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Tracking safe haven properties of cryptocurrencies during the COVID-19 pandemic: A smooth transition approach

Abir Melki a,⁎, Nourhaine Nefzi b

a LR. GEF2A, Higher Institute of Management of Tunis, University of Tunis, Tunisia
b LR. MACMA, Higher Institute of Management of Tunis, University of Tunis, Tunisia

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ABSTRACT

The study aims to examine the hedge and safe-haven properties of three heavyweight cryptocurrencies—Bitcoin, Ripple, and Ethereum—against the stock, commodity, and foreign exchange markets. The study sample covers the period of August 2011 to September 2020 and therefore includes the current coronavirus disease-2019 (COVID-19) crisis. Using a logistic smooth transition regression model (LSTR2), the study findings indicate the ability of monitored cryptocurrencies to act as safe-haven assets, but such behavior differs across markets. Interestingly, during the pandemic period, Ethereum provides the strongest safe haven function for the commodity market. According to our findings, we are mindful of that the COVID-19 outbreak provides an exciting opportunity to advance our knowledge of the prominence of new coins such as Ethereum that are gradually gaining supremacy in the cryptocurrency market to the detriment of traditional cryptocurrencies like Bitcoin.

1. Introduction

The coronavirus pandemic, discovered in December 2019 in Wuhan, China, has affected more than 200 countries. Until September 2020, it has infected almost 28 million people and caused more than 900 000 deaths worldwide.¹

The implementation of lockdown measures during the disease has severely shaken the stability of the international financial market. Baig et al. (2020) argued that rises in confirmed cases and deaths due to coronavirus are associated with a significant increase in market illiquidity and volatility. Zaremba et al. (2020) found a strong relationship between government interventions due to coronavirus and higher stock market volatility. The impact on commodity markets, such as gold and oil, has made these assets inefficient compared to the period before the pandemic (Mensi et al., 2020). A decline in the Foreign Exchange (FX) market efficiency has also been indicated in many studies, such as Aslam et al. (2020), Njindan Iyke (2020), and Okorie and Lin (2020). Studies have revealed that mainstream assets are affected by the pandemic and digital currencies have suffered important losses. An analysis conducted by Lahmiri and Bekiros (2020) suggests an upward trend in volatility and a decline in the level of stability and irregularity of cryptocurrencies during the COVID-19 crisis.

Within this environment of great loss and uncertainty caused by the ongoing COVID-19 pandemic, deep research on safe-haven

⁎ Corresponding author.
E-mail addresses: melki_abir@yahoo.fr (A. Melki), Nourhaine.Nefzi@isg.rnu.tn (N. Nefzi).

¹ https://www.worldometers.info/coronavirus/

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assets during this health crisis is needed. Following the definition of Baur and Lucey (2010), an asset is considered a weak (strong) safe haven when it is uncorrelated (negatively correlated) with another asset during market turmoil. Additionally, a weak (strong) hedge is uncorrelated (negatively correlated) with another asset on average. Traditionally, the literature suggests various safe-haven assets, including gold, commodities, Forex, and cryptocurrencies. However, the literature on the safe-haven properties of these latter candidates is still rather sparse and results are mixed.

On the one hand, several authors demonstrate the safe-haven capabilities of Bitcoin against stock markets (Dyhrberg, 2016) and currencies (Urquhart and Zhang, 2019). These studies argue that specific properties of cryptocurrencies, including independence from monetary policy, their role as a store value and the non-correlation with traditional assets strengthen their resilience during crisis periods and justify their safe-haven behavior (Baur, Hong, and Lee, 2018). Additionally, Guesmi et al. (2019) found that the introduction of Bitcoin into a portfolio, including gold and stock assets, reduces its variance during stress periods.

On the other hand, studies bring into question the safe-haven properties of cryptocurrencies. For example, Corbet, Lucey, and Yarovaya (2018) provided evidence of bubble behavior for Bitcoin and Ethereum. Smales (2019) confirms that Bitcoin is more volatile, expensive, and less liquid than traditional safe-haven assets. Klein, Thu, and Walther (2018) reported the inability of Bitcoin to be neither a hedging asset nor a safe-haven investment for traditional assets.

