News-Driven Peer Co-Movement in Crypto Markets

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Abstract

When large idiosyncratic shocks hit a cryptocurrency, some of its peers experience unusually large returns of the opposite sign. The co-movement is concentrated among peers that are co-mentioned with shocked cryptos in the news, and that are listed in the same exchanges as shocked cryptos. It is a form of mis-pricing that vanishes after several weeks, giving rise to predictable returns. We propose a profitable trading strategy that exploits this predictability, and explain our results with a slow information processing mechanism. To establish our results, we develop a novel natural language processing technology that identifies crypto peers from news data. Our results highlight the news as a key driver of co-movement among peer assets.

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

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1 Introduction

Cryptocurrencies are a new asset class that has drawn significant investor capital. According to the data site CoinMarketCap, there were more than 11,000 cryptocurrencies traded on close to 400 exchanges around the globe by the end of August 2021. The aggregate market cap of cryptocurrencies reaches above $2 trillion with over $100 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: mis-pricing among peer cryptos due to an overreaction to news reporting.

Our results are threefold. First, we empirically document co-movement among peer cryptos in response to idiosyncratic shocks. When large abnormal return shocks hit a cryptocurrency, peers that are co-mentioned in online news and co-listed in the same exchanges experience unusually large abnormal returns of the opposite sign. This empirical pattern holds after accounting for common risk factors and correlated demand shocks, and aligns with a competition effect that is also present in traditional financial markets. It is a form of mis-pricing that arises because investors overreact to pricing-irrelevant information reported in the news. Second, we show that the co-movement yields return predictability in crypto markets. We demonstrate that it takes several weeks for investors to process that they have overreacted to pricing-irrelevant news, and undo the mis-pricing of peer cryptos. This results in a predictable reversal of performance for co-listed peer cryptos. We propose a profitable trading strategy that exploits this predictable return pattern. Finally, we propose a natural language processing methodology that identifies peer linkages from co-mentions in the news. We show that the co-movement and predictability is only present among the set of peer cryptos that are identified from the news. This result highlights the outright power of news media to influence crypto co-movement.

We run event-based difference-in-difference panel regressions to identify 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 describe the methodology below). We then keep track of shocked, peer, and non-peer cryptos in the weeks surrounding an event. We analyze the total and abnormal returns, volatilities, turnover, and news 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 −14.5% 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 more frequent mentions in the news during event weeks. We establish these estimates 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]

We explain the co-movement of peer cryptos with an overreaction to news by the part of investors, similar as in Ahern and Sosyura (2015) and Barber and Odean (2008). We find that the co-movement is stronger among smaller peers with lower levels of investor attention. We also find that the co-movement primarily arises when shocks occur that are not informational 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 is not due to a release of pricing-relevant

[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).

information. When interacting our peer linkages from the news with alternative linkages, we find that all of the co-movement we establish is showcased by news peers that are also listed in the same exchanges as shocked cryptos, regardless of whether they share other fundamental linkages. We also identify abnormally high turnover for all co-listed peer cryptos during an event week. These results suggest that investors overreact to news reporting about shocked and peer cryptos, especially when it is hard for investors to disentangle the informational content of the shocks. They then move their investments from shocked to peer cryptos that are available in the same exchanges. This behavior introduces mis-pricing among co-listed peer cryptos.

Next, we show that the mis-pricing gives rise to return predictability. We document that it takes more than four weeks after a shock for the mis-pricing to vanish. Over this time period, the prices of co-listed peer cryptos diffuse down. We build trading strategies that exploit this predictable reversal of performance. Our strategies short-sell co-listed peer cryptos while going long on Bitcoin as a proxy for the market. We find that the strategy that keeps the positions open for 12 weeks generates a significant alpha of 70 basis point per week and a cumulative return of 230% without loading on the market, size, or momentum factors. This strategy has an annualized Sharpe ratio of 2.1 after accounting for realistic trading fees.

We argue that the predictability among co-listed peer cryptos is due to slow processing of information: it takes investors time to realize that they have overreacted to pricing irrelevant information. To support this interpretation, we show that reversal occurs faster among two subsets of co-listed peer cryptos that naturally have faster speeds of information processing: the subsample of co-listed peer cryptos that are larger than the cryptos that experience the shocks, and the subsample of peer cryptos that are available for trading on Kraken, one of the most liquid exchanges in the world that allows for short-selling on margin. We find that variations of our trading strategies that are restricted to shorting from these subsamples of co-listed peer cryptos have higher performance metrics for shorter holding periods, and lower performance metrics for longer holding periods. These observations support the conclusion that the predictability is sustained by the speed with which investors can process information.

Our results are highly robust. All results hold after accounting for the market, size, and momentum factors of Liu et al. (2019). We identify co-movement even if we consider regressions of raw returns as in Kwan (1996) rather than diff-in-diff regressions of abnormal returns. The co-movement arises regardless of whether the shocks hit the largest cryptos (like Bitcoin or Ethereum) or the smallest coins (which have the largest idiosyncratic volatilities). They also arise regardless of whether the shocks are exogenous or endogenous, highlighting that investors have a hard time understanding the informational content of the shocks. We find weaker evidence of competition effects among intra-industry peers, suggesting that investors primarily learn about peer cryptos from the news. We find no or opposite co-movement when we consider placebo tests in which cryptos are linked at random. This suggests that investors perceive the reporting about shocked and peer cryptos in the news to be pricing relevant, even though the shocks are purely idiosyncratic. We find weaker evidence of co-movement and predictability among co-listed peer cryptos when we consider positive rather than negative idiosyncratic shocks. A weakened response to positive shocks is consistent with behavioral biases against downside risk (Kahneman and Tversky (1979), Kuhnen (2015), and others).

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 news data to identify crypto peer linkages. We develop a novel natural language processing (NLP) methodology 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 an NLP-based classification model. Our approach is facilitated by a new service offered by Amazon called "Gecko" for which we obtain beta testing access.[2] The methodology proceeds in three steps. First, we identify co-mentions of cryptos in the same sentence of an article using a variation of the methodology of Schwenkler and Zheng (2019). We then run all sentences in which more than two cryptos are mentioned through a BERT algorithm that transforms text into a machine-processable vector representation (see Devlin et al. (2019)). Finally, we run the vector-based representation of the sentences through a deep learning classification model that labels the relationship between the co-mentioned cryptos as peer or non-peer.

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 peer or non-peer depending on whether these sentences clearly describe a peer relationship.[3] We train our labeling model on this subsample of sentences and estimate its accuracy via cross validation. The resulting model has an out-of-sample accuracy rate of 85%, indicating that our approach is highly accurate

[2]Access to Gecko was graciously provided by Sanjiv Das. Amazon aims to launch the Gecko service for broad access in the fall of 2021.

[3]The training sample of sentences is available here.

at identifying peer links in crypto news. We use our trained model to label the remaining sentences and hand-check the output to make sure the labelling is 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 the 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. 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, highlighting that investors primarily identify crypto peers from the news rather than through ad-hoc industry classifications. These results validate our approach to identify cryptocurrency peers.

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 results on co-movement and predictability can be found in Sections 4 and 6. Section 5 proposes a slow information processing mechanism that explains our findings. Section 7 provides robustness analyses. Section 8 concludes. There is an Online Appendix that is available here.

1.1 Related literature

Our paper contributes to several literature strands. The primary contributions lie at the intersection of the literature that studies cryptocurrencies, and the literature that studies financial news reporting and its influence on financial markets. On the cryptocurrency side, we show that peer linkages drive crypto co-movement after controlling for the common risk factors of Liu et al. (2019) and the correlated demand channel of Shams (2020). 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).[4] On the financial news side, we show that news reporting can induce co-movement in excess of fundamental linkages. Our findings extend those of Chahrour et al. (2019) and Schwenkler and Zheng (2019), who show that news reporting can amplify the co-movement due to economic linkages across assets. They complement Hasler and Ornthanalai (2018), who show that even economically unlinked assets may co-move in response to shocks reported in the news due to investors rebalancing their portfolios. In addition, we also show that news-based industry classification derived from a NLP methodology can be more informative than ad-hoc industry classifications assigned by humans. These results extend the findings of Hoberg and Phillips (2016), who show that NLP-driven industry classifications based on 10K text similarities are more informative about future firm outcomes than SIC or NAICS industry classifications.

Our results complement and extend those of Shams (2020). Shams (2020) establishes contagion effects among co-listed cryptos in response to correlated demand shocks. In contrast, we establish competition effects among co-listed peer cryptos in response to idiosyncratic shocks. We indeed find some evidence of contagion effects, similar as in Shams (2020), among co-listed cryptos that operate in the same industries but that are not identified as peers in online news. These results highlight that news reporting on its own can trigger vastly different performance across peer assets, complementing recent findings by Nimark and Pitschner (2019), Peress (2014), and Schwenkler and Zheng (2021). These authors highlight editorial selection in the news as a key determinant of performance for financial assets. We also find some traces of contagion when we consider systematic shocks rather than idiosyncratic shocks. These results suggests that it is hard for investors to disentangle which shocks are truly relevant for the pricing of peer cryptos. We document similar investor behavior as in Ahern and Sosyura (2015), who show that investors find it hard to process sensational news about firm mergers, leading to mis-pricing and predictability in stock markets. Li et al. (2018) document that institutions often trade on erroneous news, and that they revert their positions only several days after a news correction.

We also 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

[4] There is a growing literature considering other aspects of cryptocurrency markets. For example, 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)).

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 partnerships. Brennan et al. (1993), Chordia and Swaminathan (2000), Hou (2007), Hou and Moskowitz (2005), Lo and MacKinlay (1990), Parsons et al. (2020), and others document lead-lag relationships between the returns of large and small intra-industry peers.

The aforementioned existing studies generally document cross-momentum across economically linked assets. We, instead, document reversal for peer cryptos. The main difference between our results and the existing studies is that we consider idiosyncratic rather systematic shocks, and that our co-movement is a form of mis-pricing. We find some weaker evidence of cross-momentum when we consider shocks that are systematic in nature. Extending the existing studies, however, we find that news reporting can change the nature of the co-movement across economically linked assets because investors may misinterpret the information contained in the news. Similar phenomena have been described in Ahern and Sosyura (2015), Fitzgerald et al. (2021), and Li et al. (2018).

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. In contrast to the existing studies, we provide novel evidence of competition effects among co-listed peer assets in cryptocurrency markets. Extending the existing studies, we highlight the role that financial media plays in driving contagion versus competition effects.

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, CoinGecko, and Cryptocompare. 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.

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 was first published on Cryptocompare, and the industry classification of the crypto according to Cryptocompare.[5] We obtain from CoinAPI data on the date when a crypto first started trading on an exchange as well as a list of all exchanges on which cryptos are traded. We keep track of all exchanges on which a crypto was traded for all days in our sample.

For each crypto and day in our sample, we collect end-of-the-day closing prices, market capitalizations, and traded volumes in USD from Coingecko.[6] We compute daily log-returns and censor for each crypto the top and bottom one percent daily log-returns 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.

For each crypto and week in our sample, we collect from Coingecko the Alexa rank of the main crypto website. We also collect some additional characteristics about the different cryptos from Coingecko. We obtain information about whether the crypto 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 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 was published according to Coingecko, 3) The start date of the ICO for a crypto token according to

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

[6] 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.

Coingecko, 4) the end date of the ICO for a crypto token according to Coingecko, 5) the first date on which a crypto was traded on an exchange according to CoinAPI, and 6) the date in which content about the crypto was first published on Cryptocompare. For a crypto 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.[7] 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 span 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 cryptos) 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.

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

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

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 span 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 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. 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 the news articles available on the Cryptocompare News

API.[8] 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 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 2 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

[8] Appendix A of the Online Appendix describes the Cryptocompare News API and the types of articles that are available through this API.

news reporting tilts towards well-established cryptos, an empirical fact that is also observed in traditional financial news (Solomon and Soltes (2012)).

3 News-implied crypto network

Following Schwenkler and Zheng (2019), we consider two cryptos to be linked if they are mentioned in the same sentence of a news article.[9] However, to make sure that the two cryptos indeed share a peer link, we extend the approach of Schwenkler and Zheng (2019) by running all sentences in which at least two cryptos are mentioned through a deep learning labelling methodology. We say that two cryptos that are mentioned in the same sentence of an article are peers if our deep learning methodology classifies that sentence as peer. We 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 deep learning methodology.

