Manuscript Details

Manuscript number	RIBAF_2019_952_R1
Title	Pricing Efficiency and Arbitrage in the Bitcoin Spot and Futures Markets
Article type	Full Length Article

Abstract

This study examines the pricing efficiency for the leading cryptocurrency, Bitcoin using spot prices and all CBOE and CME futures contracts traded from January 2018 to March 2019. We find that the futures basis provide some predictive power for future changes in the spot price and in the risk premium. However, the basis of Bitcoin is a biased predictor of the future spot price changes. Cointegration tests also demonstrate that futures prices are biased predictors of spot prices. Deviations from no-arbitrage between spot and futures markets are persistent and widen significantly with Bitcoin thefts (hacks, frauds) as well as alternative cryptocurrency issuances.

Keywords	Bitcoin; cryptocurrency; speculation; efficient markets; futures arbitrage

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Submission Files Included in this PDF

File Name [File Type]

coverletterribafrevision.pdf [Cover Letter]

responsetorefereesnewf.pdf [Response to Reviewers (without Author Details)]

abstract.pdf [Graphical Abstract]

bitcointitlepage.pdf [Title Page (with Author Details)]

Bitcoinfeb12020anon.pdf [Manuscript (without Author Details)]

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To view all the submission files, including those not included in the PDF, click on the manuscript title on your EVISE Homepage, then click 'Download zip file'.

Research Data Related to this Submission

There are no linked research data sets for this submission. The following reason is given:
Data will be made available on request

February 1, 2020

Professor John W. Goodell
Editor, *Research in International Business and Finance*

Dear Professor Goodell,

Thank you very much for your invitation for revision of my paper with Seungho Lee and Nabil El Meslmani (RIBAF_2019_952) entitled: "Pricing Efficiency and Arbitrage in the Bitcoin Spot and Futures Markets," for *Research in International Business and Finance*
,
We are submitting the revision herein. This version addresses all the issues raised by the three referees, as indicated in our detailed response to the referees and in the revised version of the paper. We are grateful to you for your encouragement and to the referees for the several constructive comments that have considerably improved the quality of the paper.

We look forward to hearing from you.

Yours sincerely,

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Response to Referee Report, Reviewer #1

Research in International Business and Finance

Pricing Efficiency and Arbitrage in the Bitcoin Spot and Futures Markets,

RIBAF_2019_952

Thank you for your constructive feedback on our work, and for the opportunity to revise and resubmit our paper. We are pleased that you find the idea meritorious. We highly appreciate your comments and suggestions for improvements, which have helped us to make a substantial revision of the paper. We have addressed your remarks in the revised draft. In this document, we provide detailed responses to your specific comments (in *Italics*). Since we received reports from two other referees as well, some of the changes are due to that report. We hope for your understanding of the fact that we occasionally had to decide between suggestions made by you and the other referees.

The authors apply Fama's (1984) regression approach for speculative efficiency on Bitcoin spot and futures' prices. They find that the futures basis does provide some information on future changes in the spot price, and the risk premium, although the predictors are not unbiased. Further, they analyze systematic deviations from no-arbitrage prices and find them to widen during episodes of hackings, frauds, and issuances of alternative cryptocurrencies.

The ability of futures markets to predict subsequent spot prices has been a controversial topic for a number of years. Thus, it is a neat idea to discuss this topic for Bitcoin. However, the empirical part of the paper is too thin for a serious contribution to the existing literature. In the following, I will give more detailed comments on my opinion:

Major Comments:

1. *There is a variety of published papers dealing with the relation between the Bitcoin spot and future markets, not only Baur and Dimpfl (2018). In this paper, there is no literature review at all, although there are a few papers dealing with the same research question as yours. To make a clear contribution the existing literature, it is essential to mark out your findings against what other authors found.*

<u>Response:</u>

We appreciate these comments that allow us to better motivate the paper and to better articulate and clarify its contributions to the literature. To this end, we have rewritten the introduction, and have provided a new Literature Review section, that covers the burgeoning literature that is alluded to by the referee. This provides a basis for benchmarking our approaches and findings in terms of extant studies. As noted therein (on pages 3-6):

“Public pricing for Bitcoin commenced with the launch of the platform: BitcoinMarket.com in March 2010. The price of Bitcoin at the outset of trading was a mere $0.003. After 16 months, it soared to $31. From that time forth, Bitcoin’s price has experienced periods of extreme volatility characterized by episodes of explosive appreciations and depreciations, unhampered by regulatory price limits or circuit breakers usually present in many organized exchanges. The novelty of Bitcoin and other cryptocurrencies, as well as Bitcoin's unprecedented performance have drawn the attention of practitioners, regulators, and scholars. Indeed a considerable literature has emerged. The literature has addressed Bitcoin from a technical analysis perspective (e.g. bubbles, explosive behavior), fundamental supply analysis perspective, as well an efficient markets perspective. In regard to the former, a popular approach has adopted the speculative bubble framework (see e.g. Garcia et al. 2014; Cheah and Fry 2015; Li et al. 2018; Hafner 2018). Cheung et al. (2015) as well as Su et al. (2018). Cagli (2019) and Bouri et al (2019) provide evidence that cryptocurrencies follow an explosive process framework.

Other papers have taken a more fundamental approach, looking at basic market supply-demand factors within a commodity market perspective. Regarding the former alternative perspective is that price movements in Bitcoin can be viewed from a commodity market perspective: since mining of the cryptocurrency is a costly computational process, its price behavior may be related to basic demand/supply factors. One way to address this question is to assess the extent to which its price is equal to its intrinsic value. Under the assumption that cryptocurrency markets are perfectly competitive, analyzing the marginal mining cost of Bitcoin may provide the outline to find its appropriate intrinsic value. For instance, given the considerable gap between the market price of Bitcoin and its mining cost, which is about $4,050, one can argue that there may be other factors which affect the intrinsic value of the cryptocurrency. For example, whereas Kristoufek (2015) finds that several fundamental macroeconomic factors including usage in trade, money supply and price level may influence Bitcoin price in long run. Ciaian et al. (2016) highlight that market forces of supply and demand as well as investment attractiveness rather than macroeconomics factors play a major impact on Bitcoin price formation. Indeed Hayes (2016) introduces a model for determining the value of a bitcoin-like cryptocurrency by calculating its cost of production. He asserts that while the bubbles approach has merits, there is also some support for a fundamental price floor based on the marginal cost of production. An alternative fundamental commodity valuation perspective is provide by Shazad et al (2019) and Wang et al (2019). They argue that the cryptocurrency market can be looked at as weak "safe haven" commodities such as Gold. This contrasts with Yermack (2015) and Bauer et al (2017). Chan et al (2019) analyze the hedging ability of Bitcoin against major equity indices and uncover that Bitcoin can actually serve as a hedge for S&P500 using medium data frequency. Other studies have looked at interconnections between cryptocurrencies themselves, as well as potential causal factors for cryptocurrency returns. In this vein, Beneki et al (2019) find evidence of volatility transmission between Bitcoin and Ethereum markets, and suggest possible trading strategies across cryptocurrencies. Dastgir et al (2019) find a bi-directional causal relationship between Bitcoin attention, measured by Google trends and search queries and Bitcoin's return. These relationships are observed primarily in the tails of the returns' distribution.

A third approach, which serves as the basis of our analyses is the efficient markets perspective. Urquhart (2016) provides evidence of Fama (1970) weak form inefficiency in tests based on the dependent structure of the time series behavior of the cryptocurrency's returns. Additionally, Yonghong et al (2019), Bariviera (2017) and Zhang (2018) provide evidence of a long-term memory process in the Bitcoin market with various windows of time-serious data. Charfeddine and Maouchi (2019) show Long Range Dependence (LRD) behavior in the returns and volatility series of several cryptocurrencies. In contrast, Sensoy (2019) reveals that Bitcoin low frequency (intraday prices) prices exhibit fewer inefficiencies. Gandar et al (2018) identify potential sources of inefficiencies in the spot market: suspicious trades that have a significant impact on spot prices.

A few studies have appeared that look at the effects of trading of bitcoin futures markets on the efficiency of the Bitcoin spot markets. Köchling et al (2019) suggest that the introduction of Bitcoin futures has improved the pricing efficiency of Bitcoin spot prices. However, they do not look at the interactions between the futures and spot prices of Bitcoins. In an important paper along these lines, Baur and Dimpfl (2018) show evidence that the futures price of Bitcoin is led by its spot price. In contrast, Kapar and Olmo (2019) suggest, that while both futures and spot markets respond to common news. They also show Bitcoin futures price might provide significant information for Bitcoin spot price discovery. In a more recent paper, Fassas, Papadamou, and Koulis (2020) show similar results. They also find a bi-directional dependence of intraday volatility for both markets. None of the aforementioned studies examine whether the information imparted by futures prices may be biased.

Our study proposes to reexamine the Baur and Dimpfl (2018), Kapar and Olmo (2019) and Fassas, Papadamou, and Koulis (2020) to shed new light on predictive content of futures vs spot markets, as well as the speculative efficiency of the markets. Our approach allows us to test for potential biases in the futures basis as a predictor of spot prices and of futures prices as predictors of spot prices. In addition, we will look at the markets in terms of arbitrage efficiency: a) Do prices deviate from arbitrage bounds that give rise to profitable trading opportunities? b) Can we identify sources that are associated with persistent deviations from no-arbitrage bounds?"

2. Regarding the empirical methodology used in the paper, there are some improvements to the Fama (1984) approach discussed in the literature. Applying these more sophisticated methodologies would improve your paper significantly.

Response: Thank you very much for this excellent suggestion. To address this question, we have added an additional test of speculative efficiency to complement the Fama (1984), and Fama and French (1987) regression approach for speculative efficiency (which has also been used by Khoury et al (1991), Switzer and El-Khoury (2007), Switzer and Fan (2009), Huisman and Kilic (2012), Symeonidis et al (2012), Asche et al (2016), Stevens (2013), Wu and Zheng (2019) and several other studies).

Specifically, in this version we **perform new Cointegration Tests that for directly test whether futures prices as unbiased predictors of spot prices. As we note in the new section 3.1.2:**

"As a second test of Bitcoin Futures market efficiency, we examine the nature of the cointegration of spot and futures prices spot prices, and the potential biases of the cointegration vector. This approach typically focuses on the Keynes-Hicks and Fama (1970) weak form market/speculative market efficiency tests of the form:

$$S_t = \alpha + \beta F_{t-i} + \varepsilon_t \quad (3)$$

In this approach, market efficiency requires that futures prices should be unbiased predictors of future spot prices. Simple empirical tests of the ***speculative efficiency hypothesis*** are based on tests of the joint hypothesis $\alpha = 0, \beta = 1$ in (3).

Basic cointegration tests for Bitcoin spot and futures are provided in Kapar and Olmo (2019) and Fassas, Papadamou, et al (2020). . In this paper we use Johansen's (1988, 1991)) approach in order to test for cointegration, as well as for efficiency and bias of Bitcoin Futures. We consider a general VAR model of order k,

$$\Delta \mathbf{X}_t = \mathbf{D} + \mathbf{\Pi X_{t-1}} + \sum_{i=1}^{k-1} \mathbf{\Gamma}_i \Delta \mathbf{X}_{t-i} + \varepsilon_t \quad (4)$$

where $\Delta\mathbf{X}_t = \mathbf{X}_t - \mathbf{X}_{t-1}$; $\mathbf{D}$ is a deterministic term; $\mathbf{\Pi}$ and $\mathbf{\Gamma}$ are matrices of coefficients. The cointegration relationship is examined by looking at the rank of the coefficient of matrix $\mathbf{\Pi}$. If $\mathbf{\Pi} = 0$, there is no cointegration vector, hence no cointegration relationship.

