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Essays on Cryptocurrencies and Traditional Assets in Emerging Market Economies:

Dynamic Modelling, Connectedness, and Spillovers

By

MAURICE OMANE-ADJEPONG

A Doctoral Thesis Submitted in Fulfilment of the Requirements for the Award of

DOCTOR OF PHILOSOPHY

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UNIVERSITY OF THE WITWATERSRAND

Supervisor: Professor Imhotep Paul Alagidede

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Abstract

The last decade has experienced notable changes and unique innovations in the global financial system. In particular, the introduction of cryptocurrencies, pioneered by Bitcoin and later other alternative coins (best known as altcoins) by libertarian cryptographers after several efforts in the 1990s to usher in electronic currencies foundered, has been lauded and likewise received enormous attention worldwide, raising many concerns for governments, monetary authorities and other regulatory bodies. Originally designed as electronic cash for decentralised peer-to-peer online financial transactions, secured by cryptographic algorithms, cryptocurrency, a specialised kind of digital currency, in barely a decade of existence, is challenged with an identity crisis. The debate as to what cryptocurrency is, or has become looms in the minds of the general public, and it has been the subject of media commentary. At the same time, the limited amount of research on the topic has only raised more questions than answers. For instance, not only are the existing studies not attacking the root of the deepest questions posed by the rise of cryptocurrencies to date, but also they are not robustly studied methodologically. The depth of analysis is shallow, and the scope of the studies published on the subject matter so far is very limited, both in space and time. Additionally, the extent of the relatedness of the new digital currency market to traditional assets, especially in frontier and emerging economies remains a virgin field. This naturally raises additional concerns: does the emergence of cryptocurrencies offer any relevant economic benefits to these emerging market economies? What implications does this evolution hold for established financial systems? Answers to these questions, and many more are crucial for monetary policy effectiveness, legislation and regulation, financial system stability, the future of cryptocurrencies, and overarchingly, to illuminate the blind spots of the enthusiastic libertarian public, as well as the general investor community.

In light of the above, this thesis makes a bold attempt at addressing some of the weaknesses of extant research, extend the frontiers of knowledge in this new financial instrument, and shed insights on cryptocurrencies in emerging market economies, proxied by those in the G20. The study produced interesting juxtapositions in three essays.

The first essay examined the evolving characteristics of cryptocurrencies under five sub-themes, and presents a map for analysing the cryptocurrency market. We find that Bitcoin and the largest long-lived altcoins are collectively unique instruments that share features of paper money, security assets (mostly equities), and commodity money (such as gold and oil), making the digital currencies a "*trinity-hybrid*" financial instrument which could best operate under the private sector to complement emerging currencies and assets. For emerging market economies, cryptocurrencies, in our view, is a three-in-one financial instrument, if and only if its role is limited to exchange of goods and services, and helping facilitate transactions of various kinds. This, in turn, raises a number of possibilities for recalibrating the current financial architecture while addressing the regulatory changes that ought to be in place for a well-functioning diversified economy.

The second empirical essay found evidence in favour of an extremely weakly correlated market, and later, multifaceted economic benefits of cryptocurrency in times where emerging market economies' assets wander in distress. This positions the new currency market to the advantage of heterogeneous groups of emerging market investors. However, we caution that expectations of such derived economic benefits need to be examined further on a case by case basis, and in a measured manner, especially given that the cryptocurrency market is still at its embryonic stages of evolution.

The third and final essay allays the fears of investors and market participants, and reveals for the first time that the cryptocurrency market is less influenced by existing highly integrated instruments, and has little effect on emerging markets, and consequently pose, for now, a negligible danger. At their current level of development, some economies are not yet exposed to the variety of developments in the world of electronic commerce and payment systems that make the algorithms that power the peer-to-peer decentralised ledger platforms seamless. This may change in the future. For now, we are sure that the coming into being of cryptocurrencies is an inevitable consequence of the financial sector paradigms of the last few decades, however, the distributional consequences across regions, countries and among different market participants are largely asymmetric. The insights gleaned from this study, therefore, open doors for policymakers to properly fine-tune their economies to maximise the upside potential presented by this asset class and minimise the downside risks, in the light of what has been learned about the role of cryptocurrencies so far.

Keywords: Cryptocurrency; Emerging markets economies; Digital currency; Assets; Shock spillover; Dynamic relatedness.
Jel Classification: C10; C12; C13; C14; C16; C22; F31; G10; G11; G14; G15; G18

Outputs: Ongoing/Forthcoming Publications

Before submission of the thesis, extracts from its chapters have been presented in academic conferences, and published as proceedings and peer reviewed articles, the majority of which are still under submission. Other related published content by the candidate are also presented.

Empirical research outputs from the thesis

1. **Omane-Adjepong, M.,** Alagidede, I.P., 2020. High- and low-level chaos in the time and frequency market returns of leading cryptocurrencies and emerging assets. ***Chaos, Solitons and Fractals,*** 132. https://doi.org/10.1016/j.chaos.2019.109563. ***(Elsevier).***
2. **Omane-Adjepong, M.,** Alagidede, I.P. 2020. Dynamic linkages and economic role of leading cryptocurrencies in an emerging market. ***Asia-Pacific Financial Markets (In-press).*** *https://doi.org/10.1007/s10690-020-09306-4*. ***(Springer***).
3. **Omane-Adjepong, M.,** Alagidede, I.P., Probability distributions of returns in cryptocurrencies and emerging financial markets (***Under Review in Financial Innovation - Springer***).
4. **Omane-Adjepong, M.,** Alagidede, I.P. Herding behaviour in global virtual currency and emerging stock and exchange rate markets (***Under Review in Cogent Economics and Finance – Taylor & Francis***).
5. **Omane-Adjepong, M.,** Alagidede, I.P. Exploring return and volatility interdependence and spillovers between cryptocurrencies and emerging financial assets (***Revised-Resubmission in Financial Markets and Portfolio Management - Springer***).
6. **Omane-Adjepong, M.,** Alagidede, I.P. Modelling asymmetry and leverage in cryptocurrencies and emerging financial markets. ***Economic Papers: A journal***

of applied economics and policy (In-press). https://doi.org/10.1111/17593441.12308. ***(Wiley & Sons)***.

7. **Omane-Adjepong, M.,** Alagidede, I.P. Multifractal and market efficiency analysis of cryptocurrencies and emerging financial market assets (***Ongoing - To be Submitted to International Advances in Economic Research – Springer***).

Related published articles in peer-reviewed journals

1. **Omane-Adjepong, M.,** Alagidede, P., Akosah, N.K., 2019. Wavelet time-scale persistence analysis of cryptocurrency market returns and volatility**.** ***Physica A: Statistical Mechanics and its Applications,*** 514, 105-120. https://doi.org/10.1016/j.physa. 2018.09.013. ***(Elsevier).***
2. **Omane-Adjepong, M.,** Alagidede, I.P., 2019. Multiresolution analysis and spillovers of major cryptocurrency markets. ***Research in International Business and Finance,*** 49, 191-206**.** https://doi.org/10.1016/ j.ribaf.2019.03.003. ***(Elsevier).***
3. **Omane-Adjepong, M.,** Ababio, K.A., Alagidede, I.P., 2019. Time-frequency analysis of behaviourally classified financial markets. ***Research in International Business and Finance,*** 50, 54-69. https://doi.org/10.1016/j.ribaf.2019.04.012. ***(Elsevier)***
4. Ijasan, K., Tweneboah, G., **Omane-Adjepong, M.,** Junior, P.O., 2019. On the global integration of REITs market returns: A multiresolution analysis. *Cogent Economics & Finance*, 1690211. https://doi.org/10.1080/23322039.2019.1690211. (***Taylor & Francis***).
5. **Omane-Adjepong, M.,** Alagidede, P., Dramani, J.B., 2020. COVID-19 outbreak and behaviour of global markets: Insight from dynamic wavelet coherence analysis ***(Accepted in Intech Open).***
6. **Omane-Adjepong, M.,** Alagidede, I.P., 2020. Exploration of safe havens for Africa's stock markets: A test case under COVID-19 crisis. ***Finance Research Letters (In-press).*** https://doi.org/10.1016/j.frl.2020.101877. ***(Elsevier).***

7. **Omane-Adjepong, M.,** Alagidede, I.P., 2020. Is bitcoin a substitute for traditional commodity money? A safe haven for Africa's forex markets during the COVID-19 outbreak. Available online at: https://ssrn.com/abstract=3688625.
8. **Omane-Adjepong, M.,** Amewu, G., Alagidede, I.P., Akosah, N.K., 2020. Co-movement of Africa's emerging stock markets: A new look under the COVID-19 outbreak. Available at: https://ssrn.com/abstract=3702967.

Academic conferences

1. **Omane-Adjepong, M.,** Ababio, K.A., Alagidede, I.P., 2018. Time-frequency analysis of behaviourally classified financial asset markets. ***Proceedings of the 3rd African Review of Economics and Finance Conference, Johannesburg, South Africa, 21-22 August 2018*** *(Paper presentation by Omane-Adjepong, M.).*
2. **Omane-Adjepong, M.,** Alagidede, I.P., 2019. Probability distributions of returns in cryptocurrencies and emerging financial markets. ***Proceedings of the 4th African Review of Economics and Finance Conference, Johannesburg, South Africa, 21-22 August 2019*** *(Paper presentation by Omane-Adjepong, M.).*
3. **Omane-Adjepong, M.,** Alagidede, I.P., 2019. Probability distributions of returns in cryptocurrencies and emerging financial markets. ***Proceedings of the 10th Annual Cross-Faculty Symposium of University of The Witwatersrand, South Africa, 03-04 September 2019*** *(Paper presentation by Omane-Adjepong, M.).*
4. **Omane-Adjepong, M.,** Alagidede, I.P., 2020. Dynamic linkages and economic role of leading Cryptocurrencies in an Emerging Market. ***Proceedings of the 57th Academy of Economics and Finance, Atlanta, Georgia, 6-9 February 2020*** *(Paper presentation by Omane-Adjepong, M.).*

Declaration

I, **Maurice Omane-Adjepong**, hereby declare that this research report is my work except as indicated in the references and acknowledgements. It is submitted in fulfilment of the requirements for the award of Doctor of Philosophy degree in the field of Finance at the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination in this or any other university.

Maurice Omane-Adjepong

Doctoral research candidate



Signed on December 02, 2020

Dedication

This work is dedicated to my grandmother, **Obaapanyin Elizabeth Abena Antwiwaah,** under whose tutelage I learnt my first lesson of life's most basic principles and the need to help mankind; to my mother, Christiana Tetteh, under whose watch as a single parent, I aspired to hold up to sound social and moral standards and developed my educational credentials; to my wife Mrs Sonita Omane-Adjepong, who has been outstandingly supportive throughout this epic academic journey; to my mother-in-law, Emelia Adiyiah, and my beloved children, Nana Akosua Antwiwaah Omane-Adjepong and Maurice Omane-Adjepong Junior, the next generation of PanAfricanists.

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I say "ayekoo" (well-done) for contributing to the success of this transient life model.

Table of Content

Abstract ii

Outputs: Ongoing/Forthcoming Publications v

Declaration viii

Dedication ix

Acknowledgement x

Table of Content xii

List of Tables xviii

List of Figures xx

List of Appendices xxii

CHAPTER 1

General Introduction

1.1 Background to the Study 001

1.2 Evolution and contemporary issues of cryptocurrency 005

1.3 Aims of the Thesis 009

1.4 Significance and contribution to the body of knowledge 010

1.5 Impediments to this Thesis 013

1.6 Thesis layout 015

CHAPTER 2

Stylized Properties of Cryptocurrencies and Traditional Financial Assets of Emerging Economies

2.1 Introduction 019

2.2 Literature review **026**

2.2.1 Empirical review on probability distributions of asset returns **027**

2.2.2 Stochastic randomness, non-linearity, and chaotic reviews **043**

2.2.3 Asymmetric volatility, fractality and herding survey **050**

2.2.4 Summary of the review **057**

2.3 Data and Empirical Methods **059**

2.3.1 Data specification **060**

2.3.2 Structural break (SB) methods **062**

2.3.2.1 Markov switching dynamic regression (MS-DR) **063**

2.3.3 Non-linearity, chaotic and random processes **065**

2.3.3.1 Brock-Dechert-Scheinkman (BDS) Test **065**

2.3.3.2 Terasvirta Neural Network (TNN) Test **067**

2.3.3.3 Entropy Test for Non-linearity (ETN) **068**

2.3.3.4 Largest Lyapunov Exponent (LLE) Test **070**

2.3.4 Parametric probability distributional modelling **073**

2.3.5 Asymmetry and leverage modelling **082**

2.3.5.1 GJR-GARCH and News Impact Curve **083**

2.3.5.2 NGARCH and News Impact Curve **084**

2.3.6 Wavelet-based time-scale decomposition **085**

2.3.7 Multifractal market measures and processes **086**

2.3.8 Herding measures **089**

2.4 Empirical results and analysis **091**

2.4.1 Preliminary examination **091**

2.4.2 Analysis of halcyon and volatile market dynamics **095**

2.4.3 Parametric probability distributional properties **097**

2.4.3.1 Fitted distribution and parameter estimates **101**

2.4.3.2 P-P graphical representation and density plots **108**

2.4.3.3 Risk computation **111**

2.4.4 Non-linearity, chaotic and random behaviour **115**

2.4.4.1 Evidence of non-linearity in asset returns **115**

2.4.4.2 Chaoticity vs. Stochasticity: LLE perspective **118**

2.4.5 Asymmetry and leverage in asset markets **122**

2.4.5.1 Evidence of asymmetric behaviour **124**

2.4.5.2 Evidence of local leverage **127**

2.4.5.3 Analysis of News Impact Curves **129**

2.4.5.4 Persistence analysis **132**

2.4.6 Multifractal analysis **135**

2.4.6.1 Multifractal characteristics of asset returns **137**

2.4.6.2 Evidence of market (in)efficiency **143**

2.4.6.3 Sources of the multifractal features **145**

2.4.7 Herding behaviour **148**

2.5 Concluding remarks **156**

CHAPTER 3

Dynamic Co-variation and Diversification with Applications to Cryptocurrencies and other Financial Assets

3.1 Introduction **159**

3.2 Review of related literature **162**

3.3 Research methods **167**

3.3.1 Time-varying conditional correlation approaches **167**

3.3.2 Wavelet decomposition **170**

3.3.3 Bivariate rolling-window wavelet correlation method **171**

3.4 Data and preliminary results **173**

3.4.1 Unconditional rolling-window correlation results **174**

3.5 Evidence from time-varying dynamic conditional correlation **176**

3.6 Time-frequency analysis **181**

3.6.1 Diversification ranking based on wavelet correlation matrix **183**

3.6.2 Pairwise correlations in time-frequency domain **184**

3.6.3 Portfolio performance analysis **190**

3.7 Hedge and safe haven capabilities of cryptocurrencies **194**

3.8 Conclusions **197**

CHAPTER 4

Interdependence and Spillovers between Cryptocurrencies and Emerging Financial Assets

4.1 Introduction **200**

4.2 Related literature **203**

4.3 Empirical methodology **208**

4.3.1 Specification of conditional volatility models **209**

4.3.2 Testing for non-linear interdependence **210**

4.3.3 Hill's causality approach **212**

4.3.4 Measuring return and volatility spillovers **214**

4.4 Data and preliminary analysis **218**

4.5 Empirical results **220**

4.5.1 Non-linear time-sample causality **220**

4.5.2 Rolling-Window causality analysis **224**

4.5.3 Spillover dynamics between cryptocurrencies and emerging markets **227**

4.5.3.1 Static spillover results **228**

4.5.3.2 Rolling-Window total spillover analysis **232**

4.5.3.3 Rolling-Window gross directional spillover analysis **236**

4.5.3.4 Rolling-Window net directional spillover analysis **239**

4.5.3.5 Robustness checks **241**

4.6 Conclusions **242**

CHAPTER 5

General Conclusion

5.1 Introduction **244**

5.2 Encapsulation of the Thesis **244**

5.3 Summary of major contributions **246**

5.3.1 Distribution of returns in cryptocurrencies and emerging markets **247**

5.3.2 Chaoticity vs stochasticity: financial markets conundrum **248**

5.3.3 Asymmetry and leverage in asset markets **249**

5.3.4 Multifractal analysis and market (in)efficiency **249**

5.3.5 Do investors of cryptocurrency and emerging markets herd? **250**

5.3.6 Dynamic co-movement and economic role of cryptocurrencies **250**

5.3.7 Cryptocurrency vs other assets: Interdependence and shock transmission **251**

5.4 Concluding remarks and recommendations **252**

5.5 Areas for further research **256**

References **258**

Appendices **287**

List of Tables

Table 2.10: Summary statistics of location, dispersion, and shape of sample distribution **092**

Table 2.11: Risk-adjusted returns, randomness, serial correlation, and heteroscedasticity **093**

Table 2.12: Markov regime switching for individual and aggregate log-returns **096**

Table 2.13: Distribution diagnostics for original shuffled cryptocurrency log-returns **098**

Table 2.14: Distribution diagnostics for outlier-adjusted cryptocurrency log-returns **099**

Table 2.15: Distribution diagnostics for original shuffled log-returns of BRICS FX and stock **102**

Table 2.16: Distribution diagnostics for outlier-adjusted log-returns of BRICS FX and stock **103**

Table 2.17: Distribution diagnostics for original shuffled returns of BRICS REIT, commodity and bond **105**

Table 2.18: Distribution diagnostics for outlier-adjusted returns of BRICS REIT, commodity and bond **106**

Table 2.19: Best fitted parametric distributions for the shuffled returns **109**

Table 2.20: Best fitted distributions for the outlier-adjusted returns **110**

Table 2.21: BDS results for filtered AR(1) residuals of individual and aggregate returns **116**

Table 2.22: Estimated TNN and ETN test measures **117**

Table 2.23: Estimated LLE for low-level chaos **120**

Table 2.24: Estimated LLE for high-level chaos **120**

Table 2.25: Estimated NGARCH parameters for full sample log-returns **122**

Table 2.26: Estimated GJR-GARCH parameters for full sample log-returns **123**

Table 2.27: Estimated NGARCH parameters for the short-run scale returns **126**

Table 2.28: Estimated GJR-GARCH parameters for the short-run scale returns **126**

Table 2.29: Estimated NGARCH parameters for the long-run scale returns **128**

Table 2.30: Estimated GJR-GARCH parameters for the long-run scale returns **128**

Table 2.31: Multifractality degrees and efficiency ranking under short-to-medium-run scale **144**

Table 2.32: Multifractality degrees and efficiency ranking under long-run scale **146**

Table 2.33: Time sample OLS regression estimates for $CSSD_{m,t}$ at 5% extremes **150**

Table 2.34: Time sample OLS regression estimates for $CSAD_{m,t}$ **153**

Table 2.35: Time sample QR regression estimates for $CSAD_{m,t}$ **154**

Table 3.10: Unconditional pairwise rolling-window correlations **174**

Table 3.11: Time-domain risk-adjusted diversified portfolio performance measures **191**

Table 3.12: Frequency risk-adjusted diversified portfolio performance measures **192**

Table 3.13: Estimation of cryptocurrencies emergent role in emerging asset markets **195**

Table 4.10: Summary measures **218**

Table 4.11: TNN test results **219**

Table 4.12: Non-linear causality between Bitcoin and Emerging Assets **222**

Table 4.13: Non-linear causality between Ripple and Emerging Assets **222**

Table 4.14: RW rejection rates involving Bitcoin and Emerging market assets **225**

Table 4.15: RW rejection rates involving Ripple and Emerging market assets returns **226**

Table 4.16: Total and directional spillovers between Bitcoin and Emerging market FXs **227**

Table 4.17: Total and directional spillovers between Bitcoin and Emerging market stocks **228**

Table 4.18: Total and directional spillovers between Ripple and Emerging market Forex **229**

Table 4.19: Total and directional spillovers between Ripple and Emerging market stocks **230**

List of Figures

Fig. 2.10: Value-at-risk plots for the most appropriate fitting distributions of the shuffled log-returns **112**

Fig. 2.11: Value-at-risk plots for the most appropriate fitting distributions of the outlier-adjusted log-returns **113**

Fig. 2.12: Expected shortfall plots for the most appropriate fitting distributions of the shuffled log-returns **113**

Fig. 2.13: Expected shortfall plots for the most appropriate fitting distributions of the outlier-adjusted log-returns **114**

Fig. 2.14: News Impact Curves from the fitted NGARCH-SST model for all six asset classes **131**

Fig. 2.15: Generalized Hurst exponent h(q) vs q for the short-to-medium-run cryptocurrency series, with corresponding shuffled and surrogated series, and imposed long-run time-scale series **137**

Fig. 2.16: Generalized Hurst exponent h(q) vs q for the short-to-medium-run FX series, with corresponding shuffled and surrogated series, and imposed long-run time-scale series **139**

Fig. 2.17: Generalized Hurst exponent h(q) vs q for the short-to-medium-run stock series, with corresponding shuffled and surrogated series, and imposed long-run time-scale series **139**

Fig. 2.18: Generalized Hurst exponent h(q) vs q for the short-to-medium-run REIT series, with corresponding shuffled and surrogated series, and imposed long-run time-scale series **140**

Fig. 2.19: Generalized Hurst exponent h(q) vs q for the short-to-medium-run commodity and government bond series, with corresponding shuffled and surrogated series, and imposed long-run time-scale series **140**

Fig. 2.20: Mass exponent tau(q) vs q for asset classes under the short-to-medium-run time-scale **141**

Fig. 3.10: Pairwise rolling-window wavelet correlation (with 250 window size) for Bitcoin vs Emerging FXs **179**

Fig. 3.11: Pairwise rolling-window wavelet correlation (with 250 window size) for Bitcoin vs Emerging Stocks **183**

Fig. 3.12: Pairwise rolling-window wavelet correlation (with 250 window size) for Ripple vs. Emerging FXs **186**

Fig. 3.13: Pairwise rolling-window wavelet correlation (with 250 window size) for Ripple vs. Emerging Stocks **188**

Fig. 4.10: Rolling-Window Total Spillover Index: (a) Return; (b) Volatility **234**

Fig. 4.11: Rolling-Window Directional Spillover Index **238**

Fig. 4.12: Rolling-Window Net Spillover Index; (a) Return; (b) Volatility **240**

List of Appendices

Appendix 2.A1: Graphical plots of regime probabilities vs. daily log-returns **288**

Appendix 2.A2: P-P graphical representation of the most appropriate fitting distributions for the shuffled log-returns **291**

Appendix 2.A3: P-P graphical representation of the most appropriate fitting distributions for the outlier-adjusted log-returns **292**

Appendix 2.A4: Actual frequencies with superimposed best fitting distribution density for the shuffled log-returns **292**

Appendix 2.A5: Actual frequencies with superimposed best fitting distribution density for the outlier-adjusted log-returns **293**

Appendix 2.A6: Portfolio weights for the emerging FX time series samples **293**

Appendix 2.A7: Portfolio weights for the selected emerging stock time series samples **294**

Appendix 2.A8: Portfolio weights for the cryptocurrency time series samples **294**

Appendix A.29: Evolution of γ_2 coefficient based on 80-day rolling window OLS estimation **295**

Appendix 3.A1: Conditional correlation plots of Bitcoin vs FXs based on ADCC-AR(1)-NAGARCH(1,1) model **296**

Appendix 3.A2: Conditional correlation plots of Bitcoin vs FXs based on DCC-AR(1)-NAGARCH(1,1) model **297**

Appendix 3.A3: Conditional correlation plots of Bitcoin vs Stocks based on ADCC-AR(1)-NAGARCH(1,1) model **298**

Appendix 3.A4: Conditional correlation plots of Bitcoin vs Stocks based on DCC-AR(1)-NAGARCH(1,1) model **299**

Appendix 3.B1: Conditional correlation plots of Ripple vs FXs based on ADCC-AR(1)-NAGARCH(1,1) model **300**

Appendix 3.B2: Conditional correlation plots of Ripple vs FXs based on DCC-AR(1)-NAGARCH(1,1) model **301**

Appendix 3.B3: Conditional correlation plots of Ripple vs Stocks based on ADCC-AR(1)-NAGARCH(1,1) model **302**

Appendix 3.B4: Conditional correlation plots of Ripple vs Stocks based on DCC-AR(1)-NAGARCH(1,1) model **303**

Appendix 3.C1: Time-scale correlation ranking of Bitcoin and Latin American assets **304**

Appendix 3.C2: Time-scale correlation ranking of Bitcoin and African-European assets **305**

Appendix 3.C3: Time-scale correlation ranking of Bitcoin and East Asian assets **305**

Appendix 3.C4: Time-scale correlation ranking of Bitcoin and South Asian assets **306**

Appendix 3.C5: Time-scale correlation ranking of Ripple and Latin American assets **306**

Appendix 3.C6: Time-scale correlation ranking of Ripple and African-European assets **307**

Appendix 3.C7: Time-scale correlation ranking of Ripple and East Asian assets **308**

Appendix 3.C8: Time-scale correlation ranking of Ripple and South Asian assets **309**

Table 4.A1: Full form of abbreviated market variables **309**

Appendix 4.A1: Bitcoin-Emerging assets rolling-window pairwise net-directional return spillover index **310**

Appendix 4.A2: Bitcoin-Emerging assets rolling-window pairwise net-directional voaltility return spillover index **311**

Appendix 4.B1: Ripple-Emerging assets rolling-window pairwise net-directional return spillover index **312**

Appendix 4.B2: Ripple-Emerging assets rolling-window pairwise net-directional voaltility return spillover index **313**

Appendix 4.C1: Rolling-window total return and volatility spillover index **314**

CHAPTER 1

General Introduction

"It always seems impossible until it's done" ***Nelson Mandela***

1.1 Background to the study

The birth of a new digital currency in 2009 was least expected to be a disruptive financial technology (Fintech) solution to the existing global financial system. Earlier similar attempts in the 1990s by renowned libertarian cryptographers like David Chaum (of Ecash), Nick Szabo (of Bit gold), Wei Dai (of B-money), Hal Finney (of Reusable Proof-of-Work, simply RPOW), and Adam Back (of Hashcash) all foundered. Launched on January 3, 2009, Bitcoin which pioneers the universe of cryptocurrencies, a sub-division of digital currency, is a peer-to-peer electronic cash (Nakamoto, 2008) that triumphs on a public ledger or blockchain technology to facilitate online payments without recourse to financial intermediaries. This description is suggestive that Bitcoin was introduced foremost to function as a currency. However, for almost a year after its introduction, Bitcoin was basically worthless and mainly subjected to vague operational experiment by Satoshi Nakamoto, the pseudonymous cryptographer(s) who designed and launched the new currency.

In a dramatic turn of events, the new digital currency recorded its first-ever real-world transaction on May 22, 2010, where Bitcoin was used as a medium of payment at a convertible rate of 25 US dollars for 10,000 Bitcoins (i.e., 0.0025 US dollars per coin)[1]. Interestingly, in just five years, the purchasing power significantly rose, in equivalent, to approximately 239 US dollars per Bitcoin on May 15, 2015, and later skyrocketed

[1] Refer: https://www.coindesk.com/bitcoin-pizza-day-celebrating-pizza-bought-10000-btc; accessed on December 21, 2018.

on December 18, 2017, to around 18,871 US dollars per Bitcoin, with a 24-hour trading volume of around 13 billion US dollars[2].

Inspired by Bitcoin's successful penetration into the global market space, several other cryptocurrencies (like Ethereum, Ripple, Litecoin, etc.) with similar protocols have been created. As new currencies with barely a decade-old existence, cryptocurrencies have largely attracted a huge base of users, worldwide, flooded the headlines of mainstream and financial media, and become a concern to monetary authorities and governments. For example, Coinbase alone, one of the leading cryptocurrency exchanges report of a little above 30 million users, and holds in value, over 150 billion US dollars tradable coin supply since its inauguration in mid-2012[3]. Meanwhile, a study by Rauchs et al., (2018) which surveyed some 180 start-ups, established firms, and private persons from 47 countries, put passive users of cryptocurrency at about 139 million with 35 million "identity-verified users" prior to the last quarter of 2018. The adoption level of cryptocurrency is projected to reach several million in the next few years by different outlets. Whatever, the metrics may be, there is evidence pointing to a growing number of the cryptocurrency user base – a need requirement to hold the currency's value since a good money is supposed to thrive on wide-base adoption and trust.

The gradual recognition and adoption, pseudonymity, fully decentralised financial ecosystem, low transaction cost, the prospect for non-expensive instant money transfers via national and cross-border remittances leave many to believe that cryptocurrency could contend the functional role of government-backed fiat currencies. Yet, sceptics (like Yermack, 2014; Selgin, 2015; Kumar and Smith, 2017; Ammous, 2018; Baur et al., 2018b; Wolla, 2018; Cachanosky, 2019; Gronwald, 2019;

[2] Refer: https://coinmarketcap.com/, accessed on November 8, 2018.

[3]Refer: https://www.coinbase.com/about., accessed on January 9, 2019.

etc.) believe on the contrary. For instance, Yermack (2014) expresses that Bitcoin, the leading cryptocurrency largely fails to satisfy the criteria of being (i) a medium of exchange, (ii) a store of value, and (iii) a unit of account. In countenance, Polasik et al., (2015) and Sauer (2016) argued in principle that cryptocurrencies have the potential to become internationally accepted means of exchange or act as parallel monies to sovereign-backed currencies. Their argument is sustained in some way by Hazlett and Luther (2020), who view Bitcoin cryptocurrency as money, so far as it is commonly used as an accepted medium of exchange. Shooting down the latter standpoint, Ammous (2018), in his work had admonished that, technically fulfilling the role as a means of exchange is rather a trivial but not sufficient requirement. Kumar and Smith (2017) and Wolla (2018) acknowledged cryptocurrency as useful for payment but less desirable as a full-fledged money.

Whereas Selgin (2015) classes cryptocurrency as a synthetic commodity, Baur et al., (2018b) qualify it as a hybrid of commodity money and fiat money, and Hazlett and Luther (2020) put it as money in a relatively small domain at present. Till date, there is no consensus on the nature and designation of cryptocurrencies. Even from the legislative and regulatory perspectives, the issue has remained "cold". Most governments and central banks around the world have neither ban nor endorse its usage. To mention few exceptions, the United States (US) through its Securities and Exchange Commission refer cryptocurrencies as securities and treat them as such, while the Commodity Futures Trading Commission (CFTC) and Internal Revenue Service (IRS) of the same country respectively class them as tradable commodities and property. Japan, Mexico, South Korea, and the Swiss Canton of Zug allow cryptocurrencies for payment purposes. On the contrary, several emerging countries like Argentina, Indonesia, South Africa, among others have not yet designated a legal functional role for cryptocurrencies, however, they have gained increasing traction and usage by sections of the public – hence, warnings from monetary authorities.

From the above context, cryptocurrencies seem now to be challenged with an identity crisis. The debate continues to loom among the general public and on media platforms as mere commentary which is often rooted on uninformed and vague standpoints. Much worrying is the few strands of research articles on the subject-matter which does not also give a unified consensus, making it one of the key but overlooked emerging issues which warrants more research attention than a public commentary. The questions which still lingers on and need more scientific studies are: *Does cryptocurrency fulfil the functional role of money? Can it become a well-established national currency and/or offer any economic role? Is it currently coupling (or otherwise) with mainstream asset markets? Does its exponential growth pose any threat to the financial system of emerging market economies?*

As delineated by Bjerg (2016), answers to such questions can be deduced from the structure and constitution of cryptocurrency itself. We provide empirical responses to the questions posed by exploring some relevant financial and statistical characteristics of the new digital currencies and compare the observed features to fiat currencies and other traditional assets of emerging economies. Our exercise is purely based on unearthing (in)distinguishable financial and statistical behaviour of price changes and does not incorporate standard monetary rule characteristics, and/or technical analysis. We opine that failure for enough research work to unveil the evolving characteristics of cryptocurrencies and consequentially designate them may have dire ramifications, first, on an economy, especially emerging ones, as transactions in this market are not subjected to a centralised authority oversight, and could also have a ripple effect on household or individual income, due to the increasing usage, "illegally", in most of these jurisdictions. Second, ignoring the possible threat of a revolutionary digital money may hold implications for national (and even global) financial system stability, as the move to either ban or pretend of its non-existence by economic managers has not discouraged users, and in some instances created regulatory spillovers across cryptocurrency markets (Borri and Shakhnov, 2020).

In the nutshell, this study is the first to contextualise cryptocurrency in a particular economic bloc (i.e., emerging market economies of the G20), to study and understand the currency's evolving characteristics and shed useful light on its relatedness, economic benefits, and risk to the system. The rationale for situating cryptocurrency (or the newly introduced digital asset) in an emerging market economy setting, to explore its characteristics and economic benefits is premised on the quest of the libertarian actors and section of the investor community who seek alternative instruments that best serve their diverse interest, as for example, most advanced markets seems to be interconnected and offer relatively lesser returns on investment. We believe such cross-asset comparison would be relevant for financial and economic actors who are enthused over emerging market assets, yet, require alternative asset(s) as a means of insurance against market uncertainties or extreme market movements.

1.2 Evolution and contemporary issues of cryptocurrency

Bitcoin, the maiden burgeoning FinTech creation, which uses blockchain technology to operate a decentralised or peer-to-peer ledger was "born" in 2009 after several unsuccessful attempts by libertarian cryptographers to break the chain of sovereign-backed monopolised currencies. As described in its earlier design by Nakamoto (2008), it is electronic cash that allows for online payment based on cryptographic proof rather than trust, hence projected as a solution to the issue of double-spending. Thus, its transactions and the supply of the currency's additional unit are secured through the ideals of cryptography, therefore widely called cryptocurrency. Though the nomenclature is yet to be universally standardized, we view cryptocurrency as a sub-division of money or currency that relies on cryptographic algorithms to record and decentralise financial transactions. This makes it unique from the much-awaited sovereign digital currencies that are expected to be issued and controlled by central authorities. In describing it in 2012 using its observed characteristics, the European Central Bank refer virtual currency to be "*a type of unregulated, digital money, which is*

issued and usually controlled by its developers, and used and accepted among the members of a specific virtual community" (ECB, 2012). Therefore, in a subtle sense, cryptocurrency is a specialised kind of digital currency and also a virtual currency in some jurisdictions.

The evolution of cryptocurrency has been phenomenal, and is even lauded by its sceptics, albeit several criticisms, which is largely to be anticipated for any new financial instrument having the potentials of competing with existing ones. The financial ecosystem which started with Bitcoin, now has at the time of writing over 2000 digital currencies (refer, coinmarketcap.com/all/views/all/). However, due to the short-lived history of some newly introduced currencies, ElBahrawy et al., (2017) counted only 600 active cryptocurrencies out of about 1500 that existed in 2017. Driven by Bitcoin's successful introduction into the financial system, other leading cryptocurrencies like Ethereum, Ripple, and Litecoin (popularly termed alternative coins or altcoins) among others have been created and recognised worldwide. These four mentioned digital currencies account for over 75 percent of the market size of the universe of cryptocurrency and show relatively mega trading volumes daily. Irrespective of these developments, majority of the general public still know less about the nature of cryptocurrency and how its transactions work. *What are the operational protocols? Who are its users and how well has it been adopted? What is the legal status? What are the contemporary issues and current research trends?*

The above questions have been reviewed to some extent by studies that have sprouted lately. Our goal is not to reinvent the wheels but to touch on key research papers and highlight on their findings, and further provide, in some cases, empirical answers to the missing links. Though it is practically impossible to give details on how each cryptocurrency works, several published articles (see, Nakamoto, 2008; ECB, 2012; Böhme et al., 2015; Bjerg, 2016; Ammous, 2018; Cachanosky, 2019; Hu et al., 2019; Spithoven, 2019; etc.) have pieced together important cryptocurrency concepts (like

pseudonymity, decentralization; immutability; diversity; coins and tokens; mining pools; digital wallet; etc.), identified players in the new currency's ecosystem (miners, programmers, digital wallet services, currency trading exchanges, mixers, users, etc.), explained protocols on the supply of additional unit of cryptocurrency, and transaction-support technologies for at least four of the major cryptocurrencies (i.e., Bitcoin, Ethereum, Ripple, and Litecoin). Also, Fang et al., (2020) give a comprehensive survey covering 118 published research articles on cryptocurrency trading. As we may not want to sound repetitive on cryptocurrency's transactional operations, we refer readers to the above-mentioned articles.

On the question of its users, Rauchs et al., (2018) found in their study involving 147 countries that, private persons constitute the largest share of the cryptocurrency user base. On the broader scope, a systematic review on cryptocurrency adoption level and adoption-influencing factors are undertaken by Alzahrani and Daim (2019) and Al-Amri et al., (2019). Even though the specific rate of adoption could not be mentioned, the former authors identified, through indicators like estimated number of users, market capitalization, and daily transaction volume, to conclude on increases in the adoption level. It is also projected that cryptocurrency exchange sites' users remain the most accurate indicator to obtain the number of cryptocurrency users. After surfing through the existing literature, the authors categorized factors that influence cryptocurrency adoption decisions into four, namely technical, economic, social, and personal, and later recounted elements such as anonymity, investment opportunity, acceptance by businesses as a payment method, fast transfer of funds, low cost of transactions, and curiosity to be the most influencing user-based factors.

Further, Corbet et al., (2019), Sharma et al., (2019), and Kyriazis (2020) provide systematic analyses or reviews on cryptocurrencies as financial assets or alternative investment vehicle. Among others, Corbet et al., (2019) reviewed several articles under themes like, the evolution of cryptocurrencies and the asset class trilemma, economic

benefits or role(s) of cryptocurrencies, and market efficiency. Similar to Sharma et al., (2019), both groups of authors identified important gaps which need research attention. In a related study, Singh and Kulkarni (2019) pinpoint four key benefits of Bitcoin through a systematic literature review: (i) acceptance as a digital currency; (ii) serves as effective portfolio diversifier; (iii) offers hedging capabilities; and (iv) higher security. They also listed factors such as high volatility, weak substitute for traditional currency, uncertain regulatory impact, idiosyncratic risks, and exogenous supply as major challenges bedevilling the currency. Moreover, Kyriazis (2020) assessed a considerable number of empirical papers to determine whether Bitcoin is a globally accepted asset that has a resemblance to commodity money like gold. Basing his conclusion on the reviewed papers, the scholar alluded that, "*Bitcoin has a long way to go before it acquires the same characteristics as the safe-haven asset of gold*". More so, other relevant contemporary or emerging cryptocurrency phenomena, research hotspots, major institutions of cryptocurrency research, leading journal outlets, key scholars, and other evolution trends (including impending issues like cyber security, money laundering, etc.) in the field of the new financial ecosystem are discussed in the bibliometric review by Merediz-Solà and Bariviera (2019), Ramona et al., (2019), Giudici et al., (2020), Jiang et al., (2020), and Sokulski et al., (2020).

A hot contemporary issue in the world of cryptocurrency revolves around the heated debate on legality and regulatory framework of the new financial instrument. *Thus, is it legal to use or trade cryptocurrencies? Under whose watch should such decentralised market operate and how?* As of now, the legality and/or regulation of cryptocurrency, in our view, is jurisdiction-specific (see, GLR, 2018; Borri and Shakhnov, 2020; and Shanaev et al., 2020). For instance, GLR (2018) surveyed the legal and policy landscape pertaining to cryptocurrencies in 130 countries around the world and found that, in most of the countries, cryptocurrencies are neither banned nor legal, however, commonly across the surveyed jurisdictions, governments acting through their central

banks issued notices to warn citizens about the pitfalls of using or investing in cryptocurrencies.

In summary, we highlight a few missing links in the extant literature. First, we identify a handful of research articles that evaluate and attempt to designate cryptocurrencies as either money, commodity, or otherwise (see, Bjerg, 2016; Carrick, 2016; Ammous, 2018; Baur et al., 2018b; Wolla, 2018; Cachanosky, 2019; Gronwald, 2019; Hazlett and Luther, 2020; etc). However, their conclusions raise more questions than answers and seem not to give a unanimous standpoint, perhaps due to the triviality and limited scope in some of these studies. Also, the possible threat of the fast-growing digital currency market on existing financial system and monetary policies, with implied ramifications for economies has rarely received research attention. In light of the above, our work augments the literature by exploring and providing empirical answers to these less illuminated themes.

