Cryptocurrency Bubble on the Systemic Risk in Global Energy Companies

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ABSTRACT

Financialization has brought new challenges to the international energy markets, making energy systemic risk a more complicated issue. One of the important features is the development of cryptocurrency, which has become a critical part of the global financial markets. As a consequence, the rise and fall of cryptocurrency can have nonnegligible impacts on the systemic risks in the international energy sector. This paper empirically tests this hypothesis using the equity data of the top 100 energy companies from 2014 to 2021. Specifically, we explore the extreme shocks of cryptocurrency using multiple bubble tests, and then we test to what extent bubbles in cryptocurrency markets can affect systemic risk in the energy sector. Our empirical results show that the formation of cryptocurrency bubbles, especially when the bubbles burst, significantly increases systemic risks in the energy sector. This effect retains the same in the recent COVID-19 pandemic period. In addition, oil and gas companies play an essential channel in the risk spillover from cryptocurrency markets to the international energy markets.

Keywords: Energy companies, Cryptocurrency, Bubbles, Systemic risks, CoVaR

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1. INTRODUCTION

Recent literature demonstrates a clear trend of financialization in the international energy markets (e.g., Zhang, 2017; Wang et al., 2019a), in other words, energy commodities have shown characteristics similar to a typical financial product. While the standard demand and supply factors remain critical for energy products, capital flows from financial markets to energy markets lead to more complicated pricing mechanisms. As a consequence, non-fundamental factors, such as financial markets, speculation and sentiments have shown to be increasingly important in determining energy prices, which can generate both direct and indirect impact on energy companies (Broadstock et al., 2012). In other words, changes in energy prices can affect performance of energy companies directly, meanwhile, the price shocks can pass to energy companies indirectly via market wide responses (Broadstock et al., 2014).

One step further, financialization in energy markets also makes the determinants of systemic risks in the energy sector more complicated. On the one hand, systemic risks in energy sector link to energy security and sustainable development, thus casting an important issue for policymak-

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ers; on the other hand, when energy market integrates more with other markets and form a network, the spillover effects cannot be ignored. In fact, empirical studies have found a very diversified picture of risk spillovers between energy and other markets, for example, carbon markets (Balcılar et al., 2016); agricultural commodity markets (Shahzad et al., 2018); stock markets (Ma et al., 2019); and cryptocurrencies (Ji et al., 2019a). The linkages between the energy sector and financial markets and other commodities are not new in the literature, but the appearance of cryptocurrency in the spillover network has clear innovative features.

Despite its short history, cryptocurrency is considered one of the main challenges to the conventional financial system, and its impacts on financial markets have drawn tremendous attention to investors, academia and also regulators. Cryptocurrency is not only one type of digital currency, but also an asset to invest or hedge (Wang et al., 2019b). A few recent studies have explored the linkages between crude oil prices or energy commodities and cryptocurrency. For example, Bouri et al. (2018) find the existence of spillover effects from Bitcoin to energy commodities. Okorie and Lin (2020) also report empirical evidence that cryptocurrency and oil prices are linked. Like other financial assets, the prices of cryptocurrency have experienced frequent and large fluctuations (Gronwald, 2021). There is also clear evidence indicating the existence of multiple bubbles in cryptocurrency prices (Kyriazis et al., 2020).

Because of energy financialization and the increasingly important role of cryptocurrency in the global financial network, extreme price fluctuations or bubbles of cryptocurrency can potentially impose significant impacts on the systemic risks in the international energy sector. The mechanisms can, once again, be explained by a direct impact on energy companies and an indirect impact through market wide changes of systemic risk. To explore this issue, we extend the framework proposed by Brunnermeier et al. (2020), who establish an empirical strategy to test the role of asset bubbles on systemic risks in the banking sector. In particular, we first identify bubble dynamics in cryptocurrency prices and then use this information to test to what extent systemic risks in the energy sector respond to these bubbles.

Instead of exploring risks in energy prices, we take the risk measures of a set of international energy companies as the objectives in this research. The important role of large international energy companies is well documented in industrial transformation, upgrading, transmitting and supervising risks and uncertainties (Ji and Zhang, 2019). These top energy firms nowadays show strengthened risk connectedness (Wu et al., 2021), and their risks also act as a main contributor to system risk in the whole energy markets (Ma et al., 2019). Under international financial liberalization and frequent energy market turmoils in the recent decade, further exploring systemic risks in these firms are critical. While we have already obtained substantial knowledge on the standard risk factors for these companies, for example, oil prices (Antonakakis et al., 2018) and economic factors (Bianconi and Yoshino, 2014), there are more urgent needs to explore extreme movements in this sector and also incorporate new market dynamics into consideration. Thus, studying the systemic risks in international energy sector, particularly in the channels through asset bubbles affecting their systemic risk, have profound meanings to both practitioners and academia.

Our dataset includes the prices of a sample of the Thomson Reuters top 100 international energy companies, the cryptocurrency index (CRIX) and other related financial variables from July 2014 to March 2021. The systemic risks among energy firms are measured by the conditional value at risk *CoVaR* and Δ*CoVaR* (Adrian, 2016) relative to their local market indices. We use the CRIX index (Trimborn and Härdle, 2018) to represent the overall performance of the cryptocurrency market. Then the Backward Supremum Augmented Dickey Fuller test (Phillips et al., 2015a; Phillips et al., 2015b) is used to identify bubble dynamics in the cryptocurrency index.

The main analytical framework of our study is similar to Brunnermeier et al. (2020). We also categorize bubbles into bubble building (boom) and bubble busting (burst) phases and then measure lengths and sizes accordingly. The connectedness between systemic risks and cryptocurrency bubbles is then investigated via panel data models. The empirical results show a significant positive effect from cryptocurrency bubbles to systemic risks in energy firms, particularly during the burst of bubbles. We also find that bursts impose a larger impact on extreme downside risks. A number of robustness checks verify our main findings.

The contributions of this article can be summarized into the following four aspects: First, this paper complements the literature on the role of cryptocurrency prices in global financial markets. Instead of looking at the price movement itself, we extend the existing literature by exploring extreme price movements (i.e., bubbles) in cryptocurrency and the impacts on systemic risks. Second, we identify new evidence of energy financialization. Forming and bursting price bubbles in cryptocurrency, a new type of financial asset, can increase systemic risks in the energy sector. Third, by investigating different types of energy firms, we show that oil and gas companies play important roles in connecting shocks from the cryptocurrency market to systemic risks in other types of energy firms. Last but not least, our sample covers the recent COVID-19 pandemic period, and thus allows us to comment on the dynamic relationship in this special scenario and thus add to the large volume of literature exploring systemic risks in international energy and financial markets under the pandemic.

The rest of this paper is structured as below. Section 2 reviews relevant literature. Section 3 briefly explains the methodology on bubble detection, systemic risk measurements and the empirical model. Section 4 describes the data used in this paper. The main empirical results are reported and discussed in Section 5. Section 6 concludes the paper with further discussion on policy implications.

2. LITERATURE REVIEW

2.1 Asset bubbles and systemic risks

The concept of rational bubbles is introduced in the literature (Blanchard et al., 1982) in that bubbles are consistent with rationality. A non-fundamental component exists in prices due to self-confirming beliefs (Diba and Grossman, 1988). Technically, a significant boom in asset price driven by a systematic deviation of the market price from the fundamental value of the underlying asset can be defined as an asset price bubble (Brunnermeier and Oehmke, 2013).

In fact, bubbles exist from the very early days of the modern economy and often associate with significant economic or financial instability, and in its extreme form, crisis (Garber, 2001). One of the most well-known early stage bubbles is the Dutch tulip mania, and its consequence not only on investor losses but also hurting Dutch commerce. Commodity bubbles are no match to the consequence of financial bubbles due to financial connections and systemic risks, and financial bubbles tend to have more profound impacts both on financial markets and the aggregate economy. For example, the dot-com bubble results in a large loss in the financial market, and more severely, the burst of the sub-prime bubble eventually gives rise to the greatest recession in history (Roy and Kemme, 2020). In other words, bubbles, especially bursting of bubbles, are associated with a significant increase in systemic risks. Empirically, Schularick and Taylor (2012) use long historical data to investigate the relationship between bursting bubbles and financial crisis and evidenced significant linkage. Brunnermeier et al. (2020) discuss the channels in which asset price bubbles lead to financial stability. In their paper, motion loss and liquidity spirals due to bursting bubbles can impose significant impacts on the systemic risk in banking institutions. A strong increase in systemic risk caused by asset bubbles is found in their empirical studies. Their strategy provides new insights to study bubble-systemic risk relationships based on microeconomic level data, which also inspires the current study.

2.2 Systemic risks in the international energy sector

Energy sector plays a very special role in economic development across the world. Maintaining sustainable and affordable supplies of energy is a significant matter for national security. Typical supply factors, such as the role of OPEC and geopolitical uncertainties, are often the main concerns (Ji et al., 2019c). The scenario has changed due to energy market financialization, which leads to a large volume of literature investigating systemic risks in the international energy sector (Lautier and Raynaud, 2012; Kerste et al., 2015). With financialization, energy has not only characteristics of a typical commodity but also features of financial assets. These dual characteristics make systemic risks in the energy market more complicated. For example, Mensi et al. (2021) show that systemic risks in energy markets are higher than those in stock markets.