Our deep learning methodology is facilitated by a new machine learning service from Amazon called "Gecko."[10] The methodology consists of two steps. In the first step, it feeds into a pre-trained BERT tool all sentences in which more than two cryptos are identified. BERT stands for "Bidirectional Encoder Representations from Transformers" and is a novel natural language processing technique due to Devlin et al. (2019) that transforms text into a vectorized numerical representation that is optimized for use in machine learning models. In the second step, we feed in the numerical BERT representation of our sentences into a deep neural network that assigns a label of "peer" or "non-peer" to the crypto links identified in the sentences. We fit the deep learning methodology using a subsample of 460 manually selected sentences that clearly describe either competitive or non-competitive relationships. The subsample of sentences used for fitting the model is available here. Cross validation of our trained methodology shows that its out-of-sample accuracy for identifying competitive relationships is 85%, suggesting that our approach is highly accurate in identifying peer linkages. Once the methodology has been fitted, we use it 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

[9] 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.

[10] Sanjiv Das granted us private access to Gecko during its beta trials. A public launch of the service at Amazon is scheduled for the fall of 2021.

data. In total, we observe 328 unique connections between the 100 cryptos in our sample. This observation suggests that each crypto has 3 peers on average. Figure 4 shows the resulting network of crypto peer connections extracted from our data. The size of a node in the figure is proportional to the logarithm of the number of times a crypto 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 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 3. Consistent with the sheer supremacy of Bitcoin in terms of market capitalization, 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 4. Many of the sentences establish comparisons across cryptos. Some sentences compare 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 4 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-

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

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 5, 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 2. 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

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

Here, $\ell_{i,j,t}^{h} = (\ell_{i,j,t-1}, \ell_{i,j,t-2})$ 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 $\text{FE}_{i,j,t} = a_i + a_j + a_t$) or link fixed effects ($\text{FE}_{i,j,t} = a_{i,j} + a_t$). Table 6 reports our estimates.

Complementing the findings of Table 5, which indicate that the news is more likely to report about cryptos with similar characteristics, the estimates of Table 6 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 Co-Movement

We run event-based analyses to study the co-movement among crypto peers.

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. 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 198 distinct events, affecting 37 distinct cryptos over 110 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. The largest numbers of shocks was recorded in Q2 2019, which was a period of calm gains in crypto markets in which even small abnormal returns may have been perceived as large in standardized terms.

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

[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.

all performance measures on a rolling basis at the crypto level using the prior 60-day mean and standard deviation. Section 7.3 shows that this standardization step is key to pin down the co-movement we establish.

Figures 6 through 8 show sample means of different standardized and raw measures of market and news 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 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 turnover during the event week and the two weeks before an event.[13] These observations confirm that shocked cryptos experience significant shocks during event weeks.

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, exhibit unusually large abnormal and total returns during the event week. Figures 6 and 7 suggest that peer cryptos experiences about one-fourth of the shock that hits shocked cryptos, but in the opposite direction. Figure 8 shows that volatilities and turnover are also large during and after an event week. This suggests that the uncertainty caused by the shock affects peer cryptos. Figure 8 shows standardized measures of mentions in the news for the different asset groups. We see that peer and shocked cryptos experience more frequent mentions in the news than an average crypto during the event week.

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.[14] 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.[15] Letting (e, j) denote an event in which crypto j is shocked on week e, we estimate the following panel

[13] We define turnover as the weekly average of the logarithm of the ratio of daily trading volume over market capitalization of a crypto.

[14] We run standard panel regressions in Section 7.6.

[15] 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 $t \in \{-2, -1, 0, 1, 2\}$:

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

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 $\mathrm{FE}_{i,t,e,j} = a_i + a_j + a_{industry(i),e+t}$. These fixed effects account for omitted variation at the crypto and event levels, as well as omitted industry-wide shocks. Finally, we two-way 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 7 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 summary statistics of Table 1, the estimates of Table 7 imply in nominal terms that shocked cryptos showcase excess abnormal returns of around -14.5% and peer cryptos showcase excess abnormal returns of close to 4.5% during an event week. These estimates are both statistically and economically significant. The results of Table 7 also suggest that the effects are contained during the event week and do not endure in the weeks after.

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, turnover, and log number of news mentions. Table 8 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 volatility and turnover measures of all cryptos are elevated during an event week. Ultimately, only peer cryptos benefit from this information dissemination. Table 8 indicates that the total returns of peer cryptos are abnormally high during an event week.

5 Mechanism

We explain the crypto peer co-movement through a constrained information processing mechanism. We show that investors learn from the news about peer cryptos, and move their investments from shocked to peer cryptos that are co-listed with shocked cryptos. However, due to their limited information processing capacity, it takes investors time to understand that the shocks contain no pricing-relevant information for peer assets. This results in mis-pricing.

5.1 Mis-pricing

Table 8 hints that there may be abnormally high information diffusion during event weeks. If our shocks revealed pricing-relevant information for 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. This suggests that the competition effect we uncover may reflect a temporary mis-pricing of peer cryptos in response to pricing-irrelevant shocks.

We test this conjecture by studying 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):

$$\mathbb{E}\big[Y_{i,e+t}\,|\,X_{i,e+t},\,\text{event}=(e,j)\big] = \text{FE}_{i,t,e,j} + b_X' X_{i,e+t} + b_P \mathbb{1}_{\{i \text{ is peer of } j\}} + b_S \mathbb{1}_{\{i=j\}}$$

$$+\, b_{e,inf}\mathbb{1}_{\{t=0\}}\mathbb{1}_{\{(e,j) \text{ is inf.}\}} + b_{e,noninf}\mathbb{1}_{\{t=0\}}\mathbb{1}_{\{(e,j) \text{ is not inf.}\}}$$

$$+ b_{P,e,inf} \mathbb{1}_{\{t=0\}} \mathbb{1}_{\{i \text{ is peer of } j\}} \mathbb{1}_{\{(e,j) \text{ is inf.}\}} + b_{P,e,noninf} \mathbb{1}_{\{t=0\}} \mathbb{1}_{\{i \text{ is peer of } j\}} \mathbb{1}_{\{(e,j) \text{ is not inf.}\}}$$

$$+ b_{S,e,inf} \mathbb{1}_{\{t=0\}} \mathbb{1}_{\{i=j\}} \mathbb{1}_{\{(e,j) \text{ is inf.}\}} + b_{S,e,noninf} \mathbb{1}_{\{t=0\}} \mathbb{1}_{\{i=j\}} \mathbb{1}_{\{(e,j) \text{ is not inf.}\}} \tag{4}$$

for an event week e and window weeks $t \in \{-2, -1, 0\}$. Here, "*inf.*" is short for "informational." Table 9 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 mis-pricing of peer cryptos.

5.2 Slow information processing

If the peer co-movement we uncover is reflective of mis-pricing, then we posit that the co-movement should be stronger peers with slower information processing. We are inspired by previous studies of equity markets. 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 processing, 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 than 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, which naturally face lower levels of investor attention and lower speeds of information processing.

5.3 Alternative linkages

We investigate the transmission channel that gives rise to the co-movement we document. We first test whether alternative linkages among cryptos explain yield similar co-movement in response to our shocks. 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 trigger similar co-movement.

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.

Table 10 summarizes 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 when controlling for alternative links. We also find that intra-industry cryptos 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 4.5% 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 document is strongest among peer cryptos identified from the news.

5.4 Does news cause co-movement?

Next, we evaluate whether the news on its own causes our co-movement we document. Online news are determined by editorial selection. The selection of what linkages to report about may reveal to investors important information that is orthogonal to that captured by the more traditional intra-industry or co-listing linkages.[16] If our peer linkages are just a more timely or extensive representation of traditional linkages, then we would expect the co-movement to be concentrated among peer cryptos that also share a traditional link with a shocked crypto. If, on

[16] See Nimark and Pitschner (2019) and Schwenkler and Zheng (2021), who highlight the editorial selection process as an important signaling tool for investors to filter out pertinent information from financial news.

the other hand, our peer linkages reveal excess information beyond that revealed by a traditional link, then we would expect to the co-movement to extend beyond those peer cryptos that also share a traditional link with a shocked crypto. In the latter case, the news on its own may cause co-movement over and beyond that captured by a traditional linkage, similar as in the models of Chahrour et al. (2019) and Hasler and Ornthanalai (2018).

To answer this question, we consider impulse response functions, similar to those of Section 4.1, in which we interact our peer linkages with traditional linkages. We consider same-industry operations and co-listing in common exchanges as possible traditional links. Figures 10 and 11 contain the impulse response functions for standardized abnormal returns and turnover, while Figure A.1 in the Online Appendix contains the analogous plots for raw abnormal returns.

We first see in the top right two plots of Figures 10–11 that there are very few peer cryptos that are not co-listed.[17] This may suggest that news editors select to report about colisted assets (consistent with the link regressions of Section 3). Second, we see in the top left two plots of Figure 10 that the co-movement of Section 4 is concentrated among peer cryptos that are co-listed in common exchanges, regardless of whether they operate in the same industry or not. In the top left two plots of Figure 11 we observe that co-listed peer cryptos also experience abnormally large turnover during event weeks. Third, we observe in the bottom left plot of Figure 10 that co-listed cryptos that operate in the same industry but that are not identified as peers from the news based on our approach showcase co-movement in the same direction as shocked cryptos. Figure A.1 in the Online Appendix shows that co-listed intra-industry cryptos that are not identified as the news peers by our algorithm record an abnormal return of around -1% during event weeks, while co-listed, intra-industry, the news peer cryptos record an abnormal return of around $+3\%$ during event weeks. Finally, the bottom right three plots of Figures 10–11 show that cryptos that are not identified as peers from the news by our algorithms, and are either not co-listed or not in the same industry, do not exhibit any significant behavior during event weeks. Section B of the Online Appendix establishes analogous results by considering the interaction between our peer linkages, exchange co-listings, and either similar size or similar beta links.[18] This suggests that our findings are not restricted to the physical link of same-industry operation, but also expand to soft peer links such as having similar sizes or factor model betas.

[17] This is the reason why we are unable to run triple-differences panel regressions in this setting. The small subsample size would yield poor statistical power.

[18] We say that two cryptos have similar sizes if they fall in the same decile of the market capitalization distribution during an event week. We say that two cryptos have similar betas if each of their market, size, and momentum betas fall in the same tercile of the respective beta distribution during an event week.

Our findings yield several novel insights. Consistent with Shams (2020), we find that co-listing in an exchange is the primary channel through which shocks spread among peer cryptos. Extending Shams (2020), however, we find that co-listing linkages facilitate both a contagion effect (as in Shams (2020)) and a competition effect (as in Section 4). Whether a peer crypto experiences contagion or competition is determined by the editorial selection process: Competition only takes place among the co-listed cryptos that are also mentioned as peers in the news. These results extend Nimark and Pitschner (2019) and Schwenkler and Zheng (2021) by demonstrating that the editorial selection process is also a critically important determinant of co-movement in cryptocurrency markets. Extending Chahrour et al. (2019), we find that news reporting on its own can cause co-movement among cryptos that do not share physical connections with each other. We find that cryptos that do not operate in the same industry or have dissimilar risk factor betas may co-move as implied by a competition effect if they are described as peers in the news. These results highlight the news as an important source through which investors learn about peer cryptos. Our results suggest that investors rebalance their portfolio after large idiosyncratic shocks and move investments from shocked cryptos to co-listed peer cryptos. This behavior is similar as in the model of Hasler and Ornthanalai (2018).

All in one, the results of this section suggest that the co-movement of Section 4 arises because investors learn from the news which cryptos are peers to shocked cryptos. Investors buy those peer cryptos they identify from the news that are also co-listed in the same exchanges as shocked cryptos. However, it is hard for investors to understand that the shocks they react to are purely idiosyncratic and do not reveal pricing-relevant information for the peer cryptos they identify from the news. This results in a temporary mis-pricing of peer cryptos.

6 Predictability

The co-movement we establish should be transient if it is truly due to mis-pricing. Investors should eventually realize that the shocks they react to do not reveal pricing-relevant information, and prices should adjust. We conjecture that the prices of peer cryptos drift downward in the weeks after a shock as investors realize that they have overreacted to the original shocks.

