Peer Co-Movement in Crypto Markets

G. Schwenkler and H. Zheng*

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Abstract

We show that peer linkages induce significant price co-movement in crypto markets in excess of common risk factors and correlated demand shocks. When large abnormal return shocks hit one crypto, its peers experience unusually large abnormal returns of the opposite sign. These effects are primarily concentrated among smaller peers and revert after several weeks, resulting in predictable returns. We develop trading strategies that exploit this reversal, and show that they are profitable even after accounting for trading fees and frictions. We establish our results by identifying crypto peers through co-mentions in online news using novel natural language processing technologies.

Keywords: Cryptocurrencies, peers, co-movement, competition, natural language processing. JEL codes: G12, G14, C82.

*Schwenkler is at the Department of Finance, Santa Clara University Leavey School of Business. Zheng is at the Department of Finance, Boston University Questrom School of Business. Schwenkler is corresponding author. Email: gschwenkler@scu.edu, web: http://www.gustavo-schwenkler.com.

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1 Introduction

Cryptocurrencies are a new asset class that has drawn significant investor capital. By November 2020, there were more than 6,000 cryptocurrencies traded on over 400 exchanges around the globe. The aggregate market cap of cryptocurrencies exceeded $1 trillion in January 2021 with over $150 billion in daily trading volume. There are also close to 100 actively managed funds that currently operate in crypto markets (Bianchi and Babiak (2020)). As cryptocurrencies become more mainstream, an important question for investors is: what drives co-movement across cryptocurrencies? Gaining an understanding of the drivers of crypto co-movement is of key relevance for portfolio construction and risk management in this nascent market.

The literature has posited two channels that explain the co-movement of cryptocurrencies. One channel posits that common risk factors drive the pricing of the cross section of cryptocurrencies; see Liu and Tsyvinski (2020), Liu et al. (2019), and others. Another channel, advocated by Shams (2020), posits that correlated demand shocks among cryptos that are co-listed in an exchange are an additional source of co-variation. In this paper, we propose a third channel: co-movement due to peer linkages. Our results are threefold. First, we show that crypto peers exhibit strong co-movement after accounting for common risk factors and correlated demand shocks. The co-movement we uncover aligns with a competition effect that is also present in traditional financial markets. Second, we show that peer linkages yield return predictability in crypto markets that can be exploited through trading strategies with significant Sharpe ratios. And, third, we propose a natural language processing methodology that identifies peer linkages in crypto markets from co-mentions in online news.

We run event-based difference-in-difference panel regressions to study the co-movement of cryptocurrency peers. We analyze the weekly performance of the 100 largest cryptos by market capitalization between October 1, 2017, and November 30, 2020, and say that a crypto experiences a shock if, during an event week, it experiences a weekly abnormal return (in excess of common risk factors) that falls in the bottom decile of the distribution of abnormal returns across cryptos and time. We identify peer cryptos if they are co-mentioned with a shocked crypto in online news published during an event week using a novel machine learning methodology. We then keep track of shocked, peer, and non-peer cryptos in the weeks surrounding an event. We analyze the total and abnormal returns, total and idiosyncratic volatilities, trading volumes, as well as news and social media activity for all cryptos in our sample in the weeks surrounding an event. Our analysis is based on data collected from Coingecko, CoinAPI, and Cryptocompare. These data sources have recently been employed for the empirical analysis of cryptocurrency markets; see Griffin and Shams (2020), Li et al. (2019), and Lyandres et al. (2019), among others.

Our regressions show that the abnormal returns of shocked and peer cryptos move in opposite directions during an event week. Shocked cryptos record excess abnormal returns of −16% during event weeks. The peers of shocked cryptos record statistically significant excess abnormal returns of 4.5% during event weeks. We find that peer cryptos also experience abnormally large total returns and are more frequently mentioned in online news during event weeks. We establish these measurement while controlling for several characteristics of the cryptos as well as for crypto and industry-date fixed effects. Our results suggest that crypto peers co-move in accordance to what is commonly understood to be a competition effect in traditional financial markets (as opposed to a contagion effect).[1]

Our results are highly robust. They hold after accounting for the market, size, and momentum factors of Liu et al. (2019). Our findings are not explained by co-listing linkages that account for correlated demand shocks as in Shams (2020). We find weaker evidence in support of a competition effect among crypto peers if we consider intra-industry peers rather than news-comentioned peers. This suggests that investors primarily learn from the news about crypto peer linkages. We also find significant albeit weaker evidence in support of a competition effect governing the co-movement of peer cryptos when we consider positive rather than negative abnormal return shocks. A weakened response to positive shocks is consistent with behavioral biases against downside risk (Kahneman and Tversky (1979), Kuhnen (2015), and others).

Next, we show that peer linkages give rise to return predictability in crypto markets. We find that the co-movement we uncover primarily arises when shocks occur that are not infor-

[1]The competition effect among peers implies that prices of peer assets co-move in opposite directions when large shocks hit one asset because investors move their funds away from shocked assets and into similar unaffected assets. Evidence of competition effects in equity and bond markets has been established by Ferris et al. (1997), Hsu et al. (2010), Jorion and Zhang (2007), Slovin et al. (1999), and others. An alternative effect is contagion, which posits that the prices of peer assets co-move in the same direction when large shocks hit because investors extrapolate that peer assets may be experiencing similar shocks as shocked assets (see Gande and Parsley (2005), Lang and Stulz (1992), Li (2017), and Song and Walkling (2000), among others).

mational in nature. That is, peer co-movement is strongest in response to events that are not accompanied by abnormally high news activity, trading volumes, or idiosyncratic volatilities for shocked cryptos. This observation suggests that the co-movement we uncover is not due to a release of pricing-relevant information. Our results imply that peer cryptos are temporarily mispriced. We find that the mispricing is concentrated among peer cryptos with smaller market capitalizations than shocked cryptos. Smaller peers face lower levels of investor attention, which exacerbates mispricing due to a slower processing of information (Hou (2007)). Based on these findings, we conjecture that the prices of smaller peer cryptos must experience reversal in the weeks after an event.

Consistent with our conjecture, we find that it takes more than a month after a shock for the mispricing to vanish. Over this time period, the prices of smaller peer cryptos diffuse down. We build trading strategies that exploit the predictable reversal of performance among smaller peer cryptos. Our strategies short-sell smaller peer cryptos while going long on Bitcoin as a proxy for the market. We keep the positions open for several weeks and account for realistic trading fees.

We find that strategies that keep the positions open between 14 and 18 weeks generate significant alphas of 60 basis point per week without loading on the market, size, or momentum factors. These strategies have annualized Sharpe ratio of around 2 after fees. We find that the predictability among peer cryptos can be attributed to attention constraints. Investors react to large abnormal return shocks by shifting their investments from shocked to peer cryptos, raising the prices of peer cryptos as implied by a competition effect. Then, they slowly process that the shocks do not reveal pricing-relevant information for peer cryptos. They trade to undo the price increases over the span of several weeks, resulting in return predictability. We find that these effects are stronger for cryptos that face trading frictions, such as short-selling constraints. Our results suggest that trading frictions compound the mispricing of smaller peer cryptos, complementing similar results by Hou and Moskowitz (2005) established for equities.

Our findings hinge on how we identify peer linkages in crypto markets. Inspired by the recent approaches of Scherbina and Schlusche (2015) and Schwenkler and Zheng (2019), who document that financial news often reports about economic linkages between firms, we use online news to identify crypto peer linkages. We develop an extension of the natural language processing methodology of Schwenkler and Zheng (2019) to analyze over 200,000 online news articles collected from Cryptocompare. We say that two cryptos are peers if *(i)* they are mentioned in the same sentence of an article, and *(ii)* the sentence describes a competitive relation according to a novel BERT classification model (Devlin et al. (2019)).

Several robustness checks validate our approach. First, we use a subsample of 460 sentences that mention at least two cryptos and we manually assign a label of competition or non-competition depending on whether these sentences clearly describe a competitive relationship.[2] We train our BERT labeling model on this subsample of sentences and estimate its accuracy via cross validation.[3] The resulting model has an out-of-sample accuracy rate of 85%, suggesting that our approach is highly accurate at identifying competitive links in crypto news. We use our few-shot trained model to label the remaining sentences, and hand-check the output to make sure the results are accurate.

Next, we take all possible crypto pairs and build an indicator of whether a given pair was ever labeled as peer in our sample. We find that the likelihood that the peer indicator is positive is significantly higher if the two cryptos have similar ages, Alexa ranks, market betas, or size betas. The link likelihood is also higher if the two cryptos operate in the same industry, if they are co-listed in common exchanges, or if they are similarly popular in online news. These results hold when controlling for characteristics of the two cryptos and the crypto pair, as well as crypto fixed effects. They also hold conditionally in the time series. Our findings suggest that it is more likely that our methodology links two cryptos if they share similar characteristics – that is, if they are peers. These results validate our approach to identify cryptocurrency peers from online news. In a robustness check, we establish similar co-movement when we consider intra-industry peers rather than news co-mentioned peers. We find, however, that co-movement is strongest among news co-mentioned peers, providing further validity for our approach.

This paper is organized as follows. The remainder of this introduction discusses the related literature. Section 2 provides an overview of our data. Section 3 describes the network of cryptocurrencies extracted from our news data and shows that the linkages we identify in the news correspond to peer links. The event-based regressions can be found in Section 4 and Section

[2]The training sample of sentences is available at `www.gustavo-schwenkler.com`.

[3]The model was fitted using a pre-trained BERT model with code from Sanjiv Das.

5 provides robustness analyses. Section 6 studies the return predictability among crypto peers in response to large shocks. Section 7 concludes.

1.1 Related literature

Our paper contributes to three strands of the literature. We primarily contribute to the growing literature on cryptocurrencies. Several papers study the statistical properties of cryptocurrency returns (Griffin and Shams (2020), Li et al. (2019), Liu et al. (2019), and Scaillet et al. (2018)), initial coin offerings (Benedetti and Kostovetsky (2018), Chod and Lyandres (2019), Davydiuk et al. (2020), Gan et al. (2020), Howell et al. (2020), and Lee et al. (2019)), and blockchain-based asset pricing (Cong, He and Li (2020), Cong, Li and Wang (2020*a*), and Pagnotta and Buraschi (2018)). Our paper focuses on the co-movement of cryptocurrencies. We show that peer linkages drive crypto co-movement after controlling for the common risk factors Liu et al. (2019) and the correlated demand channel of Shams (2020).[4] We also establish return predictability in crypto markets due to peer linkages, complementing recent predictability findings by Cong, Li and Wang (2020*b*), Liu and Tsyvinski (2020), and Makarov and Schoar (2020).

We contribute to the literature on return predictability due to economic linkages. In analyzing supply chains, Barrot and Sauvagnat (2016), Cohen and Frazzini (2008), Menzly and Ozbas (2010), and others show that the asset prices of one counterparty slowly incorporate information about shocks that impact the other counterparty. Jorion and Zhang (2009) consider trade credit relationships and show that creditors exhibit persistently depressed returns and inflated CDS spreads in response to the default of a debtor. Boone and Ivanov (2012) and Cao et al. (2016) document return predictability for firms in strategic partnership alliances. Supplementing these prior studies that consider explicit contractual linkages, we find that implicit linkages such as peer relationships can also induce return predictability.[5] Our findings are aligned with the literature on lead-lag relationships in equity markets. Lo and MacKinlay (1990) document that the returns of large stocks lead those of small stocks, and Hou (2007) show that this lead-lag relationship is concentrated among intra-industry peers. Brennan et al. (1993), Chordia and

[4] Our paper is closely related to Shams (2020), who studies whether correlated demand shocks, as proxied by co-listings in common exchanges, yields crypto co-movement. We, on the other hand, study co-movement only in response to large shocks and only among peer cryptos.

[5] Lee et al. (2015) show that peer linkages explain a large fraction of the cross-sectional stock return variation.

Swaminathan (2000), and Parsons et al. (2020) explain the lead-lag relationship with investor inattention, while Hou and Moskowitz (2005) argue that market frictions are the reason for the lead-lag relationship. We find that the predictability among crypto peers is strongest among smaller peers that likely face short-selling constraints. Our results point to trading frictions exacerbating return predictability among peer cryptos, similarly as Boehmer and Wu (2012) and Saffi and Sigurdsson (2011) establish for equity markets.

Finally, we contribute to the literature that studies contagion and competition effects among peer assets. This is a rich literature that has mostly focused on equity and bond markets; see Hsu et al. (2010), Jorion and Zhang (2007), Lang and Stulz (1992), Slovin et al. (1999), Song and Walkling (2000), and others.[6] In contrast to the existing studies, we provide novel evidence of competition effects among peer assets in cryptocurrency markets.

2 Data

We obtain daily data on crypto returns and news as well as defining characteristics of the different cryptos for the time between October 1, 2017, and November 30, 2020. We collect these data from websites called CoinAPI (https://www.coinapi.io), CoinGecko (https://www.coingecko.com/en), and Cryptocompare (http://www.cryptocompare.com). CoinAPI and Cryptocompare are well-known crypto data aggregators that are often used for academic research; see Griffin and Shams (2020), Li et al. (2019), Shams (2020), and others. However, these sources do not provide reliable historical data on prices, market capitalizations, and aggregate trading volumes. We turn to CoinGecko to obtain those data. Data from CoinGecko has been used by Lee et al. (2018), Lee et al. (2019), and Lyandres et al. (2019), among others. Below, we describe in detail how we collect our data.

We construct weekly time series from daily data. Weeks in our data begin on Wednesdays and end on Tuesdays.

[6] There is a large literature that also studies how peers affect corporate policies; see Cao et al. (2019), Dessaint et al. (2018), Foucault and Fresard (2014), and Leary and Roberts (2014), among others. Our results are silent about the behavior of issuers of cryptocurrencies. We only focus on the behavior of market prices.

2.1 Asset-level data

We obtain from Cryptocompare information on characteristics of the different cryptos, such as the maximal number of mineable coins, the date in which content about a crypto asset was first published on Cryptocompare, and the industry classification of the crypto asset according to Cryptocompare.[7] We obtain these data using the Coinlist API. We obtain from CoinAPI data on the date when a crypto asset first started trading on an exchange as well as a list of all exchanges on which cryptos are traded. For each crypto asset and each day in our sample, we keep track of all exchanges on which the asset was traded.

For each crypto asset and day in our sample, we collect end-of-the-day closing prices, market capitalizations, and traded volumes in USD from Coingecko.[8] We compute daily log-returns based on these data, and censor for each crypto the top and bottom one percent daily return realizations as these are likely to be abnormal outliers. Weekly returns and trading volumes are computed as the sum of all available daily log-returns and daily trading volumes of a week. We compute time series of weekly volatilities for all cryptos as the standard deviation of the daily log-returns over the course of a week.

Coingecko also records daily social media following data. For each crypto asset and week in our sample, we collect the number of followers on Twitter and Reddit, respectively, as well as the Alexa rank of the main crypto asset website. We also collect the hourly number of active users, posts, and comments on Reddit for each crypto asset. Finally, we collect from Coingecko some additional characteristics about the different cryptos. We obtain information about whether the crypto asset is a currency or a token. If it is a currency, we obtain the date when the white paper was published. If it is a token, we obtain the start and end dates of the token's initial coin offering (ICO).

We compute the age of a crypto asset as the difference in years between the last day of a week and the earliest date among the following set of dates: 1) The first date in our sample for which Coingecko recorded a closing price, 2) The day when the white paper of a cryptocurrency

[7] We complement Cryptocompare's industry classification with data from Coingecko and Lyandres et al. (2019).

[8] Prices on Coingecko are computed as global value-weighted averages of the last traded prices before midnight GMT on all tracked exchanges. When the last available price in an exchange is not quoted in USD, Coingecko uses exchange rates from https://openexchangerates.org to convert to USD. Market capitalizations are computed as the product of the available supply and the closing price. Volumes are measured in USD and aggregated across exchanges at the end of the day.

was published according to Coingecko, 3) The start date of the ICO for a crypto token according to Coingecko, 4) the end date of the ICO for a crypto token according to Coingecko, 5) the first date on which a crypto asset was traded on an exchange according to CoinAPI, and 6) the date in which content about the crypto asset was first published on Cryptocompare. For a crypto asset that has missing market capitalization in our data, we compute a proxy of its market capitalizations as follows. We first take the product of the end-of-the-day price and the end-of-the-day floating coin supply, and replace the missing market capitalization with this value if available. When not available, we take the product of the end-of-the-day price and the total coin supply. All coins that are left with missing market capitalizations even with these proxies are excluded from our analysis. We also exclude all cryptos that traded at an average price of less than five U.S. cents over the sample horizon, as well as all stablecoins.

Out of the set of cryptos that survive all of these steps, we keep in our analysis only the largest 100 cryptos by average market capitalization throughout the sampling period.[9] These 100 cryptos cover over 95% of the total market capitalization in crypto markets. The final data set that we consider includes 87,827 crypto-week observations.

Table 1 provides summary statistics of the cryptos in our data set. Our data spans a wide cross section of assets, covering large and well-established cryptos, such as Bitcoin and Ethereum, as well as smaller and newer cryptos, such as Sushi (a decentralized finance platform for the trading of crypto assets) and Keep3rV1 (a decentralized task delegation platform). Most of the assets in our data base have a limited supply of coins. A notable exception is Ethereum, which has no hard cap on the number of mineable coins. About half of the assets in our sample went through an ICO. Figure 1 shows a classification of the industries in which our cryptos operate. About one-fourth of the assets in our sample are blockchain-specific applications, one-third provide financial or insurance solutions, and fifteen percent are coins. The remaining cryptos relate to decentralized finance, arts, entertainment, recreation, IT, communication, or wholesale and retail trade applications.