1.3 Aims of the Thesis

The thesis broadly focuses on the featured characteristics of a set of leading cryptocurrencies with prominence on selected financial and statistical properties of these new currencies, and relates the results to that of diverse asset markets from giant emerging economies. Specifically, it aims at empirically positioning cryptocurrencies in an emerging market setting to unearth (in)distinguishable characteristics based on authors' choice of five major measurable sub-themes[4]: (i) statistical distributional properties of price changes and tail risk assessment; (ii) complex dynamical structure; (iii) return-volatility relationship and volatility clustering; (iv) multifractality and

[4] Following the reviews on contemporary issues in financial markets, and the path of analysis taken by the previous works (Polasik et al., 2015; Zhang et al., 2018; Corbet et al., 2019), we selected five sub-themes to guide our analysis. We do acknowledge that the chosen sub-themes do not exhaustively describe the comprehensive behaviour of an instrument or asset market, yet a careful selection was done to include some elements which measure relevant economic and financial, as well as statistical characteristics of the asset at hand.

market (in)efficiency; and lastly, (v) herding behaviour. Deferring from the few existing studies, we sought to classify or designate the new instrument (i.e. cryptocurrency) based primarily on the observed collective characteristics from these sub-themes. In sharing the standpoint of Bjerg (2016) and ECB (2012), we are optimistic that cryptocurrency can be appropriately designated by following through its own structure and evolving nature or characteristics.

Further to the above, we investigate to provide fresh insight into the extent of relatedness for cryptocurrencies against national and regional emerging market assets. Additionally, the economic role(s) of cryptocurrencies are examined through the lens of emerging market investors.

As part of the essays, we address, empirically, possible threats or dangers that may have arisen from the fast-growing cryptocurrencies on emerging market economies. Imperatively, findings from these essays generally hold important implications for financial legislation and regulation, monetary policy schemes, financial system stability, and investment decisions.

1.4 Significance and contribution to the body of knowledge

Foremost introduced in 2009 to function as a currency, cryptocurrency is noted to have become, barely in a decade, one of such disruptive Fintech innovations which continues to attract enormous attention worldwide. However, critics of the new currency argue against its use as a perfect store of value, citing issues of high volatility and insecurity. The recognition (or otherwise) of cryptocurrency as either a means of payment, commodity money, or investment asset is subject to a particular jurisdiction. For instance, it is viewed as tradable commodities by US and Canada, allowed for payment purposes in Japan, and as securities by the US – i.e. rendering it a dual designation in the US. In the wake of this, several countries, mostly least developed and emerging economies remain indecisive of the appropriate form to class and

embrace cryptocurrencies into the realm of their financial system, yet users of these currencies are gradually increasing, locally and globally, across various trading platforms or exchanges. Ironically, the South African Reserve Bank (SARB) has neither ban nor recognised cryptocurrency as part of its payment system, and as a result issued warnings against trading or holding it, however, the country's revenue service claims it "*will continue to apply normal income tax rules to cryptocurrencies and will expect affected taxpayers to declare cryptocurrency gains or losses as part of their taxable income*"[5]. Like SARB, many governments and central banks around the world seems to be silent on the designation of cryptocurrency but are quick to serve warnings to their citizens and users about the pitfalls and unregulatory bodies that facilitate such transactions[6]. From the above dispositions, it seems obvious that cryptocurrencies are challenged with an identity and legitimacy crisis, which may have consequences for users and economic managers. The debate about the designation of cryptocurrencies appear almost abstract and is clouded with vague arguments among the general public, but has not also gained much research attention in the financial literature. Nonetheless, a strand of mushrooming works (Ammous, 2018; Baur et al., 2018b; Cacanosky, 2019; Gronwald, 2019; Kyriazis, 2020; etc.) is noted. Therefore, the justification and significance of this thesis are exemplified in the expected contributions it attempts to make to knowledge by first addressing the dearth of empirical studies. Specifically, the thesis extends the literature to a different level, by situating cryptocurrency in an emerging market economy context and compares its observed characteristics to, mainly, emerging market fiat currencies and other traditional asset classes. More importantly, the thesis dives to empirically but not technically explore (in)distinguishable characteristics between cryptocurrencies and fiat currencies of emerging economies using selected financial and statistical elements to describe the

[5] Refer, https://www.sars.gov.za/Media/MediaReleases/Pages/6-April-2018---SARS-stance-on-the-tax-treatment-of-cryptocurrencies-.aspx; accessed on August 18, 2019.
[6] Refer, https://www.loc.gov/law/help/cryptocurrency/cryptocurrency-world-survey.pdf; accessed on January 10, 2019.

markets' evolution. Tackling and diving deeper into the root of the issues through empirically backed narratives would have far-reaching consequences on the decisions of monetary authorities from emerging economies, the uncertain future of the new currency and the general populace as the world is gradually turning into a virtual community.

The second contribution is demonstrated through investigations into the nature and degree of relatedness, interdependence, and shock spillover between cryptocurrencies and conventional markets of emerging economies. As of now, these research themes have rarely been spotlighted, and even the very few in our reach are not vigorously studied contextually and does not exclusively extend over a large coverage of emerging market economies, as ours have to offer. Understanding and unravelling the financial and economic potentials as well as possible systemic risk of cryptocurrencies remain challenging but a relevant task for academic researchers and other scholars, with great importance, largely, to economic and portfolio managers, libertarian enthusiasts, and the general investor community. For example, quantifying and knowing possible shock transmissions emanating from the nascent currency market will serve as early alert signals against financial system instability.

Another piece of the thesis major contribution is evident through its range of current methodological applications, which overrides some earlier works that, in our view, were not robustly studied methodologically. The use of varied empirical econometric and statistical techniques which have seen less or in many cases no applications in this area of research constitute another notable advancement, insofar that extending or revising the frontier of methodological applications have a greater likelihood of producing robust estimations and new results which perhaps may not have been unveiled with earlier approaches.

Although this thesis is not exhaustive to all the evolving characteristics, economic benefits, and systemic risk of cryptocurrencies in the context of emerging market economies, it is hoped that the research community would be motivated through this work to have a renewed interest in the comparison and exploration of several aspects of these embryonic markets to further deepen the empirical and even theoretical answers on the appropriate designation and role of cryptocurrencies. Such collective literature may inform legislative decisions and perhaps reduce insecurity to boost the confidence of people and the general recognition of cryptocurrencies.

1.5 Impediments to this Thesis

It is obviously non-arguable that for frontier and emerging economies to fast-develop and keenly compete with well-developed and knowledge-based economies, more scientific and meaningful research work directed towards changing economic policies that would largely impact society are warranted. More so, the scientific community in the former economies are oftentimes challenged to bridge the gap between their research focus and the varying needs of society, investors, and industry. Yet, one of the major hurdles of researching frontier and emerging economies is the task of gathering or accessing reliable and well-representative data needed for insightful analysis, aimed at bringing social and sustainable economic change, and strengthening financial systems.

This current study is not immune to the above challenges. From the onset, our work suffered setbacks regarding data accessibility. That is, in addition to the cryptocurrency market, we had initially targeted to cover diverse financial markets of several frontier and emerging economies across different sub-regions. This, as expected, would have better enriched our discussion of the subject of investigation, however, we discarded frontier economies mostly due to inaccessibility of wider coverage country-specific and aggregated financial markets dataset (or indices). We

resorted to using financial markets of emerging economies. Even with that, accessibility to data such as individual country-level government bonds and real estate and investment trusts (REITs) equity indices became problematic. This was somehow anticipated because the REIT markets of most emerging economies are now developing, hence, obtaining consistent information on these markets remains challenging. The situation was even worsened when attempts were made to scale-down to frontier economies, wherefore, their exclusion from the study.

The inability to access different high-frequency market data for especially the bonds and REIT equities, as well as reliable information on trade volumes for few of the asset classes, limited the study's scope to finding further insights. Like some of the emerging financial markets, cryptocurrencies are relatively new and have short historical market information that made it more challenging, in some cases, to obtain methodologically reliable estimates. For instance, we had to devise a selection criterion to discard several of the cryptocurrencies (subjecting our work to selection biases) due to inadequate data span and short-lived markets, as we examined characteristics of the new currency market. Owing to the above, other frequency data like weekly and/or monthly data could not be considered because of the smaller number of observations, which may be highly unreliable to describe the evolving and hidden dynamics in the cryptocurrency market. The option of using intraday data was also problematic, as cryptocurrencies are traded seven days in a week, hence making it extremely difficult to synchronize the time stamp for other markets that do not trade on weekends over our chosen range of years. Thus, intraday data are well-known to be a subject of idiosyncratic elements like non-synchronous trading, measurement errors, conceptual challenges, and the phenomenon to even reconstruct the attractor in situations where tick-by-tick data, which are mostly unevenly spaced are used.

These barriers mainly accounted for the use of only daily frequency data and fewer but active digital currencies from the universe of cryptocurrencies, and financial

markets of emerging economies within the G20, incorporating the BRICS countries (Brazil, Russia, India, China, and South Africa). Though not much of a very broader coverage of traditional emerging markets as it may seem, yet the study makes relevant contributions by exploring, comparatively, some useful aspects of the markets' behaviour, and as a result provokes discussions and opens the doors for more empirical research work as quantities of the markets evolve with time.

1.6 Thesis layout

The report of the entire essays is calved into five chapters. In addition to the current section, the ensuing chapters are designed and structured as below.

Chapter Two: *Stylized Properties of Cryptocurrencies and Traditional Financial Assets of Emerging Economies* – This chapter commences the empirical works of the thesis. It focuses on estimating several financial and statistical properties of the new digital currency market, i.e. cryptocurrency and compares the observed features to long-existing emerging market assets. Unsure by many economies on the appropriate designation of cryptocurrencies, we modelled the daily price changes of the new currencies and that of different emerging market assets using twenty parametric distributions and assessed the riskiness (tail risk) of the markets. By invoking the fundamental principles of fitting statistical distribution to a given data, we initially shuffled, randomly, the individual and aggregate daily market returns by 5000 runs, and fitted in all 1280 parametric distributions to the data – to the best of our knowledge, the largest of its kind in the literature. Aside from the distributional characteristics (like the sample moments), we examine the functional form through the probability densities and further computed risk measures (VaR and ES estimations) to study the tail behaviour of the new currencies, against those of the emerging markets.

To another sub-theme under the chapter, the dynamic and complexity of the markets are investigated. In view of this, a battery of advanced empirical methods is used to investigate the dynamic structure of each market, and thereon detail report of chaotic or randomness is provided. Building on the paucity of related literature, we make a unique contribution by documenting the presence (or absence) of low- and high-level chaos in both time and trading scale samples.

Next, the return-volatility relationship of cryptocurrencies is studied. In this context, we adopt the definitions and characterization of asymmetry and leverage by Caporin and Costola (2019) to measure the two distinct financial phenomena in the digital currency market. The observed features are run parallel to asset classes of emerging economies. The key issue of concern here was to determine whether these markets exhibit similar or indistinguishable return-volatility behaviour – That is, do volatility changes (or precisely, volatility increases) in the respective markets responds more to positive (or negative) shocks? What drives this (dis)similar behaviour (if any)?

It is postulated that in an efficient market, the current price should reflect, immediately, all relevant information. This informational efficiency market phenomenon is widely known in the financial literature, but until recently, its application was scarcely documented for the cryptocurrency market. Using the multifractal detrended fluctuation analysis (MF-DFA), we explored the fractal characteristics of cryptocurrencies at two chosen time-scales over a single, as well as multitude scaling exponents. Drawing on the relationship between the Generalized Hurst exponent and the scaling exponent, we computed a market inefficiency index and uses it to examine informational inefficiency (or otherwise) and its implied ease (or difficulty) in predicting the cryptocurrency market against that of emerging markets. Not only does this approach looks different from the GARCH-type models and the popularly used semi-parametric Hurst exponent tests, but it has also rarely been applied in this perspective.

Relative to the emerging markets, investors' behaviour towards the new currency is scrutinised. Using an equally-weighted and a global minimum-variance portfolio construction approaches, we report on how traders of these markets react collectively (or otherwise) to normal and extreme price movements. *Do the traders imitate each other or a group in their trading strategies? Are there any commonalities among the trading strategy of cryptocurrency and emerging markets traders?* Empirical answers are provided using static and time-varying herding models.

Chapter Three: *Dynamic Co-variation and Diversification with Applications to Cryptocurrencies and other Financial Assets* – The main fall-out from the second chapter of this thesis shows empirically but not technically that cryptocurrencies bear very least resemblance to emerging market currencies, and for that matter, could best be viewed as a "trinity hybrid" financial instrument which may complement, for now, fiat currencies and other long-existing assets. Hence, in the broader scope, the current chapter has provided indepth insight into the extent of linkages, in both time and frequency dimensions, between cryptocurrency and traditional assets in emerging market economies. Employing refined empirical methods, the chapter further assessed the economic benefits of the most liquid and long-lived cryptocurrencies to the advantage of heterogeneous groups of investors, especially those who are enthused over emerging markets. *Could cryptocurrencies serve as effective diversifiers?*. *Can they reduce the downside risk of emerging markets during market downturn?* Detailed analysis as to whether these cryptocurrencies have the capabilities to provide such multifaceted economic roles are discussed in the chapter.

Chapter Four: *Interdependence and Spillovers between Cryptocurrencies and Emerging Financial Assets* – The last of our empirical chapters investigated the degree of threat that may have emanated from the new currency market to, perhaps, lead to an implied cause of instability in emerging financial markets. Using static and rolling-window modelling approaches, we have provided analysis about the nature and level of

interdependence and shock spillovers between the markets. More importantly, we unearthed the impact of some major cryptocurrency news events on the spillover dynamics to ascertain whether these markets collectively respond to positive and/or negative cryptocurrency news headlines.

Chapter Five: *General Conclusion* – Under this chapter, we synchronised all salient results and concisely reviewed major contributions from each of our empirical chapters. Prior to that, we began the chapter with an encapsulation of the essays and finally concluded by suggesting future research direction to the reading community.

CHAPTER 2

Stylized Properties of Cryptocurrencies and Traditional Financial Assets of Emerging Economies

"Take advantage of every opportunity; where there is none, make it for yourself" ***Marcus Garvey***

2.1 Introduction

In a compendious explanation, Kaldor (1961) coined the phrase "*stylized facts*" to represent stable common patterns that become apparent from several varied sources of empirical data. Most often, the seemingly random fluctuations of asset prices or returns do share some important statistical properties, moreover, financial markets are predominantly engulfed with some kind of generic features about the historical financial time series of the instruments traded within them. Such statistical properties, quite common across a wide range of tradable assets or instruments of any kind, markets and time horizons are popularly referred to as stylized empirical facts (Cont, 2001; Porras, 2017).

Fast forward, we view stylized facts as general statistical properties underlying the data generating process (DGP) in the prices or returns of asset classes that need to be studied to unveil the microstructure dynamics of such set of assets across time and/or trading scales or horizons. Understanding stylized properties of asset prices or returns are documented to be of importance in events of economic and financial theory constructions, risk assessment, modelling and forecasting financial markets, and subsequent evaluation of such models (Kaldor, 1961; Reiter, 1995; Cont, 2001). More so, drawing empirical evidence on over seven decades of several scholarly studies, Porras (2017, p.53) alluded that different assets in different markets are not necessarily influenced by the same information sets, especially as one turn attention on their

statistical properties. Hence, the study of stylized properties of economic/financial variables from diverse asset classes is much required to understand among others, (un)common features, like, inherent risk and volatility patterns, randomness and/or chaotic signals, informational (in)efficiency, asymmetry and/or leverage characteristics, as well as herding behaviour. In the view of Al-Yahyaee et al., (2018), analysis of stylized facts of asset returns remains one of the fundamental issues in finance theory, which presents a greater concern for academic researchers and portfolio managers.

For the past decades, several studies have estimated and reported on stylized properties for the prices and returns of various markets using financial time series from different asset classes[7], and vast economic zones or jurisdictions. However, the emergent global entrant coupled with availability of reliable market data, in the form of relatively high-frequency price movements and trade volumes of cryptocurrencies has sparked a new direction of research in empirical finance, especially in the last half-decade. The price (or value) and trade volume of the youngest financial instrument, i.e. cryptocurrencies (a specialised kind of digital currency and also a form of virtual currency) have become readily experimental tools in the market laboratory of academics, financial analysts, policymakers and regulators, and the international investor community alike.

[7] Adopting the definition in the seminal work of Greer (1997), we view an asset class as "a set of assets that bear some fundamental economic similarities to each other, and that have characteristics that make them distinct from other assets that are not part of that class". In his definitive framework, he specified asset classes in three broad levels: capital asset, store of value asset and consumable/transformable asset, but was quick to acknowledge the existence of hybrid asset and the blurriness among his superclasses. Weighing into this explanation, Burniske and White (2017) delineated distinctive characteristics that draw clearer boundaries among conventional asset classes: (1) investability, in the sense of liquidity and readily opportunity to invest; (2) distinct politico-economic features; (3) Correlations of returns – thus, the price or value of the asset should fluctuate or evolve without depending on other assets; and (4) distinguishable risk-reward features.

With its introduction and subsequent gradual recognition into the global financial ecosystem in 2009, from which Bitcoin pioneered the market, the evolution of cryptocurrencies has been phenomenal, and as a result, courted enormous global attention over the few years. Weighing on such immense interest in this new market, academic and financial analysts, policymakers, and several regulatory bodies are now much concerned than ever, with the evolving characteristics of cryptocurrencies, as the new currency market is currently challenged with an identity crisis. Intuitively, scientific exercises that give empirical shreds of evidence about the appropriate designation of cryptocurrencies into a kind of financial instrument or an asset class are required not only by investors (to guide investment and risk management strategies), but also to inform policy directions of policymakers, monetary authorities and other relevant regulatory bodies.

As sections from the paucity of the financial literature likened the characteristics of cryptocurrencies to an investment asset (Glaser et al., 2014; Chu et al., 2017; Trautman and Dorman, 2018; Berentsen and Schär, 2018; etc.), other studies view them as a monetary instrument (Nakamoto, 2008; Luther and White, 2014; Sauer, 2016; Bech and Garratt, 2017; Blau, 2018; Hazlett and Luther, 2020; etc.), a gold-like store of value asset or commodity (Bianchi, 2018), speculative asset (Yermack, 2014; Baek and Elbeck, 2015; Bouoiyour and Selmi, 2015; Bouoiyour et al., 2015; Baur et al., 2018b), or a dual hybrid asset class (Wilson-Nunn and Zenil, 2014; Polasik et al., 2015; Dyhrberg, 2016b; Wolla, 2018; Goforth, 2019; etc.). Besides, other empirical works have also explored the potential of the new digital currency as a hedge instrument and safe haven for well-developed global markets (Dyhrberg, 2016a; Bouri et al., 2017; Selmi et al., 2018; etc.).

With hindsight, it could be surmised that the kind of financial instrument often used to describe cryptocurrencies is somehow dependent on specific market jurisdictions and/or investors' appetite for risk, with less emphasis on the currencies' own structure

and evolving characteristics. A classic example is the designation of digital currencies as tradable commodities within a Commodity Exchange Act, regulated by the United States Commodity Futures Trading Commission, in a federal judge ruling (see, case 1:18-cv-10077-RWZ, document 106, p.1-11)[8], and as property (instead of currency) by the Internal Revenue Service for purposes of federal tax[9]. In her press conference in 2013, Janet Yellen, former chair of the United States Federal Reserve opened up on the function of cryptocurrency, saying, "*bitcoin at this time plays a very small role in the payment system. Is not a stable source of – store of value, and it doesn't constitute legal tender*"; but instead classified Bitcoin in her best percipience as "*a highly speculative asset*"[10] – a description which is empirically challenged from the findings of Blau (2018), Hazlett and Luther, 2020, among few others. Elsewhere, in April 2017, the Japanese Payment Services Act (art. 2, para.5) defines cryptocurrency as "*property value that can be used as payment for the purchase or rental of goods or provision of services by unspecified persons, that can be purchased or sold to unspecified, and that is transferrable via an electronic data processing system*"[11]. This operational definition eulogizes the monetary characteristic of cryptocurrencies. However, amid the ongoing debate in the financial realm, it is still not well-established as to whether the evolving nature of cryptocurrency's market features explicit characteristics of real currency, commodity, a speculative investment asset, or otherwise.

Meanwhile, establishing the distinct characteristics of cryptocurrencies is of both national and global importance in the sense that if for instance, the digital currency has the tendency of gradually becoming an internationally accepted medium of

[8] Available at https://www.cftc.gov/sites/default/files/2018-10/enfmybigcoinpayincmemorandum092618.pdf; accessed on March 20, 2/019.
[9] Abrams Rachel (2014, March 26). I.R.S Takes a Position on Bitcoin: Its Property. The NewYork Times, p. B1; online version available at https://dealbook.nytimes.com/2014/03/25/i-r-s-says-bitcoin-should-be-considered-property-not-currency/; accessed on March 30, 2019.
[10] Available at https://www.federalreserve.gov/mediacenter/files/FOMCpresconf20171213.pdf; accessed on March 25, 2019.
[11] Available at https://www.loc.gov/law/help/cryptocurrency/japan.php; accessed on March 25, 2019.

exchange (Polasik et al., 2015; Wolla, 2018), thus acting parallel to already existing and well-known standard fiat currencies (i.e. Euro, Pound, US Dollar, Yen, etc.), the result may have far-reaching fractious consequences for monetary policy direction, various central banks, fiat currency's value, investment portfolios, and generally for the global economy (Baur et al., 2018b). Also, in a situation where cryptocurrencies are now being acknowledged as channels for simple monetary transfers (Chu et al., 2015), either through remittances from overseas or to parties within the same economy, tax revenue of governments may be undermined due to the progressively decentralized peer-to-peer electronic cash payment network that eliminates intermediaries such as conventional financial institutions.

Therefore, designating cryptocurrency into a kind of known asset class or forging its own unique class is of paramount interest to all stakeholders in the national and global economy. Hence, a chunk of scientific studies or reviews is warranted to provide further understanding of their behaviour, as the dearth of the earlier ones leave more questions than answers. Thus, with the rapid market development and increasing adoption, one is only left with yet the unaddressed question of whether cryptocurrencies behave and should be treated like a monetary instrument, an investment vehicle, or commodity asset. Better still, *do they exhibit hybrid or unknown unique characteristics? Are these new currencies highly speculative?*

Although few existing studies have attempted to somehow offer empirical evidence and some explanations to these questions, there is no apparent consensus from these primers, and as such, the inconclusiveness leaves much to be desired. The handful of studies in this direction uses a single market (Bitcoin) to proxy for the universe of cryptocurrencies[12], and mainly compare its statistical properties with assets from

[12] However, there exist around 2000 cryptocurrencies, from which Bitcoin captures 32.46% of the overall market capitalization as of January 13, 2018 (refer, https://coinmarketcap.com).

advanced markets, to establish common (or divergent) properties. This may not generally connote a vast representation of the collective characteristics of cryptocurrencies. Also, the reliance on stocks, foreign exchange rates (hereafter, forex or FX) and bond markets from few developed economies (with no specific contextualization) in the earlier studies which obviously failed to incorporate traditional markets from emerging economies limit their analysis and create gaps in the international financial literature – with regards to the ensuing questions. *In what form should emerging market economies embrace digital currencies into their financial ecosystem? Apropos to known standard assets of emerging economies, what potentials do these new embryonic currencies has to offer, given their evolution over the past decade?* Answers to these debatable questions may better inform the standpoint of the libertarian general public, investors, risk managers, regulators, and central banks, and perhaps open the doors for appropriate legal framework to usher in this new financial market into a recalibrated well-diversified economy.

In addressing the identified gaps, the chapter examines stylized properties across a universe of cryptocurrencies in connection with a number of different financial assets from emerging market economies – namely, stock markets, forex, bonds, real estate and investment trusts (hereafter, REITs) and commodities. Hence, the chapter's unique contribution has to do with unveiling time and frequency characteristics of cryptocurrencies vis-à-vis fiat currencies and other distinct traditional asset markets of emerging economies. Empirical results and deductions from the analysis could well-inform governments, monetary authorities, and importantly investors and risk managers, who are enthused with emerging markets to adopt pragmatic trading and risk management strategies when using the new financial instrument or perhaps incorporating it in their respective portfolios or decision-making.

Another major contribution worth mentioning could be drawn from the chapter's measure of key relevant financial and statistical characteristics, and explanation of the

price fluctuations and current trends in the markets. Specifically, the use of refined parametric and non-parametric approaches for modelling price volatility, dynamic complexity of asset prices and/or returns, risk assessment and performance, market (in)efficiency, and herding behaviour, offer new insights and unlock hidden features of cryptocurrencies against those of emerging market assets. For example, highlights of the results have it that, in periods of extreme market movements or increased uncertainty conditions, our study reports on the likelihood of investors to suppressing their individual beliefs and understanding to merely follow build-up consensus in the market, with its implication thereof for asset pricing. There again, the assessment of chaotic signal and dynamics unlocks additional less explored avenues for the understanding, evaluation, and vision of financial markets development prospects. Such chaotic analysis may best help to comprehend patterns of irregularities in the time series of assets, bestow yardsticks for the development of financial markets, and offers platforms for assessing chances of eventualities (Klioutchnikov, et al., 2017). On the other hand, the return-volatility profile and the results of the fitted parametric distributions hold relevant implications for financial engineering (mainly derivatives), asset price modelling and forecasting, and risk management, as analysts may oftentimes require to estimate value-at-risk (VaR) and expected shortfall (ES) of an asset market.

Altogether, the chapter's analysis and inferences induce fresh insight about international financial markets, with respect to calving an identity for cryptocurrencies by studying through their structure and characteristics to shed more understanding relating to risk profile, functional form of their distributions, complexity dynamics, and investors' behaviour toward the market under different conditions, which may, in general, inform the decision-making processes of policymakers, statutory regulators, portfolio and treasury risk managers, financial analyst, and the public who are perceptive about the future of the new digital currencies.

2.2 Literature review

Although cryptocurrency is on the vogue as part of innovations in international finance, not many reviews of its continual evolutionary phases and current trends are available in the finance literature. However, owing to the astonishing surge of the market, with its wider implications for major stakeholders in different fields (economists, financial analysts, central banks, miners, regulators, investors, etc.), a call for more multidisciplinary studies is demanded to augment extant literature. Moreover, contemporary research interest in the new currency market has taken diverse paths. Polasik et al., (2015) identify four main research areas: (1) studies on technological and system security; (2) public and legal issues; (3) political, sociological and ethical concerns; and (4) economic and financial related issues, with emphasis on theory and empirical considerations.

Zhang et al., (2018) also put the literature on cryptocurrency market into three aspects: (1) inefficiency; (2) pricing dynamics and correlations with other standard financial assets; and (3) long-range dependence. To a related study by Omane-Adjepong et al., (2019), the researchers pinpoint six topical research issues making headway in the digital currency industry. The first is on efficiency and market competition; the second explores drivers of prices; the third focuses on long-memory and volatility persistence; fourth, examines price volatility, spillovers, and connectedness between cryptocurrencies and other financial assets; the fifth threads on security and payment systems; while the last streams on market evolution, legal and regulatory issues. In a systematic review of empirical literature involving papers published since 2009 up to August 2018, Corbet et al., (2019) identified three broad areas of research concentration, and further ascribed several sub-themes. Key among them include price bubbles, regulatory disorientation, cybercriminality, diversification benefits, market efficiency, and market correlation.

Interestingly, all the identified research paths by Zhang et al., (2018), and the initial four areas of Omane-Adjepong et al., (2019) are captured in the last grouping of Polasik et al., (2015) – a research area on which the current review is based. The entire review in this chapter touches on several aspects of the economic and financial characteristics of the new currency market, in relation to other well-established asset markets. There are over thousands of empirical works on statistical distributions and financial characteristics of assets returns. As it seems impossible to review all works, the current study has drawn on diverse country-specific and multi-country articles, in direct connection to various themes within the study's broad focus.

The review is structured into five thematic research sub-areas. Therefore, to best situate the chapter's contributions, we have undertaken a comprehensive review of such works under each sub-theme in-turns.

2.2.1 Empirical review on probability distributions of asset returns

It is a common knowledge that financial asset returns collected over short data frequency intervals (mainly intraday, daily or weekly) exhibit larger fluctuations which often deviate from the characteristics of a normal distribution. The distribution of these asset returns are empirically found to be mostly skewed, much peaked, and shows different right and left tails behaviours (commonly being either a Gaussian-like tail, semi-heavy tail, heavy tail or a mixture of the aforementioned). Although awareness of these features has long been created (refer, Mandelbrot, 1963; Fama, 1965; Press, 1967)[13], a quick scan through the financial literature unveil some

[13] In his seminal paper, Mandelbrot put forward that the empirical distribution of stock or commodity price changes do not well-conform to samples from normal or Gaussian populations, and as such introduced a family of probability laws (known widely as stable Paretian distributions) to capture skewness and fat tails in asset price changes (see, Mandelbrot, 1963). Similarly, to Mandelbrot, Fama (1965) also found features of leptokurtosis, peakedness and longer tails in the daily log returns or price changes of all the 30 stocks from the Dow-Jones Industrial Averages; few years later, Press in 1967 fitted Poisson mixtures of normal distributions to 10 out of the 30 Dow-Jones Industrial Averages' stocks. Press argued that his distributions outweigh the normal with the ability to explaining the skewness, peakdeness and leptokurtic characteristics of asset price changes (see, Press, 1967).

impositions of the normality assumption in traditional volatility models used for describing financial characteristics of asset returns (selected examples include the works of Shih and Yu, 2009; Gu et al., 2017; Ahmed et al., 2018; etc.). The grievous of the situation is where authors preliminary rejects normality for the distribution of sample asset returns using frequency-based graphical and/or summary statistical measures, but yet fit models to the same return series on the assumption of normality.

Perhaps, the simplicity and parsimonious nature of the normal distribution still attract its extensive use among practitioners, albeit the weaknesses to well-capture larger fluctuations and other extreme market behaviours, as often witnessed in real life asset price changes or returns. Unfortunately, misspecification of appropriate probability distribution in volatility models or for the underlying data generating process (DGP) in asset returns has far-reaching consequences in examining financial characteristics such as hedging capabilities, volatility asymmetry, informational efficiency, risk computation and reliable forecast, with wider practical implications for risk management[14], asset allocation and portfolio optimization and option pricing.

Another common practice in risk management and the finance literature has been the extensive application, or better said, the imposition of a single distribution, mostly a heavy tail distribution like the antiquated Student's *t* distribution in situations where the extreme return realizations deviate from a Gaussian-like tail[15] (see studies like

[14] As also reiterated by Gunay and Khaki (2018), the simplistic assumption of normality in financial models provide lesser chance for quantifying extreme events or tail probabilities, which as claimed by the authors may result to failures in risk management. Contrary, we believe overseeing beyond the Gaussian and its group of thin tail distributions to include heavy tail distributions (or likewise syndicates) for accurate computation of tail risk may significantly have an improve impart on quantitative analysis and practice in risk management.

[15] Widely applied as default substitute to the Gaussian, the Student's *t* distribution has probably for some time now remained the most commonly used distribution among practitioners, mainly in cases where asset returns display fatter tails (see, Ardia and Hoogerheide, 2014). This restrictive application of parametric distributions in volatility modelling of financial asset returns do not somehow allow all features of such data to present themselves accurately to analysts, thereby obscuring the data from "speaking" to us.

Alagidede, 2011; Bentes, 2015; Chen et al., 2016; Yuan et al., 2017; Nguyen and Bui, 2018; etc.). Meanwhile, empirically, asset returns graphically exhibit frequency dynamics having extreme return realizations that may exceed what perhaps could have been accounted for by such singularly imposed distributions. Besides, equality of the relative frequency of extreme return realizations in the left tail (which signifies investment losses), as well as the right tail (i.e., investment gains) may at times be overlooked. In consequence, generalizations over the practice of imposing a single distribution allow for valuable extensive coverage of varied market variations and even hidden features of an asset return series (Zhu and Galbraith, 2010).

Moreover, a broad review across asset classes highlights on diverse and comprehensive scenarios about distributional characteristics and their associated fitted parametric distributions for several financial asset returns. Beginning with international stock markets, Praetz (1972) characterizes seventeen weekly share price index series (of the Sydney Stock Exchange) as non-normally distributed and conferred a scaled *t*-distribution as simple but "excellent" and well-known fit for the variations in share returns. He further claimed unanimous superiority of the scaled *t*-distribution to the compound processes or events, stable Paretian distribution and normal distributions. However, a major critic of his distribution is its approximation to the normal for larger n, which arguably may fail to incorporate abrupt and larger or extreme fluctuations of price changes. After Praetz's work, several distributions, namely, logistic (Smith, 1981; Peiro, 1994; etc.), exponential power (Hsu, 1982; etc.), combinations of the normal distributions (Madan and Seneta, 1990; Kon, 1984; etc) among others have been used to describe changes in stock market prices.

Winding forward to current development in the area, Aparicio and Estrada (2001) test and rejected normality assumption for daily returns of 13 European stock markets,

and found strong and partial evidence in favour of the scaled *t*-distribution and a combination of normal distributions. Likewise, Egan (2007) shows departures of the S&P500 daily stock returns from the normal and log-normal distributions but reported a good fit for the index returns using the *t*-distribution with scale parameters. In assessing predictability features of 6 largest stock markets[16], Alagidede (2011) employs a single heavy tail distribution (Student's *t*) in a variant of GARCH models to report time-varying predictability for the index returns. Using the same distribution in a range of GARCH models, Nguyen and Bui (2018) model the daily returns of German's DAX30 stock index and documented appropriateness of the models. Ardia and Hoogerheide (2014) examine the impact of updating parameter estimates in different data frequencies for the S&P500 index on VaR and ES forecast using 3 distributions (Student's *t*, Gaussian, Non-parametric Gaussian Kernel) in a GARCH and GJR-GARCH framework. No attempt was made to assess adequacies of the fit, however, the authors found favour with the GJR-Student's *t* and GJR-Kernel models for their 95% and 99% VaR and ES forecast respectively. Curto et al., (2009) report on the modelling prowess of a GARCH model under Student's *t* and stable Paretian distributions for characterizing 3 well-developed stock markets (DJIA, DAX, PS120).

Elsewhere, Gencer and Demiralay (2016) found a FIAPARCH model under a skewed Student's *t* innovations as better fit over other specifications, in connection to 8 emerging stock markets[17]. To well-capture features of the S&P500 daily returns, Guo (2017) compares in-sample fit adequacies of 4 heavy tail distributions (skewed *t*, Student's *t*, normal reciprocal inverse Gaussian, generalized hyperbolic), and found the return realizations to be best modelled with the skewed *t*.

[16] CASE30 of Egypt, MASI of Morocco, FTSE/JSE of South Africa, NSE ALLSHARE of Nigeria, NSE20 of Kenya and TUNINDEX of Tunisia – constituting 90% of the stock market size and domestic company listing in the continent of Africa (Alagidede, 2011).

[17] The major equity market returns series of BRICS (Brazil, Russia, India, China, South Africa) and MIKT (Mexico, Indonesia, South Korea, Turkey) were considered in their study.

The in-sample fit superiority of the normal reciprocal inverse Gaussian (Hong et al., 2019) and the normal inverse Gaussian (Lau, 2015) has been documented for stock returns distributions. There again, the generalized hyperbolic (GH) skew Student's *t* has been introduced to examine asymmetrically heavy tails in the stock returns of S&P500 and TOPIX (see, Nakajima and Omori, 2012). More recently, the latter parametric distribution was applied alongside 2 alternatives (skew Student's *t*, symmetric Student's *t*) to model the volatility of 5 Latin American stocks[18] and the United States S&P500. Lafosse and Rodríguez (2018) found favour with the stochastic volatility model under the GH skew Student's *t*.

Empirically, we found not many current studies in the financial and risk management literature that associate variations in price changes of stock markets to thin tail distributions. To mention few, the simple Gaussian (Ahmed et al., 2018), Laplace (Linden, 2001) and GED or exponential power (Appiah-Kusi and Menyah, 2003; Bampinas et al., 2018) distributions are noted. Whereas Ahmed and co modelled market behaviour of selected emerging and advanced equity markets from Asia, Europe, Latin America, and North America, Appiah-Kusi and Menyah (2003) used EGARCH-M with a GED to assess the predictability of 11 African equities. Linden (2001) analyzes daily and weekly returns of Finland's 20 most traded stocks. Bampinas et al., (2018) examine comparative performances of 8 alternatives symmetric and asymmetric volatility models under 3 distributions (i.e., normal, Student's *t*, GED) – for adhering to stationarity and non-negativity constraints using daily returns in the universe of S&P1500. Satisfying the constraints, the EGARCH model with GED was projected over all other competitive specifications.

Turning the focus to global commodities, Gunay and Khaki (2018) empirically model and analyze the volatility of energy futures (i.e., natural gas, Brent oil, and heating oil)

[18] Namely, MERVAL of Argentina, IBOVESPA of Brazil, IPSA of Chile, IGBVL of Peru and MEXBOL of Mexico.

with GARCH and APARCH specifications under different parametric distributions (generalized extreme values - GEV, generalized asymmetric *t* - GAT, alpha-stable distributions). In their concluding remarks, the APARCH in the mode of GAT distribution is recorded to have outperformed the GARCH and other alternate distributions, with regards to modelling fatter or thicker tails in energy commodity returns. Besides, further result has it that prices in energy commodities are far wider than the popular assumption of normally distributed price changes. In analyzing the return volatility of natural gas (Henry Hub) and crude oil's (WTI) spot prices for two separate sample periods (02.01.2009-28.04.2014; 04.01.2010-28.04.2014)[19], Saltik et al., (2016) employ a range of linear and nonlinear asymmetric GARCH models under light- (generalized error distribution - GED) and heavy-tail (Skewed Student's *t* - SST) distributions, and assessed their forecast performances. Relying on loss function metrics, the conclusion from their study documented relative accurate forecast performance in favour of FIGARCH-SST (EGARCH-GED) with the first (second) sample data for both markets with varied investment risk implications.

Following the works by Nelson (1991) and Bampinas et al., (2018), Bampinas et al., (2019) preferred the GED over others to approximate the errors of their fitted rolling asymmetric GARCH model to better ensnare the conditional volatility and asymmetric leverage effects in weekly price changes of world gold and crude oil markets. Quite surprisingly, Shih and Yu (2009) fit a Gaussian distribution to explore statistical properties in the unconditional daily returns of world crude oil market and showed the relevance of the study's results for hedging and in other trading strategies. Ironically, the authors rejected normality for the market returns, and even described the return volatility as one having long tails and high peak, yet, a Gaussian distribution was solely considered to none. Their initial account on return distribution is in conformity to the work of Sharma et al., (2013), which also describes the

[19] For want of clarity, the dating structure throughout this study follows: dd.mm.year.

distributional curve of commodity returns as leptokurtic, negatively skewed and one that shows thicker tailedness behaviour.

Through a preliminary summary analysis of the distribution of sample gold returns, Bentes (2015) rejected normality due to the presence of negative skewness and leptokurtic, and as such employs, as she claims, alternative distribution (Student's *t*) in a GARCH family to assess the conditional volatility features of the market. Similarly, Dury and Xiao (2018) proffer the modelling and predictive powers of ARCH family of models under the Student's *t* at the expense of the Gaussian, in a study of China's gold market. More so, in another empirical study to explore diverse parametric distributions (normal, Student's *t*, stable, and a mixture of normal distributions) for global gold future's unconditional returns, Kumari and Tan (2013) settled on the Student's *t* as the most adequate distribution for a sample of 2,364 daily return realizations.