We evaluate this conjecture in Figure 12, which shows the cumulative returns of several sets of cryptos in the weeks after a negative abnormal return shock. Consistent with our conjecture, we see that the returns of co-listed peer cryptos are positive during an event week. This positive performance fades away after four weeks. The returns of shocked cryptos remain depressed even several weeks after an event. The remaining cryptos in our sample – those that are either not shocked or not co-listed and peers – do not showcase performance in the weeks after an event that is statistically different from that of an average crypto in our sample. These observations suggest that the returns of co-listed peer cryptos are predictable in the weeks after large abnormal return shocks. Next, we develop event-based trading strategies that exploit this return predictability.

6.1 Trading strategy

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.[19] We then collect all cryptos that we identify to be peers of a shocked crypto during the week. We short all peers that are co-listed with a shocked cryptos in an event week in order to exploit the reversal documented in Figure 12. 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.

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.[20] 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.[21]

Table 11 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). Figure 13 shows the Sharpe ratios of the strategies with different holding periods. We find that trading strategies that exploit the reversal of the peer effects we uncover and hold the short positions

[19] 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.

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

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

open for at least 6 weeks generate significant alphas of 50 to 70 bp per week at annualized Sharpe ratios of 1.2 and higher. The strategy that holds the positions open for 12 weeks achieves the highest cumulative return of 230% at a Sharpe ratio of 2.1 with statistically insignificant market, size, and momentum betas. This trading strategy significantly outperforms 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 mis-pricing of peer cryptos after large abnormal return shocks is temporary. It takes investors more than 6 weeks to trade away the effects.

6.2 Impact of information processing speed

Section 5 suggests that the mis-pricing of co-listed peer cryptos is due to an overreaction to pricing-irrelevant information by the part of investors, and that this mis-pricing can endure because it takes investors time to process the mis-pricing. The significantly positive performance of the trading strategies in Section 6.1 provides empirical support for this hypothesis. We further evaluate the hypothesis by analyzing the performance of our trading strategy restricted to subsets of cryptos that naturally have faster speeds of information processing.

We consider trading strategies that short-sell only a subset of co-listed peer cryptos: Those that are available for margin trading on Kraken, and those that have larger market capitalizations than peer cryptos. Larger assets tend to face faster speeds of information diffusion and processing (see Hou (2007)). Kraken is one of the most liquid exchanges in the world. Cryptos that are available for margin trading on Kraken likely face high levels of liquidity, low levels of frictions, and therefore also faster speeds of information processing. If the speed of information processing is a key driver of the predictability documented in Section 6.1, then we should find that the trading strategies restricted to these subsets of co-listed peer cryptos should have higher performance metrics for short holding periods, and lower performance metrics for long holding periods. This is because investors process information faster within these subsamples of cryptos, so that the returns revert at a faster rate.

Figure 13 reports the Sharpe ratios of the restricted strategies with different holding periods, and Tables A.3–A.4 in the Online Appendix report alphas, betas, and cumulative returns for the restricted strategies. Consistent with our conjecture, we see that the strategies that are restricted to the subset of co-listed peer cryptos that have higher speeds of information processing have higher Sharpe ratios for short holding periods, and lower Sharpe ratios for long holding periods. These results confirm that a slow speed of information processing enables the predictability documented in Figure 12.

6.3 Reversal vs momentum

At first sight, it may seem surprising that we find reversal for co-listed peer cryptos because several studies of equity markets often document cross-momentum among peer stocks. Cohen and Frazzini (2008) document cross-momentum in a supply chain setting. They show that it takes about a year for the stock prices of suppliers to incorporate information about shocks that hit their customers. Hou (2007) and Hou and Moskowitz (2005) also document cross-momentum by showing that the returns of small intra-industry peers adjust slower to industry shocks than large intra-industry peers, and attribute this effect to the slow information processing mechanism we also consider. We posit that the differences between our findings and those of these existing papers are due to the fact that we exclusively consider idiosyncratic shocks that do not reveal any pricing-relevant information.

To assess our conjecture, we repeat the experiment of Figure 12 but now we consider the behavior of the different groups of cryptos in response to shocks to standardized total returns (rather than standardized abnormal returns). Shocks to total returns may not be idiosyncratic in nature. They may reveal pricing-relevant information to investors, leading to different return behavior. We showcase the behavior in Figure 14.

We observe strikingly different patterns than in Figure 12. First, we find that all cryptos experience abnormally negative returns on average in the weeks after large total return shocks. This observation suggest that the total return shocks we identify reveal some pricing-relevant information. Consistent with Cohen and Frazzini (2008), Hou (2007), and Hou and Moskowitz (2005), we observe that intra-industry peers that are co-listed in common exchange with shocked cryptos, but that are not identified as peers from the news, exhibit cross-momentum. These cryptos see their returns move downwards in the weeks after total return shocks take place at a faster rate than an average crypto in the sample. In contrast to the existing studies, we also observe that cryptos that are identified as peers from the news and that are co-listed with shocked cryptos do not exhibit behavior that is statistically different than that of an average crypto in our sample. These results further accentuate the special nature of the co-listing linkages of Shams (2020). They also highlight the critical role that the news play in pointing investors to investment opportunities, complementing similar results by Barber and Odean (2008), Engelberg and Parsons (2011), Peress (2014), Schwenkler and Zheng (2021), and others for equity markets.

All in one, the results of this section show that co-listed peer cryptos exhibit predictable reversal in the weeks after large idiosyncratic shocks, and that this reversal can be exploited through profitable trading strategies. The speed of information processing is a key determinant for the persistence of the predictability. The reversal undoes mis-pricing that arises because investors overreact to idiosyncratic shocks that do not reveal pricing-relevant information for peer cryptos. Our findings are aligned with those of Ahern and Sosyura (2015), who argue that investors overreact to sensational news about firm mergers, giving rise to mis-pricing and predictability in stock markets.

7 Robustness

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

7.1 Shocks to Bitcoin or Ethereum

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 3). 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. Table A.5 in the Online Appendix reports our results. We observe similar estimates when we exclude all events in which Bitcoin or Ethereum are shocked, reenforcing our findings.

7.2 Placebo tests

We evaluate the informational content of the peer linkages we identified. It is conceivable that the news may randomly mention several cryptos in one sentence just because they are similar along pricing-irrelevant dimensions. Indeed, we know that the news tends to be biased towards reporting about larger assets (Solomon and Soltes (2012)) or assets with similar performance (Schwenkler and Zheng (2019)). As a result, there is a possibility that our peer linkages may just be random and not contain any meaningful information.

To assess whether this is the case, we re-run the regressions of Section 4 by considering random links between cryptos. We proceed as follows. During an event week, we create a random link between a shocked crypto and a different crypto by picking without replacement. Each time, we pick 3 cryptos to link with a shocked crypto given that this is the average number of links that a shocked crypto has in the news data (see Section 3). We then consider the co-movement of the randomly linked cryptos in the weeks before and after an event. We consider four different types of random links by restricting the universe of potential cryptos to link with. The first type picks cryptos at random from the full set of available cryptos. This type of link reflects uninformative linkages. The second type picks only out of the set of cryptos that have market capitalizations that fall in the same decile of the market capitalization distribution across cryptos during that week. This type captures cryptos that are linked at random just because they have similar sizes. The third type picks only out of the set of cryptos that have current-week total returns that fall in the same decile of the distribution across cryptos during the event week. This type captures cryptos that are linked at random because they have similar current performance. A final type picks only out of the set of cryptos that have past-week total returns that fall in the same decile of the distribution across cryptos during that week. This type captures cryptos that are linked at random because they have similar momentum.

Table A.6 in the Online Appendix reports the estimates of our difference-in-difference panel regressions. We cannot establish any significant co-movement if we link cryptos purely at random, or if we link cryptos at random when they have similar sizes. We find significant co-movement in the same direction – that is, contagion – among the set of cryptos that are linked at random because their current or lagged performance is similar. The difference between these results and those of Section 4 suggest that our peer linkages reflect to investors information that is different than that contained by current or lagged returns.

The results of our placebo tests confirm that the peer linkages we identify from the news convey information that investors deem to be relevant during an event week. Combined with the predictable reversal in the weeks after an event documented in Section 6, these results further validate that investors overreact to pricing-irrelevant information during an event week and that it takes them time to undue the resulting mis-pricing.

7.3 Standardization

We evaluate the impact of our standardization approach. We proposed in Section 4 to consider shocks to standardized abnormal returns because the distribution of abnormal returns is heavily skewed (see Table 1). It is possible that, in considering standardized rather than raw abnormal returns, we may have introduced a bias towards a less representative sample of shocks. To assess whether this is the case, we re-run some of the analyses of Section 4 by considering the analogous shocks to raw abnormal return shocks. We identify 198 raw abnormal return shock events, covering 37 distinct shocked cryptos over 110 distinct weeks.

Figures A.4–A.5 in the Online Appendix shows the impulse response functions for peer, shocked, and non-peer cryptos in response to raw abnormal return shocks. We again observe different behavior than in Section 4, as we cannot identify co-movement for peer cryptos during an event week. These results suggest that the standardization step we take is critical to identify co-movement and mis-pricing in crypto markets in response to idiosyncratic shocks. The reason why this is the case is that, by standardizing abnormal returns first before identifying shocks, we make sure to also consider cryptos that have low idiosyncratic volatilities as potential shocked cryptos. Those cryptos tend to be larger. Figure A.6 in the Online Appendix shows that the distribution of market capitalizations of shocked cryptos is skewed towards smaller cryptos when we consider shocks to raw abnormal returns. As a result, our standardization approach actually ensures that our sample of shocks is representative of all cryptos. The results of this section provide validation for our standardization approach.

7.4 Exogenous & endogenous shocks

Next, we evaluate whether the co-movement we establish occurs in response to exogenous or endogenous shocks. It is plausible that our co-movement may be the result of exogenous events triggering reporting about shocked cryptos, and the news pointing to cryptos that serve as alternative investments to the cryptos that experienced the shocks. It is also plausible that peer assets may not co-move at all if the shocks we identify are purely endogenous price movements that have nothing to do with new information being released to the market. To understand the influence of exogenous versus endogenous events, we re-run the regressions of Section 4 in subsamples of events that we manually label as capturing exogenous and endogenous events. We make our classified events available online here.

Table A.7 in the Online Appendix contains the estimates of our diff-in-diff panel regressions restricted to the subsamples of exogenous and endogenous shocks. We find stronger co-movement in response to exogenous shocks. However, we also find some co-movement in response to endogenous shocks. After scaling with the summary statistics of Table 1, the estimates of Table

A.7 imply in nominal terms that peer cryptos showcase excess abnormal returns of around 5.64% in response exogenous shocks, and 3.93% in response to endogenous shocks (we established an excess abnormal return of 4.5% for peer cryptos in Section 4). These results suggest that our findings are not driven by the exogenous nature of shocks. They reinforce our conclusion that investors have a hard time disentangling the informational content of the shocks.

7.5 Positive shocks

We investigate the co-movement of peer cryptos after positive shocks. We consider a crypto to be positively shocked if its weekly standardized abnormal return falls in the top decile of the distribution across cryptos and time. This approach yields 223 shock events, covering 42 distinct shocked cryptos over 109 distinct weeks. As in Section 5.4, we consider the performance of different set of cryptos in the weeks surrounding an event in Figure A.7 in the Online Appendix. We find again that the set of peer cryptos that are co-listed in common exchanges experience excess abnormal performance of the opposite sign, consistent with a competition effect. We also observe some evidence of contagion within the set of non-peer cryptos. These results again suggest that the interaction of co-listing and online-news peer linkages drives the competition effect we uncover.

We evaluate whether there is also predictability among the set of co-listed peer cryptos in the weeks after a positive idiosyncratic shock. Figure A.8 in the Online Appendix shows the cumulative returns of shocked cryptos, co-listed peer cryptos, co-listed non-peer cryptos that operate in the same industry as a shocked crypto, and all other cryptos. In contrast to the results of Section 6.1, we find that the predictability among the set of co-listed peer cryptos is much more muted. It takes only one week before the performance of a co-listed peer crypto reverts back and catches up with that of an average crypto in the market. While these results also support a competition effect, the degree of co-movement and predictability in response to positive idiosyncratic shocks is weaker than after negative idiosyncratic 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).