Much existing literature on systemic risks in the international energy markets concentrates on the macro-level, studying price dynamics and spillover effects across markets (e.g., Yang et al., 2021). Some recent works switch attention towards the micro-level by recognizing the importance of individual energy companies, especially large companies in the international energy sector (e.g., Wu et al., 2021). Under global financial liberalization and frequent market turmoil in the recent decade, the top energy firms nowadays show strengthened risk connectedness, and their risks also act as a contributor to system risk in the whole energy markets (Ma et al., 2019). Thus, studying systemic risks at the company level, particularly international energy sector, has important meanings.

2.3 Cryptocurrency bubble and energy

While existing literature has demonstrated risk spillovers between energy and stock markets or other commodity markets (Zhang and Broadstock, 2020), cryptocurrency has emerged as a new hot spot. Being a new challenge to the conventional financial system, cryptocurrency has quickly become an important player in the global capital market, though its prices often experienced frequent and large fluctuations. Some studies show that the cryptocurrency market is inefficient and predictable, indicating speculating opportunities, e.g., Atsalakis et al. (2019), Nadarajah and Chu (2017), Urquhart (2016). Another property appealing to empirical studies is the high volatility and speculative nature of cryptocurrencies. Corbet et al. (2018b) and Katsiampa (2019) apply GARCH-type models to investigate the conditional volatilities and discuss the speculative interests of popular cryptocurrencies.

A few studies have raised the importance of studying cryptocurrency bubbles. For instance, Kyriazis et al. (2020) provide a comprehensive review of literature on cryptocurrency bubbles. Unlike commodities or stocks, the fundamental values of cryptocurrencies are difficult to determine. Being a relatively new type of asset with limited information, bubbles are more likely to form in cryptocurrency markets. Price movements in cryptocurrency markets are more likely to be driven by irrational exuberance in investors' behaviours (Shiller, 2015) or speculative demands. By definition, bubbles reflect persistent price deviation from the fundamental value, and more importantly, the deviation is often following an explosive pattern, thus it allows us to identify price bubbles without knowing the true fundamentals. Technically, the explosive price movements found in the time series can be considered bubbles (Phillips et al., 2015a; Phillips et al., 2015b).

Bubbles in cryptocurrency markets are also found to be connected with other assets or cross currency types. Holub and Johnson (2019) find a strong linkage between Bitcoin bubbles and Bitcoin's peer-to-peer market during a bearish period of the year 2017. Bouri et al. (2019) trace the evolution of seven popular cryptocurrencies and conclude bubble formations among them (also see Cheung et al. (2015), and Corbet et al. (2018a)). In addition, they show that the explosive price movements in cryptocurrencies tend to be connected, in other words, there are co-explosivity in cryptocurrency markets. Further analysis by Bouri et al. (2020) finds co-jumping behavior among some cryptocurrencies, indicating the existence of cross-market risk spillovers.

Recent literature shows that cryptocurrency has a close link to energy and commodity markets. Bouri et al. (2018) show that Bitcoin returns lead to spillover effects on a few traditional trading assets, particularly commodities. Similar findings are also reported by Ji et al. (2018) using a directed acyclic graph methodology. Shahzad et al. (2019) study the safe-heaven role of Bitcoin to traditional assets, and they conclude that Bitcoin could be considered as a weak safe-heaven asset. However, Ji et al. (2020) do not support this finding, bringing the analysis into the COVID-19 pandemic phase.

In general, going through these existing works of literature suggest that studying cryptocurrency bubbles and their impacts on systemic risks in the energy sector is important. Taking a micro perspective following the empirical strategy proposed by Brunnermeier et al. (2020) can provide additional evidence to understand systemic risks in the international energy markets.

3. METHODOLOGY

3.1 Bubble detection method

In this section, we introduce the method to employ in detecting bubbles in the cryptocurrency market. The cryptocurrency bubbles are mainly detected by using two types of methods in the literature. One is to use the Backward/Generalised Supremum augmented Dickey-Fuller (BSADF) tests (Phillips et al., 2015a; Phillips et al., 2015b) to examine the time series of cryptocurrency prices and detect bubbles, see Cheung et al. (2015), Corbet et al. (2018a) and Bouri et al. (2019) for empirical examples. Another popular method is the Log Periodic Power Law (LPPL), which is usually combined with parametric time series models to indicate bubbles, see related ones (MacDonell, 2014; Wheatley et al., 2018; Shu and Zhu, 2020). In the present paper, we stick to the former method, because (1) by computing backward ADF statistics for flexible window-lengthen sub-samples, the BSADF approach is well established to obtain its asymptotic results and provides a surveillance strategy to act early warning alerts; (2) it purely detects the non-stationary explosive behaviour from the price data, which is more suitable for cryptocurrency assets with undefined fundamental values; (3) it is more intuitive and capable of detecting multiple bubbles within a given period of the dataset, evidenced by the simulation study in Phillips et al. (2015a) and Phillips et al. (2015b) as well as empirical applications, e.g., Cheung et al. (2015) and Corbet et al. (2018a).

To specify the approach of the BSADF test, we consider the following asset pricing equation:

$$y_t = \sum_{i=0}^{\infty} (\frac{1}{1+r_f})^i \mathbb{E}_t(U_{t+i}) + B_t, \tag{1}$$

where y_t is price of the asset of interest, i.e., CRIX index in our context, r_f is the risk-free rate, U_t is the latent fundamentals, and B_t is the bubble formation that is assumed to satisfy the submartingale property $\mathbb{E}(B_{t+1}) = (1+r_f)B_t$. The principle applied here is that the non-stationary or explosive behaviour of differenced price data would deduce a bubble, given that the fundamental term U_t is either to be stationary or a unit root process (Phillips and Magdalinos, 2007). From this perspective, the bubbles identified here differs from the traditional concept of rational bubble in the sense that the roots can exceed one. Conducting a unit root test recursively from the right side of the sample offers a real-time detection mechanism for asset bubbles.

The following model specification is considered to set up a testing procedure,

$$y_t = dT^{-\eta} + \theta y_{t-1} + \varepsilon_t,\ \varepsilon_t \overset{i.i.d}{\sim} N(0, \sigma^2), \theta = 1,$$

where d is a constant, T is the sample size and the localising parameter η controls the magnitude of the deterministic term as $T \to \infty$. In order to test the explosive behaviour of y_t, the above model specification is transited to a dynamic model in rolling window sub-samples under the framework of the recursive approach. To be specific, considering the rolling window regression with a sub-sample beginning from w_1th fraction of the total sample (T) and terminating at the w_2th fraction of the total sample, where $w_2 = w_l + w_l$ for a window length w_l of T_w observations, we can write

$$\Delta y_t = \alpha_{w_1,w_2} + \beta_{w_1,w_2} y_{t-1} + \sum_{i=1}^{k} \psi^i_{w_1,w_2} \Delta y_{t-i} + \varepsilon_t,\ \varepsilon_t \overset{i.i.d}{\sim} N(0, \sigma^2_{w_1,w_2}) \qquad (2)$$

where k is the lag order of the model. Implementing an ADF test to this regression model we obtain the statistic $ADF_{w_1}^{w_2}$.

In the recursive procedure, each sub-sample starts from the initial point of the sample $w_1 = 0$ and ends at $w_2 = w_l$, by expanding w_l from the smallest sample fraction w_0 to the largest sample fraction 1, we this can obtain the supreme of the ADF statistics.

$$SADF(w_0) = \sup_{w_2 \in [w_0, 1]} ADF_0^{w_2}.$$

The statistic $SADF(w_0)$ thus determines whether there is a bubble occurred in the sample. Additionally, in order to address the detection of multiple bubbles, Phillips et al. (2015a) and Phillips et al. (2015b) proposed a double recursive test denoted as the BSADF test, giving the formula,

$$BSADF_{w_2}(w_0) = \sup_{w_1 \in [0, w_2 - w_0]} ADF_{w_1}^{w_2}.$$

Comparatively, the BSADF test performs a SADF test through backward expanding sub-samples, in which the endpoint of each sub-sample is fixed by w_2 while the starting point is increasing from 0 to $w_2 - w_0$. This approach improves the detective capability for multiple bubbles because it would provide more information by adapting the true data generating mechanism. The test is also robust to short-lived blips because the detected bubble duration must exceed log(T) observations that are a condition imposed by Phillips et al. (2015a) and Phillips et al. (2015b).

The estimators of bubble origination date $\hat{w}_e$ and termination date $\hat{w}_f$ are thereby constructed by the crossing time formulas as below,

$$\hat{w}_e = \inf_{w_2 \in [w_0, 1]} \{w_2 : BSADF_{w_2} > cv_{w_2}^{a_T}\},\ \hat{w}_f = \inf_{w_2 \in [w_e + \delta \log(T)/T, 1]} \{w_2 : BSADF_{w_2} < cv_{w_2}^{a_T}\},$$

where $cv_{w_2}^{a_T}$ is the critical value at α percentile significance level based on $\lfloor Tw_2 \rfloor$ observations, for $\lfloor \cdot \rfloor$ denoting the integer part, and δ is a frequency-dependent parameter. The above formula indicates that the origination date of the bubble is the first observation whose BSADF statistic is greater than the nominal critical value, and the termination date is the last observation whose BSADF statistic is less than the critical value during the period of bubbles.