A fast glimpse through the review of return distribution for REIT asset class provides evidence, in most cases, of a single imposed distribution, mainly the normal or Gaussian, which has seen extensive empirical application in modelling variations of price changes in the asset class. The literature shows a lesser application of recently developed parametric distributions for returns and volatility distribution of REITs. Titled, "*Real Estate Is Not Normal: A Fresh Look at Real Estate Return Distributions*", Young and Graff (1995) attempt to diffuse the notion held by most peers in the real estate realm – who as claimed by them merely follow financial economics literature to assume without testing with their respective market data that REIT returns are distributed normally. Using a decade long data (of individual property price changes series from Russell-NCREIF), the authors gave a new direction to modelling REIT asset returns and concluded by revealing that investment models with a stable infinite-variance distribution offer a better description of the asset-specific risk than the popularly used normal distribution. Devaney (2001) empirically confirms Young

and Graff's assertion of infinite-variance distribution in a GARCH-M model, as he described equity REIT (EREIT) and mortgage REIT (MREIT) returns distributions as not only skewed but, in addition, characterized with leptokurtic behaviour

That notwithstanding, in a relatively current stream of works, Tsai (2013), Asteriou and Begiazi (2013) and Gu et al., (2017) all made assumptions of a normal or Gaussian distributed innovations in their respective models to "best" describe returns distributions in REIT markets. Tsai (2013) explores several statistical properties or market variations in 7 scrutinized Asian REITs (i.e., Singapore, South Korea, Malaysia, Hong Kong, Thailand, Taiwan, and Japan). In a SWARCH model with Gaussian distributed innovations, Tsai found key properties (volatility clustering, small and large variations) in almost all the studied Asian REITs, and evidence of contagion effects for South Korean, Japanese and Taiwanese REIT markets. Employing volatility models (GARCH, TGARCH, and EGARCH) under conditional distributed normal errors, Asteriou and Begiazi (2013) explore return and volatility behaviours of mortgage, equity, and the hybrid US REITs (with daily returns from September 2000-April 2012), and conclude on the sensitivity of the REIT markets to bad news. Interestingly, the authors documented rejection of the conditional normality assumption in their GARCH model, however, they upheld the same normality assumption for the EGARCH model, and report of its better description for the return distribution of the REITs. Moreover, Gu et al., (2017) investigate time-varying co-variations in global REITs with daily price changes data (03.01.2002-31.05.2016) of 15 real estate securities from different continents[20]. Although, Gu and co characterized the unconditional returns distribution of all the property indexes with fat tails, left skewness and a general deviation from normality, quite amazingly, they later

[20] That is REIT markets of Germany, France, Belgium, Netherlands, Sweden, Switzerland and UK from Europe; Hong Kong, Australia, Japan, Singapore and Philippines from Asia-Pacific; South Africa from Africa; and Canada and United States from North America

assumed normally distributed innovations in their model specification for the REIT returns.

Lee and Pai (2010) also wade into the debate to investigate whether the specification of REIT return distribution holds any impact on volatility forecasting performance. Drawing on 1,670 daily return realizations (01.01.2000-31.12.2006) from the United States National Real Estate and Investment Trusts (NAREITs), and using normal, skew generalized error distribution (SGED), and the skew *t* distributions in a GARCH-type model, their study found, in all forecast horizons, GARCH-SGED as superior fit to the US REIT return distribution. They further stressed the impact of correctly specifying a distribution that captures skewness and fat tail on forecasting, and delineated its relevance for VaR estimates and portfolio selection. The comparative usefulness of the SGED to the normal was also confirmed by Wu et al., (2011), as the authors assess possible influences of regime shift (or structural change) on the daily returns of S&P United States REITs composite index data (which spans 31.07.1989-29.02.2008). Contrary to the Gaussian distributed innovations in the work of Loo et al., (2016), Haas and Liu (2018) oppose the appropriateness of the Gaussian to the Student's *t*, which they claim the latter dominates the former distribution in both their data specifications (i.e., in- and out-of-sample weekly returns of EPRA/NAREIT global indices).

Elsewhere, Yuan et al., (2017) compare the appropriateness of the normal distribution to the Student's *t* and fit four GARCH-class models (GARCH, APACRH, GARCH-GJR, and EGARCH) under each distribution to the returns series of United States equity, mortgage, and hybrid REITs. Using daily returns data (03.01.2007-18.11.2016) of the REITs, the researchers examine the volatility forecasting performance of their different model specifications and concluded in favour of a Student's *t* distributed GARCH-GJR model, while describing the returns as one characterized by fat tails, asymmetry, and volatility clustering. With data on 20 US REITs and 20 UK listed

property securities, Bond and Patel (2003) assess skewness in the shape of the conditional market return distribution using volatility models under the Student's *t* distribution and its skewed version. Results from their study showed a rejection in 13 instances from the pool of fitted models associated with the skewed student's *t*, which was also less favoured to a time-varying skewness model in 8 cases. Perhaps, the authors' findings draw fresh insight to an aspect of the current study's broad focus, which empirically weighs on evidence from varied asset classes to caution analysts to look far beyond a mere assumption of a distribution for characterizing short interval financial asset returns.

Risk management has been pencilled by academics, financial analysts, investors, central banks, and risk portfolio managers as a key component in the global bond market. Hence, research to assess stylized properties and statistical distributions of bond market's price movement and return volatility holds much relevance to all stakeholders. Most importantly, in quantifying risk (for example, skewness risk) and return predictability with implied relevance for asset pricing (Ilmanen, 1995; Erb et al., 1999) of the market, the return and volatility distributions need to be well-specified to include extreme fluctuations or market variations. Beginning with empirical works in this direction, Erb et al., (1999) project several perspectives, prior to and during the meltdown of emerging markets, of which one was to explore risk (by broadening it to include conditional skewness risk) and expected monthly return characteristics of the bond market. Using J.P Morgan's Emerging Market Bond Index (EMBI) from January 1991 to September 1998, the scholars described emerging market bonds as largely idiosyncratic, owing to evidence of higher returns amid larger fluctuations or volatility which makes the asset quite comparably riskier. Touching on the distributional characteristics of the bonds, their study reported deviation from normality, and additionally stated findings of excess kurtosis and a range of skewness values from -0.50 to -2.10, recorded prior to, and during the meltdown respectively.

Discarding the normal and Student's *t* distributed innovations due to inadequacies, Bekdache and Baum (2000) adopt the generalized error distribution (GED) in an ambit of ARCH-class models to assess the link between term spread and (excess) returns on holding an investment in United States Treasury securities for different investment horizons (short-, intermediate- and long-tenors), and found among others, weak evidence against the inclusion of term spread in excess return models. Aas and Haff (2006) argue for the inclusion of a generalized hyperbolic (GH) skew Student's *t* distribution (a special case among the generalized hyperbolic class) as more appropriate for describing asset return distribution having polynomial and exponential tailedness behaviour. Comparing their proposed distribution to the normal inverse Gaussian and skew Student's *t* distributions across four financial asset returns, the study's findings revealed almost a stalemate model fit performance for international bond (proxy by SSBWG hedged bond index) return distribution, keenly between a fit with the GH skew Student's *t* and that of the NIG.

Not much surprisingly, studies like Mendoza (2005), Piljak (2013) and Gabriel and Lau (2014) denounce normality or Gaussian-like tailedness distribution for the return distribution of the bond market. For instance, the latter authors rejected the normality assumption for daily bond returns of member countries in the European Monetary Union (except Luxemburg) with varying maturities (1-, 3-, 5-, 10-year tenors). Relying on unconditional sample bond returns from 1999 to 2012, the authors tasked themselves to examine statistical distribution for the asset returns by choosing among four parametric distributions (normal, skew Student's *t*, Student's *t*, and stable distribution). The return distribution is found to had strongly departed from the normal (for all countries), mainly in the tails where weak (high) significance in skewness (excess kurtosis) is recorded. Further result has it that the stable distribution provides the best alternative fit which well-captures excess kurtosis with plausible benefit for risk management, as sovereign risk is unveiled as a key element in bond asset returns.

Quite recently, Clark and Baccar (2018) and Shahzad et al., (2019) report different characteristics for global bond markets. For instance, the former authors propose asymmetric GARCH-family models (AGARCH and GACRH-GJR) alongside the Student's *t* distribution to examine driving factors of yield spreads on bond indices extracted from the United States credit market. Disclosing varying effects of their seven explanatory factors on corporate yield spreads, the scholars also identified superiority of the asymmetric volatility models (for capturing skewness) and the Student's *t* (for addressing fat tailedness) to the traditional linear GARCH and normal distribution (in both in- and out-of-samples) respectively. To the other study, Shahzad et al., (2019) employ ARMA-FIGARCH models with a skewed *t* distribution to fit and explain the marginal distributions of Islamic bond and equity markets in a copula framework and concluded of safe haven and/or potential hedge characteristics of Islamic bond in benchmark Islamic stock properties.

The currency market is well-known for its highly volatile and the uncertainty it presents to international investors, monetary policy committees, financial engineers, and treasury risk and portfolio managers. These market behaviours often cause currency exchange rates to be characterized with large fluctuations, high peakedness, skewness, and varied tailedness features, which mostly makes it inadequate to describe with a mere normality assumption, or even with light tail statistical distributions. This debate has been with us for decades and still remains unsettled.

To mention a few primers in the literature on the subject of discussion, the studies of Boothe and Glassman (1987), Tucker and Pond (1988) and Fujihara and Park (1990) are noted. Using daily spot exchange rates of the Japanese Yen, UK's pound, German mark and the Canadian dollar against US dollar (from 02.01.1973-08.08.1984), Boothe and Glassman (1987) explore the fit adequacies of the stable Paretian, normal, Student's *t* and mixtures of two normal distributions, and concluded in approbation for the last two different sets of distributions. In finding alternative distribution to the

normal for characterizing price changes of six major foreign trading currencies, Tucker and Pond (1988) investigate the model fit abilities of the mixed-jump model, general stable distribution, compound normal and scaled *t* distributions, and found suitability in the former distribution over all others. Contrary to the findings of Tucker and Pond (1988), Fujihara and Park (1990) ruled-out superiority of the mixed diffusion-jump model, as they found evidence to support an ARCH process among four candidate processes (i.e., mixed diffusion-jump process, ARCH process, Student *t*, and compound normal distributions)

Coppes (1995) tests the assertion of whether price changes of currency exchange rates observed over more than a day data-frequency are distributed normally and concludes that the distribution for the monthly price changes looks more normal than that of the daily changes. Employing a general normal mixture distribution in traditional GARCH models, Alexander and Lazar (2006) provide evidence of better fit, compared to GARCH models under symmetric and skewed Student's *t* distributions for exchange rate modelling. To capture thick tail risk in currency rate returns, Gurrola (2007) found models of the skewed Student's *t* to had performed best among a mixture of normal and S_U distributions. However, the authors ascribed the models under the latter distribution as flexible and best, with respect to the performance of their VaR estimations. Incorporating the normal inverse Gaussian distribution in a FIGARCH model, Kiliç, (2007) reports of the model's in- and out-of-sample viability in explaining volatilities in the daily exchange rate returns (04.01.1999-26.12.2006) of the Euro, Swiss francs, Japanese Yen, UK's pound, German mark and the Canadian dollar against the US dollar, after downplaying on the fit adequacies of the Student's *t* and normal error distributed GARCH models. Using intraday data, Chortareas et al., (2011) examine models for achieving optimal Euro's bilateral currency rate volatility forecast, and settled on FIGARCH and ARFIMA models with Student's *t* innovations, and the expense of conventional volatility models and the normal.

In a pool of recent works on the ideal and flexible statistical distribution(s) for modelling conditional and unconditional return distributions of exchange rates, several parametric distributions like the generalized lambda (Corlu and Corlu, 2015), Student's *t* (Nadarajah et al., 2015; Abdullah et al., 2017; PETRICĂ and Stancu, 2017; Lahmiri, 2017a; Moravcová, 2018), skew *t* (Nadarajah et al., 2015), skew exponential power (Kobayashi, 2016), skewed Student's *t* (Będowska-Sójka, 2018), generalized Pareto (Liu, 2018), normal (Lahmiri, 2017a; Moravcová, 2018; Sarpong, 2019) and generalized error distributions (Lahmiri, 2017a) have been empirically found to outperformed other alternative distributions.

Corlu and Corlu (2015) examine the performance of the skewed *t*, generalized lambda distribution (GLD), normal inverse Gaussian (NIG) and the unbounded Johnson family of distributions for adequately capturing skewness and fat tails in the return distribution of 3 emerging and 6 developed currency exchange rates, as expressed in quantities of the US dollar[21]. Using daily returns from 02.01.2006 to 30.12.2011, the authors found a tie in fit performance for the GLD, skewed *t* and NIG in the tails of the return series where the computation of risk measures (such as VaR and ES) hold much importance, and further surmised that, owing to the GLD's flexibility, it should be considered as a good candidate distribution for modelling fat tail behaviour in financial asset returns. Revisiting and using the same data in the work of Corlu and Corlu (2015), Nadarajah et al., (2015) contradict the findings of the former authors by projecting much simpler distributions (Student's *t* and skew *t*) as best fits in most of the cases considered, whereas the GLD placed second to the equally performed Student's *t* and skew *t* distributions.

[21] The Brazilian real, Turkish lira, Mexican peso (from emerging economies); and Australian dollar, Canadian dollar, Euro, Swiss franc, Japanese Yen and UK's pound from developed currency markets are used in their study.

In forecasting exchange rate volatilities of the US/Euro and US/Canada daily rates, Lahmiri (2017a) considers artificial neural network (ANN) techniques and a range of conventional GARCH-type models under the normal, GED and Student's *t*, and revealed that the ANN offers an effective approach in volatility forecasting. However, comparing the volatility models alone from their study, the GARCH-normal and EGARCH-normal had the lowest forecasting errors for the US/Canada rates; whiles the US/Euro volatilities could best be forecasted with GARCH and EGARCH under GED and the Student's *t* distributions. Considering EGARCH with normality assumption (for Czech and Polish currency exchanges to the Euro – CZK/Euro and PLN/Euro) and under the Student's *t* (for the Hungarian local currency against Euro – HUF/Euro), Moravcová (2018) assesses announcements of European Central Bank and German's macroeconomic news on the conditional volatilities of the currency rates, and reports diverse economic and financial influences of such announcements.

Compared to real or fiat currency market, cryptocurrencies are noted to be somehow more volatile. These new currencies exhibit even larger volatility swings (or fluctuations) and often respond to extreme tail conditions. With such notable characterization, the return realizations of cryptocurrency exchange rates require enough studies to explore appropriate single or set of statistical distribution(s) which might well-incorporate those features. However, a search through financial economics and risk management literature shows few empirical works pioneering the area. This may not sound unusual as the new currency market is barely a decade in existence.
Best known to us, Chu et al., (2015) explicitly provide the maiden return distributional analysis of the exchange rate of cryptocurrency. Using daily returns of the Bitcoin to US dollar exchange rates (from 13.09.2011-08.05.2014), and adopting 15 parametric distributions, the scholars favoured the generalized hyperbolic distribution as best candidate for modelling and predicting future realizations of the Bitcoin exchange rate. Extending data on the number of cryptocurrencies to seven markets (Dash, Bitcoin, Litecoin, Monero, Ripple, MaidSafeCoin, and Dodge), Osterrieder (2016) re-

examine the work of Chu et al., (2015) by fitting a comparably reduced number of distributions to the daily exchange rate returns. The authors concluded against a fit from the normal but upheld the Student's *t* as an appropriate distribution for modelling exchange rate returns of cryptocurrencies.

Osterrieder and Lorenz (2016) investigate the tail risk behaviour of Bitcoin/USD exchange rate and compares it to the currency exchange rates of the G10 countries. Aside from characterizing Bitcoin returns as more volatile, much riskier and one that exhibits heavier tail features than traditional fiat currencies, the authors fit the generalized Pareto and generalized extreme value distributions to the tails of the currency returns, and showed that in cases of extreme events, losses in Bitcoin are likely to be 8 times higher than expected losses in fiat currencies. Málek and Tran (2018) rejected normality approximations for Bitcoin, Litecoin, Ethereum and Ripple exchange rate returns, and fit the normal inverse Gaussian and alpha-stable to capture as they claim, "power" tails in the return series of the markets. The study's results give more precision to the alpha-stable distributions. Similarly, Kakinaka and Umeno (2019) provide evidence to conclude that exchange rate return distribution of cryptocurrencies (like Bitcoin, Ripple, Ethereum, Monero, and Litecoin) is best approximated with thick tail levy's distribution. More so, Majoros and Zempléni (2018) extend the stable distribution to a multivariate situation and found the usefulness of the approach in modelling fat tails in the return distributions of Bitcoin, Litecoin and Ripple.

To another empirical study, Chan et al., (2017) analyze statistical properties of 7 major cryptocurrencies (thus, Bitcoin, Dash, Litecoin, Monero, MaidSafeCoin, Ripple and Dogecoin versus US dollar) and explore appropriate parametric distributions for their exchange rate returns using data from 23.06.2014 to 28.02.2017. Strongly rejecting normality for all studied currencies, the authors found the generalized hyperbolic distribution as best candidate for the return series of Bitcoin and Litecoin; the

generalized t distribution for Dogecoin; the normal inverse Gaussian distribution for Ripple, Monero, and Dash; and the Laplace distribution for MaidSafeCoin.

In modelling the conditional returns of cryptocurrency exchange rates, studies like Liu et al., (2017) and Chu et al., (2017) examine the fits of volatility models with several distributions. Comparing GARCH models under normal, Student's *t* and the normal reciprocal inverse Gaussian distributions, Liu et al., (2017) report outstanding fit performance of the GARCH-Student's *t* for describing return dynamics in Bitcoin/USD exchange rate market. On one hand, Chu et al., (2017) show evidence in support of an IGARCH model with normally distributed innovations as best for characterizing the market behaviour of nearly all their studied currencies. Also, Chen et al., (2016) provide a novel analysis on the returns of an aggregated cryptocurrency index (CRIX), by fitting to it a variant of GARCH-type models under the assumption of the Student's *t* distribution, and reported several market behaviours from the data.

Nonetheless, as it stands now, studies that compare the distributional fit characteristics of a diverse range of asset classes are virtually non-existence. Hence, empirical works to unveil the return distribution and tail behaviour that uniquely characterize asset classes are warranted.

2.2.2 Stochastic randomness, non-linearity, and chaotic reviews

International financial markets have for the past decades evolved through several forms of innovations, uncertainties and shock dynamics. For instance, the continual transformation of global financial markets and innovation growth in various aspects of the markets' microstructure have remarkably heightened uncertainties. Also, unexpected financial events or economic cycles (like the 1987 stock market crash, 1992 European exchange rate mechanism crisis, the mid-1997 Asian financial crisis, 9/11 attacks World Trade Centre, the subprime meltdown and the European sovereign

debt crises of 2007/8, and the recent Brexit brouhaha) have knowingly been documented to had influenced the time evolution and structural dynamics of global financial markets.

These external influences on financial markets mainly result in spasmodic of large and volatile movements in price changes, which often may not be well-explained by linear processes or models. Compared to linear models which are openly known for their limitedness in explaining market behaviours, except for: (i) oscillatory and explosive; (ii) oscillatory and stable; (iii) non-oscillatory and explosive; and (iv) non-oscillatory and stable dynamics, non-linear models are best suited for explaining wider types of market behaviours (Hsieh, 1991). Therefore, a naturally growing development in financial econometrics has been the modelling of the non-linear behaviour of financial markets (see, Liow and Webb, 2008; Özer and Ertokatlı, 2010; Jirasakuldech and Emekter, 2012; Bensaïda and Litimi, 2013; BenSaïda, 2015; Lahmiri and Bekiros, 2018; Gunay and Kaşkaloğlu, 2019; etc.), owing to the ongoing argument that several aspects of market behaviours may not be well-captured by linear processes.

Meanwhile, natural processes can broadly be categorized into three, namely, pure stochastic process, strong deterministic process, and dynamic process. Whereas the stochastic process is characterized by pure randomness, that is a process that generates different outputs or lack of patterns in repetitively identical conditions of the experiment, a deterministic process produces outputs which are exactly of the same nature, and could easily be predicted in every repetition of the experiment. Moreover, in general, a dynamic process could either demonstrate stochastic or deterministic behaviour (or both). More so, the family of deterministic dynamic processes, of which deterministic chaotic process is one of such classic example has received enormous attention in the natural sciences (mostly, ecology and biology, climatology, physics, and chemistry), but it is rarely mentioned in finance. The theory of chaos has long existed and remains a hot topical issue in the sciences, yet its

application to finance and economic theories date back few decades, and continues to receive inappreciable level of research attention in the financial econometrics and risk management literature, where most dynamic processes are assumed to follow a stochastic dynamic process.

In a working explanation of the chaotic theory, Kiehling (1996) defines chaos as a process which shows: (i) topologically transitivity (i.e., moves from a mode to another); (ii) sensitive dependence on initial conditions; and (iii) density of periodic points. Williams (1997) views chaos as an irregular change over a longer time period or a disorderly-looking long-term evolution that satisfies a particular mathematical benchmark, and emerges from a deterministic non-linear system. Also, Bensaïda and Litimi (2013) explain chaos as an apparent disorder in a system that however observes specific laws or rules. In the authors' definition, a small change to a complex system relying on a certain order may subsequently result in a much complex behaviour – a phenomenon which is recognized as *sensitive dependence on initial conditions*. In the context of this study, we briefly describe chaos as any non-linear deterministic process which illusively behaves randomly instead of being purely deterministic. Thus, a process that display sustained irregularity and somehow random-like behaviour. Even though the mention of non-linear processes is associated with chaoticity, further specific conditions are required to be satisfied for such non-linear processes to evolve into chaotic or very complex processes. Meaning, a deterministic dynamic process may display non-linear features, yet it could be far from being pronounced chaotic since non-linearity appears only as necessary but not sufficient condition for a chaotic process.

The main "sacred" features that characterize chaoticity is the process' sensitive dependence on initial conditions (also referred to as the butterfly effect), and the unchanging patterns with respect to localize or temporal level, often described as self-similarity or scale invariance (Kiehling, 1996; Mammadli, 2017; Lahmiri et al., 2017).

With its diverse relevance, application of chaos has generally attracted interest in multidisciplinary studies. One key reason accounting for the growing interest in the chaotic analysis of historical data is the ability of the process to distinctly verify whether disorderly-looking variations (or random-like fluctuations) actually portray an orderly system (or non-random fluctuations) in disguise. Therefore, the study of chaotic behaviour has the potential of explaining large movements, in, for instance, an economic system or financial markets which appear to be random (Hsieh, 1991; Williams, 1997, p.21). Secondly, detecting chaos may lead to greater short-term forecasting accuracy, on the account that linear forecasting models show much inappropriateness for chaotic data. Thirdly, identifying chaotic behaviour in historical data makes modelling quite easier, in as much a simpler deterministic model could best describe the variations in the data, instead of mathematically modelling such irregular evolution which supposedly arises from effects of several external factors. Lastly, analysis of chaos may reveal the time-limits of non-spurious predictions, and could further identify conditions where long-term forecasting is essentially inconsequential (Williams, 1997, p.21). Hence, the need to detect the presence (or otherwise) of chaos looks more appealing, as such analysis may help to comprehend among others the micro-behaviour of agents or participants in an economic or financial system.

Nonetheless, with the resurgence of attractiveness to non-linear deterministic processes in interdisciplinary studies (like the sciences, engineering, communication, and population studies), the financial related literature is yet to record appreciable volume of research attention. This low interest of chaotic studies in finance and its related fields has been attributed to a sundry of factors: (i) lack of lengthier data (ideally, many thousands, or in special cases, millions of data points are warranted). Even with financial assets, only a section of the market could for now afford to generate realizations (of a time series) with a magnitude of length or data points large enough to reliably apply chaos theory to it; (ii) challenges with data collected and

consistently handled in identical conditions; (iii) chaos theory works appropriately for systems of fewer variables (pragmatically, three or lesser variables); (iv) unrealistically high accuracy in the data measurements are needed; and (v) chaotic analysis requires data or time series realizations with negligible quantities of noise. That is, undesirable disturbance superimposed on (or unexplainable variability in) useful data (Kiehling, 1996; Williams, 1997, p.16).

In a real-world situation, ordinary data with quite smaller data points can rarely satisfy these conditions, and as a result, it often provides a plausible but spurious outcome. Thus, mostly concluding in favour of chaotic behaviour, where indeed the data shows otherwise. In spite of all, new and much-improved techniques and reliable datasets are speedily emerging on a regular basis to help address the aforementioned challenges. For instance, in the financial literature where empirical evidence of chaos looks inconclusive in asset markets because of numerous test specifications that require noise-free data ("clean data") to play down on measurement-error-induced chaotic detection, a rigorous test with validated power over conventional test methods has been developed to reliably unmask chaotic behaviour, even where there exists a moderate random (or heteroscedastic) noise (refer, Bensaïda and Litimi (2013). With these ongoing developments, detection of chaos in real-world data is less becoming challenging.

The primers of research on non-linear dynamics or chaotic analysis in financial markets promulgated somewhere in the mid-1980s, where the seminal work of Hinich and Patterson (1985) found non-linear as well as non-Gaussian processes to had characterized daily returns of 15 common stocks listed on the New York Stock Exchange. Investigating the behaviour of stock returns after the October 19, 1987 stock market crash, Hsieh (1991) rejected independent and identically distributed random variables for the returns of the studied markets, and disassociated the root-cause as neither the effects from regime shifts nor chaotic dynamics. Moreover, a survey of

empirical works on chaotic analysis in financial markets is provided by Kiehling (1996).

Quite recently, other empirical works on non-linear deterministic or chaotic studies have been extended to global stock (Small and Tse, 2003; Mattarocci, 2006; Özer and Ertokatlı, 2010; Zafeiriou et al., 2010; Alagidede, 2011; Park and Whang, 2012; Bensaïda and Litimi, 2013; BenSaïda, 2014; Günay, 2015; Lahmiri et al., 2017; Alves, 2019; etc.); bond (Bonilla et al., 2008; Park and Whang, 2012; etc); and REIT (Newell et al., 1997; Liow and Webb, 2008; Jirasakuldech and Emekter, 2012; Belaire-Franch and Oppong, 2013; etc.) asset markets. Other market areas of applications are reported for global commodities (Small and Tse, 2003; Lahmiri, 2017b; Lahmiri et al., 2017; Alves, 2019; etc.), as well as international currency exchange rates, particularly fiat currencies (Small and Tse, 2003; Park and Whang, 2012; Bensaïda and Litimi, 2013; BenSaïda, 2014; Kumar and Kamaiah, 2016; Mammadli, 2017; Lahmiri et al., 2017; etc), whereas the new global currency entrant (cryptocurrencies) have witnessed a smaller coverage of empirical studies (Akkaya et al., 2015; Siddiqi, 2015; Lahmiri and Bekiros, 2018; Gunay and Kaşkaloğlu, 2019; etc.).

Employing the Shannon entropy and the largest Lyapunov exponent to daily Bitcoin data (18.07.2010-23.10.2017) during periods of low and high prices, Lahmiri and Bekiros (2018) found chaotic behaviour in prices rather than returns for both distinct time periods. Opposed to the findings of Lahmiri and Bekiros (2018), Gunay and Kaşkaloğlu, 2019 investigate the presence of chaos in four major cryptocurrencies (Litecoin, Bitcoin, Ripple, and Ethereum) with data from 28.04.2013-13.01.2018, and reported non-randomness and evidence of chaotic order in the returns of the markets.

Using monthly data observations (04.1994-09.2014) of BRICS foreign exchange rates, Kumar and Kamaiah (2016) aim to detect non-linear and chaotic behaviour with a range of test methods and empirically detailed the presence of non-linearity and chaos

in price series of the currency exchange rates. Mammadli (2017) found evidence against a linear process and the presence of chaotic order in the daily returns of Turkish currency exchange rates (USD/Lira), with 1,564 time series realizations spanning 01.01.1995-31.12.2000. Besides, Lahmiri et al., (2017) explore randomness, non-linearity and chaotic dynamics of 14 major international stocks, 3 fiat currencies, and 13 commodity markets during (15.01.2007-21.12.2010) and post (01.01.2011-19.12.2016) 2007/8 global financial crisis. The authors revealed that non-linear characteristics manifest in the returns of the global markets, but could not find features of chaoticity in all such markets. It was further identified that the magnitude of randomness increased for majority of the markets in the post-crisis period. In a quite similar work, Lahmiri (2017b) establishes strong empirical evidence against chaotic order in the prices and returns of Brent and WTI crude oil markets, prior and after the global financial crisis in 2008, but found chaoticity in the volatility series of both markets for the post-crisis era.

Elsewhere, Alves (2019) uses a much shorter monthly data covering 11.2010-11.2018 to unveil chaos in the price and volatility series of US Brent oil, Wipo Limited, Nasdaq Inc., and SPDR S&P 500 ETF markets. However, unlike the historical prices and volatilities, the return series of the markets was identified to have followed a stochastic process. Günay (2015) investigates and found evidence of low to moderate degrees of chaotic features in the returns of five largest emerging stock markets (with data from 10.01.1997-30.01.2014). More so, Belaire-Franch and Oppong (2013) found non-linear features which do not lead to chaotic detection in the return series of the United Kingdom's construction and real estate markets.

In a pool of recent works toward methodological advancement, Park and Whang (2012), Bensaïda and Litimi (2013), BenSaïda (2014) and BenSaïda (2015) design and apply formal chaotic test methods (based on the popularly used Lyapunov exponent) which they claim look more robust and shows validated powers over other widely

used alternatives like the close return test, Brock-Dechert-Scheinkman (BDS) test, and several simplistic approaches based on entropy and fractal dimension estimations. The chaotic test of Park and Whang (2012) and the test in the works of BenSaïda (refer, Bensaïda and Litimi, 2013; BenSaïda, 2014; and BenSaïda, 2015) are found to provide a reasonably accurate estimate of the Lyapunov exponent in finite samples. Besides, the latter test method significantly improves upon the conventional largest Lyapunov exponent which often leads to misspecification of chaotic behaviour in noisy financial time series.

2.2.3 Asymmetric volatility, fractality and herding survey

In an increasing effort over the years, several empirical studies have attempted to explore diverse and hidden characteristics of complex financial systems with varying degree of successes. External factors like economic cycles or financial events, natural disasters, geopolitical disturbances among others have been widely reported of having caused different magnitude of changes or effects to the data generating process of complex systems. However, other phenomena, especially behavioural factors like investors' sentiments, appetite for risk, and market consensus-building which poses greater uncertainties and have the tendency to influence the microstructure of financial systems are somehow overlooked.

Also, empirical findings on the level of influences attached to these complex financial systems during prolong rise (bullish market) and decrease (bearish market) in prices and other (extreme) market conditions are rarely documented in the literature. For instance, the main causes of fractality in financial markets are often linked to long-term correlations and fat tailedness behaviour of asset returns. On one hand, major known economic cycles are at times reported as key influential factors which induce the presence of fractality and asymmetric volatility in financial asset returns. Yet, less is known about the evolving nature of influences that bullish and bearish market

periods, as well as market consensus-building (if present) wield on the characteristics of asset returns. However, aside the two well-known causes (or origins) of multifractals in assets returns, Hasan and Mohammad (2015) investigate the impact of the recent 2007/8 global financial crisis on the multifractal structure of 7 Asian stock markets (i.e., Nikkei 225, Hang Seng, Seoul composite, Shanghai composite, Sensex, Jakarta composite, and KLSE composite), while using S&P 500 for benchmarking, and found multifractality in the returns of all market indexes.

Elsewhere, Maganini et al., (2018) examine multifractal characteristics in 5 Brazilian stock index returns (including the BOVESPA index) with data from 26.06.2009 to 31.05.2017. Though evidence of multifractality is shown in the market returns, the authors downplayed its origin as neither long-term correlations of returns fluctuations nor thick tails in the distribution of the index returns. Perhaps, could any other intrinsic factors contribute to the presence of multifractals in asset returns?

As the causes of multifractal behaviour in financial market returns lingers on, Cajueiro and Tabak (2007) empirically introduce a novel direction to the discourse, by associating the origin of multifractals in asset returns to investors' herding behaviour. Using daily returns (04.01.2000-09.02.2006) of the Nikkei 225 composite index, the scholars detected multifractal features and delineated that such detection may be induced by the presence of market consensus, where investors imitate the trading strategies of each other. Although evidence of multifractality has been found in foreign currency exchange rates (Oh et al., 2012; Batten et al., 2014; Al-Yahyaee et al., 2018; Jiang et al., 2019; etc.), global commodities (Al-Yahyaee et al., 2018; Jiang et al., 2019; etc.), and recently for exchange rates of cryptocurrency markets (da Silva Filho et al., 2018; Lahmiri and Bekiros, 2018; Takaishi, 2018; etc.), the origins of such multifractal structures remains a subject for further discussion.

Moreover, in this current study, an empirical exploration for the presence (or absence) of herding behaviour in a wider financial market coverage is given utmost priority, being that comparative evidence of herding activity in different financial asset class markets is rarely reported in previous studies. Observably, studies on herding have generally been much concentrated on international equity markets (Chiang and Zheng, 2010; Lao and Singh, 2011; Filip et al., 2015; etc.) than any other financial asset market (see, the review of Spyrou, 2013). For example, Chiang and Zheng (2010) assess herding activity in 18 international stock markets, grouped into advanced stocks, Latin American stocks, and Asian index markets. Except for Latin America and the US daily industrial stock returns, the study revealed significant evidence of herding in all the remaining national markets.

Lao and Singh (2011) found evidence of herding in the Indian and Chinese stock markets, and further identified an increasing pattern of herding features in extreme market conditions for both index returns. In another study, market agents are recognized to have herd in all Central and South Eastern European major stock index markets, except for the Polish market, with responses to different herding characteristics in periods of price decreases, pre-, during-, and post-financial crisis periods (Filip et al., 2015). Also, Indārs et al., (2019) explore the existence of herding activity in the daily returns of 120 individual equities listed on the Moscow Stock Exchange (from 01.04.2008-30.12.2015) under several market prepositions and generally found evidence against herding by investors.

On a much broader perspective, Spyrou (2013) provides a detailed review of the empirical methodology and evidence of herding activity reported in different financial asset markets over several decades. Unfortunately, Spyrou's survey does not offer any information on the recent global financial market entrant (digital currencies). Nonetheless, the works of Bouri et al., (2019), Vidal-Tomás et al., (2019) and da Gama Silva et al., (2019) are noticed. Using daily returns of 14 largest cryptocurrencies

(spanning 28.04.2013-02.05.2018), Bouri et al., (2019) establish the presence of significant time-varying herding behaviour in the market by international investors. Besides, Vidal-Tomás et al., (2019) highlight the riskiness and inefficiency of 65 cryptocurrencies, owing to empirical evidence that the market shows characteristics of herding activity during downtrend periods. Although their study covered a wider representation from the universe of cryptocurrencies, it is quite obvious to conclude that several of such currencies considered are illiquid and mostly attract low volumes of trade. Employing daily market returns of 50 cryptocurrencies (01.03.2015-13.11.2018), da Gama Silva et al., (2019) investigate and analyze herding behaviour and possible contagion effect, and reported extreme market periods of adverse herding activity, coupled with a role for Bitcoin as a shock propagator.

In another development, the chunk of empirical works which demonstrates evidence for or against asymmetric return-volatility characteristics are mostly recorded in international stock markets (see among others, Christie, 1982; Campbell and Hentschel, 1992; Talpsepp and Rieger, 2010; Kumar and Maheswaran, 2012; Albu et al., 2015; Horpestad et al., 2019). This well-studied phenomenon in equity markets projects a stylized fact which portrays how the decline in prices often induce volatility increases. By extension, a purported situation where negative shocks usually increase market volatility by more than what positive shocks could do. The financial leverage and volatility feedback hypotheses are practically used to explain the existence of asymmetric volatility in stock markets.

On one hand, a major origin for the presence of asymmetry in the volatility of stock index is linked to financial leverage, where the latter phenomenon effectuates an increased relationship between the value of equity and volatility. Meaning, negative price shocks (or decline in prices) increase a firm's debt-to-equity ratio and thereof give rise to higher equity volatility in the unforeseeable future (refer, Christie, 1982). On the other hand, the volatility feedback hypothesis has it that an increase in equity

market volatility hoists expected market returns which dwindle current equity prices (refer, Campbell and Hentschel, 1992). Opposed to these theories, in the sense of not holding relevance in all cases, Baur (2012) argues against the practical application and generalization of the financial leverage and volatility feedback explanations attached to the presence of asymmetric volatility in asset markets, especially global commodities like silver and gold. The author examines volatility in the global gold market and found inverted asymmetric features, where positive shocks (or increase in prices) increase the volatility in gold by more than negative shocks. Downplaying on the two theories, he assigned the inverted asymmetric features to the safe haven characteristics of gold.

Also, Todorova (2017) revisits the inverted or inverse asymmetric volatility features of gold using high-frequency data and by initially decomposing volatility into negative and positive semi-variance. The study identified two different effects. Thus, the importance of positive semi-variance in periods where gold experience high price returns are emphasized, while the short-term negative semi-variance is found to be pervasive and shows far less volatile impact.

Baur and Dimpfl (2018a) analyze the link between returns and future market volatility in a set of agriculture, metal and energy commodities, compared to equity markets, with data from 01.01.1990 to 31.12.2017 under four different models. The study identified positive (negative) asymmetric volatility characteristics for most commodities (equity markets) in the sample data from 1990-2004 (2005-2017) and showed that the magnitude of the evidence manifests more strongly in equity markets. For both markets, the study also revealed that the nature of asymmetric volatility effect was greatly influenced by the recent global financial crisis. It again reports that financialization of commodity asset markets had major influences on the nature of the evidence.

Chevallier and Ielpo (2017) investigate leverage effect in 21 commodities and compare the resulting evidence to other asset classes (i.e., bonds, equities, and foreign currency markets). Using an EGARCH model under a combination of normal distribution (EGARCH-MN) with a recursive estimation strategy, their study unveiled the presence of leverage effects in only 4 of the 21 commodities (gold, wheat, coffee, and cocoa), and also in the bonds, equities, and foreign currency exchange rates. Further result has it that the degree of leverage effects in the US stock market are more pronounced than those found in the commodity markets. However, from an empirical standpoint, we strongly believe the authors' choice of model (i.e. EGARCH) looks flaw as leverage is practically impossible in EGARCH.

Furthermore, Baur and Dimpfl (2018b) explore to ascertain whether asymmetric volatility is present in the new currency market, i.e. cryptocurrencies. Employing 20 major cryptocurrencies, findings from their work projected the inverted asymmetric volatility characteristics in the currency market. That is volatility increase by more as inconsequential to positive shocks (price increase) than responses to negative shocks (price decrease). Interpreting the results, the authors linked the positive shocks (negative shocks) to a trading activity or strategy of uninformed (well-informed) traders. Also, the reason for such volatility increase was attributed to investors' herding behaviour, panic buying in anticipation for a rise in prices, and the display of pump-and-dump schemes.

Using foreign exchange rates of the Australian dollar, Japanese yen, British pound, and Euro against the US dollar, Wang and Yang (2009) found the presence of asymmetric volatility features in the markets and ascribed central bank intervention and base-currency effects as plausible economic explanations. Besides, the authors point out that economic reasons and factors which influences asymmetric return-volatility relationship are not sacrosanct to their assigned explanations, and hence would require further research attention. *Could inherent market conditions and investors'*

trading strategies hold any impact on the detection and nature of asymmetric and/or leverage features, multifractal structure and herding behaviour in asset markets? – empirical answers to this question hold many implications for asset return forecasting and risk management.

Meanwhile, in the financial econometrics literature, asymmetry and leverage are often used interchangeably and sometimes portray to measure the same effect, which truly does not hold. The grievousness of these inconsistencies is when conditional volatility models such as the GARCH-class of models are used to empirically estimate leverage effect. Quite intriguingly, excerpts from a few of these studies read, "… *the asymmetric leverage effect coefficients* γ *reported in Table 2 for Brent are all significantly different from 0 at 1% level in the GJR, EGARCH, APARCH, and FIAPARCH models, showing that Brent market exhibits a leverage effect*" (Wei et al., 2010). "*The EGARCH's leverage coefficient* (δ) *is significant but positive, implying that positive shocks have more impacts on conditional volatility than negative shocks*" (Chkili et al., 2014). "*As the negative impact will lead to increased leverage and risk, this asymmetry is called the leverage effect*" (Zhang et al., 2018). Elsewhere, Horpestad et al., (2019) employ the GJR and the EGARCH models and provide a report which seems to suggest the two terms are synonyms, "*The key variable of interest is the estimated coefficient* γ*, which is the leverage parameter that we are interested in. Gamma is positive and significant at the 1% level or lower for all indices. The results are therefore not mixed, although they differ with respect to the magnitude of the asymmetric volatility effect. The S&P index (US) and FTSE 100 (UK) exhibits highest magnitude of the leverage effect, with an estimated value of 0.19*".

Apparently, these inconsistencies have been highlighted by McAleer (2014), and currently in a work by Caporin and Costola (2019). These two groups of authors pinpoint that leverage is practically impossible in even the most popularly-used GARCH models, i.e. the exponential GARCH, the Glosten-Jagannathan-Runkle GARCH, etc. Nonetheless, Caporin and Costola (2019) devise new definitions for

asymmetry and leverage, which clearly distinguish between the two effects, and also offers flexible characterization to represent them. In quote, "*A GARRCH model allows for asymmetry if positive and negative shocks of the same size induce changes in the conditional variance (volatility) of different magnitude*". Also, "*A GARCH model is coherent with the presence of the leverage effect if negative shocks lead to an increase in the variance while positive shocks lead to a decrease in the variance*". By inferring from Caporin and Costola's (2019) definition, one could only conclude that the two effects are quite distinct, but leverage behaves more so as a limiting case of asymmetry. In the context of these practical coherencies, we adopt these definitions in our study.

