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The relative importance of competition to contagion: evidence from the digital currency market

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Abstract

How does the valuation change of an industry leader influence its competitors? Does it induce a competitive effect or a contagion effect? What are the driving forces of such influences? We attempted to answer these questions within digital currency markets. We found that both close and distant competitors against an industry leader experience high competitive effects, while moderate competitors experience high contagion effects. Next, we empirically demonstrated how this U-shaped pattern reduces to a linear relationship depending on the industry concentration. Lastly, we identified eight distinct information categories from a social media platform of the industry leader and compared the influence of the eight information categories on the industry leader's competitors. Our analysis suggests that the relative importance of the competitive effect to the contagion effect in the industry depends on the category of the information.

Keywords: Social media, Contagion, Competition, Information spillover, Digital economy

Introduction

How does a firm react to its competitors' information outlets? How does the intensity of the reaction vary across different competitors? These are important questions in the finance literature because the understanding of such intra-industry interactions is critical for many applications, such as portfolio management, hedging decisions, and market systematic risk measurement.

In this study, we mainly examine how changes in an industry leader's valuation affect the intra-industry rivals in the same direction (contagion effect) or in the opposite direction (competitive effect). There is a general agreement in the related literature that industry-wide information leads to a contagion effect (stock prices of competitors move in the same direction) because such information affects all competitors in the industry at the same time, while firm-specific information leads to a competitive effect (stock prices of competitors move in the opposite direction) because such information alters the competitive balance in the industry. The "net effect" we actually observe for a particular piece of information depends on the relative importance of the competitive effects to the contagion effects. Prior empirical research studied the relative importance of competition and contagion in a variety of contexts, from financial events (e.g., IPOs, bankruptcies, stock splits, merger proposals, and dividend-related issues) to non-financial events (e.g., layoff announcements, new product announcements, and privatization announcements). Past studies were largely focused on a single event. Some observed a competitive effect, while others observed a contagion effect. Even the same event, such as bankruptcy (Lang and Stulz 1992), dividend reduction (Slovin et al. 1999), and regulatory enforcement actions (Slovin et al. 1999), has been reported to cause either a net competitive effect or a net contagion effect under different conditions.

Because it is impossible for single-event studies to compare the influence of different information categories since only one type of event is studied, it is not clear how to explain the studies' contradicting empirical results. The primary mission of this paper is to test if the "net effect" depends on the category of the information being spilled over.

The rapid development of social media technologies provides us with a possible solution. Nowadays, a large amount of business information is transmitted through social media platforms at a high rate. Researchers have already realized that user-generated content on social media plays a major role in providing financial market participants with value-relevant information to help them make better investment decisions (Chen et al. 2014). We take advantage of this tremendous variety of information on social media to fill this gap.

In this article, we gradually unfold our analysis in two steps. We first investigate how market valuation changes of an industry leader affect its competitors' market valuation (a net competitive effect or a net contagion effect), and how the intensity of the net effect depends on the size of competitors (close, distant, and moderate competitors). Then we try to trace the origin of the "net effect" to the categories of the information being spilled over from the industry leader.

To preview the result: we first discovered a U-shaped relationship between net competitive effect and intra-industry competitor size. Both close and distant competitors are susceptible to an industry leader's market valuation changes, while moderate competitors are less so. We argue that this U-shaped pattern is the result of a trade-off between two mechanisms, comparability and survival concern. For close competitors, the dominating mechanism is comparability (Goins and Gruca 2008). The similarity in matters such as reputation, market demand, public awareness, resources, third-party support, and platform ecosystems, creates head-to-head competition. The competition literature also provides support for our arguments. Johansson and Keddy drew from the niche control paradigm and experimentally tested the prediction that the intensity of competition between a pair of individuals increases with the similarity between the competitors (Johansson and Keddy 1991). As a result, we expect the net competitive effect to be amplified for close competitors. By contrast, for distant competitors against the industry leader, the dominating mechanism is the survival concern. The small business literature offers abundant evidence for the positive relationship between firm size and the likelihood of survival both empirically and analytically (Agarwal and Audretsch 2001; Beck et al. 2005; Pakes and Ericson 1998). Small firms need constant innovations to survive in the market and are more vulnerable to industry leaders' challenges (Chen et al. 2005). Hence, distant competitors are expected to react more strongly to industry leaders' valuation changes as well. The joint force of the two mechanisms forms the U-shaped relationship.

Following this logic, we also predict that the comparability mechanism dominates the survival concern mechanism in an unconcentrated industry, where the competitors are more similar to each other, leading to a high proportion of close competitors. On the flip side, we predict that survival concern mechanism dominates the comparability mechanism in a concentrated industry, where most of the smaller competitors are threatened by the dominant industry leader, leading to great survivor concerns. We test this prediction within the cryptocurrency industry (a very concentrated industry), and the prediction is supported by our findings.

In the next step, we trace the source of the net effect (competitive effect or contagion effect) to the categories of the information transmitted through the industry leader's social media website. We downloaded published articles from eight distinct information categories, and then compared their influence on competitors. The eight information categories are Exchanges, Merchants, Investors, Funding, Regulation, Crime, Wallets, and Events (conferences and meetings). Our results imply that some information categories tend to induce a contagion effect (causing the price of competitors to move in the same direction), while others tend to induce a competitive effect (causing the price of competitors to move in the opposite direction).

Our research is related to a number of empirical studies examining the competitive effect and the contagion effect. Many events were studied in the past, such as bankruptcy (Ferris et al. 1997; Helwege and Zhang 2015; Lang and Stulz 1992), IPO announcements (HSU et al. 2010), new product introductions (Chen et al. 2005), merger announcements (Akhigbe and Martin 2000), dividend-related announcements (Laux et al. 1998; Slovin et al. 1999), open market repurchase (Erwin and Miller 1998), privatization announcements (Otchere 2007), layoff announcements (Goins and Gruca 2008), stock split announcements (Tawatnuntachai and D'Mello 2002), going-concern audit opinions (Elliott et al. 2006), and stock price surprises (Akhigbe et al. 2015).