In order to scrutinise the impact of bubbles features, following Brunnermeier et al. (2020), we also calculate the characteristics of bubble length and size. Each bubble episode can be separated into a boom phase and a burst phase, where the boom refers to the period when the bubble originates and reaches the price peak during the whole episode, and the burst refers to the period from the price peak to bubble termination date. Distinguishing booms from bursts not only helps us better understanding the formation of bubble, but also allow us to verify the effect of investors' irrational exuberance behaviour on the systemic risk in the international energy market. Then, we count the number of observations that a bubble booms since its origination and bursts since its peak, denoted as boom length and burst length. Moreover, we measure the size, which is calculated as the relative asset price between the current observation to the last pre-bubble observation during the boom, and the relative asset price between the current observation to the peak of the bubble episode during the burst. The bubble length and size are valued at zero outside of the bubble episodes.

3.2 Measuring systemic risk

We quantify the downside systemic risk using *CoVaR* and Δ*CoVaR* measurements (Adrian, 2016), which can be used to determine the effect of cryptocurrency bubbles on the systemic risk in the international energy sector. It is well known that given an equity return series r_t, we usually measure the downside risk via the Value-at-Risk (VaR), which is expressed as $\mathbb{P}(r_t \leq VaR_t^{\tau}) = \tau$, for the chosen percentile . By definition, the VaR measures how much the asset of interest would lose with a nominal probability during a certain trading period. The measurement can be directly estimated through the quantile regression or indirectly estimated through a GARCH-type data generating mechanism.

However, it is arguable that the VaR measurement only estimates the downside risk on its own but neglects the potential linkages between the specific share and the whole market performance. Thus, by incorporating the impact of financial distress in the whole equity market, Adrian (2016) proposed a CoVaR measurement. Given a particular equity return of *i*th energy company $r_{i,t}$, its CoVaR quantifies the VaR of this asset conditional on the fact that the whole market $r_{m,t}$ experiences an extreme downside movement, where $r_{m,t}$ is the representative market index. In the formula we have

$$\mathbb{P}(r_{i,t} \leq CoVaR_{i,t}^{\tau} \mid r_{m,t} \leq VaR_{m,t}) = \tau,$$

where $VaR_{m,t}$ is the τth quantile VaR measures of the market index return for a given time horizon.

Here we focus more on the marginal contribution of the energy companies to the entire equity market during the market distress condition. Hence, based on the estimator of $CoVaR_t$, we also calculate the Δ*CoVaR*, which is the difference between the VaR of the market as a whole conditional on the distressed market status and the VaR of the market as a whole conditional on the benchmark of the market, where the benchmark is usually considered the as median of the return distribution of market index. Thus, it gives

$$\Delta CoVaR_{m|i,t}^{\tau} = CoVaR_{m|VaR_i^{\tau},t}^{\tau} - CoVaR_{m|VaR_i^{0.5},t}^{\tau}. \quad (3)$$

Δ*CoVaR* quantifies the contribution of an energy company to the systemic risk by estimating the extra VaR of the entire equity market when this company occurs a downside risk. Following Adrian (2016), we estimate Δ*CoVaR* via a quantile regression method.

3.3 Panel data model

With the calculation of cryptocurrency bubbles and the systemic risk measures for energy companies, we next conduct a panel data analysis to investigate the effect of bubbles on systemic risk. The model regresses the measurement of $\Delta CoVaR_t$ of energy company i at time t on fixed effect β_0, the dummies of booms and bursts in the cryptocurrency market at time t, lagged firm-level characteristics, the interaction terms of the bubble with bubble and firm-level characteristics, and lagged macroeconomic and other control variables.

$$\begin{aligned}\Delta CoVaR_{i,t} = \quad & \beta_0 + \beta_1 I_t^{Bubble} + \beta_2 FirmChar_{i,t-1} + \beta_3 I_t^{Bubble} \times BubbleChar_t \\ & + \beta_4 I_t^{Bubble} \times FirmChar_{i,t-1} + \beta_5 C_{t-1} + \varepsilon_{i,t},\end{aligned} \tag{4}$$

where I_t^{Bubble} is the binary indicator of booms or bursts. Following Brunnermeier et al. (2020), we also subtract the median from firm-level and bubble characteristics for a convenient interpretation. Thus, the coefficients represent the changes in the systemic risk in the median characteristics of an energy company during a boom or burst of median size and length. To interpret coefficients, a positive (negative) $\hat{\beta}_1$ decides an increasing (decreasing) in marginal contributions of systemic risk during the bubble booms or bursts episodes. $\hat{\beta}_3$ captures the impact of bubble on systemic risk depending on firm-level characteristics, e.g., trading volume and idiosyncratic volatility. The impact depending on bubble characteristics similarly represented by $\hat{\beta}_4$, as the effect of size and length of boom and burst can vary differently to the systemic risks.

Regarding the firm-level characteristics, due to the unavailability of financial variables from companies' balance sheets at a daily frequency, we derive the related covariates from the historical trading information. One of the firm-level control variables is the trading volume. Additionally, we compute two firm-level characteristics from historical returns. The first is the idiosyncratic volatility $IV_{i,t}$ (Ang et al., 2006). For company i, we estimate $IV_{i,t}$ by fitting the following model,

$$r_{i,d} - r_{f,d} = \alpha_i + \beta_i (r_{m,d} - r_{f,d}) + \varepsilon_{i,d},$$

where the subscript $d \in [t-22, \ldots, t]$, and $r_{f,d}$ is the risk-free rate. By saving the residuals, we then compute the idiosyncratic volatility for firm i at time t as

$$IV_{i,t} = \sqrt{var(\varepsilon_{i,d})}.$$

Noted that the $IV_{i,t}$ used here is a proxy of the idiosyncratic volatility as discussed in Ang et al. (2006) by incorporating one-month historical trading information. The same idea is also used to compute another control variable—maximum daily return (Bali et al., 2011). We calculate the maximum daily returns $A_{i,t}$ by taking the maximum value of one-month historical daily returns.

$$A_{i,t} = \max(r_{i,d}), \quad d = t - 22, \ldots, t.$$

These two firm-level variables have been widely used in empirical studies, which evidences good predictabilities to cross-sectional equity returns.

Our model also controls related economic or financial variables specified in C_t. The first two variables in this category is the boom and burst of oil price bubbles detected from WTI prices. Commonly used equity and energy market indices are also included together with VIX and OVX, which are typical measurements of market volatility in equity and oil markets, respectively. Public sentiment/attention to cryptocurrency could potentially affect the role of cryptocurrency in financial markets, therefore we collect Google trend search index on "Bitcoin", the most popular cryptocurrency, and then use this index to control for public attitude in the regression.

4. DATA AND DESCRIPTIVE STATISTICS

The use of underlying data vehicles is diversified in the existing literature to presenting the asset price of cryptocurrencies. Most of the studies so far concentrated on the price of cryptocurrency themselves, e.g., the daily closing price of Bitcoin and Ethereum (Bouri et al., 2019; Corbet et al., 2018a). Although it is more practical when the object of interest lies in a particular type of cryptocurrency, the price indices are more often adopted to emphasise the whole market performance, e.g., the Bitcoin Price Index (Bouoiyour et al., 2014; Bouoiyour et al., 2016), the Bitcoin Coindesk Index (Cheah and Fry, 2015), and the CRIX index (Chen and Hafner, 2019; Hafner, 2020). Also, as Kyriazis et al. (2020) pointed out, it is more likely to find intensive bubbles in cryptocurrency indices, including the CRIX, Bitcoin price, and Mt.Gox values. A couple of reasons discussed above can help explain this statement. First, lacking information of fundamental values in cryptocurrencies leads to more speculations; and the second reason is that these cryptocurrencies tend to connected with each other, or demonstrate co-explosivity (Bouri et al., 2019; Bouri et al., 2020).

We overlook a particular type of cryptocurrency and concentrate on the CRIX index[1] (Trimborn and Härdle, 2018). The CRIX index covers the sample period since cryptocurrencies were publicly deemed as financial assets in 2014. The index's constituents are updated regularly on a quarterly basis to represent the development of the whole cryptocurrency market. For instance, in March 2021, the largest three constituents are Bitcoin (BTC, 65.2%), Ethereum (ETH, 16.1%), and Binance coin (BNB, 4.55%). Our sample starts from 31 July 2014 when the CRIX index becomes available and ends at the recent cryptocurrency trading boom on 10 March 2021, covering several "business cycles" of the cryptocurrency market. Considering the characteristic of the high volatility of cryptocurrencies, we collect daily data rather than on a monthly basis used in most studies for conventional asset pricing.

