Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company's public news and information website.

Elsevier hereby grants permission to make all its COVID-19-related research that is available on the COVID-19 resource centre - including this research content - immediately available in PubMed Central and other publicly funded repositories, such as the WHO COVID database with rights for unrestricted research re-use and analyses in any form or by any means with acknowledgement of the original source. These permissions are granted for free by Elsevier for as long as the COVID-19 resource centre remains active.
Financial implications of fourth industrial revolution: Can bitcoin improve prospects of energy investment?

Chi-Wei Su, Meng Qin, Ran Tao, Muhammad Umar

School of Economics, Qingdao University, China
Graduate Academy, Party School of the Central Committee of the Communist Party of China (National Academy of Governance), No. 100, Dayouzhuang, Haidian District, Beijing 100000, China
Qingdao Municipal Center for Disease Control & Prevention, China
School of Business, Qingdao University, China

1. Introduction

The Fourth Industrial Revolution unarguably presents tremendous changes in all aspects of human society, especially in the financial system (Min et al., 2019; Valencia et al., 2019). The cryptocurrencies and related technologies can bring enormous value to the economic and financial spheres (Lee, 2019; Perera et al., 2020), which can significantly promote the outbreak of the Fourth Industrial Revolution. As the first decentralized cryptocurrency, Bitcoin is a virtual encrypted digital currency in peer-to-peer (P2P) form which has been invented by Satoshi Nakamoto (Nakamoto, 2008). Subsequently, Bitcoin and the blockchain technology proved to be an essential component of the Fourth Industrial Revolution. Thus, exploring the relationship between Bitcoin market and its determinants is beneficial in forecasting Bitcoin price (BP). This could not only reduces the uncertainty of the Bitcoin market but can also increase the trading enthusiasm. Moreover, this exploration can help to grasp the evolutionary trends in Bitcoin and associated blockchain technology, reflecting the progress of the Fourth Industrial Revolution, which can be extremely helpful in developing future technological strategies. It is important to note that in the early days of the Bitcoin market, buyers were extremely confused about the use of it, and BP was volatile, a situation which is quite similar to the oil market in 1860 (Carlos, 1990). One can, therefore, should not ignore the possibility of observing certain interrelationship between Bitcoin and oil market (Okorie and Lin, 2020).

Doesn't matter how different the Bitcoin and oil do look as products, there are strong reasons to believe that the two have lots of similarities and they may have influences on each other's prices based on their relationship with each other. However whether this relationship is positive or negative, it would be difficult to say anything without carefully understanding the dynamics of the two markets.

Let us hypothesize that the two products have positive influences on each other's prices, in other words both Bitcoin and oil are in the same boat. This view is not an arbitrary view and has been under discussion

---

Keywords: Bitcoin price
Oil price
Granger causal relationship
Rolling-window

JEL:
C32
G12
Q43
since the birth of the digital currency market owing to the potential diversification benefits Bitcoin offered to hedge the risks not only in the oil market but in other markets as well. Since the increase in OP may trigger inflation, reduce the real income and profit, as well as diminish the public confidence (Salisu et al., 2017;Elfayoumi, 2018; Bildirici et al., 2019; Shahzad et al., 2019), more hedging assets (e.g., Bitcoin), are needed to be held to obtain diversification benefits. It is highly likely that the BP, which moves in the same direction as OP increases due to its diversification potential (Karalevičius et al., 2017; Bouoiyour et al., 2019; Fang et al., 2019). Moreover, economic and geopolitical situations also make it logical and strengthen the positive relationship between BP and OP. For instance, the policy of quantitative easing by the U.S. authorities causes dollar to depreciate, which drives BP and OP to increase since these two variables are denominated in U.S. dollars (Dyhrberg, 2016; Sun et al., 2017; Wen et al., 2017; Mcleod and Haughton, 2018; Anjum, 2019). Similarly, the departure from the quantitative easing policy has the opposite effects, which both markets observed in late 2014. The geopolitical events and conflicts that occur in the oil-producing countries, may reduce the supply of oil and increase OP and subsequent risk aversion coupled with wealth reallocation could increase the demand for Bitcoin and forces BP to move in the same direction as OP (Al-Yahyaee et al., 2019; Mamun et al., 2020). This is the phenomenon that has already been observed by market participants during the high geopolitical risk environment in 2016 (Caldara and Iacoviello, 2017).

There is an abundant literature supporting this conjecture. Dyhrberg (2016) suggests that Bitcoin is beneficial for risk-averse investors to maintain their returns if they face the expected negative shocks to the market. Gajardo et al. (2018) identify that Bitcoin has an interrelationship with commodities, such as oil, which should be taken into account when investing. Bouoiyour et al. (2019) point out that oil can be viewed as an effective safe haven against political risks, and Bitcoin also acts as a hedge to reduce the U.S. stock losses but only in the short-term, which shows that BP and OP move in the same direction. Bouri and Gupta (2019) evidence that Bitcoin is a hedge against uncertainty which partly caused by the fluctuations in OP, and based on this BP can be predicted more accurately. As high OP makes the public panic and the economy unstable, López-Cabarcos et al. (2019) indicate that investor sentiment has certain influences on BP and Bitcoin volatility. Symitsi and Chalvatzis (2019) reveal that there are significant diversification benefits from Bitcoin within traditional asset portfolios, especially in the portfolios of commodities which include oil (also Guesmi et al., 2019).