This study also relates to the spillover and co-movement literature. Co-movements have been documented in a number of markets such as S&P 500 stocks, international equity markets, all common stock lists (e.g., NYSE, AMEX, NASDAQ), and currency exchanges (Barberis et al. 2005; Boyer 2011; Brenner et al. 2009; Connolly and Wang 2003; Dajcman et al. 2012; Hameed et al. 2015; Pirinsky and Wang 2004). The explanations for co-movement are multifold, such as wealth effects (Kyle and Xiong 2001), cross-market rebalancing (Kodres and Pritsker 2002), and firm fundamental values (Barberis et al. 2005). Our research contributes to this line of literature by studying the spillover of social media information within the context of the digital currency market.

This study is also related to the literature on contagion effects in social systems. Previous studies have demonstrated that social ties lead to contagion effects in various aspects. Christakis and Fowler (2007) discovered the phenomenon that a person's chance of becoming obese increases dramatically if socially related individuals suffer from obesity. Aral and Nicolaides (2017) employed exogenous weather pattern changes to demonstrate that exercise (running) intensity is also contagious through friendship networks. (Centola 2010) studied the relationship between the spread of healthy behavior and social network structure and found that the adoption of healthy behavior is faster in clustered networks than in random networks. Our study adds to this line of literature by examining the contagion effect caused by the spread of information from social media. We found evidence that some information channels on social media induce stronger contagion effects while other information channels on social media induce stronger competitive effects.

Our research also contributes to the literature of the effect of social media on market price. Many previous studies investigated the effects of editorial news media on stock prices (Davis et al. 2012; Loughran and McDonald 2011; Tetlock 2007; Tetlock et al. 2008). With the recent development of social media, researchers quickly caught up and began to study the effects of social media (Antweiler and Frank 2004; Chen et al. 2014; Das and Chen 2007; Tumarkin and Whitelaw 2001). Several major social media communities have been explored, such as the Yahoo! Finance message board (Antweiler and Frank 2004), RagingBulls (Tumarkin and Whitelaw 2001), and Seeking Alpha (Chen et al. 2014). This article also contributes to this line of research by studying the social media value-relevance for intra-industry competitors.

Lastly, this study adds to the emerging literature on cryptocurrency. There are mainly three streams of research in this area. There is a body of literature focusing on the technology behind cryptocurrency, such as mining (Li et al. 2019), block chain (Hawlitschek et al. 2018; Saberi et al. 2019; Francisco and Swanson 2018), and smart contracts (Gatteschi et al. 2018). Other studies discuss cryptocurrency security issues due to constant security breaches in this field (Gao et al. 2018; Conti et al. 2018; Kim and Lee 2018). Our study falls into another category of literature where cryptocurrency market dynamics are studied. Omane-Adjepong and Alagidede (2019) studied the volatility spillover among different cryptocurrencies and found that diversification provided benefits for only short-term investment. Mills and Nower (2019) collected cross-sectional data from an online survey and showed a correlation between the tendency to gamble and cryptocurrency investment. They also found that trading cryptocurrencies overlaps strongly with trading high-risk stocks. Antonakakis et al. (2019) studied the co-movement of cryptocurrencies. They found that high market volatility is associated with strong market co-movement while low market volatility is associated with weak market co-movement. Caporale et al. (2018) examined the correlation between the past cryptocurrency market values and the future cryptocurrency market values and found a positive correlation. They claimed that such correlation presents evidence of market inefficiency. Bouri et al. (2018) focused on the co-explosivity (co-occurrence of price spikes) of the cryptocurrency market and found that co-explosivity exists regardless of market maturity. Our paper contributes to this line of research by examining the contagion and competitive effect among top cryptocurrencies. We found that both the close and the distant competitors of the industry leader (Bitcoin) are most susceptible to competitive effects. We also provide empirical evidence that the contagion effect and the competitive effect are induced by different types of information spreading on social media.

The remainder of the article is structured as follows. The data section presents the data used in this research. The empirical analysis section presents all the results. Then we test the robustness of our results and summarize the main findings in the conclusion section.

Data

Our research setting is the emerging digital currency industry (technically referred to as cryptocurrency), which has grown rapidly since the creation of Bitcoin in 2009. This digital currency system can be viewed as a decentralized global peer-to-peer payment network. It is a web-based system that enables users to transfer value across the globe quickly and anonymously without the need for third-party verification. Though this technology resembles the credit card payment system at first glance, there are a few fundamental differences: (1) cryptocurrency platforms have their underlying currencies, and the exchange rates with fiat currencies are decided at the dedicated exchanges; (2) there is no central authority maintaining the operations, regulating the issuance of currency, or keeping detailed record of every transaction.

As the industry leader, Bitcoin has seen significant growth since it was created. It is valued at around 100 billion US dollars in market capitalization as of November 2017. The academic literature on this phenomenon is also growing, although primarily focused on its technical aspects (Eyal and Sirer 2014; Johnson et al. 2014; Reid and Harrigan 2013).

We picked the top 25 digital currencies as the Bitcoin competitors in the sample according to the market capitalization in January 2016. The thresholds to be considered as a Bitcoin competitor are that (1) the currency has reached 1 million USD market capitalization at any time, (2) at least one direct exchange with Bitcoin exists, and (3) all the variables needed in the study are observable. The data collection period is between December 2013 and January 2016, a total of 747 trading days (every day is a trading day since the trading is non-stop in the market). The daily return is calculated based on the 0:00 GMT (Greenwich Mean Time) price and the 24:00 GMT price.

To capture the net competitive effect (relative importance of competition to contagion), we calculated the competitors' Bitcoin-denominated returns, using the prices from Bitcoin-to-Altcoin exchanges (Altcoin refers to all other Bitcoin competitors). The Bitcoin-denominated returns reflect the relative valuation changes between Bitcoin and its competitors. When Bitcoin experiences a market shock, and it induces a strong competitive effect, the prices of Bitcoin and its competitors are more likely going in opposite directions, leading to increased relative valuation changes. But if the market shock induces a strong contagion effect, prices of Bitcoin and its competitors will more likely move in the same direction, leading to decreased relative valuation changes.