If $\mathbf{\Pi} = 1$, then the two series are cointegrated (Johansen and Juselius, 1990). The trace and maximum statistics are used.[1] If the Bitcoin spot and futures contract prices are cointegrated, then a long-run relationship must exist between these two series.

Cointegration is considered as a necessary condition for market efficiency (Lai and Lai, 1991). However, in order to conclude efficiency, we also examine whether futures contracts are unbiased predictors of future spot markets i.e. $\alpha = 0$ and $\beta = 1$ In this framework, as we note (page 12):

"Using Likelihood Ratio tests, we reject the null that the cointegrating vector is given by (1,-1). Future contract prices are found to be biased predictors of future spot prices," This confirms our results from the Fama (1984), and Fama and French (1987) regression tests.

Minor Comments:

- *The introduction needs reorganization. You start with a long paragraph about the history of Bitcoin, while the reader cannot find the contribution of your paper until the end of page 2.*

Response: In this version, we have completely rewritten the introduction to focus on our contributions vis à vis the extant literature.

- *In Section 2, again, you state a lot of background information. For example, you discuss the factors which affect the intrinsic value of Bitcoin. You could shorten this passage by mentioning studies which already analyzed these questions (e.g. Kristoufek (2015) and Ciaian et al. (2016)).*

Response: As we indicate above, we have completely rewritten this section, as a new Literature Review, to better contextualize the paper (as suggested by the other referees as well) and to highlight our contributions in terms of the extant literature.

- *The quality of the figures is poor. For example, you cannot read the y-axis labels of Figure 2. If possible, try to use vector graphics.*

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[1] The trace statistic tests the null that the number of cointegrating vectors is less than or equal to *r* against and unspecified hypothesis; whereas the maximum eigenvalue statistic tests the null that the number of cointegrating vectors is *r* against an alternative of *r +1*, where *r* is the canonical correlation coefficient between the two series. Both tests are formulated as:

$$\lambda_{trace}(r) = -T\sum_{i=r+1}^{g} Ln(1-\hat{\lambda}_i),$$

$$\lambda_{\max}(r, r+1) = -TLn(1-\hat{\lambda}_{r+1})$$

Response: Thank you for noticing this. In response to Referee 2, we have deleted Figures 1 and 2. The remaining figures have been edited, as necessary to improve their legibility.

- *On page 8, you copied and pasted a whole paragraph including Table 4, which is now twice in the paper: "The Wald tests do not support unbiasedness of the predictors[...]"*

Response: Thank you for noticing this. We have removed this redundancy in this version of the paper.

Thank you again for your careful and thoughtful reading of our work. The paper has greatly benefitted from your comments.

Response to Referee Report, Reviewer 2

Research in International Business and Finance

Pricing Efficiency and Arbitrage in the Bitcoin Spot and Futures Markets,

RIBAF_2019_952

Thank you for your constructive feedback on our work, and for the opportunity to revise and resubmit our paper. We are pleased that you find our idea meritorious. We highly appreciate your comments and suggestions for improvements, which have helped us to make a substantial revision of the paper. We have addressed your remarks in the revised draft. In this document, we provide detailed responses to your specific comments (in *Italics*). Since we received reports from two other referees as well, some of the changes are due to that report. We hope for your understanding of the fact that we occasionally had to decide between suggestions made by you and the other referees.

The research idea is very promising and offers great potential to understanding the crypcurrency landscape, but the paper seems to suffer from several serious shortcomings:

1. The research question is both unclear and unmotivated. The idea seems to shift from pricing of Bitcoin to investigation of futures-spot price discovery in the Bitcoin market.

Also, it is not clear to the reader why this subject is important enough to be investigated. The motivation remains unclear both in Sections 1 and 2. Why is the topic important? Are there any other articles on the subject? What do they find? How does this paper fit in?

The only paper that is mentioned as the foundation of this paper is Baur and Dimpfl (2018). But they receive no mention in the introduction section where the contribution is discussed.

This may help you: read paragraph 1 of Kapar and Olmo (2019) for the motivation to the price discovery process of Bitcoin.

Response: We appreciate these comments that allow us to better motivate the paper, and to articulate and clarify its contributions to the literature. As noted in our response to Reviewer 1, we have rewritten the introduction, and have introduced a new Literature Review section. This provides a basis for benchmarking our approach and findings in terms of the extant literature. Thank you for pointing out the Kapar and Olmo (2019) article, which we now cite, which as you point out helps considerably in motivating our paper.

2. The literature review is very shallow. Some critical papers in this area have been ignored.

For instance,

(a) Kapar and Olmo (2019), Economics Letters https://www.sciencedirect.com/science/article/pii/So16517651830444o

(b) Akyildirim et al. (2019), Finance Research Letters https://www.sciencedirect.com/science/article/pii/S15446123193o4714

(c) Yo hong et al. (2018), Finance Research Letters https://www.sciencedirect.com/science/article/pii/S15446123173o6682

(d) Urquhart (2016), Economics Letters https://www.sciencedirect.com/science/article/pii/So1651765163o364o

Response: Thank you for suggesting these excellent citations. We have cited these articles, and several others to our new Literature Review section, where we better frame our approach and contributions. As we note in our response to Referee 1, we have organized the extant literature into three approaches: technical analysis perspective (e.g. bubbles, explosive behavior), fundamental supply analysis perspective, as well an efficient markets perspective. We note that our contributions relate to tests of efficient markets in terms of speculative efficiency. As indicated, our study test for potential biases in the futures basis as a predictor of spot prices and of futures prices as predictors of spot prices. In regard to the latter, in this version, we perform new Cointegration Tests that directly test whether futures prices are unbiased predictors of spot prices. In addition, we look at the markets in terms of arbitrage efficiency: a) Do prices deviate from arbitrage bounds that give rise to profitable trading opportunities? b) Can we identify sources that are associated with deviations from no-arbitrage bounds?

3. Even when the empirical methodology used seems relevant to the research question at hand, I have the following reservations:

(a) Why is this methodology preferred over other methods available? Do you have references to support your view that these indeed work better or have fewer problems associated with interpretation for example?

Response: Thank you for mentioning this issue.

As we note in this version of the paper in the new footnote 1, "This approach has been widely used as a benchmark test in speculative efficiency studies for a wide range of futures products. See e.g. Khoury et al (1991), Switzer and El-Khoury (2007), Switzer and Fan (2009)), Huisman and Kilic (2012), Symeonidis et al (2012), Asche et al (2016), Stevens (2013), Wu and Zheng (2019) to name a few." In addition, as discussed in our response to a similar question of referee 1 (Comment 1), in this version we perform new Cointegration Tests that for directly test whether futures prices as unbiased predictors of spot prices. These complementary results are shown in this revised version of the paper in the new section 3.1.2.

Finally, the cost of carry model benchmark and deviations from the cost of carry have been used widely in the literature to address efficiency in the no-arbitrage sense (e.g. MacKinlay and

Ramaswamy (1988), and Bhatt and Cakici (1990), Switzer et al (2000), Andani et al (2009), and Switzer et al (2013)).

(b) The results from the tables 2,3,4,5,6,9,and 10 are not well-explained. It is not sufficient to indicate the general conclusion of the coefficients. Instead, it will help if at least one coefficient per table is explained so that the reader is in a better position to read, interpret and form his own conclusions about the results.

Response: This version of the paper provides such details for each of the tables to enhance the presentation of our empirical findings

4. For me, figures 1 and 2 (Bitcoin versus 5 stock indices) are totally unnecessary. First, they are not directly helpful in understanding your research question (futures-spot price discovery) and second, it would be enough to cite some papers that document the hedging/ diversification properties of the Bitcoin if you believe that this discussion is absolutely necessary.

For instance, https://www.sciencedirect.com/science/article/pii/S10629769173o418o

Response: Thank you for this suggestion. These figures have been deleted from this version of the paper.

5. Section 4 that investigates the sources of futures-spot deviation is very interesting. However, here are my concerns:

(a) Why do you believe that frauds/ hacks and the introduction of other cryptocurrencies should affect Bitcoin efficiency?

Response: As we note in our revised paper (page 9), "Bitcoin thefts/hacks and alternative cryptocurrency issues, as they may contribute to inefficiency, through reduced liquidity and thin trading.. Bitcoin thefts and hacks serve to lower the confidence of investors in Bitcoin. Markets with compromised integrity are by their very essence inefficient. New cryptocurrencies may serve as alternatives or substitutes for Bitcoin, and their issuance should lower the demand for Bitcoin, which would contribute to market thinness. There is a fairly large literature that relates illiquid markets informational inefficiency (see e.g. Tomek, (1980), Elfakhani et al (1999), Garbade and Silber (1983), and Figuerola-Ferretti, and Gonzalo (2010)). Thin trading in spot and futures markets together impedes efficiency in terms of price discovery of both markets, which would impede arbitrage (see e.g. Adamer, Bohl, and Gross (2016) and Schroeder, Tonsor, and Coffey (2019)). Indeed, trading thinness is a key factor underlying the demise of the CBOE futures contracts for Bitcoin." Our results are consistent with these hypotheses.

(b) Are there any papers to suggest this? Which ones? What do they find?

Response: In a recent study published in *the Journal of Monetary Economics*, Gandal, Hamrick, Moore and Oberman (2018) similarly use dummy variables and document the impact of suspicious trades and potential price manipulation in the Bitcoin market. This paper documents that fraudulent activity undermines efficiency of the markets. Our paper is consistent with this result. New issues of alternative currencies can also be disruptive. We believe that our paper is the first in the literature to look at the impact of alternative cryptocurrencies to document this finding.

(c) Is your methodology of using a dummy variable for 'Newcoin' and 'Hack_Cum' already documented elsewhere? This gives greater credibility to your techniques and results.

As mentioned above (response to point b) “In a recent study published in *the Journal of Monetary Economics*, Gandal, Hamrick, Moore and Oberman (2018) similarly use dummy variables and document the impact of suspicious trades and potential price manipulation in the Bitcoin market. This paper documents that fraudulent activity undermines efficiency of the markets. Our paper is consistent with this result. New issues of alternative currencies can also be disruptive. We believe that our paper is the first in the literature to look at the impact of alternative cryptocurrencies to document this finding.”

(d) I see in your tables that the results for these tests are largely statistically significant, but once again a more detailed explanation of coefficients would be appreciated.

Response: Thank you. This version of the paper provides such details for each of the tables to enhance the presentation of our empirical findings.

6. What are the policy implications of your work? For instance, can it be used to assess the necessity of the introduction of Bitcoin futures in the first place, or point towards a desired change in the way futures markets in the Bitcoin are currently working etc.

