0.06% (p-value = 0.9330), and 6.39% (p-value = 0.0066) per week, respectively. This is also consistent with the results reported above.

S.IV.3 Return Continuation and Reversals

We shall verify the finding [reported in Section 5.3] that the media effect is not caused by return reversals of no-coverage tokens with low past returns (i.e., the alpha and generalized alpha of the self-financing long-only portfolio [that borrows fund at the risk-free rate to finance a long position in no-coverage tokens during the portfolio formation week] do not monotonically decrease from the group of tokens with lowest past returns to the group of tokens with highest past returns).

Robustness Check (i):

Table S.IV.19 (skipping one week between the portfolio formation week and the holding week) suggests that the alpha and the generalized alpha of the self-financing long-only media-based strategy are either largest or most [statistically] significant in the group of tokens with higher past returns. For example, by sorting tokens into terciles by the maximum daily return during the portfolio formation week (MAXRET), the alphas of the self-financing long-only portfolio in the three-factor model for the first, second, and third MAXRET terciles are 1.68% (p-value = 0.0443), 0.71% (p-value = 0.2248), and 4.12% (p-value = 0) per week, respectively while the generalized alphas are 0.4% (p-value = 0.6167), 0, and 2.88% (p-value = 0.001) per week, respectively. By sorting tokens into terciles by past one-week return ($r\ 1,0$), the alphas of the self-financing long-only media-based portfolio in the three-factor model for the first, second, and third $r\ 1,0$ terciles are 0.92% (p-value = 0.1075), 2.83% (p-value = 0.0082), and 2.47% (p-value = 0.0003) per week, respectively while the generalized alphas are 0, 2.15% (p-value = 0.0651), and 1.03% (p-value = 0.1495) per week, respectively. By sorting tokens into terciles by past 16-week return ($r\ 16,0$), the alphas of the self-financing long-only media-based portfolio in the three-factor model for the first, second, and third $r\ 16,0$ terciles are 1.43% (p-value = 0.0121), 1.31% (p-value = 0.0046), and 4.98% (p-value = 0.0061) per week, respectively while the generalized alphas are 0.48% (p-value = 0.4069), 0.55% (p-value = 0.2704), and 4.44% (p-value = 0.0170) per week, respectively. By sorting tokens into terciles by past 100-week return ($r\ 100,0$), the alphas of the self-financing long-only media-based portfolio in the three-factor model for the first, second, and third $r\ 100,0$ terciles are 2.85% (p-value = 0.0161), 0.1% (p-value = 0.8555), and 16.74% (p-value = 0.0115) per week, respectively while the generalized alphas are 2.79% (p-value = 0.1301), 0.11% (p-value = 0.8806), and 16.42% (p-value = 0.0099) per week, respectively. By sorting tokens into terciles by the negative of past 52-week return (NPAST52), the alphas of the self-financing long-only media-based portfolio in the three-factor model for the third, second, and first NPAST52 terciles are 3.46% (p-value = 0.1575), 0.88% (p-value = 0.0950), and 2.67% (p-value = 0.0181) per week, respectively while the generalized alphas are 5.33% (p-value = 0.1161), 0.42% (p-value = 0.4827), and 1.99% (p-value = 0.0650) per week, respectively.

As mentioned in Section 5.3, we also examine the horizon of the media effect (i.e, whether this effect remains stable over a sufficiently long holding period). We use the calendar-time overlapping approach of Jegadeesh and Titman (1993) to calculate the portfolio returns for the entire holding period. Table S.IV.22 (skipping one week in between the portfolio formation period and the holding period) suggests that the mean of the weekly returns on the composite long-short media-based portfolio is statistically significant and positive for every holding period when the portfolio formation period is one week. This time-series mean behaves like a concave function of the holding period for each portfolio formation period. The alphas of the long-short media-based strategy are also statistically significant, and they first increase with the holding period from one week to 15 weeks, then decrease for the holding periods of more than 15 weeks. Therefore, the media effect may last for many weeks before it dies out eventually. This result is thus consistent with the finding reported earlier in Table 10.

Robustness Check (ii):

Table S.IV.20 (using only currently active cryptocurrencies) suggests that the alpha and the generalized alpha of the self-financing long-only media-based strategy do not monotonically decrease from the group of tokens with lowest past returns to the group of tokens with highest past returns. By sorting tokens into terciles by the maximum daily return during the portfolio formation week (MAXRET), the alphas of the self-financing long-only media-based portfolio in the three-factor model for the first, second, and third MAXRET terciles are 0.98% (p-value = 0.1191), 1.13% (p-value = 0.0332), and 4.38% (p-value = 0.0056) per week, respectively while the generalized alphas are 0, 0.07% (p-value = 0.8929), and 3.25% (p-value = 0.003) per week, respectively. By sorting tokens into terciles by past one-week return ($r\ 1,0$), the alphas of the self-financing long-only media-based portfolio in the three-factor model for the first, second, and third $r\ 1,0$ terciles are 1.44% (p-value = 0.0226), 1.59% (p-value = 0.0485), and 2.93% (p-value = 0.003) per week, respectively while the generalized alphas are 0 (p-value = 0.9985), 0.64% (p-value = 0.2889), and 1.84% (p-value = 0.0394) per week, respectively. By sorting tokens into terciles by past 16-week return ($r\ 16, 0$), the alphas of the self-financing long-only media-based portfolio in the three-factor model for the first, second, and third $r\ 16, 0$ terciles are 2.59% (p-value = 0.0037), 0.91% (p-value = 0.0234), and 3.11% (p-value = 0.0309) per week, respectively while the generalized alphas are 1.82% (p-value = 0.0223), 0.76% (p-value = 0.1763), and 2.83% (p-value = 0.0492) per week, respectively. By sorting tokens into terciles by past 100-week return ($r\ 100, 0$), the alphas of the self-financing long-only media-based portfolio in the three-factor model for the first, second, and third $r\ 100, 0$ terciles are 3.67% (p-value = 0.0323), -0.17% (p-value = 0.7832), and 5.01% (p-value = 0.0280) per week, respectively while the generalized alphas are 3.82% (p-value = 0.0071), 0, 4.31% (p-value = 0.0142) per week, respectively. By sorting tokens into terciles by the negative of past 52-week return (NPAST52), the alphas of the self-financing long-only media-based portfolio in the three-factor model for the third, second, and first NPAST52 terciles are 3.59% (p-value = 0.0059), 0.92% (p-value = 0.1242), and 2.85% (p-value = 0.0653) per week, respectively while the generalized alphas are 2.52% (p-value = 0.0280), 0.38% (p-value = 0.5206), and 2.55% (p-value = 0.0369) per week, respectively.

Table S.IV.21 (skipping one week between the portfolio formation week and the holding week) suggests that the alpha and generalized alpha of the self-financing long-only media-related strategy are either largest or most [statistically] significant in the group of tokens with higher past returns. By sorting tokens into terciles by the maximum daily return during the portfolio formation week (MAXRET), the alphas of the self-financing long-only portfolio in the three-factor model for the first, second, and third MAXRET terciles are 1.32% (p-value = 0.0253), 0.49% (p-value = 0.4067), and 5.03% (p-value = 0.0003) per week, respectively while the generalized alphas are 0.69% (p-value = 0.4620), 0, and 4.46% (p-value = 0.0001) per week, respectively. By sorting tokens into terciles by past one-week return ($r\ 1, 0$), the alphas of the self-financing long-only media-based portfolio in the three-factor model for the first, second, and third $r\ 1, 0$ terciles are 1.54% (p-value = 0.0442), 2.77% (p-value = 0.0072), and 2.79% (p-value = 0.0014) per week, respectively while the generalized alphas are 0.32% (p-value = 0.6564), 2.20% (p-value = 0.0869), and 1.91% (p-value = 0.0361) per week, respectively. By sorting tokens into terciles by past 16-week return ($r\ 16, 0$), the alphas of the self-financing long-only media-based portfolio in the three-factor model for the first, second, and third $r\ 16, 0$ terciles are 1.89% (p-value = 0.0064), 1.70% (p-value = 0.0090), and 4.60% (p-value = 0.0043) per week, respectively while the generalized alphas are 1.44% (p-value = 0.06), 1.52% (p-value = 0.05), and 4.30% (p-value = 0.0159) per week, respectively. By sorting tokens into terciles by past 100-week return ($r\ 100, 0$), the alphas of the self-financing long-only media-based portfolio in the three-factor model for the first, second, and third $r\ 100, 0$ terciles are 4.25% (p-value = 0.0039), -0.17% (p-value = 0.7139), and 8.19% (p-value =0.0154) per week, respectively while the generalized alphas are 4.09% (p-value = 0.0189), 0, 8.61% (p-value = 0.0124) per week, respectively. By sorting tokens into terciles by the negative of past 52-week return (NPAST52), the alphas of the self-financing long-only media-based portfolio in the three-factor model for the third, second, and first NPAST52 terciles are 3.93% (p-value = 0.0282), 1.3% (p-value = 0.0470), 2.78% (p-value = 0.0232) per week, respectively while the generalized alphas are 2.93% (p-value = 0.0906), 0.82% (p-value = 0.2281), and 2.67% (p-value = 0.0429) per week, respectively.

Table S.IV.23 reports the time-series average returns and the alphas on the long-short media-based strategy over the holding horizon $J = 1, 2, \ldots, 20$ week(s) for each of the formation periods $K = 1, 5, 10$ week(s). The time-series means are statistically significant and positive for $J = 1, 2, \ldots, 15$ week(s), then they may turn negative for $J > 15$ weeks. The alphas also behave like a concave function of the holding period for a short portfolio formation period (K = 1 or 5), confirming that the media effect can last for many weeks, even among active tokens when the portfolio formation period is short. However, the alphas can disappear or become negative for a long portfolio formation period, as there are much less no-coverage tokens than high-coverage tokens in this case. These results are also confirmed in Table S.IV.24 (skipping one week in between the portfolio formation period and the holding period). This thus confirms the finding reported in Section 5.3.

Table S.IV.19: Performance of Long-Only Media-Related Trading Strategies Relative to Cryptocurrency Risk Factors (Skipping a Week between the Portfolio Formation Week and the Holding Week): All Cryptocurrencies ever listed on CoinMarketCap

This table examines the return [in excess of the common risk factors in cryptocurrency proposed by Liu et al. (2022)] of a trading strategy that borrows fund at the risk-free rate to finance an equally weighted long position in tokens with no media coverage in the subsamples of tokens sorted by cryptocurrency characteristics (defined in Table S.I.1) one at a time. Each week, tokens are sorted according to the number of news articles written about them. A token is considered to have no media coverage if no article is written about this token in a given week. A token is considered to have a high media coverage if the number of articles written about it exceeds the median in a given week. Fund is then borrowed at the risk-free rate to finance an equally weighted long position in the no-coverage tokens. The portfolio is held for one week after the portfolio formation, and it is rebalanced weekly. Alphas obtained from regressing the resulting time-series returns of this self-financing media-based portfolio on three risk factors (cryptocurrency market, size, and momentum) and the p-values [using the Newey-West standard error] of those alphas are reported. The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. Novy-Marx and Velikov's (2016) generalized alphas that account for transaction costs [calculated using the Matlab function *calcGenAlpha* provided in the second author's Github repository] and their p-values are also reported.

	One-factor model		Two-factor model		Three-factor model			
	α	p-value	α	p-value	α	p-value	generalized α	p-value
				Sort by MCAP				
0	0.0560***	0.0024	0.0486***	0.0017	0.0486***	0.0018	0.0444***	0.0017
1	0.0337**	0.0142	0.0288**	0.0309	0.0288**	0.0317	0.0223	0.1135
2	0.0024	0.5807	–0.0023	0.5398	–0.0025	0.4890	0.0000	
				Sort by AMCAP				
0	0.0600***	0.0010	0.0491***	0.0010	0.0493***	0.0011	0.0483***	0.0005
1	0.0319**	0.0209	0.0263*	0.0501	0.0263*	0.0511	0.0206	0.1447
2	0.0053	0.2782	–0.0008	0.8318	–0.0010	0.7692	0.0000	
				Sort by PRCVOL				
0	0.0499***	0.0002	0.0422***	0.0008	0.0422***	0.0008	0.0370***	0.0010
1	0.0116**	0.0272	0.0050	0.2392	0.0050	0.2464	0.0004	0.9395
2	0.0048	0.1908	–0.0003	0.9184	–0.0004	0.9090	0.0000	
				Sort by VOLSCALED				
0	0.0488***	0.0002	0.0414***	0.0006	0.0414***	0.0007	0.0358***	0.0010
1	0.0085	0.1130	0.0017	0.6495	0.0017	0.6369	0.0000	
2	0.0067*	0.0941	0.0018	0.6149	0.0020	0.5509	0.0000	
				Sort by RETVOL				
0	0.0164**	0.0265	0.0117*	0.0909	0.0116*	0.0915	0.0005	0.9386
1	0.0169**	0.0287	0.0108	0.1294	0.0107	0.1305	0.0001	0.9933
2	0.0474***	0.0001	0.0415***	0.0001	0.0414***	0.0001	0.0297***	0.0007
				Sort by IDIOVOL				
0	0.0087	0.1027	0.0067	0.2208	0.0064	0.2548	0.0000	
1	0.0154**	0.0290	0.0105*	0.0639	0.0096*	0.0812	0.0000	
2	0.0750***	0.0029	0.0743***	0.0048	0.0743***	0.0051	0.0577***	0.0091
				Sort by MAXRET				
0	0.0212**	0.0141	0.0168**	0.0476	0.0168**	0.0443	0.0040	0.6167
1	0.0129*	0.0548	0.0070	0.2473	0.0071	0.2248	0.0000	
2	0.0473***	0.0001	0.0412***	0.0001	0.0412***	0.0000	0.0288***	0.0010

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Table S.IV.19 (continued): Performance of Long-Only Media-Related Trading Strategies Relative to Cryptocurrency Risk Factors (Skipping a Week between the Portfolio Formation Week and the Holding Week): All Cryptocurrencies ever listed on CoinMarketCap