We study the non-normalised price data for bubble detections. The normalised price is occasionally considered to determine the price fluctuations from the underlying fundamental values. For instance, Phillips et al. (2015a) and Phillips et al. (2015b) performed their test to detect equity bubbles through the price to dividends data. However, because the dividends are unavailable to cryptocurrency and commodity futures, we apply the BSADF method to raw price data in our analysis. This accommodation is supported by Brunnermeier et al. (2020) that to detect bubbles in non-normalised price data would not alter the numerical results of using the normalised one.

The dataset also comprises information from equity and commodity futures markets. We collect 100 representative energy companies worldwide based on Thomson Reuters top 100 international energy leaders[2]. The sample ranges the same period as the CRIX index. Due to the lack of availability and quality of the data, we eventually stick to 72 companies and collect their daily prices and trading volumes. These companies are from 34 countries or regions, and they can be further categorized into four groups: oil and gas, equipment and services, multiline utilities, and renewable energy. Meanwhile, in order to calculate the systemic risk in these companies conditional on the corresponding market indices, we also obtain the market indices from their local stock exchanges[3]. Table 1 documents the corresponding market indices collected for each of the energy companies.

Besides, we also collect the WTI crude oil futures price and MSCI world energy sector price index from the commodity futures market, aiming to control the effect of oil price. Other control variables include the three-month T-bill rate as a proxy of the risk-free rate and two volatility in-

1. data source: https://thecrix.de/
2. https://www.thomsonreuters.com/en/products-services/energy/top-100.html
3. Some countries or regions are using the alternative market index, including Colombia by S&P500; Monaco by CAC40; Jersey by FTSE100.

Table 1: List of 72 international energy companies used as effective sample with the categorised industry, listed country, and the corresponding market indices.

Company	Industry	Country	Index	Company	Industry	Country	Index
Acea SpA	Multiline Utilities	Italy	FTSE Italy all-share	Bharat Petroleum	Oil & Gas	India	SENSEX
BP	Oil & Gas	UK	FTSE100	Cameco	Uranium	Canada	TSX
Canadian Natural Resources	Oil & Gas	Canada	TSX	China Petroleum & Chemical	Oil & Gas	China	SSEC
CMS Energy	Multiline Utilities	USA	SP500	ConocoPhillips	Oil & Gas	USA	SP500
DCC	Oil & Gas	Ireland	ISEQ overall	E.ON SE	Multiline Utilities	Germany	DAX30
Ecopetrol	Oil & Gas	Colombia	SP500	Enagás	Equipment and Services	Spain	IBEX
Enbridge Inc.	Equipment and Services	Canada	TSX	Engie	Multiline Utilities	France	CAC40
Eni	Oil & Gas	Italy	FTSE Italy all-share	First Solar	Renewable Energy	USA	SP500
Galp Energia	Oil & Gas	Portugal	PSI20	Gazprom	Oil & Gas	Russia	RTS
Global Pvq SE i I	Renewable Energy	Germany	DAX30	Grupa Lotos	Oil & Gas	Poland	WIG
Halliburton Company	Equipment and Services	USA	SP500	Hellenic Petroleum	Oil & Gas	Greece	ATHEX
Hera	Multiline Utilities	Italy	FTSE Italy all-share	Idemitsu Kosan Co., Ltd.	Oil & Gas	Japan	TOPIX
Indian Oil Corporation	Oil & Gas	India	SENSEX	IRPC	Oil & Gas	Thailand	SETI
Mangalore Refinery and Petrochemicals Ltd.	Oil & Gas	India	SENSEX	MOL	Oil & Gas	Hungary	Budapest SE
Motor Oil Hellas	Oil & Gas	Greece	ATHEX	National Grid	Multiline Utilities	UK	FTSE100
Neste Oyj	Oil & Gas	Finland	OMX	Lukoil	Oil & Gas	Russia	RTS
Oil and Natural Gas Corporation	Oil & Gas	India	SENSEX	Oil Refineries Ltd.	Oil & Gas	Israel	RF Israel
OMV AG	Oil & Gas	Austria	ATX	PetroChina Co., Ltd.	Oil & Gas	China	SSEC
Petrofac	Equipment and Services	Jersey	FTSE100	Petronas	Oil & Gas	Malaysia	KLSE
Phillips 66	Oil & Gas	USA	SP500	PKN ORLEN	Oil & Gas	Poland	WIG
PTTEP	Oil & Gas	Thailand	SETI	Reliance Industries	Oil & Gas	India	SENSEX
Repsol	Oil & Gas	Spain	IBEX	Rosneft	Oil & Gas	Russia	RTS
Royal Dutch Shell	Oil & Gas	Netherlands	AEX	Rubis	Oil & Gas	France	CAC40
RWE	Multiline Utilities	Germany	DAX30	Saipem	Equipment and Services	Italy	FTSE Italy all-share
Santos	Oil & Gas	Australia	ASX200	Saras	Oil & Gas	Italy	FTSE Italy all-share
Sasol	Oil & Gas	South Africa	JSE all-share	Saudi Basic Industries Corporation	Oil & Gas	Saudi Arabia	TADAWUL
Schlumberger	Equipment and Services	USA	SP500	Scorpio Tankers Inc.	Equipment and Services	Monaco	CAC40
Sempra Energy	Multiline Utilities	USA	SP500	Showa Shell Sekiyu K.K.	Oil & Gas	Japan	TOPIX
Siemens Gamesa Renewable Energy	Renewable Energy	Spain	IBEX	SK Innovation Co., Ltd.	Oil & Gas	South Korea	KOSPI
Snam	Equipment and Services	Italy	FTSE Italy all-share	S-Oil	Oil & Gas	South Korea	KOSPI
Statoil	Oil & Gas	Norway	OBX	Suncor Energy	Oil & Gas	Canada	TSX
SunPower	Renewable Energy	USA	SP500	Técnicas Reunidas	Equipment and Services	Spain	IBEX
Tenaris SA	Equipment and Services	Luxembourg	LUXX	Total	Oil & Gas	France	CAC40
Tullow Oil	Oil & Gas	UK	FTSE100	Tüpras	Oil & Gas	Turkey	BIST100
Ultrapar Participacoes S.A.	Oil & Gas	Brazil	SPSE	Vallourec	Related Equipment and Services	France	CAC40
Vestas	Renewable Energy	Denmark	OMX20	Woodside Petroleum	Oil & Gas	Australia	ASX200

dices, VIX and OVX, standing for the volatilities of equity and oil markets, respectively. The public sentiment on cryptocurrency is also controlled via the the Google trend data. Given that equity data is observed 5 days a week, we thus accommodate the CRIX index and crude oil futures to the same observation dates, eventually rendering a balanced panel with a time series $T = 1723$.

To understand the properties of the key variables, we look at the price data of CRIX and crude oil futures as they would be used to detect bubbles in the cryptocurrency and oil markets. For other variables, we take the log difference to get stationary sequences. The Google trend is differenced with order one to obtain a stationary sequence. Table 2 reports summary statistics of some of the key variables. The variables oil&gas, equipment&services, multiline utilities, renewable energy denote the firm returns for each energy sector. Together with dVolume and market index, these variables contain multiple series that consists of energy companies. We do not present the statistic summary for each energy firm but compute the median of those statistics to save some space. Table 2 reveals that the WTI crude oil as a conventional financial asset experienced relatively mild volatility, while the CRIX index is extremely volatile, reflecting a maniac cryptocurrency market. The equity and indices returns are all zero mean, non-normal distributed, and stationary sequences.

Table 2: Summary statistics of the representative variables, where oil&gas, equipment&services, multiline utilities, renewable energy, dVolume and market index are taking the median of the statistics of the panel data. P-values are documented for the Jarque-Bera, ADF and KPSS tests.

	Mean	SD	Skewness	Kurtosis	Min	Max	Jarque-Bera	ADF	KPSS
CRIX Price	1.5531e+04	2.1739e+04	3.2088	16.7252	342.0667	1.6194e+05	0.00	1.00	0.01
WTI Price	52.8542	13.3644	0.4252	5.8826	-37.6300	98.2900	0.00	0.16	0.01
oil&gas	9.02e-05	0.0214	-0.3995	13.7801	-0.1783	0.1475	0.00	0.00	0.10
equipment&services	-7.17e-04	0.0259	-1.1907	18.8027	-0.2611	0.1700	0.00	0.00	0.10
multiline utilities	1.83e-04	0.0164	-0.6118	16.8625	-0.1688	0.1272	0.00	0.00	0.10
renewable energy	3.88e-04	0.0294	-0.2225	11.7611	-0.2123	0.1852	0.00	0.00	0.10
dVolume	1.31e-04	0.4542	0.2191	4.8297	-2.1234	2.2450	0.00	0.00	0.10
market index	1.95e-04	0.0131	-1.1541	18.6160	-0.1361	0.0867	0.00	0.00	0.10
MSCI	-8.9338e-05	0.0177	-1.3661	28.6232	-0.2187	0.1388	0.00	0.00	0.10
VIX	4.1089e-04	0.0837	1.4955	11.6699	-0.2998	0.7682	0.00	0.00	0.10
OVX	0.00	0.0644	1.9431	37.2070	-0.6223	0.8577	0.00	0.00	0.10
dGoogle trend	0.0258	3.6695	-0.2791	113.57	-63	50	0.00	0.00	0.10

5. EMPIRICAL RESULTS

5.1 Cryptocurreny bubbles detection

This section discusses the empirical findings on to what extent systemic risks in energy companies respond to cryptocurrency bubbles. Figure 1 shows the datestamping of cryptocurrency bubbles over our sample period. The blue line from the figure indicates the evolutions of the CRIX index price, and the red line stands for the recursive BSADF statistics with its critical value at 95% significance level recorded by the green dash line. The detecting sample starts from 10 December 2014 as the first $\lfloor Tw_0 \rfloor = 92$ observations are burned for a rolling window length, and the detection continues until the end of the sample in March 2021.