Response: Thank you for mentioning these issues. In this version, we have provided some discussion of the implications of our findings for both policymakers and investors in the conclusion section. As we note there,

“Our findings should be of considerable interest for both policymakers and investors. For policy makers, our findings suggest the importance of monitoring markets for signals of fraudulent activities. Deviations from efficiency are significantly impacted by such events, and could be used as triggers to enhance market surveillance – e.g. investigating futures contract positions around such triggers. Furthermore, exchanges should be encouraged to facilitate the introduction and development of standardized contracts that guarantee spot delivery, similar to the new futures contracts that provide physical delivery of Bitcoin. For investors, our findings clearly highlight that not only is speculation in Bitcoin risky, but that that there are also significant risks associated with Bitcoin spot/future arbitrage strategies.

Minor comments:

1. *Typos in the paper must be addressed.*

2. *Sentences used are typically long and tend to get unclear in meaning. It might be advisable to stick to short and clear sentences.*

Response: Thank you. We have done considerable editorial work to rectify these issues.

Thank you again for your careful and thoughtful reading of our work. The paper has greatly benefitted from your comments.

Response to Referee Report, Reviewer 3

Research in International Business and Finance

Pricing Efficiency and Arbitrage in the Bitcoin Spot and Futures Markets,

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Thank you for your kind remarks. We are pleased that you find the paper to be a very interesting investigation. We are highly appreciative of your constructive comments and suggestions for improvements, which have helped us to make a substantial revision of the paper. We have addressed your remarks in the revised draft. In this document, we provide detailed responses to your specific comments (*in Italics*). Since we received reports from two other referees as well, some of the changes are due to that report. We hope for your understanding of the fact that we occasionally had to decide between suggestions made by you and the other referees.

- *The paper presents a very interesting empirical investigation on the speculative efficiency of Bitcoin. The structure of the paper, is fine but it needs improvement. I miss a (brief) literature review and discussion of previous literature. Published papers on cryptocurrencies is growing within leading finance and economics journals. Therefore, the authors should, first contextualize their work.*

First, the authors should cite past literature in this field, discussing informational efficiency at the initial level, to motivate the study:

1. A. F. Bariviera, The inefficiency of Bitcoin revisited: A dynamic approach. Econ. Lett. 161, 1-4 (2017).

2. B. M. Blau, Price dynamics and speculative trading in Bitcoin. Res. Int. Bus.

Financ. 43, 15-21 (2018).

3. E. Bouri, S. J. H. Shahzad, D. Roubaud, Co-explosivity in the cryptocurrency market. Financ. Res. Lett. (2018), doi:https://doi.org/10.1016/j.frl.2018.07.005.

4. J. Fry, Booms, busts and heavy-tails: The story of Bitcoin and cryptocurrency

markets? Econ. Lett. 171, 225-229 (2018).

5. P. Katsiampa, Volatility estimation for Bitcoin: A comparison of GARCH models. Econ. Lett. 158, 3-6 (2017).

6. L. Kristoufek, What Are the Main Drivers of the Bitcoin Price? Evidence from Wavelet Coherence Analysis. PLoS One. 10, eo123923 (2015).

7. I. Merediz-Sola, A. F. Bariviera, A bibliometric analysis of Bitcoin scientific *production. Res. Int. Bus. Financ. 50, 294-305 (2019).*

8. A. Urquhart, The inefficiency of Bitcoin. Econ. Lett. 148, 80-82 (2016).

9. T. V. H. Nguyen, B. T. Nguyen, T. C. Nguyen, Q. Q. Nguyen, Bitcoin return: Impacts from the introduction of new altcoins. Res. Int. Bus. Financ. 48, 420-425 (2019).

Then, the authors should study and benchmark their results with those already published on the relationship between spot and future prices in cryptocurrencies:

1. *G. M. Caporale, L. Gil-alana, A. Plastun, Persistence in the Cryptocurrency Market. Ger. Inst. Econ. Res., 1-19 (2017).*

Response: We appreciate these comments that allow us to better motivate the paper to better articulate and clarify its contributions to the literature. To this end, we have rewritten the introduction, and have provided a new Literature Review section, that covers the burgeoning literature that the referee alludes to. As discussed in our responses to Referees 1 and 2, this provides a basis for benchmarking our approaches and findings in terms of extant studies.

Thank you again for your careful and thoughtful reading of our work. The paper has greatly benefitted from your comments.

Pricing Efficiency and Arbitrage in the Bitcoin Spot and Futures Markets☆

By

Seungho Lee,[a] Nabil El Meslmani,[b] and Lorne N. Switzer[c*]

February 2020

Abstract

This study examines the pricing efficiency for the leading cryptocurrency, Bitcoin using spot prices and all CBOE and CME futures contracts traded from January 2018 to March 2019. We find that the futures basis provide some predictive power for future changes in the spot price and in the risk premium. However, the basis of Bitcoin is a biased predictor of the future spot price changes. Cointegration tests also demonstrate that futures prices are biased predictors of spot prices. Deviations from no-arbitrage between spot and futures markets are persistent and widen significantly with Bitcoin thefts (hacks, frauds) as well as alternative cryptocurrency issuances.

Pricing Efficiency and Arbitrage in the Bitcoin Spot and Futures Markets☆

By

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JEL Classification: E31; E42; G11; G12; G14

Keywords: Bitcoin; cryptocurrency; speculation; efficient markets; futures arbitrage

☆ We would like to thank the Editor, John W. Goodell, three anonymous referees, and participants at the FinteQC 2019 Conference, Levis, Quebec, and the 2019 International Conference on Digital, Innovation, Entrepreneurship & Financing, Valencia, Spain. for their helpful comments and suggestions. Financial support from the Autorité des Marchés Financiers to Switzer is gratefully acknowledged. The usual disclaimer applies.

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Pricing Efficiency and Arbitrage in the Bitcoin Spot and Futures Markets☆

February 2020

Abstract

This study examines the pricing efficiency for the leading cryptocurrency, Bitcoin using spot prices and all CBOE and CME futures contracts traded from January 2018 to March 2019. We find that the futures basis provide some predictive power for future changes in the spot price and in the risk premium. However, the basis of Bitcoin is a biased predictor of the future spot price changes. Cointegration tests also demonstrate that futures prices are biased predictors of spot prices. Deviations from no-arbitrage between spot and futures markets are persistent and widen significantly with Bitcoin thefts (hacks, frauds) as well as alternative cryptocurrency issuances.

JEL Classification: E31; E42; G11; G12; G14

Keywords: Bitcoin; cryptocurrency; speculation; efficient markets; futures arbitrage

1. Introduction

The novelty of Bitcoin and other cryptocurrencies, as well as Bitcoin's unprecedented performance and volatility since its inception, have drawn the attention of practitioners, regulators, and scholars. New spot exchanges and organized futures contracts have emerged to facilitate the appetites of investors interested in this new asset class. Extreme market volatility has given rise to widespread government regulatory interventions in Bitcoin transactions in several countries, as shown in Table 1.

[Please insert Table 1 about here]

A burgeoning academic literature has also emerged on digitalization and cryptocurrencies that crosses several disciplines, including computer science, economics, and finance. Our paper looks at Bitcoin from an "efficient markets" perspective. In particular, we provide new evidence concerning informational efficiency of Bitcoin from the perspective of speculators. Several papers have appeared that look at the informational efficiency of Bitcoin, with mixed results (e.g. Urquhart (2016), Bariviera (2017), Baur and Dimpfl (2019), Zhang (2018), Charfeddine and Maouchi (2019), Sensoy (2019), Gandar et al (2018), Köchling et al (2019) Kapar and Olmo (2019), Yonghong et al (2019), and Fassas, Papadamou, and Koulis (2020)). A number of these studies look at the informational content of futures prices vs. spot prices (e.g. Baur and Dimpfl (2019), Kapar and Olmo (2019), and Fassas, Papadamou, and Koulis (2020)). None of these studies look at the potential biases of futures prices, per se. Our study provides new evidence on this score, looking at the futures basis as a predictor of spot price changes, and at futures prices as predictors of spot prices. We also contribute to the literature by examining the nature of efficiency of Bitcoin spot and futures markets in terms of allocational efficiency using the no-arbitrage framework. In this approach, we look at deviations from no-arbitrage bounds between spot and futures markets.

Our results demonstrate that the futures basis contains information about future spot changes and the futures risk premium. However, we also show that the futures basis is a biased predictor of future spot changes. Furthermore, we find that futures prices are biased predictors of future spot prices. We also document systematic and persistent deviations from no-arbitrage prices. In addition, we identify potentially profitable risk free futures/spot trades that are not consistent with allocational efficiency. In particular, we find persistent underpricing of futures contracts. Finally, we find that deviations from no-arbitrage prices widen with Bitcoin thefts (episodes of hackings, frauds), and issuances of alternative cryptocurrencies.

The remainder of the paper is organized as follows. In the next section, we provide a brief review of the literature. Section 3 discusses the methodological approaches for the analyses. In section 4, we describe the data and present the basic results. In section 5 we look at possible underlying factors that may explain persistent inefficiencies, including thefts due to hacking and new cryptocurrency issuances. The paper concludes with a summary in section 6.

2. Literature Review

Since Bitcoin's inception, researchers have examined Bitcoin from at least three perspectives: a) technical analysis that focuses on past patterns of prices and returns; b) fundamental analyses that looks at macroeconomic and other structural drivers of returns; and c) an efficient markets perspective that looks at how market prices reflect information. In regard to: a) several papers have focused on the speculative bubble framework (see e.g. Garcia et al. (2014), Cheah and Fry (2015), Li et al. (2018), Hafner (2018)), Cheung et al. (2015) as well as Su et al. (2018). In contrast, Cagli (2019) and Bouri et al (2019) provide evidence that movements of cryptocurrencies follow explosive processes.

Other papers have taken a more fundamental approach, looking at basic market supply-demand factors within a commodity market perspective. This approach assesses the extent to which the price of Bitcoin is equal to its intrinsic value. Assuming that cryptocurrency markets are perfectly competitive, the marginal mining cost of Bitcoin can provide a floor for its intrinsic value (e.g. Hayes (2016)). Shazad et al (2019) and Wang et al (2019) argue that Bitcoin and other cryptocurrencies can be viewed as weak "safe haven" commodities, similar in character to Gold. This contrasts with Yermack (2015) and Bauer et al (2017). Chan et al (2019) analyze the hedging ability of Bitcoin against major equity indices and suggest that Bitcoin can actually serve as a hedge for S&P500 using medium frequency data. Kristoufek (2015) suggests that several fundamental macroeconomic factors influence the long-run price of Bitcoin. In contrast, Ciaian et al. (2016) argue that other factors, such as investment attractiveness, have a more prominent role in Bitcoin price formation. Other studies have highlighted interconnections between alternative cryptocurrencies. In this vein, Beneki et al (2019) find evidence of volatility transmission between Bitcoin and Ethereum markets. They suggest possible trading strategies that make use of this transmission across cryptocurrencies. Dastgir et al (2019) find a bi-directional causal relationship between Bitcoin attention, measured by Google trends and search queries and Bitcoin's return. These relationships are observed primarily in the tails of the returns' distribution.