To measure competitor size, we obtained the market capitalization data for each Bitcoin competitor in our sample and derived the daily market capitalization rank as a measure of competitor size. The rank stays relatively stable with occasional changes from time to time for most of the digital currencies. Bitcoin was ranked No.1 for the entire duration of the data collection period. An alternative competitor size measure is discussed in the robustness check section.

The other part of our dataset is the articles published on CoinDesk.com. CoinDesk.com is the world-leading information outlet on Bitcoin. There are a variety of information categories, and we selected eight of them that potentially provide relevant information for Bitcoin valuation (exclusively on Bitcoin). They are Exchanges, Merchants, Investors, Funding, Regulation, Crime, Wallets, and Events (conferences and meetings). Unfortunately, the Technology category had to be excluded because it reports technology advances for all digital currencies, and thus causes the contagion effect by design.

Coindesk.com is essentially a social media, since anyone can write an article and submit it to CoinDesk. The article will be published after CoinDesk.com approves it. We obtained all 2729 articles published in the eight selected information categories during the data collection period, along with the number of Facebook shares of each article as a proxy for its importance and relevance. The average length of the articles was 641 words.

Following the literature, we measured the sentiment of each article primarily by the fraction of negative words (Antweiler and Frank 2004; Chen et al. 2014; Loughran and McDonald 2011; Luo et al. 2013; Solomon 2012; Tetlock 2007; Tetlock et al. 2008; Tirunillai and Tellis 2012). But please note that the fraction of positive words is used in two of the eight information categories (more details later). Instead of the frequently used Harvard IV-4 lexicon lists, we chose a lexicon list developed specifically for sentiment analysis in a financial environment (Chen et al. 2014; Loughran and McDonald 2011). The negative words lexicon includes 2329 words, while the positive words lexicon collection includes 354 words.

Digital currency is used as the research setting instead of stocks for a number of identification-related advantages. First, there are far fewer confounders to worry about. Unlike stock markets, where the underlying companies of the stocks are required to disclose financial statements periodically, there is no such requirement in our setting. In addition, no professional financial analysts exist in our context, so there is no need to control for earning or price predictions. Moreover, a variety of financial indicators frequently controlled for in stock market research are not present in our research setting (e.g. Tobin's Q, advertisement spending, firm size, new product announcements, R&D expenditures, ROA, ROE, leverage, and liquidity).

Second, we have less concern about time-varying confounders in our context. Unlike a firm, all the technical specifications of a digital currency in our setting (such as block time, block hashing algorithm, transaction signature methods, and currency generation rate) are set at the time of currency creation. As a result, we have far fewer concerns about time-varying confounders compared to studies in stock markets.

Lastly, unlike the stock market, where there is constant market closure, the trading of Bitcoin is continuous (24/7). The non-stop trading feature ensures fewer behavioral biases documented in the finance literature. For example, traders are found to assume above-average afternoon risk to recover from morning losses (Coval and Shumway 2005), creating biases from the inherent value due to loss-averse traders and short-term price reverses. We are basically free of such biases in our context.

Empirical analysis

In this section, we present our analysis progressively in two steps. We first investigate the relationship between net competitive effect intensity (relative importance of competition vs. contagion) and competitor size; then we trace the origin of the net effect (either a competitive effect or a contagion effect) to the category of the information transmitted through the industry leader's social media website.

In the first step, we propose a U-shaped relationship between net competitive effect and competitor size as a result of the trade-off between two mechanisms (comparability and survival concern). For the industry leader's close competitors, the comparability mechanism dominates the survival concern. The comparability mechanism implies that similarities between close competitors regarding matters such as reputation, market demand, public awareness, financial resources, third-party support, and platform ecosystems, lead to head-to-head competition. Prior research suggests that the intensity of competition between a pair of individuals increases with high similarity between the competitors (Johansson and Keddy 1991). Hence, the competitive effect among close competitors should be amplified. However, for the industry leader's distant competitors, the survival concern mechanism will eventually outweigh the comparability mechanism. The survival concern mechanism implies that smaller competitors are more vulnerable to the industry leader's challenges, since being driven out-of-market is more likely to be a major concern for distant competitors. As a result, the competitive effect intensifies for smaller competitors as well.

We use the reaction of Bitcoin competitors' Bitcoin-denominated returns (Bitcoin competitors' relative valuation changes against Bitcoin) to Bitcoin's USD-denominated returns (Bitcoin' absolute valuation changes) to capture the intensity of the net competitive effect. To measure competitor size, previous researchers proposed many methods. The common measures include firm size and Herfindahl index. Some use the company's self-selected group of competitors listed in the company's Proxy Statement (Definitive 14A) to distinguish close rivals from distant rivals (Goins and Gruca 2008). In our study, we obtain the daily rank of market capitalization to measure Bitcoin competitors' sizes. Please note that the larger the rank, the smaller the competitor size.

To test the proposed U-shaped relationship, we calculated two interaction terms (linear and quadratic) between USD-denominated Bitcoin returns and competitor size measure (Rank) to capture how Bitcoin competitors of different sizes react to Bitcoin's price changes. We organized our analysis around the following fixed effect panel data model:

$$\begin{aligned} R_{it,BTC} = \alpha + \beta_1 Rank_{it} + \beta_2 Rank_{it}^2 + \beta_3 BTCR_{t,USD} + \beta_4 Rank_{it} \times BTCR_{t,USD} \\ + \beta_5 Rank_{it}^2 \times BTCR_{t,USD} + \delta X_{it} + i + t + \varepsilon_{it} \end{aligned} \tag{1}$$

$R_{it,\ BTC}$ is the Bitcoin-denominated return of competitor i at time t, calculated using prices on exchanges between Bitcoin and competitor i. It is always zero if i = Bitcoin. $Rank_{it}$ is the daily market capitalization rank for competitor i at time t. $Rank_{it}$ ranges from 2 to 26 since Bitcoin is always ranked No. 1. $BTCR_{t,\ USD}$ is the USD-denominated Bitcoin return at time t. X includes all the control variables used in this model. We follow the literature (Chen et al. 2014) to add the control variables. Control variables include return volatility, calculated as the sum of squared returns over the previous calendar month, 1 day lagged BTC-denominated returns, 2 days lagged BTC-denominated returns, and cumulative BTC-denominated returns over the past calendar month.