	One-factor model		Two-factor model		Three-factor model			
	α	p-value	α	p-value	α	p-value	generalized α	p-value
Sort by DAMIHUD								
0	0.0022	0.6376	–0.0033	0.3811	–0.0034	0.3702	0.0000	
1	0.0096*	0.0802	0.0032	0.4162	0.0031	0.4207	0.0000	
2	0.0816***	0.0006	0.0672***	0.0015	0.0673***	0.0015	0.0693***	0.0014
Sort by VaR								
0	0.0114*	0.0751	0.0059	0.3018	0.0060	0.3056	0.0008	0.8886
1	0.0114*	0.0809	0.0049	0.3478	0.0049	0.3468	0.0000	
2	0.0535***	0.0002	0.0389***	0.0005	0.0389***	0.0005	0.0410***	0.0011
Sort by r 1, 0								
0	0.0141**	0.0303	0.0091	0.1185	0.0092	0.1075	0.0000	
1	0.0381***	0.0065	0.0283***	0.0100	0.0283***	0.0082	0.0215*	0.0651
2	0.0300***	0.0000	0.0247***	0.0003	0.0247***	0.0003	0.0103	0.1495
Sort by r 2, 0								
0	0.0175***	0.0045	0.0131**	0.0224	0.0122**	0.0304	0.0012	0.8267
1	0.0262***	0.0013	0.0216***	0.0096	0.0211***	0.0086	0.0104	0.1693
2	0.0557**	0.0156	0.0520**	0.0291	0.0527**	0.0281	0.0389	0.1076
Sort by r 3, 0								
0	0.0241***	0.0005	0.0179***	0.0025	0.0174***	0.0021	0.0085	0.1693
1	0.0368**	0.0163	0.0239**	0.0387	0.0237**	0.0377	0.0214*	0.0643
2	0.0405***	0.0009	0.0357***	0.0050	0.0359***	0.0058	0.0249*	0.0613
Sort by r 4, 0								
0	0.0207***	0.0010	0.0152***	0.0050	0.0153***	0.0046	0.0061	0.2830
1	0.0266***	0.0099	0.0157**	0.0156	0.0158**	0.0110	0.0119	0.1636
2	0.0510***	0.0013	0.0452***	0.0040	0.0450***	0.0046	0.0363**	0.0243
Sort by r 4, 1								
0	0.0222***	0.0013	0.0155***	0.0092	0.0149**	0.0109	0.0062	0.2982
1	0.0275***	0.0068	0.0167***	0.0049	0.0162***	0.0042	0.0115	0.2039
2	0.0444***	0.0083	0.0374**	0.0233	0.0377**	0.0251	0.0288**	0.0419
Sort by r 8, 0								
0	0.0328***	0.0004	0.0288***	0.0025	0.0290***	0.0023	0.0188**	0.0103
1	0.0153**	0.0146	0.0091**	0.0439	0.0092**	0.0380	0.0017	0.7113
2	0.0533***	0.0053	0.0460***	0.0100	0.0459**	0.0103	0.0399**	0.0232
Sort by r 16, 0								
0	0.0175***	0.0024	0.0145**	0.0126	0.0143**	0.0121	0.0048	0.4069
1	0.0184***	0.0022	0.0132***	0.0045	0.0131***	0.0046	0.0055	0.2704
2	0.0566***	0.0026	0.0498***	0.0060	0.0498***	0.0061	0.0444**	0.0170

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Table S.IV.19 (continued): Performance of Long-Only Media-Related Trading Strategies Relative to Cryptocurrency Risk Factors (Skipping a Week between the Portfolio Formation Week and the Holding Week): All Cryptocurrencies ever listed on CoinMarketCap

	One-factor model		Two-factor model		Three-factor model			
	α	p-value	α	p-value	α	p-value	generalized α	p-value
					Sort by r 50, 0			
0	0.0233***	0.0085	0.0194**	0.0181	0.0190**	0.0193	0.0097	0.1905
1	0.0146**	0.0471	0.0122*	0.0985	0.0122*	0.0994	0.0021	0.7042
2	0.0410***	0.0017	0.0389***	0.0037	0.0389***	0.0037	0.0297**	0.0224
					Sort by r 100, 0			
0	0.0436***	0.0068	0.0291**	0.0116	0.0285**	0.0161	0.0279	0.1301
1	0.0141*	0.0990	0.0005	0.9240	0.0010	0.8555	0.0011	0.8806
2	0.1766**	0.0125	0.1668**	0.0106	0.1674**	0.0115	0.1642***	0.0099
					Sort by NPAST52			
0	0.0314***	0.0069	0.0268**	0.0180	0.0267**	0.0181	0.0199*	0.0650
1	0.0166**	0.0147	0.0088*	0.0953	0.0088*	0.0950	0.0042	0.4827
2	0.0672**	0.0360	0.0344	0.1629	0.0346	0.1575	0.0533	0.1161
					Sort by BETA			
0	0.0628***	0.0011	0.0599***	0.0018	0.0596***	0.0019	0.0511***	0.0044
1	0.0034	0.4616	0.0004	0.9268	0.0001	0.9754	0.0000	
2	0.0202**	0.0310	0.0169*	0.0881	0.0167*	0.0924	0.0090	0.3011
					Sort by BETA2			
0	0.0434***	0.0022	0.0403***	0.0046	0.0400***	0.0049	0.0316**	0.0219
1	0.0060	0.2743	0.0016	0.6866	0.0012	0.7700	0.0000	
2	0.0393***	0.0086	0.0287**	0.0152	0.0283**	0.0146	0.0281**	0.0324

Table S.IV.20: Performance of Long-Only Media-Related Trading Strategies Relative to Cryptocurrency Risk Factors: All Active Cryptocurrencies currently listed on CoinMarketCap

This table examines the return [in excess of the common risk factors in cryptocurrency proposed by Liu et al. (2022)] of a trading strategy that borrows fund at the risk-free rate to finance an equally weighted long position in tokens with no media coverage in the subsamples of tokens sorted by cryptocurrency characteristics (defined in Table S.I.1) one at a time. Each week, tokens are sorted according to the number of news articles written about them. A token is considered to have no media coverage if no article is written about this token in a given week. A token is considered to have a high media coverage if the number of articles written about it exceeds the median in a given week. Fund is then borrowed at the risk-free rate to finance an equally weighted long position in the no-coverage tokens. The portfolio is held for one week after the portfolio formation, and it is rebalanced weekly. Alphas obtained from regressing the resulting time-series returns of this self-financing media-based portfolio on three risk factors (cryptocurrency market, size, and momentum) and the p-values [using the Newey-West standard error] of those alphas are reported. The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. Novy-Marx and Velikov's (2016) generalized alphas that account for transaction costs [calculated using the Matlab function *calcGenAlpha* provided in the second author's Github repository] and their p-values are also reported.

	One-factor model		Two-factor model		Three-factor model			
	α	p-value	α	p-value	α	p-value	generalized α	p-value
				Sort by MCAP				
0	0.0381***	0.0001	0.0309***	0.0002	0.0305***	0.0002	0.0260***	0.0006
1	0.0626***	0.0050	0.0562**	0.0102	0.0563**	0.0103	0.0504**	0.0432
2	0.0058	0.2124	0.0024	0.5702	0.0025	0.5263	0.0000	
				Sort by AMCAP				
0	0.0417***	0.0001	0.0336***	0.0001	0.0331***	0.0002	0.0295***	0.0004
1	0.0660***	0.0033	0.0592***	0.0072	0.0593***	0.0073	0.0539**	0.0318
2	0.0026	0.5649	−0.0013	0.7365	−0.0010	0.7907	0.0000	
				Sort by PRCVOL				
0	0.0553***	0.0006	0.0493***	0.0021	0.0486***	0.0024	0.0410***	0.0004
1	0.0146***	0.0055	0.0080*	0.0585	0.0078*	0.0714	0.0020	0.6795
2	0.0025	0.4940	−0.0004	0.9046	−0.0002	0.9475	0.0000	
				Sort by VOLSCALED				
0	0.0570***	0.0017	0.0494***	0.0068	0.0479***	0.0082	0.0427***	0.0003
1	0.0129**	0.0366	0.0051	0.1353	0.0047	0.1709	0.0008	0.8621
2	0.0048	0.2803	0.0007	0.8586	0.0011	0.7662	0.0000	
				Sort by RETVOL				
0	0.0127*	0.0723	0.0075	0.2266	0.0072	0.2503	0.0000	
1	0.0155**	0.0112	0.0089**	0.0431	0.0075*	0.0735	0.0000	
2	0.0642***	0.0006	0.0592***	0.0018	0.0568***	0.0027	0.0460***	0.0006
				Sort by IDIOVOL				
0	0.0047	0.2731	0.0020	0.5955	0.0023	0.5353	0.0000	
1	0.0068	0.1207	0.0027	0.4947	0.0029	0.4616	0.0000	
2	0.0600***	0.0007	0.0522***	0.0024	0.0519***	0.0033	0.0421***	0.0010
				Sort by MAXRET				
0	0.0148**	0.0282	0.0093	0.1324	0.0098	0.1191	0.0000	
1	0.0174***	0.0057	0.0120**	0.0246	0.0113**	0.0332	0.0007	0.8929
2	0.0515***	0.0010	0.0451***	0.0047	0.0438***	0.0056	0.0325***	0.0030

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Table S.IV.20 (continued): Performance of Long-Only Media-Related Trading Strategies Relative to Cryptocurrency Risk Factors: All Active Cryptocurrencies currently listed on CoinMarketCap

	One-factor model		Two-factor model		Three-factor model			
	α	p-value	α	p-value	α	p-value	generalized α	p-value
				Sort by DAMIHUD				
0	0.0048	0.2701	0.0018	0.6558	0.0017	0.6502	0.0000	
1	0.0107*	0.0800	0.0086	0.1560	0.0082	0.1601	0.0000	
2	0.0527***	0.0005	0.0483***	0.0011	0.0478***	0.0013	0.0400***	0.0003
				Sort by VaR				
0	0.0195*	0.0624	0.0136	0.1332	0.0128	0.1543	0.0086	0.3900
1	0.0098	0.1138	0.0039	0.3701	0.0038	0.3801	0.0000	
2	0.0586***	0.0001	0.0512***	0.0002	0.0513***	0.0003	0.0451***	0.0000
				Sort by r $1,0$				
0	0.0195***	0.0038	0.0148**	0.0233	0.0144**	0.0226	0.0000	0.9985
1	0.0231***	0.0059	0.0161**	0.0395	0.0159**	0.0485	0.0064	0.2889
2	0.0386***	0.0003	0.0317***	0.0012	0.0293***	0.0030	0.0184**	0.0394
				Sort by r $2,0$				
0	0.0193***	0.0039	0.0143**	0.0195	0.0134**	0.0268	0.0023	0.7150
1	0.0199***	0.0069	0.0146**	0.0365	0.0136**	0.0406	0.0042	0.4382
2	0.0436***	0.0005	0.0330***	0.0040	0.0323***	0.0060	0.0262**	0.0113
				Sort by r $3,0$				
0	0.0198***	0.0024	0.0131**	0.0169	0.0126**	0.0194	0.0033	0.5746
1	0.0212***	0.0058	0.0125**	0.0385	0.0118*	0.0525	0.0055	0.3098
2	0.0536***	0.0012	0.0459***	0.0055	0.0438***	0.0088	0.0371**	0.0164
				Sort by r $4,0$				
0	0.0257***	0.0009	0.0201***	0.0054	0.0202***	0.0054	0.0100	0.1516
1	0.0220***	0.0081	0.0144**	0.0343	0.0138**	0.0400	0.0070	0.2213
2	0.0433***	0.0018	0.0362***	0.0081	0.0332**	0.0163	0.0283**	0.0371
				Sort by r $4,1$				
0	0.0399***	0.0003	0.0331***	0.0019	0.0327***	0.0029	0.0232**	0.0114
1	0.0210**	0.0233	0.0136	0.1110	0.0131	0.1297	0.0053	0.4226
2	0.0405***	0.0012	0.0336***	0.0052	0.0306**	0.0103	0.0245**	0.0392
				Sort by r $8,0$				
0	0.0330***	0.0002	0.0261***	0.0006	0.0257***	0.0008	0.0186**	0.0146
1	0.0198***	0.0084	0.0131**	0.0443	0.0122**	0.0477	0.0060	0.3046
2	0.0503***	0.0090	0.0393**	0.0339	0.0364*	0.0519	0.0368**	0.0469
				Sort by r $16,0$				
0	0.0318***	0.0004	0.0262***	0.0038	0.0259***	0.0037	0.0182**	0.0223
1	0.0205***	0.0046	0.0100**	0.0166	0.0091**	0.0234	0.0076	0.1763
2	0.0408***	0.0060	0.0326**	0.0249	0.0311**	0.0309	0.0283**	0.0492

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Table S.IV.20 (continued): Performance of Long-Only Media-Related Trading Strategies Relative to Cryptocurrency Risk Factors: All Active Cryptocurrencies currently listed on CoinMarketCap

	One-factor model		Two-factor model		Three-factor model			
	α	p-value	α	p-value	α	p-value	generalized α	p-value
				Sort by r 50, 0				
0	0.0327***	0.0034	0.0292**	0.0101	0.0295***	0.0090	0.0186*	0.0554
1	0.0185**	0.0129	0.0108**	0.0438	0.0105*	0.0560	0.0057	0.3312
2	0.0355**	0.0171	0.0268*	0.0566	0.0265*	0.0614	0.0238*	0.0527
				Sort by r 100, 0				
0	0.0526***	0.0049	0.0379**	0.0176	0.0367**	0.0323	0.0382***	0.0071
1	0.0059	0.4390	–0.0005	0.9388	–0.0017	0.7832	0.0000	
2	0.0559**	0.0133	0.0506**	0.0280	0.0501**	0.0280	0.0431**	0.0142
				Sort by NPAST52				
0	0.0377**	0.0168	0.0289*	0.0588	0.0285*	0.0653	0.0255**	0.0369
1	0.0163**	0.0368	0.0103	0.1042	0.0092	0.1242	0.0038	0.5206
2	0.0395***	0.0013	0.0365***	0.0047	0.0359***	0.0059	0.0252**	0.0280
				Sort by BETA				
0	0.0542***	0.0025	0.0469***	0.0052	0.0465***	0.0063	0.0420***	0.0001
1	0.0117**	0.0399	0.0061	0.1297	0.0058	0.1703	0.0006	0.9029
2	0.0117**	0.0499	0.0079	0.1433	0.0078	0.1505	0.0006	0.9092
				Sort by BETA2				
0	0.0362***	0.0011	0.0306***	0.0019	0.0307***	0.0021	0.0240**	0.0116
1	0.0111**	0.0452	0.0059	0.1279	0.0056	0.1688	0.0001	0.9875
2	0.0239**	0.0169	0.0185**	0.0317	0.0184**	0.0326	0.0127	0.1302

Table S.IV.21: Performance of Long-Only Media-Related Trading Strategies Relative to Cryptocurrency Risk Factors (Skipping a Week between the Portfolio Formation Week and the Holding Week): All Active Cryptocurrencies currently listed on CoinMarketCap

This table examines the return [in excess of the common risk factors in cryptocurrency proposed by Liu et al. (2022)] of a trading strategy that borrows fund at the risk-free rate to finance an equally weighted long position in tokens with no media coverage in the subsamples of tokens sorted by cryptocurrency characteristics (defined in Table S.I.1) one at a time. Each week, tokens are sorted according to the number of news articles written about them. A token is considered to have no media coverage if no article is written about this token in a given week. A token is considered to have a high media coverage if the number of articles written about it exceeds the median in a given week. Fund is then borrowed at the risk-free rate to finance an equally weighted long position in the no-coverage tokens. The portfolio is held for one week after the portfolio formation, and it is rebalanced weekly. Alphas obtained from regressing the resulting time-series returns of this self-financing media-based portfolio on three risk factors (cryptocurrency market, size, and momentum) and the p-values [using the Newey-West standard error] of those alphas are reported. The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. Novy-Marx and Velikov's (2016) generalized alphas that account for transaction costs [calculated using the Matlab function *calcGenAlpha* provided in the second author's Github repository] and their p-values are also reported.