A third approach, which serves as the basis of our analyses is the efficient markets perspective. Urquhart (2016) provides evidence of weak form inefficiency (Fama (1970)) in tests based on the dependent structure of the time series behavior of the cryptocurrency's returns. Additionally, Yonghong et al (2019), Bariviera (2017) and Zhang (2018) provide evidence of a long-term memory process in the Bitcoin market with various time-series windows. Charfeddine and Maouchi (2019) show Long Range Dependence (LRD) behavior in the returns and volatility series of several cryptocurrencies. In contrast, Sensoy (2019) suggests that Bitcoin prices experience fewer inefficiencies using intraday prices. Gandar et al (2018) identify potential sources of inefficiencies in the spot market: suspicious trades that have a significant impact on prices.

A few studies have appeared that look at the effects of trading of bitcoin futures markets on the efficiency of the Bitcoin spot markets. Köchling et al (2019) suggest that the introduction of Bitcoin futures has improved the pricing efficiency of Bitcoin spot prices. However, they do not look at the interactions between Bitcoin futures and spot prices. In a paper along these lines, Baur and Dimpfl (2019) show evidence that the futures price of Bitcoin is led by its spot price. In contrast, Kapar and Olmo (2019) suggest that while both futures and spot markets respond to common news, Bitcoin futures prices might provide significant information for Bitcoin spot price discovery. In a more recent paper, Fassas, Papadamou, and Koulis (2020) show similar results. They also find a bi-directional dependence of intraday volatility for both markets. None of the aforementioned studies examine whether the information imparted by futures prices may be biased.

Our study proposes to reexamine the issue of informational efficiency of Bitcoin futures contracts studied in Baur and Dimpfl (2019), Kapar and Olmo (2019) and Fassas, Papadamou, and Koulis (2020). We extend these studies with direct tests for potential biases in the futures basis as a predictor of spot prices as well as for futures prices as predictors of spot prices. In addition, we look at the markets in terms of arbitrage efficiency: a) Do prices deviate from arbitrage bounds that give rise to profitable trading opportunities; b) Can we identify sources that are associated with persistent deviations from no-arbitrage bounds?

3. Methodological Approach

3.1 Speculative Efficiency Tests

3.1.1 Bitcoin Futures Basis and Bitcoin Spot Price Changes

Similar to Baur and Dimpfl (2019) and Kapar and Olmo (2019) we examine the efficiency of the Bitcoin market using both spot prices and futures prices. As mentioned above, Baur and Dimpfl (2018) show evidence that the futures price of Bitcoin is led by its spot price, which contrasts with Kapar and Olmo (2019). In this paper we extend Baur and Dimpfl (2019) and Kapar and Olmo (2019) to the test for market efficiency by identifying distinct arbitrage opportunities for traders across spot and derivatives markets. To test this issue, we focus on periods when synchronous speculation and arbitrage can actually take place. Can futures prices serve as valid predictors of spot prices for speculative trades? To address this question, we first implement the well-known Fama (1984) regression approach, imposing the Fama and French (1987) "adding up" constraints to test for speculative efficiency.[1] The two equations estimated are as follows:

$$P_{t+1} - P_t = \alpha_1 + \beta_1(F_t - P_t) + \varepsilon_{1,t+1} \tag{1}$$

and

$$F_t - P_{t+1} = \alpha_2 + \beta_2(F_t - P_t) + \varepsilon_{2,t+1} \tag{2}$$

where P_t and F_t are the spot and future prices of Bitcoin at time t, respectively. $F_t - P_{t+1}$ defines the risk premium and $(F_t - P_t)$ refers the basis at time t. Given the adding-up constraints

[1] This approach has been widely used as a benchmark test in speculative efficiency studies for a wide range of futures products. See e.g. Khoury et al (1991), Switzer and El-Khoury (2007), Switzer and Fan (2009), Huisman and Kilic (2012), Symeonidis et al (2012), Asche et al (2016), Stevens (2013), Wu and Zheng (2019) to name a few.

(Fama and French (1987)), the estimated intercept terms α_1 and α_2 sum to zero, and the sum of the estimated slope terms $\beta_1 + \beta_2$ is equal to 1. To the extent that β_1 is positive and significant in equation (1), we will be able to infer that the basis, $(F_t - P_t)$ contains some information about the spot price change of Bitcoin in the future. Equivalently stated, the Bitcoin futures price has power to predict future spot prices. Positive and significant estimates of β_2 are consistent with a time varying risk premium. Unbiasedness of the predictors is tested by performing Wald tests of the joint hypotheses for α_1=0, β_1=1 and α_2=0, β_2=1.

3.1.2 Cointegration Tests: Futures Prices as unbiased predictors of Spot Prices

As a second test of Bitcoin Futures market efficiency, we examine the nature of the cointegration of spot and futures prices, and the potential biases of the cointegration vector. This approach typically focuses on the Keynes-Hicks and Fama (1970) weak form/speculative market efficiency tests of the form:

$$S_t = \alpha + \beta F_{t-i} + \varepsilon_t \tag{3}$$

In this approach, market efficiency requires that futures prices should be unbiased predictors of future spot prices. Simple empirical tests of the ***speculative efficiency hypothesis*** are based on tests of the joint hypothesis $\alpha = 0, \beta = 1$ in (3).

Basic cointegration tests for Bitcoin spot and futures are also provided in Kapar and Olmo (2019) and Fassas, Papadamou, et al (2020). In this paper we use Johansen's (1988, 1991) approach in order to test for cointegration, as well as for efficiency and bias of Bitcoin futures.

We consider a general VAR model of order k,

$$\Delta \mathbf{X}_t = \mathbf{D} + \mathbf{\Pi X_{t-1}} + \sum_{i=1}^{k-1} \mathbf{\Gamma}_i \Delta \mathbf{X}_{t-i} + \varepsilon_t \tag{4}$$

where $\Delta \mathbf{X}_t = \mathbf{X}_t - \mathbf{X}_{t-1}$; $\mathbf{D}$ is a deterministic term; $\mathbf{\Pi}$ and $\mathbf{\Gamma}$ are matrices of coefficients. The cointegration relationship is examined by looking at the rank of the coefficient of matrix $\mathbf{\Pi}$. If rank $\mathbf{\Pi}$ = 0, there is no cointegration vector, hence no cointegration relationship.

If rank $\mathbf{\Pi}$ = 1, then the two series are cointegrated (Johansen and Juselius (1990)). The trace and maximum statistics are used.[2] If the Bitcoin spot and futures contract prices are cointegrated, then a long-run relationship must exist between these two series.

Cointegration is considered as a necessary condition for market efficiency (Lai and Lai (1991)). However, in order to conclude efficiency, we also examine whether futures contracts are unbiased predictors of future spot markets i.e. $\alpha = 0$ and $\beta = 1$.

3.2 Futures-Spot Arbitrage Efficiency Tests

Do Bitcoin futures markets facilitate efficient pricing through arbitrage? We address this issue using the cost-of-carry model (e.g. MacKinlay and Ramaswamy (1988), Bhatt and Cakici (1990), Switzer et al (2000), Andani et al (2009), and Switzer et al (2013)). Mispricing is based on the deviation of the futures price prevailing in the market at time t for a contract with a maturity of T: $F_{(t,T)}$ and the arbitrage free expected Futures price $F^e_{(t,T)}$:

[2] The trace statistic tests the null that the number of cointegrating vectors is less than or equal to *r* against and unspecified hypothesis; whereas the maximum eigenvalue statistic tests the null that the number of cointegrating vectors is *r* against an alternative of *r +1*, where *r* is the canonical correlation coefficient between the two series. Both tests are formulated as:

$$\lambda_{trace}(r) = -T \sum_{i=r+1}^{g} Ln(1-\hat{\lambda}_i),$$

$$\lambda_{\max}(r, r+1) = -TLn(1-\hat{\lambda}_{r+1})$$

$$x_t = \left(F_{(t,T)} - F^e_{(t,T)}\right)/P_t \tag{5}$$

The mispricing term x, represents an arbitrage opportunity, which would be indicative of inefficiency. Our focus here is on the impact of Bitcoin thefts/hacks and alternative cryptocurrency issues, as they may contribute to inefficiency, through reduced liquidity and thin trading. Bitcoin thefts and hacks serve to lower the confidence of investors in Bitcoin. Markets with compromised integrity are by their very essence inefficient. New cryptocurrencies may serve as alternatives or substitutes for Bitcoin, and their issuance should lower the demand for Bitcoin, which would contribute to market thinness. There is a fairly large literature that relates illiquid markets to informational inefficiency (see e.g. Tomek, (1980), Elfakhani et al (1999), Garbade and Silber (1983), and Figuerola-Ferretti, and Gonzalo (2010)). Thin trading in spot and futures markets together impedes efficiency in terms of price discovery of both markets, which would impede arbitrage (see e.g. Adamer, Bohl, and Gross (2016) and Schroeder, Tonsor, and Coffey (2019)). Indeed, trading thinness is a key factor underlying the demise of the CBOE futures contracts for Bitcoin.

4. Data and Empirical Results

Both the Chicago Mercantile Exchange (CME) and the CBOE introduced futures contracts on Bitcoin in December 2017. Our analyses of spot-futures pricing efficiency use all contracts on these exchanges from January 2018 contracts to March 2019. The CBOE contracts are obtained from the exchange's website; spot prices and the CME contract prices are obtained from Bloomberg. We look at the monthly nearby-contracts for the CBOE and CME held to expiration as well as contracts that are rolled over 7 days before expiration. We use the 1-month US T-bill rate from the Federal

Reserve Board as the risk-free rates used in the arbitrage analyses.[3]

4.1 Speculative Efficiency Tests: Results of Fama (1984) Model with the Fama and French (1987) adding up constraints

A prerequisite condition for estimation of equations (1) and (2) is the stationarity of the data series. We conduct two standard unit root tests: augmented Dickey-Fuller (ADF) tests, and Phillips-Perron (PP) tests. The results are shown in Table 2.

[Please insert Table 2 about here]

The results reported in the table show that the basis, the risk premium, and the change in the spot prices data series are stationary, rejecting existence of unit root process. Note that the tests results are quite similar, regardless of the contract exchange (CBOE vs. CME), and rollover period (at expiration vs. rolled over to the next contract seven days prior to expiration. The test statistics for the basis are also similar to the risk premia statistics (e.g. ADF in excess of 5 in absolute value for the CBOE contracts and in the neighborhood of 4 in absolute value for the CME contracts). Therefore, we can infer that the regression models are not subject to spurious inference biases.

Table 3 presents the results of the estimation of the Fama (1984) equations (1) and (2) imposing the adding-up constraints (Fama and French (1987)), the estimated intercept terms α_1 and α_2 sum to zero, and the sum of the estimated slope terms $\beta_1 + \beta_2$ is equal to 1. Since β_1 is positive and significant for both CBOT and CME contracts in equation (1), with estimates in excess of .06 and p values less than 1% in all cases, we can infer that the basis, $(F_t - P_t)$ contains some information about the spot price change of Bitcoin in the future. Equivalently stated, the Bitcoin futures price has power

[3] Similar results are also obtained using the 3-month T-bill rate.

to predict future spot prices. The results of the estimation of equation (2) are consistent with those of equation (1). The positive and significant (with p values less than 1%) estimates of β_2 are consistent with a time varying risk premium. With the basis at time t serving as a predictor of the risk premium.