Nonetheless, the view that Bitcoin possesses the ability to avoid risks and provide good hedge and therefore it is in the same boat with oil, cannot be supported all the times. The concerns were raised by (Baek and Elbeck, 2015; Cheng and Yen, 2019) on the quality of hedge provided by Bitcoin to oil investors, if the two are not in the same boat and their prices move in opposite direction. This is exactly what happened when the Bitcoin bubble burst in 2017 and caused BP to plummet (Li et al., 2018; Xiong et al., 2019), at the time when OP was observing an upward trajectory, indicating complete inability of Bitcoin to avoid the risks of high OP. Later when economic uncertainty, such as the global trade wars, made the expected global economic outlook even worse, and the demand for oil and OP collapsed. At the same time the Bitcoin demand and BP increased in response to the actions of investors who wanted to hedge the risks and uncertainty in oil market, (Demir et al., 2018; Wu et al., 2019; Fang et al., 2019), yielding completely different directions in the prices of two assets. Bouri et al. (2017a) reveal that Bitcoin is a poor hedge or safe haven for other assets, such as oil, gold and stock. Panagiotidis et al. (2018) indicate that the impact of OP on BP is inferior to search for behaviour and gold returns. Das et al. (2019) ascertain that Bitcoin is not the superior asset over others (e.g., gold, dollar) to avoid the risks of oil volatility, also its hedging ability depends on the essence of oil risks and market environment (also Shahzad et al., 2020). Charfeddine et al. (2020) suggest that cryptocurrencies, such as Bitcoin, are poor hedging tools by analysing an investment portfolio that includes oil. Das and Dutta (2020) also suggest that the higher prices of energy (e.g., high OP) may impede the miners to break-even, which is harmful to the development of Bitcoin market, thereby affecting BP.

Additionally, the geopolitical events occurring in the non-oil-producing countries, may increase the demand for Bitcoin and BP to hedge the risks (Al-Yahyaee et al., 2019; Mamun et al., 2020), while the same events may not have significant effects on oil supply and OP (Su et al., 2019a) and therefore, offer a possibility of divergence in the prices of two assets.

Further support to this idea has been provided by the large-scale outbreak of the Corona Virus Disease 2019 (COVID-19) in January 2020 which has caused BP and OP to move in different directions. Bitcoin has performed well as a hedging asset which has driven BP to exceed $10,000, but the oil market has proven not so fortunate. Since China is the largest oil importer around the world, this infectious disease has affected many industries and society, the demand for oil has plummeted which causes OP to fall. Also, the collapse of the organization of the petroleum exporting countries (OPEC) and the failure to conclude production reduction agreement with Russia has also exacerbated the plunge in OP. Another reason of negative association between the BP and OP may the substitution effect, when high BP may increase the willingness of investors to hold Bitcoin, instead of other assets, such as oil. As a result, the reduced investment in the oil and its related markets leads to a decline in OP, and forces the two variables to move in opposite direction.

In the light of two conflicting opinions presented above we are of the view that the issue whether the Bitcoin and oil are in the same boat has not been clearly understood, examined and interpreted. We, therefore, in this paper investigate the time-varying Granger causality between BP and OP to further explain this issue and to understand the true nature between the observed prices in the two markets.

There are several contributions of this paper. To begin with, the existing studies mainly investigate the impact of OP on BP, or vice versa (Gajardo et al., 2018; Panagiotidis et al., 2018; Bouri and Gupta, 2019b; Das et al., 2019; Das and Dutta, 2020). It is obvious that there could be a bidirectional relationship between BP and OP, hence, a one-way influence cannot reflect the interaction between the two variables comprehensively. Given the limited scope of the existing studies, this study is a groundbreaking attempt to solve the issue of whether Bitcoin and oil are in the same boat or not by employing the time-varying Granger causality test. There could be however issues with the Granger causality which may not be constant between BP and OP, a dimension primarily ignored by the existing studies. To cope with this issue, we first examine the non-stable parameters in the empirical models. The results support our suspicion and provide evidence that employing the traditional Granger causal relationship test is not suitable and therefore, this paper uses the bootstrap sub-sample rolling-window Granger causality test (Balcilar et al., 2010; Su et al., 2019b, 2020a) to improve the accuracy of the outcomes. We use monthly data, covering the period of 2010:M7 to 2020:M1, to investigate the correlation between OP and BP by applying the full- and sub-sample tests. The empirical results reveal that OP has both positive and negative influences on BP, while OP is negatively affected by BP, indicating that Bitcoin and oil are not always in the same boat. Furthermore, the mutual influence between BP and OP provides insights to the investors, they can predict BP by considering the oil market and beware of the Bitcoin bubbles to diversify the risks and optimize their investment. Also, they can decide the amount to invest in the oil market, in order to obtain a more profitable portfolio. The government can benefit from this interaction to grasp the trends of BP and OP, then they can prevent the large fluctuations in Bitcoin and oil markets, in order to prompt the stable development of these two markets. By the predictions of OP, oil-importing and -exporting countries can prevent inflation and avoid the overcapacity, respectively.

The rest of the paper is arranged as follows: Section 2 explains the
empirical methods. Section 3 introduces the data. Section 4 reveals the empirical results. Section 5 summarizes the study of this paper.

2. Methodology

2.1. Bootstrap full-sample Granger causality test

According to the traditional vector autoregression (VAR) model, the Granger causality test statistics must obey the standard asymptotic distributions. In order to avoid the incorrect results and enhance the correctness of the Granger causal relationship test, the critical values of the residual-based bootstrap (RB) method are proposed by Shukur and Mantalos (1997). Additionally, they point out that RB method is appropriate for the tests with standard asymptotic distributions, even in the small samples. Shukur and Mantalos (2000) develop the likelihood ratio (LR) tests, which can be revised by the features of power and size. In this paper, we examine the mutual influences between BP and OP by employing the RB-based modified-LR test. To conduct these tests the VAR (p) system with two variables is constructed as Eq. (1):

\[ Z_t = \beta_0 + \beta_1 Z_{t-1} + \ldots + \beta_p Z_{t-p} + \mu_t \quad t = 1, 2, \ldots, T \]