[9] The original data set includes over 4,500 cryptos.

2.2 Risk factors

We follow Liu et al. (2019) and construct market, size, and momentum factors to explain the cross section of cryptocurrency returns. We begin by constructing a value-weighted market index based on the cryptos in our data. We obtain data on the 3-Month Treasury constant maturity rate from the St. Louis Fed's FRED website and use this as a proxy for the risk-free rate after scaling the rate for daily or weekly time horizons. We compute the market factor as the difference between the return of the market index and the risk-free rate. The size factor is the difference between the returns of the bottom and the top equally-weighted quintile portfolios of the market capitalization distribution during that week, in excess of the risk-free rate. For the momentum factor, we follow Jegadeesh and Titman (1993) and sort cryptos into quintiles according to their prior week's returns. The realization of the momentum factor is then computed as the difference between the current week's returns of the top and bottom equally-weighted quintile portfolios, also in excess of the risk-free rate.

Figure 2 shows the cumulative market return and weekly market volatility over our sampling horizon, together with the weekly realizations of the size and momentum factors. It also shows the market-cap-based weights that Bitcoin and Ethereum carry over time in the composition of the market index. We see that our data spans periods in which the market boomed and periods in which the market busted. We also see that our sample covers periods of high aggregate volatility and low aggregate volatility. Bitcoin and Ethereum are key drivers of aggregate performance, composing between 70% and 90% of the total market capitalization in the market.

We estimate factor betas as well as abnormal returns and idiosyncratic volatilities for each of the cryptos in our sample. We take all daily returns available for an asset and regress these on the same-day factor realizations. The estimated regression coefficients are the factor betas and the residuals are the abnormal returns. We compute the weekly idiosyncratic volatility of a crypto asset as the standard deviation of the daily abnormal returns during a given week. Table 1 reports summary statistics of the factor betas, abnormal returns, and idiosyncratic volatilities. We see that there are cryptos, such as LEO Token (a token that can be used to carry out transaction on the Bitfinex exchange), that have low market betas and provide hedges against market fluctuations. There are also cryptos that provide market betas larger than one.

Sushi, a DeFi crypto exchange, is one such crypto asset. Idiosyncratic volatilities can be large, ranging anywhere from 1.8% for RenBTC (a protocol that replicates Bitcoin in the Ethereum network) to over 46% for Sushi.

2.3 News data

We apply machine learning tools to identify cryptos mentioned in news media. For every week in our sampling horizon, we download all news articles available on the Cryptocompare News API. This API provides crypto news articles that are published in a series of online publications. Table 2 lists all the news sources aggregated in the Cryptocompare News API. In order for a news article to appear in the Cryptocompare News API, it needs to include specific keywords that suggest that the article is related to crypto markets. Cryptocompare categorizes news articles that are included in its data based on the keywords that it includes. Table 3 shows the list of news categories and associated keywords that used by the Cryptocompare News API to select which news articles enter its database. We only consider news articles that are written in English. The ultimate news data we use in our analysis includes 200,932 articles.

We apply a variation of the machine learning methodology developed by Schwenkler and Zheng (2019) to extract the names of cryptos in the news data. The methodology of Schwenkler and Zheng (2019) is a three-step methodology that identifies firm names in text data. In a first step, it uses the Stanford coreNLP package in R to identify named organizations in text data. In the second step, it exploits a proprietary machine learning methodology to select the named organizations that are firms and cluster all firm mentions that correspond to the same entity. In a final step, it matches the recognized firms with the firms contained in the CRSP / Compustat universe by using both firm names and tickers. The methodology of Schwenkler and Zheng (2019) is highly accurate, with accuracy rates in the order of 70%. We extend this methodology to identify crypto peers. We only alter the third step of the methodology. We match the recognized cryptos in our news data with those contained in the Coingecko universe. We keep track of the article and sentence identifiers, as well as publishing date for all cryptos recognized in our news data.

We identify 90 cryptos in our news data which are also included in the set of the largest 100 cryptos by market capitalization. These 90 cryptos are mentioned 607,098 times in the news. Summary statistics in Table 1 show that the distribution of crypto mentions in the news is highly skewed. Figure 3 shows that popular cryptocurrencies, such as Bitcoin, are mentioned very frequently in the news. Smaller and lesser known cryptos, such as Civic (a token used in a personal identity verification platform), are rarely mentioned.

We run zero-inflated negative binomial regressions to understand what characteristics drive the frequency with which cryptos are mentioned in the news. Letting m_i denote the number of times crypto i is mentioned in our news data, our regression specifies

$$\mathbb{E}\left[m_i \,|\, X_i\right] = (1-\pi_{i,0})\mu_i \quad \text{and} \quad \mathrm{Var}\left(m_i \,|\, X_i\right) = (1-\pi_{i,0})\left(\mu_i + \frac{1}{\theta}\mu_i^2\right),$$

where $\pi_{i,0} = \frac{e^{b_z' X_i}}{1+e^{b_z' X_i}}$, $\mu_i = e^{b_p' X_i}$, and θ is an over-dispersion parameter. Table 4 reports the estimates of b_p, b_z, and θ. The estimates suggest that the news is more likely to mention cryptos with large market capitalizations and large online following. They also suggest that the news is less likely to report about cryptos that are traded in few exchanges. These findings suggest that news reporting tilts towards well-established cryptos, an empirical fact that is also observed in traditional financial news; see Solomon and Soltes (2012).

3 Crypto peer networks

Following Schwenkler and Zheng (2019), we consider two cryptos to be linked if they are mentioned in the same sentence of a news article.[10] However, to make sure that the two cryptos indeed share a competitive link, we extend the approach of Schwenkler and Zheng (2019) by running all sentences in which at least two cryptos are mentioned through a BERT labeling model. BERT stands for Bidirectional Encoder Representations from Transformers and is a novel natural language processing technology that uses the word surroundings to identify context (Devlin et al. (2019)). We use a BERT model to determine whether a sentence describes a competitive and or a non-competitive relationship. We say that two cryptos that are mentioned in the same sentence of an article are peers if our BERT model classifies that sentence as competitive. We

[10] In analyzing how the news reports about relationships between firms, Schwenkler and Zheng (2019) show that the majority of the economically relevant information about firm linkages is communicated within sentences rather than across sentences. Those findings motivate our approach to identify connected cryptos when they are co-mentioned in the same sentence of a news article.

keep the peer link alive during the week in which the article is published. That is, all peer links are reestablished at the beginning of a week using our BERT model.

The BERT model we use is fitted to a subsample of 460 manually selected sentences that clearly describe either competitive or non-competitive relationships using Amazon AWS tools. The subsample of sentences used for fitting the model is available here. Cross validation of our trained model shows that its out-of-sample accuracy for identifying competitive relationships is 85%, suggesting that the BERT model is highly accurate in identifying peer linkages. Once the model has been fitted to the 460 pre-selected sentences, we use the BERT model to label all remaining sentences in our data. We double-check that the labels are accurate by manually evaluating a subset of the output.

Our methodology identifies 6,221 peer links. Many links are repeatedly identified in the data. In total, we observe 328 unique connections between the 100 cryptos in our sample. Figure 4 shows the resulting network of crypto interconnections extracted from our data. The size of a node in the figure is proportional to the logarithm of the number of times a crypto asset is mentioned in the news. The width of a link is proportional to the logarithm of the number of times a link is identified in the news data. It is visible that the news-implied crypto network has a star architecture, with few large nodes that are highly interconnected in the core and smaller nodes in the periphery.[11] We see that the core of the network consist of the largest cryptos by market capitalization, such as Bitcoin, Ethereum, Ripple, and Binance Coin. These four coins are also the most central nodes according to the centrality measures and the number of links for different cryptos in the network highlighted in Table 5. Consistent with the sheer supremacy of Bitcoin in terms of market capitalization, currently representing close to 70% of the total market capitalization in crypto markets, we observe that Bitcoin is much more frequently mentioned and linked in the news than other cryptos.

3.1 Peer identification

We run several analyses to assess whether we truly identify peer linkages with our approach. We begin by reporting sample sentences in which we identify some of the network links; see Table 6. Many of the sentences establish comparisons across cryptos. Some sentences compare

[11] A star architecture is characteristic of economic networks (Acemoglu et al. (2012)).

their fundamental characteristics. For example, we establish a peer link between Neo and EOS when the news compares their underlying algorithms. Other sentences compare the market performance of different cryptos. For example, we link Bitcoin and Litecoin when the news reports that some market participants perceive Litecoin to be overvalued relative to Bitcoin. The sample sentences of Table 6 suggest that many of the links in the network of Figure 4 correspond to linkages between cryptos with comparable characteristics.

We run logit regressions to dissect what factors drive whether two cryptos are linked in the network of Figure 4. We estimate a logit model of the type

$$\mathbb{P}\left[\text{Cryptos } i \text{ and } j \text{ are linked} \,|\, X_i, X_j, Y_{i,j}\right] = \frac{\mu_{i,j}}{1+\mu_{i,j}} \tag{1}$$

with $\log \mu_{i,j} = a_i + a_j + b_i' X_i + b_j' X_j + b_d' |X_i - X_j| + b_I' I_{i,j}$. Here, X_i and X_j are characteristics of cryptos i and j such as those summarized in Table 1. The term $|X_i - X_j|$ includes component-wise absolute differences of the characteristics of cryptos i and j. We include this term in our regression to assess whether it is more likely to observe a link between cryptos with similar characteristics. The variable $I_{i,j}$ includes indicators that characterize the crypto pair, such as whether one of the peer cryptos is either Bitcoin or Ethereum, whether the two cryptos are in the same industry, or whether they are co-listed in common exchanges. Finally, the parameters a_i and a_j are crypto fixed effects. Our estimates are summarized in Table 7, where the cryptos in a pair are labeled "Crypto i" and "Crypto j" in random order.

The estimates show that it is more likely to observe a link between two cryptos that are popular online (as measured by their Alexa rank) or that are often mentioned in the news. We also find that it is more likely to observe a link between cryptos that have low momentum betas and large trading volumes. These observations provide further evidence of a tilt in news reporting towards established and well-regarded assets, as also documented in Table 4. We find that the likelihood of observing a link between two cryptos is higher if the two cryptos share similar news mentions, ages, market betas, size betas, and Alexa ranks. The link likelihood is also higher if the two cryptos operate in the same industry or if they are co-listed in common exchanges. The results are robust to alternative regression specifications. Our findings suggest that it is more likely to observe a link between cryptos that are similar in terms of their ages, factor exposures, and popularity. They show that we are more likely to establish a peer link between cryptos with comparable characteristics.

Next, we study what factors drive the conditional probability of observing a link between two cryptos over time. For the 328 crypto peer pairs in our data, we construct weekly time series of an indicator $\ell_{i,j,t}$ that takes the value of one when we observe the peer link between cryptos i and j in news published in week t. The link indicator is highly persistent. We have $\mathbb{P}[\ell_{i,j,t} = 0 \,|\, \ell_{i,j,t-1} = 0] = 0.97$ and $\mathbb{P}[\ell_{i,j,t} = 1 \,|\, \ell_{i,j,t-1} = 1] = 0.38$. These measurements suggest that it is unlikely to observe random links among cryptos. However, whether or not the news reports about a link between two cryptos can change from week to week.

We run logit regressions for the weekly link indicators to understand what determines whether we observe a link in a given week. More precisely, we estimate models of the type $\mathbb{P}_t\left[\ell_{i,j,t} = 1\right] = \frac{\mu_{i,j,t}}{1+\mu_{i,j,t}}$ with

$$\log \mu_{i,j,t} = \mathrm{FE}_{i,j,t} + b_\ell' \ell^h_{i,j,t} + b_i' X_{i,t} + b_j' X_{j,t} + b_d' |X_{i,t} - X_{j,t}| + b_I' I_{i,j,t}. \tag{2}$$

Here, $\ell^h_{i,j,t} = (\ell_{i,j,t-1}, \ell_{i,j,t-2})$ is the lag-2 history of the link indicator, and $X_{i,t}$, $X_{j,t}$, $|X_{i,t} - X_{j,t}|$ and $I_{i,j,t}$ are weekly measurements of the same variables defined in Eq. (1). The models include date fixed effects and either crypto fixed effects (in which case $\mathrm{FE}_{i,j,t} = a_i + a_j + a_t$) or link fixed effects ($\mathrm{FE}_{i,j,t} = a_{i,j} + a_t$). Table 8 reports our estimates.

Complementing the findings of Table 7, which indicate that the news is more likely to report about cryptos with similar characteristics, the estimates of Table 8 highlight the persistence of the link indicator. Holding all other regressors constant, the odds of observing a link in a given week are three-times higher if a link was observed in one of the previous two weeks.

4 Event-based analysis

Now that we have established that the network of cryptos extracted from the news is a network of peers, we proceed to analyze co-movement among crypto peers. We run event-based analyses.

4.1 Impulse responses

We begin by visually analyzing the performance of peer cryptos when large abnormal return shocks take place. We consider the distribution of standardized weekly abnormal returns, where we standardize on a rolling basis using the prior 60-day average and standard deviation for each crypto asset. We say that a crypto with standardized weekly abnormal return that falls in the bottom decile of the full-sample distribution is shocked and has experienced a shock event. We take the week in which such a shock is observed as the event week. We identify 380 distinct events, affecting 66 distinct cryptos over 132 distinct weeks. Figure 5 displays the quarterly frequency of events, together with all cryptos that experience shocks in a given a quarter. Events are roughly uniformly distributed over quarters in our sample. We observe the fewest shock events in Q4 2017 when crypto markets were booming (see Figure 2). The highest numbers of shock events are recorded in Q2 2019 and Q3 2020, which were periods of calm gains in crypto markets in which even small abnormal returns may have been perceived as large given the prior history.

We break down the universe of cryptos during an event week into three disjoint groups: A group of cryptos that are shocked, a group of cryptos that are identified as peers of shocked cryptos during the event week (as defined in Section 3), and the remaining non-peer cryptos.[12] We keep track of the weekly performance of the three groups in each of the two weeks before and after an event week. To enable a comparison of performance across cryptos, we standardize all performance measures on a rolling basis at the crypto level using the prior 60-day mean and standard deviation.

Figures 6 through 8 show sample means of different standardized measures of market, news, and social media performance in the weeks surrounding an event week for the sample of shocked, peer, and non-peer cryptos, together with 95% confidence bands and population means in the whole crypto asset universe. We see that shocked cryptos experience unusual negative abnormal and total returns as well as high volatilities during the event week. They also experience elevated trading volume during the event week and the two weeks before an event. These observations confirm that shocked cryptos experience significant shocks during event weeks.

[12]Given that more than one asset may be shocked in an a given week, we orthogonalize the three asset groups by removing from the group of peer assets any asset that has also been shocked during the event week, and removing from the group of non-peer cryptos any that are either shocked or peers during the event week.

Non-peer cryptos do not experience unusual performance in the weeks surrounding an event week, suggesting that these cryptos are not affected by the distress experienced by shocked cryptos. Peer cryptos, on the other hand, do appear to be affected. We find that their abnormal and total returns are unusually high during the event week. Figure 6 suggests that peer cryptos experiences about one-fourth of the shock that hits shocked cryptos, but in the opposite direction. Figure 7 shows that volatilities are also large during and after an event week. This suggests that the uncertainty caused by the shock also affects peer cryptos.

Figure 8 shows several standardized measures of online activity for the different asset groups. We see that peer and shocked cryptos experience more frequent mentions in online news and more commenting activity on Reddit than an average crypto during the event week. The patterns in Figure 8 support an interpretation that a large abnormal return shock triggers a higher production and dissemination of information about shocked and peer cryptos, which results in increased volatilities and significantly large returns for the peer assets.

All in one, Figures 6–8 provide graphical evidence that peer linkages facilitate the spread of shocks across assets. The fact that abnormal returns move in opposite directions for peer and shocked cryptos during an event week point to a competition effect governing the co-movement of peers in cryptocurrency markets.

4.2 Regressions

To rigorously disentangle how large shocks affect crypto peers, we run difference-in-difference panel regressions during the weeks surrounding an event, controlling also for crypto and industry-date interacted fixed effects that account for potential omitted factors. We again standardize all variables to ensure comparability across cryptos.

We regress the weekly abnormal return of an asset on characteristics of the asset, an indicator of whether the asset experienced a shock during the event week, and an indicator of whether the asset was identified as peer of a shocked crypto during an event week.[13] Letting (e, j) denote an event in which crypto j is shocked on week e, we estimate the following panel

[13] More precisely, the peer indicator takes on the value of 1 if a crypto is co-mentioned with a shocked crypto in a sentence of a news article published during the event week, and the sentence is labeled as a describing a competitive relationship according to our BERT model (see Section 3).

model for all cryptos i and window weeks $t \in \{-2, -1, 0, 1, 2\}$:

$$\begin{aligned}\mathbb{E}\big[Y_{i,e+t} \,|\, X_{i,e+t},\, \text{event} = (e,j)\big] &= \text{FE}_{i,t,e,j} + b_X' X_{i,e+t} + b_e \mathbb{1}_{\{t=0\}} + b_a \mathbb{1}_{\{t>0\}} \\ &\quad + b_P \mathbb{1}_{\{i \text{ is peer of } j\}} + b_{P,e} \mathbb{1}_{\{t=0\}} \mathbb{1}_{\{i \text{ is peer of } j\}} + b_{P,a} \mathbb{1}_{\{t>0\}} \mathbb{1}_{\{i \text{ is peer of } j\}} \\ &\quad + b_S \mathbb{1}_{\{i=j\}} + b_{S,e} \mathbb{1}_{\{t=0\}} \mathbb{1}_{\{i=j\}} + b_{S,a} \mathbb{1}_{\{t>0\}} \mathbb{1}_{\{i=j\}}. \qquad (3)\end{aligned}$$

Here, $Y_{i,e+t}$ denotes the standardized abnormal return of crypto i and $X_{i,e+t}$ is a set of contemporaneous and lagged regressors measured in week $e + t$. We include crypto, shocked crypto, and industry-date interacted fixed effects so that $\text{FE}_{i,t,e,j} = a_i + a_j + a_{industry(i),e+t}$. These fixed effects account for omitted variation at the crypto and event levels, as well as omitted industry-wide shocks. Finally, we cluster standard errors by event week and industry.