From the plot, we identify two distinct bubble periods in the cryptocurrency market. The CRIX index first shows a persistent bubble-like behaviour in the year 2017, given that its price rapidly rockets to \$50,000 level despite no significant mining algorithm improvement. The second sustainable bubble period occurs during the recent pandemic period of 2020–2021, and the CRIX index continuously reaches its lifetime new peak. For example, the price for Bitcoin is about \$7,300 before the pandemic erupted, and at the end of our sample period, a buy of one bitcoin costs $41,326. This can be attributed to investors fearing that they prefer to switch their portfolio into a market without the interference of a central bank crisis; it is also benefited from the fact that digital currencies can alleviate potential liquidity constraints imposed by the local authorities. Some other short-term bubbles are also detected during 2016 and 2019, and we explain them by normal market fluctuations.

Figure 1: Cryptocurreny bubble periods detected by the BSADF statistic on CRIX index with the shaded areas indicating the bubble episodes.

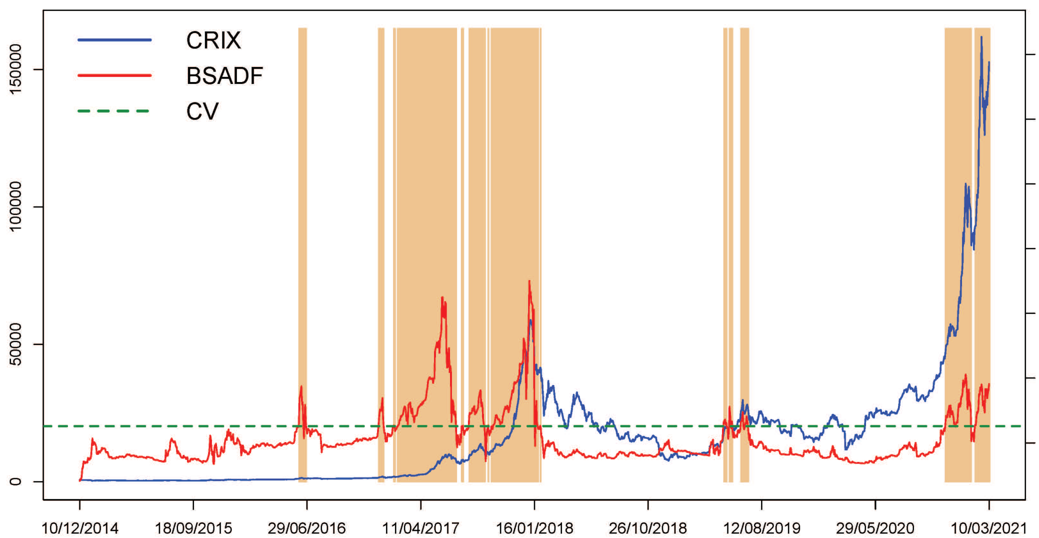


Table 3 documents the details of lengths and sizes of cryptocurrency booms and bursts during the sample period. It is noticeable the longest boom episode is from 15 February to 21 June 2017, lasting for 83 days. There are other relatively longer boom episodes in 2017, 2020 and 2021. Compared with the bubble buildings, the bubbles burst more rapidly. The columns of size quantify the magnitudes of the booms and bursts.

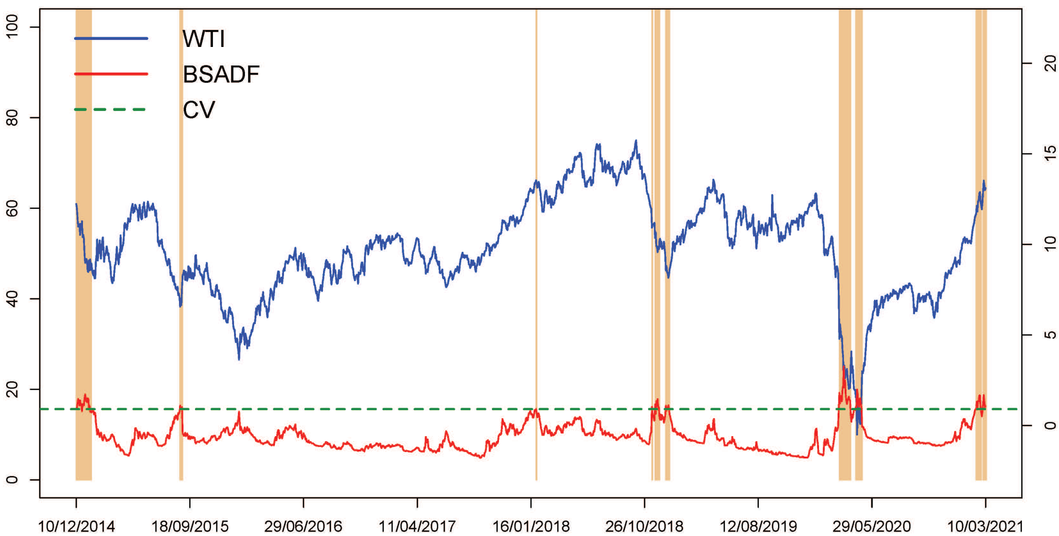
Furthermore, we implement the BSADF method to detect oil bubbles in the WTI crude oil futures price, which is considered to control the impact of crude oil futures bubbles on energy companies' performances so that concerns related to the endogeneity of cryptocurrency bubbles can be eliminated. Figure 2 displays detected oil bubbles from 2014 to 2021. Compared with the cryptocurrency index, much fewer bubbles are detected in the sample period.

Note that for oil price bubbles, the results show more negative bubbles than positive bubbles during our studied period. Negative bubbles are not unusual in financial markets. For example, Cheah and Fry (2015) investigate this issue for cryptocurrency markets. Acharya and Naqvi (2019) develop a model to explain the formation of both positive bubbles and negative bubbles. Goetzmann and Kim (2018) find negative bubbles in stock markets, where positive returns tend to follow extremely large price decline. In general, negative bubble is to capture the extreme downward price movements that are beyond the explanatory power of demand and supply (Fantazzini, 2016). The existence of these negative bubbles is also an additional confirmation of financialization in crude oil market, where speculative investments drive oil price away from its fundamental value.

Table 3: Length and size of the detected cryptocurrency bubble booms and bursts.

Bubble boom			Bubble burst		
Date	Length	Size	Date	Length	Size
08/06/2016 - 17/06/2016	6	0.3285	20/06/2016 - 21/06/2016	2	0.0789
23/06/2016 - 24/06/2016	2	0.1132	-	-	-
22/12/2016 - 04/01/2017	7	0.3699	-	-	-
15/02/2017 - 21/06/2017	83	4.5172	22/06/2017 - 07/07/2017	10	0.0704
07/08/2017 - 05/09/2017	20	0.7160	06/09/2017 - 12/09/2017	5	0.0113
09/10/2017 - 08/01/2018	61	4.3729	09/01/2018 - 16/01/2018	5	0.2658
18/01/2018 - 19/01/2018	2	0.0487	-	-	-
14/05/2019 - 17/05/2019	4	0.2192	20/05/2019 - 21/05/2019	2	0.00
28/05/2019 - 29/05/2019	2	0.1291	30/05/2019 - 31/05/2019	2	0.0080
24/06/2019 - 27/06/2019	4	0.3050	-	-	-
05/07/2019 - 10/07/2019	4	0.1364	-	-	-
17/11/2020 - 02/12/2020	10	0.2779	03/12/2020 - 10/12/2020	6	0.00
14/12/2020 - 11/01/2021	17	1.0418	12/01/2021 - 21/01/2021	7	0.0717
01/02/2021 - 23/02/2021	12	0.7650	24/02/2021 - 10/03/2021	11	0.1734

Figure 2: Oil bubble periods detected by the BSADF statistic on WTI price.