where \( p \) is selected based on the Schwarz Information Criterion (SIC), which indicates an optimal lag order. The bivariate VAR (p) system can split \( Z \) into BP and OP, that is \( Z_t = (BP, OR) \). Since, BP and OP are denominated in U.S. dollar, which may affect the interaction between these two variables (Dyhrberg, 2016; Sun et al., 2017; Men et al., 2017; Mcleod and Haughton, 2018; Anjum, 2019; Su et al., 2020b). Therefore, we choose the U.S. dollar index (USDX) as a control variable, and rewrite Eq. (2) as follow:

\[
\begin{bmatrix}
\text{BP} \\
\text{OP}
\end{bmatrix}_t = \begin{bmatrix}
\beta_{10} & \beta_{11} & \beta_{12} & \beta_{13} \\
\beta_{20} & \beta_{21} & \beta_{22} & \beta_{23}
\end{bmatrix} \begin{bmatrix}
\text{BP} \\
\text{OP}
\end{bmatrix}_{t-1} + \begin{bmatrix}
\mu_1 \\
\mu_2
\end{bmatrix},
\]

where \( \mu = (\mu_1, \mu_2)' \) is a white-noise process. \( \beta_{ij} (L) = \sum_{k=1}^{p} \beta_{ij,k} L^k \), where \( i = 1, 2, j = 1, 2, 3 \) and \( L \) is an lag operator, and there is \( L^k Z_t = Z_{t-k} \).

The null hypothesis that BP has no influences on OP, that is \( \beta_{12,k} = 0 \) for \( k = 1, 2, \ldots, \rho \), can be tested based on the Eq. (2), and it can be accepted if OP is not a Granger cause for BP, and vice versa. Also, the null hypothesis that \( \beta_{21,k} = 0 \) for \( k = 1, 2, \ldots, \rho \) suggests the changes of BP have no influence on OP can be accepted in the same way.

2.2. Parameter stability test

The supposition of the above estimation is that VAR system only has constant parameters, which is inconsistent with reality. Thus, if the parameters are non-stable, performing the full-sample test is not suitable. To deal with this issue, we employ the parameter stability tests, including Sup-F, Ave-F and Exp-F tests, developed by Andrews (1993) and Andrews and Ploberger (1994). Sup-F test can examine the sudden structural changes in parameters, Ave-F and Exp-F tests can evidence whether the parameters have a gradual change over time. Furthermore, we also use the \( L_n \) statistics test (Nykblom, 1989; Hansen, 1992), in order to evidence whether the parameters follow a random walk process. By performing the above stability tests, there must be a non-stable interaction between BP and OP if the parameters are time-varying. Hence, we should apply the sub-sample test to investigate the mutual influences between these two-time series.

2.3. Bootstrap sub-sample rolling-window Granger causality test

Balciar et al. (2010) develop this sub-sample method, in order to discrete the whole time series into small sections based on the rolling-window width. The selection of the width is complex matter. A small width may not ensure the robustness of the results, and although the large width can enhance the correctness of the results, but it may reduce the times of scrolls. We follow Pesaran and Timmermann (2005) in this regard who ascertain that this width cannot be less than 20 if the parameters in the VAR system are non-stable and the separated small parts are scrolled from the start to the end of the entire time series. We assume that the extent of the entire sample is \( L \) and the rolling-window width is \( w \). The final of every separated small part is \( w, w+1, \ldots, L \) and we can get \( w+1 \) sub-samples. Each sub-sample can obtain a Granger causality result through applying the RB-based modified-LR statistic. Next, we can obtain the outcomes of the sub-sample test. \( N^{-1} \sum_{k=1}^{w} \beta_{ij,k}^* \) and \( N^{-1} \sum_{k=1}^{w} \beta_{ij,\rho}^* \) are the mean values of a huge number of estimations, which suggest the impact of OP on BP and the influence from BP to OP, respectively. \( N \) is the frequency of bootstrap repetitions. \( \beta_{ij,k}^* \) and \( \beta_{ij,\rho}^* \) are parameters from Eq. (2). For the rejection of null hypothesis, 90% confidence interval is applied in this paper, also with the relevant lower (9th quantile) and upper (95th quantile) limits (Balciar et al., 2010).

3. Data

In this paper, we consider the monthly data from 2010:M7 to 2020:M1 to explore the Granger causal relationship between Bitcoin and oil prices, then evidence whether Bitcoin and oil are in the same boat. We use BitCoin price (BP) which is denominated in U.S. dollars\(^1\) to reflect the international Bitcoin market. We further choose West Texas Intermediate (WTI) crude oil price (OP) which is also denominated in U.S. dollars\(^2\) to represent the international oil market (Wang et al., 2011; Chiroma et al., 2015). As we have explained earlier, BP and OP may have certain relationships, which means that there may be interactions between the digital currency and international oil markets. Fig. 1 reveals the trends of BP and OP while relating these estimations. Additionally, they point out that the extent of the entire sample is \( L \) and the rolling-window width. The selection of the width is complex matter. A small width may not ensure the robustness of the results, and although the large width can enhance the correctness of the results, but it may reduce the times of scrolls. We follow Pesaran and Timmermann (2005) in this regard who ascertain that this width cannot be less than 20 if the parameters in the VAR system are non-stable and the separated small parts are scrolled from the start to the end of the entire time series. We assume that the extent of the entire sample is \( L \) and the rolling-window width is \( w \). The final of every separated small part is \( w, w+1, \ldots, L \) and we can get \( w+1 \) sub-samples. Each sub-sample can obtain a Granger causality result through applying the RB-based modified-LR statistic. Next, we can obtain the outcomes of the sub-sample test. \( N^{-1} \sum_{k=1}^{w} \beta_{ij,k}^* \) and \( N^{-1} \sum_{k=1}^{w} \beta_{ij,\rho}^* \) are the mean values of a huge number of estimations, which suggest the impact of OP on BP and the influence from BP to OP, respectively. \( N \) is the frequency of bootstrap repetitions. \( \beta_{ij,k}^* \) and \( \beta_{ij,\rho}^* \) are parameters from Eq. (2). For the rejection of null hypothesis, 90% confidence interval is applied in this paper, also with the relevant lower (9th quantile) and upper (95th quantile) limits (Balciar et al., 2010).