Table 1 presents the results. Regressions are run for four different time windows: the intra-day return reaction, the one-week cumulative return reaction, the one-month cumulative return reaction, and the three-month cumulative return reaction. Because the rank is fairly stable during the short term, concerns may arise that it is collinear with the competitor dummies to some extent. So we exclude the competitor dummies in the even columns in Table 1.

The positive coefficient estimates on the linear interaction terms and negative coefficient estimates on the quadratic interaction terms indicate that the net competitive effect dampens as the competitor size decreases initially, then intensifies again later as competitor size is small enough. Our results in Table 1 provide initial evidence that both very close and very distant competitors will experience intense net competitive effects while moderate competitors experience comparatively weaker net competitive effects. The effective coefficient estimate for $BTCR_{t,\ USD}$ (the total reaction to Bitcoin

Table 1 U-Shaped Relationship between Net Competitive Effect and Competitor Size

	(0,0)		(0,7)		(0,30)		(0,90)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Rank_{it}$	−.00061 (− 0.67)	−.00079 (− 1.22)	.00200 (0.80)	−.00129 (− 0.83)	.01341 (1.11)	−.00237 (− 0.32)	−.11734*** (− 4.4)	−.13737*** (− 9.89)
$Rank_{it}^2$	.00006 (1.60)	.00004* (1.78)	.00019* (1.82)	.00015** (2.44)	.00086* (1.72)	.00080*** (2.67)	.01028*** (8.68)	.00826*** (12.12)
$BTCR_{t,\ USD}$	−.20467** (−2.28)	−.20828** (− 2.31)	−.20667*** (− 2.82)	−.22243*** (− 3.06)	−.37810*** (− 3.83)	−.49454*** (− 5.33)	.10498 (0.58)	−.99156*** (− 5.18)
$Rank_{it} \times BTCR_{t,\ USD}$	.02397 (1.40)	.02445 (1.42)	.04348*** (3.05)	.04609*** (3.29)	.08211*** (3.51)	.10659*** (4.75)	.11481*** (4.14)	.29660*** (10.05)
$Rank_{it}^2 \times BTCR_{t,USD}$	−.00108 (− 1.53)	−.00109 (− 1.54)	−.00201*** (− 3.44)	−.00210*** (− 3.69)	−.00401*** (− 3.68)	−.00494*** (− 4.89)	−.00849*** (− 6.13)	−.01402*** (− 9.66)
Controls	√	√	√	√	√	√	√	√
Rival FE	√		√		√		√	
Time FE	√	√	√	√	√	√	√	√
R-squared	0.0267	0.0249	0.0703	0.0617	0.0890	0.0640	0.2343	0.1413
# Obs.	13,072	13,072	12,999	12,999	12,474	12,474	10,974	10,974

(1) The values in the parentheses are the standardized t-statistics of the corresponding coefficient estimates; (2) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; (3) Column 2, 4, 6, and 8 are to ease potential collinearity issue by excluding rival fixed effects; (4) The number of observations is slightly different across different model specifications because we need some extra days to calculate the 7-day, 30-day, and 90-day returns, and we lose some observations as a result

valuation changes) is shown in Eq. 2. The signs of A, B, and C are indicated according to our empirical results in Table 1.

$$\text{Effective Coefficient Estimate for } \mathrm{BTCR}_{t,USD} = \mathrm{A}(-) + \mathrm{B}(+) \times \mathrm{Rank} + \mathrm{C}(-) \times \mathrm{Rank}^2 \quad (2)$$

The negative A is the baseline reaction. The positive B captures the main effect for close competitors (comparability mechanism), and the negative C captures the main effect for distant competitors (survival concern mechanism). The smaller the effective coefficient (more to the negative direction), the larger and stronger the net competitive effect. So the intensity of the net competitive effect can be expressed by Eq. 3. The signs of A, B, and C are indicated within the parentheses.

$$Net\ Competitive\ Effect\ Intensity = -A(-) - B(+) \times Rank - C(-) \times Rank^2 \quad (3)$$

Based on our current findings, it is natural to infer that for unconcentrated industries with many comparable competitors, the comparability mechanism will dominate and the negative C in eq. 3 will become negligible, while the positive B will control the net effect. This implies an average negative relationship between net competitive effect and rank (positive average relationship between net competitive effect and competitor size). In contrast, for highly concentrated industries with many small competitors, survival concern will dominate the comparability mechanism, and the positive B will become negligible, while the negative C will control the net effect. This implies an average positive relationship between net competitive effect and rank (negative average relationship between net competitive effect and competitor size).

The digital currency market better resembles a highly concentrated industry with dominating survival concern mechanism because of the majority of small competitors. We predict that for such a highly concentrated market, the average relationship between net competitive effect and competitor size will be negative. We test this average effect prediction by including only the linear interaction term in the previous model.

Next, to verify that the variance in our explanatory variable does make the difference, we deliberately reinforce the contrast between close competitors and distant competitors by creating subsamples including only Litecoin (the closest Bitcoin competitor) and those smallest rivals ranked 15 to 26 (the most distant Bitcoin competitors). We introduce a binary variable "Minor" to indicate if the competitor is close (Minor = 0) or distant (Minor = 1). If our argument is correct, the "contrast sample" will generate more significant coefficient estimates than the baseline sample due to additional variations introduced into the key independent variables. Our argument will be further supported if this is the case.

Table 2 presents the results. The overall negative coefficient estimates for interaction terms support our prediction that the average relationship between net competitive effect and competitor size is negative for competitors. The smaller the competitor, the more susceptible it is to the industry leader.