2.2.4 Summary of the review

Highlights of the reviewed empirical studies on the various statistical and financial properties of asset markets are presented. Although the review does not give coverage to all the limitless stylized facts of asset markets, relevant behavioural, statistical, economic and financial characteristics of the markets are offered priority. On the issue of probability distributions of asset returns and risk computation (value-at-risk and expected shortfall), several standout points are noted.

First, the mere assumption of a parametric distribution as "universally best" to fit all financial data is quite disturbing. For example, a noticeable sub-culture among sections of practitioners has to do with the imposition of "supposedly" appropriate distribution for a return series, ideally because it is widely applied in the literature for financial data. This looks somewhat flawed. Second, the review pinpoints on the over-reliance on somehow older parametric distributions. Even though the emergent application of relatively new distributions is acknowledged, some practitioners (Gu et al., 2017; Ahmed et al., 2018; etc.) solely apply the normal distribution, perhaps due to its computational simplicity and parsimony. Others are intuited to the Student's *t* (Alagidede, 2011; Chen et al., 2016; Nguyen and Bui, 2018; etc.), perhaps because of its

popularity. Third, the influence of outliers in return distributions have been generally overlooked. Meanwhile, the presence of even a single outlier may have the tendency to distort a parametric distributional specification for financial data. Lastly, the distributional fit of aggregate data from a common asset class looks missing in the extant literature.

Furthermore, the usual general assumption of stochastic generated processes for complex financial systems is gradually being challenged as new evidence has it that some financial systems are indeed characterized by non-linear deterministic or simply put, chaotic behaviour. Though the chaos theory has been in existence for very long a period, much lesser application in empirical studies is documented for financial markets, especially in bond, cryptocurrency, commodity, and the REIT markets. However, with even the few empirical works on foreign currency and stock markets, the evidence of chaos still remains inconclusive due to extensive use of fairly old-fashioned chaotic test methods, which are much responsive to measurement error and have less power against noisy scalar series (Park and Whang, 2012; Bensaïda and Litimi, 2013; BenSaïda, 2015). Another missing link which deserves research attention is the exploration of the nature of randomness and chaotic signals in different classes of financial asset returns (or price changes) across varied market trading scales. *Does such evidence disappear, dissipate or strengthen under such trading time-scales?*

To another range of stylized properties, our review had its lens focused on the characteristics of return-volatility profiles, multifractality and herding behaviour in financial asset markets. From this point of view, it came to light that the presence (or absence) of (mono/multi)fractals, herding, and asymmetric volatility have predominantly been disposed of in international stock markets, in comparison to other traditional assets, as well as the new digital currency market. The evidence of these stylized facts, for instance, asymmetric volatility in stock markets have been linked with major economic theories which provide a sound explanation for such

detection. Meanwhile, same can hardly be advanced for other financial asset markets, as the origins of asymmetric volatility and multifractal structure in asset returns are not well-understood for now and required further research consideration (Cajueiro and Tabak, 2007; Wang and Yang, 2009; Maganini et al., 2018). In their study, Maganini et al., (2018) recommended forthcoming empirical works to differentiate statistical and financial behaviour in periods of different market conditions. Hailing to the likes of such call in the literature, the current study investigates whether tranquil and turbulent (or distress) market periods, including different trading horizons, exert any influences on the risk dynamics, presence (or absence) and nature of asymmetry and leverage, scaling properties, and herding behaviour in a wide range of asset classes.

In summary, a great deal of motivation is drawn from the various itemized gaps in the works reviewed. This partly drives the direction of our study. Holistically, we do not intend to reinvent the wheel, but instead, provide unique contributions by addressing the identified research gaps in the literature.

2.3 Data and empirical methods

The study employs a vast range of robust and relatively current methodologies in its thematic areas of application. Specifically, the Markov Switching Dynamic Regression (MS-DR) approach is adopted to unveil different episodes of calm and volatile regime changes in the asset markets (see, sub-section 2.3.2). A battery of competitive methods used for distinguishing non-linear and linear, as well as chaotic and stochastic dynamics, are presented under sub-section 2.3.3. Also, sub-section 2.3.4 provides extensive coverage of competitive candidate parametric distributions, while selected asymmetric conditional volatility models which capture return-volatility relationship are explained in sub-section 2.3.5. A wavelet-based time-scale decomposition method is outlined in sub-section 2.3.6. Multifractal measures and processes, as well as

statistical metrics for uncovering herding activity, are introduced respectively in sub-sections 2.3.7 and 2.3.8. Lastly, sub-section 2.3.1 specifies the nature and sources of the empirical dataset used for the study.

2.3.1 Data specification

The study considers two levels of datasets across six different financial asset classes. The first consist of individual major stocks, REITs, commodities, bilateral foreign exchange rates, and bond market data from emerging economies. The BRICS (Brazil, Russia, India, China, and South Africa) countries are used to proxy for emerging market economies. The choice of the BRICS was to have a fair representation of giant emerging economies, yet drawing such sample from at least four continents (i.e., South America, Europe, South Asia, East Asia, and Africa). Therefore, BRICS stocks (BOVESPA, MOEX, NIFTY50, SSE50, and FTSE/JSE TOP40); foreign currency market (Brazilian real, Russian ruble, Indian rupee, Chinese yuan, and the South African rand against the US dollar)[22]; REITs (S&P REIT in US dollar); bond (Government Bond Index - Emerging Markets); and commodities (proxy by gold, crude oil, and sugar in US dollar)[23] are considered. The historical daily market data for all the individual assets spans 02.01.2013 to 07.06.2019 and was gleaned from Bloomberg's database terminal. More so, our choice of the sample period was done to bring the time stamp quite closer to the commencement of commercial trading within the cryptocurrency market.

[22] Note well that we define the currency pair (cross) or the bilateral exchange rates to be the price or quantity of the United States dollar required to purchase individual BRICS foreign currencies. Thus Brazilian real/US dollar (BRL/USD), Russian rubble/US dollar (RUB/USD), Indian rupee/US dollar (INR/USD), Chinese yuan/US dollar (CNY/USD), and South African rand/US dollar (ZAR/USD).

[23] We used the market data of global gold, crude oil and sugar because collectively the BRICS countries contribute a fair percentage of these global commodities. For instance, in a 2018 release by World Gold Council, China was adjudged the world's largest producer, while Russia and South Africa ranked third and nineth respectively (Available at: https://www.gold.org/goldhub/data/historical-mine-production, accessed on June 15, 2019).

Aside from the set of data described, we also filtered 8 digital currencies from a universe of 2,092 cryptocurrencies[24] using the following stated criteria. First, we pre-filtered to discard currencies with a market cap below 100 million US dollars. Second, we summed the trading volumes of the resultant 51 currencies and computed a third quartile volume. Overall, 13 currencies with trading volumes above the quartile volume are subsequently upheld. These two criteria somehow address the liquidity challenges of digital currencies. Third, currencies with less than 24 months of active trading and non-reliable data are dropped. A final sample consisting daily market data on Bitcoin (24.04.2013-07.06.2019); Ethereum (07.08.2015-07.06.2019); Ripple (04.08.2013-07.06.2019); Litecoin (28.04.2013-07.06.2019); Dash (14.02.2019-07.06.2019); Ethereum Classic (24.07.2016-07.06.2019); NEO (09.09.2016-07.06.2019); and Zcash (29.10.2016-07.06.2019) as exchanged into quantities of the United State dollar is used in our analysis. For purposes of uniformity, all the individual data across the six asset classes are well-cleaned to downplay on the issue of non-synchronous trading days. Per the above-mentioned criteria, we classified the currencies into major or leading (Bitcoin, Ethereum, Ripple, and Litecoin) and relatively smaller (Dash, NEO, Ethereum Classic, and Zcash) digital markets.

Furthermore, the second set of data involves the aggregate series of emerging asset classes. Historical data on MSCI emerging markets index, MSCI emerging foreign exchange index, MSCI emerging markets REIT index, Government Bond Index - Emerging Markets (GBI-EM), and Bloomberg Commodity index (BCom) are sourced from Bloomberg in US dollars. The data covers periods from 02.01.2013-07.06.2019. There again, the CRIX index, obtained from https://thecrix.de/, with data coverage

[24] The data is sourced from https://coinmarketcap.com/ on 05.03.2019, and subsequently used for the filtering processes. The source produces prices and other measurable quantities on cryptocurrencies based on averages from several global exchanges. Hence, cryptocurrency quantities based on global averages are reliably produced by this source. Moreover, we updated the sourced data once on 07.06.2019 without repeating the filtering processes. More so, the market cap of the 8 chosen currencies represents approximately 77% of the combined 133 billion US dollars market cap for the 2,092 digital currencies, as of 05.03.2019.

from 31.07.2014-07.06.2019 is also considered. Like the individual asset data, the aggregate market series is paired to fix all non-synchronous days of trading. In all, the individual and aggregate market data are both used in our estimations and subsequent analysis.

The daily historical prices for each market from the six asset classes are converted to percentage log-return series using the expression: $r_{i,t} = [In(P_{i,t}) - In(P_{i,t-1})]*100$ for $i = 1, 2, ..., 32$ and $t = 2, ..., T$. From the expression, $r_{i,t}$ gives the percentage log-return series of the ith market at time $t = 2, ..., T$, where $P_{i,t}$ and $P_{i,t-1}$ are the close of day prices at day t and $t-1$ respectively.

Our choice to discard low-frequency data like weekly or monthly data stems from the fact that cryptocurrency is barely a decade-old in existence, and as such any meaningful analysis of a financial market would require more observations. Also, the use of very high-frequency data like intra-day information, in our situation was challenging, because cryptocurrency is traded seven days in a week, hence making it quite difficult to synchronize with the time-stamp for the chosen interval (or period) of coverage with the traditional asset markets which are largely not traded in the weekends. In light of the above, our decision to use a daily data could not be misplaced, as such relatively high-frequency data provides lengthier observations that may be needed to examine the evolving characteristics and other phenomena about the young cryptocurrency market, while comparing the observed features to other asset markets. Perhaps, the identified barriers account for the sole use of daily data in most research work that studies cryptocurrency against traditional asset markets.

2.3.2 Structural break (SB) methods

Different statistical test methods are designed to basically detect single and/or multiple shifts (or changes) in the dynamic movements of a time series data. However,

several of these methods do not classify the specific types of changes that occur in the series after mainly detecting and dating such changes. Also, even the majority of the commonly used break tests usually work best for low frequency data like weekly, monthly, and quarterly time series realizations. Under this sub-section, we discuss a distinct approach that possesses abilities to detect hidden changes within a short interval time series, and further identify the types of change detection that characterize the series.

2.3.2.1 Markov switching dynamic regression (MS-DR)

A common practice in modelling financial and economic data collected over a relatively shorter time interval is to preliminary examine the data structure for regime shifts or changes. These "turning points" or regime changes are treated more often as deterministic, in preference to random. However, the time series of financial and economic variables occasionally display abrupt changes that may reoccur at unknown intervals, rather than a once-off deterministic event(s).

Two key drawbacks of deterministic SB are provided in the work of Hamilton (2016). First, the author outlined the difficulty to specify such deterministic SB into models rooted in rational decision making. Second, the treatment of SB as deterministic events loses sight of perhaps recurrent market regimes or phenomena which may be induced by (un)favourable economic conditions. Unlike the deterministic SB approach, a regime-switching framework was popularised by Hamilton (1989) to capture abrupt changes in the structure of a time series. For this study, we employ the Markov Switching Dynamic Regression (MS-DR), a family of the switching regression models that build on Hamilton's (1989) Markov switching regression and the Markov switching autoregressive (MS-AR) models. Given a univariate time series $\{y_t\}_{t=1}^{T}$, the MS-DR model is expressed in our case as:

$$y_t = v(s_t) + \alpha y_{t-1} + x_t^{!}\beta + \varepsilon_t, \quad \varepsilon_t \sim N[0,\sigma^2] \qquad (2.10)$$

Here, y_t is a scalar; $x_t^{'}$ denotes a (k x 1) vector of lagged realizations of y_t, where the variables x_t and y_t are under the assumption of covariance stationary; and $s_t = i$ gives the state variable which represents regimes taken from $i = 1, 2, ..., N$ states; where ν, β, σ are state-dependent.

We consider a two-regime MS-DR model which flexibly accounts for SB endogenously and allow the time series data at hand to identify the onset and end of each regime, where in our setting, regimes 1 and 2 respectively describe halcyon and excess volatile (or turbulent) market periods. Thus, in our specification, regime 1 (halcyon market) captures periods of relatively "stable" market episodes, while excess or higher volatility defines regime 2 (turbulent or distress market). The unobserved state variable s_t in (2.10) is governed by a first-order Markov chain having transition probabilities between the two states or regimes:

$$P_{ij}(z_t) = \Pr(s_t = i | s_{t-1} = j, z_t), \quad \forall ij = 1,2; \text{ such that } \sum_{i=1}^{2} \rho_{ij} = 1 \tag{2.11}$$

Specifically, the transition probability for the state variable is given by

$$P_{ij}(z_t) = \begin{cases} \Pr[s_t = 1 | s_{t-1} = 1] = p \\ \Pr[s_t = 2 | s_{t-1} = 1] = 1 - p \\ \Pr[s_t = 2 | s_{t-1} = 2] = q \\ \Pr[s_t = 1 | s_{t-1} = 2] = 1 - q \end{cases} \tag{2.12}$$

where, from (2.11) and (2.12), z_t denotes a (q x 1) vector of predetermined variables, which as earlier defined, are lagged values of y_t that happens to influence the transition probabilities. Intuitively, P_{ij} which is the probability of switching out from state j in a certain period to state i in the subsequent period depends solely on the immediate past state. Thus, P_{ij} is defined to mean the probability of switching from regime j at time t-1 to regime i at time t. Practically, we interpret $\Pr[s_t = 2 | s_{t-1} = 2]$ to mean the probability of transitioning to a turbulence regime at time t provided that the previous state at time t-1 is in turbulence. More so, the expected time span of

regime 1 is given by $E[D_{2,t}] = (1-p)^{-1}$, and $E[D_{1,t}] = (1-q)^{-1}$ for regime 2. Therefore, a higher value of p and q translate into a longer expected duration for the process in regimes 1 and 2 respectively. In brief, the parameters of interest, thus $\Theta = (\beta, \sigma, \Pi)$ are estimated through the MLE approach, where the likelihood function is specified as:

$$L(\Theta; y_{1:T}, X_{1:T}) = f(y_{1:T}|X_{1:T}, \beta, \sigma) = \sum_{t=1}^{T} \sum_{s} f(y_t|s_t, X_t, \beta, \sigma)(s_t|\Pi) \qquad (2.13)$$

In dating the unknown SB, we made use of the smoothed regime probabilities by setting a probability cut-off at 0.80 for $s_t = i$. Meaning, market episodes with smoothed probabilities at $s_t = 2$ which are greater (lesser) than 0.80 would have higher chances of being in the state of turbulence (halcyon) market condition. As a rule of thumb for this study, the last period within the smoothed regime probabilities greater (lesser) than 0.80 is upheld as the peak (trough), hence giving rise to the dating of the unknown SB.

2.3.3 Non-linearity, chaotic and random processes

We present a set of empirical methods which offer much flexibility to distinguish between linear and non-linear phenomenon, as well as processes characterized by pure randomness and those that exhibit chaotic structures. Our choice of this relatively new and robust set of methods is informed by previous works which attempt to explore such features in asset markets with "frumpish" methods that are sometimes flawed with controversies of inefficiencies, especially in the presence of noisy financial and economic data. Perhaps, this could partly explain the inconclusiveness of the empirical evidence in asset markets.

2.3.3.1 Brock-Dechert-Scheinkman (BDS) Test

A well-known vigorous test extensively used for examining time-based serial dependence and non-linear structure in (perhaps noisy) time series data is credited to

Broock et al., (1987, 1996). The BDS test, as it is popularly called, has a null hypothesis which states that a time series sample obtained from a data generating process (DGP) is a random sample of IID realizations. The non-IID alternative hypothesis of the test describes either a non-stationary, linear or non-linear serial dependence in the series. However, after prefiltering the linear dependence in the original series (with specifications from the ARMA or GARCH-type models), the BDS test could thereafter be applied to the remaining residual series with an IID null hypothesis tested against a non-linear dependence alternative hypothesis.

Let us assume $\{w_t\}$ is a sequence of the residuals with length T. We define the "m-histories" of the residuals and denote it as:

$$w_t^m = (w_t, w_{t+1}, ..., w_{t-m+1}),\ t = 1, 2, ..., T-m+1 \qquad (2.14)$$

where m is referred to as *embedding dimension*, which is often chosen on a subjective basis, mostly over the range $2 \le m \le 15$. The dependence structure of w_t is explained by means of a correlation integral, which is a measure of the frequency with which temporal patterns or distances between locations, for instance, w_s^m and w_t^m are repeated in the series. The correlation integral at the *embedding dimension* m with the metric bound $\in$ is specified as (Broock et al., 1996):

$$C(\in, m, T) = \frac{2}{T_m(T_m - 1)} \sum_{t<s} I_{\in}(w_s^m, w_t^m) \qquad (2.15)$$

Here, $T_m = T - m + 1$; $1 \le t, s \le T - m + 1$, where $t < s$; and $I_{\in}(\bullet)$ represents an indicator function that takes on one if $\|w_s^m - w_t^m\| \le \in$ (i.e., pairs of points are much closer) and zero otherwise, with a distance measure (supremum norm) given as $\|\bullet\|$. The BDS test statistic is given by:

$$C(\in, m, T) = T^{1/2} \frac{\left(C(\in, m, T) - C(\in, 1, T)^m\right)}{\sigma(\in, m)} \qquad (2.16)$$

where, $\sigma^2(\in, m) = 4\left[4k^m + 2\sum_{j=1}^{m-1} k^{m-j} C^{2j} + (m-1)^2 C^{2m} - m^2 k C^{2m-2}\right]$ (2.17)

and $k(\in,T)$ is determined by:

$$k(\in,T)=\frac{1}{T_m(T_m-1)(T_m-2)}\sum I_{\in}(w_s^m,w_t^m)I_{\in}(w_t^m,w_r^m) \quad (2.18)$$

The test statistic asymptotically reduces to a standard normal under the null hypothesis of IID realizations for w_t.

2.3.3.2 *Terasvirta Neural Network (TNN) Test*

Teräsvirta et al., (1993) introduced a test based on the theory of neural networks to distinguish between linear and non-linear features of a time series data. Known well as Teräsvirta neural network (TNN) test, we specify the method under this sub-section. Unlike the BDS test, TNN does not require prefiltering of the linear structure in the series. Following Teräsvirta et al., (1993), let us consider a particular non-linear model given by:

$$y_t=\pi^{|}s_t+\phi(\gamma^{|}s_t)+\mu_t \quad (2.19)$$

where $s_t=(1,y_{t-1},...,y_{t-p})^{|}$ represents a vector of response variables, with $\pi^{|}=(\pi_0,\pi_1,...,\pi_p)$ as the corresponding constant term. μ_t is the error term, where $\mu_t\sim iid\,(0,\sigma^2)$ denotes a parameter vector. We set $\phi(\gamma^{|}s_t)=\theta_0\varphi(\gamma^{|}s_t)$, given that

$$\varphi(\gamma^{|}s_t)=\{1+\exp(-\gamma^{|}s_t)\}^{-1}-(1/2) \quad (2.20)$$

(2.20) is then described as a non-linear autoregressive model, where the constant term $\pi_0+\theta_0\varphi(\gamma^{|}s_t)$ is time-varying and changes smoothly from $\pi_0-\theta_0/2$ to $\pi_0+\theta_0/2$ with $\gamma^{|}s_t$. Also, (2.20) could be viewed as a special case of a given neural network model having a single hidden layer:

$$y_t=\pi^{|}s_t+\sum_{j=1}^{q}\theta_{0j}\{\varphi(\gamma_j^{|}s_t)-1/2\}+\mu_t \quad (2.21)$$

Moreover, in the scenario where $\gamma=0$, (2.20) becomes a linear model given by $y_t=\pi s_t+\mu_t$. Then, the null hypothesis is stated as:

$$H_0 : \gamma = 0 \qquad (2.22)$$

We interpret (2.22) as a null hypothesis of linearity which is tested against a non-linear alternative hypothesis, i.e., $H_1 : \gamma \neq 0$. Hence, model (2.19) is recognized under the alternative hypothesis. Teräsvirta et al., (1993) replaced ϕ in (2.19) by a suitable Taylor expansion approximation around $\gamma = 0$ to derive an appropriate test for (2.22). With that, model (2.19) becomes:

$$y_t = \tilde{\pi}^{|} s_t + \sum_{i=1}^{p}\sum_{j=1}^{p} \delta_{ij} y_{t-i} y_{t-j} + \sum_{i=1}^{p}\sum_{j=1}^{p}\sum_{k=j}^{p} \delta_{ijk} y_{t-i} y_{t-j} y_{t-k} + \tilde{\mu}_t \qquad (2.23)$$

where $\delta_{ij} = d_{ij}\theta_0\gamma_i\gamma_j\gamma_0$, with $d_{ij} = 1/36$ if $i = j$ and $d_{ij} = 1/18$, otherwise $i, j \geq 1$; and $\delta_{ijk} = d_{ijk}\theta_0\gamma_i\gamma_j\gamma_k$, with $d_{ijk} = 1/36$ if $i = j = k$, $d_{ijk} = 1/18$ if $i = j$, $j = k$ or $i = k$, $d_{ijk} = 1/16$ otherwise, $i, j, k \geq 1$. In the case where $\gamma_0 = 0$ such that $\gamma^{|} s_t = \tilde{\gamma}^{|} \tilde{s}_t$ (thus, the exponent has no intercept), then $d_{ij} = 0 \; \forall ij$. The null hypothesis associated with (2.22) is written as:

$$H_0^{|} : \delta_{ij} = 0, \; \delta_{ijk} = 0, \; i = 1, ..., p; \; k = j, ...p \qquad (2.24)$$

2.3.3.3 *Entropy Test for Non-linearity (ETN)*

Quite recently, Giannerini et al., (2015) developed a test based on a combination of entropy dependence measure to examine the non-linear structure in a time series. The entropy test for non-linear serial dependence (hereafter, ETN) is under a null hypothesis which assumes that the DGP of the series is drawn from a general linear process. Thus,

$$H_0 : Y_t = \sum_{j=1}^{\infty} \phi_j Y_{t-j} + \varepsilon_t, \; \{\varepsilon_t\} \sim iid \, N(0, \sigma_\varepsilon^2) \qquad (2.25)$$

where $\sum_{j=1}^{\infty} \phi_j^2 < \infty$ and $E(Y_t^4) < \infty$. The other form of the null hypothesis has it that the series Y_t follows a zero-mean linear stationary process:

$$H_0^{|}: Y_t = \sum_{j=1}^{\infty} \phi_j Y_{t-j} + \varepsilon_t, \ \{\varepsilon_t\} \sim iid\ f(0, \sigma_\varepsilon^2) \qquad (2.26)$$

However, the alternative hypothesis states that the DGP of Y_t deviates from a linear process or an infinite autoregressive specification like those presented in (2.25) and (2.26). In describing the ENT method, let us first consider $(Y_t, \hat{Y}_{t+k}) \sim N(0,1,\rho)$ as a standard normal random vector having the joint probability density function (p.d.f) $f_{(Y_t, Y_{t+k})}(\bullet, \bullet, \rho)$, where ρ denote a correlation coefficient at lag *k*. Then we have:

$$S_\rho(k) = 1 - \frac{2\left(1-\rho^2\right)^{1/4}}{\left(4-\rho^2\right)^{1/2}} \qquad (2.27)$$

For simplicity, let's replace $S_\rho(k)$ with S_k, and use (2.27) to obtain an estimator for S_k, by building on the sample autocorrelation $\hat{\rho}_k$ under (2.25), thus a null hypothesis which specifies that the realizations of the time series are generated from a linear Gaussian process. The parametric estimator of S_k is denoted by $\hat{S}_k^{\,p}$, where *p* simply means parametric.

There again, let $\{Y_t\}$ denotes a zero-mean stationary process under the null hypothesis, as specified in (2.25). Let also $\hat{\rho}_k$ represents the sample autocorrelation function of $\{Y_t\}$ at lag *k*, and let $\hat{S}_k^{\,p} = 1 - 2(1 - \hat{\rho}_k^{\,2})^{1/2}(4-\rho_k^2)^{-1/2}$ be taken as the associated sample estimator of S_ρ at lag *k* based on (2.27). Then, for all *k*, where $k = 0,1,2,\ldots$, Giannerini et al., (2015) specified that $n^{1/2}(\hat{S}_k^{\,p} - S_k) \to N(0, \sigma_p^2)$ in distribution, and $\sigma_p^2 = [g^{|}(\zeta)]^2$ with $\zeta = \sum_{i=1}^{\infty}\{\rho(i+k)\rho(i-k) - 2\rho_i\rho_k\}^2$ taken as the asymptotic variance of $\hat{\rho}_k$. Note well that $g(y) = 1 - 2(1-y^2)^{1/4}(4-y^2)^{-1/2}$ is a differentiable function on (0, 1), and its ith derivative $g^{(i)}(y)$ is not zero for $y \neq 0$.

Besides, in cases where no correlations are recorded, we have $g^{|}(\rho_k)=0$. Therefore, as $n\to\infty$, $\hat{S}_k^{\,p}\to S_k$ in L, hence a consistent parametric estimator for S_k is obtained.

In testing the second null hypothesis in (2.26), Giannerini et al., (2015) advanced an asymptotic distribution of the non-parametric estimator for S_k, given by:

$$\hat{S}_k^{\,u}=\frac{1}{2}\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty}\left[\left\{\hat{f}_{(Y_t,Y_{t+k})}(y_1,y_2)\right\}^{1/2}-\left\{\hat{f}_{Y_t}(y_1)\,\hat{f}_{Y_{t+k}}(y_2)\right\}^{1/2}\right]w(y_1,y_2)dy_1\,dy_2 \quad (2.28)$$

with

$$\hat{f}_{Y_t}(y)=n^{-1}\sum_{i=1}^{n}h_1^{-1}k\{(y-Y_i)/h_1\} \quad (2.29)$$

and

$$\hat{f}_{(Y_t,Y_{t+k})}(y_1,y_2)=(n-k)^{-1}\sum_{i=1}^{n-k}(h_1h_2)^{-1}k\{(y_1-Y_i)/h_1,\,(y_2,Y_{i+k})/h_2\} \quad (2.30)$$

as kernel density estimators for f_{Y_t}, $f_{Y_{t+k}}$, and $f_{(Y_t,Y_{t+k})}$; where h_1 and h_2 denote bandwidths and k represent a kernel function. Under some predefined regularity conditions (Giannerini et al., 2015), $\hat{S}_k^{\,u}\to S_k$ in L^2 and $n^{1/2}(\hat{S}_k^{\,u}-S_k)\to N(0,\sigma_u^2)$ in distribution, as $n\to\infty$. In general, the ETN test statistic for the two null hypotheses is given by:

$$\hat{T}_k=\left(\hat{S}_k^{\,u}-\hat{S}_k^{\,p}\right)^2 \text{ and } \hat{S}_k^{\,u} \text{ for } H_0 \text{ and } H_1 \text{ respectively} \quad (2.31)$$

where the measure $\hat{T}_k$ gives the squared difference between the unrestricted non-parametric estimator and that of the parametric estimator for S_k.

2.3.3.4 Largest Lyapunov Exponent (LLE) Test

Several methods have been introduced to quantify chaotic structure in time series data. Common among them are test based on estimating fractal dimensions, entropy,

and the largest Lyapunov exponent. Most of these tests show inefficiencies in the presence of noisy data – a major feature of short frequency financial and economic time series. Regardless of this drawback, the proposed test by BenSaïda and Litimi (2013) and BenSaïda (2014) provides an alternative approach to quantify noisy chaotic system.

In specifying the approach, let us consider a scalar financial time series, say $\{y\}_{t=1}^{T}$, a noisy chaotic system of the series can be written as:

$$y_t = f\left(y_{t-L}, y_{t-2L}, y_{t-3L}, ..., y_{t-mL}\right) + \varepsilon_t \qquad (2.32)$$

where L denotes the time delay parameter; t is a time script; and m gives the length of past dependence (best known as *embedding dimension*). Also, ε is the added noise term with its magnitude quantified by its variance; and f is presented as an unknown function used for approximating a chaotic map. The variance of a noise-free system is given by $Var(\varepsilon_t) = \sigma_\varepsilon^2 = 0$, and it increases with the added noise.

Following BenSaïda and Litimi (2013) and BenSaïda (2014), we specified the largest Lyapunov exponent λ of a noisy chaotic system as:

$$\lambda = \lim_{M \to \infty} \frac{1}{2M} \log(v_1) \qquad (2.33)$$

Here, M is taken as an arbitrary integer of evaluation points $M \approx T^{2/3}$; and v_1 denotes the largest eigenvalue of the matrix $(T_M U_0)'(T_M U_0)$, with $U = (1, 0, ..., 0)'$, such that

$$T_M = \prod_{t=1}^{M-1} J_{M-t} \qquad (2.34)$$

where the block-length M has equally spaced evaluations such that $M \leq T$, and J_T gives the Jacobian matrix of the chaotic map f:

$$J_T = \begin{pmatrix} \frac{\partial f}{\partial y_{t-L}} & \frac{\partial f}{\partial y_{t-2L}} & \bullet\bullet\bullet & \frac{\partial f}{\partial y_{t-mL+L}} & \frac{\partial f}{\partial y_{t-mL}} \\ 1 & 0 & \bullet\bullet\bullet & 0 & 0 \\ 0 & 1 & \bullet\bullet\bullet & 0 & 0 \\ \bullet & \bullet & \bullet & \bullet & \bullet \\ \bullet & \bullet & \bullet & \bullet & \bullet \\ \bullet & \bullet & \bullet & \bullet & \bullet \\ 0 & 0 & \bullet\bullet\bullet & 1 & 0 \end{pmatrix} \tag{2.35}$$

Even in the presence of noise, the Jacobean-based method provides consistent estimates for the Lyapunov exponent (BenSaïda, 2014). The chaotic map f could be approximated by (2.36), and estimated using non-linear least square.

$$y_t \approx \alpha_0 + \sum_{j=1}^{q} \alpha_j \varphi\left(\beta_{0,j} + \sum_{i=1}^{m} \beta_{i,j} y_{t-iL}\right) + \varepsilon_t \tag{2.36}$$

where q gives the total size of the hidden layers, with α_j as the inter-layers connection weights. Also, α_0 gives the network's threshold; ε_t denotes the noise term; and φ is a sigmoid function which appears monotone and bounded, given that $\lim_{u\to\infty} \varphi(u) = 0$ and $\lim_{u\to\infty} \varphi(u) = 1$. We follow the protocols of BenSaïda and Litimi, (2013) to determine the values for the triplet parameter (L, m, q) which describe the chaotic map's complexity. The variance of LLE is approximated by:

$$\hat{\Sigma} = \frac{1}{M} \sum_{j=-M+1}^{M-1} \left[\xi\left(\frac{j}{1.3221 \times M^{1/5}}\right) \sum_{t=|j|+1}^{M} \hat{\eta}_t \hat{\eta}_{t-|j|} \right] \tag{2.37}$$

where $M \leq T$ remained as explained; and expressions for the Quadratic Spectral kernel and the parameter $\hat{\mu}_t$ are respectively given as:

$$\xi_{QS}(z) = \frac{25}{12\pi^2 z^2}\left(\frac{\sin(6\pi z/5)}{6\pi z/5} - \cos\left(\frac{6\pi z}{5}\right)\right) \tag{2.38}$$

and

$$\hat{\eta}_t = \frac{1}{2} In\left[\frac{\max\left(eigenvalue(T_t^{|} T_t)\right)}{\max\left(eigenvalue(T_{t-1}^{|} T_{t-1})\right)}\right] - \hat{\lambda} \tag{2.39}$$

Here, T remains the length of the series and $\hat{\lambda}$ denotes the estimated LLE. A null hypothesis of $H_0 : \lambda \geq 0$ against the alternative hypothesis $H_1 : \lambda < 0$ is considered. Evidence in favour of chaotic structure is upheld if we fail to reject H_0. Given that the magnitude of λ is reliant on the divergence in the series at hand and the complexity of the map, we categorize our detection as low-, and high-level chaos by setting the maximum orders of the triple (L, m, q) to (5, 6, 5) and (8, 10, 8) respectively. Finally, the test statistic for examining chaoticity in a time series is given by:

$$\hat{W} = M^{1/2} \times \hat{\lambda} \xrightarrow{asymptotically} N\left(0, \hat{\Sigma}\right) \tag{2.40}$$

2.3.4 Parametric probability distributional modelling

Undoubtedly, evidence from empirical studies has shown that financial market returns collected over weekly, daily or intra-daily (short frequency) intervals are characterized by higher peaks, negative and positive skewness, and has heavier extreme tails as earlier described. One major task which remains challenging is to approximate the return series to a statistical distribution that could comprehensively capture the very large changes (or fluctuations) and all other hidden information contained in the market returns. In this study, we consider a wide range of parametric distributions to describe the return distribution of six asset classes using both individual and aggregate return series.

Given that X_i is a continuous random variable (c.r.v) of the log-return series for the ith asset, and $f(x_i)$ is assumed to be the probability density function (p.d.f) of X_i, where $F(x_i)$ is also taken as the cumulative distribution function (c.d.f) of X_i, we postulate that the dynamic movement of X_i is well-approximated with one of the twenty specified parametric distributions in the ensuing paragraphs. Our choice for these set of distributions is in twofold: (1) To combine and assess the appropriateness

of both old and relatively new distributions, and their extension to allow for asymmetry (or otherwise) in a single study that explores return distributions of financial markets; and (2) Given a competitive pool of light and heavy tail distributions, we investigate the chance to which one group dominates the other with respect to capturing various features of asset return movements.

• Light Tailed Distributions[25]

(1) the normal distribution (ND) which is non-arguably among the commonly used continuous distributions has a p.d.f given by:

$$f(x) = \frac{1}{\sqrt{2\pi\sigma}} \exp\left\{ -\frac{(x-\mu)^2}{2\sigma^2} \right\} \tag{2.41}$$

for $x \in (-\infty, \infty)$, and its parameters $\mu \in (-\infty, \infty)$ and $\sigma > 0$;

(2) the skew normal distribution (SND) of Azzalini (1985) is given by:

$$f(x) = \frac{2}{\sigma} \phi\left\{ \frac{(x-\mu)}{\sigma} \right\} \Phi\left\{ \lambda \frac{(x-\mu)}{\sigma} \right\} \tag{2.42}$$

for $x \in (-\infty, \infty)$, $\mu \in (-\infty, \infty)$, $\lambda \in (-\infty, \infty)$, and $\sigma > 0$, while $\phi(\bullet)$ and $\Phi(\bullet)$ respectively represent the standard normal density and cumulative distribution function. The skew normal reduces to the standard normal if the skewness parameter λ is set to zero (i.e., $\lambda = 0$);

(3) the Laplace distribution (LPD) of Laplace (1774) is given by:

$$f(x) = \frac{1}{2\sigma} \exp\left\{ -\frac{|x-\mu|}{\sigma} \right\} \tag{2.43}$$

for $x \in (-\infty, \infty)$, $\mu \in (-\infty, \infty)$ and $\sigma > 0$;

(4) the skew Laplace distribution (SLPD) with p.d.f specified in Aryal and Nadarajah (2005) as:

[25] Note well that the arrangement of the distributions does not imply order of importance, popularity, or appropriateness to modelling financial markets.

$$f(x)=\begin{cases}\dfrac{1}{2\sigma}\exp\left\{-\dfrac{(1+|\lambda|)(|x-\mu|)}{\sigma}\right\}, & if\ \ \lambda x\le 0\\ \dfrac{1}{\sigma}\exp\left(-\dfrac{(|x-\mu|)}{\sigma}\right)\left\{1-\dfrac{1}{2}\exp\left(-\dfrac{\lambda x}{\sigma}\right)\right\}, & if\ \ \lambda x>0\end{cases} \tag{2.44}$$

for $x\in(-\infty,\infty)$, $\mu\in(-\infty,\infty)$ and $\sigma>0$. The standard Laplace distribution is derived from (2.44) if $\lambda=0$.

(5) the Cauchy distribution (CAUC) has its p.d.f is given by:

$$f(x)=\frac{\sqrt{2}}{\nu\sigma\pi\left\{\left(\dfrac{2|x-\mu|^2}{(\nu\sigma)^2}\right)+1\right\}} \tag{2.45}$$

where $x\in(-\infty,\infty)$, $\mu\in(-\infty,\infty)$, and $\sigma>0$. In the case where $\nu=\sqrt{2}$, the p.d.f of the standard parameterization for the Cauchy distribution is expressed as:

$$f(x)=\frac{1}{\sigma\pi\left\{\left(\dfrac{|x-\mu|^2}{\sigma}\right)+1\right\}}$$

(6) the generalized error distribution (GED) of Subbotin (1923) is given by:

$$f(x)=\frac{\beta}{2\sigma\Gamma(1/\beta)}\exp\left\{-\left(\frac{|x-\mu|}{\sigma}\right)^{\beta}\right\} \tag{2.46}$$

for $x\in(-\infty,\infty)$, $\mu\in(-\infty,\infty)$, $\beta>0$, and $\sigma>0$, where $\Gamma(a)=\int_0^{\infty}t^{a-1}\exp(-t)\,dt$ is an expression which defines the gamma function. Also known as the exponential power distribution (EPD), the GED nests the normal, uniform, and Laplace distributions given that $\beta=2$, $\beta\to+\infty$, and $\beta=1$ respectively.

(7) the skewed exponential power distribution (SEPD) of Zhu and Zinde-Walsh (2009) is given by:

$$f(x)=k\begin{cases}\exp\left\{-\dfrac{1}{p}\left(\left|\dfrac{x-\mu}{2\alpha\sigma}\right|^{p}\right)\right\}, & if\ \ x\le\mu\\ \exp\left\{-\dfrac{1}{p}\left(\left|\dfrac{x-\mu}{2(1-\alpha)\sigma}\right|^{p}\right)\right\}, & if\ x>\mu\end{cases} \tag{2.47}$$

for $x \in (-\infty, \infty)$, $\mu \in (-\infty, \infty)$, and the skewness and shape parameters are non-negative, i.e., $\alpha, \sigma, p > 0$, where for $k = 1/\{2\sigma A_0(p)\}$ with $A_0(x) = x^{(1/x)-1}\Gamma(1/x)$. The GED is a special case of SEPD if $\alpha = 1/2$. SEPD also nests the skewed Laplace and the skew normal in cases where $p = 1$ and $p = 2$ respectively.

(8) the logistic distribution (LGD) has its p.d.f as:

$$f(x) = \frac{1}{\sigma}\exp\left\{-\frac{(x-\mu)}{\sigma}\right\}\left[1+\exp\left\{-\frac{(x-\mu)}{\sigma}\right\}\right]^{-2} \tag{2.48}$$

for $x \in (-\infty, \infty)$, $\mu \in (-\infty, \infty)$, and $\sigma > 0$;

(9) the Azzalini's skew-logistic distribution (Azzalini, 1985), hereafter SLGD, which was re-echoed in a work by Gupta and Kundu (2010) has its p.d.f given by:

$$f(x) = \frac{2\sigma e^{-\sigma(x-\mu)}}{\left(1+e^{-\sigma(x-\mu)}\right)^2\left(1+e^{-\lambda\sigma(x-\mu)}\right)} \tag{2.49}$$

where $x \in (-\infty, \infty)$, $\mu \in (-\infty, \infty)$, $\sigma > 0$, and $\lambda > 0$.

• Heavy Tailed Distributions

(1) the Student's t distribution (ST) of Gosset (1908) does not incorporate asymmetry but remains a widely used and simplest heavy tail distribution. With parameters μ, σ, and ν, its p.d.f is given by:

$$f(x) = \frac{K(\nu)}{\sigma}\left\{1+\frac{(x-\mu)^2}{\sigma^2\nu}\right\}^{-(1+\nu)/2} \tag{2.50}$$

for $x \in (-\infty, \infty)$, $\mu \in (-\infty, \infty)$, $\nu > 0$ and $\sigma > 0$, with $K = \nu^{1/2}B(\nu/2, 1/2)$ where the beta function $B(\bullet,\bullet)$ is defined by $B(a,b) = \int_0^1 t^{a-1}(1-t)^{b-1}dt$. The ST nest the normal as $\nu \to \infty$.