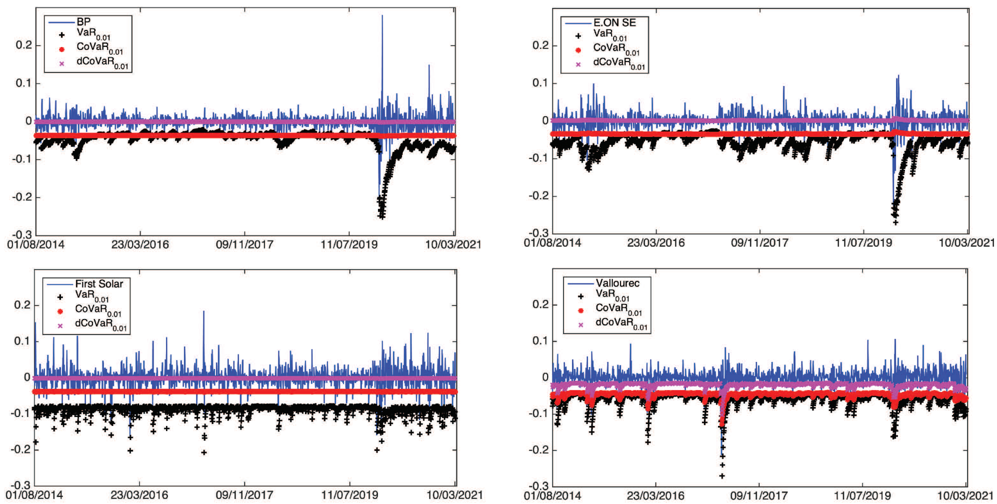


5.2 Systemic risks in energy sector

We also obtain the systemic risk measurements for top energy companies using the methods as described in Section 3.2. We compute the systemic risk measures $\Delta CoVaR$ and $CoVaR$ at two different quantiles, when $\tau = 0.01$ and 0.05, for each of the energy companies. These measures will be used as the dependent variables in the panel data models.

Figure 3 shows the plots of $\Delta CoVaR$ and $CoVaR$ of four representative energy companies from each of energy sectors, when the nominal quantile $\tau = 0.01$, namely, BP for the sector of oil and gas; E.ON SE for the sector of multiline utilities; First Solar for the sector of renewable energy; Vallourec for the sector of equipment and services. The standard VaR measures are also plotted for references. The VaR measures manifestly capture the downside risks during the time of financial system distress, e.g., the market panic triggered by the coronavirus pandemic in March 2020. The measures $\Delta CoVaR$ and $CoVaR$ evolve similarly, although they have a relatively smaller scaling after conditioning on the market downside risks. Similar patterns are also observed when we set a higher quantile of downside risk with $\tau = 0.05$.

Figure 3: Plots of the risk measures *VaR*, *CoVaR* and Δ*CoVaR* for the representative energy companies when the quantile $\tau = 0.01$.



5.3 Panel model analysis

Now we are ready to estimate the panel data model (4) given in Section 3.3. By truncating the rolling window for the BSADF bubble detection approach, our dataset eventually reaches a balanced panel with $T = 1436$ and $N = 72$. It is notable that our panel data set is different from usual macroeconomic studies in which the cross-sections N are larger than the time series T. Nonetheless, we consider a fixed effect estimator, as the fixed effect estimator is consistent as long as either N or T goes to infinity [Wooldridge, 2010]. To specify the models, below we first denote all explanatory variables according to the categories labelled in Model (4),

- I_t^{Bubble}

  (1) CRIX bubble boom: $\boxed{CM_t}$, CRIX bubble burst: $\boxed{CT_t}$;
- $FirmChar_{i,t}$

  (2) Volume: $\boxed{U_{i,t}}$, Idiosyncratic volatility: $\boxed{IV_{i,t}}$; Max: $\boxed{A_{i,t}}$;
- $I_t^{Bubble} \times CRIX\ BubbleChar_t$

  (3) $CM_t \times$ bubble boom size: $\boxed{MS_t}$, $CT_t \times$ bubble burst size: $\boxed{TS_t}$;

  (4) $CM_t \times$ bubble boom length: $\boxed{ML_t}$, $CT_t \times$ bubble burst length: $\boxed{TL_t}$;
- $I_t^{Bubble} \times FirmChar_{i,t}$

  (5) $CM_t \times U_{i,t}$: $\boxed{MU_{i,t}}$, $CT_t \times U_{i,t}$: $\boxed{TU_{i,t}}$;

  (6) $CM_t \times IV_{i,t}$: $\boxed{MV_{i,t}}$, $CT_t \times IV_{i,t}$: $\boxed{TV_{i,t}}$;

  (7) $CM_t \times A_{i,t}$: $\boxed{MA_{i,t}}$, $CT_t \times A_{i,t}$: $\boxed{TA_{i,t}}$;

- C_t

  (8) WTI bubble boom: $\boxed{WM_t}$, WTI bubble burst: $\boxed{WT_t}$;

  (9) Market index: $\boxed{M_{i,t}}$, MSCI energy index: $\boxed{E_t}$, VIX: $\boxed{V_t}$, OVX: $\boxed{O_t}$;

  (10) Google trend: $\boxed{G_t}$.

Next, we form six model specifications to investigate the predictability of cryptocurrency bubbles on the systemic risks in energy companies. Table 4 displays the independent variables that are included from Model 1 to Model 6. Models 1–2 only regress the systemic risks on the binary bubble variables, and the effect of crude oil bubbles is controlled. Models 3–4 extend to explain the firm-level characteristics and the interactions with the bubble indicators, including the trading volume, idiosyncratic volatility and maximum returns. Model 5–6 further consider macroeconomic control variables, including the market returns and MSCI world energy sector index returns for Model 5, and additional VIX, OVX returns and the differenced Google trend data for Model 6.

Table 4: Abbreviations of the independent variables in Model 1–6.

	I_t^{Bubble}	$FirmChar_{i,t-1}$	$I_t^{Bubble} \times BubbleChar_t$	$I_t^{Bubble} \times FirmChar_{i,t-1}$	$C_{i,t-1}$
Model 1	$CM_t, CT_t,$ WM_t, WT_t				
Model 2	$CM_t, CT_t,$ WM_t, WT_t		$ML_t, TL_t,$ MS_t, TS_t		
Model 3	$CM_t, CT_t,$ WM_t, WT_t	$U_{i,t}$	$ML_t, TL_t,$ MS_t, TS_t	$MU_{i,t}, TU_{i,t}$	
Model 4	$CM_t, CT_t,$ WM_t, WT_t	$U_{i,t}, IV_{i,t}, A_{i,t}$	$ML_t, TL_t,$ MS_t, TS_t	$MU_{i,t}, TU_{i,t}$	
Model 5	$CM_t, CT_t,$ WM_t, WT_t	$U_{i,t}, IV_{i,t}, A_{i,t}$	$ML_t, TL_t,$ MS_t, TS_t	$MU_{i,t}, TU_{i,t}$	$M_{i,t}, E_t$
Model 6	$CM_t, CT_t,$ WM_t, WT_t	$U_{i,t}, IV_{i,t}, A_{i,t}$	$ML_t, TL_t,$ MS_t, TS_t	$MU_{i,t}, TU_{i,t}$	$M_{i,t}, E_t,$ V_t, O_t, G_t

Table 5 demonstrates the fixed effect estimations of all models with the dependent variables $\Delta CoVaR$ and $CoVaR$, when the nominal quantile set $\tau = 0.01$. Overall, cryptocurrency bubbles are associated with a significantly positive contribution to systemic risks, and this effect is manifest particularly during the bubble burst periods. The findings of regressing $CoVaR$ or $\Delta CoVaR$ on explanatory variables generally remain consistent. To be specific, when the marginal contribution to systemic risk $\Delta CoVaR$ is considered, the results of Model 1 show that the coefficients on CRIX boom and bursts are significantly positive signed after controlling the crude oil bubbles. The results of Model 2 reveals that a longer boom will positively impact the systemic risk, while a sudden and short burst is more harmful to the system. This is a reasonable finding because rapid collapses usually come with market panic. Regarding the size of bubbles, we identify that a strong boom tends to be followed by a more harmful result, which is consistent with the statement of Brunnermeier and Oehmke (2013). Interestingly, the burst sizes are not showing a significant effect on $\Delta CoVaR$.

Meanwhile, the adjusted coefficient of determination R^2 for models 1 and 2 is zero. This fact does not improve when we include firm-level trading volumes and their interaction terms in Model 3, despite the trading volume itself is significant to explain the systemic risk. The adjusted R^2 of Model 4 rises to 6% once firm-level idiosyncratic volatility and maximum returns are explained, and both variables are significantly negatively signed, for the reason that higher volatility or maximum returns increase systemic risks. Models 5 and 6 control more variables of the equity market, energy