This average negative relationship is more pronounced during the longer term, as both the coefficient estimates and the statistical significance level become larger for longer time window estimation. This pattern is probably caused by the nature of high price volatility in the digital currency market. Any short-term competition or contagion effect may be concealed and confused by the high volatility. But during the long term,

Table 2 Average Relationship between Net Competitive Effect and Competitor Size

	(0,0)		(0,7)		(0,30)		(0,90)	
	Baseline	Contrast	Baseline	Contrast	Baseline	Contrast	Baseline	Contrast
Panel 1: Interact with rank								
$Rank_{it}$	.00098*** (3.50)	.00104** (2.08)	.00720*** (7.77)	.00686*** (4.93)	.03679*** (9.42)	.03966*** (6.58)	.06507*** (15.55)	.22015*** (14.45)
$BTCR_{t,\ USD}$	−.08045 (−1.49)	.09562 (1.26)	.02606 (0.46)	.28892*** (4.38)	.06653 (0.76)	.14871 (1.24)	.45115** (2.29)	.91241*** (2.82)
$Rank_{it} \times BTCR_{t,\ USD}$	−.00339 (−0.78)	−.01121** (−2.05)	−.00776** (−1.96)	−.02090*** (−5.05)	−.01893** (− 2.48)	−.02010*** (− 2.59)	−.04709*** (− 4.76)	−.09621*** (− 7.56)
Controls&FE	√	√	√	√	√	√	√	√
R-squared	0.0262	0.0410	0.0606	0.1048	0.0883	0.1174	0.1149	0.2951
# Obs.	13,072	6272	12,999	6233	12,474	5960	10,974	5180
Panel 2: Interact with Minor								
$Minor_{it}$	.00314 (0.30)	−.00310 (−0.56)	.01122** (2.11)	−.03413** (−2.51)	.00208 (0.04)	−.17684*** (−3.04)	.53573*** (11.51)	.03429 (0.54)
$BTCR_{t,\ USD}$	−.14091*** (−4.91)	.03313 (0.48)	−.07499** (−2.13)	.12918*** (2.95)	−.16200** (−2.45)	.09299 (0.92)	−.07871 (−0.43)	.19147 (0.62)
$Minor_{it} \times BTCR_{t,\ USD}$	.04754 (0.88)	−.12249 (−1.50)	.01319 (0.26)	−.18140*** (−3.51)	.00392 (0.05)	−.25557** (−2.96)	−.04046 (− 0.37)	−.54270*** (− 4.72)
Controls&FE	√	√	√	√	√	√	√	√
R-squared	0.0252	0.0397	0.0580	0.1006	0.0809	0.1132	0.0913	0.2509
# Obs.	13,072	6272	12,999	6233	12,474	5960	10,974	5180

(1) The values in the parentheses are the standardized t-statistics of the corresponding coefficient estimates. (2) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. (3) The number of observations is slightly different across different model specifications because we need some extra days to calculate the 7-day, 30-day, and 90-day returns, and we lose some observations as a result

the relationship becomes clear as the information finally "wears in" and as the price changes caused by the fundamentals finally outweigh the influence of high short-term volatility.

By comparing the results from the contrast sample with the results from the baseline sample, we notice that the interaction terms generated from the contrast samples are not only more significant but also much larger in scale than those generated from the baseline samples, which confirms our expectation that enhanced variation in the independent variables leads to more significant and larger coefficient estimates. This is especially true in the bottom panel. So we are more confident that the variations in the independent variables do contribute to the change of the net competitive effect across different competitors. Figure 1 in Appendix summarizes the current results. Both close competitors and distant competitors are susceptible to competition from the industry leader, while the competitors with moderate sizes are less so.

Next, we investigate if the realization of a net competitive effect or a net contagion effect is related to the category of the information spilled over from the industry leader. We observed information flows under eight different information categories from CoinDesk, a social media news site that specializes in Bitcoin.

CoinDesk sorts published articles into different categories. We selected eight of them that are potentially relevant to Bitcoin fundamentals and valuations. They are Regulation, Exchanges, Merchants, Funding, Crime, Investors, Wallets, and Events (conferences with Bitcoin themes). We downloaded 2729 articles published on these eight information channels, along with the cumulative Facebook shares of each article. We assume that the articles about more important issues are more frequently shared.

To measure the information content conveyed by each article, we followed the literature and used the negative words or positive words percentages. The lexicon list used is designed exclusively for financial analysis (Loughran and McDonald 2011). The descriptive statistics for each information channel are presented in Table 3. Avg.FaceBook Share is the average number of Facebook shares across all published articles in that channel; # articles is the total number of articles published under each channel within our data collection period; Avg.Neg% is the average negative words percentage for all articles under each channel; Avg.Pos% is the average positive words percentage for all articles under each channel; %NetNeg > 0 is the percentage of articles with more negative words than positive words; Avg. NetNeg% is the average net negative words percent for all articles under each channel; and *P*-value Avg. NetNeg% is the *p*-value of a t-test with null hypothesis being that Avg. NetNeg% is zero.

From Table 3, we know that people share articles published in the Merchants category more often than those published in other channels. By contrast, the number of Facebook shares for the Crime-related articles is the lowest. It is also interesting to compare the %NetNeg > 0 (percentage of articles with more negative words than positive words) across different channels. The Crime channel shows the largest %NetNeg > 0 measure (96.51%). This is reasonable because almost all crime-related articles convey negative information.