(2) the skew t distribution (SD) of Azzalini and Capitanio (2003) is given by:

$$f(x) = \frac{K(\nu)}{\sigma}\left\{1+\frac{(x-\mu)^2}{\sigma^2\nu}\right\}^{-(1+\nu)/2} + \frac{2K^2(\nu)\lambda(x-\mu)}{\sigma^2}\,{}_2F_1\left\{\frac{1}{2}, \frac{1+\nu}{2} : \frac{3}{2}; -\frac{\lambda(x-\mu)^2}{\sigma^2\nu}\right\} \tag{2.51}$$

for $x \in (-\infty,\infty)$, $\mu \in (-\infty,\infty)$, $\lambda \in (-\infty,\infty)$, $\nu > 0$ and $\sigma > 0$, with

$${}_2F_1(a,b,c;x) = \sum_{k=0}^{\infty} \frac{(a)_k (b)_k}{(c)_k} \frac{x^k}{k!}, \text{ where } (e)_k = e(e+1)...,(e+k-1)$$

(3) the skewed Student's t distribution (SST) of Zhu and Gabraith (2010) is given by:

$$f(x) = \frac{1}{\sigma} K(\nu) \begin{cases} \left\{1 + \frac{1}{\nu}\left(\frac{(x-\mu)}{2\alpha\sigma}\right)^2\right\}^{-(\nu+1)/2}, & \text{if } x \le \mu \\ \left\{1 + \frac{1}{\nu}\left(\frac{(x-\mu)}{2(1-\alpha)\sigma}\right)^2\right\}^{-(\nu+1)/2}, & \text{if } x > \mu \end{cases} \tag{2.52}$$

for $x \in (-\infty,\infty)$ and $\mu \in (-\infty,\infty)$ where the boundary conditions of the skewness, scale, and shape parameters are given as $\alpha \in (0,1)$, $\sigma > 0$, and $\nu > 0$. The density is negatively (positively) skewed when $\alpha > 1/2$ ($\alpha < 1/2$). The standard Student's t is obtained from (2.52) if $\alpha = 1/2$. Also, SST reduces to the skewed Cauchy when ν takes on 1 ($\nu = 1$)and to the skewed normal distribution when ν assumes ∞ ($\nu = \infty$).

(4) the generalized t distribution (GT) of McDonald and Newey (1988) is given by:

$$f(x) = \frac{p}{2\sigma\nu^{1/p} B(1/p,\nu)} \left\{1 + \frac{1}{\nu}\left(\frac{|x-\mu|^p}{\sigma^p}\right)\right\}^{-(\nu+1/p)} \tag{2.53}$$

for $x \in (-\infty,\infty)$, $\mu \in (-\infty,\infty)$, $\sigma > 0$, $p > 0$, and $\nu > 0$. Under different parameter conditions, GT nests the ST, Box-Tiao power exponential (BT), Laplace, normal and the Cauchy distributions. For instance, the BT is the limiting case of GT as $\nu \to \infty$; and ST with 2ν degrees of freedom where $p = 2$ and $\sigma = \sqrt{2\alpha}$ is also a special case of GT;

(5) the normal inverse Gaussian distribution (NIG) of Barndorff-Nielsen (1977) is given by:

$$f(x) = \frac{(\gamma/\delta)\alpha}{\sqrt{2\pi}\, K_{-1/2}(\delta\gamma)} \exp\{\beta(x-\mu)\}\left\{\delta^2 + (x-\mu)^2\right\} K_{-1}\left\{\alpha\sqrt{\delta^2 + (x-\mu)^2}\right\} \tag{2.54}$$

for $x \in (-\infty,\infty)$, $\mu \in (-\infty,\infty)$, $\alpha > 0$, $\delta > 0$, $\beta > 0$, $\gamma = \sqrt{(\alpha^2 - \beta^2)}$ and

$$K_v(x)=\begin{cases}\dfrac{\pi\csc(\pi v)}{2}\left\{I_{-v}(x)-I_v(x)\right\}, & if\ v\notin Z\\ \lim\limits_{\mu\to v}K_\mu(x), & if\ v\in Z\end{cases},$$

where, $I_v(x)=\sum_{k=0}^{\infty}\frac{1}{\Gamma(k+v+1)k!}\left(\frac{x}{2}\right)^{2k+v}$ is an expression for the modified Basel function

(6) the hyperbolic distribution (HYP) of Barndorff-Nielsen (1977) is given by:

$$f(x)=\frac{(\gamma/\delta)^{\lambda}\alpha^{-1/2}}{\sqrt{2\pi}\,K_1(\delta\gamma)}\left\{\delta^2+(x-\mu)^2\right\}^{1/2}\times K_{1/2}\left\{\alpha\sqrt{\delta^2+(x-\mu)^2}\right\}\exp\{\beta(x-\mu)\} \tag{2.55}$$

for $x\in(-\infty,\infty)$, $\mu\in(-\infty,\infty)$, $\alpha>0$, $\delta>0$, $\beta>0$, and $\gamma=\sqrt{(\alpha^2-\beta^2)}$

(7) the generalized hyperbolic distribution (GHYP) of Barndorff-Nielsen (1977) is given by:

$$f(x)=\frac{(\gamma/\delta)^{\lambda}\alpha^{1/2-\lambda}}{\sqrt{2\pi}\,K_\lambda(\delta\gamma)}\left\{\delta^2+(x-\mu)^2\right\}^{\lambda-1/2}\times K_{\lambda-1/2}\left\{\alpha\sqrt{\delta^2+(x-\mu)^2}\right\}\exp\{\beta(x-\mu)\} \tag{2.56}$$

for $x\in(-\infty,\infty)$, $\mu\in(-\infty,\infty)$, $\lambda\in(-\infty,\infty)$ $\alpha>0$, $\delta>0$, $\beta>0$, and $\gamma=\sqrt{(\alpha^2-\beta^2)}$. Several variants of the GH family can be deduced from (2.56). For instance, the NIG, NRIG, and HYP are obtained if $\lambda=-1/2$, $\lambda=1/2$, and $\lambda=1$ respectively. More so, we could derive the normal as a limiting case of GHYP as $\delta\to\infty$ and $\delta/\alpha\to\sigma^2$.

(8) the generalized hyperbolic distribution skew Student's *t* distribution (GH-SST) of Aas and Haff (2006) is given by:

$$f(x)=\frac{2^{1-v/2}\delta^v|\beta|^{(v+1)/2}K_{(v+1)/2}\left\{\sqrt{\beta^2(\delta^2+(x-\mu)^2)}\right\}\exp\{\beta(x-\mu)\}}{\Gamma\left(\frac{v}{2}\right)\sqrt{\pi}\left\{\sqrt{\delta^2+(x-\mu)^2}\right\}^{(v+1)/2}} \tag{2.57}$$

for $x\in(-\infty,\infty)$, $\mu\in(-\infty,\infty)$, $v>0$, $\delta>0$, and $\beta>0$. Given that $\lambda=-v/2$ and $\alpha\to|\beta|$, the GH-SST becomes a particular case of the GHYP. GH-SST is specially known for having one of its tails behaving as polynomial while the other tail shows a Gaussian-like tail behaviour.

(9) the skewed generalized *t* distribution (SGT) of Theodossiou (1998) is given by:

$$f(x)=C\begin{cases}\left[\left\{1+\left(\frac{p}{\nu-2}\right)\theta^{-p}\right\}\left\{(1-\lambda)^{-p}\left|\frac{x}{\sigma}\right|^{p}\right\}\right]^{-(\nu+1)/p}, & if\ x<0\\ \left[\left\{1+\left(\frac{p}{\nu-2}\right)\theta^{-p}\right\}\left\{(1+\lambda)^{-p}\left|\frac{x}{\sigma}\right|^{p}\right\}\right]^{-(\nu+1)/p}, & if\ x\geq 0\end{cases} \qquad (2.58)$$

for $x\in(-\infty,\infty)$, $\lambda\in(-1,1)$, $p>0$, $\nu>0$, where C and θ are the normalizing constant terms, and p and ν are parameters which drive the height and tails of the density function. The SGT nests the four- (GT, SGED, and SD), three- (SLPD, GED, SND, and ST), and two-parameter (ND, LPD, and CAUC) sets of distributions. Specifically, the SGT incorporates the GT with $\lambda=0$; the SGED with $\nu=\infty$; SD with $p=2$; the ST with $\lambda=0$ and $p=2$; GED with $\lambda=0$ and $\nu=\infty$; SND with $p=2$ and $\nu=\infty$; and SLPD with $p=1$ and $\nu=\infty$. Others include the Laplace with $\lambda=0$, $p=1$ and $\nu=\infty$; normal with $\lambda=0$, $p=2$ and $\nu=\infty$; and finally the Cauchy with $\lambda=0$, $p=2$ and $\nu=1/2$.

(10) the skewed generalized error distribution (SGED) of Theodossiou (2015) is given by:

$$f(x)=\frac{p^{1-1/p}}{2\varphi}\Gamma\left(\frac{1}{p}\right)^{-1}\exp\left\{-\frac{1}{p}\frac{|u|^{p}}{\{1+\mathrm{sgn}(u)\lambda\}^{p}\varphi^{p}}\right\} \qquad (2.59)$$

for $x\in(-\infty,\infty)$, $-1\leq\lambda\leq 1$, $p>0$, and sgn denotes a sign function which assumes 1 for $u>0$ and -1 for $u<0$, and $\Gamma(\bullet)$ is a gamma function expressed in the functional form as $\Gamma(a)=\int_{0}^{\infty}t^{a-1}\exp(-t)dt$. The GED is nested in SGED for $\lambda=0$; Laplace for $\lambda=0$ and $p=1$; the skew normal for $p=2$; and normal for $\lambda=0$ and $p=2$.

(11) the generalized lambda distribution (GLD) of Freimer et al., (1988) with inverse c.d.f is given by:

$$F^{-1}(x)=\lambda_1+\frac{1}{\lambda_2}\left\{\left(\frac{u^{\lambda_3}-1}{\lambda_3}\right)-\left(\frac{(1-u)^{\lambda_4}-1}{\lambda_4}\right)\right\} \qquad (2.60)$$

for $x \in (-\infty, \infty)$, $0 \leq u \leq 1$, where λ_1, λ_2, λ_3, and λ_4 are respectively the location, scale, skewness and kurtosis parameters, such that $\lambda_1, \lambda_2, \lambda_3, \lambda_4 > 0$.

In estimating the parameters of our choice of distributions, we employed the maximum likelihood estimate (MLE) approach. A brief specification of the MLE is given as follows. Let us consider that $x_1, x_2, ..., x_n$ are independent realizations drawn from the r.v X, and the vector $\Theta = (\omega_1, \omega_2, ..., \omega_k)^{|}$ be taken as parameters assigned to describe the distribution of X. Then, the MLE of the vector of parameters is the very ones that maximize the likelihood function.

$$L(\Theta) = \prod_{i=1}^{n} f(x_i; \Theta) \tag{2.61}$$

The log-likelihood (LL) function to be maximized is generally expressed by;

$$InL(\Theta) = \sum_{i=1}^{n} f(x_i; \Theta) \tag{2.62}$$

where $f(\bullet)$ is the p.d.f of X having parameters $\Theta = (\omega_1, \omega_2, ..., \omega_k)^{|}$. Provided that the optimal value for Θ remains unknown as in many cases, an estimated value $\hat{\Theta}$ is often adopted in practice. As the size of *n* is reasonably large in our case, we expect our estimator $\hat{\Theta}$ to converge to an optimal value for its estimate Θ. Thus, we denote $\hat{\Theta} = \left(\hat{\omega}_2, \hat{\omega}_2, ..., \hat{\omega}_k \right)^{|}$ as an unbiased estimator for $\Theta = (\omega_1, \omega_2, ..., \omega_k)^{|}$ under the MLE approach[26].

Moreover, one of the challenging tasks in this area of study has to do with the phenomenon where analysts have to cautiously devise measures to clearly distinguish the appropriateness of keenly competing parametric distributional fits to a given empirical data. Besides, owing to the popularity and empirical evidence supporting a

[26] It is worth putting across that the R Statistical software provides numerical optimization functionalities en route the routine *optim*, which was employed in the optimization processes for our parameter estimations (See, Team, 2018).

number of these distributions in the financial econometrics literature, as well as the (in)direct relationships among several of them (i.e., nested distributions), a robust measure(s) to differentiate their fit performances in relation to capturing stable and extreme volatile market information is needed. In this study, we adopt a pair of distributional-based measures that quantify the discrepancy between the hypothetical distribution relative to the empirical distribution. The Kolmogorov-Smirnov and Cramér-von Mises measures, popularly termed as empirical cumulative distribution function (ecdf)-based measures are used to discriminate among the fitted distributions. These measures have the capabilities to foretell how well (or otherwise) a distribution fits a given market data.

The hypothesis and test statistics of the two ecdf-based measures are onwardly discussed. Let X be a random variable and $F(x)$ be taken as the theoretical cumulative distribution function. Given that $F(x,\theta)$ is a c.d.f of a given distribution, we test the null hypothesis $H_0 : F(x) \in \{F(x,\theta),\ \theta \in \Theta\}$ – thus, the considered distribution is an appropriate fit for the given data; against an alternative hypothesis which states that $H_1 : F(x) \notin \{F(x,\theta),\ \theta \in \Theta\}$, where the unknown parameters θ have a domain Θ, and could easily be substituted with its estimator $\hat{\theta}$.

The Kolmogorov-Smirnov statistic (Kolmogorov, 1933; Smirnov, 1948), given by $KS = \sqrt{n}\ \underset{x \in \Re}{Sup} \left| F_x(x) - F(x,\theta) \right|$ computes the maximum difference between the empirical c.d.f and theoretical probabilities. We uphold H_0 if KS becomes relatively smaller, else H_0 is rejected for KS values larger than the critical values of the test. Though widely used as an adequacy measure, the KS loses its test power in the tails but tends to poses higher sensitivity near the middle or centre of the candidate distribution.

With test statistic given by $CM = \sum_{i=1}^{n}\left[F(x_i,\theta) - \frac{2i-1}{2n} \right] + \frac{1}{12n}$, the Cramér-von Mises measure is based on a quadratic distance between $F(x)$ and $F(x,\theta)$, i.e., the sum of squared discrepancies between the latter functions (Cramér, 1928; von Mises, 1928). Quite specifically, we adopt the CM as our adequacy benchmark measure due to its widely known superior power over the KS. Among others, the CM has a low tendency to the occurrence of type II error, given a much wider range of plausible alternative hypotheses, as compared to other competitive ecdf-based measures.

2.3.5 Asymmetry and leverage modelling

Quite unarguably, the most popular univariate conditional volatility models extensively used to unveil volatility characteristics of financial data are the standard Autoregressive Conditional Heteroscedasticity (ARCH) model of Engle (1982), with its extension to Generalized ARCH (GARCH) by Bollerslev (1986), the exponential GARCH (EGARCH) pioneered by Nelson (1991), and the Glosten-Jagannathan-Runkle GARCH (GJR-GARCH) by Glosten et al., (1993). More so, the Threshold GARCH (of Zakoian, 1994), as well as the Asymmetric Power ARCH (of Ding et al., 1993) and its variants are also noted. From the empirical perspective, these univariate conditional volatility models are feasible for studying various volatility and financial characteristics, which includes but not limited to volatility clustering, long-term dependence (or long-memory), power-law correlation, and non-linear dependence.

Among the above-mentioned models, the EGARCH and the GJR-GARCH are the most often employed GARCH-class models used in estimating asymmetry and supposedly leverage effect in financial/economic variables. However, in his work, McAleer (2014) pinpoints the flaws in this practice and show clearly that these two conditional volatility models are rather feasible for capturing asymmetry but practically impossible for detecting and quantifying leverage effect. For instance, given the conditional variance of the EGARCH(1, 1) model as:

$$\log(h_t) = \omega + \alpha\,\varepsilon_{t-1} + \gamma\left(|\varepsilon_{t-1}| - E|\varepsilon_{t-1}|\right) + \beta\log(h_{t-1}) \qquad (2.63),$$

McAleer (2014) and Caporin and Costola (2019) put forward that the presence of asymmetry and/or leverage in (2.63) depends on α and γ. Thus, asymmetry is present if $\gamma > 0$, and for leverage, $\gamma < 0$ and $\gamma < \alpha < -\gamma$. McAleer (2014) then argued that leverage is not applicable in (2.63), because α and γ should always be non-negative since they are variances emanating from stochastic processes. Meanwhile, Caporin and Costola (2019) proposed a new definition which distinct asymmetry from leverage. Therefore, following the latter authors' characterization of asymmetry and leverage in relation to conditional variance and the news impact curve (NIC), we adopt two applicable conditional volatility models and explain them accordingly.

Beforehand, we deduce the conditional mean equation as follows. Given that $\{r_t\}_{t=1}^{T}$ gives the daily return series of a financial time series data, we first specify an AR(1) process to account for short-term dependence in the return process, bearing in mind the presence or activities of speculative or noisy traders.

$$r_t = \phi\, r_{t-1} + \varepsilon_t \qquad (2.64)$$

Model (2.64) represents the mean equation of the return process. The conditional variance models are duly specified in the ensuing procedure.

2.3.5.1 GJR-GARCH and News Impact Curve

The conditional variance equation of the GJR-GARCH(1, 1) model is express as:

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \gamma\varepsilon_{t-1}^2\left[I(\varepsilon_{t-1} < 0)\right] + \beta h_{t-1} \qquad (2.65)$$

where $I(\bullet)$ denotes indicator function; the parameter γ gives the coefficient of the asymmetry effect; and $\omega > 0$, $\alpha \geq 0$, $\beta \geq 0$, and $\gamma \geq 0$ remains as sufficient conditions for positivity of the conditional variances. Drawing on the new definition of asymmetry, the NIC which also determines the extent to which news has an impact

on conditional variances (or volatility) could be deployed to assess such effect. Fast forward, the NIC for the GJR-GARCH model is given by:

$$NIC(\varepsilon_{t-1}) = \begin{cases} A + \alpha\varepsilon_{t-1}^2, & \varepsilon_{t-1} \geq 0 \\ A + (\alpha + \gamma)\varepsilon_{t-1}^2, & \varepsilon_{t-1} < 0 \end{cases} \tag{2.66}$$

where $A \equiv (\omega + \beta\sigma^2)$; σ denotes the standard deviation of the unconditional return; and ω, β and γ are parameters associated with (2.65). According to Caporin and Costola (2019), a GARCH model allows for asymmetry if $NIC(\theta) \neq NIC(-\theta)$ $\forall$ shocks θ. Hence, for the GJR-GARCH, asymmetry is present if the estimated coefficient which corresponds to the sign of the shock deviate from zero, i.e. $\gamma \neq 0$. As earlier mentioned, leverage does not apply to the GJR-GARCH model.

2.3.5.2 NGARCH and News Impact Curve

The conditional variance equation of the Non-linear Asymmetric GARCH (NGARCH) of Engle and Ng (1993), a variant of the conventional Asymmetric GARCH, thus NGACRH(1, 1) is given by:

$$h_t = \omega + \alpha\left(\varepsilon_{t-1} + \gamma\sqrt{h_{t-1}}\right)^2 + \beta h_{t-1} \tag{2.67}$$

where h_t is the conditional variance at time *t*; and the parameter γ apparently drives the presence (or otherwise) of asymmetric and/or local leverage. Moreover, the NIC for the NGARCH model is also expressed as:

$$NIC(\varepsilon_{t-1}) = A + \alpha(\varepsilon_{t-1} - \gamma\sigma)^2 \tag{2.68}$$

where $A \equiv (\omega + \beta\sigma^2)$. In the case where $\gamma = 0$, the NGARCH becomes symmetric, and $NIC(\theta) = NIC(-\theta)$, i.e. $(\theta - \gamma)^2 = (-\theta - \gamma)^2$ (Caporin and Costola, 2019). Hence, asymmetry is presence for NGARCH if $\gamma \neq 0$. On the other hand, since the first partial derivative of the NGARCH's NIC model, thus $\partial NIC(\varepsilon_{t-1})/\partial\varepsilon_{t-1} = 2\alpha(\varepsilon_{t-1} - \gamma\sigma)$, then the presence of local leverage becomes feasible. Thus, by inference, the NIC decreases after the derivative to incorporate positive shocks lesser than γ when $\gamma > 0$. More so, we could also deduce negativity for $\varepsilon_{t-1} < \gamma$ given that $\gamma > 0$. Therefore, in coherence

with the definition of local leverage which states that "A GARCH model allows for local leverage if the $\partial NIC(\varepsilon_{t-1})/\partial\varepsilon_{t-1} < 0$ for a subset of $\Theta = (0, +\infty)$ where Θ is the positive fraction of the support of ε_{t-1}" (Caporin and Costola, 2019), the NGARCH model becomes practically possible for detecting local leverage. Hence, its adoption in our study to explore asymmetry and/or local leverage is not misplaced.

2.3.6 Wavelet-based time-scale decomposition

Under this sub-section, we briefly specify a wavelet-based decomposition method used for transforming a given time series data into frequency or time-scale constituents, with a multiresolution which correspond to such scale[27]. We employ the Maximal Overlap Discrete Transformation (i.e. MODWT) and a Daubechies' (1992) least asymmetric filter (of length 8 – LA (8)) which draw on a multiresolution technique to numerically decompose the given original time series into different levels of resolutions, best known as time-scales. The time series realizations are then filtered into wavelet-based coefficients, marked as D1, D2, …, D7, with the resultant lower to higher resolutions or scales respectively associated to the periodicity range of 2~4 (scale D1); 4~8 (scale D2); 8~16 (scale D3); 16~32 (scale D4); 32~64 (scale D5); 64~128 (scale D6); and 128~256 (scale D7) day bands. The wavelet decomposition process also generates a smoothing component S6, which represents the trend coefficient of the time series at hand.

Two of the decomposed time-scale series, thus return series from the intraweek (2~4 day band) and the weekly (4~8 day band) scales are chosen to investigate the presence (or absence) of complex dynamic behaviour in the specified data in sub-section 2.4.4. Also, using the derived return series from scales D1 (intraweek frequency band) and D4 (fortnight to monthly frequency band), we document the featured characteristics

[27] For detailed description of the decomposition process, readers are referred to the methods under Chapter 3.

of asymmetry and/or local leverage in the markets. Our choice of these time-scales is not done arbitrary but rather premised on a hypothetical assumption that rational market participants mat not hold these risky assets, especially the currencies on a very long time-scale.

2.3.7 Multifractal market measures and processes

In practice, several financial and economic time series data display non-linear scaling functions. The dynamics of such data may often not be well-captured by one particular exponent of scale, but instead a multifractal structure (i.e., different scales of time). In attempts to examine multifractal features in time series data, many kinds of empirical methods have been proposed. We only describe one such method which exhibits much robustness. Building on the widely used detrended fluctuation analysis (DFA), Kantelhardt *et al*., (2002) proposed a multifractal detrended fluctuation analysis (MF-DFA) which generalizes on the former method, and possesses the following comparative advantages: (i) MF-DFA does not require the modulus maxima procedure, and hence does not involve more effort in programming than the conventional DFA; and (ii) it allows for a reliable analysis of multifractal non-stationary time series by relaxing the transformation assumption.

The MF-DFA generally extends the original DFA method in five procedural steps. Basically, the initial three steps of the MF-DFA is much identical to that of the DFA. Following Kantelhardt *et al*., (2002), we specify the MF-DFA procedure. Let us consider the time series x_k, with length N, thus $\{x_k : k = 1,2,...,N\}$ and assume the series is of compact support. Here, support is referred as the set of the indices k with non-zero values x_k, and it is termed compact if $x_k = 0$ (interpreted to mean having no value at k) for an insignificant fraction of the series only. The time series at hand is analyzed as a one-dimensional structure with values assigned to each point and

considers the multifractality of these values. We then specify the MF-DFA procedure as follows.

(a) Step I: *Determine the "profile".*

$$Y(i) \equiv \sum_{k=1}^{i} \left[x_k - \bar{x} \right], \qquad for\ i = 1, 2, ..., N \tag{2.69}$$

Here, subtraction of the mean $\bar{x}$ is not compulsory since it would even be eliminated through a detrending procedure in step three.

(b) Step II: *Divide the "profile"* $Y(i)$ *into* N_s *non-overlapping segments of equal lengths s, where* $N_s \equiv \text{int}\left(N/s\right)$.

Since the length N of the series is often not multiple of the considered time scale s, a short part at the end of the "profile" may remain. In an attempt not to disregard this part of the series, the same procedure is repeated, starting from the opposite end. Hence, in total, $2N_s$ segments are obtained.

(c) Step III: *Calculate the local trend for each of the* $2N_s$ *segments by a least-square fit of the series. Thereafter, determine the variance.*

$$F^2(v,s) \equiv \frac{1}{S} \sum_{i=1}^{s} \left\{ Y\left[(v-1)s + i\right] - y_v(i) \right\}^2, \quad for\ each\ segment\ v,\ v = 1, ..., N \tag{2.70}$$

and;

$$F^2(v,s) \equiv \frac{1}{S} \sum_{i=1}^{s} \left\{ Y\left[N - (v - N_s)s + i\right] - y_v(i) \right\}^2, \quad for\ \ v = N_s + 1, ..., 2N_s \tag{2.71}$$

where $y_v(i)$ is the fitting polynomial in segment v. As a matter of consideration, linear, quadratic, cubic or higher-order polynomials can be used in the fitting procedure.

(d) Step IV: *Average over all segments to obtain the* q^{th} *order fluctuation function.*

$$F_q(s) \equiv \left\{ \frac{1}{2N_s} \sum_{v=1}^{2N_s} \left[F^2(s,v) \right]^{q/2} \right\}^{1/q} \tag{2.72}$$

where in general, the index variable q can take any real value except zero. For $q = 2$, the original DFA procedure is retrieved. According to Kantelhardt et al., (2002), for

$q = 0$, the averaging procedure in (2.72) cannot be determined directly, instead, a logarithmic averaging procedure is employed:

$$F_0(s) = \exp\left[\frac{1}{4N_s}\sum_{v=1}^{2N_s} In\left(F^2(v,s)\right)\right] \tag{2.73}$$

(e) Step V: *Determine the scaling behaviour of the fluctuation functions by analyzing log-log plots* $F_q(s)$ *versus s for each value of q.*

If the series x_i is long-range power-law correlated, $F_q(s)$ increases for large values of *s*, as power-law demands.

$$F_q(s) \sim s^{h(q)} \tag{2.74}$$

In general, the scaling exponent, $h(q)$ may depend on *q*, and it is popularly known as the generalized Hurst exponent *H*, given that under a stationary series $h(2)$ is identical to *H*. Therefore, in cases where $h(q)$ does not depend on *q*, the time series x_k becomes monofractal and could best be explained with a single exponent across the time scales. On the other hand, given that $h(q)$ depend on *q*, the series x_k would be described as multifractal which would be characterized by several exponents over the time scales. This happens because $h(q)$ describes different scaling behaviour for small (if $q < 0$) and large ($q > 0$) fluctuations, hence giving prominence to multifractal analysis as a study of possible changes in the fluctuations within a time series over varied time scales. Intuitively, the time series at hand exhibits persistent properties if $0.5 < H < 1$; anti-persistent if $0 < H < 0.5$; and random walk (or short memory) if $H = 0.5$.

Moreover, as defined by the standard partition function-based multifractal formalism (Kantelhardt et al., 2002), the nexus between the multifractal scaling exponents $\tau(q)$ and the Hurst exponent *H* is expressed as:

$$\tau(q) = qh(q) - 1, \quad \tau(q) = qH - 1 \tag{2.75}$$

Another approach through which we can observe multifractal time series is to use a Legendre transform where *q* and $\tau(q)$ relate to α and $f(\alpha)$:

$$f(\alpha) = \alpha q - \tau(q) \tag{2.76}$$

$$\alpha = \frac{d}{dq}\tau(q) \tag{2.77}$$

and the fractal dimension of the series $f(\alpha)$ (also known as the singularity spectrum or multifractal spectrum) characterized by α and directly related to $h(q)$ is defined as:

$$\alpha = h(q) + qh'(q) \quad \text{and} \quad f(\alpha) = q[\alpha - h(q)] + 1 \tag{2.78}$$

where α is the Hölder exponent (singular exponent).

2.3.8 Herding measures

Do financial asset investors merely follow market consensus or simply imitate the trading strategies of each other (or a group) during periods of market downturns? To provide fresh insight into this inconclusive phenomenon, we employ the proposed approach of Christie and Huang (1995) to examine the presence (or absence) of herding activity in six asset classes. According to Christie and Huang, investors' decision to invest in an asset market is dependent on the comprehensive prevailing market conditions. In periods of extreme market conditions (or movements), individual asset returns show unlikely deviations from the overall market returns. Most expectedly, individual returns tend to well-cluster or held around the ensemble market returns. Under such occurrence, a market participant's investment decision-making is much likely to imitate the collective actions or the consensus in the market, as a result of individuals suppressing their unique trading information about the market.

Herding then becomes quite prevalent for this clustering condition where dispersion is observed at a very minimal level. However, in periods of relatively stable market conditions, an increase or higher level of dispersion (i.e., a substantial deviation of individual returns from the market returns) is predicted by rational asset-pricing models because the trading decisions of market participants are based on each person's diverse understanding and/or priors of the market. A cross-sectional standard deviation (CSSD) measure is suggested by Christie and Huang (1995) to

quantify the returns dispersion relative to the market returns average. The CSSD measure or statistic is expressed as:

$$CSSD_{m,t} = \left\{ \frac{\sum_{i=1}^{N} (r_{i,t} - r_{m,t})^2}{N-1} \right\}^{1/2} \tag{2.79}$$

where $r_{i,t}$ denotes the returns of asset *i* at trading time *t*; $r_{m,t}$ represents the cross-sectional returns average of the asset market portfolio at time *t*; and *N* gives the countable number of asset returns in the portfolio. As earlier explained, the presence of herding activity is upheld if the individual returns co-move simultaneously (perhaps in magnitude) with the market returns average, thus predicting evidence of low or no dispersion. Meanwhile, during periods of market stress, Christie and Huang (1995) cautioned analysts to differentiate between increased dispersion attributed to rational asset-pricing models and low dispersion levels induced by the presence of herding. In a regression approach, the authors isolated the dispersion level measured by $CSSD_{m,t}$ in the extremes (upper and lower tails) of the market returns distribution. A test is conducted to verify the discrepancies of these extreme tails dispersions from the market returns average level of dispersion.

$$CSSD_{m,t} = \alpha + \gamma_1^L D_t^L + \gamma_2^U D_t^U + \nu_t \tag{2.80}$$

Here, ν_t is the error term and D_t^L and D_t^U are regression dummies, where $D_t^L = 1$ if the market returns at time *t* are within the extreme lower tail of the returns distribution and $D_t^L = 0$ otherwise. Also, $D_t^U = 1$ given that the market returns at time *t* are within the extreme upper tail of the returns distribution and $D_t^U = 0$ otherwise. From (2.80), α gives the average dispersion (excluding the extreme tails), while significant positive coefficients for γ_1 and γ_2 are predicted based on rational asset-pricing models, and significant negative estimates for γ_1 and γ_2 signify the presence of herding. Ideally, (2.80) provides a much flexible way to measure changes in investor behaviour under extreme market movements relatively to stable markets.

Moreover, in an alternative approach to measure return dispersion, Chang et al., (2000) developed the cross-sectional absolute deviation (CSAD) statistic which complements the CSSD. The CSAD is rooted in the notion that the rational asset-pricing models do in addition to predicting increases in the dispersion of the individual returns relative to the market returns, also assume a linear relationship. The relationship only becomes non-linear if market participants tend to mimic the consensus in the market (or follow the crowd) at the expense of their individual priors or beliefs. The CSAD statistic is given by:

$$CSAD_{m,t} = \frac{1}{N}\left\{\sum_{i=1}^{N}\left(\left|r_{i,t} - r_{m,t}\right|\right)\right\} \tag{2.81}$$

To allow for a non-linear relationship between $r_{m,t}$ and $CSAD_{m,t}$ under periods of market stress, we specify (Chang et al., 2000):

$$CSAD_{m,t} = \alpha + \gamma_1\left|r_{m,t}\right| + \gamma_2 r_{m,t}^2 + \nu_t \tag{2.82}$$

where α , $r_{m,t}$, and ν_t remain as earlier defined; $\left|r_{m,t}\right|$ denotes the absolute value term; and $r_{m,t}^2$ represents the squared term of the market returns. Generally, herding activity is absent if the boundary conditions $\gamma_1 > 0$ and $\gamma_1 = 0$ are satisfied. Specifically, we observe anti-herding activity if γ_1 has a positive and statistically significant coefficient. Also, if the estimated coefficient for γ_2 becomes negative and significant, we conclude in favour of herding activity.

2.4 Empirical results and analysis

2.4.1 Preliminary examination

To kick start our analysis, we present summary measures computed on the 32 market variables, which cut across six different asset classes. Tables 2.10 and 2.11 display a number of sample moments and simple distributional measures for the daily log-returns of the individual and aggregate market data. Except for NEO, all the individual cryptocurrency markets recorded non-negative daily average returns as

high as 0.206% to 0.451%. This contrasts the negative daily returns at all levels for the BRICS bilateral foreign currencies (FXs) and commodities.

With standard deviations far exceeding 1% (i.e. 5.059-12.494%), it is conspicuous to tag the cryptocurrency market as much risky, relative to the asset markets of the BRICS. However, unlike the FX market, the BRICS stock and REIT equities respectively display higher standard deviation values, ranging from 1.152-2.032% and 1.697-2.535%. Though the riskiness level of the cryptocurrency market is unspeakably high, a measured pronouncement could somehow be advanced to describe the stock and REIT equities, which trails under half-way or far lesser (in magnitude) behind the former. These deductions also remain valid as we consider the widened range between the maximum and minimum return values, as well as the interquartile. Among the aggregate markets, CRIX (4.438%), MSCI EM REIT (1.199%), and MSCI EMI (0.866%) exhibit threat of high risk, while MSCI EM FX consistently announces itself as relatively less risky (0.290%) asset market.

Table 2.10: Summary statistics of location, dispersion, and shape of sample distribution

	Mean	Max	Min	Q1	Q3	Std. Dev	Kurtosis	Skewness
Bitcoin	0.252	52.08	-26.62	-1.53	2.16	5.059	11.23	0.428
Litecoin	0.206	80.00	-51.39	-2.42	2.05	7.712	19.06	1.693
Ripple	0.284	75.08	-51.29	-2.75	2.30	8.593	14.36	1.658
Ethereum	0.451	51.08	-136.13	-3.02	3.42	9.096	53.17	-2.833
Ethereum Classic	0.349	144.69	-46.61	-3.15	3.31	9.755	65.70	4.293
DASH	0.434	136.58	-86.02	-3.07	3.14	9.384	44.78	2.675
NEO	0.432	144.24	-51.08	-4.92	4.26	12.494	28.12	2.668
ZCASH	-0.436	64.99	-93.97	-3.84	3.66	9.467	19.65	-1.218
BRL/USD	-0.039	5.25	-7.36	-0.60	0.52	0.995	3.47	-0.131
RUB/USD	-0.020	5.19	-5.09	-0.23	0.21	0.502	17.66	-0.168
INR/USD	-0.014	3.47	-3.18	-0.24	0.23	0.455	6.68	-0.430
CNY/USD	-0.006	1.13	-1.84	-0.09	0.08	0.205	7.84	-0.368
ZAR/USD	-0.034	5.05	-4.80	-0.62	0.56	0.980	1.37	-0.144
BOVESPA	-0.010	10.63	-17.53	-1.22	1.13	2.032	4.53	-0.251
MOEX	-0.009	13.67	-13.30	-0.95	0.92	1.754	8.92	-0.533
NIFTY50	0.029	6.20	-7.51	-0.57	0.66	1.152	5.03	-0.528
SSE50	0.018	7.69	-10.13	-0.64	0.73	1.619	5.68	-0.565
FTSE/JSE TOP40	-0.010	5.79	-8.05	-0.85	0.88	1.482	1.49	-0.328
Brazil REIT	-0.025	10.87	-21.14	-1.20	1.21	2.209	6.73	-0.389
Russia REIT	-0.040	18.22	-27.61	-1.21	1.17	2.535	19.69	-1.007
China REIT	0.010	9.62	-9.47	-0.93	0.90	1.736	2.79	0.090
India REIT	-0.018	12.46	-8.18	-0.96	0.96	1.763	3.35	0.094

South A. REIT	-0.023	14.26	-14.91	-0.91	-0.90	1.697	10.50	-0.432
Crude Oil	-0.033	11.63	-10.79	-1.09	1.08	2.123	3.10	0.021
Gold	-0.013	4.58	-9.51	-0.48	0.45	0.903	9.98	-0.795
Sugar	-0.025	8.72	-5.04	-0.91	0.82	1.552	1.66	0.349
CRIX	0.234	19.85	-25.33	-1.31	2.13	4.438	4.93	-0.517
MSCI EM FX	-0.002	1.75	-1.66	-0.16	0.17	0.290	2.07	-0.100
MSCI EMI	-0.003	3.22	-5.13	-0.50	0.50	0.866	1.88	-0.315
MSCI EM REIT	-0.014	5.43	-6.99	-0.69	0.68	1.199	2.11	-0.162
BCOM	-0.036	2.99	-3.94	-0.48	0.42	0.760	1.40	-0.168
GBI-EM	-0.005	3.53	-4.00	-0.33	0.34	0.569	3.57	-0.211

Additional results from Table 2.10 reveals negative skewness coefficient for 2 out of the 8 individual cryptocurrencies, 3 out of the 5 REITs, and for all the FX and stock market returns. This signifies that the FX and stock markets of the BRICS are more likely to realize non-positive daily returns in moments of any economic downturn, compared to the cryptocurrencies and that of the REITs. The kurtosis coefficient appears very high for all markets, especially the cryptocurrencies. Such evidence of high peakedness indicates probably the existence of non-normally distributed daily returns. More so, at all levels of the markets, the Breusch-Godfrey and Durbin-Watson tests document vast evidence in favour of serial correlation (refer, Table 2.11). A unanimous result could not be obtained from the Rank, Bartels, and Cox-Stuart randomness test. Noticeably, the Bartels' test results which report evidence against IID-ness for some markets seem to contradict the output from the Rank and Cox-Stuart's. Also, based on the Goldfeld-Quandt and Harrison-McCabe tests, we found no clear evidence of heteroscedasticity in the log-returns on the markets.