The coefficients $b_{S,e}$, $b_{S,a}$, $b_{P,e}$, and $b_{P,a}$ capture the excess abnormal return due to being shocked and peer during an event week or in the weeks after an event. We expect these regression coefficients to be statistically significant and large if an asset is impacted by the shock that hits a peer. This should particularly hold during the event week; that is, for $b_{S,e}$ and $b_{P,e}$. The signs of the coefficients are indicative of the kind of effect driving the spread of shocks across peer cryptos. If $b_{S,e}$ and $b_{P,e}$ share the same sign, then this advocates for the contagion effect. In contrast, opposite signs for $b_{S,e}$ and $b_{P,e}$ point to a competition effect.

Table 9 displays the estimates of our regressions. Consistent with Figures 6–8, we find that the peer and shocked cryptos experience large excess abnormal returns during an event week. The excess abnormal return of a shocked crypto during an event week is significantly negative, consistent with a shocked asset experiencing a significant and unanticipated abnormal return shock in that week. In contrast, the excess abnormal return of a peer crypto during an event week is significantly positive. These results hold when controlling for standard predictors and fixed effects. After scaling with the mean and standard deviation of weekly abnormal returns of Table 1, the estimates of Table 9 imply in nominal terms that shocked cryptos showcase excess abnormal returns of around -16% and peer cryptos showcase excess abnormal returns of close to 4.5% during an event week. These estimates are both statistically and economically significant.

To further understand how shocks spread across peer cryptos, we estimate diff-in-diff panel regressions analogous to (3) for the standardized total returns, volatilities, log volume, and log number of news mentions. Table 10 summarizes our findings. We find that shocked cryptos experience elevated trading activity and elevated news reporting in the weeks surrounding event. The news also reports significantly more frequently about peer cryptos during an event week. This elevated reporting activity facilitates information diffusion: We find that the volatilities of all cryptos are elevated during an event week. Ultimately, only peer cryptos benefit from this information dissemination. Table 10 indicates that the total returns of peer cryptos are abnormally high during an event week.

4.3 Informational events

If shocks revealed information that is relevant for the pricing of peer cryptos, then we would expect that the prices of peer cryptos move in the same direction as the prices of shocked cryptos during event weeks. However, our evidence points in the opposite direction. We conclude that our negative abnormal return shocks must not contain pricing-relevant information and the competition effect we uncover is a temporary mispricing of peer assets.

To test whether our conclusion is justified, we study the behavior of peer and shocked cryptos in the weeks surrounding events when controlling for the informational content of a shock. We consider a shock to be informational in nature if, during the event week, the shocked crypto experiences either abnormally frequent news mentions, large trading volume, or large idiosyncratic volatility. More precisely, we say that a shock is informational in nature if the standardized number of news mentions, the standardized log trading volume, or the standardized idiosyncratic volatility of a shocked crypto during an event week falls in the top decile of its full-sample distribution.

We estimate the following extension of Model (3):

$$\begin{aligned}
\mathbb{E}\big[Y_{i,e+t}\,|\,X_{i,e+t},\,\text{event}=(e,j)\big] &= \text{FE}_{i,t,e,j} + b_X' X_{i,e+t} + b_P \mathbb{1}_{\{i \text{ is peer of } j\}} + b_S \mathbb{1}_{\{i=j\}} \\
&+ b_{e,inf}\mathbb{1}_{\{t=0\}}\mathbb{1}_{\{(e,j) \text{ is informational}\}} + b_{e,noninf}\mathbb{1}_{\{t=0\}}\mathbb{1}_{\{(e,j) \text{ is not informational}\}} \\
&+ b_{P,e,inf}\mathbb{1}_{\{t=0\}}\mathbb{1}_{\{i \text{ is peer of } j\}}\mathbb{1}_{\{(e,j) \text{ is informational}\}} + b_{P,e,noninf}\mathbb{1}_{\{t=0\}}\mathbb{1}_{\{i \text{ is peer of } j\}}\mathbb{1}_{\{(e,j) \text{ is not inf.}\}} \\
&+ b_{S,e,inf}\mathbb{1}_{\{t=0\}}\mathbb{1}_{\{i=j\}}\mathbb{1}_{\{(e,j) \text{ is informational}\}} + b_{S,e,noninf}\mathbb{1}_{\{t=0\}}\mathbb{1}_{\{i=j\}}\mathbb{1}_{\{(e,j) \text{ is not informational}\}} \qquad (4)
\end{aligned}$$

for an event week e and window weeks $t \in \{-2, -1, 0\}$. Table 11 reports our estimates.

We find that the excess abnormal performance of peer cryptos during an event week only occurs when events are not informational in nature. We conclude this regardless of whether we determine that a shock is informational in nature by looking at the number of news mentions, the log trading volume, or the idiosyncratic volatility of the shocked crypto during the event week. These results support our conclusion that the co-movement of peer cryptos in response to large abnormal return shocks reflects a temporary mispricing of peer cryptos.

4.4 Size effects

If the peer co-movement we uncover is indeed reflective of mispricing, then prior studies of equity markets tell us that co-movement should be stronger among smaller peers. Lo and MacKinlay (1990) establish that stock returns of large firms lead those of small firms. Brennan et al. (1993), Chordia and Swaminathan (2000), and Parsons et al. (2020) explain the lead-lag relationship with investor inattention: Firms with lower levels of investor attention experience slow information diffusion, which leads to a delayed response to the information that is revealed by unexpected shocks. Hou (2007) show that the lead-lag phenomenon is concentrated among intra-industry peers. Based on these prior results, we analyze whether our results are concentrated among peers with smaller market capitalizations than shocked cryptos.

In Figure 9, we breakdown the standardized abnormal return of peer cryptos according to whether they have larger or smaller market capitalizations than shocked cryptos. We see that the strongest co-movement is exhibited by peers with smaller market capitalizations that shocked cryptos. Consistent with Lo and MacKinlay (1990), Hou (2007), and others, these observations indicate that the crypto co-movement we document is concentrated among smaller peers.

All in one, the results of this section show that peer cryptos experience abnormally positive performance while shocked cryptos experience abnormally negative performance when large abnormal return shocks occur. Our results provide strong evidence in support of a competition effect driving the co-movement of peer cryptos in response to negative shocks. We interpret from our results that crypto peer co-movement in response to large abnormal return shocks is due to a slow diffusion of information among smaller peers. This gives rise to temporary mispricing across peer assets. We exploit this mispricing through trading strategies in Section 6.

5 Robustness

We carry out several experiments to assess the robustness of our findings.

5.1 Alternative links

We investigate whether crypto co-movement after large shocks primarily takes place among the peer linkages we identified from online news. There exist other connections among cryptos that may also yield co-movement. Shams (2020) shows that cryptos that are traded in common exchanges tend to co-move due to correlated demand shocks. Florysiak and Schandlbauer (2019) find large commonalities between the white papers of cryptos that operate in the same industry, which may also drive crypto price co-movement. We therefore study whether same-industry or exchange co-listing linkages subsume our findings.

We run difference-in-difference panel regressions similar to those of Section 4.2 in which we also control for whether a crypto operates in the same industry as a shocked crypto and whether a crypto is co-listed in the same exchange as a shocked crypto. However, we now leave out the two weeks after an event (window weeks $t = 1$ and $t = 2$ in Eq. (3)) given that we found no abnormal performance during those weeks in Section 4.2.

Columns (1) through (3) of Table 12 summarize our results. We find that peer cryptos, as we define them in this paper, exhibit the most statistically and economically significant abnormal price reaction during an event week. Cryptos that operate in the same industry as shocked cryptos also experience significant abnormally positive performance. Their price reaction, however, is much less economically significant than that of peer cryptos. Peer cryptos record an excess abnormal return of around 4.3% during an event week, while same-industry cryptos only record an excess abnormal return of around 0.7%. Cryptos that are co-listed in the same exchanges do not experience significant excess abnormal returns during an event week. These results suggest that the co-movement we have documented primarily runs through peer linkages, such as those we identify from the news or intra-industry connections.

Next, we evaluate whether our results are primarily driven by shocks that affect Bitcoin or Ethereum. These two cryptos command up to 90% of the market capitalization in our market (see Figure 2). They are also among the most frequently identified cryptos in our news data

(Table 5). As a result, shocks that affect Bitcoin or Ethereum may be unique in the way they affect all other cryptos. We re-run our difference-in-difference panel regressions in a subsample of our data in which we exclude all cases in which Bitcoin or Ethereum are shocked to understand whether our effects are primarily driven by the uniqueness of these cryptos. Columns (4) through (6) of Table 12 report our results. We observe similar estimates when we exclude all events in which Bitcoin or Ethereum are shocked, reenforcing our results.

All in one, the results of Table 12 validate our findings. Peer cryptos co-move after large shocks in accordance to a competition effect, and this co-movement occurs most strongly among crypto peers identified from the news.

5.2 Positive shocks

We further investigate the co-movement of peer cryptos after positive shocks. We now consider a crypto to be shocked if its weekly standardized abnormal return falls in the top decile of the distribution across cryptos and time. This approach yields 394 shock events, covering 70 distinct shocked cryptos over 135 distinct weeks. As in Section 4.3, we regress several measures of market performance on characteristics of the cryptos in our sample while controlling for industry, crypto, and time fixed effects. Table 13 summarize our findings.

Our estimates provide evidence that, when positive shocks occur, peer cryptos also react in a way that is consistent with a competition effect. While shocked cryptos experience significantly large and positive abnormal returns during an event week, peer cryptos experience significantly large and negative abnormal returns. In nominal terms, the estimates of Table 13 indicate that shocked and peer cryptos record excess abnormal returns of 16.3% and -3.6% when positive informational shocks take place, respectively. We find that peer cryptos are mentioned more frequently in the news during an event week, and that the volatilities of peer and shocked cryptos are also abnormally large after an event takes place.

All in one, the results of this section show establish co-movement across peer cryptos also in response to positive abnormal return shocks. The co-movement is also consistent with a competition effect that posits that the prices of peer assets co-move in opposite directions. However, co-movement is weaker after positive shocks than after negative shocks. Such an asymmetric response to negative versus positive shocks is consistent with behavioral loss aversion theories (see Kahneman and Tversky (1979), Kuhnen (2015), and others).

6 Trading strategies

Our results suggest that the crypto co-movement we uncover is due to mispricing that arises because of slow information processing among smaller peer cryptos. As a result, our effects should be transient. Investors should eventually realize that abnormal return shocks do not reveal pricing-relevant information about peer cryptos and trade away their abnormal performance. We therefore conjecture that the prices of peer cryptos revert after negative abnormal return shocks.

We evaluate this conjecture in Figure 10, which shows the cumulative returns of peer cryptos in the weeks after a negative abnormal return shock, broken down according to whether a peer has smaller or larger market capitalization than a shocked crypto. Consistent with our conjecture, we see that the returns of smaller peer cryptos are positive during an event week. This positive performance fades away in the weeks after an event. After four weeks, the cumulative returns of smaller peer cryptos are statistically indistinguishable from those of an average crypto in our sample. These observations suggest that the returns of smaller peer cryptos are predictable in the weeks after a large abnormal return shock. That is, when we observe an abnormal return shock, we can predict that the prices of smaller peer cryptos will move downward in the weeks after the shock. Motivated by these observations, we develop event-based trading strategies that exploit this return predictability.

We construct our trading strategies as follows. At the end of any any given week, we compute standardized abnormal returns and say that a crypto is shocked if the observed standardized abnormal return lands in the bottom decile of the at-that-moment historically observed distribution of standardized abnormal returns across time and cryptos.[14] We then collect all cryptos that we identify to be peers of a shocked crypto during the week. We short all peers that have smaller market capitalizations than shocked cryptos in an event week in order to exploit the reversal documented in Figure 10. We also long Bitcoin in the equivalent amount in order to keep the strategy market neutral. We keep our short and long positions open for several weeks.

[14] We base the selection of shocks on the at-the-moment historically observed distribution data rather than the full-sample distribution to avoid forward-looking biases.

The short positions are equally weighted. We assume that shorting occurs on margin at a 1x leverage ratio, with Bitcoin as collateral. Because of this, each week we can only invest a fraction of wealth in new short positions. If we hold the positions open for H weeks, then on any given week we can only invest a fraction of $\frac{1}{H+1}$ of the available wealth into new short positions. We include several fees in our analysis. We take a bid-ask spread of 50 bp, which is a conservative estimate for crypto markets based on prior studies.[15] We also assume that opening a short position costs 2 bp and that maintaining a short position open for a week costs an additional 84 bp. Our estimates are based on the margin fee schedule outlined by Kraken, one of the largest crypto exchanges in the world.[16]

Table 14 summarizes the performance of our trading strategy, where we vary the number of weeks over which we hold the long and short positions open (i.e., the holding period). We find that trading strategies that exploit the reversal of the peer effects we uncover and hold the short positions open for at least 9 weeks generate significant alphas of 40 to 60 bp per week at annualized Sharpe ratios of 1.3 and higher. The strategies that hold the positions open between 14 and 18 weeks achieves the highest Sharpe ratio of around 2 with statistically insignificant market, size, and momentum betas. These trading strategies significantly outperform the crypto market and Bitcoin, which only have annualized Sharpe ratios of 0.53 and 0.73 over the sample period, respectively. Our results show that the mispricing of peer cryptos after large abnormal return shocks is temporary. It takes investors more than 9 weeks to trade away the effects.

6.1 Market frictions

It is surprising that it takes investors several weeks to trade away the peer effects we uncover. However, persistent mispricing across peer assets has also been observed in equity markets. Cohen and Frazzini (2008) show in a supply chain setting the it takes about a year for the stock prices of suppliers to incorporate information about shocks that hit their customers. Hou (2007) documents that the returns of small intra-industry peers adjust slower to industry shocks than large intra-industry peers. Hou and Moskowitz (2005) attribute the slow adjustment process to market frictions. Stocks that are hard to short-sell, illiquid, highly volatile, or less visible

[15] Makarov and Schoar (2020) estimate the average bid-ask spread across crypto exchanges to be 10 bp.

[16] See `https://support.kraken.com/hc/en-us/articles/206161568-What-are-the-fees-for-margin-trading-` for Kraken's margin fee schedule.

should inherently showcase slower information processing. Based on these prior studies, we study whether the crypto peer mispricing we document can be attributed to market frictions.

In Table 15, we report performance metrics for a variant of the event-based trading strategy which short-sell only smaller peers that are available for margin trading on Kraken. Kraken is one of the largest and most liquid crypto exchanges in the world, and it allows for short-selling on margin. Market frictions should therefore be of little relevance for cryptos that are available for margin trading on Kraken.

Table 15 shows that the strategies that are constrained to cryptos with margin trading on Kraken generally have weaker performance metrics. The Sharpe ratios of the constrained strategies are about 25% lower than those of the unconstrained strategies that hold the positions open for the same amount of time. The weekly alphas of the constrained strategies are also 10 to 20 bp lower than those of the unconstrained strategies. The highest Sharpe ratio of the constrained strategy is achieved for shorter holding periods, suggesting that information processing is faster for the cryptos that can be shorted on margin on Kraken. These results suggest that trading frictions exacerbate mispricing across peer cryptos, complementing similar results for equity markets by Boehmer and Wu (2012) and Saffi and Sigurdsson (2011).

Nevertheless, we still find evidence of predictability among the more liquid cryptos that can be shorted on margin on Kraken. This can be observed by the statistical significance of the weekly alphas of the constrained strategies in Table 15. We conclude that trading frictions contribute to the return predictability across peer cryptos, but are not the sole responsible. Given the results of Section 4, which show that there is higher information production and dissemination about peer cryptos during event weeks, we conclude that the predictability we uncover must be due to investor attention constraints. Investor digest only slowly over time that large abnormal return shocks do not reveal pricing-relevant information for peer cryptos. The slow processing of information results in predictable returns.

All in one, the results of this section show that peer linkages induce predictable returns in crypto markets in the weeks after large shocks. Predictability is concentrated among smaller peers that face trading frictions, such as short-selling constraints. Our findings highlight that co-movement among peer cryptos is a transient phenomenon that can be exploited with profitable trading strategies.

7 Conclusion

We document significant co-movement in cryptocurrency markets due to peer linkages. When large abnormal return shocks hit one crypto, peers of that crypto experience unusually large abnormal returns of the opposite sign. This co-movement aligns with a competition effect that is common in traditional financial markets. It vanishes after about 4 weeks and results in predictable returns among peer cryptos. We develop trading strategies that exploit the return predictability we uncover, and show that the strategies are profitable even after accounting for realistic trading fees and frictions. Our results are based on peer linkages identified by co-mentions in online news. We facilitate the identification of crypto peer linkages from news data by implementing novel natural language processing tools. Our results highlight peer linkages as a key channel explaining the co-movement of cryptocurrencies in addition to common risk factors and correlated demand shocks.

References

Acemoglu, Daron, Vasco M. Carvalho, Asuman Ozdaglar and Alireza Tahbaz-Salehi (2012), 'The network origins of aggregate fluctuations', *Econometrica* **80**(5), 1977–2016.