[Please insert Table 3 about here]

The Wald tests do not support unbiasedness of the predictors, since the joint tests for α_1=0, β_1=1 and α_2=0, β_2=1 are significant, with p values all less than 1% for all the contracts examined, as shown in Table 4. As indicated therein, changes in the basis (or futures prices) are not reflected as commensurate changes in spot prices or in the futures risk premium. More specifically, the current basis overestimates the change in spot prices, and underestimates the risk premium.

[Please insert Table 4 about here]

4.2 Cointegration Test Results

Before conducting the cointegration tests, we first test for the order of integration in each of the spot and the futures series using various unit root tests. Table 5 shows the Augmented Dickey-Fuller (ADF) tests and Phillips-Perron (PP) tests for the log Bitcoin spot prices and the corresponding CBOE and CME log futures prices. In all cases we cannot reject the hypothesis of unit roots for log price and log futures price levels at better than 1% significance levels, with ADF test statistics ranging from -1.4 to -2.4. Furthermore, the first differences of the spot contract, and all futures contracts, are stationary, with highly significant ADF test statistics ranging from about -17 to -18. Similar conclusions are obtained using the PP test statistics.

[Please insert Table 5 about here]

Based on the results derived from equations (3) and (4), the futures basis contains information, albeit biased, about future spot price changes. This implies that there exists a linear relationship between the spot and the futures series that is expected to be stationary. In other words, a cointegrating relationship is expected to exist between the two series as represented in (3). As shown in Table 6, the test statistics reject the assumption of no-cointegration. The trace statistics exceed the 5% critical value of 12.32 for all contracts, irrespective of the futures holding period.

[Please insert Table 6 about here]

Table 7 shows the Normalized coefficients of the cointegration vector. For all of the contracts, the estimated log futures coefficient is approximately -1.04, and is significant at the 1% level. This confirms that each of the price series contains some information that is useful in predicting its counterpart. Is this information unbiased?

[Please Insert Table 7 about here]

Table 8 specifically tests the issue of whether the futures contracts are efficient and unbiased predictors of future spot prices i.e. testing market efficiency by examining the joint hypothesis of $\alpha = 0$ and $\beta = 1$. Based on the estimated Likelihood Ratio statistics, which range from 5 to over 7, we reject the null that the cointegrating vector is given by (1,-1). Bitcoin futures contract prices are therefore biased predictors of future spot prices.

[Please insert Table 8 about here]

4.3 Futures-Spot Arbitrage Test Results

As discussed above, mispricing is based on the deviation of the futures price prevailing in the market at time t for a contract with a maturity of T: $F_{(t,T)}$ and the arbitrage free expected Futures price

$F^e_{(t,T)}$:

$$x_t = \left(F_{(t,T)} - F^e_{(t,T)}\right)/P_t$$

where $F_{(t,T)}$ is Bitcoin future price at time t with the maturity date of T, and $F^e_{(t,T)} = P_t e^{rf*(t-T)}$, where rf is risk free rate. Descriptive statistics of the mispricing term and absolute value of the mispricing term are presented in Table 9. On average, the mispricing terms are negative, which is indicative of futures underpricing. The positive skew statistics are indicative of a distribution biased to underpricing. This is consistent with a discount to futures during bearish market conditions, which is largely characteristic of the Bitcoin markets since the introduction of futures contracts.

[Please insert Table 9 about here]

5. Sources of Impediments of Futures-Spot Arbitrage: Thefts/Hacks and Alternative Cryptocurrency Issuances

Several factors might serve as sources of deviations from futures-spot arbitrage. Such factors would include trading frictions due to the extreme volatility of the markets that could inhibit or restrict trading in futures. For example, both the CBOE and CME impose price limits/circuit breakers for Bitcoin futures contracts.[4] In addition, failures of significant spot exchanges would adversely affect both long and short trading of spot Bitcoins. Regarding the latter, given the lack of physical delivery of the physical product at expiration combined with an illiquid spot market may inhibit short selling.[5]

[4] During the period analyzed in this paper the CBOE imposed two-minute trading halts for its Bitcoin contracts if the best bid in the XBT futures contract that is closest to expiration exceeds or falls below the daily settlement price of this contract of the previous business day by 10 percent or more. At the resumption of trading, if the best bid of the contract exceeds or falls below the settlement price of the previous day's contract by at least 20 percent, a 5 minutes trading halt is imposed. CME applies price limits (circuit breakers) of 7%, 13%, and 20% to the futures fixing price. See https://www.reuters.com/article/uk-bitcoin-futures-contracts/bitcoin-futures-contracts-at-cme-and-cboe-idUSKBN1E92K9 and https://www.cmegroup.com/trading/equity-index/us- index/bitcoin_contract_specifications.html

[5] A number of exchanges do provide contracts for short selling. See: https://99bitcoins.com/short-sell-bitcoin/

Our focus here is on the impact of thefts (incidents of hacking) and alternative cryptocurrency issues. With regard to the former, although Bitcoin has been touted for the integrity of its security system, several incidences of thefts (through hacking) highlight its actual vulnerabilities: A recent example is the case of Quadriga.[6] The chronology of major events involving Bitcoin exchanges security events (hacks and frauds) is shown in Figure 1 and Table 10 below.

[Please insert Figure 1 and Table 10 about here]

Bitcoin thefts (hacks and frauds) undermine the reliability of transactions in the spot market. Buying spot bitcoin is more difficult in a market where liquidity is compromised. This reduces the incentive of spot arbitrageurs to take positions in the market.

As can be seen in figures 2 and 3, mispricing and absolute mispricing the exhibit a significant spike in the first week of November 2018. This month was particularly bearish, with bitcoin exhibiting a monthly decline of about 37%. Was the jump in Bitcoin mispricing attributable to security concerns related to hacking and other forms of fraud? Notable examples were the thefts of Bithumb and Zaif, where several thousand BTCs disappeared. These events resulted in losses of $31 million and $60 million U.S. dollars to owners respectively.

[Please insert Figures 2 and 3 about here]

While Bitcoin is the leading cryptocurrency market, it does not have a monopoly on the market: a number of competing virtual currencies have been issued in recent years. Table 11 provides

[6] Doug Alexander, Quadriga Crypto Mystery Deepens With 'Cold Wallets' Found Empty, Bloomberg, March 1, 2019, https://www.bloomberg.com/news/articles/2019-03-01/quadriga-has-6-cold-wallets-but-they-don-t-hold-any-crypto, accessed on April 13, 2019

a list of major alternative cryptocurrencies issuances (initial coin offerings or ICOs) and their release dates.

[Please insert Table 11 about here]

As these new cryptocurrencies may serve as alternatives or substitutes for Bitcoin, their issuance should lower the demand for Bitcoin, which, aside from contributing to the bearish bias of the markets (from the skewness in returns) would contribute to market thinness. Market thinness is generally associated with informational inefficiency, as discussed above.

Figure 4 superimposes these alternative coin releases on the path of Bitcoin prices since April 2010.

[Please insert Figure 4 about here]

Note that the alternative coins have been released at discrete points in time. Discerning their impact on Bitcoin prices on the release dates is not clear-cut, however. For example, Litecoin, Stellar, Ripple, Tether, and Ethereum were launched before 2017, and no observable impact on Bitcoin prices is evident on release days. EOS, Bitcoin Cash, and TRON were launched during a bullish period of the Bitcoin market, while Bitcoin SV was introduced in the more bearish period. None of these releases has an apparent immediate effect on the market. One explanation is that Bitcoin is still the dominant player among the cryptocurrencies. In fact, the market capitalization of Bitcoin is five times larger than Ripple, which is the second biggest cryptocurrency market as of January 30, 2019. This distinguishable market capitalization of Bitcoin imply that the alternatives may not have sufficient market shares to influence Bitcoin's price.

A casual glance at Figures in the period up to 2017 suggests that the impacts of Bitcoin security concerns and new coin releases on the price of Bitcoin were muted. One could argue that up until 2017, the legitimacy of the market was still in question. This changed with the launching of futures contracts on Bitcoin in December 2017, on both the CBOE and the CME. An alternative perspective is that the effects of new issues of alternative currencies should be cumulative, as they receive acceptance in the markets; their effects might not be confined to the issuance day alone but for a few days subsequent to their issuance.

To formally capture the impacts of these events on Bitcoin's price, we regress the mispricing term, x_t on dummy variables that represent events of identified Bitcoin hacks/frauds issue as well as alternative coin releases. In a recent study, Gandar, Hamrick, Moor and Oberman (2018) similarly use dummy variables to look at the impact of suspicious trades and potential price manipulation in the Bitcoin market. The model as follows:

$$x_t = \alpha + \beta_1 * Hack\_Cum_{\mathrm{t}} + \beta_2 * NewCoin_{\mathrm{t}} + \varepsilon_t \quad (5)$$

where $Hack\_Cum_{\mathrm{t}}$ is cumulative amount of stolen Bitcoin by the time t, $NewCoin_{\mathrm{t}}$ is dummy variable indicating new cryptocurrency release dates, and ε_t is the error term. For $NewCoin_{\mathrm{t}}$, only top 50 cryptocurrencies in market capitalization are considered, as of April 11, 2019.[7] The results of the estimation of (5) using OLS are shown in Table 12.

[Please insert Table 12 about here]

Looking at the constant term in Table 12, our regression results show that Bitcoin Futures contracts are underpriced by between 7-8% for the CBOT Contracts; the "no-arbitrage" underpricing is even higher for the CME contracts (12.9-14%), Furthermore, we note that thefts/hacks of Bitcoin as well as new cryptocurrency releases amplify the inefficiency. Alternative coin release variable also shows significant coefficients except for CBOE's futures contract with nearby rollover data series.

[7] Data Source: https://coinmarketcap.com/

Overall, both Bitcoin security concerns and new cryptocurrency releases may lead considerable gap between the futures price and spot price in the future. As shown in Table 12, thefts/hacks and alternative cryptocurrencies are associated with larger mispricing. New coin issues have a large direct effect, increasing the (underpricing) arbitrage deviation of Bitcoin futures by 3-5% for CBOE contracts, and by 6-8% for CME contracts. Thefts/hacks are also highly significant both economically and statistically. At the margin, based on the estimates of Table 12, thefts in an increment of 1000 Bitcoins will increase the arbitrage futures discount by about 2%. In sum, our results on thefts/hacks and new cryptocurrency release are consistent with our expectations since a) thefts/hacks directly undermine the spot market. Short selling spot bitcoin when futures are underpriced is more difficult in a market where liquidity is compromised. This reduces the incentive of spot arbitrageurs to take positions in the market; b) Buying spot may be less attractive to the extent that alternative or substitute cryptocurrencies are available.

To test for the robustness of the results, we also estimated the model using EGARCH, to capture the effects of skewness and leptokurtosis in the mispricing terms (from Table 9), as well as of time varying asymmetric volatility. The results are shown in Table 13 below, where the coefficients and their respective p value significance levels are reported. As can be seen, our inferences concerning Bitcoin hacks and alternative cryptocurrency releases are unchanged. The degree of arbitrage underpricing is about 4% smaller in all the estimations using EGARCH, although underpricing remains economically and statistically significant for both the CBOE and CME contracts. Furthermore, all of the EGARCH coefficients C(7) are less than one, indicating that while cumulative hack and new currency release effects may be significant, persistence of GARCH effects is not.