With the onset of the pandemic, the focus on whether cryptocurrencies act as safe-haven investments during such a period becomes more urgent. Corbet, Hou, et al. (2020) argued that large cryptocurrencies are not only useful for diversification of benefits but also present safe-haven assets during the COVID-19 pandemic. In contrast, Conlon and McGee (2020) show an increase in portfolio downside risk after a small allocation of Bitcoin during the pandemic. This result is supported by Corbet, Larkin, and Lucey (2020) who demonstrated the role of Bitcoin as amplifiers of contagion rather than a hedge or safe instrument over the COVID-19 pandemic. Conlon et al. (2020) found that Bitcoin and Ethereum are not safe havens for almost monitored indices, while Ji, Zhang, and Zhao (2020) suggested that Bitcoin and Forex currencies are weak safe-haven tools during the COVID-19 pandemic. Naeem et al. (2020) demonstrate that, while Bitcoin is just a diversifier for commodities during the post crush period, Ethereum and Ripple are the most superior hedge and strongest safe-haven assets. More recently, through DCC regressions, Mariana et al. (2020) profess that Bitcoin and Ethereum are suitable as short-term safe-havens, with Ethereum a better safe-haven than Bitcoin.

This study is related to the literature on whether cryptocurrencies (especially Bitcoin, Ethereum, and Ripple) are hedges, and/or safe havens to stocks, commodity, and foreign exchange (FX) markets under the colossal pandemic crisis.

Our econometric framework is based on the Beckmann, Berger, and Czudaj (2015) methodology. The authors employ the Exponential Smooth Transition Regression (ESTR) model to describe the hedge and safe-haven properties of gold. In this paper, we use, however, the second-order logistic function that allows a slower transition between market states, compared to the exponential function. This provides a more realistic description of market behavior given that investors do not respond simultaneously to news, and thus, it takes time for the market to react. The paper covers a sample period running from August 18, 2011, to September 4, 2020, on a daily frequency and therefore includes the current COVID-19 crisis. To our knowledge, no research has been conducted on the safe-haven properties of cryptocurrencies during the coronavirus outbreak using this approach.

As will be revealed, our findings indicate that, contrary to the Bitcoin showing neither safe-haven nor hedge behavior during the sample period, Ethereum acts as a strong safe-haven for the commodity market. During the COVID-19 period, Ripple shows a safe-haven behavior toward the FX market. Interestingly, Ethereum is found to be better than Bitcoin as a safe-haven asset for commodity market during the same period. These results showcase the potential of cryptocurrencies other than Bitcoin to serve as a safe-haven asset, while previous studies mainly highlight the useful role of Bitcoin.

Our findings are useful for investors and financial advisors searching for the validity of cryptocurrencies to hedge extreme negative movements in stock, commodity, and FX markets, and to improve risk management decisions of their portfolio.

The remainder of the paper proceeds as follows: Section 2 outlines the methodology and describes the data, Section 3 presents the empirical result, and Section 4 summarizes and concludes our findings.

2. Data and methodology

We consider the following three largest cryptocurrencies (in terms of market capitalization): Bitcoin, Ethereum, and Ripple. MSCI world, Gold Bullion LBM, and EUR/USD returns are selected as proxies for the stock, commodity, and foreign exchange (FX) markets, respectively. The sample covers the period of August 18, 2011, to September 4, 2020, except for Ethereum and Ripple, where the data started on August 10, 2015. The daily return series are defined as follows:

\[ R_t = \log \left( \frac{P_t}{P_{t-1}} \right) \] (1)

With \( R_t \) is the return series at date \( t \), and \( P_t \) and \( P_{t-1} \) are the variable prices at \( t \) and \( t-1 \), respectively.\(^4\)

\(^2\) According to Baur and Lucey (2010), an asset is defined as a safe haven when it is negatively correlated with other assets or portfolios during market turmoil.

\(^3\) https://www.coinmarketcap.com/

\(^4\) Descriptive statistics for all return series are presented in Appendix Table A.1.
We start by illustrating cryptocurrency movements during the outbreak of COVID-19, which would provide some initial guidance regarding the safe-haven features of these currencies. As observed in Fig. 1, all currencies have experienced significant downward pressure on February 2020 and have been moving at a very similar trend during this period, before starting escalating again in March 2020.

Table 1 displays the summary statistics of return series during the pandemic. All cryptocurrencies exhibit higher returns and larger variability than financial markets, highlighting the influence of the COVID-19 period on the latter. The return distribution for all series is negatively skewed, except for the FX market, while all variables are heavy tailed. Jarque-Bera (JB) test confirms the leptokurtic

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5 Following Conlon and McGee (2020b), we define the COVID-19 outbreak as the period stretching from March, 21 2019, through September, 04 2020.
behavior of return series. Overall, Table 1 supports the typical conclusion that asset returns are asymmetric and non-Gaussian.