\(^{1}\) BP in U.S. dollars is taken from the Yahoo Finance (https://finance.yahoo.com/quote/BTC-USD?p=BTC-USD&.tsrc=fin-srch).

\(^{2}\) OP in U.S. dollars is taken from the Energy Information Administration (https://www.eia.gov/petroleum/).

\(^{3}\) Al Qaeda is an Islamic military organization founded in the late Soviet Union’s invasion of Afghanistan in 1988. It is considered as a global terrorist organization.
trade disputes, have slowed the global economy and led to a decline in oil demand and OP. Additionally, the increasing demand for Bitcoin as a hedging asset drives BP to soar. The COVID-19 breaks out in January 2020, which also makes BP and OP move in different directions. Hence, Bitcoin and oil are not always in the same boat. Furthermore, both BP and OP are denominated in U.S. dollars which may influence the fluctuations in BitCoin and oil markets. An interest rate cut may decrease the value of the U.S. dollar (e.g., quantitative easing policy), which may lead to the rise in BP and OP, and vice versa (e.g., Federal Reserve Board plans to raise interest rates). Thus, the U.S. dollar index (USDX)\(^2\) may have effects on the interaction between BP and OP, then we choose it as a control variable in Eq. (2). Generally, the mutual influence between BP and OP is complicated, as well as affected by USDX.

Table 1 reports descriptive statistics. The averages of BP, OP, and USDX suggest that they are centred at 2209.370, 71.986 and 88.725, respectively. The positive skewness can re-ect that BP and OP, and vice versa (e.g., Federal Reserve Board plans to raise interest rates). Thus, the U.S. dollar index (USDX)\(^2\) may have effects on the interaction between BP and OP, then we choose it as a control variable in Eq. (2). Generally, the mutual influence between BP and OP is complicated, as well as affected by USDX.

Table 2 shows that BP, OP, and USDX have right-skewed distribution, while USDX has left-skewed distribution. Furthermore, both BP and OP are denominated in U.S. dollars which may influence the fluctuations in BitCoin and oil markets. An interest rate cut may decrease the value of the U.S. dollar (e.g., quantitative easing policy), which may lead to the rise in BP and OP, and vice versa (e.g., Federal Reserve Board plans to raise interest rates). Thus, the U.S. dollar index (USDX)\(^2\) may have effects on the interaction between BP and OP, then we choose it as a control variable in Eq. (2). Generally, the mutual influence between BP and OP is complicated, as well as affected by USDX.

The Jarque-Bera index points out that BP, OP, and USDX are significantly non-normally distributed at 1% level. Therefore, it is not appropriate to employ the traditional Granger test. This paper therefore employs the bootstrap sub-sample rolling-window test to explore the mutual influences between BP and OP. Also, these three variables (BP, OP, and USDX) are taken in their natural logarithms form to avoid the potential heteroscedasticity.

4. Empirical results

In order to examine the unit roots, this paper applies the Augmented Dickey-Fuller (Dickey and Fuller, 1981), Phillips-Perron (PP, 1988) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS, 1992) tests. The outcomes of the above tests are reported in Table 2, and we can conclude that BP, OP, and USDX are I(1). Then, we use the first differences of these three variables to construct the Granger causality test models, which can ensure the stationary of the time series.

The VAR system, based on Eq. (2), is performed to test the full-sample Granger causality between BP and OP. We choose the optimal lag order of 2 based on the SIC. Table 3 reports the results of the full-sample test, the p-values point out that there is an influence from OP to BP at a 1% level, while BP cannot significantly affect OP. These findings are not consistent with the previous studies (Panagiotidis et al., 2018; Das et al., 2019).

The full-sample estimation in the bivariate VAR system assumes that the parameters are constant and there is only one Granger causality in the whole period. However, if there are structural changes, the Granger causality between BP and OP is non-constant (Balcilar and Ozdemir, 2013). We employ Sup-F, Ave-F and Exp-F tests (Andrews, 1993; Andrews and Ploberger, 1994) to examine the parameter stability, and also use the Lc statistics test (Nyblom, 1989; Hansen, 1992) to examine whether the parameters follow a random walk process. The results of parameter stability test are highlighted in Table 4.

Sup-F test indicates that BP and the VAR system have sudden structural changes at the 1% level, while OP has it at 5% level. Ave-F test highlights the parameters can change over time in BP at the 5% level. OP can accept the alternative hypothesis of evolution along the time trajectory through Exp-F test at the 5% level, while BP and the VAR system are at the 1% level. Additionally, the null hypothesis of \(Lc\) statistics test can be rejected at 5% level, revealing that the parameters in the VAR system do not follow a random walk process. Therefore, through the parameter stability test, we can conclude that there is a non-stable interrelationship between BP and OP, and the full-sample test is not suitable for this paper. Subsequently, we apply the bootstrap sub-sample rolling-window Granger causality test to investigate the...

---

\(^1\) USDX is taken from the Federal Reserve Board (https://www.federalreserve.gov/RELEASES/h10/).  
\(^2\) The leptokurtic distribution shows a much higher peak around the mean value, and fat tails, or higher densities of values at the extreme ends of the probability curve. The platykurtic distribution is exactly the opposite.
time-varying interaction between these two variables. Also, we choose the rolling-window width of 24-months, in order to ensure the accuracy of the Granger causal relationship analysis. We can evidence whether the null hypothesis that OP does not Granger cause BP (or BP does not Granger cause OP) can be accepted or rejected. Moreover, the orientation of the influence from OP to BP (or the effects of BP on OP) can also be acquired.

Figs. 2 and 3 reveal the p-values and the orientation of the influences from OP to BP. OP Granger causes BP during the periods of 2013:M1–2013:M10, 2016:M8–2017:M6 and 2018:M12–2019:M1 at the 10% significance level. And during these periods, both positive effects (2013:M1–2013:M10 and 2016:M8–2017:M6) and negative effects (2018:M12–2019:M1) exist from OP to BP.