	One-factor model		Two-factor model		Three-factor model			
	α	p-value	α	p-value	α	p-value	generalized α	p-value
				Sort by MCAP				
0	0.0485***	0.0001	0.0416***	0.0004	0.0416***	0.0004	0.0365***	0.0004
1	0.0542**	0.0215	0.0449**	0.0323	0.0449**	0.0326	0.0415*	0.0641
2	0.0045	0.3605	−0.0006	0.8999	−0.0005	0.8999	0.0000	
				Sort by AMCAP				
0	0.0497***	0.0000	0.0432***	0.0003	0.0432***	0.0003	0.0375***	0.0002
1	0.0494**	0.0331	0.0394*	0.0519	0.0394*	0.0527	0.0369*	0.0923
2	0.0051	0.2274	0.0004	0.9077	0.0004	0.8982	0.0000	
				Sort by PRCVOL				
0	0.0708***	0.0002	0.0641***	0.0012	0.0636***	0.0012	0.0571***	0.0001
1	0.0116**	0.0386	0.0039	0.3327	0.0040	0.3148	0.0000	
2	0.0042	0.3224	−0.0010	0.8005	−0.0008	0.8237	0.0000	
				Sort by VOLSCALED				
0	0.0778***	0.0042	0.0722**	0.0145	0.0717**	0.0145	0.0641***	0.0016
1	0.0097**	0.0458	0.0034	0.3184	0.0035	0.3034	0.0000	
2	0.0081*	0.0821	0.0033	0.4119	0.0034	0.3702	0.0000	
				Sort by RETVOL				
0	0.0151**	0.0259	0.0084	0.1424	0.0083	0.1430	0.0000	
1	0.0237**	0.0197	0.0153*	0.0716	0.0153*	0.0729	0.0070	0.4599
2	0.0630***	0.0001	0.0504***	0.0005	0.0504***	0.0005	0.0447***	0.0001
				Sort by IDIOVOL				
0	0.0088	0.1079	0.0057	0.2914	0.0056	0.2994	0.0000	
1	0.0174**	0.0268	0.0101	0.1347	0.0098	0.1330	0.0006	0.9330
2	0.0811***	0.0023	0.0691***	0.0065	0.0696***	0.0065	0.0639***	0.0066
				Sort by MAXRET				
0	0.0243**	0.0183	0.0136**	0.0303	0.0132**	0.0253	0.0069	0.4620
1	0.0137*	0.0714	0.0051	0.3899	0.0049	0.4067	0.0000	
2	0.0635***	0.0001	0.0502***	0.0004	0.0503***	0.0003	0.0446***	0.0001

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Table S.IV.21 (continued): Performance of Long-Only Media-Related Trading Strategies Relative to Cryptocurrency Risk Factors (Skipping a Week between the Portfolio Formation Week and the Holding Week): All Active Cryptocurrencies currently listed on CoinMarketCap

	One-factor model		Two-factor model		Three-factor model			
	α	p-value	α	p-value	α	p-value	generalized α	p-value
				Sort by DAMIHUD				
0	0.0034	0.4413	−0.0025	0.5026	−0.0024	0.4923	0.0001	
1	0.0149**	0.0183	0.0073	0.1133	0.0074	0.1121	0.0013	0.8058
2	0.0798***	0.0032	0.0573***	0.0091	0.0571***	0.0098	0.0675***	0.0046
				Sort by VaR				
0	0.0106*	0.0739	0.0054	0.2563	0.0054	0.2627	0.0000	
1	0.0191**	0.0452	0.0136	0.1279	0.0134	0.1302	0.0077	0.4154
2	0.0689***	0.0001	0.0528***	0.0001	0.0527***	0.0001	0.0558***	0.0001
				Sort by r 1, 0				
0	0.0226***	0.0065	0.0155**	0.0446	0.0154**	0.0442	0.0032	0.6564
1	0.0383***	0.0045	0.0278***	0.0079	0.0277***	0.0072	0.0220*	0.0869
2	0.0387***	0.0001	0.0278***	0.0013	0.0279***	0.0014	0.0191**	0.0361
				Sort by r 2, 0				
0	0.0239***	0.0005	0.0164***	0.0017	0.0161***	0.0015	0.0070	0.2719
1	0.0247***	0.0048	0.0162**	0.0155	0.0159**	0.0130	0.0091	0.2599
2	0.0375***	0.0010	0.0275***	0.0068	0.0281***	0.0074	0.0205*	0.0597
				Sort by r 3, 0				
0	0.0233***	0.0005	0.0157***	0.0018	0.0155***	0.0014	0.0074	0.2092
1	0.0444**	0.0128	0.0338**	0.0308	0.0336**	0.0306	0.0293**	0.0480
2	0.0405***	0.0004	0.0302***	0.0039	0.0305***	0.0049	0.0247**	0.0408
				Sort by r 4, 0				
0	0.0230***	0.0005	0.0149***	0.0019	0.0147***	0.0016	0.0075	0.2140
1	0.0498***	0.0074	0.0355**	0.0194	0.0354**	0.0193	0.0351**	0.0179
2	0.0401***	0.0007	0.0307***	0.0062	0.0308***	0.0069	0.0252**	0.0350
				Sort by r 4, 1				
0	0.0210***	0.0012	0.0147**	0.0101	0.0148***	0.0086	0.0048	0.4477
1	0.0466**	0.0164	0.0343**	0.0265	0.0343**	0.0264	0.0311**	0.0457
2	0.0328***	0.0067	0.0254**	0.0294	0.0253**	0.0311	0.0171*	0.0970
				Sort by r 8, 0				
0	0.0326***	0.0003	0.0241***	0.0044	0.0241***	0.0045	0.0183**	0.0167
1	0.0254***	0.0072	0.0177**	0.0210	0.0177**	0.0198	0.0118*	0.0943
2	0.0608***	0.0039	0.0493**	0.0111	0.0493**	0.0113	0.0474**	0.0190
				Sort by r 16, 0				
0	0.0279***	0.0004	0.0194***	0.0060	0.0189***	0.0064	0.0144*	0.0600
1	0.0282***	0.0026	0.0173***	0.0099	0.0170***	0.0090	0.0152*	0.0599
2	0.0553***	0.0012	0.0457***	0.0038	0.0460***	0.0043	0.0430**	0.0159

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Table S.IV.21 (continued): Performance of Long-Only Media-Related Trading Strategies Relative to Cryptocurrency Risk Factors (Skipping a Week between the Portfolio Formation Week and the Holding Week): All Active Cryptocurrencies currently listed on CoinMarketCap

	One-factor model		Two-factor model		Three-factor model			
	α	p-value	α	p-value	α	p-value	generalized α	p-value
Sort by r 50, 0								
0	0.0291***	0.0013	0.0234***	0.0084	0.0229***	0.0088	0.0153**	0.0406
1	0.0182**	0.0114	0.0114*	0.0762	0.0115*	0.0761	0.0058	0.3453
2	0.0443***	0.0007	0.0366***	0.0035	0.0366***	0.0038	0.0330**	0.0146
Sort by r 100, 0								
0	0.0551***	0.0022	0.0416***	0.0030	0.0425***	0.0039	0.0409**	0.0189
1	0.0053	0.3465	–0.0020	0.6657	–0.0017	0.7139	0.0000	
2	0.0985**	0.0167	0.0855**	0.0158	0.0819**	0.0154	0.0861**	0.0124
Sort by NPAST52								
0	0.0382***	0.0039	0.0275**	0.0219	0.0278**	0.0232	0.0267**	0.0429
1	0.0205**	0.0119	0.0130**	0.0469	0.0130**	0.0470	0.0082	0.2281
2	0.0428**	0.0181	0.0395**	0.0278	0.0393**	0.0282	0.0293*	0.0906
Sort by BETA								
0	0.0608***	0.0012	0.0532***	0.0037	0.0532***	0.0037	0.0491***	0.0043
1	0.0131**	0.0173	0.0063	0.2017	0.0063	0.2002	0.0022	0.6130
2	0.0259**	0.0192	0.0054	0.4557	0.0054	0.4524	0.0149	0.1579
Sort by BETA2								
0	0.0440***	0.0056	0.0371**	0.0174	0.0372**	0.0162	0.0320**	0.0303
1	0.0145***	0.0093	0.0077*	0.0890	0.0077*	0.0884	0.0037	0.4053
2	0.0402***	0.0082	0.0207*	0.0707	0.0207*	0.0736	0.0292**	0.0383

Table S.IV.22: Performance of Media-Related Trading Strategies Relative to Cryptocurrency Risk Factors for Different Portfolio Formation and Holding Periods (Skipping a Week between the Portfolio Formation Period and the Holding Period): All Cryptocurrencies ever listed on CoinMarketCap

This table reports the average returns [in excess of the common risk factors in cryptocurrency proposed by Liu et al. (2022)] of a trading strategy that longs tokens with no media coverage over the past K weeks and shorts tokens with high media coverage over the past K weeks (K = 1, 5, 10). In each portfolio formation period, tokens are sorted according to the average number of news articles written about them per week in this period. A token is considered to have no media coverage if no article is written about this token. A token is considered to have a high media coverage if the average number of articles written about it per week exceeds the median during the period. Both the long and short positions are equally weighted, and they are held for the entire holding period of J weeks after portfolio formation ($J = 1, 2, \ldots, 20$). Therefore, in any given week, the strategy holds a composite portfolio consisting of the long/short/long-short portfolio initiated K weeks prior to this week as well as the portfolios initiated in the previous $K - 1$ weeks. These portfolios have overlapping holding periods at the end of each week if $J > 1$. The return of the composite portfolio in a week is then calculated by averaging the returns [of the portfolios with overlapping holding periods] from their initiation weeks to this week [as described in Jegadeesh and Titman (1993)]. The resulting time-series returns on the composite long-short portfolio are regressed on three risk factors (cryptocurrency market, size, and momentum). Alphas obtained from this regression are then reported, and p-values [using the Newey-West standard error] are in parentheses. The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. Note that a cryptocurrency is included if its market capitalization is at least one million during the portfolio formation week while its name and symbol are mentioned in at least 100 articles throughout the sample period.

Holding period (J week(s))	Time-series mean	One-factor model	Two-factor model	Three-factor model	Average number of tokens		
					Media coverage		
					No	Low	High
Panel A: Formation period (K) = 1 week							
1	0.0122***	0.0134***	0.0141***	0.0139***	147.78	195.26	177.05
	(0.0000)	(0.0000)	(0.0001)	(0.0001)			
3	0.0143***	0.0136***	0.0139***	0.0139***			
	(0.0000)	(0.0000)	(0.0001)	(0.0001)			
6	0.0192***	0.0179***	0.0180***	0.0180***			
	(0.0000)	(0.0000)	(0.0000)	(0.0000)			
9	0.0217***	0.0195***	0.0178***	0.0177***			
	(0.0000)	(0.0000)	(0.0000)	(0.0000)			
12	0.0225***	0.0204***	0.0202***	0.0203***			
	(0.0000)	(0.0001)	(0.0001)	(0.0001)			
15	0.0223***	0.0225***	0.0238***	0.0237***			
	(0.0000)	(0.0002)	(0.0001)	(0.0001)			
18	0.0153***	0.0143***	0.0154***	0.0154***			
	(0.0000)	(0.0000)	(0.0000)	(0.0000)			
20	0.0147***	0.0132***	0.0143***	0.0143***			
	(0.0000)	(0.0000)	(0.0000)	(0.0000)			
Panel B: Formation period (K) = 5 weeks							
1	0.0059***	0.0059**	0.0057**	0.0057**	74.67	230.60	219.04
	(0.0061)	(0.0124)	(0.0271)	(0.0281)			
3	0.0082***	0.0091***	0.0072***	0.0071***			
	(0.0006)	(0.0006)	(0.0048)	(0.0040)			
6	0.0086***	0.0083***	0.0075**	0.0074**			
	(0.0013)	(0.0037)	(0.0127)	(0.0116)			
9	0.0084***	0.0080**	0.0073**	0.0073**			
	(0.0030)	(0.0121)	(0.0243)	(0.0229)			
12	0.0083***	0.0081**	0.0086**	0.0086**			
	(0.0085)	(0.0335)	(0.0298)	(0.0291)			
15	0.0081**	0.0084**	0.0087**	0.0087**			
	(0.0135)	(0.0407)	(0.0438)	(0.0435)			
18	0.0034	0.0019	0.0020	0.0020			
	(0.1412)	(0.4527)	(0.4301)	(0.4170)			
20	0.0029	0.0021	0.0023	0.0023			
	(0.1900)	(0.3940)	(0.3350)	(0.3295)			

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Table S.IV.22 (continued): Performance of Media-Related Trading Strategies Relative to Cryptocurrency Risk Factors for Different Portfolio Formation and Holding Periods (Skipping a Week between the Portfolio Formation Period and the Holding Period): All Cryptocurrencies ever listed on CoinMarketCap

Holding period (J week(s))	Time-series mean	One-factor model	Two-factor model	Three-factor model	Average number of tokens		
					Media coverage		
					No	Low	High
Panel C: Formation period (K) = 10 weeks							
1	0.0044***	0.0040**	0.0033*	0.0034*	48.80	238.62	229.55
	(0.0094)	(0.0238)	(0.0844)	(0.0769)			
3	0.0064***	0.0064***	0.0056**	0.0057**			
	(0.0060)	(0.0046)	(0.0128)	(0.0100)			
6	0.0076***	0.0069**	0.0062**	0.0062**			
	(0.0043)	(0.0111)	(0.0319)	(0.0312)			
9	0.0082***	0.0061**	0.0055*	0.0055*			
	(0.0068)	(0.0499)	(0.0941)	(0.0924)			
12	0.0091***	0.0080**	0.0081*	0.0082*			
	(0.0085)	(0.0372)	(0.0589)	(0.0607)			
15	0.0104***	0.0085**	0.0087*	0.0087*			
	(0.0075)	(0.0370)	(0.0657)	(0.0660)			
18	0.0049*	0.0043	0.0041	0.0040			
	(0.0682)	(0.1177)	(0.1475)	(0.1512)			
20	0.0053**	0.0049*	0.0050*	0.0048*			
	(0.0492)	(0.0718)	(0.0730)	(0.0736)			

Table S.IV.23: Performance of Media-Related Trading Strategies Relative to Cryptocurrency Risk Factors for Different Portfolio Formation and Holding Periods: All Active Cryptocurrencies currently listed on CoinMarketCap

This table reports the average returns [in excess of the common risk factors in cryptocurrency proposed by Liu et al. (2022)] of a trading strategy that longs tokens with no media coverage over the past K weeks and shorts tokens with high media coverage over the past K weeks (K = 1, 5, 10). In each portfolio formation period, tokens are sorted according to the average number of news articles written about them per week in this period. A token is considered to have no media coverage if no article is written about this token. A token is considered to have a high media coverage if the average number of articles written about it per week exceeds the median during the period. Both the long and short positions are equally weighted, and they are held for the entire holding period of J weeks after portfolio formation ($J = 1, 2, \ldots, 20$). Therefore, in any given week, the strategy holds a composite portfolio consisting of the long/short/long-short portfolio initiated K weeks prior to this week as well as the portfolios initiated in the previous $K - 1$ weeks. These portfolios have overlapping holding periods at the end of each week if $J > 1$. The return of the composite portfolio in a week is then calculated by averaging the returns [of the portfolios with overlapping holding periods] from their initiation weeks to this week [as described in Jegadeesh and Titman (1993)]. The resulting time-series returns on the composite long-short portfolio are regressed on three risk factors (cryptocurrency market, size, and momentum). Alphas obtained from this regression are then reported, and p-values [using the Newey-West standard error] are in parentheses. The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. Note that a cryptocurrency is included if its market capitalization is at least one million during the portfolio formation week while its name and symbol are mentioned in at least 100 articles throughout the sample period.