On the other hand, Merchant- and Funding-related articles are at the other extreme with just over 20% of articles with more negative words than positive words (22.49% and 26.35% respectively). This is reasonable as well since Merchant-related articles (articles about Bitcoin-accepting businesses) and Funding-related articles (Bitcoin venture capitals and angel investment funding) convey primarily positive information. The other measures (Avg.Neg%,

Table 3 Descriptive Statistics: Information Channels

	Regulation	Exchanges	Merchants	Funding
Avg.FaceBook Shares	151.71	154.05	253.9	253.9
# Articles	683	591	338	148
Avg.Neg%	1.98%	11.88%	0.71%	0.76%
Avg.Pos%	0.87%	0.87%	1.08%	1.17%
% NetNeg > 0	77.45%	63.11%	22.49%	26.35%
Avg. NetNeg%	1.11%	1.01%	−0.37%	−0.41%
P-value Avg. NetNeg%	0	0	0.011	0
Candidate	Contagion Effect	Competitive Effect	Competitive Effect	Unsure
	Crime	Investors	Wallets	Events
Continued				
Avg.FaceBook Shares	117.55	176.61	190.84	147.03
# Articles	315	280	176	198
Avg.Neg%	4.05%	1.04%	1.12%	1.04%
Avg.Pos%	0.59%	1.12%	0.88%	1.05%
% NetNeg > 0	96.51%	40.71%	50%	41.92%
Avg. NetNeg%	3.46%	−0.07%	0.25%	−0.01%
P-value Avg. NetNeg%	0	0.23	0.02	0.39
Candidate	Unsure	Unsure	Unsure	Unsure

Avg.Pos%, and Avg. NetNeg%) show similar patterns. Hence, it is inappropriate to measure the Merchant- and Funding-related articles using negative-word percentages, which is the common practice in related literature. Instead, we measure the sentiments of the Merchant- and Funding-related articles using positive-word percentages. To be consistent with the measurement of other information channels (other information channels are measured with negative words percentages), we multiply by −1 the positive-word percentage measures for Merchants and Funding. The variations are retained after reversing the sign. We call the unified measure the information negativity measure.

Because very often there is more than one article published on the same day, it is necessary to assign proper weight to each of the articles to calculate the weighted sentiment for each day. We decided to use daily Facebook-share-weighted sentiment. We assume that the number of Facebook shares indicates the importance of the article. Please note that we did not normalize the total weights to 1 during each day because a normalized measure fails to distinguish the importance of articles across different days.

A fixed effect panel data regression is used to test the net effect exerted by each information channel. For each information channel i (i = 1 to 8), subsamples including only the days with at least one published article in channel i are created. Other information channels j (j ≠ i) are controlled in the model. We organize the analysis around the following regression specification.

$$\begin{aligned} R_{it,USD} = \alpha &+ \beta_1 Rank_{it} + \beta_2 Rank_{it}^2 + \beta_3 FocalInforChannel_t + \beta_4 Rank_{it} \\ &\times FocalInforChannel_t + \beta_5 Rank_{it}^2 \times FocalInforChannel_t \\ &+ \beta_6 ControlInforChannel_t + \delta X_{it} + i + t + \varepsilon_{it} \end{aligned} \tag{4}$$

The key independent variable is $\text{FocalInforChannel}_t$, while $\text{ControlInforChannel}_t$ is the vector of all other information channels other than the focal channel. X_{it} includes all other controls such as USD-denominated return volatility, calculated as the sum of squared daily returns over the previous calendar month, one day lagged USD-denominated returns, two-day lagged USD-denominated returns, and cumulative USD-denominated returns over the past calendar month.

Table 4 presents the results. Following the literature, we estimate the model using both time windows before the publish date and time windows after the publish date (Akhigbe and Martin 2000; Slovin et al. 1999; Tawatnuntachai and D'Mello 2002). Regressions are run for each information channel-to-time window pair. To keep concise, we present only the key results in Table 4. Every information channel-to-time window pair generates three coefficient estimates for β_3 in Eq. 4. Taking the Regulation-to-(− 3,0) pair as an example, the number on the top − 0.00019 is the β_3 estimate with no interaction terms in the model, the number in the middle −.00281 is the β_3 estimate with only linear interaction terms in the model, and the number at the bottom − 0.00219 is the β_3 estimate with both linear and quadratic interaction terms in the model. The second column of Table 4 shows the information negativity measurement.

Not every coefficient estimate is statistically significant. A recent study shows that the "wear-in" time differs across different types of information outlets. Among different types of media such as web blogging, consumer rating, social media, Google search,

Table 4 The Origin of the Realized Effect in Social Media Information Spillover

	Measurement	(−3,0)	(−1,0)	(0,0)	(0,1)	(0,3)
Regulation	Neg%	−.00019	.00022	.00033	.00018	.00317
		−.00281*	−.00242**	−.00286**	−.00300*	.00031
		−.00219	−.00112	−.00116	.00030	.00272
Exchange	Neg%	.00094	.00122***	.00115***	.00073	.00194**
		.00005	.00057	0.00050	.00064	.00260*
		−.0017	1.30E-06	−0.00003	.00022	.00108
Merchants	-Pos%	.00142	−.0007	−0.00071	−.00025	.00173
		.00051	−.00191	−0.00171	−.00085	.00379
		.00690**	.00244	0.00199	.00274	.00881**
Wallets	Neg%	−.00152***	−.00054**	−.00050**	−.00206***	−.00091**
		−.00198***	−.00087**	−.00073*	−.00161**	.00019
		−.00261**	−.00169**	−.00168**	−.00527**	−.00379*
Events	Neg%	−.00136	.00045	.00005	−.00290***	−.00351*
		−.00129	−.00050	−.00095	−.00476***	−.00301
		−.00574*	−.00472**	−.00505**	−.00520**	−.00298
Crime	Neg%	.00147**	.00018	.00028	.00030	−.00004
		.00234**	.00038	.00067	.00060	.00168
		.00128	.00013	.00037	−.00017	.00121
Investors	Neg%	.00022	.00033	.00059	−.00137	−.00094
		−.00236	−.00091	−.00080	−.00340**	−.00394*
		.00034	−.00074	−.00094	−.00319	−.00241
Funding	-Pos%	−.00255**	−.00031	.00025	.0008	.00172
		−.00340	−.00260*	−.00188	−.00317	−.00174
		−.00073	−.00010	−.00070	−.00248	−.00164

Each information channel-to-time window pair generates three coefficient estimates for β_3 in eq. 4. For each pair, the top number is $\widehat{\beta_3}$ with no interaction term in the model, the middle number is $\widehat{\beta_3}$ with only linear interaction term in the model, and the bottom number is $\widehat{\beta_3}$ with both linear and quadratic interaction terms in the model and conventional media, the social media has the shortest "wear-in" time (Luo et al. 2013). The results suggest that Regulation-, Wallet-, Event-, Investor-, and Funding-related information exert a dominating contagion effect, while Merchant- and Crime-related information exert a dominating competitive effect. For each of the information channels, the signs for the significant coefficient estimates are consistent.