[Please insert Table 13 about here]

6. Conclusion

This study looks at the efficiency of the Bitcoin spot and futures markets using synchronous end of day trading data. We find that the futures basis does provide some information on future changes in the spot price, and the risk premium, although the predictors are not unbiased. Changes in the basis are not reflected as commensurate changes in spot prices or in the futures risk premium. In addition, while Bitcoin spot and futures are cointegrated, Bitcoin futures are biased predictors of spot prices, which is not consistent with (weak-form) speculative efficiency.

We also find deviations from futures-spot arbitrage that are not consistent with market efficiency. Several factors might explain this result. Such factors would include trading frictions that would be exacerbated by extreme volatility of the markets. The results herein document that deviations from arbitrage bounds widen significantly as a consequence of thefts/hacks that leave clients and traders bereft. Deviations from arbitrage bounds also increase with alternative cryptocurrency issuances.

Our findings should be of considerable interest for both policymakers and investors. For policy makers, our findings suggest the importance of monitoring markets for signals of fraudulent activities. Deviations from efficiency are significantly impacted by such events, and could be used as triggers to enhance market surveillance – e.g. investigating futures contract positions around such triggers. Furthermore, exchanges should be encouraged to facilitate the introduction and development of standardized contracts that guarantee spot delivery, similar to the new futures contracts that provide physical delivery of Bitcoin. For investors, our findings clearly highlight that not only is speculation in Bitcoin risky, but that that there are also significant risks associated with Bitcoin spot/future arbitrage strategies.

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Figure 1. BitCoin Prices and Major Exchange Hacks (March 2010 – January 2019)

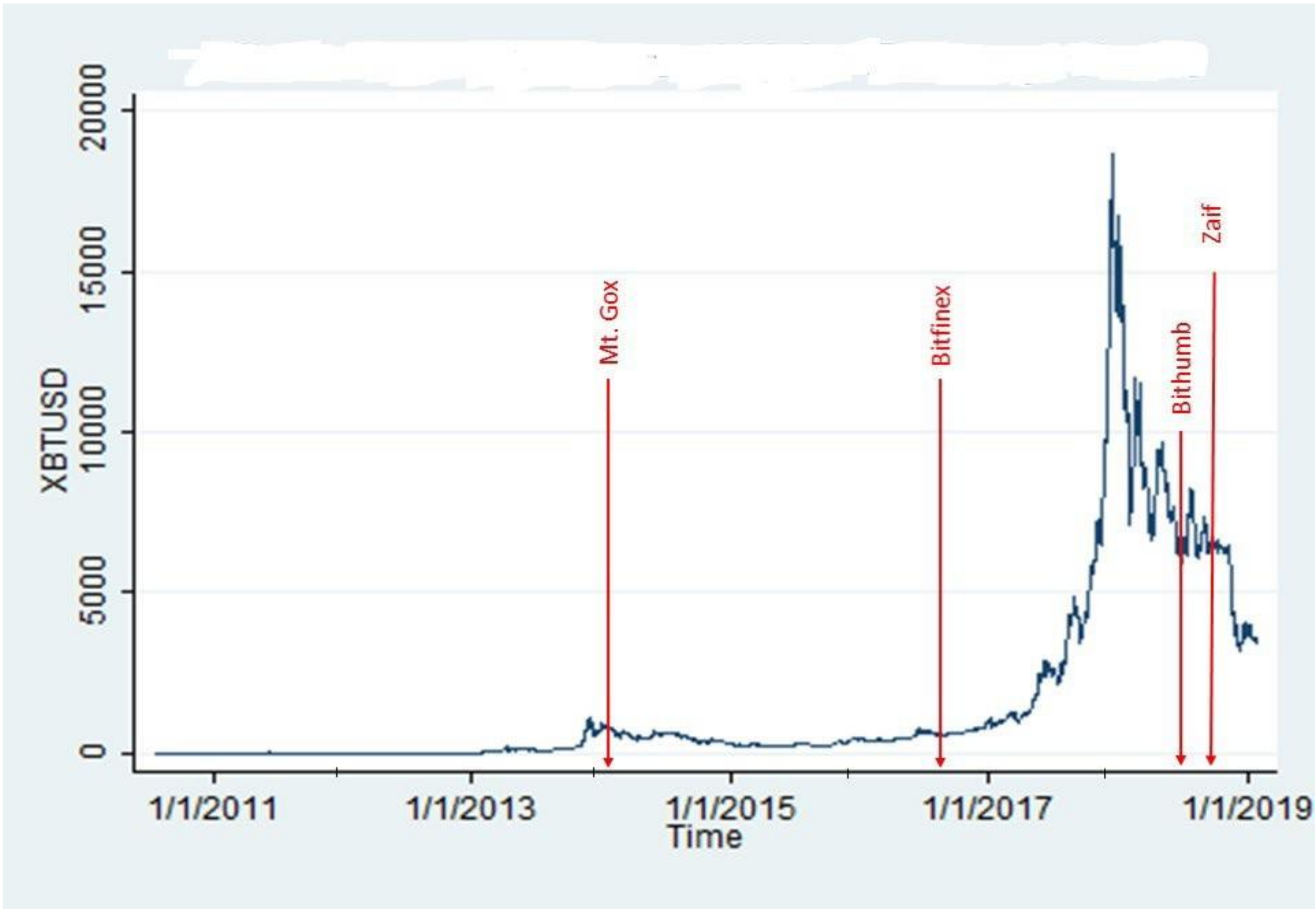

Figure 2. Bitcoin Futures Mispricing Terms (CBOE: December 2017 – March 2019, CME: January 2018 – March 2019)

Figure 3. Absolute Value of Bitcoin Futures Mispricing Terms (CBOE: December 2017 – March 2019, CME: January 2018 – March 2019)

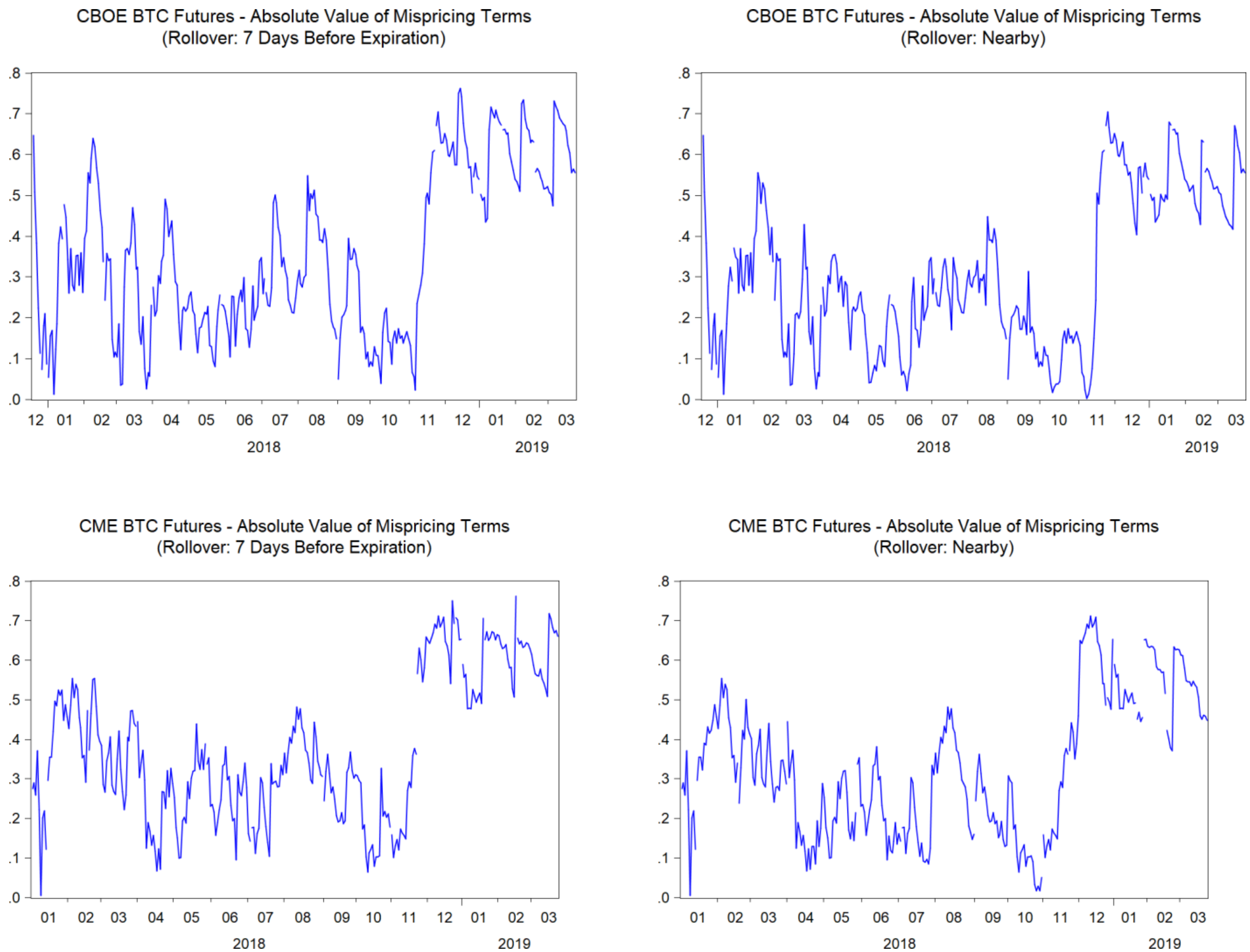

Figure 4. BitCoin Prices and Alternative Coins Releases (March 2010 – January 2019)