Barrot, Jean-Noël and Julien Sauvagnat (2016), ' Input Specificity and the Propagation of Idiosyncratic Shocks in Production Networks', *The Quarterly Journal of Economics* **131**(3), 1543–1592.

Benedetti, Hugo and Leonard Kostovetsky (2018), Digital tulips? returns to investors in initial coin offerings. WBS Finance Group Research Paper No. 254.

Bianchi, Daniele and Mykola Babiak (2020), On the performance of cryptocurrency funds. Working Paper.

Boehmer, Ekkehart and Juan (Julie) Wu (2012), 'Short Selling and the Price Discovery Process', *The Review of Financial Studies* **26**(2), 287–322.

Boone, Audra L. and Vladimir I. Ivanov (2012), 'Bankruptcy spillover effects on strategic alliance partners', *Journal of Financial Economics* **103**(3), 551–569.

Brennan, Michael J., Narasimhan Jegadeesh and Bhaskaran Swaminathan (1993), 'Investment analysis and the adjustment of stock prices to common information', *The Review of Financial Studies* **6**(4), 799–824.

Cao, Jie, Hao Liang and Xintong Zhan (2019), 'Peer effects of corporate social responsibility', *Management Science* **65**(12), 5487–5503.

Cao, Jie, Tarun Chordia and Chen Lin (2016), 'Alliances and return predictability', *Journal of Financial and Quantitative Analysis* **51**(5), 1689–1717.

Chod, Jiri and Evgeny Lyandres (2019), A theory of icos: Diversification, agency, and information asymmetry. Working Paper.

Chordia, Tarun and Bhaskaran Swaminathan (2000), 'Trading volume and cross-autocorrelations in stock returns', *The Journal of Finance* **55**(2), 913–935.

Cohen, Lauren and Andrea Frazzini (2008), 'Economic links and predictable returns', *The Journal of Finance* **63**(4), 1977–2011.

Cong, Lin William, Ye Li and Neng Wang (2020*a*), Token-based platform finance. Working Paper.

Cong, Lin William, Ye Li and Neng Wang (2020*b*), 'Tokenomics: Dynamic Adoption and Valuation', *The Review of Financial Studies* . Forthcoming.

Cong, Lin William, Zhiguo He and Jiasun Li (2020), 'Decentralized mining in centralized pool', *Review of Financial Studies* . Forthcoming.

Davydiuk, Tetiana, Deeksha Gupta and Samuel Rosen (2020), De-crypto-ing signals in initial coin offerings: Evidence of rational token retention. Working Paper.

Dessaint, Olivier, Thierry Foucault, Laurent Frésard and Adrien Matray (2018), 'Noisy Stock Prices and Corporate Investment', *The Review of Financial Studies* **32**(7), 2625–2672.

Devlin, Jacob, Ming-Wei Chang, Kenton Lee and Kristina Toutanova (2019), 'BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding'.

Ferris, Stephen P., Narayanan Jayaraman and Anil K. Makhija (1997), 'The response of competitors to announcements of bankruptcy: An empirical examination of contagion and competitive effects', *Journal of Corporate Finance* **3**(4), 367 – 395.

Florysiak, David and Alexander Schandlbauer (2019), The information content of ico white papers. Working Paper, University of Southern Denmark.

Foucault, Thierry and Laurent Fresard (2014), 'Learning from peers' stock prices and corporate investment', *Journal of Financial Economics* **111**(3), 554 – 577.

Gan, Rowena J., Gerry Tsoukalas and Serguei Netessine (2020), 'Initial Coin Offerings, Speculators, and Asset Tokenization', *Management Science* . Forthcoming.

Gande, Amar and David C. Parsley (2005), 'News spillovers in the sovereign debt market', *Journal of Financial Economics* **75**(3), 691–734.

Griffin, John M. and Amin Shams (2020), 'Is bitcoin really un-tethered?', *The Journal of Finance* . Forthcoming.

Hou, Kewei (2007), 'Industry Information Diffusion and the Lead-lag Effect in Stock Returns', *The Review of Financial Studies* **20**(4), 1113–1138.

Hou, Kewei and Tobias J. Moskowitz (2005), 'Market Frictions, Price Delay, and the Cross-Section of Expected Returns', *The Review of Financial Studies* **18**(3), 981–1020.

Howell, Sabrina T, Marina Niessner and David Yermack (2020), 'Initial Coin Offerings: Financing Growth with Cryptocurrency Token Sales', *The Review of Financial Studies* . Forthcoming.

Hsu, Hung-Chia, Adam V. Reed and Jörg Rocholl (2010), 'The New Game in Town: Competitive Effects of IPOs', *The Journal of Finance* **65**(2), 495–528.

Jegadeesh, Narasimhan and Sheridan Titman (1993), 'Returns to buying winners and selling losers: Implications for stock market efficiency', *The Journal of Finance* **48**(1), 65–91.

Jorion, Philippe and Gaiyan Zhang (2007), 'Good and bad credit contagion: evidence from credit default swaps', *Journal of Financial Economics* **84**(3), 860–883.

Jorion, Philippe and Gaiyan Zhang (2009), 'Credit contagion from counterparty risk', *The Journal of Finance* **64**(5), 2053–2087.

Kahneman, Daniel and Amos Tversky (1979), 'Prospect theory: An analysis of decision under risk', *Econometrica* **47**(2), 263–291.

Kuhnen, Camelia M. (2015), 'Asymmetric learning from financial information', *The Journal of Finance* **70**(5), 2029–2062.

Lang, Larry and Rene Stulz (1992), 'Contagion and competitive intra-industry effects of bankruptcy announcements', *Journal of Financial Economics* **32**, 45–60.

Leary, Mark T. and Michael R. Roberts (2014), 'Do peer firms affect corporate financial policy?', *The Journal of Finance* **69**(1), 139–178.

Lee, Charles M.C., Paul Ma and Charles C.Y. Wang (2015), 'Search-based peer firms: Aggregating investor perceptions through internet co-searches', *Journal of Financial Economics* **116**(2), 410 – 431.

Lee, David, Li Guo and Yu Wang (2018), Cryptocurrency: A new investment opportunity? Working Paper.

Lee, Jongsub, Tao Li and Donghwa Shin (2019), The wisdom of crowds in fintech: Evidence from initial coin offerings. Working Paper.

Li, Nan (2017), Who are my peers? labor market peer firms through employees' internet co-search patterns. Working Paper.

Li, Tao, Donghwa Shin and Baolian Wang (2019), Cryptocurrency pump-and-dump schemes. Working Paper.

Liu, Yukun and Aleh Tsyvinski (2020), 'Risks and Returns of Cryptocurrency', *The Review of Financial Studies* . Forthcoming.

Liu, Yukun, Aleh Tsyvinski and Xi Wu (2019), Common risk factors in cryptocurrency. NBER Working Paper No. 25882.

Lo, Andrew W. and A. Craig MacKinlay (1990), 'When Are Contrarian Profits Due to Stock Market Overreaction?', *The Review of Financial Studies* **3**(2), 175–205.

Lyandres, Evgeny, Berardino Palazzo and Daniel Rabetti (2019), Do tokens behave like securities? an anatomy of initial coin offerings. Working Paper.

Makarov, Igor and Antoinette Schoar (2020), 'Trading and arbitrage in cryptocurrency markets', *Journal of Financial Economics* **135**(2), 293–319.

Menzly, Lior and Oguzhan Ozbas (2010), 'Market segmentation and cross-predictability of returns', *The Journal of Finance* **65**(4), 1555–1580.

Pagnotta, Emiliano and Andrea Buraschi (2018), An equilibrium valuation of bitcoin and decentralized network assets. Working Paper.

Parsons, Christopher A, Riccardo Sabbatucci and Sheridan Titman (2020), 'Geographic Lead-Lag Effects', *The Review of Financial Studies* . Forthcoming.

Saffi, Pedro A. C. and Kari Sigurdsson (2011), 'Price efficiency and short selling', *The Review of Financial Studies* **24**(3), 821–852.

Scaillet, Olivier, Adrien Treccani and Christopher Trevisan (2018), 'High-Frequency Jump Analysis of the Bitcoin Market', *Journal of Financial Econometrics* .

Scherbina, Anna and Bernd Schlusche (2015), Economic linkages inferred from news stories and the predictability of stock returns. Working Paper.

Schwenkler, Gustavo and Hannan Zheng (2019), The network of firms implied by the news. Working Paper, Boston University.

Shams, Amin (2020), The structure of cryptocurrency returns. Working Paper.

Slovin, Myron B., Marie E. Sushka and John A. Polonchek (1999), 'An analysis of contagion and competitive effects at commercial banks', *Journal of Financial Economics* **54**(2), 197 – 225.

Solomon, David and Eugene Soltes (2012), Managerial control of business press coverage. Working Paper.

Song, Moon H and Ralph A Walkling (2000), 'Abnormal returns to rivals of acquisition targets: A test of the 'acquisition probability hypothesis'', *Journal of Financial Economics* **55**(2), 143 – 171.

	Obs.	Mean	Median	Std dev.	Min.	Max.
Age (years)	100	3.62	3.42	1.92	0.09 (Keep3rV1)	11.92 (Bitcoin)
Market capitalization (million USD)	100	2550.96	147.39	15261.61	18.20 (OriginTrail)	148738.18 (Bitcoin)
Had ICO indicator	100	0.40	0.00	0.49	0.00 (Bitcoin)	1.00 (Ethereum)
Maximum mineable coin supply (million units)	90	104271.82	381.57	948366.19	0.01 (RenBTC)	9000000.00 (Compound Coin)
Daily circulating coin supply (million units)	45	2328.35	282.81	9442.56	1.00 (Maker)	57152.92 (Crypto.com Coin)
Average weekly return	100	−0.35%	−0.15%	3.18%	−18.37% (Filecoin)	7.66% (UMA)
Average weekly volatility	100	15.05%	13.91%	5.70%	4.04% (LEO Token)	49.27% (Sushi)
Number of listing exchanges	100	51.83	34.50	55.84	1.00 (Blockstack)	293.00 (Bitcoin)
Average daily trading volume (million USD)	100	237.05	9.27	1148.50	0.19 (Terra)	10538.99 (Bitcoin)
Twitter followers per day (x 10^3)	98	98.50	48.76	150.40	2.33 (Monacoin)	896.06 (Binance Coin)
Reddit subscribers per day (x 10^3)	79	40.13	6.81	132.61	0.03 (SingularityNET)	1080.58 (Bitcoin)
Hourly number of active users on Reddit (x 10^3)	79	0.90	0.78	0.99	0.00 (NuCypher)	7.19 (Bitcoin)
Hourly number of posts on Reddit	100	0.40	0.11	0.76	0.00 (Sushi)	4.76 (Bitcoin)
Hourly number of comments on Reddit	100	8.70	0.57	32.14	0.00 (Sushi)	294.01 (Bitcoin)
Daily Alexa rank (x 10^3)	100	394.36	198.04	639.96	1.29 (Binance Coin)	5359.90 (NEAR)
Market beta	100	1.00	1.04	0.23	0.11 (LEO Token)	1.49 (Sushi)
Size beta	100	0.44	0.34	0.58	−0.33 (Bitcoin Cash)	4.03 (Hegic)
Momentum beta	100	−0.13	−0.13	0.19	−1.41 (Keep3rV1)	0.86 (Hegic)
Average weekly abnormal return	100	0.01%	0.01%	1.03%	−5.16% (Filecoin)	7.57% (Hegic)
Average weekly idiosyncratic volatility	100	11.86%	10.64%	5.89%	1.82% (RenBTC)	46.50% (Sushi)
Average number of mentions per week in news	100	8.41	0.70	33.91	0.00 (Keep3rV1)	287.04 (Bitcoin)

Table 1: Summary statistics of the characteristics of the cryptos in our data. Our sample includes 100 distinct cryptos and spans the time period between October 1, 2017, and November 30, 2020. The above statistics are time series moments over crypto lifetimes that overlapped with our sample. The data are obtained from CoinAPI, CoinGecko, and Cryptocompare. Market betas, abnormal returns, and idiosyncratic variances are the results of asset-level factor regressions; see Section 2.2. The cryptos in parentheses give samples of the assets that achieve the minimum and maximum for each variable.

99bitcoins	AMB Crypto	Bitcoin Magazine	Bitcoin.com
Bitcoinerx	Bitcoinist	Blokt	CCN
Chaindd	Chaintimes	CoinDesk	CoinGape
CoinJoker	Coinnounce	CoinSpeaker	CoinTelegraph
Cointelligence	CriptoNoticias	Crypto Briefing	Crypto CoreMedia
Crypto Potato	Crypto Watch	CryptoCompare	CryptoGlobe
CryptoInsider	CryptoNewsReview	CryptoNewsZ	Cryptopolitan
CryptoSlate	CryptoVest	Decrypt	DiarioBitcoin
EspacioBit	Ethereum World News	ETHNews.com	Finance Magnates
Live Bitcoin News	NewsBTC	NullTx	The Daily Hodl
TheBlock	TimesNext	TrustNodes	Yahoo Finance Bitcoin

Table 2: News sources aggregated on the Cryptocompare News API.

Category	Keywords
ADA	ADA, CARDANO
Altcoin	ALTCOIN, ALTCOINS
Asia	ASIA, CHINA, KOREA, JAPAN, HONG, SINGAPORE, TAIWAN
BCH	BCH, BITCOINCASH
	(must include "BITCOIN CASH")
Blockchain	BLOCKCHAIN, PROTOCOL, SCALING
BTC	BTC, BITCOIN, SATOSHI
	(exclude if "BITCOIN CASH" appears)
Business	BUSINESS, INVESTOR, INVESTORS, REVENUE, PROFIT,
	ENTERPRISE, COMMERCE, STOCK
Commodity	COMMODITIES, OIL, OIL-BACKED
DASH	DASH, DIGITALCASH
ETC	ETC, ETHEREUMCLASSIC
	(exclude if "ETHEREUM CLASSIC" appears)
ETH	ETH, ETHEREUM, VITALIK, FOUNDATION
	(exclude if "ETHEREUM CLASSIC" appears)
Exchange	EXCHANGE, BITFINEX, POLONIEX, BINANCE
Fiat	FIAT, RESERVE, GOLD, GOLD-BACKED, BANK,
	DOLLAR, POUND, EURO, YEN
ICO	ICOS, ICO, OFFERING, TOKEN, TOKENS, RAISE, RAISED
LTC	LTC, LITECOIN
Market	MARKET, MARKETS, ANALYSIS, INDEX, PRICES
Mining	MINING, HASHRATE, HASHING, POOLS, REWARD
Regulation	REGULATION, LEGAL, LAW, TAX, TAXES, SENATE,
	LEGISLATION, PRESIDENT, TREASURY, SEC, BOE
Sponsored	SPONSORED, FEATURED, PRESS RELEASE, PRESS RELEASES
Trading	TECHNICAL, TRADING, FUNDAMENTALS, PRICE, BULL,
	BEAR, BULLISH, BEARISH, RALLY
Technology	SOFTWARE, TECHNOLOGY, TECH
TRX	TRX, TRONIX
USDT	USDT, TETHER
Wallet	LEDGER, TREZOR, KEEPKEY, COINOMI,
	JAXX, MYETHERWALLET
XMR	XMR, MONERO
XRP	XRP, RIPPLE
XTZ	XTZ, TEZOZ
ZEC	ZEC, ZCASH

Table 3: News categories and associated keywords for the news data available on the Cryptocompare News API. For a news article to be included in the Cryptocompare News API, it needs to have been published in one of the sources listed in Table 2 and include at least one of the keywords listed in this table. Cryptocompare categorizes news articles as highlighted above depending on their keywords.

		(1)	(2)	(3)	(4)
Count model (b_p)	Intercept	*** −10.053	−0.825	*** 8.861	−0.422
		(−7.345)	(−0.551)	(3.308)	(−0.106)
	Log market capitalization	*** 0.898			* 0.454
		(11.217)			(2.538)
	Age	−0.056			−0.139
		(−0.672)			(−1.358)
	Log weekly volume		*** 0.509		0.040
			(4.852)		(0.276)
	Weekly return		5.830		2.423
			(1.559)		(0.519)
	Weekly volatility		** −4.635		−0.912
			(−2.659)		(−0.404)
	$\lvert\beta_{\text{market}} - 1\rvert$		−1.246		−1.232
			(−1.696)		(−1.522)
	# Exchanges		0.005		0.009
			(1.172)		(1.598)
	Log Twitter followers			*** 0.657	0.106
				(5.335)	(0.878)
	Log Alexa rank			*** −0.713	* −0.236
				(−5.304)	(−2.181)
Zero-inflation model (b_z)	Intercept	* 15.692	2.034	4.610	5.976
		(2.027)	(0.376)	(0.634)	(0.269)
	Log market capitalization	* −0.933			−0.598
		(−2.135)			(−0.437)
	Age	−0.252			−0.287
		(−0.975)			(−0.621)
	Log weekly volume		−0.026		−0.029
			(−0.070)		(−0.050)
	Weekly return		9.938		2.721
			(0.728)		(0.106)
	Weekly volatility		−1.590		−4.701
			(−0.236)		(−0.512)
	$\lvert\beta_{\text{market}} - 1\rvert$		0.199		−0.127
			(0.093)		(−0.046)
	# Exchanges		* −0.240		* −0.260
			(−2.574)		(−2.262)
	Log Twitter followers			−0.533	0.562
				(−1.388)	(0.813)
	Log Alexa rank			−0.110	0.222
				(−0.310)	(0.389)
Number of cryptos		100	100	97	97
Over-dispersion parameter ($\log\theta$)		−0.090	−0.142	−0.517	0.109

Table 4: Zero-inflated negative binomial regressions of the number of times a crypto asset is identified in the news data. All characteristics are measured as averages across weekly observations in the data; see Table 1 for summary statistics. "# Exchanges" counts the number of exchanges on which a crypto asset is traded. "Log shape parameter" is the logarithm of the estimated shape parameter of the negative binomial distribution. The values in parentheses give the z-values of the different estimates. ***, **, and * denote significance at the 99.9%, 99%, and 95% confidence levels, respectively.