The positive effects of OP on BP can confirm that Bitcoin and oil are in the same boat. The slow recovery of the global economy has increased the demand for oil (Hammou et al., 2010). The instability in the Middle East (e.g., the Syrian war and the Libyan civil war) has cut oil supplies (Su et al., 2020a). In addition, the U.S. dollar, which is the denominated currency of OP, has depreciated due to the quantitative easing policy (Sun et al., 2017; Wen et al., 2017; Mcleod and Haughton, 2018; Anjum, 2019). All of these cause OP to be at a high level during the period of 2013:M1–2013:M10. There are three reasons that can explain the transmission mechanism from OP to BP. Firstly, the rise in OP may trigger inflation, reduce the real income of residents and the profit margins of companies, especially in oil-importing countries (Salisu et al., 2017; Elfayoumi, 2018). Then, the public confidence declines, which in turn stimulates them to hold hedging assets (e.g., Bitcoin) to avoid the risks of the high OP. Thereby, the increasing demand for Bitcoin drives BP to rise. Secondly, the instability in the Middle East and the Cyprus crisis not only cause OP to increase, but also make the investor sentiment low. They are more willing to purchase Bitcoin to avoid the risks of geopolitical events, which drives BP to soar (Ciaian et al., 2014; Bouri et al., 2017b; Wang et al., 2019; Mamun et al., 2020). Thirdly, BP is also denominated in U.S. dollars, which indicates a negative relationship between BP and USDX (Dyhrberg, 2016). Although the U.S. economy has recovered, the quantitative easing policy has kept USDX at a relatively low level, which leads BP and OP to move in the same direction. Also, the value of the U.S. dollar's investment is low, which increases the demand for other assets (e.g., Bitcoin), thereby causing BP to further rise. On the basis of above explanations, the positive influence from OP to BP during the period of 2013:M1–2013:M10 can be proved and rationalized.

From 2016, oil has experienced a rise in its price. The U.S. Federal Reserve Board has announced that it would keep its Federal Funds Rate unchanged, causing the dollar to depreciate. The OPEC has agreed to cut the production in its member states, also the geopolitical events (e.g., the counterattacks to the “Islamic State”, the civil war in Syria) make oil supply decline. Although other events, such as the Brexit and the U.S. presidential election (Donald J. Trump v.s. Hillary D. R. Clinton), lead OP to fluctuate slightly, the overall upward trend is unchanged. We can explain the rise in BP caused by OP in four ways. Firstly, the high OP may trigger inflation, reduce the real income of residents and the profit margins of companies, especially in oil-importing countries (Salisu et al., 2017; Elfayoumi, 2018; Shahzad et al., 2019; Bildirici et al., 2019). Then, they are more willing to hold Bitcoin to avoid the risks of the high OP, which drives BP to increase. Secondly, the falling USDX not only causes OP to rise but also leads BP to increase due to it’s denomination in U.S. dollars. Thirdly, the geopolitical events in the Middle East increase OP, and also reduce the consumer confidence and investor sentiment. Then, they tend to store assets with hedging ability to reduce losses, increasing the demand for Bitcoin the price of which is already on an upward trend, and then BP increases (Ciaian et al., 2014; Bouri et al., 2017b; Wang et al., 2019; Mamun et al., 2020). Also, the Brexit and the U.S. presidential election bring uncertainty to the world (Davis, 2016), which further increases the demand for Bitcoin and BP. Fourthly, the rising trend of BP has attracted more investors to invest, especially in China, Japan and South Korea, further prompting BP to soar in 2017 (Li et al., 2018; Xiong et al., 2019). Thus, we can evidence that OP can positively affect BP during the period of 2016:M8–2017:M6.

However, the view that Bitcoin and oil are in the same boat cannot be supported by the negative influence of both variables on each other. There are three reasons to explain the rise in OP. Firstly, the Federal Reserve Board has signalled interest rate cuts, and the yen has experienced huge fluctuations against most G10 currencies and some emerging markets.

Table 4

| Tests   | BP Statistics | p-value | OP Statistics | p-value | VAR system Statistics | p-value |
|---------|---------------|---------|---------------|---------|------------------------|---------|
| Sup-F   | 94.423∗∗∗     | 0.003   | 24.706∗∗∗     | 0.019   | 57.156∗∗∗              | 0.000   |
| Ave-F   | 13.428∗       | 0.018   | 9.451∗        | 0.153   | 16.965                 | 0.185   |
| Exp-F   | 43.334∗       | 0.000   | 9.148∗        | 0.017   | 24.820∗∗              | 0.000   |
| Lc     |               |         |               |         | 5.693∗                 | 0.022   |

Notes: To calculate p-values using 10,000 bootstrap repetitions.

∗ and ∗∗ denote significance at the 5% and 1% level, respectively.

![Fig. 2: Bootstrap p-values of rolling test statistic testing the null hypothesis that OP does not Granger cause BP.](image)

![Fig. 3: Bootstrap estimates of the sum of the rolling-window coefficients for the impact of OP on BP.](image)

---

6 To test the robustness of the empirical analysis, the study also applies the widths of 20-, 28- and 32-months to investigate the causal relationship, and the outcomes are unanimous with 24-months rolling-window.