Table 2.11: Risk-adjusted returns, randomness, serial correlation, and heteroscedasticity

	GSR	Rank	Bartels	Cox-S	BG	DW	GQ	HM
Bitcoin	0.049	1.26	-0.50	405	1.71	2.06	0.82	0.55
Litecoin	0.026	1.03	1.17	416	3.44***	1.91**	0.77	0.56
Ripple	0.032	-0.34	-2.31**	369	27.31*	1.73*	1.02	0.50
Ethereum	0.048	-0.72	-1.31	244	9×10^{-4}	1.77*	0.37	0.73
Ethereum Classic	0.035	0.69	1.64	176	12.62*	1.97	0.34	0.74
DASH	0.046	0.80	-0.26	348	7.67*	2.00	0.39	0.72
NEO	0.034	-0.05	0.43	171	0.97	2.06	0.20	0.83
ZCASH	-0.048	0.98	-0.78	163	4.37**	1.83**	0.26	0.79
BRL/USD	-0.046	0.42	2.99*	435	11.08*	2.16	0.88	0.53
RUB/USD	-0.052	1.32	0.49	460*	0.52	2.03	0.32	0.76
INR/USD	-0.046	-0.21	2.80*	416	6.22*	2.12	0.44	0.69
CNY/USD	-0.062	-1.11	1.97**	435	0.48	2.03	2.54*	0.28*

ZAR/USD	-0.041	1.05	0.68	437	0.04	1.99	1.43*	0.41*
BOVESPA	-0.008	1.83***	-0.73	431**	0.93	1.95	0.85	0.54
MOEX	-0.009	1.52	-2.32**	418	2.43	1.92***	0.39	0.72
NIFTY50	0.019	-0.05	-3.83*	390	11.34*	1.83***	0.45	0.69
SSE50	0.007	0.77	-0.80	396	1.12	1.95	0.36	0.73
FTSE/JSE TOP40	-0.011	0.16	-0.44	406	1.60	1.93	1.19*	0.46*
Brazil REIT	-0.014	0.39	-1.08	398	0.19	1.98	0.80	0.55
Russia REIT	-0.019	-0.66	0.20	396	0.17	1.98	0.32	0.76
China REIT	0.002	1.54	-3.82*	437	20.36*	1.78*	0.99	0.50
India REIT	-0.014	-1.13	-4.60*	408	25.27*	1.75*	0.53	0.65
South Africa REIT	-0.018	-0.91	-2.45**	381	6.48*	1.87*	0.92	0.52
Crude Oil	-0.019	1.22	1.77***	422	10.55*	2.16	0.75	0.57
Gold	-0.022	1.00	1.89***	424	0.18	2.02	0.42	0.70
Sugar	-0.021	0.39	-0.39	411	0.71	1.96	1.28*	0.44*
CRIX	0.051	2.30**	-1.01	337	1.36	1.93	2.12*	0.32*
MSCI EM FX	-0.028	1.03	-4.30*	447***	21.78*	1.77*	0.94	0.52
MSCI EMI	-0.011	0.90	-8.69*	429	65.56*	1.60*	0.81	0.55
MSCI EM REIT	-0.017	1.33	-6.32*	446	31.56*	1.72*	0.90	0.53
BCOM	-0.057	0.93	1.18	425	8.44*	2.14	0.84	0.54
GBI-EM	-0.021	1.52	-4.70*	456**	28.26*	1.74*	0.85	0.54

Note: The randomness for all market variables was done using the rank method by Mann (1945) and Kendall (1990), as well as Bartels' (1982), and Cox and Stuart's (1955) test methods. Besides, we adopted the BG test of Breusch's (1978) and Godfrey's (1978) for examining the presence of serial correlation. This was augmented by the DW method developed by Durbin and Watson (1950, 1951, and 1971). There again, the GQ and HM tests respectively put forward by Goldfeld and Quandt (1965) and Harrison and McCabe (1979) were employed to test for heteroscedasticity. Moreover, the generalized Sharpe ratio (GSR) which draws on a mean-variance-skewness framework is considered in assessing the risk-adjusted return performances across the six asset classes. The GSR is computed using. The risk-free value for our computation is deduced from the Fed's daily 3-month T-Bill sample data (refer, https://fred.stlouisfed.org). Statistical significance level: "*"1%; "**"5%; and "***"10%.

To another set of results, the generalized Sharpe ratio (GSR) which measures risk-adjusted return performance is computed for the undiversified portfolios, and presented in Table 2.11. Comparably, the cryptocurrency market gives the best portfolio return performance, followed by the stock and REIT equities of the BRICS. Though found to be highly risky, investors are somewhat compensated for holding an asset from the cryptocurrency market. Among these markets, Bitcoin had the highest GSR, while NIFTY50 and SSE50 look promising for the BRICS stocks. The Chinese REIT outperformed all competitors within the BRICS scope of markets. Moreover, the emergence of Bitcoin as the best performed market among the cryptocurrencies does not pose many surprises as it has over the decade remained the most liquid and a market leader among its class.

2.4.2 Analysis of halcyon and volatile market dynamics

Table 2.12 displays results on the Markov switching regression (MSDR) model for the markets. Weighing on the MSDR results, we document different episodes of regime changes and behaviour for the markets. The estimated state-dependent parameters, that is v_1 and v_2, as well as σ_1 and σ_2 represent respectively the expected values and standard deviations of the regimes. Specifically, v_1 (σ_1) is the expected value (standard deviation) reported for the calm or halcyon regime (regime 1); and v_2 (σ_2) denote the expectation (standard deviation) for the turbulent regime (regime 2). From the table's results, we could recognize that majority of the cryptocurrencies recorded negative daily expected returns under regime 2. Except for Bitcoin, SSE50, and CRIX, all the markets toggle between positive and negative daily average returns under the two regimes.

Observably, the regime-based daily average return values for Bitcoin (0.22% and 0.26%) and SSE50 (0.03% and 0.01%) are respectively consistent with the 0.252% and 0.018% non-regime average returns reported under Table 2.10. We also find the expectation of the BRICS FX market in regime 2 to be in some way closer to the cryptocurrencies (in terms of direction) but moves far apart in magnitude. This contrasts the behaviour of the BRICS stock market which recorded positive expected values for all its variables under regime 2. The findings suggest that in turbulent market conditions, negative daily average returns may be prevalent for the cryptocurrencies, as well as the BRICS FXs, while the converse holds for the stocks.

In both regimes, the cryptocurrencies exhibit the highest level of volatility, as the markets (individual and aggregate) show standard deviation values far beyond 1%. The evidence of high-risk market is also witnessed for the BRICS REITs where the estimated standard deviation consistently deviates upwards from 1%. With $\sigma_1 < 1\%$ for all the FXs, and $\sigma_2 < 1\%$ for RUB/USD, INR/USD, CNY/USD, and MSCI EM FX, we

reasonably conclude in favour of a relatively lower risk for the BRICS traditional currency market. Such lower risk level is highly manifested under the calm regime than could be observed for the turbulent regime. Collectively, based on the σ_1 and σ_2 estimates, the cryptocurrencies are ranked first as the riskiest instrument or asset in both regimes, followed respectively by the REIT, stock, and commodity markets.

Table 2.12: Markov regime switching for individual and aggregate log-returns

	ν_1	ν_2	σ_1	σ_2	$P_{s_t}=1$	$P_{s_t}=2$	$D_t=1$	$D_t=2$
Bitcoin	0.22 [0.30]	0.26 [0.07]	7.433	1.743	0.7744	0.8383	4.43	6.18
Litecoin	-0.23 [0.09]	0.89 [0.55]	2.323	12.60	0.8369	0.6770	6.13	3.10
Ripple	1.92 [0.74]	-0.65 [0.11]	14.49	3.063	0.7700	0.9018	4.35	10.2
Ethereum	1.42 [0.54]	-0.37 [0.16]	10.78	2.852	0.7494	0.7941	3.99	4.86
Ethereum Classic	0.84 [0.67]	-0.40 [0.19]	11.31	3.150	0.7845	0.8416	4.64	6.31
DASH	2.10 [0.75]	-0.38 [0.15]	14.30	3.730	0.7835	0.9039	4.62	10.4
NEO	5.58 [2.74]	-0.53 [0.31]	27.69	6.340	0.7589	0.9483	4.15	19.3
ZCASH	-0.52 [0.27]	1.64 [1.23]	4.712	13.43	0.8531	0.5905	6.81	2.44
BRL/USD	-0.01 [0.01]	-0.10 [0.05]	0.652	1.261	0.9809	0.9781	52.4	45.7
RUB/USD	-0.01 [0.01]	-0.05 [0.04]	0.282	0.871	0.9935	0.9806	153.9	51.6
INR/USD	-0.05 [0.04]	-0.00 [0.01]	0.709	0.321	0.9634	0.9872	27.3	78.1
CNY/USD	0.00 [0.00]	-0.01 [0.01]	0.079	0.277	0.9400	0.9409	16.7	16.9
ZAR/USD	0.00 [0.03]	-0.14 [0.08]	0.766	1.390	0.8726	0.6451	7.85	2.82
BOVESPA	-0.18 [0.11]	0.09 [0.05]	2.650	1.444	0.9736	0.9821	37.9	55.9
MOEX	-0.12 [0.25]	0.00 [0.53]	3.415	1.325	0.9657	0.9942	29.2	172.4
NIFTY50	-0.19 [0.18]	0.05 [0.03]	2.128	0.897	0.8829	0.9821	8.54	55.9
SSE50	0.03 [0.03]	0.01 [0.07]	0.886	2.402	0.9669	0.9414	30.2	17.1
FTSE/JSE TOP40	-0.34 [0.15]	0.12 [0.05]	1.934	1.098	0.4161	0.7543	1.71	4.07
Brazil REIT	0.03 [0.06]	-0.23 [0.21]	1.646	3.478	0.9652	0.8800	28.7	8.33
Russia REIT	-0.29 [0.26]	0.02 [0.06]	4.425	1.612	0.8742	0.9642	7.95	27.9
China REIT	-0.09 [0.04]	0.13 [0.09]	1.026	2.293	0.8628	0.8294	7.29	5.86
India REIT	-0.01 [0.16]	-0.03 [0.14]	1.174	2.419	0.9514	0.9181	20.6	12.2
South Africa REIT	-0.51 [0.32]	0.04 [0.04]	3.120	1.243	0.7572	0.9604	4.12	25.3
Crude Oil	0.02 [0.04]	-0.14 [0.14]	1.359	3.117	0.9912	0.9803	113.6	50.8
Gold	-0.10 [0.11]	0.01 [0.02]	1.577	0.613	0.2427	0.8255	1.32	5.73
Sugar	-0.14 [0.05]	0.20 [0.13]	1.070	2.132	0.7693	0.5643	4.33	2.30
CRIX	0.10 [0.26]	0.35 [0.09]	6.081	1.699	0.8987	0.9044	9.87	10.5
MSCI EM FX	0.02 [0.01]	-0.03 [0.02]	0.201	0.366	0.9377	0.9209	16.1	12.6
MSCI EMI	0.12 [0.04]	-0.25 [0.07]	0.659	0.908	0.5856	0.2877	2.41	1.40
MSCI EM REIT	-0.07 [0.07]	0.02 [0.03]	1.570	0.873	0.9623	0.9780	26.5	45.5
BCOM	-0.01 [0.02]	-0.09 [0.04]	0.552	0.966	0.9919	0.9873	123.5	78.7
GBI-EM	-0.06 [0.04]	0.02 [0.01]	0.796	0.409	0.9273	0.9662	13.8	29.6

Note: The standard errors associated with the expected values in each regime are reported in the square parenthesis.

Furthermore, the expected duration of the markets under the calm and turbulent regimes are reported in the last two columns of Table 2.12. Noticeably, the average length of the cryptocurrency market to stay in a turbulent regime $D_t = 2$ looks a little longer than the duration in a calm regime $D_t = 1$. Similar revelation is noticed for the

BRICS stocks, while the remaining markets show a mixed result. The same conclusion is reached from the time plots of the daily log-returns with the imposed extracted regime smoothing probabilities (refer, *Appendix 2.A1*). This signifies that in events of market downturn, there is perhaps a low tendency for the cryptocurrencies and the BRICS stocks to bounce out quickly from such harsh market condition.

Lastly, using the filtered smoothing probabilities, we report the peaks and troughs, and their corresponding dating which mark identified market phases or structural breaks within the log-returns of the studied aggregate data. For brevity, the results of the individual markets are discarded. Apparently, all the markets are characterized by several market phases which are not uniformly spread across the asset classes (refer, *Appendix B2.1*).

2.4.3 Parametric probability distributional properties

Numerous parametric distributions have over the past years been reported in various empirical studies as appropriate fits for capturing financial or economic data which display diverse market characteristics. Whiles some studies (for instance, Linden, 2001; Linden, 2005; Sarpong, 2019; etc.) favours distributions with simple and parsimonious parameter representation, others report adequacies for light, semi-heavy, and heavy tail distributions having complex parameterization (to mention few, see Bond and Patel, 2003; Gabriel and Lau, 2014; Corlu and Corlu, 2015; Guo, 2017; etc). In several cases, a single or quite fewer distributions purported to be appropriate in some previous studies or deemed popular are merely adopted in modelling a given empirical data without placing much emphasis on the sample distributional features of the data at hand.

This arbitrary choice of statistical distributions without ample recourse to the empirical features of the data being considered may sometimes not best represent the

entire information conveyed by the data, especially the tail risk dynamics. To adequately capture all such information, some analysts have resorted to fitting a range of plausible candidate parametric distributions to log-returns of assets, mainly three or more to ascertain the most appropriate fit. A scan through recent literature identified several works, among them notably include Corlu and Corlu (2014), Nadarajah et al., (2015), Chu et al., (2015), Osterrieder (2016), and Chan et al., (2017). The first two groups of authors fitted respectively 5 and 8 parametric distributions to the returns of 9 foreign exchange rate variables. Chu et al., (2015) fitted the highest number of distributions (i.e. 15 distributions) to the log-returns of an asset (Bitcoin), while Osterrieder (2016) and Chu et al., (2017) fitted respectively 7 and 8 competitive distributions to 7 most popular cryptocurrencies.

Table 2.13: Distribution diagnostics for original shuffled cryptocurrency log-returns

	BTC	LTC	XRP	ETH	ETHCL	Dash	NEO	ZCASH	CRIX
Panel A: Kolmogorov-Smirnov goodness-of-test results									
ND	0.121[a]	0.146[a]	0.164[a]	0.121[a]	0.132[a]	0.138[a]	0.118[a]	0.119[a]	0.116[a]
SND	0.120[a]	0.154[a]	0.171[a]	0.122[a]	0.142[a]	0.146[a]	0.123[a]	0.122[a]	0.116[a]
LPD	0.048[b]	0.359[a]	0.064[a]	0.045[b]	0.046	0.046[a]	0.039	0.038	0.040[b]
SLPD	0.045[a]	0.052[a]	0.067[a]	0.037	0.028	0.037[b]	0.054[c]	0.036	0.414[b]
CAUC	0.030	0.031	0.030	0.042[c]	0.049[c]	0.040[b]	0.051[c]	0.043	0.037[c]
GED	0.018	0.052[a]	0.029	0.031	0.035	0.049[a]	0.149[a]	0.030	0.019
SEPD	0.022	0.074[a]	0.022	**0.018**	0.033	0.022	0.141[a]	0.030	0.019
LGD	0.077[a]	0.077[a]	0.093[a]	0.073[a]	0.069[a]	0.064[a]	0.057[b]	0.062[b]	0.073[a]
SLGD	0.079[a]	0.078[a]	0.096[a]	0.073[a]	0.068[a]	0.066[a]	0.059[b]	0.062[b]	0.073[a]
ST	0.030	0.034	0.039[b]	0.042[c]	0.041	0.033	0.050[c]	0.023	0.032
SD	0.031[c]	0.031	0.014[c]	0.027	0.031	0.022	**0.035**	0.023	0.036[c]
SST	0.029	0.030	0.033[c]	0.027	0.028	0.023	0.035	0.023	0.032
GT	0.018	**0.027**	0.025	0.039	0.039	0.037[c]	0.071[a]	0.024	0.017
NIG	0.020	0.037[b]	0.019	0.031	0.028	0.020	0.039	0.022	0.022
HYP	0.044[a]	0.052[a]	0.067[a]	0.038	0.029	0.037[c]	0.054[c]	0.036	0.044[b]
GHYP	0.225[a]	0.035[c]	0.016	0.020	0.141[a]	**0.019**	0.217[a]	0.021	0.019
GH-SST	0.026	0.033[c]	0.025	0.112[a]	0.136[a]	NCP	NCP	0.072[a]	0.031
SGED	0.157[a]	0.035[c]	0.025	0.020	**0.021**	0.028	0.105[a]	0.030	0.019
SGT	**0.016**	0.029	**0.015**	0.020	0.026	0.028	0.069[a]	0.022	**0.015**
GLD	0.024	0.362[a]	0.021	0.031	0.030	0.022	0.037	**0.020**	0.183[a]
Panel B: Cramer-Von Mises goodness-of-fit test results									
ND	9.672[a]	10.00[a]	14.30[a]	6.242[a]	4.716[a]	10.00[a]	3.018[a]	3.320[a]	5.712[a]
SND	9.667[a]	11.40[a]	14.20[a]	6.251[a]	4.608[a]	9.838[a]	2.845[a]	3.303[a]	5.677[a]
LPD	0.852[a]	69.50[a]	1.703[a]	0.437[c]	0.190	0.671[b]	0.216	0.157	0.400[c]
SLPD	0.813[a]	0.751[a]	1.722[a]	0.283	0.107	0.358[c]	0.454[c]	0.132	0.433[c]
CAUC	0.187	0.436[c]	0.252	0.450[c]	0.337	0.613[b]	0.447[c]	0.216	0.210
GED	0.130	0.678[b]	0.317	0.208	0.213	0.763[a]	3.657[a]	0.132	0.070
SEPD	0.147	2.289[a]	0.090	**0.037**	0.118	0.117	4.277[a]	0.104	0.057

LGP	3.386[a]	2.794[a]	4.930[a]	1.635[a]	0.881[a]	2.118[a]	0.439[c]	0.736[b]	2.053[a]
SLGP	3.268[a]	2.823[a]	4.976[a]	1.625[a]	0.883[a]	2.112[a]	0.418[c]	0.709[b]	1.970[a]
ST	0.318	0.329	0.594[b]	0.346	0.166	0.321	0.281	0.078	0.273
SD	0.341	0.326	0.633[b]	0.164	0.093	0.108	**0.169**	0.074	0.314
SST	0.312	0.297	0.512[b]	0.156	0.082	0.102	0.176	0.074	0.267
GT	0.112	**0.294**	0.280	0.253	0.213	0.514[b]	0.712[b]	0.059	0.047
NIG	0.125	0.370[c]	0.132	0.119	0.090	0.085	0.227	0.051	0.173
HYP	0.809[a]	0.752[a]	1.711[a]	0.284	0.105	0.355[c]	0.454[c]	0.132	0.433[c]
GHYP	33.40[a]	0.446[c]	0.047	0.047	5.241[a]	**0.081**	7.927[a]	0.053	0.073
GH-SST	NCP	0.307	0.224	NCP	NCP	NCP	NCP	NCP	0.282
SGED	**0.065**	0.413[c]	0.133	0.053	**0.073**	0.132	1.690[a]	0.102	0.063
SGT	0.085	0.349[c]	**0.046**	0.071	0.082	0.237	0.835[a]	**0.037**	**0.051**
GLD	0.184	63.70[a]	0.175	0.144	0.091	0.099	0.201	0.066	14.10[a]

The re-coloured values are the minimum measures of CM or KS for the row entries. The Statistical significance levels are specified here as: "1% = a"; "5% = b"; and "10% = c".

Table 2.14: Distribution diagnostics for outlier-adjusted cryptocurrency log-returns

	BTC	LTC	XRP	ETH	ETHCL	Dash	NEO	ZCASH	CRIX
Panel A: Kolmogorov-Smirnov goodness-of-test results									
ND	0.115[a]	0.139[a]	0.158[a]	0.115[a]	0.112[a]	0.117[a]	0.099[a]	0.092[a]	0.244[a]
SND	0.116[a]	0.145[a]	0.171[a]	0.111[a]	0.098[a]	0.118[a]	0.100[a]	0.091[a]	0.113[a]
LPD	0.046[a]	0.359[a]	0.062[a]	0.041[c]	0.038	0.041[b]	0.043	0.034	0.039[b]
SLPD	0.044[a]	0.049[a]	0.064[a]	0.038	0.029	0.029	0.053[c]	0.026	0.042[b]
CAUC	0.029	0.031	0.031	0.044[b]	0.048[c]	0.039[b]	0.051[c]	0.043	0.037[c]
GED	0.018	0.057[a]	0.029	0.033	0.031	0.041[b]	0.091[a]	0.028	**0.017**
SEPD	0.014	0.065[a]	0.021	0.020	0.032	0.024	0.137[a]	0.025	0.019
LGD	0.075[a]	0.074[a]	0.091[a]	0.069[a]	0.062[a]	0.059[a]	0.053[c]	0.056[b]	0.071[a]
SLGD	0.074[a]	0.076[a]	0.094[a]	0.070[a]	0.063[a]	0.060[a]	0.055[c]	0.056[b]	0.071[a]
ST	0.030	0.034[c]	0.040[b]	0.043[c]	0.039	0.032	0.050[c]	0.024	0.033
SD	0.031[a]	0.033[c]	0.034[c]	0.028	0.028	0.025	0.035	0.024	0.031
SST	0.028	**0.030**	0.033[c]	0.028	0.028	0.023	**0.035**	0.024	0.033
GT	0.017	0.041[b]	0.024	0.034	0.033	0.037[c]	0.152[a]	0.026	0.018
NIG	0.021	0.037[b]	0.019	0.027	0.030	0.020	0.037	**0.017**	0.022
HYP	0.044[a]	0.049[a]	0.064[a]	0.038	0.029	0.028	0.060[b]	0.026	0.042[b]
GHYP	0.015	0.036[b]	0.263[a]	**0.014**	**0.027**	0.021	0.218[a]	0.022	0.020
GH-SST	0.027	0.033[c]	0.025	0.031	0.034	0.118[a]	0.038	0.024	0.031
SGED	0.014	0.039[b]	0.022	0.031	0.033	0.024	0.133[a]	0.021	0.018
SGT	**0.014**	0.040[b]	**0.016**	0.023	0.030	**0.018**	0.100[a]	0.040	0.028
GLD	0.025	0.034[c]	0.022	0.029	0.032	0.022	0.037	0.021	0.028
Panel B: Cramer-Von Mises goodness-of-fit test results									
ND	8.526[a]	11.40[a]	13.20[a]	4.134[a]	4.630[a]	6.974[a]	1.918[a]	2.158[a]	37.00[a]
SND	8.515[a]	9.956[a]	14.20[a]	3.838[a]	2.357[a]	6.859[a]	1.798[a]	2.153[a]	5.315[a]
LPD	0.759[a]	69.40[a]	1.565[a]	0.372[c]	0.128	0.542[b]	0.237	0.128	0.365[c]
SLPD	0.731[b]	0.659[b]	1.570[a]	0.211	**0.061**	0.244	0.397[c]	0.064	0.391[c]
CAUC	0.181	0.440[c]	0.256	0.492[c]	0.323	0.589[b]	0.452[c]	0.197	0.204
GED	0.127	0.610[b]	0.314	0.223	0.158	0.519[b]	1.161[a]	0.117	**0.047**
SEPD	0.060	1.408[a]	0.079	0.066	0.094	0.096	3.182[a]	0.065	0.061
LGP	3.179[a]	2.548[a]	4.674[a]	1.414[a]	0.673[b]	1.809[a]	0.346	0.581[b]	1.953[a]
SLGP	3.055[a]	2.594[a]	4.721[a]	1.385[a]	0.673[b]	1.793[a]	0.323	0.571[b]	1.881[a]
ST	0.321	0.313	0.592[b]	0.366[c]	0.144	0.271	0.278	0.092	0.282
SD	0.319	0.321	0.520[b]	0.171	0.086	0.108	0.168	0.083	0.279
SST	0.306	**0.295**	0.498[b]	0.170	0.084	0.101	**0.168**	0.084	0.277
GT	0.100	0.546[b]	0.280	0.224	0.166	0.487[b]	5.493[a]	0.086	0.056
NIG	0.137	0.370[c]	0.140	0.105	0.103	0.096	0.218	0.046	0.179
HYP	0.734[b]	0.651[b]	1.565[a]	0.211	0.062	0.224	0.504[b]	0.064	0.394[d]
GHYP	0.062	0.450[c]	0.049	**0.026**	0.104	0.087	8.066[a]	0.059	0.071

GH-SST	0.241	0.299	0.233	0.188	0.105	8.535[a]	0.180	0.089	0.291
SGED	0.059	0.352[c]	0.079	0.103	0.099	0.099	2.573[a]	**0.046**	0.053
SGT	**0.039**	0.435	**0.049**	0.061	0.111	**0.059**	1.282[a]	0.236	0.255
GLD	0.196	0.318	0.184	0.150	0.098	0.107	0.193	0.070	0.246

The re-coloured values are the minimum measures of CM or KS for the row entries. The Statistical significance levels are specified here as: "1% = a"; "5% = b"; and "10% = c".

Weighing on the ongoing drive in the literature, our study makes a significant twist to the narrative by considering a wider scope of prospective distributions to be fitted to diverse market variables. Thus, motivated by the insurgence of the cryptocurrency market over the recent decade, where its distributional properties and market dynamics are widely unexplored amidst traditional assets, our study offers noteworthy contributions.

First, the extensive coverage of parametric distributions in a single study which explores distributional characteristics of asset returns is a contribution worth mentioning. From our checks, this study would be the first to consider 20 candidate parametric distributions for modelling the log-returns of a financial dataset. This practice increases the chance of finding a distribution that best captures, if not all, most of the variations and hidden properties in the data at hand, rather than the imposition of a single or fewer distribution that has been popularized in the finance literature. Second, employing 26 individual and 6 aggregate market variables from diverse asset classes, a range of competitive candidate distributions are fitted to capture the return information of each market. Altogether, 1,280 competitive distributional fits are recorded, from which best fitting distributions are conferred. This paves way for a direct comparison of how the cryptocurrency market behaves in relation to traditional assets of the BRICS, through assessment of the functional form and tail riskiness. Third, a novel contribution is divulged as we compare the parametric distributional fit of outlier-adjusted log-returns to randomly shuffled log-returns. Lastly, we compute the VaR and ES risk measures for the market variables to uncover the riskiness of the cryptocurrencies vis-à-vis the traditional assets of the BRICS.

2.4.3.1 Fitted distribution and parameter estimates

The fundamental underlying principles that usually requires attention when fitting statistical distribution(s) to a given time series data are that, (i) the realizations of such data are assumed to follow an IID process, (ii) there is no evidence of serial correlation in the series, and (iii) the data series does not exhibit features of heteroscedasticity. Meanwhile, previous studies from which parametric distributions are fitted to financial/economic time series data either adopt the practice of merely assuming without testing for the above-mentioned conditions (eg. Corlu and Corlu, 2014) or remained absolutely silent about the phenomenon (see, Nadarajah et al., 2015; Osterrieder, 2016; Kobayashi, 2016; Eom et al., 2019; Sarpong, 2019; etc.). That notwithstanding, further scan through existing literature revealed two studies (Chu et al., 2015; and Chan et al., 2017) which tested for all three assumptions. Yet, quite startlingly, Chan et al., (2017) conferred evidence against serially correlated log-returns of seven most popular cryptocurrencies, a situation which from our checks looks rare for this asset class. Out of curiosity, we probed further, only to find out that the authors failed to neither produced results in their study nor mentioned where such results could be accessed to confirm their claims.

Prior to fitting the candidate distributions to the log-returns of the individual and aggregate market data, we tested for randomness (i.e. IID-ness), serial correlation, and heteroscedasticity. Although the results show substantial evidence against heteroscedasticity, the log-returns are marked with conflicting IID-ness results and a significant presence of serial correlation which could not be merely overlooked (refer, Table 2.11). These features are very often expected for financial returns.

Moreover, to correct for the teeming presence of serial correlation, and to ensure much considerable evidence of completely random returns, the realizations of the time series

log-returns are randomly shuffled[28]. It is worth mentioning that the practice of randomly shuffling the realizations of an original return series collapses any temporal correlations while maintaining the observed distributional characteristics of the data. Also, being cautious of the possible influence of outliers, we tested the log-returns for the presence of outliers using Grubbs' (1950) test method for two outliers on opposite tails. The log-returns of all the studied market variables recorded outliers at both tails[29]. We, therefore, adjusted the log-return series by simply removing the outliers. In all, 20 candidate parametric distributions are fitted to the outlier-adjusted log-returns and the originally shuffled log-returns of the 32 variables, summing up to a total of 1,280 distributional fits.

Table 2.15: Distribution diagnostics for original shuffled log-returns of BRICS FX and stock

	BRL	RUB	INR	CNY	ZAR	EM FX	BOV	MOEX	NIFTY	SSE	JSE	EMI
Panel A: Kolmogorov-Smirnov goodness-of-test results												
ND	0.034[a]	0.094[a]	0.058[a]	0.089[a]	0.032[c]	0.041[a]	0.040[b]	0.054[a]	0.054[a]	0.096[a]	0.039[b]	0.046[a]
SND	0.035[b]	0.095[a]	0.057[a]	0.089[a]	0.029	0.039[b]	0.041[b]	0.056[a]	0.052[a]	0.097[a]	0.036[b]	0.040[b]
LPD	0.034[c]	0.042[a]	0.032[a]	0.026	0.052[a]	0.031[c]	0.426[a]	0.039[b]	0.033[c]	0.024	0.030	0.036[b]
SLPD	0.032[a]	0.039[b]	0.033[a]	0.030	0.042[a]	0.032[c]	0.038[b]	0.039[b]	0.021	0.026	0.032[c]	0.031[c]
CAUC	0.058[a]	0.044[a]	0.061[a]	0.041[b]	0.071[a]	0.063[a]	0.064[a]	0.060[a]	0.060[a]	0.040[b]	0.067[a]	0.064[a]
GED	0.019	0.052[a]	0.022	0.091[a]	0.026	0.012	0.019	0.029	0.022	0.025	0.014	0.017
SEPD	0.017	0.046[a]	0.024	0.036[b]	0.019	0.012	0.018	0.029	0.014	0.022	0.012	0.012
LGD	0.015	0.034[c]	0.024	0.045[a]	0.022	0.017	0.016	0.017	0.028	0.054[a]	0.014	0.021
SLGD	**0.013**	0.038[b]	0.019	0.045[a]	0.018	0.014	0.015	0.017	0.022	0.053[a]	0.012	0.015
ST	0.015	0.031[c]	0.017	0.024	0.021	0.016	0.017	0.014	0.019	0.017	0.011	0.018
SD	0.014	0.031[c]	0.012	0.022	0.015	0.014	NCP	0.014	0.016	0.018	0.058[a]	0.015
SST	0.014	0.031[c]	**0.011**	**0.022**	0.015	0.015	0.015	0.014	0.016	0.018	0.013	0.016
GT	0.017	0.031	0.017	0.038[b]	0.020	0.015	0.017	0.010	0.017	0.015	0.012	0.015
NIG	0.015	0.030	0.014	0.022	0.018	0.011	0.015	0.016	0.012	0.013	0.011	0.012
HYP	0.016	**0.028**	0.014	NCP	0.017	0.010	**0.014**	0.016	0.011	0.026	0.011	**0.010**
GHYP	0.015	0.031	0.015	0.123[a]	0.018	0.010	0.016	0.014	0.016	**0.012**	0.012	NCP
GH-SST	0.015	NCP	0.015	NCP	0.018	0.014	NCP	0.014	0.017	0.017	0.013	0.016
SGED	0.017	0.046[a]	0.024	0.042[a]	0.019	0.103[a]	0.018	0.029	0.014	0.024	0.012	0.012
SGT	0.015	0.028	0.017	0.031[c]	**0.014**	**0.010**	0.017	**0.010**	**0.010**	0.014	**0.010**	0.012
GLD	0.016	0.030	0.015	0.022	0.019	0.013	0.015	0.016	0.015	0.015	0.011	0.013
Panel B: Cramer-Von Mises goodness-of-fit test results												
ND	0.697[b]	5.002[a]	2.002[a]	4.923[a]	0.439[c]	0.832[a]	0.770[a]	1.965[a]	1.976[a]	5.810[a]	0.698[b]	0.964[a]
SND	0.687[b]	4.994[a]	1.872[a]	4.889[a]	0.356[c]	0.781[a]	0.758[a]	1.956[a]	1.838[a]	5.809[a]	0.651[b]	0.824[a]
LPD	0.573[b]	0.293	0.468[b]	0.158	0.921[a]	0.454[c]	0.660[b]	0.420[c]	0.355[c]	0.194	0.441[c]	0.501[b]
SLPD	0.570[b]	0.245	0.361[c]	**0.096**	0.852[a]	0.427[c]	0.575[b]	0.417[c]	0.166	0.207	0.450[c]	0.375[c]
CAUC	1.267[a]	0.942[a]	1.318[a]	0.075[a]	1.734[a]	1.226[a]	1.411[a]	1.277[a]	1.098[a]	0.439[c]	1.196[a]	1.250[a]

[28] In our case, the number of random shuffling is set to 5000 runs. We believe shuffling 5000 runs would increase our chances of obtaining a complete randomised returns.

[29] The results of the outliers (datapoint and its detection date) are not presented, but could readily be made available upon a simple request.

GED	0.123	0.528[a]	0.214	3.806[a]	0.128	0.044	0.118	0.183	0.175	0.118	0.029	0.077
SEPD	0.117	0.437[c]	0.150	0.377[c]	0.071	0.030	0.097	0.187	0.045	0.111	0.043	0.025
LGP	0.028	0.572[b]	0.198	0.924[a]	0.091	0.075	0.049	0.095	0.268	1.531[a]	0.033	0.120
SLGP	**0.018**	0.528[b]	0.097	0.801[a]	0.055	0.038	0.038	0.101	0.163	1.510[a]	0.040	0.046
ST	0.036	0.141	0.094	0.144	0.085	0.062	0.044	0.031	0.106	0.095	0.025	0.094
SD	0.029	0.138	0.029	0.107	0.032	0.041	NCP	0.032	0.045	0.080	1.794[a]	0.046
SST	0.029	**0.137**	**0.029**	0.107	0.032	0.032	**0.031**	0.032	0.046	0.080	0.042	0.047
GT	0.061	0.157	0.093	0.397[c]	0.082	0.038	0.044	0.024	0.095	0.052	**0.015**	0.068
NIG	0.043	0.200	0.049	0.170	0.045	0.021	0.042	0.057	0.034	0.049	0.033	0.029
HYP	0.051	0.170	0.051	NCP	0.043	0.016	0.042	0.060	0.024	0.202	0.032	**0.023**
GHYP	0.032	0.153	0.044	7.653[a]	0.045	**0.016**	0.040	0.033	0.053	0.043	0.034	NCP
GH-SST	0.032	NCP	0.044	NCP	0.046	0.041	NCP	0.034	0.060	0.096	0.040	0.049
SGED	0.119	0.435[c]	0.150	0.767[a]	0.071	6.844[a]	0.097	0.185	0.046	0.126	0.042	0.025
SGT	0.046	0.204	0.055	0.267	**0.028**	0.019	0.032	**0.024**	**0.022**	**0.043**	0.028	0.024
GLD	0.044	0.157	0.054	0.128	0.059	0.026	0.046	0.052	0.049	0.071	0.029	0.038

The re-coloured values are the minimum measures of CM or KS for the row entries. The Statistical significance levels are specified here as: "1% = a"; "5% = b"; and "10% = c".

Table 2.16: Distribution diagnostics for outlier-adjusted log-returns of BRICS FX and stock

	BRL	RUB	INR	CNY	ZAR	EM FX	BOV	MOEX	NIFTY	SSE	JSE	EMI
Panel A: Kolmogorov-Smirnov goodness-of-test results												
ND	0.031[c]	0.088[a]	0.075[a]	0.082[a]	0.032[c]	0.041[a]	0.037[b]	0.050[a]	0.499[a]	0.093[a]	0.035[b]	0.044[a]
SND	0.031[c]	0.091[a]	0.052[a]	0.082[a]	0.026	0.037[b]	0.035[b]	0.053[a]	0.047[a]	0.093[a]	0.033[c]	0.038[b]
LPD	0.036[b]	0.042[a]	0.033[c]	0.178[a]	0.052[a]	0.032[c]	0.044[a]	0.040[b]	0.034[b]	0.022	0.031[c]	0.037[b]
SLPD	0.034[a]	0.035[b]	0.033[c]	0.028	0.043[a]	0.034[b]	0.040[b]	0.040[b]	0.023	0.024	0.033[c]	0.032[c]
CAUC	0.059[a]	0.045[a]	0.062[a]	0.041[a]	0.072[a]	0.238[a]	0.064[a]	0.061[a]	0.060[a]	0.040[b]	0.067[a]	0.065[a]
GED	0.017	0.048[a]	0.022	0.091[a]	0.026	0.013	0.015	0.028	0.019	0.024	0.012	0.016
SEPD	0.017	0.036[b]	0.059[a]	0.034[c]	0.016	**0.009**	**0.014**	0.026	0.013	0.024	0.011	0.011
LGD	0.015	0.031[c]	0.022	0.043[a]	0.023	0.250[a]	0.016	0.016	0.027	0.053[a]	0.013	0.020
SLGD	0.015	0.036[b]	0.017	0.043[a]	0.019	0.012	0.017	0.017	0.021	0.052[a]	0.011	0.015
ST	0.015	0.032[c]	0.018	0.023	0.021	0.017	0.017	0.014	0.020	0.018	0.012	0.019
SD	**0.015**	0.032[c]	0.042[a]	0.022	0.015	0.015	0.016	0.013	0.017	0.019	0.012	0.017
SST	0.015	0.032[c]	**0.011**	0.022	0.014	0.014	0.016	0.013	0.017	0.018	0.013	0.017
GT	0.016	0.031[c]	0.045[a]	0.039[b]	0.020	0.014	0.017	0.011	0.016	0.017	0.012	0.014
NIG	0.015	0.031	0.012	**0.022**	0.016	0.012	0.017	0.014	0.013	0.013	0.011	0.013
HYP	0.016	0.029	0.014	0.028	0.016	0.010	0.016	0.016	**0.010**	0.024	0.010	0.011
GHYP	0.017	0.031[c]	0.013	0.124[a]	0.016	0.010	0.017	0.013	0.015	**0.011**	0.010	0.011
GH-SST	0.016	NCP	0.013	0.022	0.016	0.015	0.018	0.012	0.018	0.018	0.012	0.017
SGED	0.017	0.037[b]	0.022	0.115[a]	0.016	0.173[a]	0.015	0.026	0.013	0.024	0.011	0.011
SGT	0.016	**0.029**	0.012	0.026	**0.014**	0.013	0.016	**0.010**	0.011	0.015	**0.010**	**0.011**
GLD	0.016	0.031[c]	0.014	0.022	0.017	0.013	0.018	0.014	0.016	0.015	0.011	0.015
Panel B: Cramer-Von Mises goodness-of-fit test results												
ND	0.482[b]	4.037[a]	3.284[a]	4.230[a]	0.400[c]	0.724[b]	0.503[b]	1.581[a]	1.662[a]	5.374[a]	0.567[b]	0.826[a]
SND	0.496[b]	3.956[a]	1.453[a]	4.232[a]	0.278	0.629[b]	0.524[b]	1.558[a]	1.521[a]	5.384[a]	0.537[b]	0.702[b]
LPD	0.624[b]	0.296	0.515[b]	20.93[a]	0.952[a]	0.491[b]	0.701[b]	0.449[c]	0.378[c]	0.170	0.467[b]	0.525[b]
SLPD	0.627[b]	0.265	0.388[c]	**0.085**	0.886[a]	0.467[b]	0.645[b]	0.460[c]	0.190	0.173	0.477[b]	0.404[c]
CAUC	1.276[a]	0.957[a]	1.350[a]	0.748[a]	1.760[a]	41.93[a]	1.419[a]	1.293[a]	1.110[a]	0.449[c]	1.206[a]	1.263[a]
GED	0.085	0.445[c]	0.191	3.834[a]	0.126	0.044	0.078	0.153	0.142	0.111	0.021	0.071
SEPD	0.083	0.411[c]	1.069[a]	0.383[c]	0.057	0.025	0.073	0.157	0.032	0.119	0.029	0.019
LGP	0.026	0.479[b]	0.176	0.832[a]	0.100	49.87[a]	0.042	0.070	0.236	1.437[a]	0.026	0.111
SLGP	**0.025**	0.440[c]	0.070	0.735[b]	0.061	0.030	0.048	0.084	0.136	1.418[a]	0.031	0.042
ST	0.032	0.139	0.097	0.134	0.088	0.078	0.044	0.029	0.111	0.099	0.028	0.105
SD	0.027	**0.133**	0.633[b]	0.105	0.032	0.054	0.039	0.029	0.052	0.086	0.042	0.054
SST	0.028	0.133	**0.027**	0.104	0.029	0.029	0.039	0.029	0.052	0.085	0.042	0.054
GT	0.058	0.168	0.720[b]	0.425[c]	0.089	0.042	0.044	**0.024**	0.094	0.059	0.015	0.068
NIG	0.039	0.188	0.037	0.169	0.036	0.028	0.049	0.052	0.035	0.048	0.030	0.033

HYP	0.045	0.191	0.042	0.085	0.037	0.022	0.048	0.057	**0.023**	0.176	0.028	0.025
GHYP	0.058	0.158	0.035	7.743[a]	0.036	**0.020**	0.050	0.034	0.045	**0.042**	0.027	0.021
GH-SST	0.035	NCP	0.036	0.116	0.037	0.052	0.054	0.033	0.065	0.100	0.039	0.057
SGED	0.084	0.383[c]	0.111	5.448[a]	0.057	15.34[a]	0.074	0.157	0.032	0.119	0.030	0.020
SGT	0.056	0.138	0.030	0.206	**0.028**	0.027	**0.038**	0.024	0.024	0.045	**0.025**	**0.019**
GLD	0.042	0.544	0.039	0.127	0.044	0.033	0.057	0.047	0.052	0.076	0.028	0.044

The re-coloured values are the minimum measures of CM or KS for the row entries. The Statistical significance levels are specified here as: "1% = a"; "5% = b"; and "10% = c".