		# Mentions	# Links	HC	EVC
Top 10 (# mentions)	BTC	207329	13598	0.017	0.280
	ETH	88456	9131	0.018	0.247
	XRP	86254	3690	0.015	0.083
	BNB	50009	4158	0.017	0.075
	BCH	38797	4464	0.013	0.124
	BSV	12095	822	0.012	0.016
	LTC	10787	1246	0.012	0.030
	ADA	9184	822	0.013	0.012
	XLM	8947	1002	0.013	0.011
	DASH	8943	514	0.013	0.006
Bottom 10 (# mentions)	ARDR	40	1	0.007	0.000
	TRAC	32	0	0.000	0.000
	MLN	27	2	0.009	0.000
	DCR	22	2	0.009	0.000
	RLC	20	2	0.009	0.000
	MAID	18	5	0.009	0.000
	NRG	17	1	0.007	0.000
	GLM	14	2	0.009	0.000
	MATH	11	0	0.000	0.000
	STRAX	7	0	0.000	0.000

Table 5: Number of mentions in the news, number of links, and eigenvalue and harmonic centrality scores for the 10 most and least frequently mentioned cryptos in our data. "HC" stands for harmonic centrality and "EVC" stands for eigenvector centrality. Both centrality scores are normalized to sum up to one across the 100 cryptos in our sample. The harmonic centrality of node i is given by $\sum_{j \neq i} \frac{1}{d_{i,j}}$, where $d_{i,j}$ is the length of the shortest path that connects nodes i and j, and $\frac{1}{d_{i,j}} = 0$ if no path exists between i and j. If $A = (a_{i,j})$ is the adjacency matrix of a network so that $a_{i,j} = 1$ if there exists at least one link between nodes i and j, then the eigenvector centrality of node i is given by the i-th entry of the eigenvector that corresponds to the largest eigenvalue of A.

Link	Sample sentence
(IOTA, Mobius)	*“Among companies that aim at using Blockchain to disrupt the app market are Mobius, ChainLink, and IOTA”*
(Bitcoin, Qtum)	*“The Bitcoin and Ethereum alternative, QTUM, recently completed its main net upgrade on Binance, allowing users to have access to coins .”*
(Bitcoin, Ethereum)	*“Unless BTC faces its scalability issues, he said, the next five years will see ETH surge.”*
(Ethereum, Stellar Lumens)	*“While NEM, NEO, Waves, and Stellar attracted a lot of attention in 2017, no other blockchain platform managed to rival Ethereum.”*
(Ethereum, Neo)	*“The rally was led by NEO, the “Chinese Ethereum”, a network that has lagged in development compared to other blockchains, and hardly hosts any distributed apps.”*
(Bitcoin, XRP)	*“He continues, adding that BTC is expensive and XRP is designed for global cross border payments because it is cheap and settlement is almost instantaneous: ‘There is basically no value for Bitcoin.”’*
(Dash, Maker)	*“There are now several functional DAOs for cryptocurrencies such as Digix, Dash (DASH) , or Maker (MKR).”*
(Bitcoin, Litecoin)	*“In fact, Mike Novogratz, the head of Galaxy Digital, recently explained that LTC is overvalued and that investors should buy BTC instead.”*
(Ethereum, XRP)	*“Additionally, UK ’s Financial Conduct Authority analogized XRP to ETH, which it recognized as a hybrid utility / exchange token, not a security token.”*
(EOS, Neo)	*“Shin has a good point here, although we do have cryptocurrencies that use more energy-efficient algorithms, such as NEO, which use a ‘Proof-of-Stake’ (PoS) algorithm, and EOS, which uses a ‘Delegated Proof-of-Work’ (DPoS) algorithm.”*

Table 6: Sample sentences in which we identify links between two cryptos.

		(1)	(2)	(3)	(4)	(5)
Intercept		*** −18.295	*** −18.125	*** −19.466	*** −18.440	*** −19.446
		(−75.841)	(−79.159)	(−56.972)	(−68.526)	(−50.333)
Crypto i (b_i)	News mentions	*** 11.945	*** 8.383	*** 7.924	*** 10.771	*** 6.972
		(9.160)	(6.550)	(6.201)	(10.182)	(6.472)
	Age	*** 0.506	** 0.385	* 0.350	*** 0.531	0.306
		(3.720)	(2.860)	(2.384)	(4.159)	(1.828)
	Log market cap.		*** 0.680			0.469
			(3.937)			(1.250)
	Log weekly volume			* 0.529		0.377
				(2.335)		(1.534)
	Weekly return			0.574		0.372
				(1.834)		(1.251)
	Weekly volatility			−0.576		−0.569
				(−1.084)		(−1.124)
	$\lvert\beta_{\text{market}} - 1\rvert$			0.328		0.161
				(1.490)		(0.681)
	β_{size}			−0.128		0.264
				(−0.283)		(0.501)
	β_{momentum}			** −1.042		** −1.162
				(−2.868)		(−3.287)
	Log Alexa rank				* −0.320	−0.276
					(−2.091)	(−1.518)
Crypto j (b_j)	News mentions	*** 12.699	*** 9.042	*** 8.325	*** 11.365	*** 7.343
		(9.219)	(6.784)	(6.486)	(9.991)	(6.618)
	Age	* 0.378	0.255	0.148	** 0.463	0.221
		(2.452)	(1.700)	(0.893)	(2.978)	(1.225)
	Log market cap.		*** 0.488			0.111
			(4.742)			(0.436)
	Log weekly volume			*** 0.773		** 0.643
				(5.225)		(3.324)
	Weekly return			* 0.490		0.268
				(2.551)		(1.678)
	Weekly volatility			* −0.925		−0.478
				(−2.421)		(−1.195)
	$\lvert\beta_{\text{market}} - 1\rvert$			−0.022		−0.162
				(−0.146)		(−0.846)
	β_{size}			* 0.742		0.535
				(2.305)		(1.466)
	β_{momentum}			*** −0.882		*** −1.008
				(−3.479)		(−3.899)
	Log Alexa rank				*** −0.492	*** −0.570
					(−5.538)	(−5.451)
Absolute differences (b_d)	News mentions	*** −15.414	*** −10.657	*** −10.005	*** −13.767	*** −8.876
		(−8.616)	(−6.251)	(−5.886)	(−9.374)	(−6.178)
	Age	*** −1.093	*** −1.061	*** −1.000	*** −1.180	*** −1.000
		(−7.894)	(−7.774)	(−6.752)	(−7.929)	(−6.003)
	Log market cap.		*** −0.445			−0.178
			(−3.493)			(−1.107)
	Log weekly volume			0.018		0.169
				(0.119)		(1.030)
	Weekly return			−0.324		−0.074
				(−1.247)		(−0.376)
	Weekly volatility			−0.443		−0.392
				(−1.026)		(−0.766)
	β_{market}			* −0.437		* −0.460
				(−2.385)		(−2.270)
	β_{size}			*** −1.359		*** −1.317
				(−3.950)		(−3.788)
	β_{momentum}			−0.106		−0.215
				(−0.314)		(−0.669)
	Log Alexa rank				*** −0.487	** −0.366
					(−4.267)	(−3.164)
Indicators (b_I)	Links Bitcoin	*** −2.738	** −2.081	* −1.839	*** −2.515	−1.087
		(−3.761)	(−2.648)	(−1.997)	(−3.638)	(−1.350)
	Links Ethereum	0.073	0.227	−0.405	0.125	−0.193
		(0.196)	(0.573)	(−0.735)	(0.323)	(−0.355)
	Same industry	*** 0.902	*** 0.775	*** 0.678	*** 0.881	** 0.689
		(5.053)	(4.065)	(3.508)	(4.595)	(3.393)
	Co-listing	*** 14.462	*** 14.056	*** 14.243	*** 14.318	*** 14.017
		(56.100)	(54.406)	(39.952)	(50.710)	(35.013)

Table 7: Logit regressions of the probability that a pair of cryptos is linked in the news. Eq. (1) describes the regression specification. Cryptos in a pair are labeled "Crypto i" and "Crypto j" at random. All characteristics are measured as time series averages at the crypto level; see Table 1 for summary statistics. We standardize all regressors (except the indicators) with their cross-sectional means and standard deviations. The indicator "Links Bitcoin" ("Links Ethereum") is equal to 1 is one of the two cryptos is Bitcoin (Ethereum). The indicator "Same industry" is 1 is both cryptos are in the same industry (see Figure 1). The indicator "Co-listing" is 1 if the two cryptos are traded on common exchanges. All regressions include crypto fixed effects and assume that the distribution of link indicators is overdispersed. Standard errors are based on sandwich estimators clustered at the crypto level. The values in parentheses give t-statistics. ***, **, and * denote significance on the 99.9%, 99%, and 95% confidence levels, respectively.

		(1)	(2)	(3)	(4)	(5)	(6)
	Intercept	*** −12.937	*** −11.959	*** −18.602	*** −13.175	*** −11.789	*** −18.090
		(−12.260)	(−8.076)	(−10.066)	(−11.594)	(−7.337)	(−9.677)
LI (b_ℓ)	Lag 1	*** 1.425	*** 1.427	*** 1.055	*** 1.390	*** 1.397	*** 1.047
		(11.767)	(11.430)	(9.011)	(11.518)	(11.273)	(8.923)
	Lag 2	*** 1.213	*** 1.185	*** 0.833	*** 1.192	*** 1.195	** 0.854
		(8.344)	(8.039)	(6.187)	(8.116)	(8.089)	(5.945)
Crypto i (b_i)	News mentions	*** 0.001	*** 0.001	*** 0.003	*** 0.002	*** 0.002	** 0.003
		(5.196)	(4.675)	(4.326)	(8.500)	(8.202)	(4.982)
	Log market cap.	0.099	0.094	−0.025	0.110	0.093	−0.612
		(1.597)	(1.547)	(−0.358)	(1.609)	(1.376)	(−1.622)
	Log weekly volume	0.093	0.100	0.075	0.186	0.161	0.224
		(1.771)	(1.960)	(1.445)	(1.511)	(1.286)	(2.084)
	Weekly return	0.298	0.230	0.160	0.296	0.147	0.153
		(0.994)	(0.728)	(0.443)	(0.784)	(0.356)	(0.350)
	Weekly volatility	0.356	0.483	0.620	−0.077	0.461	1.164
		(0.459)	(0.603)	(0.743)	(−0.085)	(0.482)	(1.425)
	Log Alexa rank		−0.035	−0.054		0.208	−0.145
			(−0.811)	(−1.145)		(0.388)	(−0.300)
Crypto j (b_j)	News mentions	** 0.001	*** 0.001	*** 0.003	** 0.001	* 0.001	** 0.003
		(3.130)	(3.333)	(4.836)	(2.639)	(2.450)	(5.506)
	Log market cap.	* 0.131	0.093	0.109	* 0.150	0.095	0.073
		(2.462)	(1.643)	(1.620)	(2.463)	(1.450)	(0.197)
	Log weekly volume	*** 0.133	*** 0.158	0.027	0.153	0.158	0.148
		(3.506)	(3.793)	(0.520)	(1.392)	(1.462)	(1.373)
	Weekly return	0.509	0.646	** 0.703	0.326	0.507	0.460
		(1.654)	(1.886)	(2.789)	(0.877)	(1.219)	(1.644)
	Weekly volatility	0.862	0.775	0.696	0.670	0.502	−0.074
		(1.158)	(0.974)	(0.963)	(0.780)	(0.527)	(−0.077)
	Log Alexa rank		−0.028	0.026		−0.012	0.098
			(−0.649)	(0.411)		(−0.015)	(0.157)
Absolute differences (b_d)	News mentions			** −0.002			** −0.002
				(−3.471)			(−3.860)
	Age			−0.055			−0.096
				(−0.424)			(−0.708)
	Log market cap.			* −0.148			−0.148
				(−2.105)			(−2.024)
	Log weekly volume			* −0.109			−0.103
				(−2.313)			(−1.949)
	Weekly return			−0.026			−0.358
				(−0.055)			(−0.558)
	Weekly volatility			0.497			0.493
				(0.361)			(0.374)
	β_{market}			0.628			0.724
				(1.089)			(1.087)
	β_{size}			−0.318			−0.343
				(−0.703)			(−0.699)
	β_{momentum}			−2.011			−1.935
				(−1.752)			(−1.720)
	Log Alexa rank			0.010			−0.000
				(0.198)			(−0.004)
Indicators (b_I)	Links Bitcoin			* 0.889			* 0.982
				(2.531)			(2.861)
	Links Ethereum			* 0.742			* 0.702
				(2.761)			(2.581)
	Same industry			*** 0.648			** 0.670
				(3.972)			(4.163)
	Co-listing			*** 11.654			*** 11.801
				(16.798)			(15.524)
	Includes lagged regressors?	N	N	N	Y	Y	Y
	Fixed effects	Link, Date	Link, Date	Crypto, Date	Link, Date	Link, Date	Crypto, Date
	Crypto-week obs.	22350	21120	21120	16506	15164	18015
	Link obs.	1351	2583	1302	1302	1014	1067
	Unique crypto pairs	315	314	314	302	302	313
	Unique cryptos	59	58	58	51	51	58

Table 8: Logit regressions of the indicator that a crypto link is observed in the news in a given week. Eq. (2) describes the regression specification. Cryptos in a pair are labeled "Crypto i" and "Crypto j" at random and the order in a pair is kept fixed over time. Table 1 provides summary statistics for all regressors. We remove the top and bottom 1% cross-sectional observations for each time series prior to running the regressions to ensure robustness. The panel "LI" gives the regression coefficients for the lagged link indicator; all other panels are described in the caption of Table 7. All regressions include fixed effects and assume that the distribution of link indicators is overdispersed. Some regressions include one and two-week lagged observations of the regressors. Clustered standard errors are based on sandwich estimators. The values in parentheses give t-statistics. ***, **, and * denote significance on the 99.9%, 99%, and 95% confidence levels, respectively.

			(1)	(2)	(3)
b_X	IR	Lag 1	−0.030	−0.029	−0.030
			(−1.953)	(−1.939)	(−1.943)
		Lag 2	−0.009	−0.008	−0.009
			(−0.614)	(−0.596)	(−0.603)
	Vol.	Lag 0	0.050	0.050	0.050
			(2.334)	(2.333)	(2.331)
		Lag 1	0.015	0.015	0.015
			(0.775)	(0.752)	(0.753)
		Lag 2	0.023	0.022	0.022
			(1.435)	(1.419)	(1.418)
	Idio. vol.	Lag 0	*** 0.189	*** 0.189	*** 0.189
			(9.207)	(9.233)	(9.229)
		Lag 1	* −0.037	* −0.037	* −0.037
			(−3.413)	(−3.347)	(−3.342)
		Lag 2	0.006	0.006	0.006
			(0.314)	(0.310)	(0.312)
	Log volume	Lag 0	*** 0.248	*** 0.247	*** 0.247
			(17.618)	(17.885)	(17.889)
		Lag 1	*** −0.222	*** −0.220	*** −0.220
			(−13.892)	(−13.898)	(−13.899)
		Lag 2	* −0.036	* −0.036	* −0.036
			(−2.628)	(−2.607)	(−2.610)
	MC	Lag 0	** −0.137	** −0.135	** −0.135
			(−5.358)	(−5.283)	(−5.282)
b_e				** −0.014	** −0.013
				(−3.833)	(−3.613)
b_a					0.002
					(1.339)
b_P				0.001	−0.002
				(0.302)	(−0.093)
b_S				0.019	0.045
				(0.445)	(1.029)
$b_{P,e}$				*** 0.375	*** 0.378
				(7.183)	(6.480)
$b_{P,a}$					0.007
					(0.178)
$b_{S,e}$				*** −1.339	*** −1.365
				(−22.383)	(−23.035)
$b_{S,a}$					−0.054
					(−1.498)
Crypto-week obs.			8240	8240	8240
Adjusted R^2			0.103	0.108	0.108

Table 9: Difference-in-difference panel regressions of abnormal returns in the weeks surrounding a large negative abnormal return shock. We estimate the model in Eq. (3). All regressions include crypto, shocked crypto, and industry-date fixed effects. All regressors except the indicators and log market capitalization are standardized. We standardize a time series at the crypto-level using the mean and standard deviation in the 60-day window prior to any given week. We remove the top and bottom 1% cross-sectional observations for each time series prior to running the regressions to ensure robustness. "IR" stands for abnormal return, "Vol." for total volatility, "Idio. vol." for idiosyncratic volatility, and "MC" for log market capitalization. Standard errors are clustered by event week and industry. The values in parentheses give t-statistics. ***, **, and * denote significance on the 99.9%, 99%, and 95% confidence levels, respectively.