Robustness tests

In this section, we perform a series of robustness tests to verify our results. First, we check the robustness of our results to the choice of different competitor size measures. We then address the potential endogeneity concern of the variable Rank_{it}.

Alternative measure for competitor size

In our main results, the rank of market capitalization is used to measure competitor size. This measure reflects the relatively stable position of the competitor in the industry within the short term, but it conceals the information about higher-frequency (daily) changes. To address this concern, we devised an alternative measure of competitor size and tested the robustness of our main results to it. The alternative measure is $\ln\left(\frac{BTCMarketCap}{CompetitorMarketCap}\right)$, which reflects the relative size of Bitcoin against its competitors. Logarithmic smoothing is applied to make the data well-behaved.

Table 5 reports the results for the new measure. The variable CS_{it} is the new competitor size measure. The intra-day reaction model is not included because the results are not significant in the main study. Table 5 indicates a U-shaped relationship between net competitive effect and competitor size, which is consistent with our main analysis.

Endogeneity issue

If the key variable Rank_{it} is endogenous, the estimated coefficients are biased away from zero, threatening the validity of our main results. Because the Rank_{it} is relatively stable during the short term, we can treat it as exogenously given. The endogeneity problem may arise when $\mathrm{R}_{it,\ \mathrm{BTC}}$ (the relative valuation changes between Bitcoin and its competitors) is large enough to affect the rank. In order to be secure, we test the robustness of our results using instrumental variable regressions in this section. Because the variable Rank_{it} is also involved in the

Table 5 Robustness Check for the U-Shaped Relationship

	(0,7)	(0,30)	(0,90)
CS_{it}	.00941 (0.48)	−.44780*** (−3.55)	−1.41782*** (−9.31)
CS_{it}^2	.00525*** (3.15)	.06539*** (5.99)	.19882*** (15.35)
$BTCR_{t,\ USD}$	−1.20356*** (−4.66)	−2.76415*** (− 3.23)	−4.19491*** (−5.38)
$CS_{it} \times BTCR_{t,\ USD}$	.35911*** (3.74)	.83725*** (2.73)	1.11609*** (4.26)
$CS_{it}^2 \times BTCR_{t,USD}$	−0.0260*** (−3.31)	−.06067** (− 2.42)	−.07625*** (− 3.64)
FE and Controls	√	√	√
R-squared	0.1002	0.1686	0.4921
# Obs.	12,999	12,474	10,974

(1) The values in the parentheses are the standardized t-statistics of the corresponding coefficient estimates; (2) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; (3) CS_{it} is the measure for degree of competition, $\ln\left(\frac{BTCMarketCap}{CompetitorMarketCap}\right)$. (4) The number of observations is slightly different across different model specifications because we need some extra days to calculate the 7-day, 30-day, and 90-day returns, and we lose some observations as a result

interaction terms, we have to avoid the "forbidden regression" (Wooldridge 2010). The t-statistics from the "forbidden regression" are generally invalid, even asymptotical.

According to a recent study, under some weak conditions, the interaction term can be classified as exogenous, and the ordinary least-squares estimators of the interaction term coefficients are consistent and asymptotically normally distributed if only one of the two interacted regressors are endogenous (Bun and Harrison 2014). However, the coefficient estimates for the main effect are not consistent in this case (although the main effect is not of interest in our study). We follow the literature and use the following instruments for the U-shaped relationship regression (Bun and Harrison 2014). All the other exogenous variables are also included.

$$Z_{it}^{U} = \begin{bmatrix} 1 & BTCR_{t,USD} & Rank_{it-1} & Rank_{it-1} \times BTCR_{t,USD} & Rank_{it-1}^{2} & Rank_{it-1}^{2} \times \ BTCR_{t,USD} \end{bmatrix}' \tag{5}$$

The estimates are presented in the IV columns in Table 6. Reassuringly, non-IV and IV estimators produce similar coefficient estimates. This provides evidence that our results are robust to instrumental variable estimators.

Conclusion

This article revisited an important question: how do firms react to shocks occurring to their intra-industry competitor? Why does the contagion effect dominate at some times and the competitive effect dominate during other times? We contribute to the literature by reconciling the discrepancies of previous findings. We empirically show that the realized net effect (the relative importance of competitive effect to contagion effect) depends on (1) the relative size of intra-industry competitors; and (2) the type of information spilling over the social media.

For close competitors to the industry leader, the similarity in factors such as reputation, market demand, public awareness, resources, third-party support, and platform ecosystems,

Table 6 IV Estimator Analysis for the U-shaped Relationship

	(0,7)		(0,30)		(0,90)	
	Original	IV	Original	IV	Original	IV
$Rank_{it}$	.00200 (0.80)	.00183 (0.71)	.01341 (1.11)	.01237 (0.99)	−.11734*** (−4.4)	−.12140*** (− 4.48)
$Rank_{it}^{2}$	.00019* (1.82)	.00020* (1.91)	.00086* (1.72)	.00095* (1.84)	.01028*** (8.68)	.01061*** (8.76)
$BTCR_{t,\ USD}$	−.20667*** (−2.82)	−.20739*** (− 2.82)	−.37810*** (−3.83)	−.37314*** (− 3.77)	.10498 (0.58)	.19056 (1.04)
$Rank_{it} \times BTCR_{t,\ USD}$	.04348*** (3.05)	.04397*** (3.07)	.08211*** (3.51)	.08302*** (3.53)	.11481*** (4.14)	.09550*** (3.51)
$Rank_{it}^{2} \times BTCR_{t,USD}$	−.00201*** (−3.44)	−.00204*** (− 3.47)	−.00401*** (− 3.68)	−.00410*** (− 3.71)	−.00849*** (−6.13)	−.00775*** (−5.73)
FE & Controls	√	√	√	√	√	√
R-squared	0.0703	0.0705	0.0890	0.0893	0.2343	0.2344
# Obs.	12,999	12,999	12,474	12,474	10,974	10,974

(1) The values in the parentheses are the standardized t-statistics of the corresponding coefficient estimates; (2) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. (2) The number of observations is slightly different across different model specifications because we need some extra days to calculate the 7-day, 30-day, and 90-day returns, and we lose some observations as a result

drives up the competitive effect, causing competitors' valuations to move in the opposite direction when there is a market shock. For distant competitors to the industry leader, the survivor concern is at play, and they also react intensively to shocks occurring to the industry leader. The joint force of these two mechanisms creates a U-shaped relationship between the intensity of the competitive effect and the competitor size, and we empirically confirmed it with our analysis.