Table 5: Fixed effect estimation by regressing systemic risk measures $\Delta CoVaR$ and $CoVaR$ on explanatory variables when $\tau = 0.01$ with *, ** and * representing the significance at 90%, 95% and 99%, respectively.**

response	ΔCoVaR					
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
CM_t	8.69e-4***	4.81e-4***	4.83e-4***	5.97e-4***	2.29e-4**	2.18e-4**
CT_t	3.23e-4**	8.56e-4***	8.69e-4***	9.11e-4***	6.61e-4***	6.14e-4***
WM_t	2.50e-3***	2.50e-3***	2.50e-3***	2.60e-3***	8.63e-4***	9.86e-4***
WT_t	−1.80e-4	−1.71e-4	−1.70e-4	2.18e-4	−2.20e-3***	−2.20e-3***
ML_t		3.46e-4***	3.46e-5***	2.38e-5***	3.93e-5***	3.97e-5***
TL_t		−1.06e-4**	−1.08e-4**	−9.66e-5**	1.25e-6	1.25e-6
MS_t		−2.90e-4***	−2.90e-4***	−1.89e-4*	−3.36e-4***	−3.42e-4***
TS_t		−1.16e-4	−1.64 − 4	1.10e-3	−8.54e-4	−9.22e-4
$U_{i,t}$			−1.03e-4**	−1.67e-4***	−1.53e-4***	−1.60e-4***
$MU_{i,t}$			1.09e-5	4.20e-5	3.57e-5	−3.57e-5
$TU_{i,t}$			−7.82e-5	−5.30e-5	−1.87e-5	−2.97e-5
$IV_{i,t}$				−0.1843***	−0.1767***	−0.1763***
$A_{i,t}$				−0.0259***	−0.0297***	−0.0296***
$M_{i,t}$					0.0085***	0.0085***
E_t					0.0194***	0.0219***
V_t						0.0013***
O_t						−0.0022***
G_t						−2.55e-5
Adj R^2	0.00	0.00	0.00	0.07	0.10	0.10
response	CoVaR					
CM_t	8.60e-4***	4.75e-4***	4.77e-4***	5.91e-4***	2.24e-4**	2.13e-4**
CT_t	2.58e-4*	8.43e-4***	8.54e-4***	8.92e-4***	6.43e-4***	5.97e-4***
WM_t	2.50e-3***	2.50e-3***	2.50e-3***	2.60e-3***	8.65e-4***	9.86e-4***
WT_t	−1.25e-4	−1.23e-4	−1.12e-4	2.84e-4*	−2.20e-3***	−2.21e-3***
ML_t		3.43e-5***	3.43e-5***	2.32e-5***	3.87e-5***	3.90e-5***
TL_t		−1.19e-4***	−1.20e-4***	−1.09e-4**	−1.11e-5	−1.11e-5
MS_t		−2.88e-4***	−2.88e-4***	−1.85e-4*	−3.32e-4***	−3.37e-4***
TS_t		−4.61e-4	−5.00e-4	8.17e-4	−0.0012	−0.012
$U_{i,t}$			−1.01e-4**	−1.67e-4***	−1.52e-4***	−1.59e-4***
$MU_{i,t}$			3.81e-6	3.57e-5	2.94e-5	2.94e-5
$TU_{i,t}$			−4.14e-5	−1.55e-5	1.87e-5	7.76e-6
$IV_{i,t}$				−0.1945***	−0.1869***	−0.1864***
$A_{i,t}$				−0.0247***	−0.0285***	−0.0284***
$M_{i,t}$					0.0085***	0.0085***
E_t					0.0195***	0.0219***
V_t						0.0013***
O_t						−0.0022***
G_t						−2.21e-6
Adj R^2	0.00	0.00	0.00	0.08	0.10	0.10

commodity, the volatility indices returns, which are significant and further improving adjusted R^2 to 10%. The Google trend data, as the proxy of public sentiment to cryptocurrency, does not add significant predictability to the systemic risks in energy sector. Nonetheless, it is remarkable that the cryptocurrency bubbles are still significantly positively signed by controlling firm-level characteristics and other market variables, as we observed from Model 1 and 2. Particularly, the coefficients of bubble bursts become more significant with higher magnitude, while the coefficients of booms are less significant with lower values, indicating a prudential effect of cryptocurrency bubble bursts.

Additionally, we also regress all the six models on the systemic risk measures when the nominal quantile is set by $\tau = 0.05$. Table 6 documents the estimation results. The overall significance and signs of the coefficients are in concordance with the previous findings in the case of $\tau = 0.01$. Comparatively, the coefficient sizes are relatively smaller, indicating that cryptocurrency bubbles make a stronger impact on the extreme downside risks to the energy sector.

5.4 Further Robustness checks

This section conducts further robustness checks. We first assess the effect of cryptocurrency bubbles on the systemic risk among different sectors of energy firms, and we then re-estimate the model for sample periods to reflect the normal bubble episodes (December 2014–September 2019) and the bubble episode during the Covid-19 pandemic (September 2019–March 2021). Model 6 is implemented throughout the robustness checks, given that all the control variables are involved.

In the first robustness analysis, we group the energy firms into four industrial sectors, including oil&gas, equipment&services, multiline utilities and renewable sectors, as documented in Table 1. Table 7 shows the estimation results when the dependent variable systemic risk measures $\Delta CoVaR$ and $CoVaR$ are calculated at the quantile $\tau = 0.01$. Specifically, the results reveal that the systemic risks in oil&gas-sectored firms, accounting for the largest proportion of energy firms, are positively affected by the cryptocurrency bubbles, which remains consistent with the main findings of Table 5. On the contrary, the bubbles either insignificantly or less significantly affect the systemic risks in other non-oil&gas firms. In particular, the bubble booms even negatively affect the systemic risks in multiline utilities firms. Generally, it is convinced that the oil&gas firms play an essential role in the transmitting channel from the cryptocurrency market to the international energy market.

The second robustness analysis considers the effect of cryptocurrency bubbles during the recent Covid-19 pandemic. The Covid-19 pandemic brought an unprecedented effect to the whole financial system (Naeem et al., 2021; Vidal-Tomás, 2021). In order to distinguish the effect of bubbles during the normal and the pandemic phases, we turn back to all energy firms and split the whole sample into two time-spans, from 11 December 2014 to 2 September 2019 representing market normal phase, and from 3 September 2019 to 10 March 2021 representing the pandemic sub-sample. Recall that Figure 1 shows that several bubble episodes are spotted in the first sub-sample during the years of 2016–2019, while the CRIX index only behaves bubble-like characteristic at the end of 2020 and the beginning of 2021 in the second sub-sample. Table 8 displays the results of model 6 by regressing the systemic risks on explanatory variables in two sub-samples. The estimation results indicate that although the burst booms become insignificant in sub-samples, the burst of cryptocurrency bubbles brings the systemic risk a significantly positive effect in both market normal or the pandemic periods. Interestingly, despite that the control variable of crude oil bubble burst WT_t is significant in both sub-samples, its effect turns the opposite way in the pandemic sub-sample. This can be understood by the fact that the pandemic outbreak has bottomed the crude oil under its fundamental values. Such negative bubbles result in an abnormal effect on the systemic risks in energy firms, as discussed in Fantazzini (2016).

Table 6: Fixed effect estimation by regressing systemic risk measures $\Delta CoVaR$ and $CoVaR$ on explanatory variables when $\tau = 0.05$ with *, ** and * representing the significance at 90%, 95% and 99%, respectively**

response	ΔCoVaR					
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
CM_t	4.48e-4***	2.33e-4***	2.34e-4***	2.93e-4***	9.85e-5*	9.23e-5*
CT_t	1.50e-4**	4.27e-4***	4.33e-4***	4.60e-4***	3.28e-4***	3.01e-4***
WM_t	1.30e-3***	1.30e-3***	1.30e-3***	1.40e-3***	4.50e-4***	5.20e-4***
WT_t	−1.81e-4**	−1.78e-4**	−1.78e-4**	1.91e-4	−1.30e-3***	−1.30e-3***
ML_t		1.98e-5***	1.98e-5***	1.45e-5***	2.27e-5***	2.29e-5***
TL_t		−5.37e-4**	−5.43e-4**	−4.97e-5**	2.08e-6	2.14e-6
MS_t		−1.75e-4***	−1.75e-4***	−1.23e-4**	−2.01e-4***	−2.04e-4***
TS_t		−2.95e-4	−3.18e-4	3.31e-4	−7.16e-4	−7.54e-4
$U_{i,t}$			−4.17e-5**	−7.92e-5***	−7.16e-5***	−7.57e-5***
$MU_{i,t}$			2.52e-6	1.82e-5	1.49e-5	1.50e-5
$TU_{i,t}$			−3.70e-5	−2.46e-5	−6.44e-5	−1.29e-5
$IV_{i,t}$				−0.0848***	−0.0807***	−0.0805***
$A_{i,t}$				−0.0155***	−0.0175***	−0.0174***
$M_{i,t}$					0.0045***	0.0045***
E_t					0.0103***	0.0117***
V_t						7.70e-4***
O_t						−0.0013***
G_t						−1.54e-6
Adj R^2	0.00	0.00	0.00	0.06	0.09	0.09
response	CoVaR					
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
CM_t	4.51e-4***	2.38e-4***	2.39e-4***	2.98e-4***	1.04e-4*	9.77e-5*
CT_t	1.27e-4**	4.29e-4***	4.34e-4***	4.60e-4***	3.28e-4***	3.01e-4***
WM_t	1.30e-3***	1.30e-3***	1.30e-3***	1.40e-3***	4.50e-4***	5.20e-4***
WT_t	−1.64e-4**	−1.60e-4*	−1.60e-4*	3.83e-5	−1.30e-3***	−1.20e-3***
ML_t		1.95e-5***	1.95e-5***	1.41e-5***	2.23e-5***	2.26e-5***
TL_t		−6.00e-5**	−6.06e-5**	−5.57e-5**	−4.05e-6	−3.96e-6
MS_t		−1.71e-4***	−1.71e-4***	−1.20e-4**	−1.98e-4***	−2.01e-4***
TS_t		−5.01e-4	−5.20e-4	1.35e-4	−9.11e-4	−9.48e-4
$U_{i,t}$			−4.62e-5*	−7.86e-5***	−7.10e-5***	−7.52e-5***
$MU_{i,t}$			−1.73e-6	1.41e-5	1.08e-5	1.09e-5
$TU_{i,t}$			−2.06e-5	−7.99e-5	1.01e-5	3.60e-6
$IV_{i,t}$				−0.0869***	−0.0829***	−0.0827***
$A_{i,t}$				−0.0152***	−0.0172***	−0.0171***
$M_{i,t}$					0.0045***	0.0045***
E_t					0.0103***	0.0117***
V_t						7.74e-4***
O_t						−0.0012***
G_t						−1.52e-6
Adj R^2	0.00	0.00	0.00	0.06	0.09	0.10