Holding period (J week(s))	Time-series mean	One-factor model	Two-factor model	Three-factor model	Average number of tokens		
					Media coverage		
					No	Low	High
Panel A: Formation period (K) = 1 week							
1	0.0114***	0.0101***	0.0108***	0.0106***	172.83	198.66	178.92
	(0.0008)	(0.0023)	(0.0012)	(0.0022)			
3	0.0149***	0.0128***	0.0137***	0.0137***			
	(0.0001)	(0.0001)	(0.0001)	(0.0002)			
6	0.0156***	0.0168***	0.0179***	0.0181***			
	(0.0000)	(0.0000)	(0.0000)	(0.0000)			
9	0.0191***	0.0196***	0.0200***	0.0199***			
	(0.0001)	(0.0001)	(0.0001)	(0.0001)			
12	0.0211***	0.0212***	0.0219***	0.0222***			
	(0.0001)	(0.0011)	(0.0007)	(0.0006)			
15	0.0213***	0.0228***	0.0234***	0.0237***			
	(0.0003)	(0.0016)	(0.0008)	(0.0007)			
18	0.0141***	0.0142***	0.0157***	0.0162***			
	(0.0005)	(0.0025)	(0.0009)	(0.0005)			
20	0.0121***	0.0113***	0.0129***	0.0137***			
	(0.0014)	(0.0097)	(0.0028)	(0.0013)			
Panel B: Formation period (K) = 5 weeks							
1	0.0035	0.0008	−0.0000	−0.0003	90.24	242.10	227.73
	(0.1164)	(0.6824)	(0.9938)	(0.8854)			
3	0.0075***	0.0062**	0.0055**	0.0051**			
	(0.0031)	(0.0152)	(0.0334)	(0.0490)			
6	0.0069***	0.0064**	0.0066**	0.0064**			
	(0.0095)	(0.0206)	(0.0187)	(0.0263)			
9	0.0071**	0.0062*	0.0061*	0.0058*			
	(0.0128)	(0.0622)	(0.0628)	(0.0803)			
12	0.0053	0.0040	0.0042	0.0040			
	(0.1014)	(0.3194)	(0.2911)	(0.3125)			
15	0.0046	0.0031	0.0045	0.0045			
	(0.1473)	(0.4329)	(0.2435)	(0.2602)			
18	0.0007	−0.0002	0.0006	0.0004			
	(0.8097)	(0.9573)	(0.8612)	(0.9057)			
20	0.0004	−0.0002	0.0004	0.0003			
	(0.8726)	(0.9436)	(0.9035)	(0.9315)			

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Table S.IV.23 (continued): Performance of Media-Related Trading Strategies Relative to Cryptocurrency Risk Factors for Different Portfolio Formation and Holding Periods: All Active Cryptocurrencies currently listed on CoinMarketCap

Holding period (J week(s))	Time-series mean	One-factor model	Two-factor model	Three-factor model	Average number of tokens		
					Media coverage		
					No	Low	High
Panel C: Formation period (K) = 10 weeks							
1	0.0013	0.0013	0.0001	−0.0003	61.30	250.37	243.13
	(0.5288)	(0.5433)	(0.9526)	(0.8768)			
3	0.0024	0.0002	−0.0011	−0.0013			
	(0.3627)	(0.9379)	(0.6602)	(0.5920)			
6	0.0030	0.0025	0.0023	0.0024			
	(0.2602)	(0.3955)	(0.4152)	(0.4137)			
9	0.0037	0.0020	0.0018	0.0013			
	(0.2061)	(0.5104)	(0.5556)	(0.6784)			
12	0.0033	0.0009	0.0005	−0.0000			
	(0.3031)	(0.7941)	(0.8788)	(0.9929)			
15	0.0027	0.0005	0.0002	−0.0005			
	(0.4103)	(0.894)	(0.9529)	(0.8935)			
18	−0.0018	−0.0035	−0.0044	−0.0050			
	(0.5365)	(0.2922)	(0.2001)	(0.1482)			
20	−0.0023	−0.0040	−0.0047	−0.0053			
	(0.4560)	(0.2551)	(0.1837)	(0.1346)			

Table S.IV.24: Performance of Media-Related Trading Strategies Relative to Cryptocurrency Risk Factors for Different Portfolio Formation and Holding Periods (Skipping a Week between the Portfolio Formation Period and the Holding Period): All Active Cryptocurrencies currently listed on CoinMarketCap

This table reports the average returns [in excess of the common risk factors in cryptocurrency proposed by Liu et al. (2022)] of a trading strategy that longs tokens with no media coverage over the past K weeks and shorts tokens with high media coverage over the past K weeks (K = 1, 5, 10). In each portfolio formation period, tokens are sorted according to the average number of news articles written about them per week in this period. A token is considered to have no media coverage if no article is written about this token. A token is considered to have a high media coverage if the average number of articles written about it per week exceeds the median during the period. Both the long and short positions are equally weighted, and they are held for the entire holding period of J weeks after portfolio formation ($J = 1, 2, \ldots, 20$). Therefore, in any given week, the strategy holds a composite portfolio consisting of the long/short/long-short portfolio initiated K weeks prior to this week as well as the portfolios initiated in the previous $K - 1$ weeks. These portfolios have overlapping holding periods at the end of each week if $J > 1$. The return of the composite portfolio in a week is then calculated by averaging the returns [of the portfolios with overlapping holding periods] from their initiation weeks to this week [as described in Jegadeesh and Titman (1993)]. The resulting time-series returns on the composite long-short portfolio are regressed on three risk factors (cryptocurrency market, size, and momentum). Alphas obtained from this regression are then reported, and p-values [using the Newey-West standard error] are in parentheses. The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. Note that a cryptocurrency is included if its market capitalization is at least one million during the portfolio formation week while its name and symbol are mentioned in at least 100 articles throughout the sample period.

Holding period (J week(s))	Time-series mean	One-factor model	Two-factor model	Three-factor model	Average number of tokens		
					Media coverage		
					No	Low	High
Panel A: Formation period (K) = 1 week							
1	0.0109***	0.0096***	0.0088**	0.0085**	172.71	198.62	178.90
	(0.0017)	(0.0050)	(0.0224)	(0.0273)			
3	0.0132***	0.0111***	0.0103***	0.0102***			
	(0.0002)	(0.0005)	(0.0052)	(0.0059)			
6	0.0172***	0.0168***	0.0168***	0.0167***			
	(0.0000)	(0.0000)	(0.0001)	(0.0001)			
9	0.0209***	0.0203***	0.0203***	0.0202***			
	(0.0000)	(0.0001)	(0.0000)	(0.0001)			
12	0.0236***	0.0249***	0.0240***	0.0238***			
	(0.0000)	(0.0002)	(0.0001)	(0.0001)			
15	0.0242***	0.0240***	0.0245***	0.0243***			
	(0.0001)	(0.0006)	(0.0002)	(0.0002)			
18	0.0151***	0.0142***	0.0170***	0.0170***			
	(0.0002)	(0.0027)	(0.0004)	(0.0004)			
20	0.0131***	0.0113***	0.0138***	0.0138***			
	(0.0008)	(0.0102)	(0.0018)	(0.0017)			
Panel B: Formation period (K) = 5 weeks							
1	0.0030	0.0031	0.0021	0.0021	90.15	242.15	227.70
	(0.1950)	(0.1846)	(0.3034)	(0.2965)			
3	0.0040*	0.0021	0.0007	0.0008			
	(0.0654)	(0.3226)	(0.7376)	(0.7245)			
6	0.0037	0.0029	0.0023	0.0024			
	(0.1651)	(0.2913)	(0.3694)	(0.3609)			
9	0.0039	0.0029	0.0034	0.0034			
	(0.1860)	(0.3822)	(0.2752)	(0.2793)			
12	0.0026	0.002	0.0025	0.0026			
	(0.4287)	(0.6125)	(0.5285)	(0.5189)			
15	0.0016	0.0010	0.0025	0.0026			
	(0.6380)	(0.8032)	(0.5291)	(0.5036)			
18	−0.0022	−0.0028	−0.0013	−0.0012			
	(0.4535)	(0.4252)	(0.7024)	(0.7242)			
20	−0.0026	−0.0033	−0.0020	−0.0020			
	(0.3745)	(0.3088)	(0.5207)	(0.5374)			

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Table S.IV.24 (continued): Performance of Media-Related Trading Strategies Relative to Cryptocurrency Risk Factors for Different Portfolio Formation and Holding Periods (Skipping a Week between the Portfolio Formation Period and the Holding Period): All Active Cryptocurrencies currently listed on CoinMarketCap

Holding period (J week(s))	Time-series mean	One-factor model	Two-factor model	Three-factor model	Average number of tokens: Media coverage		
					No	Low	High
Panel C: Formation period (K) = 10 weeks							
1	0.0006	0.0014	0.0005	0.0004	61.30	250.31	243.13
	(0.7972)	(0.4912)	(0.8238)	(0.8298)			
3	0.0006	−0.0008	−0.0016	−0.0017			
	(0.8281)	(0.7602)	(0.5249)	(0.4898)			
6	0.0027	0.0011	0.0004	0.0003			
	(0.2952)	(0.6787)	(0.8824)	(0.9123)			
9	0.0026	0.0012	0.0012	0.0010			
	(0.3699)	(0.6853)	(0.7120)	(0.7377)			
12	0.0025	−0.0000	−0.0004	−0.0006			
	(0.4464)	(0.9923)	(0.9090)	(0.8733)			
15	0.0021	0.0003	−0.0002	−0.0003			
	(0.5487)	(0.9351)	(0.9667)	(0.9412)			
18	−0.0032	−0.0045	−0.0058	−0.0059			
	(0.3296)	(0.1983)	(0.1291)	(0.1220)			
20	−0.0039	−0.0057	−0.0072*	−0.0073*			
	(0.2454)	(0.1157)	(0.0692)	(0.0656)			

S.IV.4 Media, Size, Idiosyncratic Volatility, Liquidity, Value-at-Risk, and Beta

We replicate the analysis presented in Section 5.4 to confirm that the media effect is not subsumed under other anomalies related to size, idiosyncratic volatility, VaR, and beta, but it may be subsumed under the liquidity effect. As above, we shall report the results of two robustness checks using (i) all cryptocurrencies while skipping one week between the portfolio formation week and the holding week, and (ii) only active cryptocurrencies.

Robustness Check (i):

The results in this subsection are reported in Table S.IV.25. Double-sorting tokens by average market capitalization (AMCAP) as the first sorting variable and media coverage as the second sorting variable reveals that, controlling for size, there is a statistically significant no-coverage premium before transaction costs among small tokens (5.23% with t-statistic = 3.23) and a statistically insignificant no-coverage premium in the other two AMCAP terciles, which is similar to the results reported in Section 4. Double-sorting tokens by media coverage (as the first sorting variable) and AMCAP (as the second sorting variable) reveals that, controlling for media coverage, there is a significant large-market capitalization premium before transaction costs among high-coverage tokens (4.01% with t-statistic = 2.78), which is consistent with the finding reported in Table 12 (without skipping one week between the portfolio formation week and the holding week), and a significant small-market capitalization premium before transaction costs among no-coverage tokens (2.69% with t-statistic = 3.03). Therefore, the large-size effect is only observed among high-coverage tokens while the small-size effect is only observed among no-coverage tokens. These results suggest that the media effect is clearly not subsumed under the size effect.

Double-sorting tokens by idiosyncratic volatility (IDIOVOL) as the first sorting variable and media coverage as the second sorting variable reveals that, controlling for IDIOVOL, we find a statistically significant no-coverage premium before costs among tokens with high idiosyncratic volatility (6.49% with t-statistic = 2.69) and an insignificant premium in the other two IDIOVOL terciles. Double-sorting tokens by media coverage (as the first sorting variable) and IDIOVOL (as the second sorting variable) reveals that, controlling for media coverage, we do not find any significant IDIOVOL premium before costs in any media coverage-based tercile. Therefore, the media effect is not subsumed under the idiosyncratic volatility effect.

Double-sorting tokens by Amihud's (2002) illiquidity measure (DAMIHUD) as the first sorting variable and media coverage as the second sorting variable reveals that, controlling for illiquidity, there is a statistically significant no-coverage premium before costs among less liquid tokens (8.34% with t-statistic = 2.33) and this premium disappears as liquidity increases, which is consistent with the finding reported in Table 12. Double-sorting tokens by media coverage (as the first sorting variable) and DAMIHUD (as the second sorting variable) reveals that, controlling for media coverage, there is a statistically significant high-illiquidity premium before costs among no-coverage tokens (4.40% with t-statistic = 2.57), which is consistent with the finding reported in Table 12, and this premium disappears as media coverage increases. Therefore, it seems that there is a strong correlation between media coverage and liquidity, and thus the media effect may be subsumed under the liquidity effect. To verify this claim, we also use log average daily volume times price (PRCVOL) and the PRCVOL scaled by market capitalization (VOLSCALED) as other proxies of liquidity.

Double-sorting tokens by PRCVOL as the first sorting variable and media coverage as the second sorting variable reveals that, controlling for illiquidity, there is a statistically significant no-coverage premium before costs among tokens in the low or medium PRCVOL tercile (4.18% with t-statistic = 2.04 and 1.38% with t-statistic = 2.51, respectively) . Double-sorting tokens by media coverage (as the first sorting variable) and PRCVOL (as the second sorting variable) suggests that, controlling for media coverage, there is a significant high-illiquidity premium before costs only among no- or low-coverage tokens (2.44% with t-statistic = 2.77 and 1.15% with t-statistic = 2.07, respectively) and a significant low-illiquidity premium before costs among high-coverage tokens (1.59% with t-statistic = 2.16). This result implies that the media effect is not subsumed under the liquidity effect. In addition, double-sorting tokens by VOLSCALED as the first sorting variable and media coverage as the second sorting variable reveals that, controlling for illiquidity, there is a significant no-coverage premium before costs only among less liquid tokens (4.36% with t-statistic = 2.15). Double-sorting tokens by media coverage (as the first sorting variable) and VOLSCALED (as the second sorting variable) suggests that, controlling for media coverage, there is a significant high-illiquidity premium before costs only among no- or low-coverage tokens (2.31% with t-statistic = 2.22 and 1.23% with t-statistic = 2.49, respectively). Therefore, there is a mixed evidence that the media effect is subsumed under the liquidity effect, which is consistent with the results reported in Section 5.4.

Double-sorting tokens by Value-at-Risk (VaR) as the first sorting variable and media coverage as the second sorting variable reveals that, controlling for VaR, there is a statistically significant no-coverage premium before costs among tokens in the high VaR group (5.22% with t-statistic = 2.65). Double-sorting tokens by media coverage (as the first sorting variable) and VaR (as the second sorting variable) suggests that, controlling for media coverage, there is a statistically significant low-VaR premium among high-coverage tokens (1.42% with t-statistic = 2.08). Although this result is not entirely consistent with the result reported in Table 12, but it still implies that the media effect is clearly not subsumed under the VaR effect.

Double-sorting tokens by BETA as the first sorting variable and media coverage as the second sorting variable reveals that, controlling for BETA, there is a statistically significant and large no-coverage premium before costs among tokens in the lowest or highest BETA group (5.13% with t-statistic = 2.50 and 2.66% with t-statistic = 2.26, respectively). Double-sorting tokens by media coverage (as the first sorting variable) and BETA (as the second sorting variable) suggests that, controlling for media coverage, there is an insignificant low-beta premium before costs in every media coverage-based tercile. Therefore, the media effect is clearly not subsumed under the BETA effect, which is also consistent with the results reported in Section 5.4.