7.6 Alternative regression

Finally, one may be concerned that our difference-in-difference approach may not be adequate to identify the co-movement we claim to document. We explore an alternative approach to identify co-movement that is inspired by Kwan (1996). Assuming that (t, j) denotes an event in which crypto j is shocked on week t, we estimate the following model for $i \neq j$:

$$\mathbb{E}\big[Y_{i,t} \,|\, X_{i,t},\, \text{event} = (t,j)\big] = \text{FE}_{i,t,j} + b_X' X_{i,t} + b_e' \overrightarrow{Y}_{j,t} + b_P' \mathbb{1}_{\{i \text{ is peer of } j\}} \overrightarrow{Y}_{j,t}. \tag{5}$$

Here, $Y_{i,t}$ denotes raw abnormal return of crypto i, $X_{i,t}$ is a set of contemporaneous and lagged regressors, and $\overrightarrow{Y}_{j,t}$ is a vector that contains the contemporaneous and lagged raw abnormal returns of the shocked crypto. We include crypto and event week fixed effects so that $\text{FE}_{i,t,j} = a_i + a_t$, and we cluster standard errors by event week.

The coefficient b_P captures the average excess abnormal return of a peer during an event week. If this coefficient is statistically significant and negative for the event week, then it tells us that peer assets move in the opposite direction than shocked cryptos during an event week, consistent with Section 4. The parameter b_e captures the market-wide contagion effects that may be triggered by the shocks.

Table A.8 in the Online Appendix reports our estimates. We observe that the parameter b_P is statistically significant and negative, confirming the results of Section 4. The estimates indicate that peer cryptos experience about one-fourth of the shocks that shocked cryptos experience, albeit in the opposite direction. We establish similar measurements in Section 4 through our diff-in-diff approach, validating our approach. Extending our previous results, though, we find that the whole market experiences weak contagion during event weeks. We observe this through the significance and positive sign of the parameter estimate for b_e during an event week. The estimate suggests that all cryptos abnormally lose 40 bp on average when negative abnormal return shocks take place.

8 Conclusion

We document significant co-movement in cryptocurrency markets along the interaction of peer and co-listing linkages. When large idiosyncratic shocks hit one crypto, cryptos that are identified as peers in the news and that are listed in the same exchanges as shocked cryptos experience unusually large abnormal returns of the opposite sign. This co-movement is a type of mis-pricing that aligns with a competition effect that is common in traditional financial markets. The mis-pricing vanishes after four weeks and results in predictable returns because of slow information processing. We develop trading strategies that exploit the mis-pricing and show that the strategies are profitable after accounting for realistic trading fees. To obtain our results, we develop novel natural language processing tools that facilitate the identification of crypto peer linkages from news data.

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	Obs.	Mean	Median	Std dev.	Min.	Max.
Age (years)	100	3.62	3.42	1.92	0.09	11.92
					(Keep3rV1)	(Bitcoin)
Market capitalization (million USD)	100	2550.96	147.39	15261.61	18.20	148738.18
					(OriginTrail)	(Bitcoin)
Had ICO indicator	100	0.40	0.00	0.49	0.00	1.00
					(Bitcoin)	(Ethereum)
Maximum mineable coin supply (million units)	90	104271.82	381.57	948366.19	0.01	9000000.00
					(RenBTC)	(Compound Coin)
Daily circulating coin supply (million units)	45	2328.35	282.81	9442.56	1.00	57152.92
					(Maker)	(Crypto.com Coin)
Average weekly return	100	−0.35%	−0.15%	3.18%	−18.37%	7.66%
					(Filecoin)	(UMA)
Average weekly volatility	100	15.05%	13.91%	5.70%	4.04%	49.27%
					(LEO Token)	(Sushi)
Number of listing exchanges	100	51.83	34.50	55.84	1.00	293.00
					(Blockstack)	(Bitcoin)
Average weekly trading volume (million USD)	100	351.10	10.92	1789.58	0.14	16507.30
					(OriginTrail)	(Bitcoin)
Average weekly turnover	100	−2.12	−2.62	3.11	−6.45	14.07
					(Celsius Network)	(NuCypher)
Daily Alexa rank (x 10^3)	100	394.36	198.04	639.96	1.29	5359.90
					(Binance Coin)	(NEAR)
Market beta	100	1.00	1.04	0.23	0.11	1.49
					(LEO Token)	(Sushi)
Size beta	100	0.44	0.34	0.58	−0.33	4.03
					(Bitcoin Cash)	(Hegic)
Momentum beta	100	−0.13	−0.13	0.19	−1.41	0.86
					(Keep3rV1)	(Hegic)
Average weekly abnormal return	100	0.01%	0.01%	1.03%	−5.16%	7.57%
					(Filecoin)	(Hegic)
Average weekly idiosyncratic volatility	100	11.86%	10.64%	5.89%	1.82%	46.50%
					(RenBTC)	(Sushi)
Average number of mentions per week in news	100	8.41	0.70	33.91	0.00	287.04
					(Keep3rV1)	(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. Turnover is defined as the logarithm of the ratio of daily trading volume over market capitalization. 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.

		(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 2: Zero-inflated negative binomial regressions of the number of times a crypto is identified in 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 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 3: 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 4: 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 5: 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 $^{\cdot}$ denote significance on the 99.9%, 99%, 95%, and 90% 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 6: 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 5. 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 $\cdot$ denote significance on the 99.9%, 99%, 95%, and 90% confidence levels, respectively.

			(1)	(2)	(3)
b_X	IR	Lag 1	-0.030	-0.030	-0.030
			(-1.783)	(-1.716)	(-1.807)
		Lag 2	0.004	0.004	0.004
			(0.296)	(0.281)	(0.290)
	Vol.	Lag 0	· 0.037	· 0.037	· 0.037
			(2.295)	(2.213)	(2.291)
		Lag 1	0.028	0.027	0.027
			(1.808)	(1.703)	(1.762)
		Lag 2	0.018	0.019	0.019
			(0.848)	(0.841)	(0.862)
	Idio. vol.	Lag 0	*** 0.193	*** 0.193	*** 0.193
			(9.059)	(8.938)	(9.060)
		Lag 1	* -0.030	* -0.029	* -0.029
			(-3.347)	(-2.556)	(-3.338)
		Lag 2	0.006	0.005	0.005
			(0.214)	(0.191)	(0.193)
	Log volume	Lag 0	*** 0.253	*** 0.253	*** 0.253
			(12.180)	(11.932)	(12.285)
		Lag 1	*** -0.222	*** -0.221	*** -0.221
			(-13.482)	(-13.160)	(-13.360)
		Lag 2	* -0.042	* -0.042	* -0.042
			(-2.838)	(-2.655)	(-2.796)
	MC	Lag 0	** -0.143	** -0.142	** -0.142
			(-5.167)	(-5.061)	(-5.116)
b_e				** -0.018	* -0.017
				(-3.861)	(-3.393)
b_a					0.001
					(0.292)
b_P				-0.008	-0.010
				(-0.725)	(-0.479)
b_S				-0.038	-0.019
				(-0.719)	(-0.347)
$b_{P,e}$				*** 0.380	*** 0.382
				(6.713)	(6.372)
$b_{P,a}$					0.004
					(0.118)
$b_{S,e}$				*** -1.216	*** -1.235
				(-24.561)	(-22.352)
$b_{S,a}$					-0.039
					(-1.737)
Crypto-week obs.			9702	9702	9702
Adjusted R^2			0.120	0.126	0.126

Table 7: 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%, 95%, and 90% confidence levels, respectively.

			Return	Volatility	Turnover	News
b_X	News	Lag 1				** 0.121
						(4.998)
		Lag 2				* 0.041
						(2.465)
	Return	Lag 0		0.017	· 0.058	· −0.049
				(0.325)	(2.285)	(−2.115)
		Lag 1	−0.022	0.094	0.032	−0.021
			(−1.575)	(1.331)	(1.207)	(−1.747)
		Lag 2	0.002	−0.012	−0.023	0.012
			(0.244)	(−0.340)	(−1.091)	(0.687)
	IR	Lag 0		** 0.188	· 0.037	· 0.052
				(4.784)	(2.020)	(2.086)
		Lag 1		−0.050	−0.026	*** 0.032
				(−0.859)	(−1.283)	(5.554)
		Lag 2		0.017	−0.007	−0.012
				(0.464)	(−0.505)	(−0.772)
	Vol.	Lag 0	· 0.026		· 0.027	−0.013
			(1.984)		(2.198)	(−1.059)
		Lag 1	0.013	*** 0.097	−0.016	−0.010
			(0.834)	(8.202)	(−1.538)	(−0.525)
		Lag 2	−0.001	** 0.036	−0.000	0.008
			(−0.060)	(5.087)	(−0.024)	(0.746)
	Idio. vol.	Lag 0	*** 0.146		*** 0.145	*** 0.058
			(8.929)		(7.393)	(5.664)
		Lag 1	* −0.025		** −0.045	* 0.023
			(−2.666)		(−4.758)	(3.419)
		Lag 2	0.015		−0.018	−0.006
			(0.697)		(−1.225)	(−0.613)
	Log volume	Lag 0	*** 0.205	*** 0.299		** 0.068
			(9.082)	(12.035)		(4.702)
		Lag 1	*** −0.188	*** −0.120		−0.018
			(−11.144)	(−27.758)		(−1.287)
		Lag 2	* −0.033	* −0.048		−0.011
			(−2.563)	(−2.581)		(−1.364)
	Turnover	Lag 1			*** 0.562	
					(30.013)	
		Lag 2			** 0.049	
					(3.500)	
	MC	Lag 0	*** −0.133	−0.027	0.002	0.045
			(−6.654)	(−1.385)	(0.119)	(1.495)
b_e			· −0.004	· 0.011	* 0.006	0.002
			(−2.017)	(2.305)	(3.457)	(0.747)
b_P			−0.012	0.022	0.007	−0.028
			(−1.002)	(1.645)	(0.430)	(−1.310)
b_S			0.006	0.001	0.037	0.009
			(0.213)	(0.051)	(1.778)	(0.555)
$b_{P,e}$			*** 0.234	−0.028	0.029	** 0.107
			(7.421)	(−0.884)	(0.485)	(3.931)
$b_{S,e}$			*** −0.766	** 0.261	0.038	0.057
			(−9.892)	(4.548)	(0.544)	(0.990)
Crypto-week obs.			9753	9850	9342	9048
Adjusted R^2			0.115	0.103	0.392	0.019

Table 8: Difference-in-difference panel regressions of total returns, volatility, turnover, 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%, 95%, and 90% confidence levels, respectively.

			Criterion to identify informational events		
			Log mentions	Log volume	Idio. vol.
b_X	IR	Lag 1	−0.021	−0.021	−0.020
			(−1.597)	(−1.529)	(−1.496)
		Lag 2	0.011	0.007	0.006
			(0.895)	(0.633)	(0.531)
	Vol.	Lag 0	0.032	0.032	0.032
			(1.578)	(1.536)	(1.573)
		Lag 1	0.016	0.018	0.015
			(1.141)	(1.312)	(1.027)
		Lag 2	0.013	0.007	0.009
			(0.594)	(0.360)	(0.438)
	Idio. vol.	Lag 0	*** 0.187	*** 0.188	*** 0.188
			(9.105)	(8.289)	(8.601)
		Lag 1	* −0.027	* −0.033	* −0.030
			(−2.394)	(−3.109)	(−2.668)
		Lag 2	0.020	0.023	0.023
			(0.724)	(0.830)	(0.816)
	Log volume	Lag 0	*** 0.270	*** 0.274	*** 0.272
			(15.075)	(14.348)	(14.937)
		Lag 1	*** −0.224	*** −0.222	*** −0.225
			(−11.924)	(−11.779)	(−11.614)
		Lag 2	* −0.044	* −0.045	* −0.044
			(−3.046)	(−2.932)	(−2.974)
	MC	Lag 0	** −0.136	** −0.138	** −0.139
			(−5.102)	(−5.187)	(−5.039)
b_P			0.015	0.001	0.007
			(1.077)	(0.040)	(0.414)
b_S			−0.030	0.005	−0.021
			(−0.500)	(0.119)	(−0.428)
$b_{e,inf}$			−0.005	0.001	* −0.022
			(−0.884)	(0.078)	(−2.605)
$b_{e,noninf}$			* −0.017	* −0.019	* −0.018
			(−2.760)	(−3.024)	(−3.082)
$b_{P,e,inf}$			0.269	0.197	0.112
			(1.637)	(0.844)	(1.445)
$b_{P,e,noninf}$			*** 0.360	** 0.401	*** 0.441
			(5.906)	(5.162)	(6.180)
$b_{S,e,inf}$			*** −1.550	*** −1.661	*** −1.556
			(−8.577)	(−7.711)	(−13.313)
$b_{S,e,noninf}$			*** −1.190	*** −1.220	*** −1.171
			(−22.763)	(−21.782)	(−24.878)
Crypto-week obs.			9022	9086	9024
Number of events			130	138	138
Number of informational events			16	11	20
Adjusted R^2			0.115	0.118	0.119

Table 9: Difference-in-difference panel regressions of abnormal returns in response to large negative abnormal return shocks that are informational in nature. We estimate models of the Type (4), and brake down the sample of shocks into informational and non-informational shocks. We say that a shock is informational if 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. 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%, 95%, and 90% confidence levels, respectively.