Table 7: Fixed effect estimation by regressing systemic risk measures $\Delta CoVaR$ and $CoVaR$ on explanatory variables of Model 6 in four different industry groups when $\tau = 0.01$ with *, ** and * representing the significance at 90%, 95% and 99%, respectively.**

	oil&gas		equipment&services		multiline utilities		renewable energy	
response	ΔCoVaR	CoVaR	ΔCoVaR	CoVaR	ΔCoVaR	CoVaR	ΔCoVaR	CoVaR
CM_t	2.82e-4***	2.62e-4**	2.43e-4	2.24e-4	−5.15e-4***	−5.10e-4***	2.91e-5	2.93e-5
CT_t	4.25e-4*	4.10e-4*	7.18e-4*	7.65e-4**	5.45e-4	5.21e-4	4.49e-4	5.27e-4
WM_t	9.58e-4***	0.0010***	−2.90e-4	−3.59e-4	−4.53e-4	−4.44e-4	−0.0014***	−0.0014***
WT_t	−0.0014***	−0.0013***	−2.06e-4	−9.32e-5	−5.84e-4*	−6.00e-4**	−5.71e-4	−6.58e-4
ML_t	2.79e-5***	2.73e-5***	7.06e-5***	6.95e-5***	6.00e-5**	6.03e-5**	7.23e-5**	7.05e-5**
TL_t	3.82e-5	2.25e-5	−1.68e-4**	−2.17e-4***	−3.53e-4***	−3.31e-4***	2.25e-4**	1.51e-4**
MS_t	−2.47e-4**	−2.42e-4*	−7.80e-4*	−7.80e-4*	−7.09e-4*	−7.07e-4*	-5.04e-4	-4.92e-4
TS_t	2.09e-4	2.67e-4	5.07e-4	1.48e-4	−0.0057**	−0.0057**	9.62e-4	0.0011
$U_{i,t}$	−2.60e-4***	−2.60e-4***	−1.53e-4*	−1.51e-4*	−1.98e-4***	−1.99e-4***	−2.79e-5	−2.62e-5
$MU_{i,t}$	1.20e-4	1.15e-4	−8.72e-5	−8.69e-5*	1.41e-4	1.41e-4	−3.21e-5	−3.49e-5
$TU_{i,t}$	1.51e-5	8.47e-5	−6.67e-5	−1.49e-4*	5.51e-4	5.50e-4	−1.06e-4	−9.63e-5
$IV_{i,t}$	−0.2618***	−0.2730***	−0.2758***	−0.2772***	−0.4628***	−0.4618***	−0.1206***	−0.1276***
$A_{i,t}$	−0.0347***	−0.0331***	0.0028	0.0020	−0.0143**	−0.0128***	0.0073***	0.0081***
$M_{i,t}$	0.0119***	0.0118***	0.0074***	0.0074***	0.0106***	0.0106***	0.0073***	0.0073***
E_t	0.0195***	0.0196***	0.0123***	0.0122***	0.0125***	0.0125***	0.0044***	0.0043**
V_t	0.0016***	0.0016***	−5.48e-5	−6.72e-5	2.91e-4	2.87e-4	−0.0011***	−0.0011***
O_t	−6.88e-4*	−6.47e-4*	−5.54e-4	−5.15e-4	3.09e-4	2.98e-4	3.26e-4	3.59e-4
G_t	−2.69e-6	−2.66e-6	−6.03e-6	−6.10e-6	−1.05e-5	−1.03e-5	−6.67e-7	−7.74e-7
Adj R^2	0.12	0.13	0.00	0.00	0.00	0.00	0.00	0.00

Table 8: Fixed effect estimation by regressing systemic risk measures $\Delta CoVaR$ and $CoVaR$ on explanatory variables of Model 6 in sample periods (11-December-2014 to 2-September-2019 and 3-September-2019 to 10-March-2021) when $\tau = 0.01$ with *, ** and * representing the significance at 90%, 95% and 99%, respectively.**

	11 December 2014 – 2 September 2019		3 September 2019 – 10 March 2021	
response	$\Delta CoVaR$	$CoVaR$	$\Delta CoVaR$	$CoVaR$
CM_t	−6.96e-5	−8.60e-5	−4.608e-4	−1.35e-4
CT_t	4.95e-4***	4.78e-4***	0.0018***	0.0017***
WM_t	7.10e-4***	7.84e-4***	0.0033***	0.0033***
WT_t	−0.0016***	−0.0014***	0.0042***	0.0043***
ML_t	3.21e-5***	3.16e-5***	−8.87e-5	1.04e-4
TL_t	−2.40e-4***	−2.37e-4***	−5.67e-4***	−6.08e-4***
MS_t	−3.12e-4***	−3.08e-4***	−0.0019	−0.0022
TS_t	0.0024*	0.0024*	−0.0116***	−0.0144***
$U_{i,t}$	−1.34e-4***	−1.36e-4***	−2.47e-4	−2.51e-4
$MU_{i,t}$	2.82e-5	3.06e-5	1.75e-4	9.86e-4
$TU_{i,t}$	−3.17e-5	−3.07e-5	1.24e-4	2.53e-4
$IV_{i,t}$	−0.2159***	−0.2370***	−0.1244***	−0.1451***
$A_{i,t}$	−0.0157***	−0.0193***	−0.0725***	−0.0689***
$M_{i,t}$	−0.0245***	−0.0239***	0.0832***	0.0832***
E_t	−0.0039***	−0.0038***	0.0147***	0.0145***
V_t	5.07e-4**	5.01e-4**	0.0056***	0.0055***
O_t	−7.99e-4***	−7.80e-4**	−0.0023***	−0.002***
G_t	1.11e-6	1.23e-6	1.26e-6	1.57e-6
$Adj R^2$	0.07	0.08	0.10	0.11

6. CONCLUSION

In this paper, we extend the empirical framework proposed by Brunnermeier et al. (2020) to study the boom and burst of cryptocurrency bubbles and their impacts on the systemic risks in international top energy companies. We apply the BSADF approach to identify multiple bubbles in the cryptocurrency index and then use CoVaR and delta CoVaR to measure systemic risks. A statistically significant relationship is found to confirm our hypothesis. In particular, the burst of bubbles contributes more to the increasing systemic risks in the energy sector. Oil and gas companies are essential among all energy firms and act as a transmitting channel to other types of energy firms. This relationship remains robust in the most recent COVID-19 pandemic period.

Our research has a few interesting contributions to the existing literature. First, we provide additional evidence on energy financialization. Development in financial markets, i.e., cryptocurrency, can have a profound impact on energy markets by increasing systemic risks. Second, asset bubbles not only can induce macro-level uncertainties but also lead to micro-level instability in energy markets. Third, we show that the recent COVID-19 pandemic, a unique period, does not change the significance of this effect.

These findings can also lead to a number of policy implications relevant to managers and regulators. For the executives of main energy firms, they should pay attention to the fluctuation of cryptocurrency prices, especially when observing pricing bubbles in the markets. These extreme movements in cryptocurrency markets may associate with extreme price movements in energy markets, which will generate direct losses to their companies. Meanwhile, the bubbles in cryptocurrencies can induce higher systemic risks in the whole energy sector, leading to stronger needs to hedge against such risks. Existing literature on "safe-haven assets" suggests that cryptocurrency may act as a safe-haven asset, but the findings here show that extra caution should be taken when forming hedging strategies using cryptocurrency, as the frequent bubbles can cause higher risks. Regulators may not be able to control cryptocurrencies directly, but they should take cryptocurrency bubbles as a signal for increasing systemic risks in stock market, or specifically, energy sector and respond to such shocks accordingly.

Looking forward from the current work there are a number of possible extensions, which connect commodity market financialization and systemic risks in financial markets, both important issues in financial markets. Following the recent literature, hedging increasingly more complicated systemic risks is a critical matter for both investors and regulators. Cryptocurrencies and commodities have been added to the basket as safe-haven assets [Ji et al., 2020], but if their extreme price movements coincide with market systemic risk, then the ability to hedge against the risks falls. The current analytical framework can therefore be extended to investigate hedging performance of cryptocurrencies and other commodities. One limitation of our study is that a relatively short period is used for empirical study, more importantly, energy sector has experienced dramatic changes during this sample period. While this adds to the value of our study, it may challenge the possibility of generalizing to other sectors, which worth further exploration.

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