7 The G10 includes Belgium, Netherlands, Canada, Sweden, France, Switzerland, Germany, the U.K., Italy, the U.S. and Japan.
(e.g., China) currencies. All of them lead investors to be more inclined to invest in another asset, such as the oil and its related products, which in turn drives OP to rise. Secondly, on December 1, 2018, China and the U.S. have negotiated that no additional tariffs would be imposed from January 1, 2019. As a result, the economy is expected to be improved, which leads to the demand for oil and OP to further increase (Hammou et al., 2010). Thirdly, due to the resolute implementation of production reduction agreements by major oil-producing countries, such as Saudi Arabia and Russia, oil supply has continued to decline, which causes OP to rise especially during the period of 2018:M12–2019:M1. Nevertheless, BP does not move in the same direction as OP to be helpful in avoiding the risks, and it can be explained from three aspects. To begin with, the Bitcoin bubble bursts in 2017, and since then BP decreases sharply (Li et al., 2018; Xiong et al., 2019). This burst is mainly caused by the massive sell-off of Bitcoin asset in Mt. Gox, a bitcoin exchange based in Japan, and the subsequent herd behaviour8 of investors, as well as government policy constraints (e.g., the U.S. Securities and Exchange Commission has hinted at strengthening supervision and crackdown on unregistered online digital asset trading platforms). Additionally, the economy was expected to be improved, as a result there was a positive reinforcement for public and countries to purchase more oil but which decreases the demand for Bitcoin to avoid the risks of trade policy uncertainty (Gaiain et al., 2014; Bouri et al., 2017b; Wang et al., 2019; Mamun et al., 2020). Furthermore, the rise in OP and the sharp decline in BP make the public less willing to hold Bitcoin, since it is not as valuable as oil and its related products. Hence, we can argue that these reasons provide sufficient justification for the negative influence from OP to BP during the period of 2018:M12–2019:M1.

Figs. 4 and 5 underline the bootstrap p-values and the orientation of the impacts from BP to OP. BP Granger causes OP during the periods of 2013:M12–2014:M1 at the 10% significance level. There is a negative effect from BP to OP, indicating that Bitcoin and oil are not in the same boat. After the outbreak of the Cyprus crisis, the public was in danger and they rushed to exchange their currencies for Bitcoin to avoid policy risks. Also, Bitcoin was increasingly recognized by investors around the world, especially after Germany officially admitted the legal and tax status of Bitcoin on August 19, 2013. Therefore we can say, the rising BP attracts more investors to invest in the Bitcoin market, which leads it to further increase during the periods of 2013:M12–2014:M1. The public also considers that Bitcoin has more investment prospects than oil, and they seem more willing to hold Bitcoin, which causes the oil demand and OP to decrease during this period. In addition, the U.S. government has appeared 16-days shutdown, due to the disputes of a short-term increase in the debt ceiling. Then, the whole of society has been brought to a high degree of uncertainty, which has continued to put downward pressure on OP. Therefore, the negative influence of BP on OP during the period of 2013:M12–2014:M1 can be evidenced.

To sum up, the results of the bootstrap full-sample Granger causality test suggest that OP Granger causes BP, but the opposite is not significantly established. However, this result may not be comprehensive as the parameters in the VAR system are supposed to be stable. The parameter stability tests prove that these two variables and the VAR system have sudden structural changes. Hence, in this paper, we apply the sub-sample test to explore the time-varying interrelationship between BP and OP. The empirical results evidence that there are both positive and negative influences from OP to BP. The positive effect indicates that Bitcoin can be viewed as an asset to avoid the risks of the high OP, also we can conclude that Bitcoin and oil are in the same boat since the value of Bitcoin will enhance if OP is high. However, this view cannot be supported by the negative effects. The burst of the bubble makes Bitcoin incapacitated to hedge the risks of the high OP, which also highlights that there is a negative effect from OP to BP. In turn, BP has a negative influence on OP, revealing that oil has fewer investment prospects than Bitcoin during the few periods, which also indicates that high BP may threaten the demand for oil to invest and also OP.

5. Conclusion

As one of the core factors of the Fourth Industrial Revolution, Bitcoin has certain interactions with the global economy (e.g., international energy market), which provides insights that could be useful for the development of the cryptocurrency market. With the continuous progress of blockchain, Internet of Things, cloud computing, big data, artificial intelligence and other technologies, the transformation of society has increased dramatically. Amongst all above mentioned technologies, cryptocurrencies have enormous potential to promote the reduction of international transaction fees and liquidity costs, and efficiently complete the movement of international wealth. Secondly, the improvement of the encryption technology and the reinforcement of the market supervision reduce the large fluctuations in the prices of cryptocurrencies, which makes them more acceptable to the public. Thereby, the view that Bitcoin can be considered as a hedging asset is becoming more reliable over time. Thirdly, Bitcoin is the first Internet-scale open platform for value exchange. With blockchain technology supporting a wide range of value exchanges, it will inevitably bring about an explosion of tradable assets and spawn a greater industry wave which in conjunction with many innovative forces could promote the progress of human society.

---

8 Herd behavior describes the herd mentality of economic individuals, that is, if Mt. Gox sells Bitcoin, other investors do the same.
This paper explores the Granger causality between the Bitcoin and oil markets, in order to evidence whether or not Bitcoin and oil are in the same boat. We perform the sub-sample test to investigate the mutual influence between BP and OP. The empirical results establish that there are both positive and negative influences from OP to BP. On the one hand, the positive effect indicates that Bitcoin can be considered as an asset to hedge the risks of the high OP, and we can also evidence that Bitcoin and oil are in the same boat. On the other hand, the negative influences are not consistent with this view particularly when we see the negative effect from OP to BP, which can be explained by the burst of the Bitcoin bubble that has weakened its hedging ability. In addition, OP can be negatively affected by BP, pointing out that Bitcoin has more investment prospects than oil during several periods, which also reveals that the demand for oil to invest can be threatened by the high OP. By analysing the time-varying interrelationship between BP and OP, we can conclude that Bitcoin and oil are in the same boat during certain periods, but this is not always the case.