			Return	Vol.	Log volume	News
b_X	News	Lag 1				** 0.125
						(4.561)
		Lag 2				* 0.048
						(2.836)
	Return	Lag 0		0.032	* 0.103	* −0.045
				(0.736)	(3.124)	(−2.399)
		Lag 1	−0.024	0.108	* 0.091	−0.029
			(−1.776)	(1.676)	(3.396)	(−1.872)
		Lag 2	−0.008	−0.002	−0.019	0.014
			(−0.731)	(−0.056)	(−1.397)	(0.802)
	IR	Lag 0		*** 0.185	0.052	0.048
				(5.413)	(2.049)	(2.087)
		Lag 1		−0.061	0.007	** 0.038
				(−1.171)	(0.332)	(5.268)
		Lag 2		0.019	0.012	−0.012
				(0.536)	(0.968)	(−0.795)
	Vol.	Lag 0	0.037		0.040	−0.008
			(2.340)		(2.360)	(−0.872)
		Lag 1	0.005	*** 0.107	* −0.024	−0.011
			(0.242)	(8.633)	(−2.677)	(−0.623)
		Lag 2	0.001	* 0.028	−0.012	0.003
			(0.058)	(3.445)	(−1.176)	(0.304)
	Idio. vol.	Lag 0	*** 0.143		*** 0.146	*** 0.058
			(9.000)		(9.867)	(8.230)
		Lag 1	* −0.031		** −0.033	* 0.022
			(−2.785)		(−4.073)	(3.047)
		Lag 2	0.014		−0.003	−0.002
			(0.851)		(−0.206)	(−0.310)
	Log volume	Lag 0	*** 0.209	*** 0.307		** 0.067
			(12.001)	(11.602)		(5.126)
		Lag 1	*** −0.196	*** −0.132	*** 0.581	−0.013
			(−13.168)	(−14.329)	(29.160)	(−0.803)
		Lag 2	−0.026	* −0.047	** 0.056	−0.009
			(−2.085)	(−2.704)	(3.724)	(−1.186)
	MC	Lag 0	*** −0.129	−0.030	** 0.046	0.049
			(−6.671)	(−1.660)	(3.891)	(1.837)
b_e			−0.003	* 0.014	−0.000	0.005
			(−1.129)	(3.131)	(−0.054)	(1.202)
b_a			0.004	0.005	* −0.003	* 0.005
			(1.795)	(1.144)	(−2.609)	(2.704)
b_P			−0.018	−0.006	0.012	0.015
			(−1.197)	(−0.280)	(0.592)	(0.648)
b_S			0.061	−0.020	*** 0.082	** 0.088
			(2.187)	(−0.574)	(8.020)	(5.087)
$b_{P,e}$			*** 0.241	−0.008	0.038	* 0.074
			(7.193)	(−0.233)	(0.822)	(3.298)
$b_{P,a}$			0.029	0.039	−0.031	* −0.085
			(1.428)	(1.341)	(−1.851)	(−3.327)
$b_{S,e}$			*** −0.945	*** 0.321	0.064	0.087
			(−10.588)	(5.594)	(2.069)	(1.702)
$b_{S,a}$			* −0.092	0.081	−0.046	*** −0.119
			(−3.411)	(1.706)	(−1.604)	(−5.598)
Crypto-week obs.			10007	10116	9816	9298
Adjusted R^2			0.132	0.123	0.456	0.034

Table 10: Difference-in-difference panel regressions of total returns, volatility, log trading volume, and the log number of mentions in the news in the weeks surrounding a large negative abnormal return shock. We estimate models of the type (3). All regressions include crypto, shocked crypto, and industry-date interacted fixed effects. All regressors except the indicators and log market capitalization are standardized at the crypto-level using the rolling prior 60-day means and variances. We remove the top and bottom 1% cross-sectional observations for each time series prior to running the regressions to ensure robustness. "AR" stands for the autoregressive coefficients, "Ret." for total return, "Idio. ret." for abnormal return, "Vol." for total volatility, "Idio. vol." for idiosyncratic volatility, "MC" for log market capitalization, "ALV" for abnormal log trading volume, and "News" stands for standardized log news mentions. Standard errors are clustered by event week and industry. The values in parentheses give t-statistics. ***, **, and * denote significance on the 99.9%, 99%, and 95% confidence levels, respectively.

			Criterion to identify informational events		
			Log mentions	Log volume	Idio. vol.
b_X	IR	Lag 1	−0.025	−0.024	−0.025
			(−1.988)	(−1.857)	(−1.885)
		Lag 2	−0.007	−0.007	−0.007
			(−0.494)	(−0.571)	(−0.535)
	Vol.	Lag 0	0.046	0.043	0.043
			(2.152)	(1.927)	(1.976)
		Lag 1	0.007	0.008	0.007
			(0.338)	(0.402)	(0.349)
		Lag 2	0.022	0.018	0.019
			(1.212)	(1.051)	(1.083)
	Idio. vol.	Lag 0	*** 0.185	*** 0.186	*** 0.187
			(9.012)	(8.610)	(8.911)
		Lag 1	* −0.035	* −0.038	* −0.036
			(−2.755)	(−2.996)	(−2.767)
		Lag 2	0.013	0.015	0.014
			(0.542)	(0.621)	(0.593)
	Log volume	Lag 0	*** 0.261	*** 0.263	*** 0.262
			(16.623)	(15.000)	(15.501)
		Lag 1	*** −0.223	*** −0.222	*** −0.225
			(−12.418)	(−12.951)	(−13.502)
		Lag 2	* −0.040	* −0.042	* −0.040
			(−2.448)	(−2.554)	(−2.573)
	MC	Lag 0	*** −0.136	*** −0.134	*** −0.137
			(−5.691)	(−5.685)	(−5.524)
b_P			0.023	0.013	0.016
			(1.546)	(0.646)	(0.921)
b_S			0.042	0.047	0.051
			(0.969)	(1.321)	(1.355)
$b_{e,inf}$			−0.004	−0.006	** −0.022
			(−1.751)	(−1.515)	(−3.525)
$b_{e,noninf}$			* −0.013	* −0.012	* −0.010
			(−3.127)	(−3.396)	(−3.040)
$b_{P,e,inf}$			0.272	0.201	0.139
			(1.733)	(0.831)	(1.879)
$b_{P,e,noninf}$			*** 0.358	** 0.397	*** 0.434
			(6.068)	(5.260)	(6.330)
$b_{S,e,inf}$			*** −1.820	*** −1.678	*** −1.939
			(−10.960)	(−12.785)	(−8.618)
$b_{S,e,noninf}$			*** −1.260	*** −1.336	*** −1.277
			(−23.624)	(−27.878)	(−22.819)
Crypto-week obs.			8240	9641	9641
Number of events			264	277	277
Number of informational events			45	26	39
Adjusted R^2			0.134	0.134	0.135

Table 11: Difference-in-difference panel regressions of abnormal returns a large negative abnormal return shock that is informational in nature. We brake down the study according to how we determine whether an event is informational, which is when either the standardized weekly log mentions in the news, the standardized log trading volume, or the standardized idiosyncratic volatility of a shocked crypto lands in the top decile of the corresponding historical distribution across cryptos and time. We estimate models of the type (4). All regressions include crypto, shocked crypto, and industry-date interacted fixed effects. All regressors except the indicators and log market capitalization are standardized at the crypto-level using the rolling prior 60-day means and variances. We remove the top and bottom 1% cross-sectional observations for each time series prior to running the regressions to ensure robustness. “IR” stands for abnormal return, “Vol.” for total volatility, “Idio. vol.” for idiosyncratic volatility, and “MC” for log market capitalization. Standard errors are clustered by event week and industry. The values in parentheses give t-statistics. ***, **, and * denote significance on the 99.9%, 99%, and 95% confidence levels, respectively.

			(1)	(2)	(3)	(4)	(5)	(6)
			Whole sample			Excluding BTC or ETH events		
b_X	IR	Lag 1	−0.024	0.007	−0.024	−0.026	−0.026	−0.026
			(−1.826)	(0.338)	(−1.709)	(−2.054)	(−1.844)	(−1.849)
		Lag 2	−0.007	0.005	−0.007	−0.010	−0.010	−0.010
			(−0.587)	(0.247)	(−0.522)	(−0.735)	(−0.638)	(−0.636)
	Vol.	Lag 0	0.043	0.002	0.043	0.046	0.046	0.046
			(1.973)	(0.057)	(1.886)	(2.021)	(1.929)	(1.928)
		Lag 1	0.007	* 0.065	0.007	0.008	0.008	0.008
			(0.366)	(3.010)	(0.363)	(0.376)	(0.368)	(0.367)
		Lag 2	0.020	* 0.066	0.020	0.020	0.020	0.020
			(1.151)	(3.275)	(1.103)	(1.181)	(1.142)	(1.137)
	Idio. vol.	Lag 0	*** 0.187	** 0.142	*** 0.187	*** 0.184	*** 0.184	*** 0.184
			(8.936)	(4.213)	(8.604)	(9.254)	(8.747)	(8.779)
		Lag 1	* −0.037	** −0.061	* −0.037	* −0.040	* −0.040	* −0.040
			(−2.903)	(−4.158)	(−2.635)	(−3.101)	(−2.916)	(−2.915)
		Lag 2	0.014	0.001	0.014	0.014	0.014	0.014
			(0.609)	(0.029)	(0.595)	(0.612)	(0.595)	(0.594)
	Log volume	Lag 0	*** 0.261	*** 0.262	*** 0.261	*** 0.261	*** 0.261	*** 0.261
			(15.502)	(15.733)	(15.205)	(16.852)	(16.416)	(16.450)
		Lag 1	*** −0.224	*** −0.227	*** −0.224	*** −0.224	*** −0.224	*** −0.224
			(−13.182)	(−10.363)	(−12.366)	(−11.937)	(−11.119)	(−11.160)
		Lag 2	* −0.040	* −0.058	* −0.040	−0.038	−0.038	−0.038
			(−2.544)	(−2.884)	(−2.396)	(−2.087)	(−1.930)	(−1.933)
	MC	Lag 0	*** −0.135	** −0.094	** −0.135	*** −0.140	*** −0.141	*** −0.141
			(−5.562)	(−5.284)	(−5.332)	(−5.864)	(−5.616)	(−5.578)
b_e			** −0.025	−0.127	0.038	** −0.023	0.050	0.038
			(−5.088)	(−2.292)	(0.845)	(−4.930)	(1.013)	(0.829)
$b_{industry}$			0.001		0.000	−0.002		−0.003
			(0.339)		(0.081)	(−0.857)		(−0.831)
$b_{colisted}$				−0.023	0.030		0.034	0.034
				(−0.599)	(0.679)		(0.749)	(0.766)
b_P			0.015	−0.040	0.014	0.044	0.042	0.043
			(0.682)	(−1.475)	(0.592)	(1.595)	(1.473)	(1.538)
b_S			0.050	0.025	0.078	* 0.100	* 0.132	* 0.132
			(1.151)	(0.338)	(1.368)	(2.482)	(2.766)	(2.780)
$b_{industry,e}$			*** 0.060		*** 0.062	*** 0.062		*** 0.063
			(13.973)		(11.517)	(18.913)		(13.696)
$b_{colisted,e}$				−0.147	−0.068		−0.064	−0.066
				(−1.828)	(−1.347)		(−1.180)	(−1.282)
$b_{P,e}$			*** 0.364	** 0.511	*** 0.368	** 0.323	** 0.344	** 0.327
			(6.556)	(5.295)	(6.836)	(3.678)	(3.856)	(3.776)
$b_{S,e}$			*** −1.349	*** −1.621	*** −1.412	*** −1.328	*** −1.407	*** −1.389
			(−22.001)	(−20.340)	(−23.510)	(−17.002)	(−17.763)	(−17.875)
Crypto-week obs.			9642	9642	9642	9580	9580	9580
Adjusted R^2			0.135	0.119	0.135	0.133	0.133	0.133

Table 12: Difference-in-difference panel regressions of abnormal returns in the weeks surrounding a negative abnormal return shock, controlling for alternative implicit linkages across across cryptos. We estimate extensions of the model in Eq. (3) that include controls for whether two cryptos are colisted on the same exchange (subscript "*colisted*") and whether two cryptos operate in the same industry (subscript "*industry*"). All regressions include crypto, shocked crypto, and industry-date interacted fixed effects. All regressors except the indicators and log market capitalization are standardized at the crypto-level using the rolling prior 60-day means and variances. We remove the top and bottom 1% cross-sectional observations for each time series prior to running the regressions to ensure robustness. "IR" stands for abnormal return, "Vol." for total volatility, "Idio. vol." for idiosyncratic volatility, and "MC" for log market capitalization. Standard errors are clustered by event week and industry. The values in parentheses give t-statistics. ***, **, and * denote significance on the 99.9%, 99%, and 95% confidence levels, respectively.

			IR	Vol.	Log volume	News
b_X	News	Lag 1				*** 0.107
						(7.159)
		Lag 2				* 0.041
						(2.425)
	Return	Lag 0		0.022	* 0.100	−0.029
				(0.499)	(2.584)	(−1.810)
		Lag 1		0.107	* 0.079	−0.023
				(1.487)	(3.480)	(−0.989)
		Lag 2		0.081	−0.002	** 0.036
				(1.872)	(−0.302)	(4.180)
	IR	Lag 0		*** 0.193	0.049	0.032
				(5.826)	(1.739)	(1.566)
		Lag 1	−0.035	−0.062	0.019	0.032
			(−1.925)	(−1.066)	(1.047)	(2.164)
		Lag 2	−0.002	−0.045	0.007	*** −0.033
			(−0.163)	(−1.177)	(1.085)	(−19.787)
	Vol.	Lag 0	0.031		* 0.038	−0.004
			(1.808)		(2.453)	(−1.169)
		Lag 1	0.007	*** 0.109	−0.017	−0.013
			(0.613)	(9.479)	(−1.285)	(−0.942)
		Lag 2	0.009	** 0.036	−0.004	** 0.021
			(0.689)	(3.636)	(−0.384)	(3.562)
	Idio. vol.	Lag 0	*** 0.212		*** 0.164	*** 0.057
			(8.825)		(17.911)	(9.547)
		Lag 1	−0.028		** −0.049	*** 0.029
			(−2.271)		(−4.711)	(9.239)
		Lag 2	0.001		−0.006	* −0.015
			(0.101)		(−0.554)	(−3.415)
	Log volume	Lag 0	*** 0.220	*** 0.314		*** 0.082
			(12.565)	(11.868)		(7.148)
		Lag 1	*** −0.202	*** −0.133	*** 0.572	−0.021
			(−13.949)	(−8.401)	(36.145)	(−1.464)
		Lag 2	** −0.035	* −0.044	** 0.059	−0.005
			(−4.493)	(−2.965)	(4.544)	(−0.797)
	MC	Lag 0	** −0.129	* −0.050	** 0.055	0.049
			(−4.184)	(−2.769)	(3.827)	(2.154)
b_e			−0.001	−0.002	0.002	−0.001
			(−0.248)	(−0.576)	(1.196)	(−0.425)
b_a			−0.002	−0.000	** 0.005	0.001
			(−0.995)	(−0.164)	(4.642)	(0.874)
b_P			−0.015	** −0.060	0.031	0.006
			(−0.455)	(−4.173)	(2.133)	(0.283)
b_S			0.039	0.002	0.006	* 0.033
			(1.309)	(0.154)	(0.298)	(2.635)
$b_{P,e}$			** −0.307	0.094	0.039	* 0.095
			(−3.625)	(2.074)	(0.937)	(2.487)
$b_{P,a}$			−0.019	* 0.067	* −0.050	* −0.058
			(−0.305)	(2.877)	(−2.796)	(−3.051)
$b_{S,e}$			*** 1.371	** 0.231	0.073	*** 0.207
			(18.184)	(5.250)	(1.448)	(10.100)
$b_{S,a}$			−0.052	** 0.087	−0.026	* −0.044
			(−0.650)	(3.639)	(−1.039)	(−2.409)
Crypto-week obs.			8232	8378	8075	7659
Adjusted R^2			0.144	0.098	0.401	0.025

Table 13: Difference-in-difference panel regressions of abnormal returns, volatility, log trading volume, and the log number of mentions in the news in the weeks surrounding a large positive shock. We estimate models of the type (3). All regressions include crypto, shocked crypto, and industry-date interacted fixed effects. All regressors except the indicators and log market capitalization are standardized at the crypto-level using the rolling prior 60-day means and variances. We remove the top and bottom 1% cross-sectional observations for each time series prior to running the regressions to ensure robustness. “AR” stands for the autoregressive coefficients, “Ret.” for total return, “Idio. ret.” for abnormal return, “Vol.” for total volatility, “Idio. vol.” for idiosyncratic volatility, “MC” for log market capitalization, “ALV” for abnormal log trading volume, and “News” stands for standardized log news mentions. Standard errors are clustered by event week and industry. The values in parentheses give t-statistics. ***, **, and * denote significance on the 99.9%, 99%, and 95% confidence levels, respectively.