Robustness Check (ii):

Table S.IV.26 presents the results obtained from all currently active cryptocurrencies. Double-sorting tokens by average market capitalization (AMCAP) as the first sorting variable and media coverage as the second sorting variable reveals that, controlling for size, there is also a statistically significant no-coverage premium before costs among small tokens (2.71% with t-statistic = 3.08) and a statistically insignificant premium in the other two AMCAP terciles, which is consistent with the results reported in Section 5.4. Double-sorting tokens by media coverage (as the first sorting variable) and AMCAP (as the second sorting variable) reveals that, controlling for media coverage, there is a significant large-market capitalization premium before costs among high-coverage tokens (1.60% with t-statistic = 2.36) – tokens with large (small) market capitalization yield high (low) average returns – and a significant small-market capitalization premium among no-coverage tokens (2.07% with t-statistic = 2.74) – tokens with large (small) market capitalization yield low (high) average returns. Therefore, the media effect is not subsumed under the size effect.

Double-sorting tokens by idiosyncratic volatility (IDIOVOL) as the first sorting variable and media coverage as the second sorting variable reveals that, controlling for IDIOVOL, we do not find a statistically significant no-coverage premium before costs in every IDIOVOL tercile. Thus, the media effect and the idiosyncratic volatility effect may be unrelated. Double-sorting tokens by media coverage (as the first sorting variable) and IDIOVOL (as the second sorting variable) reveals that, controlling for media coverage, we find a significant high-IDIOVOL premium before costs among no-coverage tokens (2.90% with t-statistic = 2.16) – tokens with high (low) idiosyncratic volatility yield high (low) average returns, which is consistent with the conventional risk-return trade-off – and an insignificant IDIOVOL premium among other tokens. Therefore, the media effect is also not subsumed under the idiosyncratic volatility effect.

Double-sorting tokens by Amihud's (2002) illiquidity measure (DAMIHUD) as the first sorting variable and media coverage as the second sorting variable reveals that, controlling for illiquidity, there is a statistically significant no-coverage premium before costs among less liquid tokens (5.04% with t-statistic = 3.02), and this premium disappears as liquidity increases, which is aligned with the result reported in Section 5.4. Double-sorting tokens by media coverage (as the first sorting variable) and DAMIHUD (as the second sorting variable) reveals that, controlling for media coverage, there is a statistically significant high-illiquidity premium before costs among no-coverage tokens (3.85% with t-statistic = 2.87) – tokens with high (low) illiquidity yield high (low) average returns – and a significant low-illiquidity premium before costs among high-coverage tokens (1.58% with t-statistic = 2.12) – tokens with high (low) illiquidity yield low (high) average returns, which is clearly not consistent with the result reported earlier. Therefore, the media effect is not subsumed under the liquidity effect in the sample of active cryptocurrencies. The reason is that most active tokens receive high media coverage at some point, thus they are usually traded more actively than non-active tokens. Therefore, we have obtained mixed evidences about the liquidity effect among active cryptocurrencies. To verify this result, we also use PRCVOL and VOLSCALED as other proxies of liquidity.

Double-sorting tokens by PRCVOL as the first sorting variable and media coverage as the second sorting variable reveals that, controlling for illiquidity, there is a statistically insignificant no-coverage premium before costs among tokens in every PRCVOL tercile. Double-sorting tokens by media coverage (as the first sorting variable) and PRCVOL (as the second sorting variable) suggests that, controlling for media coverage, there is a significant low-illiquidity premium before costs only among no-coverage tokens. Moreover, double-sorting tokens by VOLSCALED as the first sorting variable and media coverage as the second sorting variable reveals that, controlling for illiquidity, there is a significant no-coverage premium before costs only among least liquid tokens (4.77% with t-statistic = 3.14). Double-sorting tokens by media coverage (as the first sorting variable) and VOLSCALED (as the second sorting variable) suggests that, controlling for media coverage, there is a significant high-illiquidity premium before costs only among no- or low- coverage tokens (3.19% with t-statistic = 3.68 and 1.69% with t-statistic = 2.07, respectively). Therefore, we have found a weak evidence that the media effect is subsumed under the liquidity effect among active cryptocurrencies.

Double-sorting tokens by Value-at-Risk (VaR) as the first sorting variable and media coverage as the second sorting variable reveals that, controlling for VaR, there is a statistically significant no-coverage premium before costs among tokens in the high VaR tercile (3.48% with t-statistic = 2.26). Double-sorting tokens by media coverage (as the first sorting variable) and VaR (as the second sorting variable) suggests that, controlling for media coverage, there is some high-VaR premium before costs only among no-coverage tokens (2.03% with t-statistic = 1.64) and some low-VaR premium among high-coverage tokens (0.67% with t-statistic = 1.76). Thus, the media effect is not subsumed under the VaR effect, which is also consistent with the result reported in Section 5.4.

Double-sorting tokens by BETA as the first sorting variable and media coverage as the second sorting variable reveals that, controlling for BETA, there is a statistically significant and large no-coverage premium before costs only among tokens in the low BETA tercile (3.36% with t-statistic = 2.73). Double-sorting tokens by media coverage (as the first sorting variable) and BETA (as the second sorting variable) suggests that, controlling for media coverage, there is an insignificant beta premium before costs in every media coverage-based tercile. This result suggests that the media effect cannot be subsumed under the BETA effect, which is consistent with the result obtained earlier.

Table S.IV.27 reports the results obtained from all currently active cryptocurrencies with one week skipped between the portfolio formation week and the holding week. Double-sorting tokens by average market capitalization (AMCAP) as the first sorting variable and media coverage as the second sorting variable reveals that, controlling for size, there is also a statistically significant no-coverage premium before costs among small tokens (3.83% with t-statistic = 2.54) and an insignificant premium in the other two AMCAP terciles. Double-sorting tokens by media coverage (as the first sorting variable) and AMCAP (as the second sorting variable) reveals that, controlling for media coverage, there is a significant large-market capitalization premium before costs among high-coverage tokens (3.40% with t-statistic = 2.94) and a significant small-market capitalization premium among no-coverage tokens (2.34% with t-statistic = 3.22). This result is consistent with those obtained without the one-week skipping (cf. Table S.IV.26).

Double-sorting tokens by idiosyncratic volatility (IDIOVOL) as the first sorting variable and media coverage as the second sorting variable reveals that, controlling for IDIOVOL, we do not find a statistically significant no-coverage premium before costs in every IDIOVOL tercile. Thus, the media effect and the idiosyncratic volatility effect may be unrelated. Double-sorting tokens by media coverage (as the first sorting variable) and IDIOVOL (as the second sorting variable) reveals that, controlling for media coverage, we also do not find a significant IDIOVOL premium before costs in every IDIOVOL tercile. Therefore, the media effect and the idiosyncratic volatility effect may not be related.

Double-sorting tokens by Amihud's (2002) illiquidity measure (DAMIHUD) as the first sorting variable and media coverage as the second sorting variable reveals that, controlling for illiquidity, there is a statistically significant no-coverage premium before costs among tokens in the middle DAMIHUD tercile (1.57% with t-statistic = 2.07). Double-sorting tokens by media coverage (as the first sorting variable) and DAMIHUD (as the second sorting variable) reveals that, controlling for media coverage, there is a statistically significant high-illiquidity premium before costs among no-coverage tokens (7.06% with t-statistic = 2.76) and an insignificant illiquidity premium among low- or high-coverage tokens. Therefore, the media effect is clearly not subsumed under the liquidity effect in this case. We also use PRCVOL and VOLSCALED as other proxies of liquidity to verify this result.

Double-sorting tokens by PRCVOL as the first sorting variable and media coverage as the second sorting variable reveals that, controlling for illiquidity, there is a statistically significant no-coverage premium before costs among tokens in the low-PRCVOL tercile (7.85% with t-statistic = 2.03). Double-sorting tokens by media coverage (as the first sorting variable) and PRCVOL (as the second sorting variable) suggests that, controlling for media coverage, there is a significant low-illiquidity premium before costs among no- or low-coverage tokens (3.10% with t-statistic = 3.62 and 1.74% with t-statistic = 2.39, respectively) and a significant high-illiquidity premium before costs among high-coverage tokens (1.56% with t-statistic = 2.42). Moreover, double-sorting tokens by VOLSCALED as the first sorting variable and media coverage as the second sorting variable reveals that, controlling for illiquidity, there is a significant no-coverage premium before costs only among least liquid tokens (7% with t-statistic = 2.38). Double-sorting tokens by media coverage (as the first sorting variable) and VOLSCALED (as the second sorting variable) suggests that, controlling for media coverage, there is a significant high-illiquidity premium before costs among no- or low- coverage tokens (3.10% with t-statistic = 3.49 and 2.09% with t-statistic = 2.47, respectively). This is also consistent with the result reported for the case without the one-week skipping.

Double-sorting tokens by Value-at-Risk (VaR) as the first sorting variable and media coverage as the second sorting variable reveals that, controlling for VaR, we do not find a statistically significant no-coverage premium before costs among tokens in every VaR tercile. Double-sorting tokens by media coverage (as the first sorting variable) and VaR (as the second sorting variable) suggests that, controlling for media coverage, there is some high-VaR premium before costs only among no-coverage tokens (2.27% with t-statistic = 1.77). Thus, the media effect is not related to the VaR effect in this case.

Double-sorting tokens by BETA as the first sorting variable and media coverage as the second sorting variable reveals that, controlling for BETA, there is a statistically insignificant no-coverage premium before costs among tokens in every BETA tercile. Double-sorting tokens by media coverage (as the first sorting variable) and BETA (as the second sorting variable) suggests that, controlling for media coverage, we also do not find any significant beta premium before costs in every media coverage-based tercile. This result suggests that the media effect is clearly not subsumed under the BETA effect, which is also consistent with the results obtained earlier.

Table S.IV.25: Media Effect versus other Cryptocurrency Characteristics (Skipping a Week between the Portfolio Formation Week and the Holding Week): All Cryptocurrencies ever listed on CoinMarketCap

This table examines whether the media effect is subsumed under another cryptocurrency characteristic effect. We double-sort tokens by two variables (media coverage and a cryptocurrency characteristic defined in Table S.I.1). We first sort tokens into terciles by the first sorting variable. In each of these terciles, we further sort tokens into three subsamples by the second sorting variable. We then form three sub-portfolios by (i) longing the tokens in the first subsample, or (ii) shorting the tokens in the third subsample, or (iii) simultaneously longing the tokens in the first subsample while shorting the tokens in the third subsample for every first sorting variable except VaR (in this case, the tokens in the first/third subsample are shorted/longed respectively) during the portfolio formation week (the portfolio-forming and rebalancing procedure is described in Table 4 above). All portfolios are equally weighted. Excess returns (in percentage) are computed using the DGTW characteristic-based benchmark methods. All *t*-statistic values (in parentheses) use the Newey-West standard error.

Second sorting var / First sorting var	Long		Short		Long-Short	
	Before trans. cost	After trans. cost	Before trans. cost	After trans. cost	Before trans. cost	After trans. cost
			Double-sort by (AMCAP, Newspaper Coverage)			
0	0.99	−0.62	2.83	−1.93	5.23	−0.90
	(0.61)	(−0.39)	(2.19)	(−1.50)	(3.23)	(−0.56)
1	1.40	−0.35	−0.47	−5.29	0.93	−5.41
	(2.08)	(−0.52)	(−0.83)	(−9.46)	(1.03)	(−6.03)
2	0.38	−1.06	−0.25	−5.01	0.13	−5.97
	(1.16)	(−2.98)	(−1.17)	(−23.21)	(0.60)	(−25.70)
			Double-sort by (Newspaper Coverage, AMCAP)			
0	2.34	0.78	−0.12	−4.88	2.69	−3.62
	(2.70)	(0.93)	(−0.59)	(−24.09)	(3.03)	(−4.17)
1	-0.60	−3.49	−0.12	−4.89	−0.78	−8.44
	(-1.18)	(−6.63)	(−0.50)	(−20.80)	(−1.28)	(−13.81)
2	-3.20	−6.24	−0.23	−4.97	−4.01	−11.77
	(-2.41)	(−4.73)	(−1.78)	(−38.81)	(−2.78)	(−8.25)
			Double-sort by (IDIOVOL, Newspaper Coverage)			
0	0.47	−2.57	0.16	−4.58	3.33	−4.39
	(1.12)	(−6.13)	(0.85)	(−23.73)	(1.72)	(−2.28)
1	-0.00	−3.16	0.34	−4.44	0.51	−7.32
	(-0.01)	(−5.01)	(0.98)	(−12.74)	(0.74)	(−10.76)
2	2.07	−0.66	2.79	−2.08	6.49	−0.98
	(1.31)	(−0.41)	(2.51)	(−1.88)	(2.69)	(−0.40)
			Double-sort by (Newspaper Coverage, IDIOVOL)			
0	0.40	−2.51	−2.35	−7.20	−0.94	−8.39
	(0.99)	(−6.11)	(−1.65)	(−5.05)	(−0.56)	(−5.03)
1	-0.40	−3.92	−0.35	−5.21	−2.13	−10.30
	(-1.11)	(−10.02)	(−0.49)	(−7.27)	(−1.52)	(−7.36)
2	-0.35	−3.18	1.28	−3.58	1.09	−6.36
	(-1.28)	(−11.17)	(1.95)	(−5.50)	(1.62)	(−9.72)
			Double-sort by (DAMIHUD, Newspaper Coverage)			
0	-0.06	−1.76	−0.27	−5.02	−0.34	−6.69
	(-0.15)	(−4.00)	(−1.15)	(−21.64)	(−0.96)	(−17.51)
1	0.22	−1.70	0.94	−3.86	1.52	−5.00
	(0.57)	(−4.65)	(2.04)	(−8.45)	(1.96)	(−6.65)
2	4.37	2.59	1.65	−3.16	8.34	1.97
	(2.01)	(1.18)	(1.16)	(−2.23)	(2.33)	(0.55)
			Double-sort by (Newspaper Coverage, DAMIHUD)			
0	0.17	−1.41	−4.80	−9.55	−4.40	−10.74
	(0.65)	(−4.96)	(−2.89)	(−5.75)	(−2.57)	(−6.21)
1	-0.23	−3.10	−0.14	−4.93	−0.32	−7.98
	(-1.01)	(−11.29)	(−0.24)	(−8.64)	(−0.56)	(−14.15)
2	0.14	−1.58	0.93	−3.88	0.03	−6.49
	(1.03)	(−10.89)	(1.07)	(−4.46)	(0.03)	(−6.53)

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Table S.IV.25 (continued): Media Effect versus other Cryptocurrency Characteristics (Skipping a Week between the Portfolio Formation Week and the Holding Week): All Cryptocurrencies ever listed on CoinMarketCap