			(1)	(2)	(3)
b_X	IR	Lag 1	−0.019	0.015	−0.019
			(−1.473)	(0.732)	(−1.483)
		Lag 2	0.006	0.025	0.007
			(0.535)	(1.334)	(0.547)
	Vol.	Lag 0	0.033	−0.017	0.032
			(1.617)	(−0.536)	(1.610)
		Lag 1	0.016	* 0.060	0.015
			(1.120)	(2.533)	(1.092)
		Lag 2	0.010	· 0.057	0.010
			(0.478)	(2.207)	(0.498)
	Idio. vol.	Lag 0	*** 0.188	** 0.147	*** 0.188
			(8.748)	(4.408)	(8.670)
		Lag 1	* −0.030	* −0.044	* −0.030
			(−2.655)	(−2.957)	(−2.716)
		Lag 2	0.022	0.010	0.022
			(0.829)	(0.383)	(0.816)
	Log volume	Lag 0	*** 0.272	*** 0.275	*** 0.271
			(15.012)	(15.953)	(14.925)
		Lag 1	*** −0.224	*** −0.239	*** −0.224
			(−12.048)	(−10.412)	(−12.055)
		Lag 2	* −0.043	* −0.060	* −0.043
			(−2.956)	(−2.974)	(−2.944)
	MC	Lag 0	** −0.138	** −0.088	** −0.140
			(−5.072)	(−4.458)	(−5.193)
b_e			** −0.020	· −0.098	−0.014
			(−3.958)	(−2.044)	(−0.237)
$b_{industry}$			0.003		* 0.005
			(1.872)		(2.554)
$b_{colisted}$				−0.021	0.018
				(−0.323)	(0.262)
b_P					0.005
					(0.254)
b_S			−0.022	−0.079	0.010
			(−0.388)	(−0.761)	(0.120)
$b_{industry,e}$			** 0.064		*** 0.044
			(5.054)		(5.543)
$b_{colisted,e}$				−0.109	−0.014
				(−1.474)	(−0.223)
$b_{P,e}$					*** 0.374
					(6.367)
$b_{S,e}$			*** −1.226	*** −1.470	*** −1.233
			(−23.187)	(−18.052)	(−27.545)
Crypto-week obs.			9095	9095	9095
Adjusted R^2			0.117	0.114	0.119

Table 10: Difference-in-difference panel regressions of abnormal returns in the weeks surrounding a negative abnormal return shock, controlling for alternative 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%, 95%, and 90% confidence levels, respectively.

Holding period	Alpha	Beta Market	Beta Size	Beta Momentum	Cumulative return	Average return	Volatility
1	-0.004	* -0.070	** -0.131	0.071	-39.74%	-0.31%	3.76%
	(-1.367)	(-2.128)	(-2.919)	(1.386)			
2	-0.000	-0.027	0.042	-0.019	-6.39%	-0.04%	3.83%
	(-0.078)	(-0.788)	(0.877)	(-0.346)			
3	0.001	-0.038	-0.023	0.055	30.00%	0.16%	3.80%
	(0.382)	(-1.115)	(-0.493)	(1.016)			
4	0.002	* -0.071	-0.046	0.038	50.00%	0.25%	3.80%
	(0.726)	(-2.075)	(-0.977)	(0.712)			
5	0.004	-0.016	-0.009	0.039	109.84%	0.46%	3.38%
	(1.562)	(-0.505)	(-0.205)	(0.802)			
6	* 0.005	-0.034	-0.044	-0.006	136.64%	0.54%	3.12%
	(2.041)	(-1.208)	(-1.126)	(-0.139)			
7	* 0.005	0.005	-0.030	-0.022	131.90%	0.53%	2.87%
	(2.152)	(0.198)	(-0.821)	(-0.508)			
8	* 0.005	-0.012	-0.017	0.045	157.93%	0.60%	2.63%
	(2.601)	(-0.495)	(-0.506)	(1.164)			
9	** 0.006	-0.005	-0.000	0.007	160.31%	0.61%	2.53%
	(2.830)	(-0.221)	(-0.010)	(0.185)			
10	** 0.006	0.021	-0.054	-0.049	156.44%	0.61%	2.51%
	(2.820)	(0.908)	(-1.718)	(-1.285)			
11	** 0.006	-0.014	-0.030	-0.000	184.78%	0.68%	2.42%
	(3.217)	(-0.615)	(-0.944)	(-0.008)			
12	*** 0.007	-0.022	-0.022	-0.022	230.11%	0.78%	2.50%
	(3.650)	(-0.922)	(-0.667)	(-0.556)			
13	*** 0.007	-0.007	-0.031	0.013	207.97%	0.74%	2.41%
	(3.465)	(-0.307)	(-0.961)	(0.340)			
14	*** 0.007	-0.025	-0.025	-0.021	226.63%	0.78%	2.33%
	(3.913)	(-1.123)	(-0.786)	(-0.582)			
15	*** 0.007	-0.015	-0.040	0.013	209.49%	0.75%	2.25%
	(3.771)	(-0.716)	(-1.271)	(0.361)			
16	*** 0.007	-0.020	-0.052	0.043	204.45%	0.75%	2.21%
	(3.611)	(-0.976)	(-1.584)	(1.197)			
17	*** 0.007	0.011	-0.027	-0.011	195.01%	0.73%	2.15%
	(3.808)	(0.553)	(-0.823)	(-0.310)			
18	*** 0.007	-0.029	-0.039	0.032	191.34%	0.73%	2.07%
	(3.828)	(-1.426)	(-1.268)	(0.901)			
19	*** 0.007	-0.009	0.012	-0.011	187.66%	0.72%	2.08%
	(4.020)	(-0.410)	(0.371)	(-0.294)			
20	*** 0.007	0.011	-0.031	0.039	188.77%	0.73%	2.02%
	(3.821)	(0.528)	(-1.008)	(1.114)			

Table 11: Performance metrics for event-based trading strategies that exploit the predictability documented in Figure 12. Each week, we short-sell cryptos that are co-listed peers of a crypto that is shocked, and go long on Bitcoin. 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 $\cdot$ denote significance on the 99.9%, 99%, 95%, and 90% confidence levels, respectively.

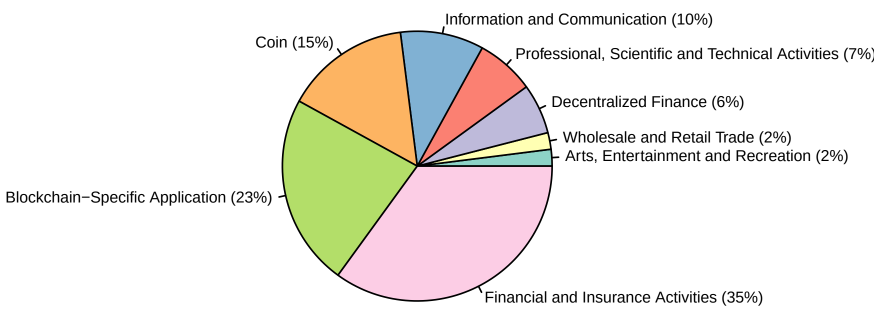
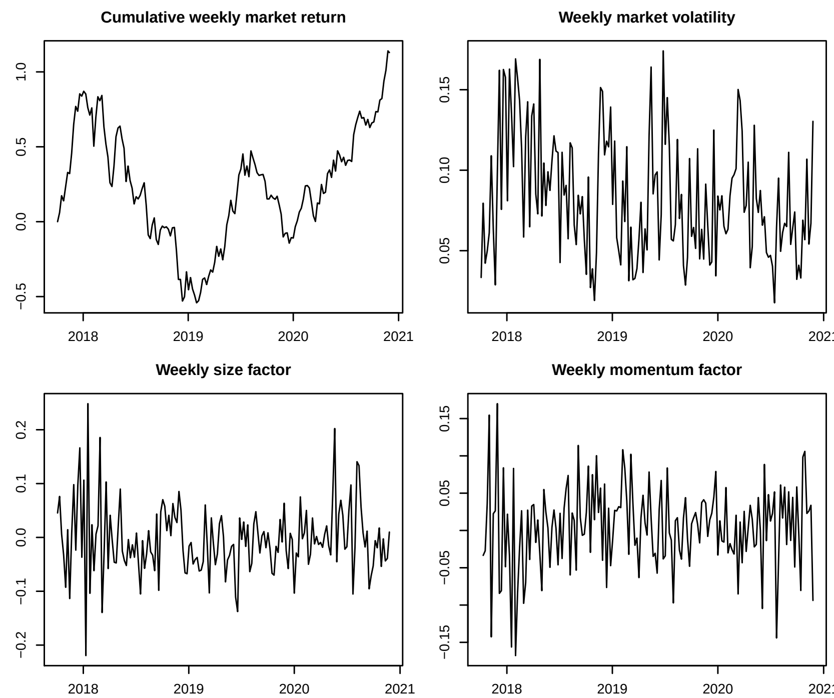
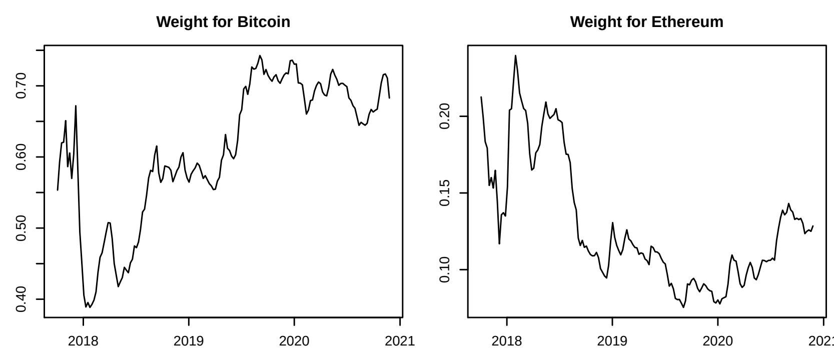


Figure 1: Classification of the industries in which cryptos in our data sample operate. We obtain industry classification data from Cryptocompare. Whenever unavailable, we complement the data with industry classifications from Coingecko and from Lyandres et al. (2019). We manually classify any asset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

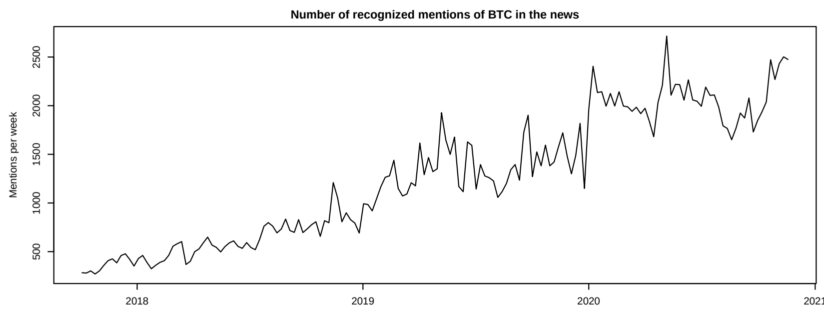


(a) Cumulative weekly market returns and volatility, together with size and momentum factors.