The CM and KS measures, which have the test powers to assess and foretell the performances of each fitted candidate distribution are presented in Tables 2.13 to 2.18. Note well that the red-coloured entries in the tables represent the overall column minimum of the CM or KS measure. Additionally, we report the estimated parameters and their corresponding standard errors (where applicable) of the best fitted statistical distributions for the shuffled log-returns and the outlier-adjusted log-returns in Tables 2.19 and 2.20 respectively. Owing to its known superiority, the CM measure (reported at 3 decimal places) is used in selecting the most appropriate fitting distributions. However, in situations where there is a tie, we consider as many decimal places, and if that couldn't split the tie, we separate them using the very ones with the lowest or minimum KS measures.

As would be much expected in our case, we observe that the heavy tail distributions far outclass the light tail distributions. This truly speaks to the descriptive measures in our preliminary analysis, where all markets paraded skewness and kurtosis measures (refer, Table 2.10) which could hardly be described dominantly with light tail distributions. Out of the 64 best fitting distributions for both the shuffled and outlier-adjusted log-returns, the skew generalized *t* (SGT) ranked first with 21 number of best fits, followed by the skew Student's *t* (SST), the generalized hyperbolic (GHYP), and the skew *t* (SD) with 10, 8, and 5 number of best fits respectively. These four distributions account for a total of 21 (approximately 66%) and 23 (approximately 72%) of the best fitting distributions, out of the 32 each for the shuffled and outlier log-returns respectively.

By inferring from the results, we are much convinced that for the dataset considered, distributions with complex parameterization (i.e. a greater number of parameters) fit better than those with parsimonious parameter representation. These contrast the distributional choice made by Osterrieder (2016), which was based on the notion of simplicity. The author in his work opted for the 3-parameter Student's *t*, taken from among what he claims as similarly performed heavy tail distributions, even as the only criterium, i.e the log-likelihood favours the hyperbolic in four (Bitcoin, Ripple, Litecoin, and Doge) out of the 7 studied cryptocurrency markets.

Table 2.17: Distribution diagnostics for original shuffled returns of BRICS REIT, commodity and bond

	B.reit	R.reit	I.reit	C.reit	S.reit	EM reit	Oil	Gold	Sugar	BCOM	GBI-EM
Panel A: Kolmogorov-Smirnov goodness-of-test results											
ND	0.444[a]	0.070[a]	0.049[a]	0.057[a]	0.053[a]	0.040[b]	0.060[a]	0.063[a]	0.045[a]	0.033[c]	0.041[a]
SND	0.045[s]	0.071[a]	0.050[a]	0.056[a]	0.054[a]	0.039[b]	0.060[a]	0.063[a]	0.043[a]	0.033[c]	0.042[a]
LPD	0.027	0.029	0.028	0.017	0.030	0.036[b]	0.028	0.024	0.039[b]	0.044[a]	0.041[a]
SLPD	0.029	0.024	0.022	0.021	0.032[c]	0.033[b]	0.021	0.023	0.042[a]	0.044[a]	0.042[a]
CAUC	0.059[a]	0.050[a]	0.056[a]	0.054[a]	0.058[a]	0.059[a]	0.058[a]	0.055[a]	0.058[a]	0.061[a]	0.067[a]
GED	0.021	0.033[c]	0.017	0.018	0.023	0.018	0.020	0.019	0.025	0.017	0.023
SEPD	0.086[a]	0.031	0.013	0.013	0.025	0.017	0.015	0.018	0.024	0.018	0.023
LGD	0.019	0.023	0.025	0.029	0.016	0.016	0.031[c]	0.026	0.026	0.016	0.014
SLGD	0.019	0.023	0.025	0.029	0.017	0.017	0.027	0.026	0.022	0.012	0.012
ST	0.017	0.022	0.020	0.021	0.015	0.016	0.019	0.012	0.024	0.015	0.016
SD	0.015	0.021	0.018	0.021	0.014	0.015	0.015	0.012	0.020	**0.012**	0.015
SST	**0.015**	0.021	0.018	0.019	0.014	0.015	0.015	0.012	0.020	0.012	0.015
GT	0.019	0.022	0.014	0.016	0.015	0.013	0.017	0.011	0.025	0.016	0.014
NIG	0.018	**0.021**	0.016	0.015	0.017	0.015	0.013	0.011	0.020	0.013	0.017
HYP	0.018	0.024	0.012	**0.010**	0.015	0.013	0.014	0.014	**0.020**	0.013	0.016
GHYP	NCP	0.021	0.014	0.011	NCP	NCP	0.014	0.011	0.020	0.013	0.015
GH-SST	NCP	0.021	0.019	0.020	NCP	0.017	0.017	NCP	0.021	0.013	0.015
SGED	0.019	0.031	0.013	0.013	0.025	0.017	0.015	0.018	0.024	0.018	0.023
SGT	0.017	0.021	**0.011**	0.010	**0.013**	**0.013**	**0.012**	0.010	0.021	0.013	**0.011**
GLD	0.018	0.022	0.017	0.018	0.016	0.016	0.014	**0.010**	0.021	0.014	0.017
Panel B: Cramer-Von Mises goodness-of-fit test results											
ND	1.069[a]	2.695[a]	1.639[a]	2.102[a]	1.864[a]	0.886[a]	2.405[a]	2.616[a]	0.758[a]	0.659[b]	0.808[a]
SND	1.077[a]	2.681[a]	1.625[a]	2.057[a]	1.839[a]	0.900[a]	2.366[a]	2.580[a]	0.631[b]	0.625[b]	0.748[a]
LPD	0.396	0.295	0.225	0.130	0.372c	0.428[c]	0.262	0.205	0.693[b]	0.640[b]	0.746[a]
SLPD	0.374[c]	0.235	0.176	0.105	0.370[c]	0.394[c]	0.129	0.197	0.651[b]	0.630[b]	0.734[b]
CAUC	1.037[a]	0.956[a]	0.996[a]	0.879[a]	0.146[a]	1.157[a]	1.031[a]	1.008[a]	1.283[a]	1.416[a]	1.559[a]
GED	0.131	0.498[b]	0.064	0.068	0.203	0.072	0.182	0.110	0.191	0.084	0.174
SEPD	2.805[a]	0.449[c]	0.033	0.040	0.194	0.060	0.102	0.053	0.152	0.068	0.158
LGP	0.086	0.146	0.234	0.419[c]	0.079	0.082	0.494[b]	0.290	0.117	0.054	0.054
SLGP	0.090	0.132	0.237	0.413[c]	0.066	0.090	0.351[c]	0.265	0.082	0.033	0.039
ST	0.064	**0.087**	0.088	0.147	0.035	0.056	0.161	0.028	0.113	0.046	0.063
SD	0.056	0.087	0.066	0.220	0.030	0.048	0.071	0.025	0.078	0.028	0.050
SST	**0.055**	0.087	0.066	0.104	0.030	0.048	0.071	0.025	**0.077**	**0.028**	0.050
GT	0.073	0.204	0.052	0.065	0.028	0.046	0.144	0.025	0.165	0.048	0.044
NIG	0.063	0.155	0.042	0.054	0.059	0.044	0.056	0.023	0.100	0.031	0.067

HYP	0.074	0.255	0.027	**0.028**	0.060	0.041	0.036	0.038	0.118	0.033	0.068
GHYP	NCP	0.087	0.034	0.029	NCP	NCP	0.040	0.023	0.119	0.032	0.048
GH-SST	NCP	0.088	0.077	0.115	NCP	0.059	0.109	NCP	0.081	0.033	0.048
SGED	0.119	0.462[b]	0.034	0.039	0.194	0.060	0.053	0.102	0.146	0.067	0.158
SGT	0.063	0.219	**0.021**	0.029	**0.024**	**0.036**	**0.025**	0.021	0.119	0.035	**0.030**
GLD	0.065	0.120	0.058	0.086	0.051	0.053	0.090	**0.021**	0.088	0.033	0.072

The re-coloured values are the minimum measures of CM or KS for the row entries. The Statistical significance levels are specified here as: "1% = a"; "5% = b"; and "10% = c".

Table 2.18: Distribution diagnostics for outlier-adjusted returns of BRICS REIT, commodity and bond

Panel A: Kolmogorov-Smirnov goodness-of-test results

	B.reit	R.reit	I.reit	C.reit	S.reit	EM reit	Oil	Gold	Sugar	BCOM	GBI-EM
ND	0.042[b]	0.059[a]	0.048[a]	0.054[a]	0.046[a]	0.035[b]	0.059[a]	0.054[a]	0.042[a]	0.031[c]	0.035[b]
SND	0.039[b]	0.059[a]	0.047[a]	0.053[a]	0.046[a]	0.035[b]	0.057[a]	0.054[a]	0.040[b]	0.031[c]	0.035[b]
LPD	NCP	0.031	0.029	0.018	0.033[c]	0.037[b]	0.028	0.025	0.039[b]	0.045[a]	0.043[a]
SLPD	0.032[c]	0.026	0.024	0.020	0.034[c]	0.034[b]	0.023	0.023	0.042[a]	0.045[a]	0.042[a]
CAUC	0.058[a]	0.051[a]	0.057[a]	0.054[a]	0.058[a]	0.059[b]	0.058[a]	0.056[a]	0.058[a]	0.147[a]	0.067[a]
GED	0.020	0.033[c]	0.015	0.017	0.020	0.016	0.020	0.017	0.025	0.016	0.021
SEPD	0.016	0.028	0.013	0.012	0.021	0.015	0.014	0.016	0.023	0.017	0.021
LGD	0.018	**0.020**	0.024	0.028	0.014	0.016	0.030	0.024	0.026	0.015	0.014
SLGD	0.017	0.020	0.025	0.028	**0.012**	0.016	0.025	0.024	0.022	0.013	0.013
ST	0.016	0.021	0.021	0.022	0.014	0.017	0.020	0.013	0.025	0.015	0.015
SD	**0.014**	0.021	0.020	0.020	0.012	0.014	0.016	0.013	0.020	0.012	0.014
SST	0.014	0.021	0.019	0.020	0.012	0.015	0.016	0.013	0.020	0.012	0.014
GT	0.019	0.023	0.013	0.016	0.014	0.014	0.018	0.012	0.025	0.016	0.014
NIG	0.015	0.022	0.017	0.017	0.016	0.015	0.013	0.010	0.020	0.014	0.016
HYP	0.016	0.026	0.013	0.011	0.016	0.013	0.013	0.012	**0.019**	0.013	0.016
GHYP	0.016	0.033[c]	NCP	**0.011**	0.013	**0.012**	0.013	**0.010**	0.020	0.013	0.015
GH-SST	0.014	NCP	0.021	0.021	0.011	0.016	0.017	0.013	0.021	0.014	0.014
SGED	0.016	0.034[c]	0.013	0.012	0.020	0.015	0.014	0.016	0.023	0.016	0.021
SGT	0.019	0.023	**0.012**	0.013	0.013	0.013	**0.011**	0.011	0.021	**0.012**	**0.012**
GLD	0.015	0.022	0.019	0.019	0.015	0.015	0.544	0.011	0.021	0.014	0.017

Panel B: Cramer-Von Mises goodness-of-fit test results

ND	0.719[b]	1.744[a]	1.367[a]	1.868[a]	1.178[a]	0.740[b]	2.195[a]	1.872[a]	0.659[b]	0.546[b]	0.574[b]
SND	0.684[b]	1.736[a]	1.381[a]	1.853[a]	1.184[a]	0.733[b]	2.086[a]	1.859[a]	0.543[b]	0.528[b]	0.555[b]
LPD	NCP	0.358[c]	0.248	0.139	0.427[c]	0.466[b]	0.265	0.232	0.724[b]	0.666[b]	0.795[b]
SLPD	0.417[c]	0.321	0.204	0.113	0.435[c]	0.424[c]	0.157	0.224	0.676[b]	0.673[b]	0.780[a]
CAUC	1.056[a]	0.970[a]	0.999[a]	0.880[a]	1.158[a]	1.777[a]	1.061[a]	1.022[a]	1.296[a]	14.73[a]	1.569[a]
GED	0.090	0.412[c]	0.053	0.060	0.137	0.061	0.177	0.076	0.179	0.072	0.135
SEPD	0.070	0.379[b]	0.032	0.034	0.135	0.044	0.070	0.051	0.135	0.059	0.124
LGP	0.077	0.102	0.205	0.382[c]	0.045	0.075	0.461[a]	0.232	0.116	0.047	0.050
SLGP	0.071	0.092	0.213	0.379[c]	0.038	0.074	0.298	0.210	0.081	0.033	0.039
ST	0.066	0.077	0.095	0.153	0.026	0.064	0.173	0.034	0.113	0.047	0.054
SD	0.054	**0.075**	0.079	0.115	**0.022**	0.050	0.076	0.031	**0.076**	0.032	0.042
SST	0.054	0.076	0.077	0.115	0.022	0.050	0.076	0.031	0.077	**0.032**	0.042
GT	0.079	0.230	0.043	0.060	0.029	0.053	0.155	0.028	0.168	0.050	0.047
NIG	0.053	0.135	0.053	0.064	0.043	0.040	0.052	0.020	0.095	0.033	0.056
HYP	0.062	0.321	0.034	0.031	0.047	0.035	**0.029**	0.029	0.115	0.033	0.059
GHYP	0.065	0.483[b]	NCP	**0.031**	0.024	**0.034**	0.029	**0.020**	0.116	0.034	0.045
GH-SST	0.056	NCP	0.093	0.130	0.024	0.059	0.107	0.032	0.081	0.038	0.043
SGED	0.070	0.506[b]	0.032	0.034	0.131	0.041	0.052	0.069	0.137	0.058	0.123
SGT	0.095	0.232	**0.025**	0.044	0.026	0.043	0.032	0.025	0.127	0.034	**0.033**
GLD	**0.052**	0.102	0.075	0.100	0.039	0.049	0.088	0.023	0.085	0.036	0.062

The re-coloured values are the minimum measures of CM or KS for the row entries. The Statistical significance levels are specified here as: "1% = a"; "5% = b"; and "10% = c".

With only 3 and 2 combined number of best fit respectively for skew Laplace (SLPD) and skew logistics (SLGD), these two distributions are ranked best among the light tail cohort of distributions. Ironically, the widely preferred generalized error distribution (GED) and the Student's *t* (ST) recorded a single best fit each under the outlier-adjusted log-returns for the former, and the shuffled log-returns for the latter. Hence, in an attempt to solely approximate the latter distributions to the returns or innovations of the studied markets, analysts are to remain a little cautious. Furthermore, the normal and its skew version (ND and SND) show consistent inadequacies, and duly ranked as the worst-performed distributions among the candidate distributions. Ranked as the poorest fit to the log-returns of Bitcoin, the same conclusion was made by Chu et al., (2015) for ND and SND. The not too well or inadequate fit performances of the Laplace (LPD) and logistic (LGD) distributions look quite indifferent but relatively better than the Cauchy and normal, as well as it's variant.

Moreover, critical scrutiny of the results in Tables 2.13-2.18 reveals a considerable difference between the distributional fits for the shuffled log-returns and that of the outlier-adjusted log-returns. Though the aforementioned findings remained same, in 22 instances, the best fitting distributions under the shuffled log-returns are overturned when weighed up under the outlier-adjusted returns. In a broader spectrum, the current finding depicts that the issue of outliers cannot merely be downplayed in distributional fit for financial/economic time series variables. Paradoxically, the behaviour of the two currencies, i.e. the BRICS FX and cryptocurrencies differ as the former consistently recorded the same best fitting distributions across the shuffled and outlier-adjusted returns (except for RUB/USD). This is in sharp contrast to the cryptocurrencies and the remaining BRICS assets, particularly the stocks, as both displays, not much dissimilar distributional characteristics.

Unlike the individual log-returns, none of the light tail distributions could best fit the aggregate log-return variables. Meaning, the aggregate log-returns of all the markets across the asset classes exhibit heavy taildness characteristics which cannot be well-captured by light tail distributions. Comparably, the tails of the cryptocurrencies, the BRICS stocks, REITs, commodities, and the bond return series are relatively heavier, as they seem to be best captured by the heavy tail distributions, compared to the BRICS FX which consistently favours two light tail distributions.

Noticeably, for both shuffled and outlier-adjusted log-returns, the skew generalized *t* appears to be very domineering, because it is counted 3-times each as best fitting distribution for the cryptocurrencies and the BRICS stocks. The same distribution became dominant for the BRICS REITs under the shuffled returns but lost its dominance to the skew *t* and the generalized hyperbolic under the outlier-adjusted returns. Hence, from an empirical standpoint, we surmise that there exists nothing like a "universally best" fitting distribution. In our view, a statistical distribution is only pronounced best (worst) because it fits a particular empirical data at a defined time and/or scale sample quite well (poor).

2.4.3.2 P-P graphical representation and density plots

To further assess the adequacies for the best fitting distributions, we employ the probability-probability (P-P) plots, as well as a diagrammatic representation of the original frequencies with superimposed best density fits. The P-P gives a graphical output of the values for the empirical c.d.f $F(x)$ plotted against the fitted c.d.f $\hat{F}(x,\theta)$. The two approaches visually display how best (or otherwise) the fitted distributions capture all information contained in the dataset. For brevity, we record these adequacies for the aggregate market variables.

Table 2.19: Best fitted parametric distributions for the shuffled returns

	Shuffled return distributions	
	Fitted	Estimated Parameters
Bitcoin	SGED	$\hat{\mu}$=0.257[0.020]; $\hat{\sigma}$=4.997[0.199]; $\hat{\lambda}$=0.011[0.005]; $\hat{\nu}$=0.690[0.030];
Litecoin	GT	$\hat{\mu}$=-0.434[0.000]; $\hat{\sigma}$=35.75[6.308]; $\hat{p}$=1.453[0.038]; $\hat{\nu}$=1.391[0.036];
Ripple	SGT	$\hat{\mu}$=0.160[0.000]; $\hat{\sigma}$=9.291[0.000]; $\hat{\lambda}$=0.079[0.006]; $\hat{p}$=0.876[0.000]; $\hat{\nu}$=4.433[0.000]
Ethereum	SEPD	$\hat{\mu}$=0.514[0.023]; $\hat{\sigma}$=8.354[0.270]; $\hat{\alpha}$=0.099[0.005]; $\hat{p}$=0.717[0.037]
Ethereum Classic	SGED	$\hat{\mu}$=0.453[0.020]; $\hat{\sigma}$=8.346[0.050]; $\hat{\lambda}$=0.067[0.005]; $\hat{\nu}$=0.718[0.023];
DASH	GHYP	$\hat{\mu}$=-0.557; $\hat{\alpha}$=0.064; $\hat{\beta}$=0.013; $\hat{\delta}$=3.248; $\hat{\lambda}$=-0.329
NEO	SD	$\hat{\mu}$=0.212[0.445]; $\hat{\sigma}$=28.86[18.50]; $\hat{\lambda}$=0.098[0.047]; $\hat{\nu}$=1.039[0.053];
ZCASH	SGT	$\hat{\mu}$=-0.294[0.000]; $\hat{\sigma}$=9.282[0.706]; $\hat{\lambda}$=0.030[0.035]; $\hat{p}$=1.280[0.161]; $\hat{\nu}$=3.061[1.008]
BRL/USD	SLGD	$\hat{\mu}$=-0.039[0.008]; $\hat{\sigma}$=1.040[0.018]; $\hat{\gamma}$=-0.027[0.007]
RUB/USD	SST	$\hat{\mu}$=-0.016; $\hat{\sigma}$=0.563; $\hat{\alpha}$=0.990; $\hat{\nu}$=2.662
INR/USD	SST	$\hat{\mu}$=-0.014; $\hat{\sigma}$=0.455; $\hat{\alpha}$=0.918; $\hat{\nu}$=4.182
CNY/USD	SLPD	$\hat{\mu}$=-0.006[0.002]; $\hat{\sigma}$=0.189[0.004]; $\hat{\lambda}$=-0.023[0.003]
ZAR/USD	SGT	$\hat{\mu}$=-0.036[0.024]; $\hat{\sigma}$=0.982[0.023]; $\hat{\lambda}$=-0.076[0.036]; $\hat{p}$=2.143[0.263]; $\hat{\nu}$=3.151[1.290]
BOVESPA	SST	$\hat{\mu}$=-0.160; $\hat{\sigma}$=2.019; $\hat{\alpha}$=0.978; $\hat{\nu}$=5.975
MOEX	SGT	$\hat{\mu}$=0.006[0.041]; $\hat{\sigma}$=1.747[0.078]; $\hat{\lambda}$=-0.002[0.037]; $\hat{p}$=2.437[0.306]; $\hat{\nu}$=1.455[0.360]
NIFTY50	SGT	$\hat{\mu}$=0.030[0.028]; $\hat{\sigma}$=1.146[0.037]; $\hat{\lambda}$=-0.083[0.032]; $\hat{p}$=1.682[0.199]; $\hat{\nu}$=3.284[1.208]
SSE50	SGT	$\hat{\mu}$=0.035[0.038]; $\hat{\sigma}$=1.676[0.099]; $\hat{\lambda}$=0.014[0.032]; $\hat{p}$=1.274[0.160]; $\hat{\nu}$=3.365[1.391]
FTSE/JSE TOP40	GT	$\hat{\mu}$=0.017[0.034]; $\hat{\sigma}$=1.483[0.035]; $\hat{p}$=1.678[0.218]; $\hat{\nu}$=6.240[4.262]
Brazil REIT	SST	$\hat{\mu}$=-0.017; $\hat{\sigma}$=2.204; $\hat{\alpha}$=1.023; $\hat{\nu}$=4.810
Russia REIT	ST	$\hat{\mu}$=-0.029[0.049]; $\hat{\sigma}$=2.520[0.136]; $\hat{\nu}$=1.682[0.163]
India REIT	SGT	$\hat{\mu}$=-0.015[0.044]; $\hat{\sigma}$=1.761[0.049]; $\hat{\lambda}$=0.034[0.028]; $\hat{p}$=1.447[0.267]; $\hat{\nu}$=6.527[6.362]
China REIT	HYP	$\hat{\mu}$=-0.120[0.062]; $\hat{\alpha}$=0.857[0.038]; $\hat{\beta}$=0.044[0.025]; $\hat{\delta}$=0.447[0.177]
South A. REIT	SGT	$\hat{\mu}$=-0.017[0.041]; $\hat{\sigma}$=1.678[0.071]; $\hat{\lambda}$=-0.033[0.035]; $\hat{p}$=2.123[0.276]; $\hat{\nu}$=1.825[0.522]
Crude Oil	SGT	$\hat{\mu}$=-0.045[0.052]; $\hat{\sigma}$=2.142[0.070]; $\hat{\lambda}$=-0.087[0.030]; $\hat{p}$=1.426[0.168]; $\hat{\nu}$=4.760[2.317]
Gold	GLD	$\hat{\lambda}_1$=-0.002; $\hat{\lambda}_2$=2.685; $\hat{\lambda}_3$=-0.159; $\hat{\lambda}_4$=-0.128
Sugar	SST	$\hat{\mu}$=-0.029; $\hat{\sigma}$=1.571; $\hat{\alpha}$=1.067; $\hat{\nu}$=5.456
CRIX	SGT	$\hat{\mu}$=0.399[0.063]; $\hat{\sigma}$=5.295[0.417]; $\hat{\lambda}$=0.026[0.014]; $\hat{p}$=1.073[0.076]; $\hat{\nu}$=3.351[0.656]
MSCI EM FX	GHYP	$\hat{\mu}$=0.031; $\hat{\alpha}$=6.118; $\hat{\beta}$=-0.390; $\hat{\delta}$=0.236; $\hat{\lambda}$=1.005
MSCI EMI	HYP	$\hat{\mu}$=0.142[0.052]; $\hat{\alpha}$=2.019[0.139]; $\hat{\beta}$=-0.196[0.078]; $\hat{\delta}$=0.650[0.138]
MSCI EM REIT	SGT	$\hat{\mu}$=-0.012[0.029]; $\hat{\sigma}$=1.198[0.029]; $\hat{\lambda}$=0.018[0.029]; $\hat{p}$=1.518[0.182]; $\hat{\nu}$=7.616[5.243]
BCOM	SST	$\hat{\mu}$=-0.037; $\hat{\sigma}$=0.765; $\hat{\alpha}$=0.957; $\hat{\nu}$=6.345
GBI-EM	SGT	$\hat{\mu}$=-0.005[0.014]; $\hat{\sigma}$=0.570[0.017]; $\hat{\delta}$=-0.067[0.036]; $\hat{p}$=2.275[0.292]; $\hat{\nu}$=2.059[0.653]

In a [b]; "a" denote the estimated distribution parameter, and "b" is the corresponding standard error.

Table 2.20: Best fitted distributions for the outlier-adjusted returns

	Outlier-adjusted return distributions	
	Fitted	Estimated Parameters
Bitcoin	SGT	$\hat{\mu}$=0.289[0.036]; $\hat{\sigma}$=5.204[0.191]; $\hat{\lambda}$=0.016[0.009]; $\hat{p}$=0.925[0.037]; $\hat{\nu}$=5.885[0.560]
Litecoin	SST	$\hat{\mu}$=-0.052; $\hat{\sigma}$=92.81; $\hat{\alpha}$=1.028; $\hat{\nu}$=2.002;
Ripple	SGT	$\hat{\mu}$=0.143[0.025]; $\hat{\sigma}$=8.752[0.139]; $\hat{\lambda}$=0.077[0.007]; $\hat{p}$=0.850[0.020]; $\hat{\nu}$=5.349[0.177]
Ethereum	GHYP	$\hat{\mu}$=-0.415; $\hat{\alpha}$=0.131; $\hat{\beta}$=0.017; $\hat{\delta}$=0.917; $\hat{\lambda}$=0.437
Ethereum Classic	SLPD	$\hat{\mu}$=0.100[0.000]; $\hat{\sigma}$=7.452[0.273]; $\hat{\lambda}$=0.071[0.000]
DASH	SGT	$\hat{\mu}$=0.396[0.000]; $\hat{\sigma}$=8.314[0.326]; $\hat{\lambda}$=0.114[0.009]; $\hat{p}$=1.051[0.042]; $\hat{\nu}$=4.753[1.164]
NEO	SST	$\hat{\mu}$=0.164; $\hat{\sigma}$=21.76; $\hat{\alpha}$=1.104; $\hat{\nu}$=2.143
ZCASH	SGED	$\hat{\mu}$=-0.186[0.000]; $\hat{\sigma}$=8.402[0.000]; $\hat{\lambda}$=5.294[0.000]; $\hat{k}$=0.861[0.059]
BRL/USD	SLGD	$\hat{\mu}$=-0.028[0.073]; $\hat{\sigma}$=0.528[0.070]; $\hat{\gamma}$=0.994[0.088]
RUB/USD	SD	$\hat{\mu}$=-0.018[0.011]; $\hat{\sigma}$=0.538[0.046]; $\hat{\lambda}$=-0.018[0.032]; $\hat{\nu}$=1.382[0.110]
INR/USD	SST	$\hat{\mu}$=-0.016; $\hat{\sigma}$=0.445; $\hat{\alpha}$=0.908; $\hat{\nu}$=4.515
CNY/USD	SLPD	$\hat{\mu}$=-0.004[0.002]; $\hat{\sigma}$=0.187[0.004]; $\hat{\lambda}$=-0.017[0.003]
ZAR/USD	SGT	$\hat{\mu}$=-0.039[0.024]; $\hat{\sigma}$=0.970[0.021]; $\hat{\lambda}$=-0.088[0.035]; $\hat{p}$=2.027[0.256]; $\hat{\nu}$=4.275[2.278]
BOVESPA	SGT	$\hat{\mu}$=-0.004[0.050]; $\hat{\sigma}$=1.978[0.048]; $\hat{\lambda}$=-0.007[0.035]; $\hat{p}$=1.906[0.251]; $\hat{\nu}$=4.145[2.195]
MOEX	GT	$\hat{\mu}$=0.006[0.037]; $\hat{\sigma}$=1.700[0.067]; $\hat{p}$=2.344[0.301]; $\hat{\nu}$=1.656[0.453]
NIFTY50	HYP	$\hat{\mu}$=0.191[0.049]; $\hat{\alpha}$=1.412[0.074]; $\hat{\beta}$=-0.132[0.048]; $\hat{\delta}$=0.478[0.131]
SSE50	GHYP	$\hat{\mu}$=0.010; $\hat{\alpha}$=0.512; $\hat{\beta}$=0.004; $\hat{\delta}$=0.665; $\hat{\lambda}$=-0.051
FTSE/JSE TOP40	SGT	$\hat{\mu}$=-0.003[0.037]; $\hat{\sigma}$=1.461[0.032]; $\hat{\delta}$=-0.050[0.031]; $\hat{\mu}$=1.540[0.213]; $\hat{p}$=16.95[29.44]
Brazil REIT	GLD	$\hat{\lambda}_1$=-0.050; $\hat{\lambda}_2$=0.939; $\hat{\lambda}_3$=-0.034; $\hat{\lambda}_4$=-0.074
Russia REIT	SD	$\hat{\mu}$=-0.036[0.059]; $\hat{\sigma}$=2.429[0.115]; $\hat{\lambda}$=-0.007[0.031]; $\hat{\nu}$=1.820[0.192]
India REIT	SGT	$\hat{\mu}$=-0.027[0.043]; $\hat{\sigma}$=1.729[0.044]; $\hat{\lambda}$=0.023[0.027]; $\hat{p}$=1.389[0.177]; $\hat{\nu}$=9.965[9.225]
China REIT	GHYP	$\hat{\mu}$=-0.093; $\hat{\alpha}$=0.951; $\hat{\beta}$=0.032; $\hat{\delta}$=0.013; $\hat{\lambda}$=1.317
South A. REIT	SD	$\hat{\mu}$=-0.010[0.040]; $\hat{\sigma}$=1.621[0.055]; $\hat{\lambda}$=-0.023[0.035]; $\hat{\nu}$=2.292[0.270]
Crude Oil	HYP	$\hat{\mu}$=0.236[0.075]; $\hat{\alpha}$=0.717[0.029]; $\hat{\beta}$=-0.066[0.022]; $\hat{\delta}$=0.521[0.191]
Gold	GHYP	$\hat{\mu}$=0.020; $\hat{\alpha}$=1.111; $\hat{\beta}$=-0.041; $\hat{\delta}$=0.829; $\hat{\lambda}$=-0.498
Sugar	SD	$\hat{\mu}$=-0.030[0.038]; $\hat{\sigma}$=1.552[0.043]; $\hat{\lambda}$=0.065[0.033]; $\hat{\nu}$=2.928[0.459]
CRIX	GED	$\hat{\mu}$=0.282[0.017]; $\hat{\sigma}$=4.395[0.171]; $\hat{\beta}$=0.760[0.038]
MSCI EM FX	GHYP	$\hat{\mu}$=0.042; $\hat{\alpha}$=7.767; $\hat{\beta}$=-0.565; $\hat{\delta}$=0.068; $\hat{\lambda}$=2.375
MSCI EMI	SGT	$\hat{\mu}$=-0.002[0.021]; $\hat{\sigma}$=0.855[0.019]; $\hat{\lambda}$=-0.078[0.028]; $\hat{p}$=1.467[0.136]; $\hat{\nu}$=17.31[18.10]
MSCI EM REIT	GHYP	$\hat{\mu}$=-0.066; $\hat{\alpha}$=1.668; $\hat{\beta}$=0.043; $\hat{\delta}$=0.000; $\hat{\lambda}$=1.940
BCOM	SST	$\hat{\mu}$=-0.033; $\hat{\sigma}$=0.755; $\hat{\alpha}$=0.967; $\hat{\nu}$=6.952
GBI-EM	SGT	$\hat{\mu}$=-0.002[0.013]; $\hat{\sigma}$=0.559[0.015]; $\hat{\lambda}$=-0.055[0.036]; $\hat{p}$=2.129[0.275]; $\hat{\nu}$=2.642[0.994]

In a [b]; "a" denote the estimated distribution parameter, and "b" is the corresponding standard error.

The P-P plots for the shuffled and outlier-adjusted aggregate data are shown respectively in *Appendices 2.A2* and *2.A3*. Conspicuously, we could deduce that the

best fitting distributions reasonably capture the entire informational spread of the markets. Be as it may, there are a handful of infractions as we turn attention to the density plots (refer, *Appendices 2.A4 and 2.A5*). For CRIX, the best fitting distribution's density captures the left and right tails, middle, and the peak quite well. This becomes even better as we adjust for outliers. For MSCI EM FX, the best fitting density captures the middle, the peak, left and right tails of the data well, with negligible infractions. For MSCI EM, the best fitting density captures the middle and right tail portions of the data well, but the peak and left tail show visible infractions. For MSCI, the best fitting density captures the middle, left and right tails of the data well, but shows a little infraction at the peak. For BCOM, the best fitting density captures the middle portion of the data well, but fairly shows a good fit at the peak and tails. Lastly, for GBI-EM, the best fitting density captures the information at the middle, left and right tails quite well, but leaves few uncaptured information at the peak.

2.4.3.3 Risk computation

One of the major challenges of the investor community and asset managers has to do with the level of exposed risk in terms of holding an asset for a time period. Rationally, the riskiness of the asset may influence the duration to keep holding onto it. In quantifying this type of financial risk, the VaR and ES measures are widely adopted for the task. Specifically, given the c.d.f $\hat{F}(\bullet)$ of a fitted distribution, the VaR and ES which correspond to the probability p, where $0 < p < 1$ could respectively be described with the following expressions:

$$VaR = \hat{F}^{-1}(p) \tag{2.83}$$

$$ES = \frac{1}{p}\int_0^p \hat{F}^{-1}(u)\,du \tag{2.84}$$

Using (2.83) and (2.84), we compute the VaR and ES of the best fitting distributions for the market data over a range of probability values[30]. The VaR(p) and ES(p) values are then plotted against p, which in our case, is chosen to sequentially range from 0.01 to 0.99 with 100 divisions.

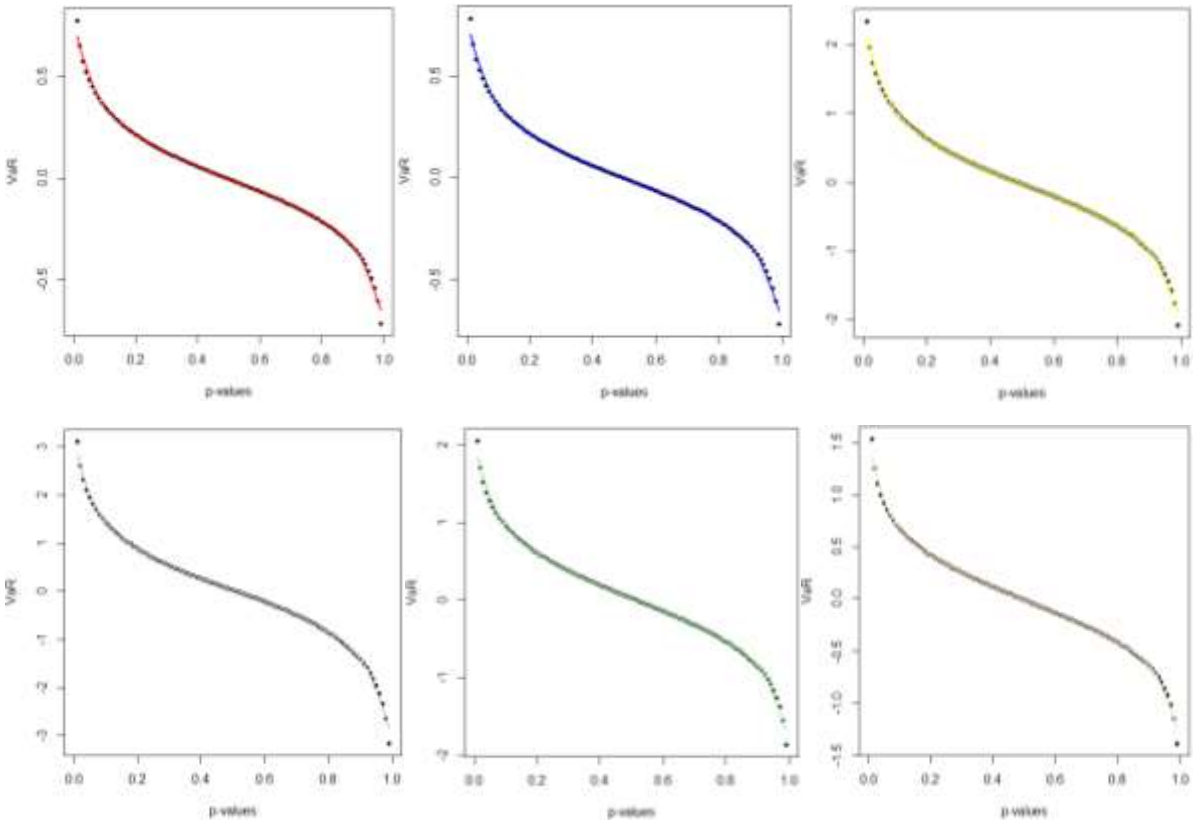


Fig. 2.10: Value-at-risk plots for the most appropriate fitting distributions of the shuffled log-returns. *Note: CRIX (first row, left), MSCI EM FX (first row, middle), MSCI EMI (first row, right), MSCI EM REIT (second row, left), BCOM (second row, middle), and GBI-EM (second row, right) aggregate asset classes.*

[30] For brevity and want of space, we only report results of the aggregate market variables. The results of the individual markets would be made available upon request.