Second sorting var / First sorting var	Long		Short		Long-Short	
	Before trans. cost	After trans. cost	Before trans. cost	After trans. cost	Before trans. cost	After trans. cost
	Double-sort by (PRCVOL, Newspaper Coverage)					
0	2.14	0.32	2.12	−2.67	4.18	−2.22
	(1.62)	(0.24)	(1.43)	(−1.80)	(2.04)	(−1.10)
1	0.29	−1.47	1.01	−3.79	1.38	−4.98
	(0.72)	(−3.66)	(2.44)	(−9.18)	(2.51)	(−9.26)
2	0.12	−1.35	0.02	−4.73	0.54	−5.58
	(0.53)	(−5.63)	(0.13)	(−30.27)	(1.20)	(−12.62)
	Double-sort by (Newspaper Coverage, PRCVOL)					
0	2.26	0.53	−0.05	−4.80	2.44	−4.05
	(2.68)	(0.62)	(−0.23)	(−21.36)	(2.77)	(−4.48)
1	0.52	−2.38	0.54	−4.23	1.15	−6.51
	(0.99)	(−4.43)	(2.30)	(−17.98)	(2.07)	(−11.57)
2	-2.23	−5.24	0.03	−4.73	−1.59	−9.35
	(-2.15)	(−5.11)	(0.18)	(−32.66)	(−2.16)	(−12.77)
	Double-sort by (VOLSCALED, Newspaper Coverage)					
0	2.52	0.69	1.78	−3.02	4.36	−2.07
	(1.93)	(0.53)	(1.42)	(−2.41)	(2.15)	(−1.04)
1	-0.27	−2.10	0.53	−4.27	0.88	−5.55
	(-0.54)	(−4.18)	(1.55)	(−12.56)	(1.32)	(−8.48)
2	-0.15	−1.70	0.66	−4.10	0.59	−5.61
	(-0.47)	(−4.59)	(2.44)	(−15.25)	(1.33)	(−13.40)
	Double-sort by (Newspaper Coverage, VOLSCALED)					
0	2.37	0.64	−0.16	−4.87	2.31	−4.13
	(2.59)	(0.69)	(−0.58)	(−17.9)	(2.22)	(−3.88)
1	0.31	−2.57	0.89	−3.86	1.23	−6.39
	(0.67)	(−5.14)	(2.82)	(−12.30)	(2.49)	(−12.22)
2	-1.95	−4.88	0.42	−4.33	−1.02	−8.68
	(-2.15)	(−5.42)	(2.47)	(−25.55)	(−1.59)	(−13.42)
	Double-sort by (VaR, Newspaper Coverage)					
0	0.21	−1.50	0.09	−4.68	0.49	−5.84
	(0.55)	(−3.88)	(0.59)	(−31.83)	(0.93)	(−11.18)
1	-0.14	−2.06	0.77	−4.02	0.65	−5.88
	(-0.36)	(−5.58)	(2.28)	(−11.84)	(1.35)	(−12.50)
2	2.10	0.34	1.52	−3.32	5.22	−1.17
	(2.08)	(0.35)	(1.32)	(−2.90)	(2.65)	(−0.60)
	Double-sort by (Newspaper Coverage, VaR)					
0	2.11	0.38	−0.46	−5.21	1.32	−5.14
	(2.25)	(0.42)	(−0.89)	(−10.17)	(1.17)	(−4.59)
1	-0.47	−3.37	0.48	−4.30	0.78	−6.89
	(-0.85)	(−5.95)	(2.13)	(−19.06)	(1.21)	(−10.18)
2	-1.84	−4.73	0.06	−4.70	−1.42	−9.05
	(-2.00)	(−5.21)	(0.32)	(−25.62)	(−2.08)	(−13.7)
	Double-sort by (BETA, Newspaper Coverage)					
0	2.20	0.54	1.62	−3.17	5.13	−1.13
	(1.78)	(0.44)	(1.89)	(−3.69)	(2.50)	(−0.56)
1	-0.50	−2.24	0.66	−4.12	0.10	−6.25
	(-0.98)	(−4.42)	(2.50)	(−15.49)	(0.22)	(−13.33)
2	0.87	−0.86	0.50	−4.29	2.66	−3.67
	(1.85)	(−1.79)	(1.15)	(−9.89)	(2.26)	(−3.10)
	Double-sort by (Newspaper Coverage, BETA)					
0	1.62	−0.02	−1.20	−5.98	1.13	−5.30
	(1.41)	(−0.02)	(−2.21)	(−11.05)	(0.82)	(−3.94)
1	-0.50	−3.21	−0.04	−4.84	−0.26	−7.77
	(-0.97)	(−5.80)	(−0.12)	(−13.24)	(−0.33)	(−9.54)
2	-1.74	−4.21	0.58	−4.20	−0.79	−8.03
	(-2.21)	(−5.34)	(1.40)	(−10.19)	(−1.31)	(−13.45)

Table S.IV.26: Media Effect versus other Cryptocurrency Characteristics: All Active Cryptocurrencies currently listed on CoinMarketCap

This table examines whether the media effect is subsumed under another cryptocurrency characteristic effect. We double-sort tokens by two variables (media coverage and a cryptocurrency characteristic defined in Table S.I.1). We first sort tokens into terciles by the first sorting variable. In each of these terciles, we further sort tokens into three subsamples by the second sorting variable. We then form three sub-portfolios by (i) longing the tokens in the first subsample, or (ii) shorting the tokens in the third subsample, or (iii) simultaneously longing the tokens in the first subsample while shorting the tokens in the third subsample for every first sorting variable except VaR (in this case, the tokens in the first/third subsample are shorted/longed respectively) during the portfolio formation week (the portfolio-forming and rebalancing procedure is described in Table 4 above). All portfolios are equally weighted. Excess returns (in percentage) are computed using the DGTW characteristic-based benchmark methods. All t-statistic values (in parentheses) use the Newey-West standard error.

Second sorting var / First sorting var	Long		Short		Long-Short	
	Before trans. cost	After trans. cost	Before trans. cost	After trans. cost	Before trans. cost	After trans. cost
Double-sort by (AMCAP, Newspaper Coverage)						
0	1.53	−0.10	0.54	−4.24	2.71	−3.47
	(1.62)	(−0.11)	(1.30)	(−10.25)	(3.08)	(−3.97)
1	2.60	0.69	0.80	−4.02	4.00	−2.53
	(1.95)	(0.51)	(1.11)	(−5.34)	(1.77)	(−1.13)
2	0.59	−0.81	−0.49	−5.25	0.11	−5.93
	(1.95)	(−2.37)	(−2.73)	(−29.46)	(0.48)	(−22.62)
Double-sort by (Newspaper Coverage, AMCAP)						
0	1.86	0.31	−0.15	−4.92	2.07	−4.24
	(2.59)	(0.44)	(−0.73)	(−23.52)	(2.74)	(−5.67)
1	-0.09	−2.99	0.04	−4.73	0.57	−7.09
	(-0.17)	(−4.96)	(0.15)	(−18.7)	(0.77)	(−9.40)
2	-1.25	−4.27	−0.31	−5.06	−1.60	−9.36
	(-1.94)	(−6.55)	(−2.50)	(−40.52)	(−2.36)	(−13.75)
Double-sort by (IDIOVOL, Newspaper Coverage)						
0	0.29	−2.76	−0.26	−5.00	0.16	−7.56
	(0.77)	(−7.09)	(−1.80)	(−35.01)	(0.36)	(−16.97)
1	0.12	−2.98	0.26	−4.51	0.45	−7.32
	(0.21)	(−5.27)	(0.72)	(−12.36)	(0.84)	(−13.61)
2	1.30	−1.42	−3.60	−8.48	−2.07	−9.54
	(0.62)	(−0.68)	(−0.78)	(−1.84)	(−0.31)	(−1.41)
Double-sort by (Newspaper Coverage, IDIOVOL)						
0	0.11	−2.78	−3.59	−8.45	−2.90	−10.34
	(0.37)	(−8.85)	(−2.43)	(−5.71)	(−2.16)	(−7.77)
1	-0.05	−3.57	0.01	−4.86	−1.15	−9.35
	(-0.25)	(−17.07)	(0.01)	(−5.70)	(−0.79)	(−6.44)
2	0.08	−2.80	1.03	−3.82	0.93	−6.57
	(0.52)	(−16.71)	(1.65)	(−6.17)	(1.49)	(−10.75)
Double-sort by (DAMIHUD, Newspaper Coverage)						
0	0.39	−1.29	−0.34	−5.10	0.06	−6.25
	(1.16)	(−3.52)	(−2.18)	(−32.74)	(0.20)	(−18.82)
1	-0.47	−2.63	0.51	−4.29	0.61	−6.14
	(-0.63)	(−3.60)	(1.79)	(−15.11)	(0.99)	(−9.91)
2	2.60	0.87	2.47	−2.34	5.04	−1.29
	(1.70)	(0.57)	(2.17)	(−2.07)	(3.02)	(−0.78)
Double-sort by (Newspaper Coverage, DAMIHUD)						
0	0.05	−1.51	−4.07	−8.84	−3.85	−10.17
	(0.26)	(−6.79)	(−3.18)	(−6.88)	(−2.87)	(−7.63)
1	-0.03	−2.96	−0.66	−5.46	−0.32	−8.03
	(-0.15)	(−10.78)	(−0.62)	(−5.07)	(−0.28)	(−7.11)
2	0.19	−1.49	1.27	−3.54	1.58	−4.89
	(1.43)	(−10.20)	(1.67)	(−4.66)	(2.12)	(−6.31)

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Table S.IV.26 (continued): Media Effect versus other Cryptocurrency Characteristics: All Active Cryptocurrencies currently listed on CoinMarketCap

First sorting var \ Second sorting var	Long		Short		Long-Short	
	Before trans. cost	After trans. cost	Before trans. cost	After trans. cost	Before trans. cost	After trans. cost
Double-sort by (PRCVOL, Newspaper Coverage)						
0	2.64	0.67	−1.53	−6.33	0.36	−6.17
	(1.84)	(0.47)	(−0.72)	(−2.98)	(0.11)	(−1.97)
1	0.19	−1.75	0.45	−4.36	0.62	−5.92
	(0.33)	(−3.00)	(1.20)	(−11.74)	(0.80)	(−7.74)
2	-0.90	−2.38	0.03	−4.73	−0.65	−6.77
	(-1.15)	(−3.07)	(0.19)	(−31.89)	(−1.21)	(−12.71)
Double-sort by (Newspaper Coverage, PRCVOL)						
0	2.69	0.84	0.39	−4.37	3.30	−3.31
	(2.61)	(0.83)	(1.64)	(−18.40)	(3.63)	(−3.71)
1	-0.64	−3.55	0.37	−4.41	1.71	−5.98
	(-0.65)	(−3.61)	(1.02)	(−12.15)	(1.74)	(−6.04)
2	-0.78	−3.79	−0.07	−4.83	−0.93	−8.68
	(-1.22)	(−5.86)	(−0.68)	(−46.68)	(−1.45)	(−13.42)
Double-sort by (VOLSCALED, Newspaper Coverage)						
0	3.38	1.37	0.40	−4.41	4.77	−1.84
	(2.41)	(1.00)	(0.78)	(−8.65)	(3.14)	(−1.24)
1	0.01	−1.93	0.51	−4.29	0.70	−5.86
	(0.01)	(−3.85)	(1.38)	(−11.56)	(1.18)	(−9.91)
2	-0.66	−2.22	0.21	−4.56	−0.13	−6.33
	(-1.31)	(−4.45)	(1.23)	(−26.56)	(−0.39)	(−17.73)
Double-sort by (Newspaper Coverage, VOLSCALED)						
0	2.62	0.78	0.39	−4.36	3.19	−3.38
	(2.52)	(0.77)	(1.32)	(−15.01)	(3.68)	(−3.97)
1	-0.78	−3.67	0.63	−4.12	1.69	−5.95
	(-0.71)	(−3.34)	(1.76)	(−11.48)	(2.07)	(−7.17)
2	-0.70	−3.62	0.18	−4.57	−0.62	−8.28
	(-1.14)	(−5.81)	(1.49)	(−37.64)	(−0.99)	(−13.14)
Double-sort by (VaR, Newspaper Coverage)						
0	0.17	−1.51	−0.00	−4.77	0.42	−5.88
	(0.43)	(−3.61)	(−0.03)	(−27.89)	(0.93)	(−12.69)
1	0.24	−1.62	0.61	−4.20	0.82	−5.65
	(0.67)	(−4.17)	(1.79)	(−12.42)	(1.79)	(−12.45)
2	2.36	0.55	0.23	−4.61	3.48	−2.98
	(1.85)	(0.44)	(0.46)	(−9.30)	(2.26)	(−1.97)
Double-sort by (Newspaper Coverage, VaR)						
0	2.49	0.74	−0.00	−4.75	2.03	−4.47
	(2.24)	(0.68)	(−0.00)	(−12.53)	(1.64)	(−3.62)
1	-1.37	−4.28	0.31	−4.46	0.78	−6.87
	(-1.09)	(−3.39)	(1.48)	(−20.78)	(1.08)	(−9.13)
2	-1.10	−3.98	−0.14	−4.90	−0.67	−8.27
	(-1.87)	(−6.54)	(−0.89)	(−30.53)	(−1.76)	(−20.67)
Double-sort by (BETA, Newspaper Coverage)						
0	2.40	0.73	0.79	−4.00	3.36	−2.89
	(2.00)	(0.62)	(2.13)	(−10.77)	(2.73)	(−2.39)
1	0.01	−1.66	0.11	−4.68	−0.25	−6.53
	(0.03)	(−3.58)	(0.49)	(−21.70)	(−0.34)	(−9.26)
2	0.11	−1.53	0.57	−4.22	0.75	−5.51
	(0.20)	(−2.66)	(1.36)	(−10.03)	(1.25)	(−8.98)
Double-sort by (Newspaper Coverage, BETA)						
0	1.35	−0.31	−1.24	−6.02	−0.55	−6.99
	(1.14)	(−0.26)	(−1.50)	(−7.24)	(−0.30)	(−3.96)
1	-1.85	−4.58	0.46	−4.34	−1.27	−8.80
	(-1.79)	(−4.44)	(0.94)	(−8.83)	(−1.23)	(−8.62)
2	-0.96	−3.45	0.53	−4.26	−0.42	−7.68
	(-1.74)	(−6.25)	(1.40)	(−11.34)	(−1.13)	(−20.75)

Table S.IV.27: Media Effect versus other Cryptocurrency Characteristics (Skipping a Week between the Portfolio Formation Week and the Holding Week): All Active Cryptocurrencies currently listed on CoinMarketCap

This table examines whether the media effect is subsumed under another cryptocurrency characteristic effect. We double-sort tokens by two variables (media coverage and a cryptocurrency characteristic defined in Table S.I.1). We first sort tokens into terciles by the first sorting variable. In each of these terciles, we further sort tokens into three subsamples by the second sorting variable. We then form three sub-portfolios by (i) longing the tokens in the first subsample, or (ii) shorting the tokens in the third subsample, or (iii) simultaneously longing the tokens in the first subsample while shorting the tokens in the third subsample for every first sorting variable except VaR (in this case, the tokens in the first/third subsample are shorted/longed respectively) during the portfolio formation week (the portfolio-forming and rebalancing procedure is described in Table 4 above). All portfolios are equally weighted. Excess returns (in percentage) are computed using the DGTW characteristic-based benchmark methods. All t-statistic values (in parentheses) use the Newey-West standard error.