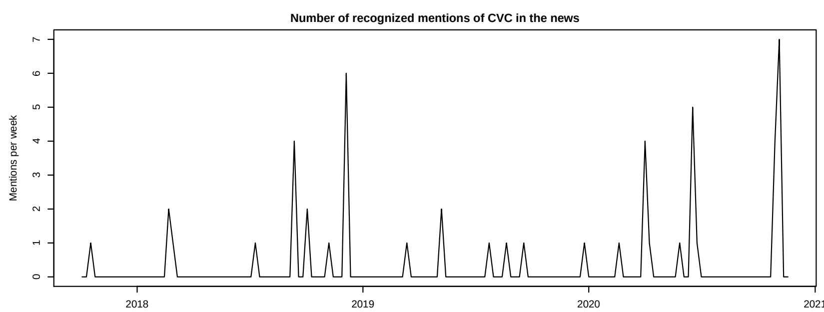


(b) Market capitalization weights for Bitcoin and Ethereum.

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.

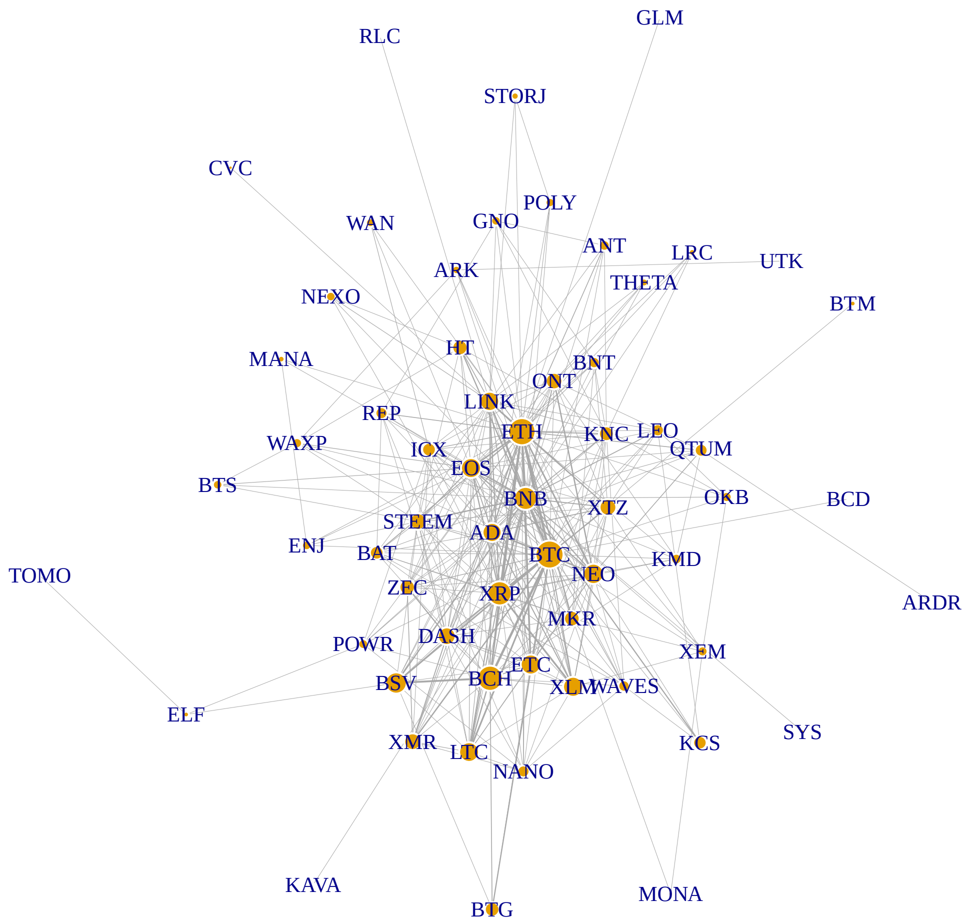


Figure 4: Network of cryptos implied by the full news data sample covering the period October 1, 2017, through November 30, 2020. The size of a node is proportional to the logarithm of the number of times that crypto is mentioned in the news. The width of a link between two cryptos is proportional to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

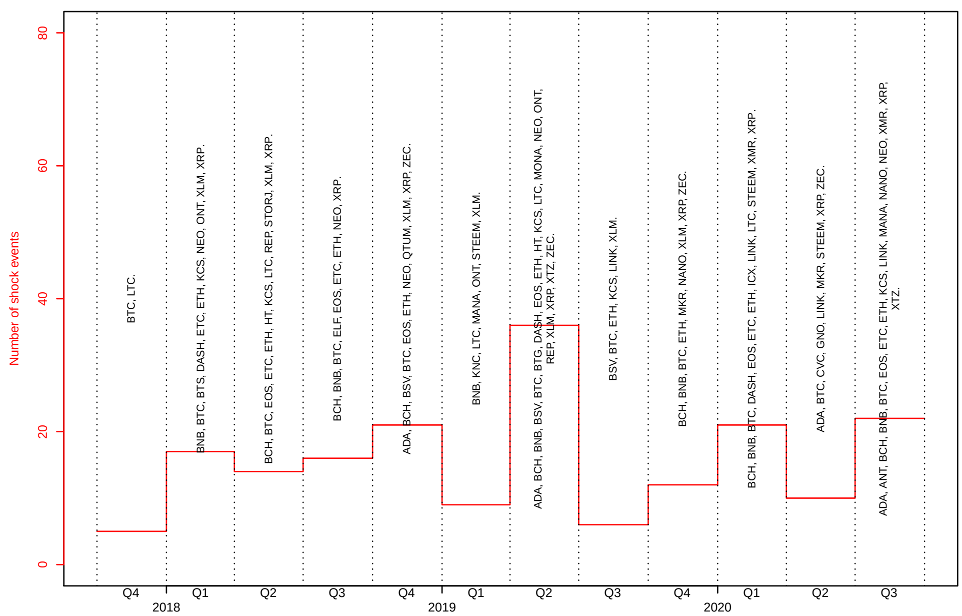
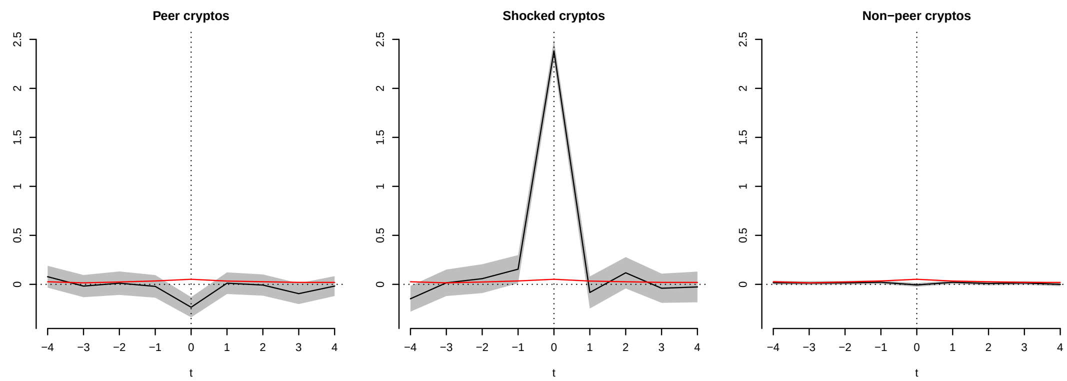
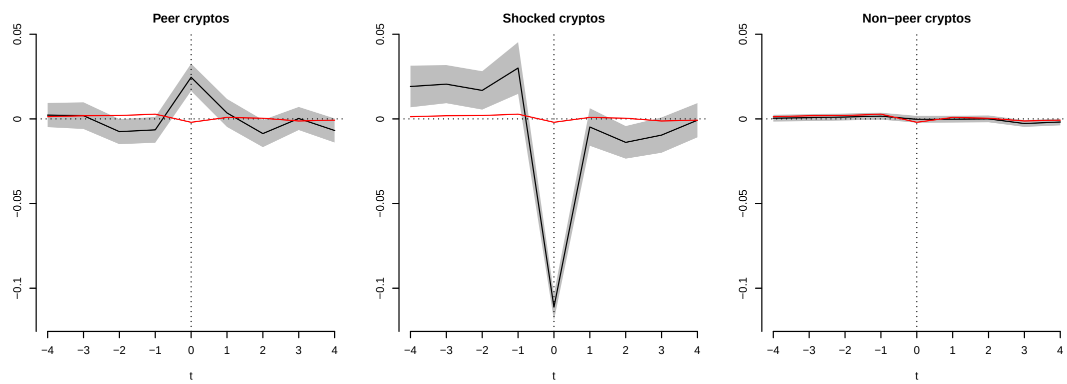


Figure 5: Shock events in our sample. We collect all cryptos that at some point in a quarter experience standardized weekly abnormal returns that land in the lowest decile of the empirical distribution across time and cryptos in our data. The red line shows the quarterly number of shock events identified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

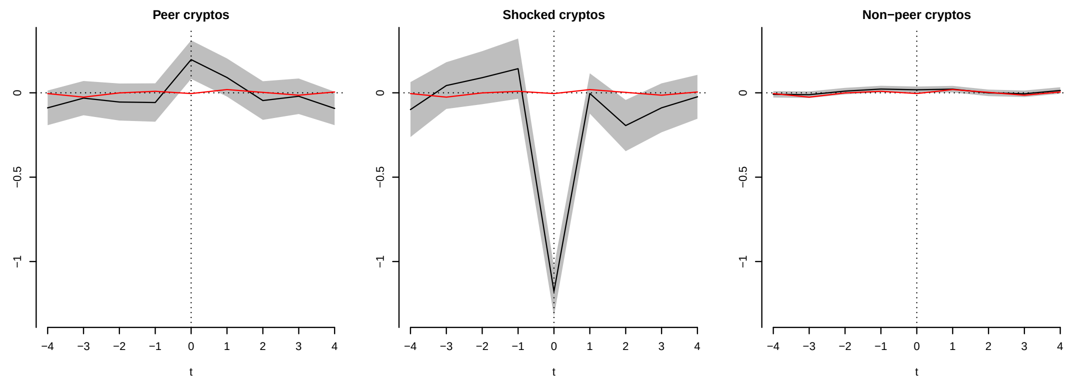


(a) Standardized abnormal return in week $e+t$, where e is the event week.

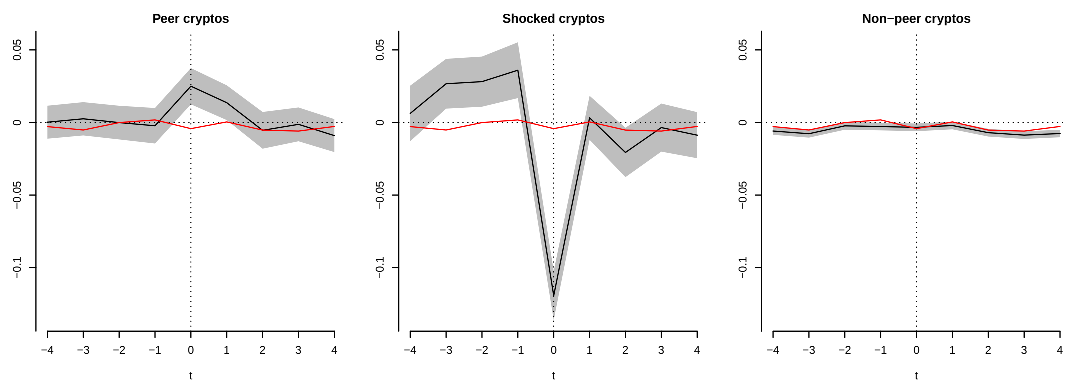


(b) Raw abnormal return in week $e+t$, where e is the event week.

Figure 6: Sample means of standardized and raw abnormal returns for the sample of shocked, peer, and non-peer cryptos in the weeks surrounding an event. Table 1 provides summary statistics of the raw idiosyncratic returns. 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.