To examine the behavior of cryptocurrencies during stable and volatile periods, we employ a smooth transition regression (STR) model, which has the following expression:

\[ RC_t = a_1 + \beta_1 R_{M,t} + [a_2 + \beta_2 R_{M,t}]G(zt; \gamma, c) + \varepsilon_t \]

(1)

where \( R_{C,t} \) denotes cryptocurrency return; \( R_{M,t} \) is the market return; \( \gamma \) measures the transition speed between regimes; \( c \) is a threshold parameter; and \( G(\cdot) \) is the transition function that depends on the transition variable \( z_t \), as well as the parameters \( \gamma \) and \( c \). In this study, \( z_t \) is chosen as the lagged market return.

Terasvirta and Anderson (1992) distinguish between two main forms of the STR model, namely, the logistic smooth transition regression (LSTR) and the exponential smooth transition regression (ESTR). The LSTR model incorporates two main functions: the first order logistic function (LSTR1) and the second-order logistic function (LSTR2). Both LSTR2 and ESTR meet our objective, i.e., the detection of the behavior of each currency in stable and volatile regimes. However, we limit our empirical investigation to the second-order logistic function that allows a slower re-switching between regimes compared to the exponential function. This provides a more realistic description of market behavior given that investors do not respond simultaneously to news, and thus, it takes time for the market to react.

\( G(\cdot) \) in the LSTR2 model is defined as follow:

\[ G(z_t, \gamma, c) = \left[ 1 + \exp \left\{ -\gamma(z_t - c_1)(z_t - c_2) \right\} \right]^{-1}, \gamma > 0 \]

(2)

\( G(\cdot) \) is bounded between zero and 1. It takes a value of zero if it is in the lower regime, i.e., stable period (where \( a_1 + \beta_1 \) belong) and unity if it is in the upper regime, i.e., volatile period (where \( a_1 + \beta_2 \) and \( \beta_1 + \beta_2 \) are estimated). The function is symmetric about the point \( z_t = c_2 \), while its minimal value lies between 0 and 0.5 (stable regime). The volatile regime is observed when \( \lim_{z_t \to \pm \infty} G = 1 \).

As mentioned in Beckmann et al. (2015), hedging and safe-haven properties can be tested by examining \( \beta_1 \) and \( \beta_1 + \beta_2 \) respectively. Precisely, a cryptocurrency is identified as a strong (weak) hedging asset for a specific market if \( \beta_1 \) is significantly negative (not significantly different from zero), while it is considered a strong (weak) safe-haven asset if \( \beta_1 + \beta_2 \) is significantly negative (not significantly different from zero).

To test the non-linearity of the relationship, we employ the Luukkonen, Saikkonen, and Teräsvirta (1988) test procedure which consists of replacing the transition function by the third-order Taylor approximation:

\[ R_{C,t} = \mu_1 + \varphi_1 R_{M,t} + \varphi_2 R_{M,t} z_t + \varphi_3 R_{M,t} z_t^2 + \varphi_4 R_{M,t} z_t^3 + \varepsilon_t \]

(3)

where the parameter vectors \( \varphi_1, \varphi_2, \varphi_3 \) are multiples of \( \gamma \).

The linear model is included in Eq. (1) for \( G(zt, \gamma, c) = 0 \) and the null hypothesis for which the linear model is adequate is tested under the hypothesis \( H_0: \varphi_i = 0 \) with \( i = 1, 2, 3 \) against \( H_1: \) at least one \( \varphi_i \neq 0 \) (Terasvirta 1998). The test results can also identify the appropriate transition variable, i.e., the one showing the smallest p-value.

Once the null hypothesis of linearity is rejected, the choice between LSTR1 and LSTR2 is made by applying the following hypothesis test sequence:

- \( H_{03}: \varphi_3 = 0 \)
- \( H_{02}: \varphi_2 = 0 | \varphi_3 = 0 \)
- \( H_{01}: \varphi_1 = 0 | \varphi_3 = \varphi_2 = 0 \)

We use a grid search over \( \gamma \) and \( c \) to find the appropriate initial estimates, and thereafter, we proceed with the estimation of \( \gamma \) and \( c \) using the Newton-Raphson algorithm.