Second sorting var / First sorting var	Long		Short		Long-Short	
	Before trans. cost	After trans. cost	Before trans. cost	After trans. cost	Before trans. cost	After trans. cost
Double-sort by (AMCAP, Newspaper Coverage)						
0	2.33	0.70	1.65	−3.13	3.83	−2.35
	(2.00)	(0.60)	(2.37)	(−4.50)	(2.54)	(−1.57)
1	-0.63	−2.56	−0.58	−5.41	−0.11	−6.64
	(-0.25)	(−0.99)	(−0.53)	(−4.88)	(−0.04)	(−2.40)
2	0.39	−1.02	−0.35	−5.11	0.06	−5.99
	(1.32)	(−3.15)	(−1.62)	(−23.41)	(0.31)	(−28.09)
Double-sort by (Newspaper Coverage, AMCAP)						
0	1.74	0.20	−0.04	−4.80	2.34	−3.97
	(3.09)	(0.36)	(−0.19)	(−22.65)	(3.22)	(−5.49)
1	-0.44	−3.35	−0.22	−4.99	−0.60	−8.27
	(-0.95)	(−6.64)	(−0.99)	(−21.93)	(−0.98)	(−13.03)
2	-2.63	−5.67	−0.34	−5.10	−3.40	−11.17
	(-2.42)	(−5.29)	(−2.50)	(−36.76)	(−2.94)	(−9.78)
Double-sort by (IDIOVOL, Newspaper Coverage)						
0	0.37	−2.67	0.19	−4.56	2.05	−5.67
	(0.92)	(−6.43)	(1.10)	(−26.41)	(1.62)	(−4.47)
1	-0.89	−4.01	0.34	−4.44	−0.31	−8.09
	(-0.65)	(−2.95)	(0.88)	(−11.55)	(−0.29)	(−7.56)
2	-0.25	−2.98	1.53	−3.34	2.96	−4.51
	(-0.08)	(−0.99)	(1.95)	(−4.27)	(1.40)	(−2.14)
Double-sort by (Newspaper Coverage, IDIOVOL)						
0	0.22	−2.68	−2.72	−7.59	−1.99	−9.44
	(0.65)	(−7.84)	(−2.30)	(−6.39)	(−0.96)	(−4.55)
1	-0.15	−3.67	−0.27	−5.14	−1.12	−9.32
	(-0.67)	(−14.81)	(−0.39)	(−7.48)	(−1.04)	(−8.65)
2	-0.24	−3.13	0.82	−4.03	−0.03	−7.53
	(-0.74)	(−9.24)	(1.74)	(−8.68)	(−0.04)	(−10.57)
Double-sort by (DAMIHUD, Newspaper Coverage)						
0	-0.22	−1.90	0.21	−4.54	0.06	−6.25
	(-0.50)	(−3.93)	(0.65)	(−13.90)	(0.11)	(−11.65)
1	-0.78	−2.96	1.58	−3.23	1.57	−5.19
	(-0.65)	(−2.47)	(2.03)	(−4.16)	(2.07)	(−6.86)
2	2.61	0.88	−0.30	−5.11	3.14	−3.19
	(0.90)	(0.31)	(−0.20)	(−3.38)	(1.04)	(−1.05)
Double-sort by (Newspaper Coverage, DAMIHUD)						
0	-0.17	−1.73	−5.30	−10.07	−7.06	−13.39
	(-0.46)	(−4.57)	(−2.28)	(−4.34)	(−2.76)	(−5.24)
1	-0.21	−3.13	−0.43	−5.23	−1.15	−8.87
	(-0.56)	(−7.68)	(−0.65)	(−7.96)	(−1.38)	(−10.79)
2	0.12	−1.56	0.03	−4.77	−0.20	−6.68
	(0.79)	(−9.66)	(0.04)	(−5.90)	(−0.26)	(−8.89)

Continued on next page

Table S.IV.27 (continued): Media Effect versus other Cryptocurrency Characteristics (Skipping a Week between the Portfolio Formation Week and the Holding Week): All Active Cryptocurrencies currently listed on CoinMarketCap

First sorting var \ Second sorting var	Long		Short		Long-Short	
	Before trans. cost	After trans. cost	Before trans. cost	After trans. cost	Before trans. cost	After trans. cost
Double-sort by (PRCVOL, Newspaper Coverage)						
0	2.97	1.01	1.85	−2.95	7.85	1.31
	(1.43)	(0.49)	(1.41)	(−2.27)	(2.03)	(0.34)
1	-1.31	−3.26	2.09	−2.72	0.77	−5.77
	(-1.51)	(−3.81)	(2.60)	(−3.39)	(1.29)	(−9.42)
2	-0.21	−1.69	−0.01	−4.77	−0.12	−6.24
	(-0.53)	(−4.18)	(−0.04)	(−28.26)	(−0.30)	(−16.24)
Double-sort by (Newspaper Coverage, PRCVOL)						
0	2.15	0.32	0.07	−4.7	3.10	−3.51
	(2.18)	(0.33)	(0.35)	(−23.76)	(3.62)	(−4.10)
1	0.87	−2.06	0.33	−4.45	1.74	−5.96
	(1.31)	(−2.90)	(1.47)	(−19.69)	(2.39)	(−7.80)
2	-2.59	−5.60	−0.01	−4.76	−1.56	−9.32
	(-2.54)	(−5.59)	(−0.06)	(−39.25)	(−2.42)	(−14.65)
Double-sort by (VOLSCALED, Newspaper Coverage)						
0	3.44	1.43	1.31	−3.50	7.00	0.39
	(1.99)	(0.84)	(1.32)	(−3.54)	(2.38)	(0.14)
1	-0.90	−2.86	0.99	−3.81	−0.01	−6.57
	(-1.96)	(−6.21)	(2.34)	(−9.02)	(−0.03)	(−15.06)
2	-0.18	−1.75	0.21	−4.56	0.18	−6.02
	(-0.67)	(−5.84)	(0.98)	(−21.02)	(0.54)	(−18.88)
Double-sort by (Newspaper Coverage, VOLSCALED)						
0	2.03	0.20	0.04	−4.71	3.10	−3.46
	(1.66)	(0.16)	(0.21)	(−22.60)	(3.49)	(−3.91)
1	0.87	−2.02	0.88	−3.88	2.09	−5.55
	(1.38)	(−2.98)	(2.13)	(−9.44)	(2.47)	(−6.34)
2	-2.31	−5.23	0.16	−4.60	−1.10	−8.76
	(-2.27)	(−5.18)	(1.05)	(−29.82)	(−1.72)	(−13.82)
Double-sort by (VaR, Newspaper Coverage)						
0	-0.32	−2.01	0.06	−4.71	−0.23	−6.55
	(-0.75)	(−4.76)	(0.40)	(−33.66)	(−0.56)	(−15.64)
1	0.03	−1.85	0.94	−3.86	0.86	−5.61
	(0.06)	(−3.58)	(2.32)	(−9.32)	(1.46)	(−10.30)
2	2.63	0.80	0.09	−4.76	2.69	−3.79
	(1.95)	(0.60)	(0.08)	(−4.60)	(1.32)	(−1.87)
Double-sort by (Newspaper Coverage, VaR)						
0	2.41	0.64	−0.07	−4.81	2.27	−4.24
	(2.12)	(0.57)	(−0.19)	(−13.92)	(1.77)	(−3.32)
1	-0.19	−3.10	0.48	−4.29	1.24	−6.42
	(-0.31)	(−4.67)	(2.07)	(−18.47)	(1.70)	(−8.19)
2	-0.87	−3.75	0.01	−4.75	0.85	−6.76
	(-1.21)	(−5.35)	(0.05)	(−30.17)	(0.76)	(−6.05)
Double-sort by (BETA, Newspaper Coverage)						
0	0.26	−1.43	1.35	−3.43	2.52	−3.74
	(0.18)	(−1.00)	(2.24)	(−5.71)	(1.65)	(−2.47)
1	0.00	−1.66	0.75	−4.03	0.94	−5.34
	(0.00)	(−3.40)	(2.04)	(−11.01)	(1.88)	(−10.75)
2	-0.84	−2.49	0.71	−4.08	0.61	−5.66
	(-0.62)	(−1.83)	(1.72)	(−9.85)	(0.40)	(−3.68)
Double-sort by (Newspaper Coverage, BETA)						
0	-0.18	−1.85	−0.70	−5.49	−0.17	−6.61
	(-0.12)	(−1.24)	(−0.90)	(−6.96)	(−0.08)	(−3.19)
1	-1.57	−4.30	0.79	−4.01	−1.06	−8.59
	(-1.36)	(−3.71)	(0.97)	(−4.91)	(−1.15)	(−9.28)
2	-1.60	−4.08	0.78	−4.01	−0.72	−7.99
	(-1.93)	(−4.96)	(2.36)	(−12.23)	(−1.26)	(−13.87)

S.V Comparing the Media Effect with Other Cryptocurrency Characteristic-Based Effects: A Robustness Check

In this section, we replicate the analysis [described in Section 6] to verify that (1) the size effect, the volatility effect, the momentum effect, the liquidity effect, the VaR effect, and the media effect are the strongest for cryptocurrencies before accounting for transaction costs; and that (2) a long-only strategy [that longs tokens in the lowest/highest characteristic-based tercile] may profit after accounting for transaction costs while a long-short strategy may not. We conduct this robustness check using (i) all cryptocurrencies while skipping one week between the portfolio formation week and the holding week, and (ii) only active cryptocurrencies.

Robustness Check (i):

Table S.V.28 reports the average returns (and their t-statistics), the average turnovers, and the average transaction costs of the tercile portfolios and the long-short portfolio [that longs tokens in the first/last tercile and shorts tokens in the last/first tercile, as specified in the second column] as well as the average number of tokens per week in each tercile. The average returns on the first tercile portfolio are highest for AMCAP (4.75%), PRCVOL (5.37%), VOLSCALED (5.23%), No. of articles (4.65%), and $r\ 100, 0$ (3.83%) while the average returns on the last tercile portfolio are highest for RETVOL (4.58%), IDIOVOL (4.34%), DAMIHUD (6.66%), and VaR (5.46%). The average returns on the long-short portfolios are highest and statistically significant for AMCAP (3.54% with t-statistic = 4.55), PRCVOL (4.60% with t-statistic = 5.61), VOLSCALED (4.29% with t-statistic = 5.02), RETVOL (3.28% with t-statistic = 5.86), IDIOVOL (3.51% with t-statistic = 4.37), MAXRET (2.66% with t-statistic = 5.18), DAMIHUD (5.67% with t-statistic = 5.46), VaR (4.20% with t-statistic = 5.09), and No. of articles (3.06% with t-statistic = 3.66). We also observe that, for every sorting characteristic other than VaR, the average turnover in the first tercile portfolio (and thus the average transaction cost) are always much lower than in the last tercile portfolio. Moreover, all the long-short strategies based on a cryptocurrency characteristic (including the media-based strategy) are not profitable after accounting for transaction costs. However, the long-only strategies [that long tokens in the first tercile based on AMCAP, PRCVOL, VOLSCALED, No. of articles, or $r\ 100, 0$; or in the last tercile based on RETVOL, MAXRET, DAMIHUD, or VaR] may yield a positive average net-of-costs return. These results are consistent with the findings reported in Table 13.

Robustness Check (ii):

Table S.V.29 reports the average returns (and their t-statistics), the average turnovers, and the average transaction costs of the tercile portfolios and the long-short portfolio [that longs tokens in the first/last tercile and shorts tokens in the last/first tercile, as specified in the second column] as well as the average number of tokens per week in each tercile. The average returns on the first tercile portfolio are highest for AMCAP (5.35%), PRCVOL (5.90%), VOLSCALED (6.29%), No. of articles (4.79%), and $r\ 100, 0$ (4.64%) while the average returns on the last tercile portfolio are highest for RETVOL (5.53%), IDIOVOL (5.97%), MAXRET (5.56%), DAMIHUD (7.25%), VaR (4.68%), and $r\ 8, 0$ (5.40%). The average returns on the long-short portfolios are highest and statistically significant for AMCAP (3.99% with t-statistic = 5.10), PRCVOL (4.80% with t-statistic = 4.78), VOLSCALED (5.21% with t-statistic = 4.76), RETVOL (3.91% with t-statistic = 4.11), MAXRET (3.95% with t-statistic = 4.24), DAMIHUD (5.97% with t-statistic = 5.02), VaR (3.22% with t-statistic = 4.41), and No. of articles (2.95% with t-statistic = 3.82). All the long-short strategies based on a cryptocurrency characteristic (including the media-based strategy) do not withstand transaction costs while the long-only strategies [that long tokens in the first tercile based on AMCAP, PRCVOL, VOLSCALED, No. of articles, or $r\ 100, 0$; or in the last tercile based on RETVOL, IDIOVOL, MAXRET, DAMIHUD, VaR, or $r\ i, 0$ for $i = 1, 2, 3, 4, 8$] may yield a positive average net-of-costs return.

Table S.V.30 reports the same statistics as in Table S.V.29 with one week skipped between the portfolio formation week and the holding week. The average returns on the first tercile portfolio are highest for AMCAP (4.87%), PRCVOL (6.09%), VOLSCALED (5.84%), No. of articles (5.15%), and $r\ 100, 0$ (5.16%) while the average returns on the last tercile portfolio are highest for RETVOL (5.19%), IDIOVOL (6.13%), MAXRET (4.65%), DAMIHUD (8.16%), and VaR (6.25%). The average returns on the long-short portfolios are highest and statistically significant for AMCAP (3.48% with t-statistic = 4.79), PRCVOL (4.95% with t-statistic = 5.55), VOLSCALED (4.48% with t-statistic = 5.11), RETVOL (3.43% with t-statistic = 4.69), MAXRET (2.82% with t-statistic = 5.76), DAMIHUD (6.99% with t-statistic = 4.36), VaR (4.90% with t-statistic = 4.48), and No. of articles (3.15% with t-statistic = 3.36). As noted above, all the long-short strategies based on a cryptocurrency characteristic (including the media-based strategy) do not withstand transaction costs while the long-only strategies [that long tokens in the first tercile based on AMCAP, PRCVOL, VOLSCALED, No. of articles, or $r\ 100, 0$; or in the last tercile based on RETVOL, IDIOVOL, MAXRET, DAMIHUD, VaR, or $r\ i, 0$ for $i = 1, 2$] may yield a positive average net-of-costs return. Once again, these results are consistent with the findings reported in Table 13.

Table S.V.28: Average Weekly Cryptocurrency Returns, Turnovers, and Transaction Costs across Terciles Formed by Sorting Tokens by a Cryptocurrency Characteristic (Skipping a Week between the Portfolio Formation Week and the Holding Week): All Cryptocurrencies ever listed on CoinMarketCap

This table presents average weekly returns, turnovers, and transaction costs for tokens in each of the terciles formed by sorting tokens according to the cryptocurrency characteristics (listed in Table S.I.1) one at a time. For every sorting characteristic (*sort char*), we divide our sample of cryptocurrencies into terciles enumerated as 0, 1, and 2 at the end of the portfolio formation week (for the media coverage, the first tercile consists of tokens with no media coverage while the last tercile consists of tokens with high media coverage with the median being used to divide the covered tokens into low- and high-coverage groups, as described in Table 4). We then compute the average returns of the three tercile portfolios using individual cryptocurrency returns in the holding week. All the portfolios are equally weighted. We also report the average turnovers and transaction costs of the portfolios of tokens in the first (and last) terciles and their long-short (LS) portfolio as well as the average net-of-costs returns of the LS portfolio. Note that a cryptocurrency is included if its market capitalization is at least one million during the portfolio formation week while its name and symbol are mentioned in at least 100 articles throughout the sample period. All the t-statistic values use the Newey-West standard error.