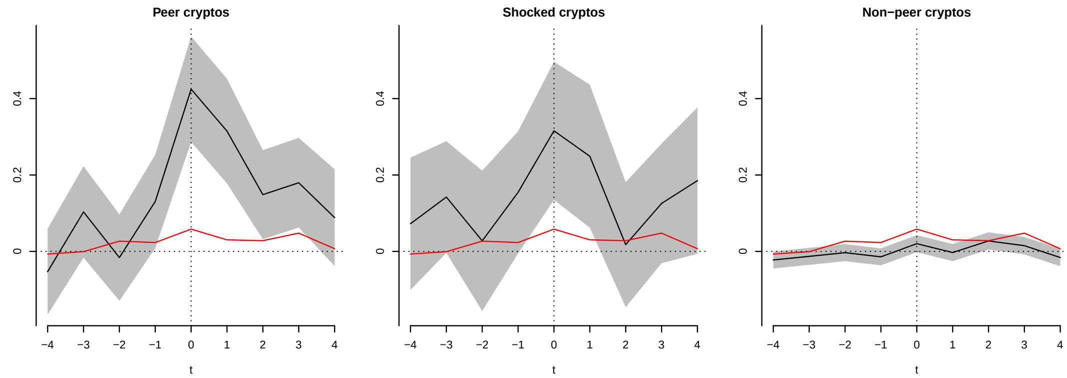


(a) Standardized return in week $e + t$, where e is the event week.

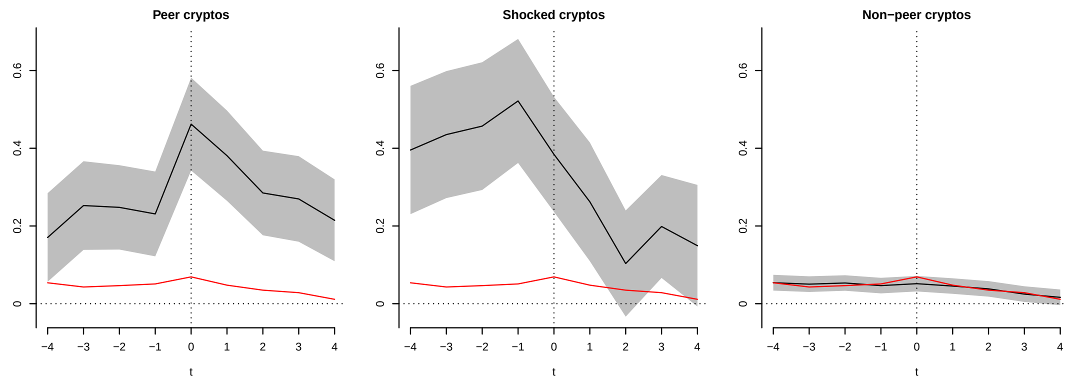


(b) Raw return in week $e + t$, where e is the event week.

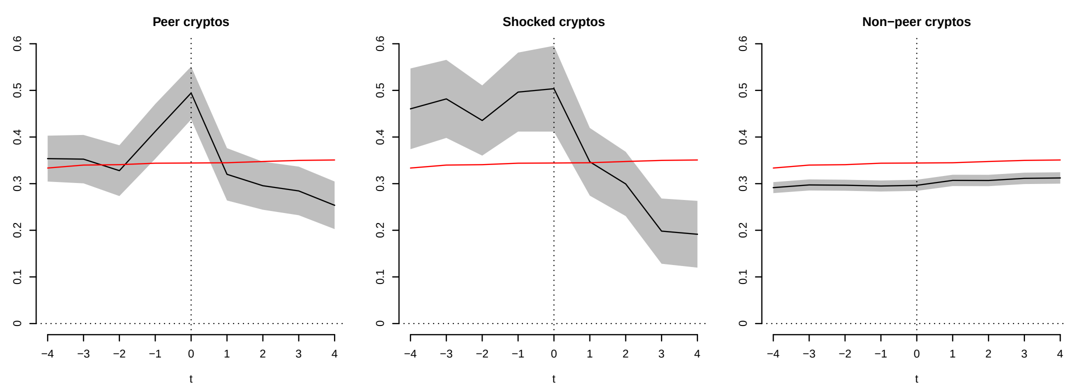
Figure 7: Sample means of standardized and raw returns for the sample of shocked, peer, and non-peer cryptos in the weeks surrounding an event. Table 1 provides summary statistics of the raw returns. We standardize a time series for each asset on a rolling basis using the mean and standard deviation 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.

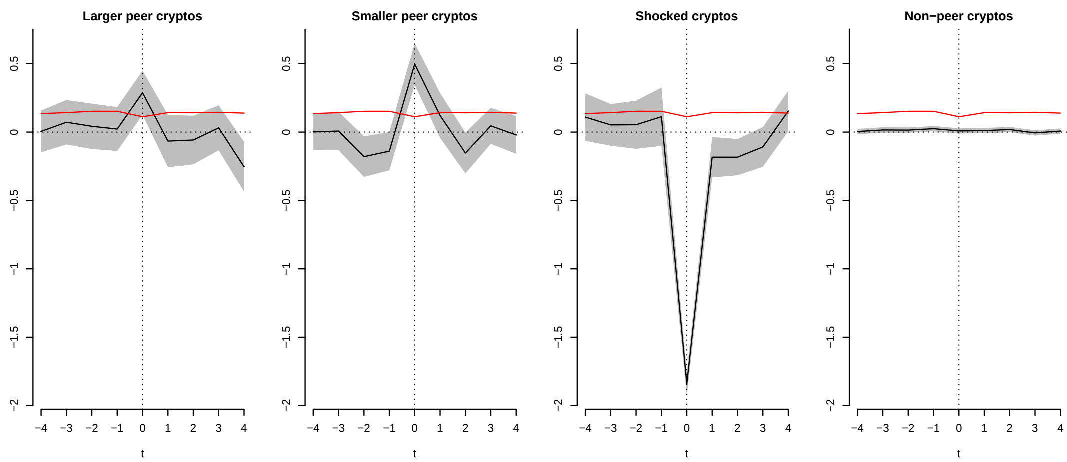


(b) Standardized turnover in week $e+t$, where e is the event week. Turnover is defined as the weekly average of the logarithm of the ratio of daily trading volume over market cap.

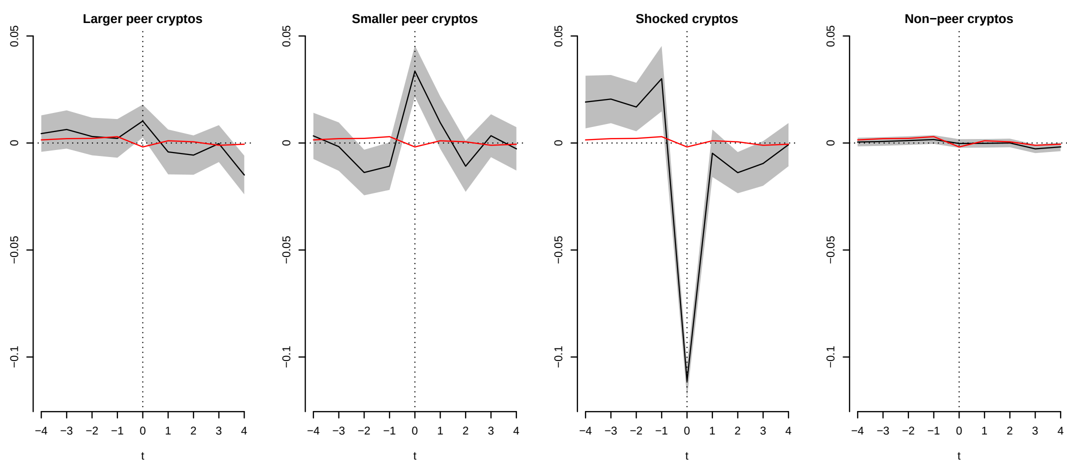


(c) Standardized log-mentions in news in week $e+t$, where e is the event week.

Figure 8: Sample means of standardized volatility, turnover, and log news mentions for the sample of shocked, peer, and non-peer cryptos in the weeks surrounding an event. Table 1 provides summary statistics of the raw measures. 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) Raw abnormal returns in week e + t, where e is the event week.

Figure 9: Sample means of standardized and raw abnormal 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 raw measures and Section 2 describes how the raw 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.

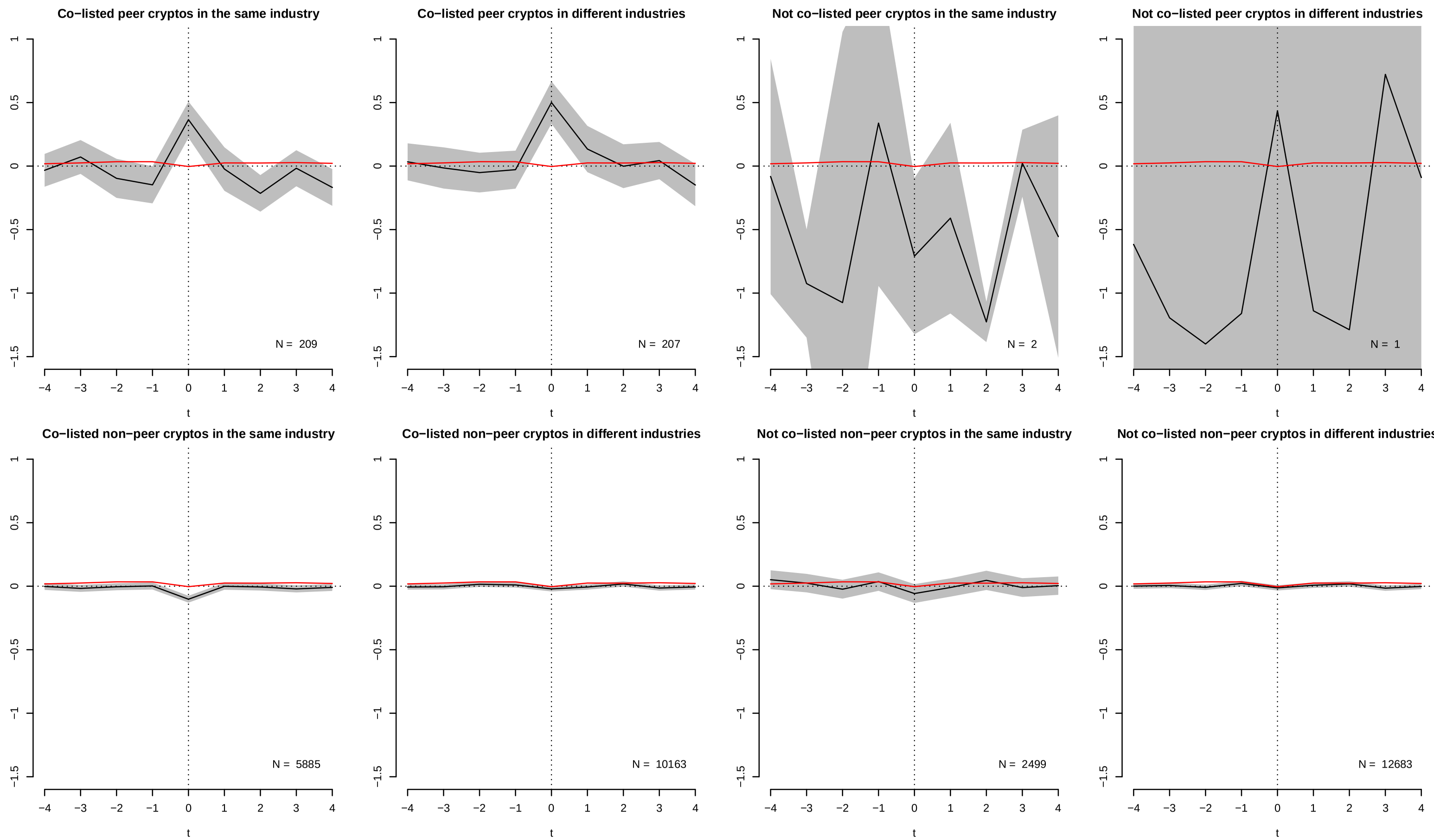


Figure 10: Sample means of standardized abnormal returns for the sample of shocked, non-peers, and peer cryptos that are either co-listed in the same exchanges or operate in the same industries as shocked cryptos. Table 1 provides summary statistics of the raw measures and Section 2 describes how the raw 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. The value of N in each plot indicates the size of the respective subsample of cryptos.