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6 We have ascertained that all series returns are stationary using Augmented Dickey–Fuller and Philips–Perron tests
7 For the selection of the transition function, more details are presented in Appendix A
8 The grid search algorithm is a non-linear optimization algorithm that determines the optimal values of \( \gamma \) and \( c \) which minimize the residual sum of squares

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Table 1

|                | MSCI | FX   | COM  | Bitcoin | Ethereum | Ripple |
|----------------|------|------|------|---------|----------|--------|
| Mean           | 0.00026 | 0.00032 | 0.0013 | 0.0018 | 0.0047 | 0.00075 |
| Std.           | 0.02  | 0.004923 | 0.011 | 0.053 | 0.06  | 0.054  |
| Kurtosis       | 8.83 | 1.68 | 4168 | 38.28 | 27.26 | 14.27 |
| JB test        | 666.116 | 21.46 | 144.85 | 11,852.44 | 6179.67 | 1701.52 |
| (0.000)        | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
Table 2
Linearity test and model identification (Entire Period).

| Markets | Z lag | F-stat     | F4         | F3         | F2         | Model   |
|---------|-------|------------|------------|------------|------------|---------|
| Bitcoin | MSCI  | 1          | 9.286e-07  | 1.91e-03   | 2.9535e-03 | 8.03e-04 | LSTR1   |
| COMD    | 2     | 3.373e-03  | 8.77e-03   | 1.5458e-02 | 4.27e-01   | LSTR1   |
| FX      | 1     | 2.23e-02   | 1.468e-01  | 1.42e-02   | 3.0e-01    | LSTR1   |
| Ripple  | MSCI  | 1          | 2.0063e-02 | 2.1e-01    | 1.8307e-02 | 1.42e-01 | LSTR2   |
| COMD    | 9     | 3.373e-03  | 8.77e-03   | 1.5458e-02 | 4.27e-01   | LSTR2   |
| FX      | 3     | 2.0592e-02 | 2.7645e-01 | 7.8707e-01 | 2.52e-03   | LSTR2   |

Note: This table displays the linearity test and the model identification for stock (MSCI), commodity (COMD) and foreign exchange (FX) markets. The different p-values of F-statistics are estimated as suggested by Luukkonen et al. (1988). The test is executed for j lag orders, where j = 1, 2, … 10, and the lagged variable with the strongest test rejection (the smallest p-value) is selected as the appropriate transition variable.

Table 3
LSTR2 Estimation results – Entire Period.

|            | Bitcoin | Ethereum | Ripple |
|------------|---------|----------|--------|
|            | FX      | MSCI     | COMD   | MSCI     | COMD   |
| α1         | 0.00166 | 0.00457**| 0.00163| 0.0033   | 0.002  |
| (0.0012)   | (0.0021)| (0.0046) | (0.0023)| (0.002)  |
| β1         | 0.237   | 0.53**   | 1.07***| 0.47*    | 0.4    |
| (0.242)    | (0.226) | (0.325)  | (0.27) | (0.27)   |
| α2         | 0.026***| -0.0412* | 0.144***| -0.017   | 0.027  |
| (0.0056)   | (0.22)  | (0.05)   | (0.011)| (0.04)   |
| β2         | 0.09    | 3.7288** | -6.29* | 1.707*** | 8.05***|
| (0.84)     | (0.637) | (3.415)  | (0.5)  | (1.93)   |
| γ          | 7336    | 1.013    | 201*   | 3.49     | 63.14  |
| (4653)     | (0.000) | (0.117)  | (7.56) | (25,444) |
| C1         | -0.009  | -0.035***| -0.045***| -0.016***| -0.025***|
| (1069)     | (0.000) | (0.0058) | (0.001)| (0.005)  |
| C2         | 0.013   | 0.0584***| 0.0367***| 0.057*** | 0.05***|
| (1561)     | (0.000) | (0.006)  | (0.0009)| (0.001)  |

Note: This table displays the estimates of LSTR2 given the Eqs. (1) and (2). Numbers in parentheses are standard errors. ‘***’, ‘**’, and ‘*’ denote significance at 1%, 5%, and 10%, respectively.