Clarifying the demand for Bitcoin to avoid the risks of the fluctuations in the oil market and the transmission mechanism between BP and OP can give lessons to investors and governments. On the one hand, OP can affect BP during certain periods. Thus, investors can predict BP more accurately according to the fluctuations in OP and determine the amount to invest in the Bitcoin market. Also, they can consider Bitcoin as an asset in the portfolio, in order to diversify the risks and optimize their investment. More importantly, they should beware of the Bitcoin bubbles to avoid herd behaviour, reduce the losses and maintain their returns. The government can also grasp the trend of BP based on OP, in order to implement related policies to prevent the Bitcoin bubbles or the plunge in BP which may reduce the public confidence and hinder the economic stability. By this way, relevant authorities can promote the healthy growth of the Bitcoin market. On the other hand, the increase in BP may lead OP to fall during a few periods. Hence, investors should decide the amount to invest in the oil market by considering the changes in BP, then they can obtain the optimal proportion of the portfolio and make it more profitable, in order to maximize their returns. In addition, oil-importing countries can grasp the trend of OP to reduce or increase the amount to import, then they can prevent inflation and minimize the costs. Others can avoid the overcapacity and maintain national wealth-income by adjusting production, especially for countries or regions where oil is the pillar industry (e.g., Russia, the Middle East). Also, the government is able to capture the fluctuations in the oil market, then, taking measures in advance to ensure the stable development of its energy system and national economy. In the future study, we will consider whether the Fourth Industrial Revolution can strengthen the hedging ability of Bitcoin. Also, the relationships between Bitcoin market and other energy or energy assets (e.g., natural gas and energy futures) should be taken into consideration.

Author statement

Chi Wei Su: Conceptualization, Methodology, Software Meng Qin: Data curation, Writing- Original draft preparation. Ran Tao: Visualization, Investigation. Muhammad Umar: Writing, Reviewing and Editing

References

Al-Yahyaee, K.H., Rehman, M.U., Menzi, W., Al-Jarrah, I.M.W., 2019. Can uncertainty indices predict Bitcoin prices? A revised analysis using partial and multifactor wavelet approaches. North Am. J. Econ. Finance 49 (C), 47–56.
Andrews, D.W.K., 1993. Tests for parameter instability and structural change with unknown change point. Econometrica 61, 821–856.
Andrews, D.W.K., Ploberger, W., 1994. Optimal tests when a nuisance parameter is present only under the alternative. Econometrica 62, 1383–1414.
Anjuum, H., 2019. Estimating volatility transmission between oil prices and the US dollar exchange rate under structural breaks. J. Econ. Financ. 43, 750–763.
Bae, C., Elleek, M., 2015. Bitcoin as an investment or speculative vehicle? A first look. Appl. Econ. Lett. 22 (1), 30–34.