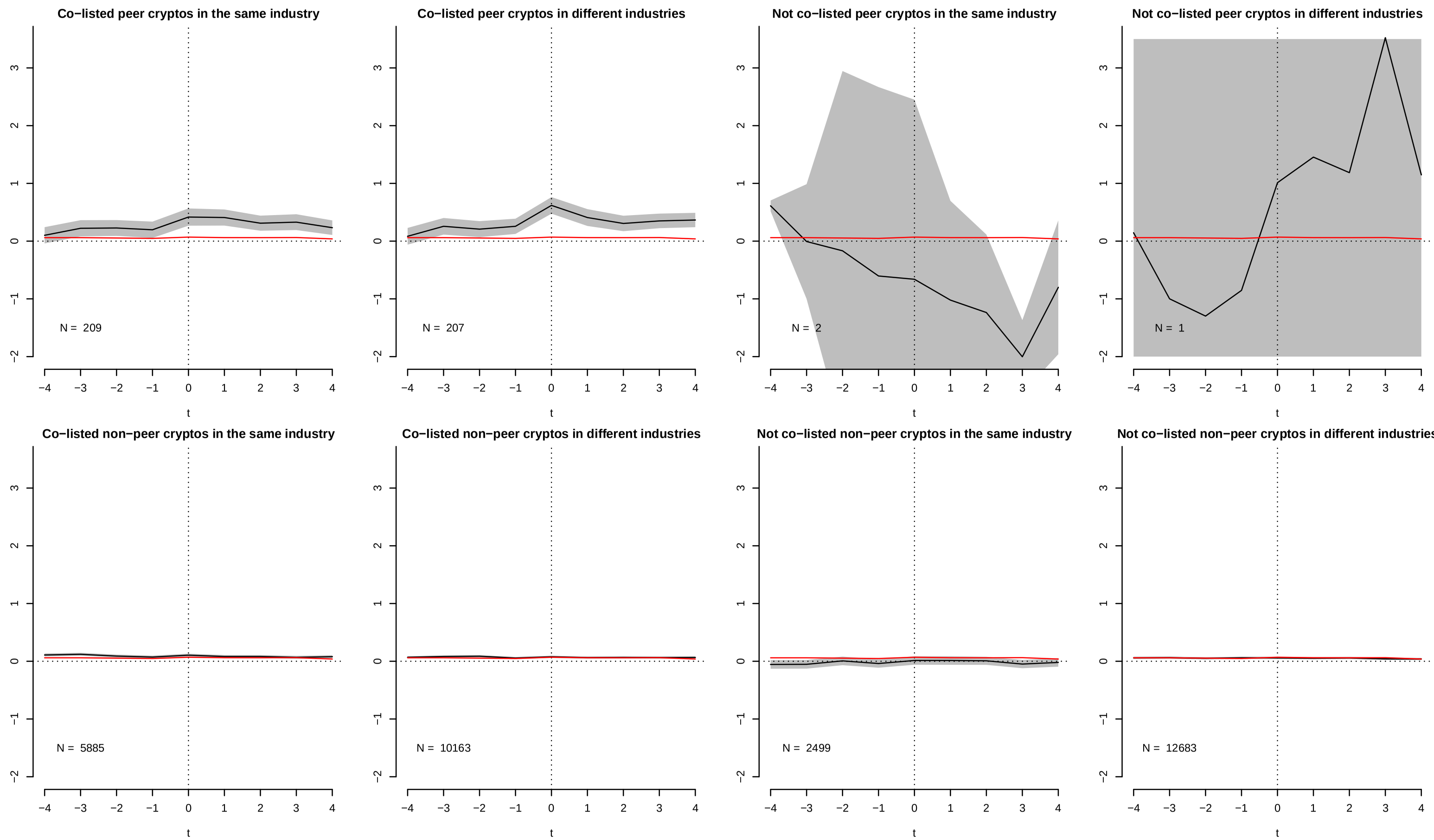


Figure 11: Sample means of standardized turnover for the sample of shocked, non-peers, and peer cryptos that are either co-listed in the same exchanges or operate in the same industries as shocked cryptos. Table 1 provides summary statistics of the raw measures and Section 2 describes how the raw measures 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. The value of N in each plot indicates the size of the respective subsample of cryptos.

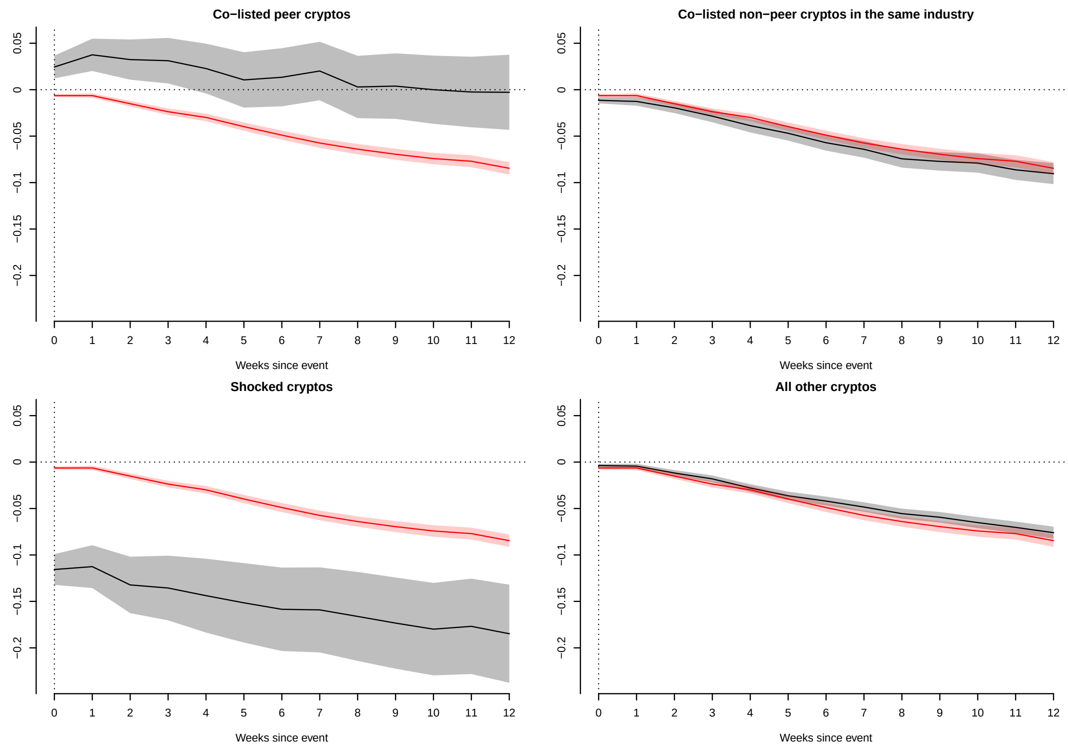


Figure 12: Cumulative total returns for co-listed peer cryptos, co-listed non-peer cryptos in the same industry as shocked cryptos, shocked cryptos, and all other cryptos in the weeks after a standardized total return shock event. The black lines give the weekly cumulative total return in week $e+t$, where e is an event week and $1 \leq t \leq 12$, 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, while the shaded pink regions gives 95% asymptotic confidence bands. 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.

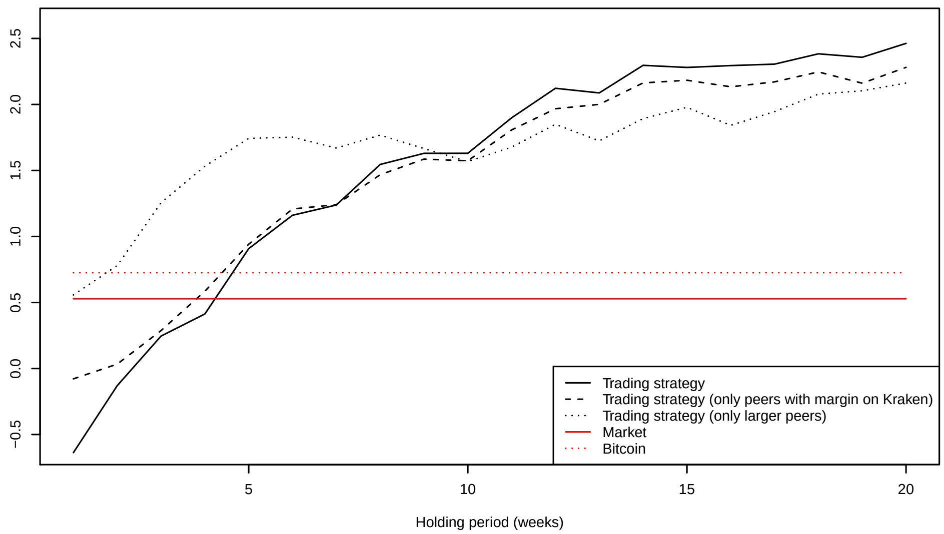


Figure 13: Annualized Sharpe ratios of our event-based trading strategies with different holding periods. Each week, we short-sell cryptos that are co-listed peers of a crypto that is shocked, and go long on Bitcoin. We hold the positions open for several weeks (the holding period). All short positions 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.

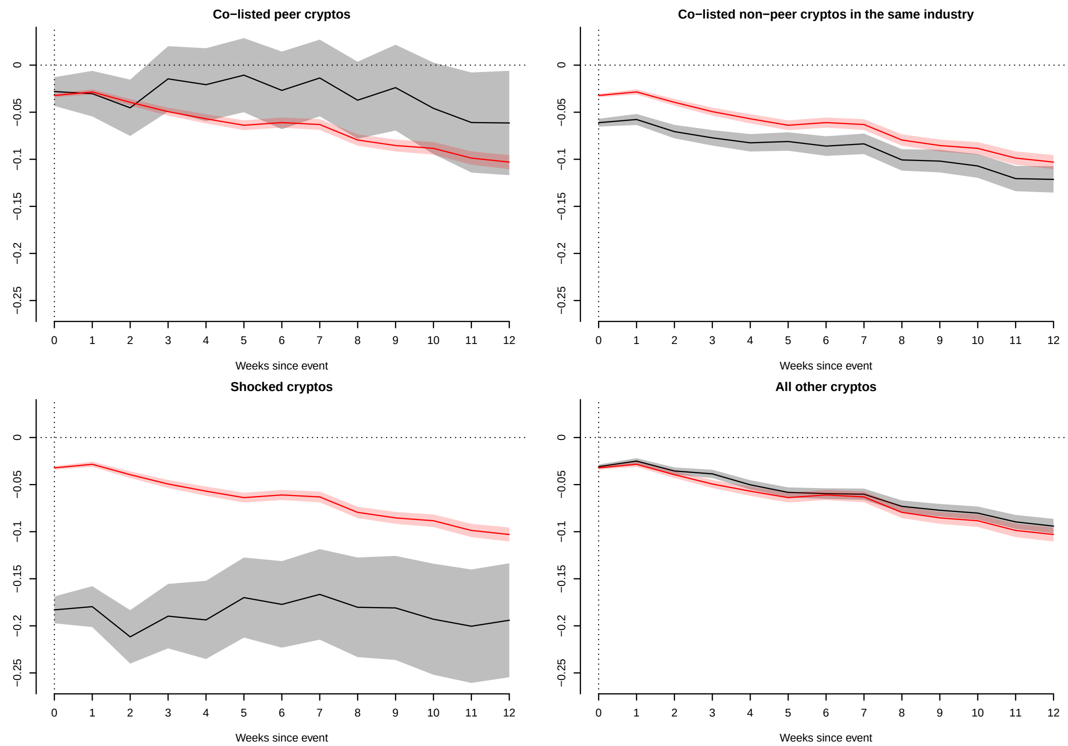


Figure 14: Cumulative total returns for co-listed peer cryptos, co-listed non-peer cryptos in the same industry as shocked cryptos, shocked cryptos, and all other cryptos in the weeks after a standardized total return shock event. We say that a crypto with standardized weekly total return that falls 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 143 distinct events, affecting 41 distinct cryptos over 57 distinct weeks. The black lines give the weekly cumulative total return in week $e+t$, where e is an event week and $1 \leq t \leq 12$, 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, while the shaded pink regions gives 95% asymptotic confidence bands. 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.