Table 4
LSTR2 Estimation results (COVID19 period).

|            | Bitcoin | Ethereum | Ripple |
|------------|---------|----------|--------|
|            | MSCI    | COMD     | MSCI   | COMD   |
| Z lags     | 1       | 1        | 1      | 1      | 1      | 1 |
| α1         | -0.022  | -0.001   | 0.003  | -0.00063| -0.02  | 0.07***| -0.06 |
| (0.02)     | (0.0025)| (0.0026)| (0.003)| (0.019) | (0.09) | (0.08) |
| β1         | 0.237   | 0.53**   | 1.07***| 1.07*** | 67.9***| 12.16***|
| (0.57)     | (0.26)  | (0.31)   | (0.4)  | (13.07) | (2.92) |
| α2         | 0.03    | 0.06***  | -0.06***| 0.06    | 0.024  | -0.35***| 0.06 |
| (0.02)     | (0.018) | (0.021)  | (0.02) | (0.095) | (0.08) |
| β2         | -3.56***| -2.94*** | 3.7***  | -2.45***| -66.91***| -11.56***|
| (0.6)      | (0.87)  | (1.04)   | (0.44) | (13.1)  | (2.97) |
| γ          | 2.35    | 1.85     | 9.26   | 10.8    | 180.63*| 7944 |
| C1         | -0.1*** | -0.03*** | -0.038***| -0.03***| -0.01***| -0.06***| 0.03***|
| (0.0021)   | (0.003) | (0.003)  | (0.005)| (0.0003)| (0.00) |
| C2         | -0.03***| 0.025*** | 0.057***| 0.024***| -0.03***| -0.06***| 0.00***|
| (0.004)    | (0.0017)| (0.0006)| (0.0008)| (0.0033)| (0.00) |

Note: This table presents the estimated results of LSTR2 model during the COVID-19 period after rejecting the linearity hypothesis. Z lags is the lagged transition variable with the strongest test rejection (the smallest p-value). Numbers in parentheses are standard errors. ‘***’, ‘**’, and ‘*’ denote significance at 1%, 5%, and 10%, respectively.
3. Empirical results

We start our analysis by conducting the linearity test on a set of transition variables delayed from one to 10. The transition variable is selected as the one showing the smallest p-value. Table 2 displays the linearity test results during the sample period and the appropriate model for each case. As mentioned previously, only the second-order logistic function can describe the behavior of cryptocurrencies in two different states of the market. Given the estimated results, we investigate, on the one hand, the hedge and safe-haven properties of Bitcoin in the FX market and, on the other hand, Ripple and Ethereum behaviors in stock and commodity markets.

Table 3 presents results for the LSTR2 model during the entire period. Notably, the estimated coefficients indicate significant differences among the three monitored cryptocurrencies regarding the hedge and safe-haven properties. Indeed, Ethereum exhibits a strong safe-haven function for the commodity market since \((\beta_1 + \beta_2)\) are significantly negative. Ripple does not exhibit a hedge/safe-haven functions in the stock and commodity markets given the positive estimated values of \(\beta_1\) and \(\beta_2\). Bitcoin also appears as neither a hedge nor a safe-haven for all the three markets, confirming the conclusions of Conlon et al. (2020), Conlon and McGee (2020), and Corbet, Larkin, et al. (2020). The estimated values of \(\gamma\) differ across markets highlighting the usefulness of the selected approach (Beckmann et al., 2015).

In an attempt to assess whether the behavior of the three monitored cryptocurrencies has changed during the COVID-19 pandemic, we re-estimate the model by splitting the sample into two sub-periods: before COVID-19 and during COVID-19. As seen in Table 4,
Ripple is found to be a weak safe-haven asset for the FX market given that $\beta_1 + \beta_2 \approx 0$, i.e., the two markets are almost uncorrelated during the pandemic period. We did not find a hedge or safe-haven functions provided by Bitcoin before the onset of the coronavirus. However, this coin shows a strong safe-haven behavior toward the commodity market during the pandemic scenario ($\beta_1 + \beta_2 = -1.14$). Interestingly, Ethereum is found to be a strong safe-haven for the commodity market during the pre-crisis and the COVID-19 periods. This rather result could be due to considerable price fluctuations of the commodity market observed after the financial crisis (Wu et al., 2020). By comparing the behavior of Ethereum and Bitcoin against the commodity market during the COVID-19 pandemic, it is clear that Ethereum outperforms Bitcoin as a safe-haven since $\beta_1 + \beta_2 = -1.91$.

Fig. 2 illustrates how the transition function of the commodity market is switching between stable and volatile regimes during the entire period. The role of Ethereum as a safe-haven asset can be observed in regimes such as the COVID-19 period where the commodity market exhibits negative trends, but where the Ethereum performance is nevertheless positive.