Sort char	Long-short (LS)	Average returns (%)				t-statistics for LS portfolios	Average turnover (%)			Average transaction cost (%)			Average net-of-costs returns for LS portfolios (%)	t-statistics of net-of-costs returns for LS portfolios	Average number of tokens per week		
		0	1	2	LS		0	2	LS	0	2	LS			0	1	2
AMCAP	0-2	4.75	2.28	1.21	3.54	4.55	12.72	98.68	111.46	0.60	4.65	5.25	−1.69	−2.22	160.14	213.06	160.42
PRCVOL	0-2	5.37	1.37	0.77	4.60	5.61	13.26	96.91	110.19	0.63	4.57	5.19	−0.71	−0.88	158.34	211.40	158.85
VOLSCALED	0-2	5.23	1.34	0.94	4.29	5.02	13.05	95.44	108.33	0.62	4.50	5.11	−0.89	−1.06	158.45	211.33	158.81
RETVOL	2-0	1.30	2.10	4.58	3.28	5.86	26.68	76.39	104.88	1.26	3.60	4.94	−1.81	−3.29	160.70	213.17	159.30
IDIOVOL	2-0	0.83	1.44	4.34	3.51	4.37	25.03	78.36	105.06	1.18	3.69	4.95	−1.78	−2.24	125.59	166.23	124.54
MAXRET	2-0	1.38	2.33	4.04	2.66	5.18	30.52	73.90	106.92	1.44	3.48	5.04	−2.56	−5.09	160.68	212.95	159.38
DAMIHUD	2-0	0.98	1.24	6.66	5.67	5.46	8.95	92.92	101.87	0.42	4.38	4.80	0.71	0.69	161.32	213.05	158.79
VaR	2-0	1.26	1.93	5.46	4.20	5.09	94.79	15.43	110.32	4.47	0.73	5.20	−1.04	−1.29	154.38	205.71	154.14
r 1, 0	2-0	2.01	2.15	3.82	1.81	3.38	36.57	68.36	107.62	1.72	3.22	5.07	−3.56	−6.72	160.48	212.89	159.45
r 2, 0	2-0	2.51	1.92	4.04	1.53	1.87	27.71	78.18	107.87	1.31	3.69	5.09	−3.81	−4.68	160.17	212.45	159.12
r 3, 0	2-0	2.25	1.94	3.80	1.55	2.51	23.99	82.17	107.55	1.13	3.87	5.07	−3.78	−6.11	159.67	211.83	158.69
r 4, 0	2-0	2.84	1.76	3.28	0.44	0.79	21.68	84.48	107.37	1.02	3.98	5.06	−4.84	−8.59	159.52	211.73	158.50
r 4, 1	2-0	2.71	2.40	2.68	−0.04	−0.07	25.27	80.73	106.35	1.19	3.81	5.01	−5.16	−10.04	159.52	211.67	158.51
r 8, 0	2-0	2.59	1.69	3.67	1.08	1.59	17.74	88.74	107.22	0.84	4.18	5.05	−4.29	−6.31	157.22	208.56	156.30
r 16, 0	2-0	2.58	1.79	3.54	0.96	1.40	14.96	91.47	106.99	0.71	4.31	5.04	−4.39	−6.38	153.23	203.38	152.31
r 50, 0	0-2	2.49	1.26	2.32	0.17	0.28	12.31	94.53	107.18	0.58	4.46	5.05	−5.02	−8.40	125.87	166.54	124.57
r 100, 0	0-2	3.83	1.79	4.10	−0.27	−0.20	11.53	95.58	107.43	0.54	4.51	5.06	−5.90	−4.24	104.75	138.52	103.76
NPAST52	2-0	2.11	1.09	2.98	0.88	1.49	11.97	91.85	104.37	0.56	4.33	4.92	−4.30	−7.34	123.85	164.26	123.14
BETA	2-0	2.88	0.94	2.54	−0.34	−0.52	10.21	96.62	106.90	0.48	4.56	5.04	−5.65	−8.62	125.73	166.44	124.80
BETA2	2-0	2.09	0.93	3.33	1.24	1.79	9.78	96.55	106.48	0.46	4.55	5.02	−4.12	−5.95	125.74	166.43	124.79
No. of articles	0-2	4.65	2.21	1.60	3.06	3.66	19.67	79.26	103.23	0.93	3.73	4.87	−1.92	−2.31	167.42	191.07	175.13

Table S.V.29: Average Weekly Cryptocurrency Returns, Turnovers, and Transaction Costs across Terciles Formed by Sorting Tokens by a Cryptocurrency Characteristic: All Active Cryptocurrencies currently listed on CoinMarketCap

This table presents average weekly returns, turnovers, and transaction costs for tokens in each of the terciles formed by sorting tokens according to the cryptocurrency characteristics (listed in Table S.I.1) one at a time. For every sorting characteristic (*sort char*), we divide our sample of cryptocurrencies into terciles enumerated as 0, 1, and 2 at the end of the portfolio formation week (for the media coverage, the first tercile consists of tokens with no media coverage while the last tercile consists of tokens with high media coverage with the median being used to divide the covered tokens into low- and high-coverage groups, as described in Table 4). We then compute the average returns of the three tercile portfolios using individual cryptocurrency returns in the holding week. All the portfolios are equally weighted. We also report the average turnovers and transaction costs of the portfolios of tokens in the first (and last) terciles and their long-short (LS) portfolio as well as the average net-of-costs returns of the LS portfolio. Note that a cryptocurrency is included if its market capitalization is at least one million during the portfolio formation week while its name and symbol are mentioned in at least 100 articles throughout the sample period. All the t-statistic values use the Newey-West standard error.

Sort char	Long-short (LS)	Average returns (%)				t-statistics for LS portfolios	Average turnover (%)			Average transaction cost (%)			Average net-of-costs returns for LS portfolios (%)	t-statistics of net-of-costs returns for LS portfolios	Average number of tokens per week		
		0	1	2	LS		0	2	LS	0	2	LS			0	1	2
AMCAP	0-2	5.35	2.87	1.36	3.99	5.10	12.61	98.63	111.28	0.59	4.65	5.25	−1.52	−1.98	167.16	222.58	167.42
PRCVOL	0-2	5.90	1.96	1.10	4.80	4.78	13.54	96.92	110.49	0.64	4.57	5.21	−0.60	−0.61	165.42	220.06	165.69
VOLSCALED	0-2	6.29	1.99	1.08	5.21	4.76	13.59	95.60	109.06	0.64	4.51	5.14	−0.19	−0.18	165.45	220.11	165.60
RETVOL	2-0	1.62	2.26	5.53	3.91	4.11	26.62	76.49	105.09	1.26	3.61	4.95	−1.36	−1.44	167.90	222.53	166.28
IDIOVOL	2-0	1.15	1.63	5.97	4.82	2.48	25.26	78.52	105.55	1.19	3.70	4.98	−0.41	−0.21	138.99	184.03	138.00
MAXRET	2-0	1.60	2.26	5.56	3.95	4.24	30.42	74.16	106.99	1.43	3.50	5.04	−1.41	−1.52	167.81	222.33	166.40
DAMIHUD	2-0	1.28	1.74	7.25	5.97	5.02	9.04	93.07	102.11	0.43	4.39	4.81	0.71	0.60	168.36	222.52	165.83
VaR	2-0	1.46	2.10	4.68	3.22	4.41	94.70	15.42	110.19	4.46	0.73	5.19	−2.14	−2.99	161.75	215.40	161.70
r 1, 0	2-0	2.55	2.34	4.41	1.87	2.15	36.91	68.27	107.98	1.74	3.22	5.09	−3.41	−3.94	167.56	222.33	166.56
r 2, 0	2-0	2.31	2.19	4.35	2.03	3.06	27.84	78.24	108.17	1.31	3.69	5.10	−3.13	−4.77	167.78	222.59	166.76
r 3, 0	2-0	2.65	2.12	4.45	1.79	2.15	24.25	82.13	107.85	1.14	3.87	5.08	−3.42	−4.09	167.30	222.11	166.47
r 4, 0	2-0	2.85	1.95	4.29	1.44	1.61	22.03	84.48	107.93	1.04	3.98	5.09	−3.78	−4.21	166.90	221.48	166.03
r 8, 0	2-0	3.15	1.75	5.40	2.25	1.27	17.92	88.72	107.54	0.84	4.18	5.07	−3.01	−1.70	165.04	219.16	164.26
r 16, 0	2-0	3.37	1.85	2.90	−0.47	−0.78	15.09	91.45	107.15	0.71	4.31	5.05	−5.68	−9.34	159.74	212.32	159.04
r 50, 0	0-2	3.22	1.53	2.26	0.96	1.42	12.39	94.55	107.39	0.58	4.46	5.06	−4.44	−6.60	139.31	184.31	137.91
r 100, 0	0-2	4.64	1.63	1.87	2.77	1.60	11.80	95.14	107.33	0.56	4.49	5.06	−3.10	−1.81	120.72	159.72	119.75
r 4, 1	2-0	3.36	2.21	3.13	−0.24	−0.38	25.60	80.54	106.52	1.21	3.80	5.02	−5.60	−9.00	166.84	221.52	166.00
NPAST52	2-0	2.26	1.56	3.06	0.80	1.44	12.18	91.69	104.54	0.57	4.32	4.93	−4.43	−7.69	137.60	182.45	136.99
BETA	2-0	2.50	1.74	2.97	0.47	0.67	10.09	96.73	106.91	0.48	4.56	5.04	−4.84	−6.95	139.11	184.25	138.16
BETA2	2-0	1.92	1.73	3.60	1.68	2.57	9.65	96.63	106.47	0.45	4.56	5.02	−3.55	−5.44	139.12	184.25	138.16
No. of articles	0-2	4.79	2.47	1.83	2.95	3.82	19.97	79.43	104.07	0.94	3.73	4.91	−2.13	−2.76	185.63	193.65	177.88

Table S.V.30: Average Weekly Cryptocurrency Returns, Turnovers, and Transaction Costs across Terciles Formed by Sorting Tokens by a Cryptocurrency Characteristic (Skipping a Week between the Portfolio Formation Week and the Holding Week): All Active Cryptocurrencies currently listed on CoinMarketCap

This table presents average weekly returns, turnovers, and transaction costs for tokens in each of the terciles formed by sorting tokens according to the cryptocurrency characteristics (listed in Table S.I.1) one at a time. For every sorting characteristic (*sort char*), we divide our sample of cryptocurrencies into terciles enumerated as 0, 1, and 2 at the end of the portfolio formation week (for the media coverage, the first tercile consists of tokens with no media coverage while the last tercile consists of tokens with high media coverage with the median being used to divide the covered tokens into low- and high-coverage groups, as described in Table 4). We then compute the average returns of the three tercile portfolios using individual cryptocurrency returns in the holding week. All the portfolios are equally weighted. We also report the average turnovers and transaction costs of the portfolios of tokens in the first (and last) terciles and their long-short (LS) portfolio as well as the average net-of-costs returns of the LS portfolio. Note that a cryptocurrency is included if its market capitalization is at least one million during the portfolio formation week while its name and symbol are mentioned in at least 100 articles throughout the sample period. All the t-statistic values use the Newey-West standard error.

Sort char	Long-short (LS)	Average returns (%)				t-statistics for LS portfolios	Average turnover (%)			Average transaction cost (%)			Average net-of-costs returns for LS portfolios (%)	t-statistics of net-of-costs returns for LS portfolios	Average number of tokens per week		
		0	1	2	LS		0	2	LS	0	2	LS			0	1	2
AMCAP	0-2	4.87	3.83	1.39	3.48	4.79	12.55	98.65	111.23	0.59	4.65	5.24	−1.91	−2.68	166.98	222.42	167.32
PRCVOL	0-2	6.09	1.75	1.14	4.95	5.55	13.48	96.92	110.44	0.64	4.57	5.21	−0.37	−0.43	165.26	219.94	165.60
VOLSCALED	0-2	5.84	1.74	1.36	4.48	5.11	13.54	95.60	109.01	0.64	4.51	5.14	−0.80	−0.93	165.31	219.98	165.51
RETVOL	2-0	1.76	2.41	5.19	3.43	4.69	26.64	76.53	105.11	1.26	3.61	4.96	−1.82	−2.51	167.79	222.38	166.11
IDIOVOL	2-0	1.12	1.52	6.13	5.01	2.97	25.28	78.55	105.57	1.19	3.70	4.98	−0.25	−0.15	138.76	183.76	137.75
MAXRET	2-0	1.83	2.54	4.65	2.82	5.76	30.44	74.18	107.02	1.44	3.50	5.05	−2.56	−5.30	167.69	222.18	166.25
DAMIHUD	2-0	1.17	1.84	8.16	6.99	4.36	9.05	93.10	102.14	0.43	4.39	4.82	1.93	1.20	168.27	222.37	165.64
VaR	2-0	1.34	2.00	6.25	4.90	4.48	94.69	15.37	110.14	4.46	0.72	5.19	−0.43	−0.39	161.56	215.23	161.58
r 1, 0	2-0	2.55	2.54	4.00	1.45	3.14	36.87	68.28	107.98	1.74	3.22	5.09	−3.88	−8.45	167.42	222.17	166.43
r 2, 0	2-0	3.33	2.25	4.05	0.72	0.93	27.81	78.22	108.13	1.31	3.69	5.10	−4.58	−5.86	167.63	222.44	166.62
r 3, 0	2-0	3.26	2.35	3.73	0.47	0.76	24.20	82.12	107.81	1.14	3.87	5.08	−4.88	−7.91	167.16	221.96	166.32
r 4, 0	2-0	3.66	2.46	3.25	−0.42	−0.74	21.97	84.49	107.89	1.04	3.98	5.09	−5.79	−10.11	166.76	221.33	165.88
r 4, 1	2-0	3.78	2.71	2.92	−0.86	−0.45	25.59	80.61	106.57	1.21	3.80	5.02	−7.67	−3.98	166.70	221.37	165.85
r 8, 0	2-0	3.02	2.28	3.54	0.52	0.80	17.89	88.72	107.51	0.84	4.18	5.07	−4.86	−7.49	164.91	218.99	164.11
r 16, 0	2-0	3.08	2.17	3.37	0.29	0.45	15.04	91.45	107.11	0.71	4.31	5.05	−5.00	−7.75	159.60	212.12	158.87
r 50, 0	0-2	3.10	1.79	2.45	0.65	1.09	12.31	94.56	107.31	0.58	4.46	5.06	−4.53	−7.60	139.08	184.02	137.68
r 100, 0	0-2	5.16	1.65	3.85	1.31	0.52	11.75	95.13	107.28	0.55	4.48	5.06	−5.35	−2.15	120.35	159.24	119.38
NPAST52	2-0	2.40	1.72	3.30	0.90	1.61	12.20	91.82	104.69	0.58	4.33	4.94	−4.29	−7.61	137.35	182.17	136.74
BETA	2-0	3.11	1.54	2.91	−0.20	−0.34	10.10	96.80	107.00	0.48	4.56	5.04	−5.47	−9.52	138.87	183.96	137.94
BETA2	2-0	2.22	1.76	3.39	1.18	1.84	9.66	96.70	106.56	0.46	4.56	5.02	−4.09	−6.42	138.88	183.95	137.94
No. of articles	0-2	5.15	2.59	2.01	3.15	3.36	19.98	79.35	104.08	0.94	3.73	4.91	−1.98	−2.12	184.88	193.82	178.01

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