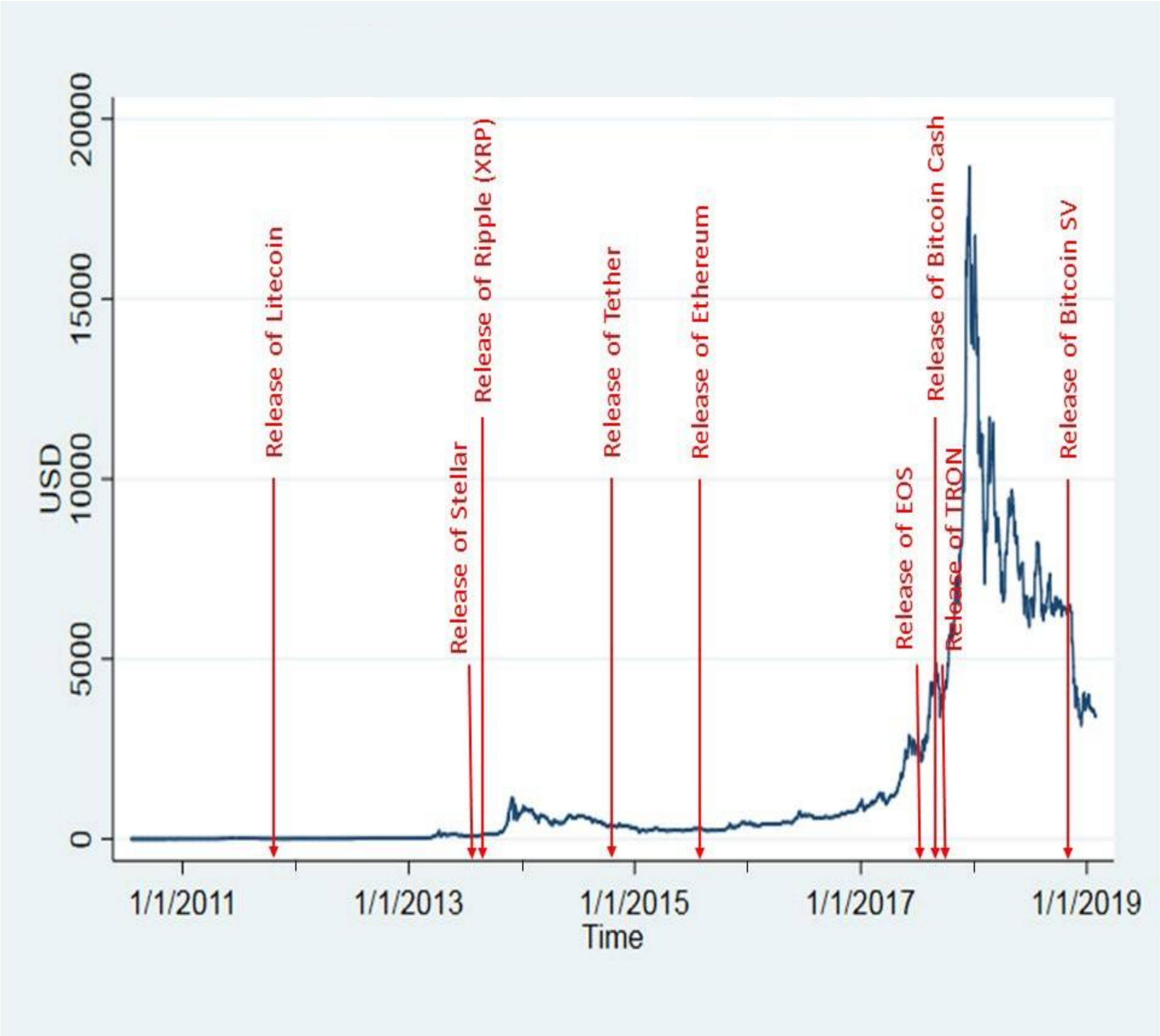

Table 1. Chronology of Government Regulations on Bitcoin Transactions

Date	Country	Description
June 4, 2018	The United States	The Securities and Exchange Commission announced that Valerie A. Szczepanik has been named Associate Director of the Division of Corporation Finance and Senior Advisor for Digital Assets and Innovation for Division Director Bill Hinman, the newly created branch to manage cryptocurrency.
January 22, 2018	South Korea	South Korea brought in a regulation that requires all Bitcoin traders to reveal their identity, thus putting a ban on anonymous trading of bitcoins
January 19, 2018	The United States	The Commodities Futures Trading Commission (CFTC) filed charges against two cryptocurrency fraud cases.
December 27, 2017	South Korea	Korea's government announced that it will impose additional measures to regulate speculation in cryptocurrency trading within the country.
December 6, 2017	South Korea	Korea's Financial Services Commission issued a ban on the trading of Bitcoin futures, prompting several securities firms to cancel seminars scheduled in December for bitcoin future investors
November 11, 2017	The United States	Treasury Secretary Steven Mnuchin mentioned he had established working-groups at treasury looking at bitcoin and that it is something they will be watching "very carefully."
September 29, 2017	The United States	The U.S. Securities and Exchange Commission (the SEC) filed a civil complaint in the U.S. District Court for the Eastern District of New York against the sponsors of two "initial coin offerings" (ICOs) for alleged violations of U.S. securities laws
September 4, 2017	China	China banned all companies and individuals from raising funds through ICO activities, reiterating that ICOs are considered illegal activity in the country
July 25, 2017	The United States	The SEC issued an investor bulletin about initial coin offerings, saying they can be "fair and lawful investment opportunities" but can be used improperly. The SEC has issued three enforcement actions against ICO sponsors- one halt and exposure of two alleged frauds. SEC Chairman Clayton has also expressed concern about market participants who extend to customers credit in U.S.
July 1, 2017	The United States	The National Conference of Commissioners on Uniform State Laws voted to approve a model act providing for the regulation of digital currency business at state level

[Source 1: www.marketwatch.com / Here's how the U.S. and the world regulate bitcoin and other cryptocurrencies by Francine McKenna, accessed on February 9, 2018]
[Source 2: https://www.sec.gov/news/press-release/2018-102 / [Press Release] SEC Names Valerie A. Szczepanik Senior Advisor for Digital Assets and Innovation, accessed on Jan 31, 2019]

Table 2. Unit Root Test Statistics for Fama (1984) Model with Fama-French (1987) constraints

Panel A: CBOE BTC Futures Contracts				
Rollover	Nearby		7 Days	
Unit Root Test	ADF	PP	ADF	PP
Change in spot	-9.8827***	-16.6816***	-9.5041***	-16.6831***
Basis	-5.7320***	-5.9340***	-5.6850***	-5.8364***
Risk premium	-5.2160***	-5.9993***	-5.7349***	-5.9359***

Panel B: CME BTC Futures Contracts				
Rollover	Nearby		7 Days	
Unit Root Test	ADF	PP	ADF	PP
Change in spot	-9.2851***	-16.3040***	-9.3170***	-16.3587***
Basis	-3.9440***	-4.0684***	-3.9631***	-4.0850***
Risk premium	-4.2704***	-4.4147***	-4.2883***	-4.4295***

*** p<0.01, ** p<0.05, * p<0.1

Table 3. Results of Fama (1984) Model with Fama-French (1987) constraints

Panel A: CBOE BTC Futures Contracts						
Rollover	Nearby			7 Days		
Equation (1): $P_{t+1}-P_t=\alpha_1+\beta_1*(F_t-P_t)+\varepsilon_{1,t+1}$						
	α_1	β_1	F-Stat	α_1	β_1	F-Stat
Coefficient	97.3997**	0.0606***	13.7553***	102.3019**	0.0625***	15.4107***
Standard Error	42.8474	0.0163	-	42.3927	0.0159	-
Probability	0.0237	0.0002	0.0002	0.0164	0.0001	0.0001
Equation (2): $F_t- P_{t+1} =\alpha_2+\beta_2*(F_t - P_t)+\varepsilon_{2,t+1}$						
	α_2	β_2	F-Stat	α_2	β_2	F-Stat
Coefficient	-97.3997**	0.9394***	3308.2470***	-102.3019**	0.9375***	3462.0300***
Standard Error	42.8474	0.0163	-	42.3927	0.0159	-
Probability	0.0237	0.0000	0.0000	0.0164	0.0000	0.0000

Panel B: CME BTC Futures Contracts						
Rollover	Nearby			7 Days		
Equation (1): $P_{t-1}-P_t=\alpha_1+\beta_1*(F_t-P_t)+\varepsilon_{1,t+1}$						
	α_1	β_1	F-Stat	α_1	β_1	F-Stat
Coefficient	132.2801***	0.0663***	15.8842***	133.3589***	0.0665***	16.1867***
Standard Error	48.3904	0.0166	-	48.1787	0.0165	-
Probability	0.0066	0.0001	0.0001	0.0060	0.0001	0.0001
Equation (2): $F_t- P_{t+1} =\alpha_2+\beta_2*(F_t - P_t)+\varepsilon_{2,t+1}$						
	α_2	β_2	F-Stat	α_2	β_2	F-Stat
Coefficient	-132.2801***	0.9337***	3151.8007***	-133.3589***	0.9335***	3187.6110***
Standard Error	48.3904	0.0166	-	48.1787	0.0165	-
Probability	0.0066	0.0000	0.0000	0.0060	0.0000	0.0000

*** p<0.01, ** p<0.05, * p<0.1

Table 4. Wald Test Results of Fama (1984) Model with Fama and French (1987) Constraints

Panel A: CBOE BTC Futures Contracts						
Rollover		Nearby			7 Days	
Equation (1): $P_{t+1}-P_t=\alpha_1+\beta_1*(F_t-P_t)+\varepsilon_{1,t+1}$						
	$\alpha_1=0, \beta_1=1$	$\alpha_1=0$	$\beta_1=1$	$\alpha_1=0, \beta_1=1$	$\alpha_1=0$	$\beta_1=1$
F-statistic	3484.2530***	5.1673**	3308.2470***	3616.0850***	5.8235**	3462.0300***
df	(2, 313)	(1, 313)	(1, 313)	(2, 314)	(1, 314)	(1, 314)
Probability	0.0000	0.0237	0.0000	0.0000	0.0164	0.0000
Equation (2): $F_t- P_t=\alpha_2+\beta_2*(F_t - P_t)+\varepsilon_{2,t+1}$						
	$\alpha_2=0, \beta_2=1$	$\alpha_2=0$	$\beta_2=1$	$\alpha_2=0, \beta_2=1$	$\alpha_2=0$	$\beta_2=1$
F-statistic	6.9956***	5.1673**	13.7553***	7.8213***	5.8235**	15.4107***
df	(2, 313)	(1, 313)	(1, 313)	(2, 314)	(1, 314)	(1, 314)
Probability	0.0011	0.0237	0.0002	0.0005	0.0164	0.0001

Panel B: CME BTC Futures Contracts						
Rollover		Nearby			7 Days	
Equation (1): $P_{t+1}-P_t=\alpha_1+\beta_1*(F_t-P_t)+\varepsilon_{1,t+1}$						
	$\alpha_1=0, \beta_1=1$	$\alpha_1=0$	$\beta_1=1$	$\alpha_1=0, \beta_1=1$	$\alpha_1=0$	$\beta_1=1$
F-statistic	4000.8910***	7.4726***	3151.8007***	4069.5259***	7.6619***	3187.6109***
df	(2, 300)	(1, 300)	(1, 300)	(2, 302)	(1, 302)	(1, 302)
Probability	0.0000	0.0066	0.0000	0.0000	0.0060	0.0000
Equation (2): $F_t- P_t=\alpha_2+\beta_2*(F_t - P_t)+\varepsilon_{2,t+1}$						
	$\alpha_2=0, \beta_2=1$	$\alpha_2=0$	$\beta_2=1$	$\alpha_2=0, \beta_2=1$	$\alpha_2=0$	$\beta_2=1$
F-statistic	8.0422***	7.4726***	15.8842***	8.1939***	7.6619***	16.1867***
df	(2, 300)	(1, 300)	(1, 300)	(2, 302)	(1, 302)	(1, 302)
Probability	0.0004	0.0066	0.0001	0.0003	0.0060	0.0001

*** p<0.01, ** p<0.05, * p<0.1

Table 5. Unit Root Test Statistics for Bitcoin Spot and Futures Series

Panel A: CBOE BTC Futures Contracts

Rollover	Nearby				7 Days					
Unit Root Test	ADF		PP		ADF				PP	
	Level	1st Diff	Level	1st Diff	Level	1st Diff			Level	1st Diff
Log(Spot)	-1.429	-17.624***	-1.463	-17.627***	-1.423	-17.635***			-1.459	-17.639***
Prob.	0.5689	0.0000	0.551	0.000	0.571	0.000			0.553	0.000
Log(Futures)	-2.399	-18.060***	-2.386	-18.063***	-2.393	-18.172***			-2.382	-18.169***
Prob.	0.143	0.0000	0.146	0.000	0.144	0.000			0.148	0.000