Results presented so far are in line with Naeem et al. (2020) who find that Ethereum constitutes one of the strongest safe-haven assets for commodities. However, our findings have extended our knowledge about cryptocurrencies’ ability to outperform Bitcoin and act as a safe-haven asset during the COVID-19 period.

Two main attributes of Ethereum may explain our findings. First, Bitcoin is gradually losing its supremacy in the cryptocurrency market to the detriment of new rival cryptocurrencies (Bouri, Hussain Shahzad, and Roubaud, 2020). Second, the dramatic decline experienced by Bitcoin during COVID-19 has encouraged investors to transfer their funds to more attractive havens like Ethereum characterized by a low transaction fee and an advanced blockchain technology. Indeed, Ethereum is the second most decentralized cryptocurrency in the world and has low dependence on Bitcoin. Thus, investors who are seeking diversification and minimizing risk may have recourse to this currency as a store value and an effective tool that minimizes risk.

4. Conclusion

This study set out to assess the hedge and safe-haven properties of the three heavyweight cryptocurrencies, namely, Bitcoin, Ethereum, and Ripple, against the stock, foreign exchange, and commodity markets. The investigation accounts for the COVID-19 period that presents an initial testing ground for the safe-haven properties of cryptocurrencies. Using a second-order LSTR model, our results highlight the ability of Ripple to act as a weak safe-haven asset for the forex market during the pandemic crisis. Moreover, while Bitcoin and Ripple show neither a safe-haven nor a hedge for the three markets, they provide, respectively, safe-haven functions for the commodity and FX markets during the pandemic period. One unanticipated finding was the behavior shown by Ethereum. Indeed, this currency outperformed Bitcoin by providing a stronger safe-haven for the commodity market during both the pre-crisis and COVID-19 periods. These findings are consistent with those of Mariana, Ekaputra, and Husodo (2020) who argue that although both cryptocurrencies exhibit safe-haven features, Ethereum appears to be a better safe-haven than Bitcoin.

In summary, our work sheds light on the useful role of cryptocurrencies other than Bitcoin, such as Ripple and specifically Ethereum, to exert their safe-haven function during extreme downward situations. Our results also support Corbet, Hou, et al.’s (2020) findings arguing that using cryptocurrencies as safe-haven investments during stress periods presents a significant alert for policymakers to focus on cryptocurrencies and adjust their monetary policy decisions.

Finally, one important limitation that needs to be mentioned is the non-consideration of the heteroscedasticity problem presented in cryptocurrency behavior. Thus, as an interesting path for further research, we would suggest an empirical analysis that accounts for the GARCH effect. Further studies also need to be conducted to investigate the safe-haven qualities of stablecoins during the disease period.

Authorship contributions

Category 1

Conception and design of study: Abir Melki (A.Melki), Nourhaine Nefzi (N.Nefzi),
Acquisition of data: Nourhaine Nefzi (N.Nefzi)
Analysis and/or interpretation of data: Nourhaine Nefzi (N.Nefzi)

Category 2

Drafting the manuscript: Abir Melki (A.Melki), Nourhaine Nefzi (N.Nefzi), revising the manuscript critically for important intellectual content: Abir Melki (A.Melki), Nourhaine Nefzi (N.Nefzi),

Category 3

Approval of the version of the manuscript to be published (the names of all authors must be listed): Abir Melki (A.Melki); Nourhaine Nefzi (N.Nefzi),

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9 Based on sequential testing procedure of Terasvirta and Anderson (1992), LSTR2 is identified as the appropriate model for Ethereum-commodity market and Ripple-stock market during the pre-crisis period. The estimated results are presented in Appendix B.2.
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Appendix A. Selection of STR function

The decision rule for choosing between the LSTR1 and LSTR2 model is given as follows:

- The rejection of $H_{02} : \phi 3 = 0$ implies the selection of the LSTR1 model. If $H_{02}$ is not rejected, then we proceed to test $H_{02} : \phi 2 = 0 | \phi 3 = 0$.
- Rejection of $H_{02}$ involves the selection of the LSTR2 model as appropriate. If $H_{02}$ is not rejected, we proceed to test $H_{01} : \phi 1 = 0 | \phi 3 = \phi 2 = 0$.
- Rejection of $H_{01}$ involves the selection of the LSTR1 model.

Overall, if $H_{02}$ has the strongest rejection (the lowest p-value), the LSTR2 model is selected; otherwise, we choose the LSTR1 specification.\(^\text{10}\)

Appendix B

Tables B.1 and B.2

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