We then proceed further to trace the origin of the contagion effect and the competitive effect from eight different social media information channels (regulation, exchanges, merchants, funding, crime, investors, wallets, and events). We showed empirical evidence that some types of information induce the contagion effect (e.g., regulation-related information), while other types of information induce the competitive effect (e.g., exchange-related and merchant-related information).

Our main finding shows that when market shocks occur, the valuation of competitors in the same industry may go the same direction or the opposite direction depending on the relative competitor size and the type of the market shocks. Our insight reconciles the previous studies reporting different findings.

This research is among the few examining the emerging cryptocurrency market. After almost 10 years since its beginning, the market is still in its infancy stage, and so is the related academic literature. From the perspective of social science, the cryptocurrency market provides many identification advantages over stock markets, such as fewer confounding factors, fewer time-varying variables, less necessary controls, and less behavioral bias concerns. In addition, the cryptocurrency market is a perfect test bed for purely speculative markets since there is barely any fundamental information associated with cryptocurrencies.

There are several limitations in this study. The major drawback is that the cryptocurrency industry is so concentrated that we are unable to empirically test the upward-sloping line in Figure 1 in Appendix+ even if only top rivals are selected in an attempt. Future research may verify the missing half in other industries or when the cryptocurrency market becomes less concentrated. In addition, because of the high concentration, we had to exclude many small rivals (some too tiny to be possibly relevant).

There are many ways to extend the current study. When quantifying social media discussions, the majority of the related literature relies on sentiment measures. But recently, other measures for group discussions are being suggested, such as the degree of consensus between individual messages and the collective wisdom (Li et al. 2018; Zhang et al. 2019). Strong consensus in the group discussion may signify the "Hidden Profile" effect (Qiu et al. 2016), causing individuals to refrain from sharing private information if the consensus in the group discussion is too overwhelming. The strong consensus may also reduce the information diversity in the group discussion, resulting in increased redundancy, which damages the overall informativeness of the discussion. Future research may look into the implications of the group discussion consensus in social media.

With the growing amount of data generated in financial systems, researchers have started using machine learning methodologies to study contagions in the financial networks (Kou et al. 2019). Future research may also try predicting the contagion effect and the competitive effect among intra-industry rivals with such methodologies. Machine learning algorithms typically achieve high prediction accuracy and offer insights as to how well we can explain market contagion with given variables.

Appendix

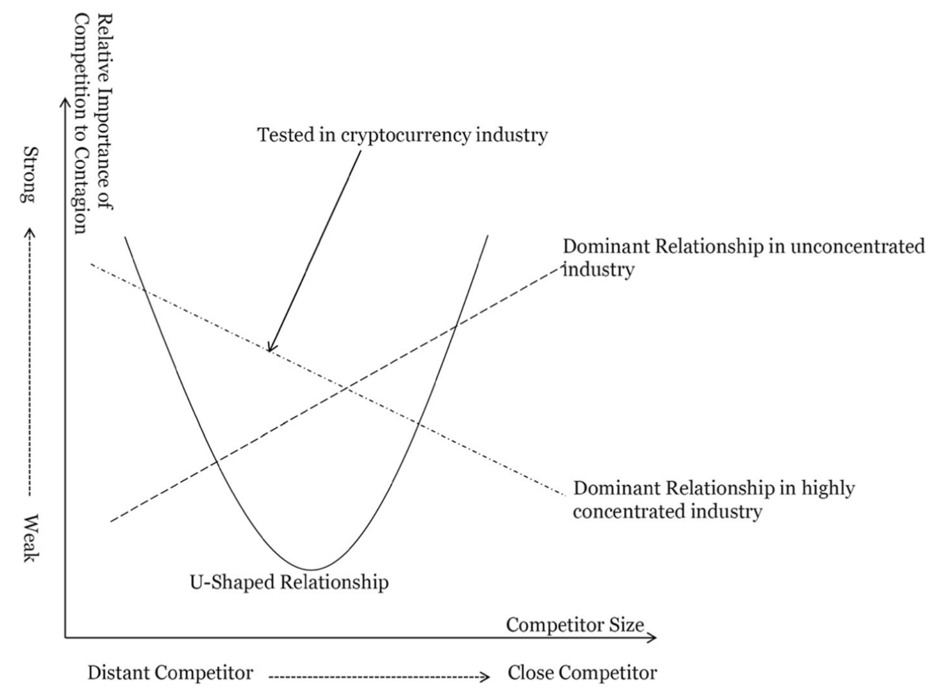

Fig. 1 Relationship between Net Competitive Effect and Competitor Size

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Authors' contributions
PX collected the Bitcoin market data and performed the main empirical analysis. JW and HD collected and analyzed the CoinBase News Articles, proposed and performed the robustness check. PX, JW, and HD contributed in writing and revising the manuscript. PX revised the paper for the first-round revision. All authors read and approved the final manuscript.

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Availability of data and materials
The datasets analyzed during the current study are available on the following websites:

Data	Source
Bitcoin Price	https://www.investing.com/crypto/bitcoin/btc-usd
BTC-denominated Altcoin price	https://poloniex.com/exchange#btc_xrp
Cryptocurrency Market Capitalization	https://coinmarketcap.com/
CoinDesk news	https://www.coindesk.com/

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