Short all smaller peers								
Holding period	Alpha	Beta Market	Beta Size	Beta Momentum	Cumulative return	Average return	Volatility	Sharpe ratio
4	0.000	-0.026	0.015	0.033	5.09%	0.03%	3.46%	0.002
	(0.026)	(−0.832)	(0.342)	(0.679)				
5	0.002	-0.020	-0.015	0.012	43.31%	0.22%	3.14%	0.439
	(0.767)	(−0.703)	(−0.384)	(0.264)				
6	0.002	-0.031	-0.058	-0.012	56.19%	0.28%	2.87%	0.617
	(1.059)	(−1.179)	(−1.607)	(−0.284)				
7	0.003	0.027	0.006	0.003	67.08%	0.32%	2.65%	0.788
	(1.339)	(1.109)	(0.182)	(0.082)				
8	0.004	-0.015	-0.006	0.026	86.00%	0.40%	2.42%	1.068
	(1.821)	(−0.663)	(−0.186)	(0.717)				
9	* 0.004	-0.008	0.009	0.029	104.61%	0.46%	2.34%	1.297
	(2.246)	(−0.373)	(0.299)	(0.805)				
10	* 0.005	0.007	-0.024	-0.057	120.54%	0.51%	2.40%	1.416
	(2.527)	(0.304)	(−0.793)	(−1.555)				
11	** 0.005	-0.009	-0.024	0.010	130.88%	0.54%	2.26%	1.608
	(2.694)	(−0.408)	(−0.823)	(0.278)				
12	** 0.006	-0.034	-0.031	-0.030	161.57%	0.63%	2.34%	1.811
	(3.130)	(−1.555)	(−1.007)	(−0.829)				
13	** 0.006	-0.007	-0.017	0.012	152.14%	0.61%	2.26%	1.815
	(3.031)	(−0.322)	(−0.580)	(0.341)				
14	** 0.006	-0.024	-0.015	-0.002	159.42%	0.63%	2.20%	1.936
	(3.281)	(−1.149)	(−0.503)	(−0.047)				
15	** 0.006	-0.002	-0.041	-0.001	153.56%	0.62%	2.15%	1.941
	(3.197)	(−0.118)	(−1.348)	(−0.023)				
16	** 0.006	* -0.043	-0.038	0.063	158.63%	0.64%	2.11%	2.034
	(3.230)	(−2.152)	(−1.239)	(1.873)				
17	** 0.006	0.019	-0.018	-0.019	145.54%	0.61%	2.13%	1.919
	(3.205)	(0.920)	(−0.566)	(−0.538)				
18	** 0.005	-0.014	-0.012	0.002	135.49%	0.58%	2.01%	1.946
	(3.229)	(−0.697)	(−0.382)	(0.047)				
19	** 0.005	0.016	0.011	0.003	117.36%	0.53%	1.96%	1.815
	(3.030)	(0.802)	(0.378)	(0.086)				
20	** 0.004	-0.006	-0.012	0.053	112.02%	0.52%	1.85%	1.867
	(2.843)	(−0.342)	(−0.427)	(1.659)				

Table 14: Performance metrics for event-based trading strategies that exploit the predictability documented in Figure 10. Each week, we short-sell cryptos that are peers of a crypto that is shocked, and go long on Bitcoin. We short-sell on margin only those peer cryptos that have smaller market capitalizations than shocked cryptos. We hold the positions open for several weeks (the holding period). All short positions are equally weighted. If the strategy keeps a position open for H weeks, then each week the strategy only invests a fraction of $1/(H+1)$ of the available wealth into new short positions. The long positions are of an equivalent amount to keep the strategy market neutral. Returns are computed as follows. Each week, we compute the P&L of the short positions that are closed on that week. We then compute the return in that week as the ratio of the P&L with respect to the terminal wealth of the prior week. We subtract from the returns the following fees: A 50 bp bid-ask spread for each transaction, a 2 bp point fee to open a short position, and a 84 bp fee to keep a short position open for a week. In total, if a short position is held open for H weeks, then we assume a fee of $50 + 2 + 84H$ bp. The alpha, average return, and volatility are measured on a weekly scale while the Sharpe ratio is annualized. The betas are computed with respect to a 3-factor model that includes market, size, and momentum factors as used by Liu et al. (2019). The construction of the market, size, and momentum factors is described in Section 2.2. The values in parentheses give t-statistics. ***, **, and * denote significance on the 99.9%, 99%, and 95% confidence levels, respectively.

Short only smaller peers with margin trading on Kraken								
Holding period	Alpha	Beta			Cumulative return	Average return	Volatility	Sharpe ratio
		Market	Size	Momentum				
9	0.004	-0.023	-0.014	0.029	85.01%	0.39%	2.27%	1.135
	(1.927)	(−1.083)	(−0.473)	(0.821)				
10	* 0.004	-0.003	0.005	-0.058	92.68%	0.42%	2.39%	1.165
	(2.168)	(−0.119)	(0.176)	(−1.575)				
11	* 0.004	0.017	-0.004	0.005	94.64%	0.43%	2.20%	1.294
	(2.200)	(0.832)	(−0.134)	(0.146)				
12	* 0.004	* -0.051	* -0.069	0.005	112.75%	0.49%	2.23%	1.469
	(2.390)	(−2.492)	(−2.401)	(0.137)				
13	* 0.004	0.007	-0.014	0.018	105.90%	0.48%	2.06%	1.526
	(2.514)	(0.355)	(−0.526)	(0.556)				
14	** 0.005	-0.008	-0.012	0.009	112.25%	0.50%	2.08%	1.597
	(2.663)	(−0.401)	(−0.427)	(0.260)				
15	* 0.004	-0.003	-0.041	-0.021	103.38%	0.47%	2.01%	1.557
	(2.586)	(−0.158)	(−1.460)	(−0.653)				
16	* 0.004	* -0.046	-0.028	0.056	103.42%	0.48%	2.00%	1.577
	(2.502)	(−2.472)	(−0.952)	(1.745)				
17	* 0.004	-0.004	0.008	0.013	90.74%	0.44%	1.90%	1.515
	(2.550)	(−0.223)	(0.272)	(0.407)				
18	* 0.004	-0.020	-0.010	0.031	83.66%	0.41%	1.79%	1.520
	(2.440)	(−1.123)	(−0.354)	(1.001)				
19	* 0.004	0.024	-0.023	-0.052	72.81%	0.37%	1.76%	1.383
	(2.439)	(1.360)	(−0.890)	(−1.706)				
20	0.003	-0.006	-0.045	* 0.058	69.72%	0.36%	1.64%	1.443
	(1.943)	(−0.370)	(−1.845)	(2.066)				

Table 15: Performance metrics for event-based trading strategies that exploit the predictability documented in Figure 10. Each week, we short-sell cryptos that are peers of a crypto that is shocked, and go long on Bitcoin. We short-sell on margin only those peers that have smaller market capitalizations than shocked cryptos and are available for margin trading with a USD account on Kraken (Bitcoin, Bitcoin Cash, Cardano, Chainlink, Dash, EOS, Ethereum, Ethereum Classic, Litecoin, Monero, XRP, Tezos, and Tron). We hold the positions open for several weeks (the holding period). All short positions are equally weighted. If the strategy keeps a position open for H weeks, then each week the strategy only invests a fraction of $1/(H+1)$ of the available wealth into new short positions. The long positions are of an equivalent amount to keep the strategy market neutral. Returns are computed as follows. Each week, we compute the P&L of the short positions that are closed on that week. We then compute the return in that week as the ratio of the P&L with respect to the terminal wealth of the prior week. We subtract from the returns the following fees: A 50 bp bid-ask spread for each transaction, a 2 bp point fee to open a short position, and a 84 bp fee to keep a short position open for a week. In total, if a short position is held open for H weeks, then we assume a fee of $50 + 2 + 84H$ bp. The alpha, average return, and volatility are measured on a weekly scale while the Sharpe ratio is annualized. The betas are computed with respect to a 3-factor model that includes market, size, and momentum factors as used by Liu et al. (2019). The construction of the market, size, and momentum factors is described in Section 2.2. The values in parentheses give t-statistics. ***, **, and * denote significance on the 99.9%, 99%, and 95% confidence levels, respectively.

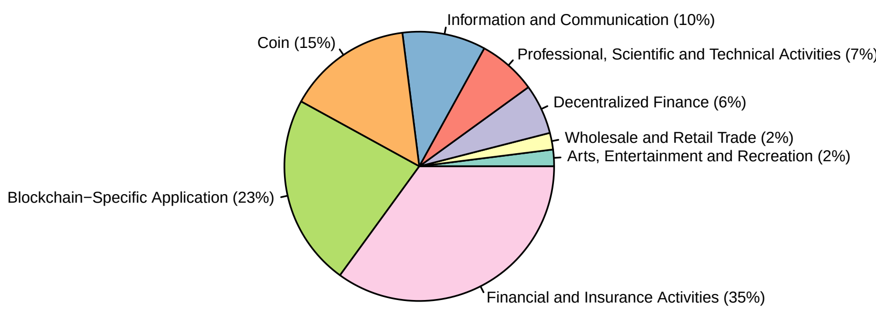
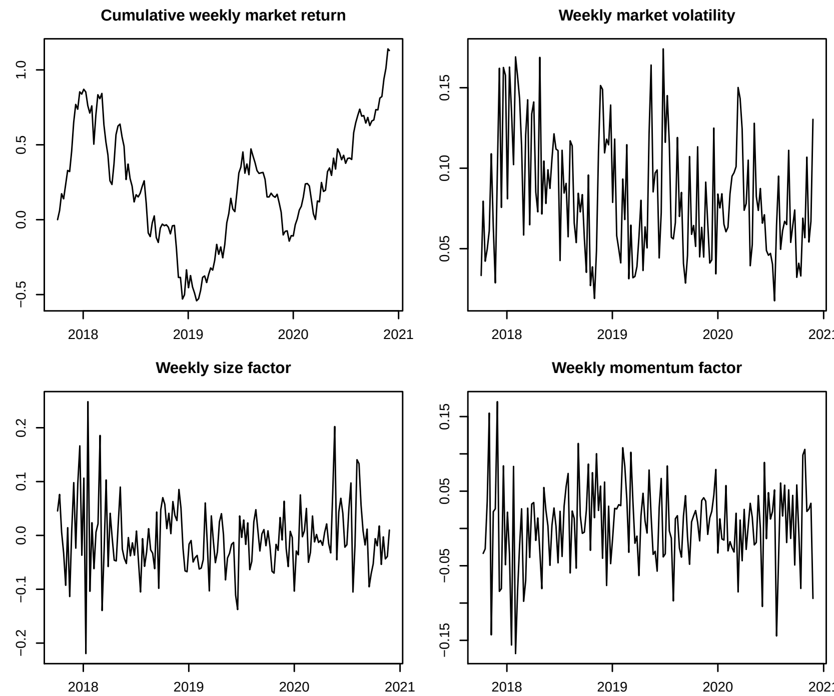
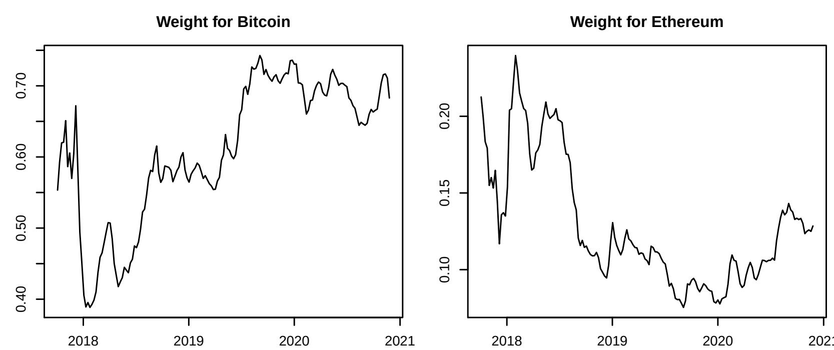


Figure 1: Classification of the industries in which cryptos in our data sample operate. We obtain industry classification data from Cryptocompare. Whenever unavailable, we complement the data with industry classifications from Coingecko and from Lyandres et al. (2019). We manually classify any asset that remains unclassified after the previous steps.

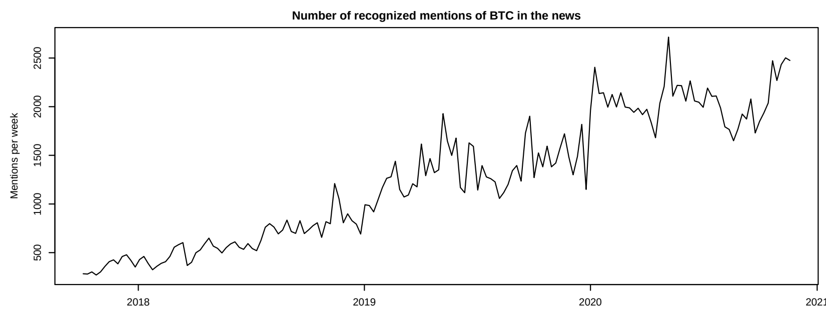


(a) Cumulative weekly market returns and volatility, together with size and momentum factors.

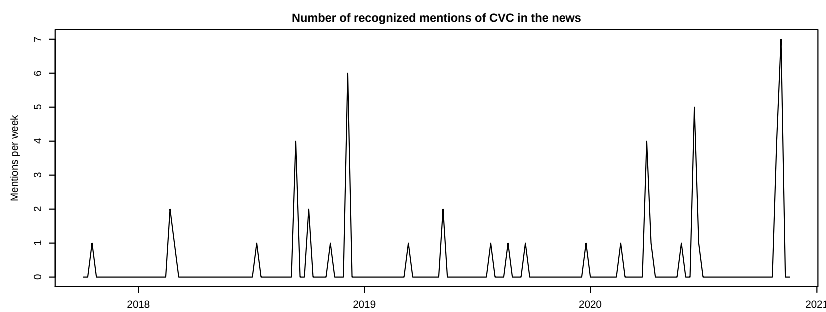


(b) Market capitalization weights for Bitcoin and Ethereum.

Figure 2: Market index, market volatility, size and momentum risk factors, and market-capitalization weights. For a given week, we consider all cryptos in our sample that were available for trade on at least one exchange in that week and compute a market index as the market-cap-weighted average of the returns of all such cryptos. We compute the aggregate volatility as the standard deviation of market-cap-weighted daily returns in a week, and we take into account the return correlation across different assets. The market capitalizations weights corresponds to the weights that Bitcoin and Ethereum carry in our market index. The construction of the size and momentum factors is described in Section 2.2.



(a) Number of daily mentions of Bitcoin in our news data.



(b) Number of daily mentions of Civic in our news data.

Figure 3: Time series of the number of times different cryptos are mentioned in our news data.

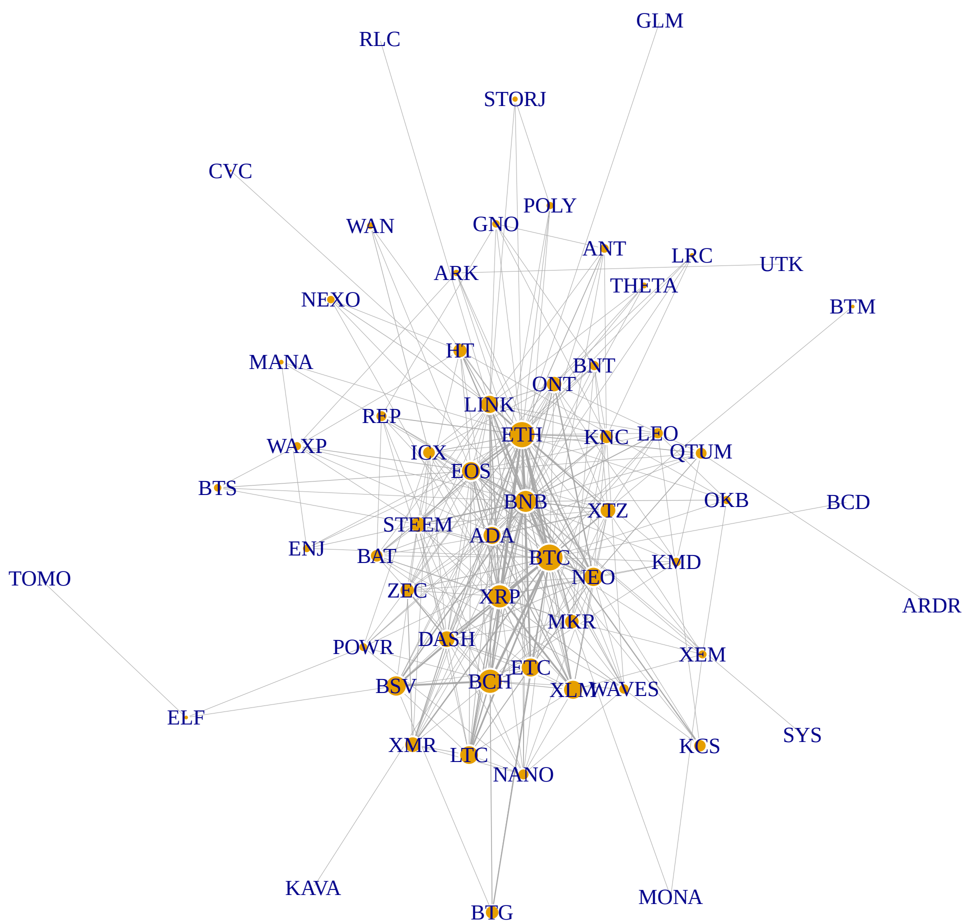


Figure 4: Network of cryptos implied by the full news data sample covering the period October 1, 2017, through November 30, 2020. The size of a node is proportional to the logarithm of the number of times that crypto is mentioned in the news. The width of a link between two cryptos is proportional to the logarithm of the number of times that link is identified in the news data.