Panel B: CME BTC Futures Contracts

Rollover	Nearby				7 Days					
Unit Root Test	ADF		PP		ADF		DF-GLS		PP	
	Level	1st Diff	Level	1st Diff	Level	1st Diff	Level	1st Diff	Level	1st Diff
Log(Spot)	-1.449	-17.236***	-1.487	-17.241***	-1.884	-17.294***	-0.898	-17.128***	-1.489	-17.299***
Prob.	0.558	0.000	0.539	0.000	0.339	0.000	0.369	0.000	0.538	0.0000
Log(Futures)	-1.868	-18.081***	-1.882	-18.084***	-1.884	-18.211***	0.514	-16.627***	-1.895	-18.204***
Prob.	0.347	0.000	0.341	0.000	0.339	0.000	0.607	0.000	0.335	0.000

*** p<0.01, ** p<0.05, * p<0.1

Table 6. Johansen Cointegration Tests

Panel A - CBOE BTC Futures Contracts - Nearby				
Johansen cointegration tests (trace statistics)				
Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.035777	14.46208	12.32090	0.0216
At most 1	0.009724	3.058645	4.129906	0.0951
Johansen cointegration tests (max statistics)				
None *	0.035777	11.40343	11.22480	0.0465
At most 1	0.009724	3.058645	4.129906	0.0951
Panel B - CBOE BTC Futures Contracts – 7 Days				
Johansen cointegration tests (trace statistics)				
Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.035639	14.02397	12.32090	0.0257
At most 1	0.008338	2.629049	4.129906	0.1240
Johansen cointegration tests (max statistics)				
None *	0.035639	11.39493	11.22480	0.0467
At most 1	0.008338	2.629049	4.129906	0.1240
Panel C - CME BTC Futures Contracts - Nearby				
Johansen cointegration tests (trace statistics)				
Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None	0.030496	11.97057	12.32090	0.0572
At most 1	0.008891	2.679314	4.129906	0.1202
Johansen cointegration tests (max statistics)				
None	0.030496	9.291256	11.22480	0.1073
At most 1	0.008891	2.679314	4.129906	0.1202
Panel D - CME BTC Futures Contracts – 7 Days				
Johansen cointegration tests (trace statistics)				
Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None	0.029995	11.84491	12.32090	0.0600
At most 1	0.008729	2.647663	4.129906	0.1225
Johansen cointegration tests (t max statistics)				
None	0.029995	9.197250	11.22480	0.1113
At most 1	0.008729	2.647663	4.129906	0.1225

Table 7. Cointegrating Vector: Normalized cointegrating coefficients (standard error in parentheses, t-statistic in square brackets).

Panel A - CBOE BTC Futures Contracts - Nearby	
Log Spot	Log futures
1.000000	-1.042556 ***
	(0.00933)
	[-111.737]
Panel B - CBOE BTC Futures Contracts – 7 Days	
Log Spot	Log futures
1.000000	-1.043027 ***
	(0.00939)
	[-111.093]
Panel C - CME BTC Futures Contracts - Nearby	
Log Spot	Log futures
1.000000	-1.042110 ***
	(0.00962)
	[-108.346]
Panel D - CME BTC Futures Contracts – 7 Days	
Log Spot	Log futures
1.000000	-1.042463***
	(0.00974)
	[-107.076]

*** p<0.01, ** p<0.05, * p<0.1

Table 8. Test of Cointegrating Restrictions

Panel A - CBOE BTC Futures Contracts - Nearby				
Hypothesized No. of CE(s)	Restricted log-likelihood	LR Statistic	Degrees of Freedom	Probability
1	1012.885	7.309007	1	0.006861
Panel B - CBOE BTC Futures Contracts – 7 Days				
Hypothesized No. of CE(s)	Restricted log-likelihood	LR Statistic	Degrees of Freedom	Probability
1	1014.078	7.708341	1	0.005497
Panel C - CME BTC Futures Contracts - Nearby				
Hypothesized No. of CE(s)	Restricted log-likelihood	LR Statistic	Degrees of Freedom	Probability
1	972.8091	5.548736	1	0.018494
Panel D - CME BTC Futures Contracts – 7 Days				
Hypothesized No. of CE(s)	Restricted log-likelihood	LR Statistic	Degrees of Freedom	Probability
1	977.4012	5.500964	1	0.019006

Table 9. Descriptive Statistics of Mispricing Term and Absolute Value of Mispricing Term

Exchange	CBOE				CME			
Rollover	Nearby		7 Days		Nearby		7 Days	
Error Term	x	abs (x)	x	abs (x)	x	abs (x)	x	abs (x)
Mean	-0.2939	0.3082	-0.3440	0.3567	-0.3193	0.3297	-0.3701	0.3794
Median	-0.2741	0.2779	-0.3169	0.3238	-0.3072	0.3101	-0.3413	0.3444
Maximum	0.6466	0.7049	0.6466	0.7630	0.3705	0.7121	0.3705	0.7629
Minimum	-0.7049	0.0021	-0.7630	0.0119	-0.7121	0.0050	-0.7629	0.0050
Std. Dev.	0.2060	0.1838	0.2185	0.1971	0.1909	0.1724	0.1987	0.1802
Skewness	0.3613	0.3385	0.3667	0.2875	0.2200	0.3021	0.2797	0.2661
Kurtosis	4.1289	2.0015	4.0265	1.8848	3.2911	2.1240	3.4094	2.0116
Jarque-Bera	23.7310	19.2207	21.0208	20.7939	3.5141	14.2957	6.1069	16.0157
Probability	0.0000	0.0001	0.0000	0.0000	0.1726	0.0008	0.0472	0.0003
Observations	317	317	317	317	303	303	305	305

Table 10. Chronology of Major Bitcoin Exchange Hacks

Year	Month	Exchange	Amount Stolen (BTC)
2012	March	Bitcoinica	46,703
2012	May	Bitcoinica	18,000
2012	August	Bitcoin Ponzi	265,678
2012	September	Bitfloor	24,000
2014	February	Mt. Gox	850,000
2014	July	Cryptsy	13,000
2015	January	Bitstamp	19,000
2015	February	BTER	7,170
2016	August	Bitfinex	120,000
2017	December	NiceHash	4,736
2018	April	CoinSecure	438
2018	June	Bithumb	2,016
2018	September	Zaif	5,966
2018	October	MapleChange	919
2019	February	Quadriga	154

Table 11. Top 10 Cryptocurrencies by Market Capitalization

Rank	Name	Market Capitalization (As of January 30, 2019)	Initial Release
1	Bitcoin	$60,329,884,225	January 9, 2009
2	Ripple (XRP)	$12,444,402,901	August 11, 2013
3	Ethereum	$11,041,665,977	July 30, 2015
4	EOS	$2,098,395,149	June 26, 2017
5	Tether	$2,034,826,407	October 6, 2014
6	Bitcoin Cash	$1,983,990,236	August 1, 2017
7	Litecoin	$1,889,854,900	October 7, 2011
8	TRON	$1,653,533,859	September 12, 2017
9	Stellar	$1,551,518,489	July 31, 2014
10	Bitcoin SV	$1,119,643,115	November 25, 2018

[Source 1: CoinMarketCap / https://coinmarketcap.com, accessed on Jan 31, 2019]
[Source 2: coinbase / https://www.coinbase.cm/price, accessed on Jan 31, 2019]

Table 12. OLS Estimates of Daily Futures Mispricing Regression with Hack/Stolen Bitcoin and New Cryptocurrency Issue Effects

Estimation equation:

$$x_t = c_1 + c_2 HackCum + c_3 \text{NewCoin} + \epsilon_t$$

HackCum constitutes cumulative amount of stolen Bitcoin from December 2017 (in thousands of Bitcoins). N*ewCoin* variable is a dummy variable capturing new cryptocurrency release events, which has value of 1 from D_{-1} to D_{+5} of new coin releases, and 0 otherwise. The datasets have two different types of rollover methodologies: nearby and 7 days before expiration, and each methodology is presented in Nearby and 7 Days rows, respectively.

Exchange	Rollover	Variable	Coefficient	Std. Error	t-Stat	Prob		
CBOE	Nearby	Constant	-0.0706***	0.0259	-2.7314	0.0067		
		Cumulative Hack	-0.0240***	0.0000	-9.6612	0.0000		
		New Coin	-0.0325	0.0252	-1.2868	0.1991	R-square	0.2292
	7 Days	Constant	-0.0869***	0.0268	-3.2424	0.0013		
		Cumulative Hack	-0.0272***	0.0000	-10.5906	0.0000		
		New Coin	-0.0538**	0.0265	-2.0330	0.0429	R-square	0.2636
CME	Nearby	Constant	-0.1288***	0.0257	-5.0207	0.0000		
		Cumulative Hack	-0.0193***	0.0000	-7.8814	0.0000		
		New Coin	-0.0709***	0.0243	-2.9113	0.0039	R-square	0.1781
	7 Days	Constant	-0.1402***	0.0265	-5.2922	0.0000		
		Cumulative Hack	-0.0235***	0.0000	-9.3695	0.0000		
		New Coin	-0.0645***	0.0246	-2.6260	0.0091	R-square	0.2276

*** p<0.01, ** p<0.05, * p<0.1

Table 13. EGARCH Results of Daily Futures Mispricing Regression with Hack/Stolen Bitcoin Effects and New Currency Issue Effects

Estimation equation:

$$x_t = c_1 + c_2 HackCum + c_3 \text{NewCoin} + \epsilon_t$$

$$\log(\sigma_t^2) = c_4 + c_5 \frac{|\epsilon_{t-1}|}{\sqrt{\sigma_{t-1}^2}} + c_6 \frac{\epsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} + c_7 \log(\sigma_{t-1}^2)$$

HackCum constitutes cumulative amount of stolen Bitcoin from December 2017 (in thousands of Bitcoins).. N*ewCoin* variable refers dummy variable of new cryptocurrency release. The dummy variable has value of 1 from D_{-1} to D_{+5} of new coin releases, otherwise 0. The datasets have two different types of rollover methodologies: nearby and 7 days before expiration, and each methodology is presented in Nearby and 7 Days columns, respectively. Coefficients and P-values indicators)

Exchange	CBOE		CME	
Rollover	Nearby	7 Days	Nearby	7 Days
C(1)	-0.0337***	-0.0188*	-0.1175***	-0.0854***
C(2)	-0.0352***	-0.0379***	-0.0277***	-0.0338***
C(3)	-0.0180***	-0.0786***	-0.0825***	-0.0511***
C(4)	-2.0316***	-1.9698***	-2.2689***	-2;2581***
C(5)	1.3016***	1.1201***	1.3440***	1.2992***
C(6)	0.1619	0.1337	0.2019	0.1753
C(7)	0.8034***	0.7644***	0.7555***	0.7395***
R-squared	0.0853	0.1980	0.0186	0.1445

*** p<0.01, ** p<0.05, * p<0.1

Credit Author Statement

Research in International Business and Finance

Pricing Efficiency and Arbitrage in the Bitcoin Spot and Futures Markets,

RIBAF_2019_952

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