Balciar, M., Ozdemir, Z., 2013. The export-output growth nexus in Japan: a bootstrap rolling window approach. Empir. Econ. 44, 639–660.
Balciar, M., Ozdemir, Z.A., Arslan turk, Y., 2010. Economic growth and energy consumption causal nexus viewed through a bootstrap rolling window. Energy Econ. 32 (1), 1481–1490.
Bildirici, M.E., Badur, M.M., 2019. The effects of oil and gasoline prices on confidence and stock return of the energy companies for turkey and the US. Energy 173, 1234–1241.
Bouyouc, J., Selm, R., Wobar, M.E., 2019. Safe havens in the face of presidential election: uncertainty: a comparison between Bitcoin, oil and precious metals. Appl. Econ. Financ. 51 (57), 6076–6088.
Bouri, E., Gupta, R., 2019. Predicting Bitcoin returns: comparing the roles of newspaper and internet search-based measures of uncertainty. Finance Research Letters. 10138 Published Online.
Bouri, E., Molnár, P., Azzi, G., Roubas, D., Haggas, L.I., 2017a. On the hedge and safe haven properties of Bitcoin: is it really more than a diversifier? Financ. Res. Lett., 20, 75–84.
Bouri, E., Gupta, R., Tiwar, A.K., Roubas, D., 2017b. Does Bitcoin hedge global uncertainty? Evidence from wavelet-based quantile-in-quantile regressions. Financ. Res. Lett. 23, 87–95.
Caldana, D., Iacoviello, M., 2017. Measuring geopolitical risk. Working Paper. Board of Governors of the Federal Reserve System.
Carlos, E.S., 1990. Long-term evolution of oil prices 1860–1987. Energy Policy 18 (2), 170–174.
Charfeddine, L., Benlahga, N., Maoouchi, Y., 2020. Investigating the dynamic relationship between cryptocurrencies and conventional assets: implications for financial investors. Econ Model 85, 198–217.
Cheng, H.P., Yen, K.C., 2019. The relationship between the economic policy uncertainty and the cryptocurrency market. Financ. Res. Lett., 10138 Published Online.
Chiroma, H., Abdulkareem, S., Herawan, T., 2015. Evolutionary neural network model for West Texas Intermediate crude oil price prediction. Appl. Energy 142, 266–273.
Ciaian, P., Rajcaniova, M., Kancs, D., 2014. The economics of Bitcoin price formation. Appl. Econ. 46 (19), 1795–1803.
Das, D., Dutta, A., 2020. Bitcoin’s energy consumption: is it the Achilles heel to miner's revenue. Econ. Lett. 186, 108530.
Das, D., Roux, C.L.L., Jana, R.K., Dutta, A., 2019. Does Bitcoin hedge crude oil implied volatility and structural shocks? A comparison with gold, commodity and the US dollar. Financ. Res. Lett., 10135 Published Online.
Davis, S.J., 2016. An index of global economic policy uncertainty. NBER Working Paper. National Bureau of Economic Research, Inc.
Demir, E., Guogor, G., Lau, K.C.M., Vigne, S.A., 2018. Does Economic policy uncertainty predict the Bitcoin returns? An empirical investigation. Financ. Res. Lett. 26, 145–149.
Dickey, D.A., Fuller, W.A., 1981. Likelihood ratio statistics for autoregressive time series with a unit root. Econometrics 49, 1057–1072.
Dyhrberg, A.H., 2016. Bitcoin, gold and the dollar – A GARCH volatility analysis. Financ. Res. Lett. 16, 85–92.
Eflyoumi, K., 2018. The balance sheet effects of oil market shocks: an industry level analysis. J. Bank Financ. 95, 112–127.
Pang, L., Bouri, E., Gupta, R., Roubaud, D., 2019. Does global economic uncertainty matter for the volatility and hedging effectiveness of Bitcoin? Int. Rev. Financ. Anal. 61, 29–36.
Gajardo, G., Kristjanpoller, W.D., Minutolo, M., 2018. Does Bitcoin exhibit the same asymmetric multifractal cross-correlations with crude oil, gold and DJIA as the euro, great British pound and yen. Chaos Solitons Fractals 109, 195–205.
Guesmi, K., Saadi, S., Abid, I., Ftiti, Z., 2019. Portfolio Diversification using forecasts with a unit root. J. Forecasting 48, 612–629.
Hammoudeh, S., Bhar, R., Thompson, M.A., 2010. A GARCH volatility analysis. Financ. Res. Lett. 8, 207–214.
Hansen, B.E., 1995. Tests for parameter instability in regressions with I(1) processes. J. Bus. Econ. Stat. 20, 45–59.
Karalevičius, V., Buchanan, B., Tasca, P., 2017. Using sentiment analysis to predict intraday Bitcoin price movements. J. Risk Financ. 19 (1), 56–75.
Kwiatkowski, D., Phillips, P.C.B., Schmidt, P., Shin, Y., 1992. Testing the null hypothesis of stationarity against the alternative of a unit root: how sure are we that economic time series have a unit root? Econometrics 54, 159–178.
Lee, J.Y., 2019. A decentralized token economy: how blockchain and cryptocurrency can transform business. Bus. Econ. Stat. 20, 45–59.
Li, Z.Z., Tao, R., Su, C.W., Leont, O.R., 2018. Does Bitcoin bubble burst. Qual. Quant. 53 (2), 1–15.
López-Cabarcos, M.A., Pérez-Picio, A.M., Peleire-Chouss, J., Sević, A., 2019. Bitcoin volatility, stock market and investor sentiment. Are they connected? Financ. Res. Lett., 10139 Published Online.
Mamun, M.A., Uddin, G.S., Suleman, M.T., Kang, S.H., 2020. Geopolitical risk, uncertainty and Bitcoin investment. Physica A 545, 121309.
McDonald, R.C.D., Haughton, A.Y., 2018. The value of the US dollar and its impact on oil prices: evidence from a non-linear asymmetric cointegration approach. Energy Econ. 70, 61–69.
Min, J., Yoo, J., Hong, J., Lee, S., Jung, T., Kim, I., Song, J., 2019. The Fourth Industrial Revolution and its impact on occupational health and safety, worker’s compensation and labor conditions. Saf. Health Work 10 (4), 400–408.
Nakamoto, S., 2008. Bitcoin: a peer-to-peer electronic cash system. .
Newey, W.K., West, K.D., 1987. A simple, positive semi-definite, heteroskedasticity: in autocorrelation consistent covariance matrix. Econometrica 55, 703–708.
Nyblom, J., 1989. Testing for the constancy of parameters over time. Journal of the American Statistical Association 84, 223–230.
Ökokie, D.I., Lin, B., 2020. Crude oil price and cryptocurrencies: evidence of volatility
connectedness and hedging strategy. Energy Econ. 87, 104703.
Panagiotidis, T., Stengos, T., Vravosinos, O., 2018. On the determinants of Bitcoin returns: a LASSO approach. Financ. Res. Lett. 27, 235–240.
Perera, S., Nanayakkara, S., Rodrigo, M.N.N., Senaratne, S., Weinand, R., 2020. Blockchain technology: is it hype or real in the construction industry? J. Ind. Inf. Int. 17, 100125.
Pesaran, M.H., Timmermann, A., 2005. Small sample properties of forecasts from autoregressive models under structural breaks. J. Econometrics 129, 183–217.
Phillips, P.C.B., Perron, P., 1988. Testing for a unit root in time series regression. Biometrika 75, 335–346.
Salisu, A.A., Isah, K.O., Oyewole, O.J., Akanni, L.O., 2017. Modelling oil price-inflation nexus: the role of asymmetries. Energy 125, 97–106.
Shahzad, S.J.H., Bouri, E., Raza, N., Roubaud, D., 2019. Asymmetric impacts of disaggregated oil price shocks on uncertainties and investor sentiment. Rev. Quant. Financ. Account. 52 (3), 901–921.
Shahzad, S.J.H., Bouri, E., Roubaud, D., Kristoufek, L., 2020. Safe haven, hedge and diversification for G7 stock markets: gold versus Bitcoin. Econ. Model. 87, 212–224.
Shukur, G., Mantalos, P., 1997. Size and power of the RESET test as applied to systems of equations: a bootstrap approach. Working Paper. Department of Statistics, University of Lund.
Dr Chi-Wei Su is a full professor in School of Economics, Qingdao University. He majors in Finance and economic field and excellent in Time Series Analysis. He has already published more than 170 papers in SCIE and SSCI indexed journals.
Dr. Meng Qin majors in Econometric Method and she has already published 10 papers in SCIE and SSCI indexed journals.
Dr Ran Tao major in Engineering and Applied Science and she is familiar with Statistical software and Data Analysis Methods. She has already published 50 papers in SCIE and SSCI indexed journals.
Muhammad Umar is a Ph.D. scholar in the School of Business of Qingdao University, China. He has 12 years of work experience in different Academic and Research Institutions. His research interests focus on technological-based finance, financial markets, risk management, energy finance, and project finance. Umar’s work is featured in a variety of well-reputed journals including, Energy, Resources Policy, Economic Research-Ekonomska Istraživanja, Journal of Environmental Management, Science of the Total Environment, and Regional Studies in Marine Science.