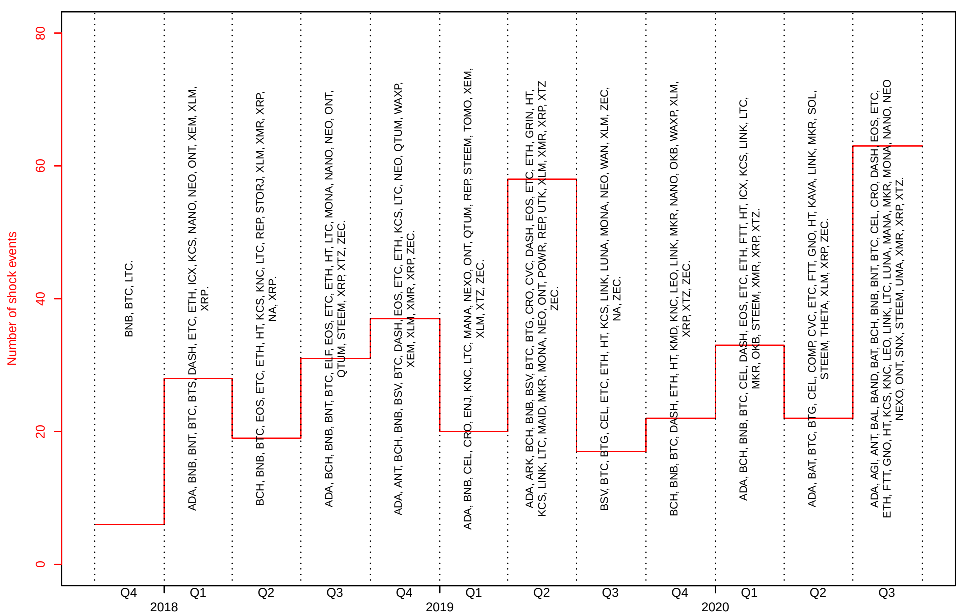
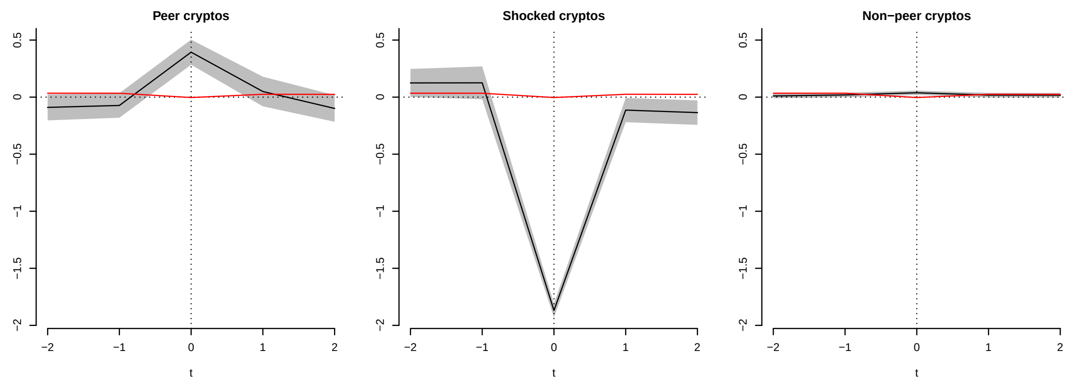
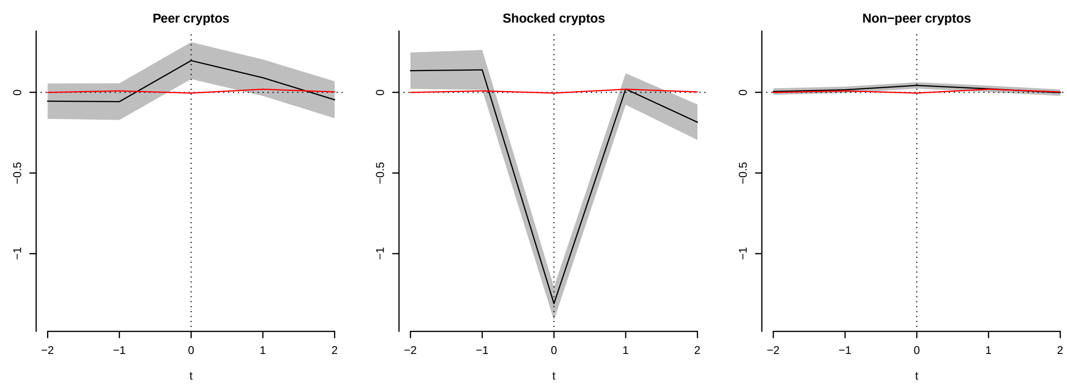


Figure 5: Shock events in our sample. We collect all cryptos that at some point in a quarter experience standardized weekly abnormal returns that land in the lowest decile of the empirical distribution across time and cryptos in our data. The red line shows the quarterly number of shock events identified this way. The texts state the cryptos that experienced a shock event in a given quarter.

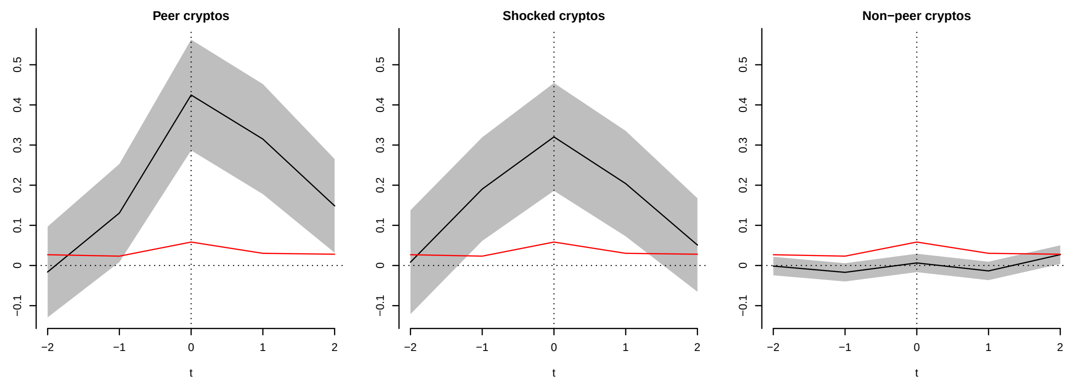


(a) Standardized abnormal return in week $e + t$, where e is the event week.

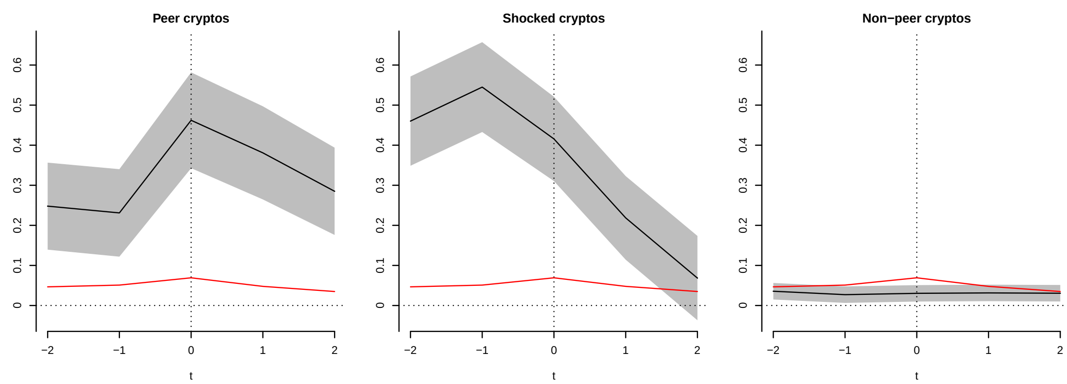


(b) Standardized return in week $e + t$, where e is the event week.

Figure 6: Sample means of standardized idiosyncratic and total returns for the sample of shocked, peer, and non-peer cryptos in the weeks surrounding an event. Table 1 provides summary statistics of the unstandardized return measures and Section 2 describes how the unstandardized measures are constructed. We standardize a time series for each asset on a rolling basis using the mean and standard deviation of each performance measure in the 60-day window prior to any given week. We remove the top and bottom 1% cross-sectional observations for each time series when computing cross-sectional moments. The black lines give the weekly sample mean in each asset group, while the red line gives the weekly population mean in the whole universe of cryptos. The grey shaded areas give 95% asymptotic confidence bands. Note that we do not record the exact day of the event week in which the shock occurs. As a result, Week "e" is the week in which the event occurs, not the exact day in which the event takes place.

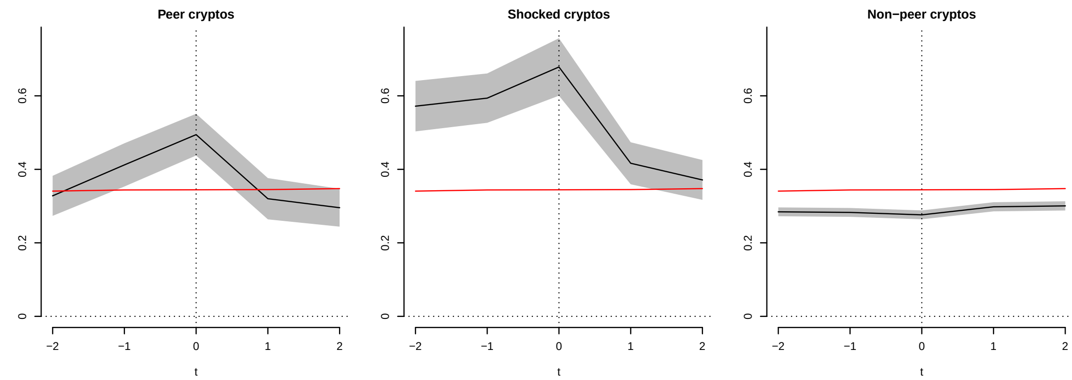


(a) Standardized volatility in week $e + t$, where e is the event week.

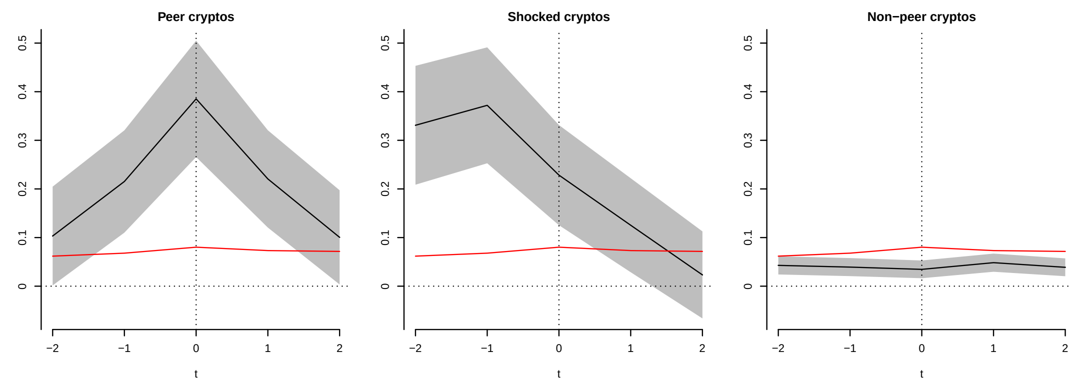


(b) Standardized log-volume in week $e + t$, where e is the event week.

Figure 7: Sample means of standardized volatility and log-volume for the sample of shocked, peer, and non-peer cryptos in the weeks surrounding an event. Table 1 provides summary statistics of idiosyncratic volatilities and Section 2 describes how the unstandardized measures are constructed. We standardize a time series for each asset on a rolling basis using the mean and standard deviation of each performance measure in the 60-day window prior to any given week. We remove the top and bottom 1% cross-sectional observations for each time series when computing cross-sectional moments. The black lines give the weekly sample mean in each asset group, while the red line gives the weekly population mean in the whole universe of cryptos. The grey shaded areas give 95% asymptotic confidence bands. Note that we do not record the exact day of the event week in which the shock occurs. As a result, Week "e" is the week in which the event occurs, not the exact day in which the event takes place.

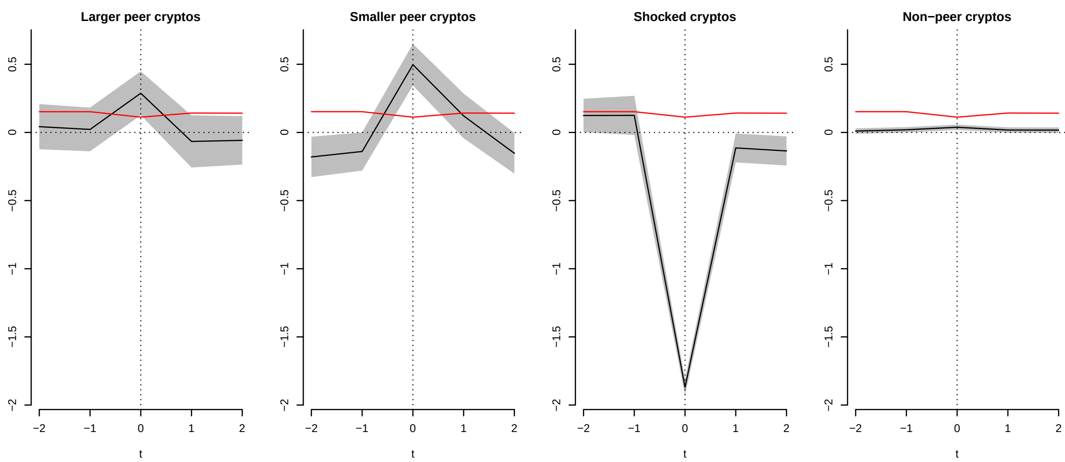


(a) Standardized log-mentions in news in week $e + t$, where e is the event week.

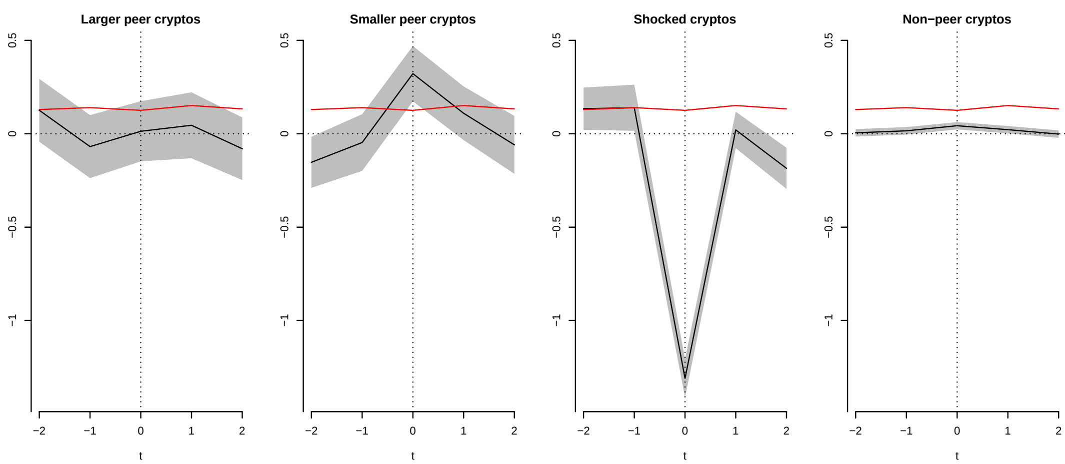


(b) Standardized number of comments on Reddit in week $e + t$, where e is the event week.

Figure 8: Sample means of standardized log-mentions in news and number of comments on Reddit for the sample of shocked, peer, and non-peer cryptos in the weeks surrounding an event. Table 1 provides summary statistics of the unstandardized measures and Section 2 describes how the unstandardized measures are constructed. We standardize a time series for each asset on a rolling basis using the mean and standard deviation of each performance measure in the 60-day window prior to any given week. We remove the top and bottom 1% cross-sectional observations for each time series when computing cross-sectional moments. The black lines give the weekly sample mean in each asset group, while the red line gives the weekly population mean in the whole universe of cryptos. The grey shaded areas give 95% asymptotic confidence bands. Note that we do not record the exact day of the event week in which the shock occurs. As a result, Week "e" is the week in which the event occurs, not the exact day in which the event takes place.



(a) Standardized abnormal returns in week e + t, where e is the event week.



(b) Standardized total returns in week e + t, where e is the event week.

Figure 9: Sample means of standardized abnormal and total returns for the sample of shocked, non-peers, larger peers, and smaller peers in a given event week. We say a peer crypto is larger (smaller) if, during the event week, the market capitalization of the crypto is larger (smaller) than the market capitalization of the shocked crypto. Table 1 provides summary statistics of the unstandardized measures and Section 2 describes how the unstandardized measures are constructed. We standardize a time series for each asset on a rolling basis using the mean and standard deviation of each performance measure in the 60-day window prior to any given week. We remove the top and bottom 1% cross-sectional observations for each time series when computing cross-sectional moments. The black lines give the weekly sample mean in each asset group, while the red line gives the weekly population mean in the whole universe of cryptos. The grey shaded areas give 95% asymptotic confidence bands.

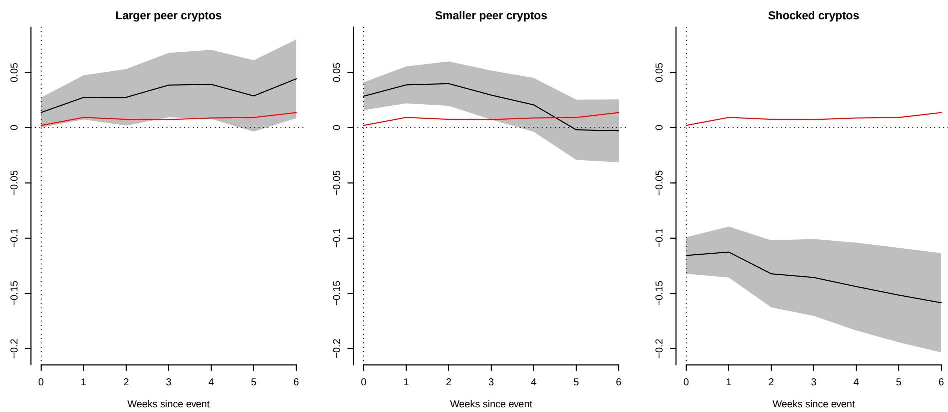


Figure 10: Cumulative total returns for larger and smaller peer cryptos in the weeks after a shock event. We say a peer crypto is larger (smaller) if, during the event week, the market capitalization of the crypto is larger (smaller) than the market capitalization of the shocked crypto. The black lines give the weekly cumulative total return in week $e + t$, where e is an event week and $1 \leq t \leq 6$, on average across all cryptos that are identified as larger or smaller peers during an event week. The grey shaded areas give 95% asymptotic confidence bands. The red line gives the average weekly cumulative return in the whole universe of cryptos. We remove the top and bottom 1% cross-sectional observations for each time series when computing cross-sectional moments. Table 1 provides summary statistics of the return measures.