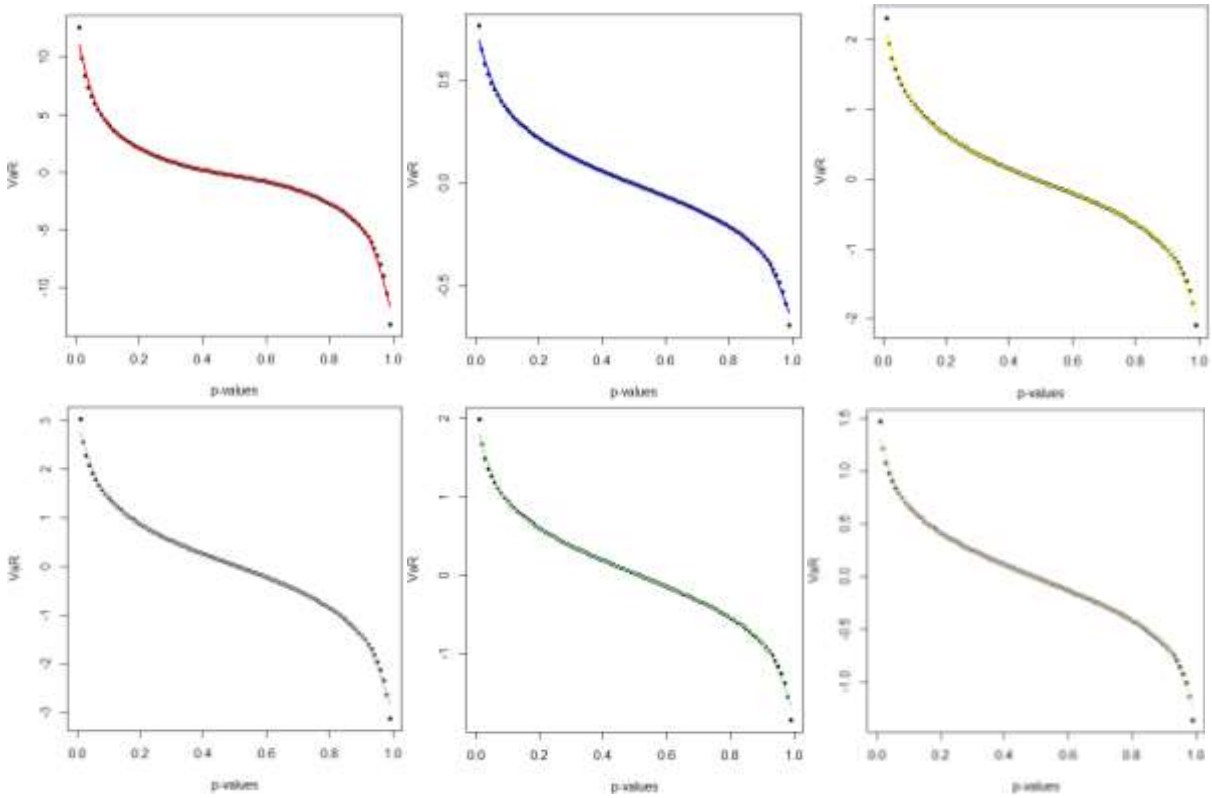


Fig. 2.11: Value-at-risk plots for the most appropriate fitting distributions of the outlier-adjusted log-returns. *Note: CRIX (first row, left), MSCI EM FX (first row, middle), MSCI EMI (first row, right), MSCI EM REIT (second row, left), BCOM (second row, middle), and GBI-EM (second row, right) aggregate asset classes.*

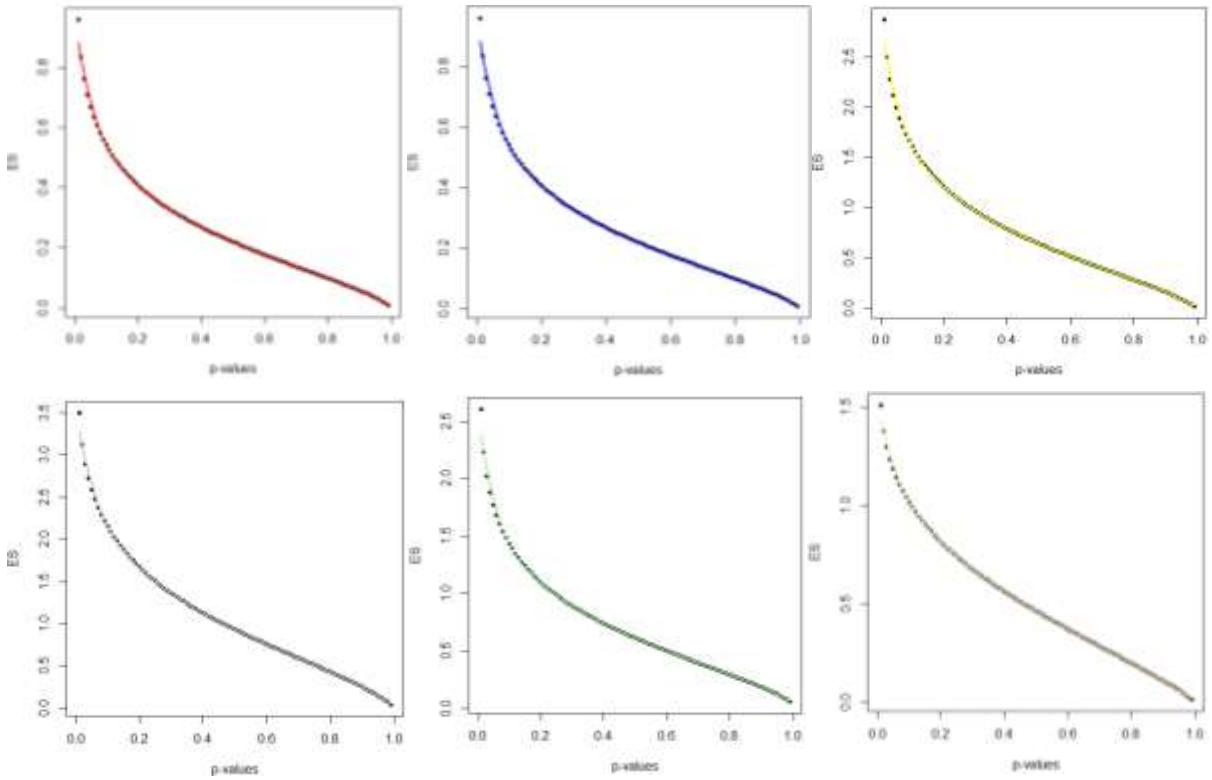


Fig. 2.12: Expected shortfall plots for the most appropriate fitting distributions of the shuffled log-returns. *Notes: CRIX (first row, left), MSCI EM FX (first row, middle), MSCI EMI (first row, right), MSCI EM REIT (second row, left), BCOM (second row, middle), and GBI-EM (second row, right) aggregate asset classes.*

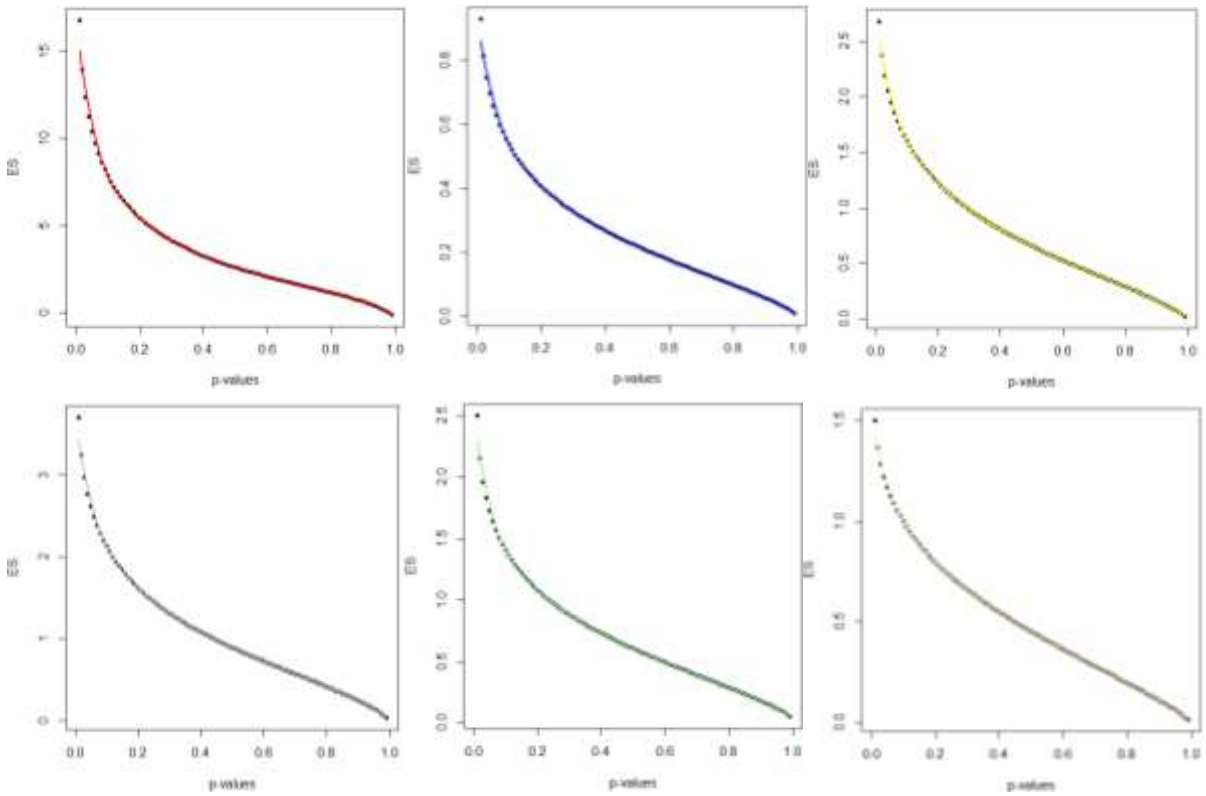


Fig. 2.13: Expected shortfall plots for the most appropriate fitting distributions of the outlier-adjusted log-returns. *Note: CRIX (first row, left), MSCI EM FX (first row, middle), MSCI EMI (first row, right), MSCI EM REIT (second row, left), BCOM (second row, middle), and GBI-EM (second row, right) aggregate asset classes.*

Basically, we examine the tail risk of the data. From the VaR and ES plots (refer, Figs. 2.10-2.13), it is discernible to describe the markets as risky. However, the riskiness of the markets differs. Regarding the VaR of the shuffled log-returns, the MSCI EM REIT, MSCI EMI, and BCOM exhibit respectively the highest risk at both tails. The CRIX and the MSCI EM FX recorded relatively the lowest risk behaviour at the extremes. Nonetheless, after adjusting for outliers, the riskiness of CRIX became more apparent, with quite sharper and step inclination and declination at the tails, unveiling a high volatility behaviour for the cryptocurrency market. This, therefore, depicts that the riskiness of CRIX is sensitive to outliers. Moreover, we arrive at similar conclusions as the ES plots are also considered.

In all, the risk level at the extremes looks excessively high for CRIX[31]; and moderately high for MSCI EM REIT and MSCI EMI; whereas MSCI EM FX shows a comparably lower risk behaviour. As would have been expected, the cryptocurrencies are to possess currency features which may not deviate much from traditional FXs, yet paradoxically we document a situation where currencies take much resemblance of the featured distributional and risk characteristics of equities. The riskiness of the cryptocurrencies is reiterated in a work by Gunay and Kaşkaloğlu, (2019), which projected the currency market as too risky for naive investors, and further tagged it as even riskier than the illustrative image portrayed in the mainstream media and other related channels. This heightened riskiness of the markets, especially for the cryptocurrencies could be as a result of the challenges associated with its security and regulatory framework, uncertainty of factors that drive the market's price surges, and possibly the usual bubble-like price development speculation.

2.4.4 Non-linearity, chaotic and random behaviour

2.4.4.1 Evidence of non-linearity in asset returns[32]

As a precursor to the outlined BDS modelling procedure in sub-section 2.3.3.1, a linear model based on the autoregressive process of order one, i.e. AR(1) is fitted to the log-returns to pre-whiten the residuals of the series before advancing to examine for evidence of linear dependence. In guiding against a fluke result, the BDS test could by selecting two epsilon values (0.5 and 1.5) under a combination of low, intermediate, and high embedding dimensions (2, 5, and 10). As cautioned by Koller and Fischer (2002), choosing too smaller (larger) epsilon and embedding dimension values has the tendency to capture too few (many) sample datapoints for the test.

[31] The relatively riskiness of the cryptocurrency market (proxy by CRIX) is not startling, as most unmatured assets display such characteristics at their early evolutionary stages.

[32] Although the results of the regime-switching model (RSM) in the previous chapter indicate the presence of significant regimes, which largely implies non-lineraity, we opted to ascertain the sensitivity of the results to the RSM approach, by using a battery of other non-linearity tests.

Table 2.21: BDS results for filtered AR(1) residuals of individual and aggregate returns

	0.5_σ			1.5_σ		
	$m = 2$	$m = 5$	$m = 10$	$m = 2$	$m = 5$	$m = 10$
Bitcoin	9.2 [0.000]	20.7 [0.000]	9.5 [0.000]	8.4 [0.000]	12.3 [0.000]	16.9 [0.000]
Litecoin	13.0 [0.000]	23.2 [0.000]	83.7 [0.000]	8.7 [0.000]	11.2 [0.000]	13.7 [0.000]
Ripple	16.9 [0.000]	29.4 [0.000]	126.1[0.000]	13.5 [0.000]	18.7 [0.000]	22.1 [0.000]
Ethereum	8.4 [0.000]	14.2 [0.000]	55.8 [0.000]	7.8 [0.000]	8.8 [0.000]	10.4 [0.000]
Ethereum Classic	5.5 [0.000]	9.6 [0.000]	20.5 [0.000]	5.4 [0.000]	7.8 [0.000]	9.4 [0.000]
DASH	9.3 [0.000]	19.3 [0.000]	56.6 [0.000]	9.2 [0.000]	12.0 [0.000]	16.1 [0.000]
NEO	4.5 [0.000]	9.9 [0.000]	27.2 [0.000]	7.7 [0.000]	9.6 [0.000]	11.6 [0.000]
ZCASH	6.6 [0.000]	9.3 [0.000]	27.5 [0.000]	5.6 [0.000]	7.4 [0.000]	9.4 [0.000]
BRL/USD	5.9 [0.000]	9.5 [0.000]	31.5 [0.000]	5.5 [0.000]	9.6 [0.000]	14.9 [0.000]
RUB/USD	12.3 [0.000]	21.0 [0.000]	75.8 [0.000]	15.8 [0.000]	22.2 [0.000]	30.1 [0.000]
INR/USD	7.3 [0.000]	13.4 [0.000]	32.6 [0.000]	8.4 [0.000]	12.7 [0.000]	17.2 [0.000]
CNY/USD	13.7 [0.000]	39.3 [0.000]	338.9[0.000]	8.7 [0.000]	14.2 [0.000]	20.4 [0.000]
ZAR/USD	2.7 [0.006]	5.9 [0.000]	18.0 [0.000]	4.4 [0.000]	6.7 [0.000]	10.6 [0.000]
BOVESPA	3.0 [0.002]	7.4 [0.000]	22.6 [0.000]	3.4 [0.001]	7.4 [0.000]	11.8 [0.000]
MOEX	5.6 [0.000]	11.8 [0.000]	29.0 [0.000]	6.5 [0.000]	12.1 [0.000]	17.8 [0.000]
NIFTY50	3.5 [0.000]	8.1 [0.000]	15.3 [0.000]	4.4 [0.000]	8.8 [0.000]	12.0 [0.000]
SSE50	5.4 [0.000]	13.7 [0.000]	62.4 [0.000]	6.4 [0.000]	11.1 [0.000]	17.7 [0.000]
FTSE/JSE TOP40	3.4 [0.001]	6.4 [0.000]	15.3 [0.000]	3.7 [0.000]	8.4 [0.000]	11.9 [0.000]
Brazil REIT	3.9 [0.000]	7.3 [0.000]	1.44 [0.150]	4.4 [0.000]	7.9 [0.000]	10.3 [0.000]
Russia REIT	7.1 [0.000]	13.7 [0.000]	47.3 [0.000]	7.7 [0.000]	11.6 [0.000]	15.0 [0.000]
India REIT	5.4 [0.000]	10.2 [0.000]	17.9 [0.000]	5.2 [0.000]	8.8 [0.000]	12.7 [0.000]
China REIT	4.4 [0.000]	8.3 [0.000]	22.4 [0.000]	3.0 [0.003]	6.6 [0.000]	11.0 [0.000]
South Africa REIT	4.0 [0.000]	7.6 [0.000]	18.1 [0.000]	4.3 [0.000]	7.1 [0.000]	9.8 [0.000]
Crude Oil	9.0 [0.000]	16.1 [0.000]	41.7 [0.000]	10.6 [0.000]	16.2 [0.000]	25.5 [0.000]
Gold	1.0 [0.335]	3.5 [0.000]	6.0 [0.000]	2.1 [0.037]	5.1 [0.000]	7.7 [0.000]
Sugar	3.3 [0.001]	6.0 [0.000]	47.7 [0.000]	2.4 [0.018]	3.6 [0.000]	7.2 [0.000]
CRIX	8.5 [0.000]	22.2 [0.000]	110.1[0.000]	5.9 [0.000]	9.8 [0.000]	14.8 [0.000]
MSCI EM FX	2.5 [0.013]	5.0 [0.000]	4.9 [0.000]	2.0 [0.046]	5.5 [0.000]	8.6 [0.000]
MSCI EMI	1.8 [0.069]	5.3 [0.000]	7.8 [0.000]	2.0 [0.043]	8.1 [0.000]	13.0 [0.000]
MSCI EM REIT	2.9 [0.003]	8.1 [0.000]	16.0 [0.000]	2.8 [0.006]	7.3 [0.000]	11.1 [0.000]
BCOM	5.6 [0.000]	8.0 [0.000]	9.6 [0.000]	5.6 [0.000]	8.4 [0.000]	12.4 [0.000]
GBI-EM	5.0 [0.000]	12.7 [0.000]	27.0 [0.000]	4.7 [0.000]	9.4 [0.000]	13.2 [0.000]

Results pertaining to the BDS test of the AR(1) pre-whitened residuals for all returns across the asset classes are shown in Table 2.21. Under all combinations of the epsilon and embedding dimension specifications, the null hypothesis of linear dependence is rejected for the markets at a higher significance level, with almost all the probability values of the test being zero. This immense evidence against IID-ness of the return realizations suggests emphatically that the market datasets are characterized by non-linear dependence structure. Though it sounds much compelling, the finding is not uncommon for financial asset returns.

Table 2.22: Estimated TNN and ETN test measures

	TNN		ETN		
	lag p	Test measure	lag p	lag 3	lag 5
Bitcoin	06	3.76 [0.0000]	[0.000]	[0.000]	[0.000]
Litecoin	10	4.53 [0.0000]	[0.000]	[0.000]	[0.000]
Ripple	09	5.20 [0.0000]	[0.000]	[0.000]	[0.000]
Ethereum	01	17.9 [0.0000]	[0.000]	[0.100]	[0.100]
Ethereum Classic	04	2.80 [0.0000]	[0.700]	[0.000]	[0.000]
DASH	10	3.53 [0.0000]	[0.000]	[0.000]	[0.000]
NEO	02	3.33 [0.0017]	[0.000]	[0.000]	[0.000]
ZCASH	04	6.89 [0.0000]	[0.000]	[0.000]	[0.000]
BRL/USD	01	7.56 [0.0005]	[0.000]	[0.000]	[0.100]
RUB/USD	09	6.48 [0.0000]	[0.000]	[0.000]	[0.000]
INR/USD	10	3.23 [0.0000]	[0.000]	[0.000]	[0.000]
CNY/USD	01	10.2 [0.0000]	[0.000]	[0.000]	[0.000]
ZAR/USD	01	3.34 [0.0356]	[0.000]	[0.000]	[0.100]
BOVESPA	01	2.81 [0.0605]	[0.000]	[0.000]	[0.000]
MOEX	02	5.62 [0.0000]	[0.000]	[0.000]	[0.000]
NIFTY50	01	8.84 [0.0002]	[0.000]	[0.000]	[0.000]
SSE50	09	2.66 [0.0000]	[0.000]	[0.000]	[0.000]
FTSE/JSE TOP40	01	2.46 [0.0858]	[0.000]	[0.000]	[0.200]
Brazil REIT	01	0.81 [0.4450]	[0.100]	[0.000]	[0.100]
Russia REIT	04	6.53 [0.0000]	[0.000]	[0.000]	[0.000]
India REIT	01	4.08 [0.0171]	[0.000]	[0.000]	[0.000]
China REIT	02	0.89 [0.5096]	[0.000]	[0.000]	[0.000]
South Africa REIT	04	6.82 [0.0000]	[0.000]	[0.000]	[0.100]
Crude Oil	02	8.63 [0.0000]	[0.000]	[0.000]	[0.000]
Gold	10	2.21 [0.0000]	[0.300]	[0.000]	[0.000]
Sugar	01	6.28 [0.0019]	[0.000]	[0.500]	[0.000]
CRIX	04	2.60 [0.0000]	[0.100]	[0.000]	[0.000]
MSCI EM FX	10	1.70 [0.0000]	[0.100]	[0.400]	[0.000]
MSCI EMI	10	1.74 [0.0000]	[0.300]	[0.000]	[0.000]
MSCI EM REIT	01	5.38 [0.0047]	[0.100]	[0.000]	[0.000]
BCOM	02	3.44 [0.0012]	[0.000]	[0.000]	[0.000]
GBI-EM	01	1.06 [0.3461]	[0.200]	[0.000]	[0.000]

For purposes of robustness, we tested again for the presence (or absence) of linearity using the TNN and the entropy-based ETN methods. It is instructive noting that these two methods do not require pre-whitening of the series. Besides, mindful of the sensitivity of the tests, especially the TNN towards arbitrary lag length, we opted for an optimal lag length p, selected from a fitted autoregressive process using the AIC function (of Akaike 1974). More so, we chose to report the ETN test at two additional lags, which correspond to 3 (mid-week) and 5 working days of the week. Like the BDS, the TNN and ETN test results (refer, Table 2.22) noticeably re-affirm the non-linear structure of all the market variables, with few deviations in isolated cases. Altogether,

the substantial evidence against IID-ness cannot be challenged as results from different test specifications unswervingly conclude almost same. Hence, the existence of non-linear structure in the markets, by virtue of the BDS, TNN, and ETN provides an avenue to further explore complex dynamics that may perhaps characterize their respective data generating processes.

2.4.4.2 Chaoticity vs. Stochasticity: LLE perspective

We investigate to empirically ascertain whether the daily log-returns of the asset classes follow a non-linear complex dynamic chaotic process or are drawn from a stochastic process. Using the LLE approach to detect low-level chaos, we initially set the maximum orders of the triplet (*L*, *m*, *q*) which marks the complexity of the chaotic map to (*5*, *5*, *6*). Afterwards, the complexity of the map is augmented to a maximum of (*8*, *10*, *8*), in search of high-level chaotic evidence[33]. Our choice of the triplet orders is inspired by the protocols delineated in the work of BenSaïda and Litimi (2013). Instructively, rejecting the null hypothesis which states the presence of chaos, i.e. $H_0 : \lambda \geq 0$ at these high-specified orders duly implies the rejection of chaos (Litimi et al., 2019). We uphold the presence of chaos if $\lambda > 0$, a transition-to-chaos if $\lambda = 0$, and no evidence of chaos if $\lambda < 0$. Besides, owing to the limited range of values for the logistic, the sigmoid function is used in this study for the neural network computation (see, BenSaïda and Litimi, 2013; and BenSaïda, 2015).

Results of the estimated LLE parameter λ and its corresponding probability value (in square bracket)[34] of the test are reported in Tables 2.23 and 2.24. There is substantial evidence to reject the presence of low-level chaos for all studied markets across time and scale. Specifically, the estimated LLE parameter λ is negative and highly

[33] Note: The higher orders of the triplet (*L*, *m*, *q*) are computationally least efficient compared to the lower orders. In our case, the estimation of the former took on the average 25 minutes while the latter appropriate lasted averagely 3 minutes.

[34] The red-coloured entries denote a failed rejection of the null hypothesis, signifying that chaos is present.

significant for the market variables in the full and intraweek frequency band. This opposes the findings of Gunay and Kaşkaloğlu, (2019), which from our checks remains the only study that explores chaos in more cryptocurrency markets in a similar time sample. For the weekly scale (4~8 day band), only four markets (ZAR/USD, FTSE/JSE TOP40, Chinese REIT, and MSCI EMI) show evidence of chaos. Noticeably, in all levels of the markets (i.e., the individual and aggregate markets from the six asset classes), the value of λ under the full sample increases in magnitude from a lower to a higher negative value when estimated under the scale samples. In two of the markets (ZAR/USD and MSCI EMI), a transition-to-chaos for the weekly scale is recorded as λ assumes lower negative values in the full sample but swiftly increases across the scales to nearly zero.

Except for NEO which clasps between negative and positive values within the scales, there is strong evidence against high-level chaos in the full and intraweek scale samples (refer, Table 2.24). However, evidence of high-level chaos is found to be concealed in the weekly scale, as in majority of the cases, we failed to reject the null hypothesis of the LLE test. Observably, all market variables of the cryptocurrencies and the BRICS stock announces significant evidence in favour of high-level chaos in their weekly scale samples. In contrast, the log-returns of crude oil, gold, sugar, and GBI-EM are seen to consistently follow a non-linear stochastic process rather than chaoticity.

Moreover, given the completely random nature of the market returns, we surmise that there would be less or no chance for accurate predictability in the full and intraweek scale samples. On the contrary, a system generated by a chaotic process can easily be predicted in the short-term with greater accuracy (Williams, 1997, p.21; Yousefpoor et al., 2008; Lahmiri and Bekiros, 2019). Hence, at the weekly scale, the returns of all markets from the cryptocurrencies and that of the BRICS stocks, including some selected markets from the BRICS FX and REIT equity may easily be

predicted with high accuracy level, hence giving opportunities for exploitation by market agents and/or participants.

Table 2.23: Estimated LLE for low-level chaos

	Full sample		2~4 day band		4~8 day band	
	lambda (λ)	P-value	Lambda (λ)	P-value	Lambda (λ)	P-value
Bitcoin	-0.3175	[0.00000]	-0.1323	[0.00000]	-0.0664	[0.00019]
Litecoin	-0.2345	[0.00000]	-0.1292	[0.00000]	-0.0670	[0.00008]
Ripple	-0.3123	[0.00000]	-0.1083	[0.00000]	-0.0320	[0.02460]
Ethereum	-0.2907	[0.00000]	-0.1237	[0.00000]	-0.0669	[0.01120]
Ethereum Classic	-0.4068	[0.00000]	-0.1199	[0.00001]	-0.0357	[0.00830]
DASH	-0.4324	[0.00000]	-0.1533	[0.00000]	-0.0451	[0.00770]
NEO	-0.2836	[0.00000]	-0.1190	[0.00029]	-0.0457	[0.09790]
ZCASH	-0.3097	[0.00000]	-0.1103	[0.00025]	-0.0645	[0.00210]
BRL/USD	-0.4470	[0.00000]	-0.1446	[0.00000]	-0.0643	[0.00007]
RUB/USD	-0.3766	[0.00000]	-0.1208	[0.00000]	-0.0645	[0.00063]
INR/USD	-0.4618	[0.00000]	-0.1164	[0.00000]	-0.0759	[0.00045]
CNY/USD	-0.3631	[0.00000]	-0.1283	[0.00000]	-0.0584	[0.00096]
ZAR/USD	-0.4819	[0.00000]	-0.1447	[0.00000]	**0.0026**	**[0.53780]**
BOVESPA	-0.4901	[0.00000]	-0.1272	[0.00000]	-0.0699	[0.00024]
MOEX	-0.4536	[0.00000]	-0.1258	[0.00000]	-0.0691	[0.00027]
NIFTY50	-0.4259	[0.00004]	-0.1293	[0.00000]	-0.0761	[0.00001]
SSE50	-0.3061	[0.00000]	-0.1225	[0.00000]	-0.0587	[0.00020]
FTSE/JSE TOP40	-0.4572	[0.00000]	-0.1380	[0.00000]	**-0.0146**	**[0.34940]**
Brazil REIT	-0.4698	[0.00000]	-0.1331	[0.00000]	-0.0702	[0.00021]
Russia REIT	-0.4685	[0.00000]	-0.1329	[0.00000]	-0.0648	[0.00000]
India REIT	-0.4522	[0.00000]	-0.1411	[0.00000]	-0.0627	[0.00010]
China REIT	-0.4245	[0.00000]	-0.1424	[0.00000]	**0.0661**	**[0.99990]**
South A. REIT	-0.4743	[0.00000]	-0.1316	[0.00000]	-0.0594	[0.00027]
Crude Oil	-0.5376	[0.00000]	-0.1168	[0.00000]	-0.0612	[0.00150]
Gold	-0.4901	[0.00000]	-0.1485	[0.00000]	-0.0644	[0.00002]
Sugar	-0.4538	[0.00000]	-0.1305	[0.00000]	-0.0653	[0.00002]
CRIX	-0.2862	[0.00000]	-0.1328	[0.00000]	-0.0577	[0.00150]
MSCI EM FX	-0.4357	[0.00000]	-0.1513	[0.00000]	-0.0511	[0.00046]
MSCI EMI	-0.4186	[0.00000]	-0.1458	[0.00000]	**0.0024**	**[0.58450]**
MSCI EM REIT	-0.4177	[0.00000]	-0.1418	[0.00000]	-0.0574	[0.00010]
BCOM	-0.4679	[0.00000]	-0.1418	[0.00000]	-0.0592	[0.00006]
GBI-EM	-0.5068	[0.00000]	-0.1460	[0.00000]	-0.0370	[0.00005]

Table 2.24: Estimated LLE for high-level chaos

	Full sample		2~4 day band		4~8 day band	
	lambda (λ)	P-value	Lambda (λ)	P-value	Lambda (λ)	P-value
Bitcoin	-0.1447	[0.00000]	-0.0839	[0.00003]	**0.1048**	**[1.00000]**
Litecoin	-0.1309	[0.00002]	-0.0621	[0.00069]	**0.0791**	**[0.99980]**
Ripple	-0.1693	[0.00000]	-0.0658	[0.00170]	**0.2208**	**[1.00000]**
Ethereum	-0.1276	[0.00001]	-0.0952	[0.00006]	**0.2263**	**[1.00000]**
Ethereum Classic	-0.1592	[0.00030]	-0.0561	[0.00730]	**0.1007**	**[0.99970]**
DASH	-0.1974	[0.00008]	-0.0530	[0.00000]	**0.2773**	**[1.00000]**
NEO	-0.1149	[0.00046]	**-0.0182**	**[0.21580]**	**0.1187**	**[0.99970]**
ZCASH	-0.1334	[0.00020]	-0.0634	[0.01000]	**0.1495**	**[1.00000]**
BRL/USD	-0.2351	[0.00000]	-0.0785	[0.00033]	-0.0549	[0.00880]

RUB/USD	-0.2069	[0.00000]	-0.1034	[0.00001]	**0.0379**	**[0.99980]**
INR/USD	-0.1852	[0.00000]	-0.0863	[0.00036]	**0.0246**	**[0.93390]**
CNY/USD	-0.1792	[0.00000]	-0.0953	[0.00027]	-0.0257	[0.00003]
ZAR/USD	-0.2092	[0.00000]	-0.0913	[0.00023]	**0.0026**	**[0.53780]**
BOVESPA	-0.1961	[0.00000]	-0.0957	[0.00022]	**0.0422**	**[0.97890]**
MOEX	-0.2027	[0.00000]	-0.0796	[0.00000]	**0.0950**	**[1.00000]**
NIFTY50	-0.2108	[0.00056]	-0.0759	[0.00009]	**0.0639**	**[0.99920]**
SSE50	-0.1331	[0.00000]	-0.0802	[0.00047]	**0.0144**	**[0.80180]**
FTSE/JSE TOP40	-0.1282	[0.00000]	-0.0954	[0.00032]	**-0.0146**	**[0.34940]**
Brazil REIT	-0.2009	[0.00000]	-0.1082	[0.00013]	**0.0913**	**[1.00000]**
Russia REIT	-0.2041	[0.00000]	-0.0872	[0.00042]	**0.0831**	**[1.00000]**
India REIT	-0.1839	[0.00180]	-0.0755	[0.00011]	-0.0451	[0.03020]
China REIT	-0.2055	[0.00000]	-0.0770	[0.00014]	**0.0661**	**[0.99990]**
South A. REIT	-0.2044	[0.00000]	-0.0811	[0.00072]	**0.0117**	**[0.67190]**
Crude Oil	-0.2008	[0.00000]	-0.0925	[0.00061]	-0.0411	[0.00650]
Gold	-0.1338	[0.00000]	-0.0765	[0.00100]	-0.0529	[0.00470]
Sugar	-0.1680	[0.00230]	-0.0922	[0.00034]	-0.0456	[0.01030]
CRIX	-0.1694	[0.00068]	-0.1033	[0.00022]	**0.0359**	**[0.94680]**
MSCI EM FX	-0.2189	[0.00000]	-0.0812	[0.00026]	**0.0034**	**[0.61970]**
MSCI EMI	-0.2468	[0.00000]	-0.0432	[0.02690]	**0.1094**	**[1.00000]**
MSCI EM REIT	-0.2038	[0.00010]	-0.0885	[0.00016]	-0.0440	[0.01950]
BCOM	-0.2270	[0.00000]	-0.0886	[0.00049]	**0.0314**	**[0.95530]**
GBI-EM	-0.2152	[0.00026]	-0.0879	[0.00010]	-0.0290	[0.03700]

In summary, the LLE test results give a clear indication that chaos is not present in the log-returns of the six asset classes when considered under the full and intraweek scale (except NEO) samples. Nonetheless, stronger evidence against stochasticity is observed as almost all the asset classes, except for the commodities recorded high-level chaos. Evidentially, without the commodities at play, the characteristics exhibited by the markets looks somehow undistinguishable.

In hindsight, we conclude by pitching the key contributions of our study. Firstly, drawing from a range of tests which include a newly developed entropy-based test, evidence of non-linear dependence structure is documented across the log-returns of six different asset classes, comprising both individual and aggregate markets. Secondly, a unique path is chartered as we explore low-, and high-level chaos in time and frequency samples for diverse asset classes. Though a similar work by Lahmiri (2017c) on the Moroccan exchange rate is noted, our scope of market and empirical investigation for chaos move beyond the narrow focus of Lahmiri's study.

2.4.5 *Asymmetry and leverage in asset markets*

From an empirical perspective, the linkages between asset price returns and their corresponding volatility changes have become one of the recent topical issues in the financial literature. The two most popular financial phenomena mainly employed to assess return-volatility behaviours are asymmetry and leverage. A quick through a section of the literature leaves one to basically conclude that asymmetry and leverage are two different terms used for the same purpose (see, Engle and Ng, 1993; Ding et al., 1993; Wei, 2010; Zhang et al., 2018; etc.). In this midst of this development, a number of studies (Wei, 2010; Chkili et al., 2014; Chevallier and Ielpo, 2017; Zhang et al., 2018; Horpestad et al., 2019; etc.) have attempted to report leverage effect in financial/economic variables using well-known GARCH-type models (particularly, the EGARCH, GJR-GARCH, APARCH, TARCH, and the Fractional Integrated ARCH). In a strong criticism leveled against the above-mentioned practices, McAleer (2014), Chu et al., (2017), and Caporin and Costola (2019) argued quite clearly that leverage is not in any of these GARCH-type models. Besides, the former and latter authors delineated a clearer distinction between asymmetry and leverage as two separate phenomena which measure different effects.

Table 2.25: Estimated NGARCH parameters for full sample log-returns

	Generalized Hyperbolic					skew Student's t				
	α	β	p	γ	BIC	α	β	p	γ	BIC
Bitcoin	0.174[a]	0.821[a]	**0.915**	-0.159	5.509	0.170[a]	0.825[a]	0.893	-0.150	5.529
Litecoin	0.139[a]	0.860[a]	**1.004**	0.011	6.061	0.133[a]	0.865[a]	1.040	0.061	6.076
Ripple	0.348[a]	0.637[a]	**0.938**	-0.113	6.290	0.294[b]	0.702[a]	0.924	-0.104	6.309
Ethereum	0.276[a]	0.706[a]	**1.022**	0.080	6.652	0.301[a]	0.696[a]	1.057	0.098	6.653
Ethereum Classic	0.233[c]	0.715[a]	**0.903**	-0.089	6.692	0.254[b]	0.736[a]	0.881	-0.187	6.696
DASH	0.177[a]	0.809[a]	1.038	0.103	6.571	0.175[a]	0.824[a]	**1.037**	0.060	6.570
NEO	0.177[b]	0.781[a]	**0.817**	**-0.282[d]**	7.232	0.220[b]	0.770[a]	0.865	-0.211	7.244
ZCASH	0.176[b]	0.780[a]	1.031	0.150	6.880	0.181[b]	0.793[a]	**1.079**	0.161	6.876
BRL/USD	0.034[a]	0.931[a]	1.455	0.982[a]	2.691	0.034[a]	0.931[a]	**1.705**	**0.976[a]**	2.686
RUB/USD	0.115[a]	0.862[a]	1.161	0.369[a]	0.860	0.116[a]	0.861[a]	**1.259**	**0.368[a]**	0.856
INR/USD	0.050[b]	0.920[a]	1.261	0.582[b]	1.002	0.052[b]	0.916[a]	**1.431**	**0.601[b]**	0.998
CNY/USD	0.129[a]	0.869[a]	0.962	-0.073	-0.822	0.130[a]	0.868[a]	**0.942**	-0.074	-0.827
ZAR/USD	0.333[a]	0.950[a]	1.324	0.681[a]	2.734	0.033[a]	0.950[a]	**1.522**	**0.689[a]**	2.729
BOVESPA	0.056[a]	0.887[a]	1.324	0.763[a]	4.160	0.056[a]	0.886[a]	**1.526**	**0.762[a]**	4.155
MOEX	0.033[a]	0.924[a]	1.469	1.025[a]	3.680	0.032[a]	0.924[a]	**1.742**	**1.019[a]**	3.677
NIFTY50	0.053[a]	0.793[a]	1.632	1.574[a]	2.893	0.052[a]	0.791[a]	**2.062**	**1.605[a]**	2.889
SSE50	0.080[a]	0.916[a]	**0.972**	-0.050	3.398	0.086[a]	0.913[a]	0.974	-0.035	3.400

FTSE/JSE TOP40	0.029[a]	0.893[a]	1.714	1.586[a]	3.525	0.030[a]	0.892[a]	2.119	1.552[a]	3.521
Brazil REIT	0.070[b]	0.872[a]	1.160	0.436[c]	4.308	0.071[b]	0.871[a]	1.267	0.434[c]	4.303
Russia REIT	0.019[a]	0.957[a]	1.513	1.075[a]	4.353	0.018[a]	0.957[a]	1.771	1.107[a]	4.348
India REIT	0.073[b]	0.901[a]	1.073	0.199	3.836	0.074[b]	0.899[a]	1.116	0.191	3.835
China REIT	0.055[b]	0.923[a]	1.109	0.261	3.811	0.056[b]	0.929[a]	1.167	0.249	3.808
South A. REIT	0.022[a]	0.935[a]	1.592	1.270[a]	3.677	0.022[a]	0.936[a]	1.905	1.279[a]	3.673
Crude Oil	0.047[a]	0.924[a]	1.342	0.740[a]	4.040	0.045[a]	0.926[a]	1.550	0.758[a]	4.036
Gold	0.021[a]	0.973[a]	0.964	-0.062	2.424	0.021[a]	0.974[a]	0.959	-0.049	2.420
Sugar	0.028[a]	0.967[a]	1.154	0.319[c]	3.664	0.029[a]	0.967[a]	1.199	0.273	3.664
CRIX	0.183[a]	0.813[a]	0.926	-0.139	5.400	0.174[a]	0.823[a]	0.992	-0.109	5.411
MSCI EM FX	0.020[a]	0.960[a]	1.383	0.807[a]	0.293	0.020[a]	0.960[a]	1.601	0.815[a]	0.288
MSCI EMI	0.035[a]	0.871[a]	1.638	1.462[a]	2.393	0.036[a]	0.866[a]	2.056	1.485[a]	2.390
MSCI EM REIT	0.072[a]	0.859[a]	1.246	0.629[a]	3.099	0.074[a]	0.860[a]	1.393	0.600[a]	3.095
BCOM	0.036[a]	0.951[a]	1.200	0.444[a]	2.203	0.037[a]	0.095[a]	1.328	0.441[a]	2.198
GBI-EM	0.087[c]	0.857[a]	1.123	0.360[c]	1.603	0.085[a]	0.858[a]	1.222	0.365[c]	1.598

Table 2.26: Estimated GJR-GARCH parameters for full sample log-returns

	Generalized Hyperbolic					skew Student's t				
	α	β	p	γ	BIC	α	β	p	γ	BIC
Bitcoin	0.189[a]	0.824[a]	0.998	-0.031	5.510	0.179[a]	0.827[a]	0.996	-0.016	5.531
Litecoin	0.152[a]	0.863[a]	1.000	-0.030	6.060	0.143[a]	0.869[a]	0.979	-0.024	6.076
Ripple	0.378[a]	0.657[a]	1.000	-0.070	6.290	0.320a	0.709[a]	0.989	-0.059	6.309
Ethereum	0.260[b]	0.707[a]	0.978	0.021	6.652	0.286[a]	0.695[a]	1.002	0.034	6.654
Ethereum Classic	0.293[c]	0.706[a]	0.944	-0.110	6.691	0.397[b]	0.704[a]	0.989	-0.193	6.694
DASH	0.153[a]	0.809[a]	0.992	0.060	6.570	0.160[a]	0.824[a]	1.002	0.029	6.570
NEO	0.225[b]	0.788[a]	0.969	-0.089	7.233	0.274[c]	0.775[a]	0.994	-0.094	7.245
ZCASH	0.139[c]	0.794[a]	0.961	0.058	6.880	0.133[c]	0.809[a]	0.991	0.074	6.870
BRL/USD	0.025[c]	0.932[a]	0.992	0.068[a]	2.699	0.025[d]	0.932[a]	1.009	0.068[a]	2.694
RUB/USD	0.071[a]	0.872[a]	0.991	0.095[a]	0.861	0.072[a]	0.870[a]	1.016	0.096[a]	0.857
INR/USD	0.035[d]	0.923[a]	0.982	0.048[b]	1.006	0.037[c]	0.920[a]	0.995	0.051[b]	1.003
CNY/USD	0.141[a]	0.872[a]	0.999	-0.028	-0.822	0.143[a]	0.871[a]	0.992	-0.028	-0.828
ZAR/USD	0.009	0.961[a]	0.996	0.052[a]	2.732	0.009	0.961[a]	1.721	0.052[a]	2.727
BOVESPA	0.042[b]	0.891[a]	0.968	0.071[c]	4.169	0.042[b]	0.890[a]	0.987	0.071[c]	4.164
MOEX	0.024[d]	0.936[a]	0.984	0.048[b]	3.690	0.025[d]	0.936[a]	0.997	0.048[c]	3.687
NIFTY50	0.000	0.884[a]	0.884	0.150[a]	2.908	0.000	0.886[a]	0.998	0.148[a]	2.940
SSE50	0.085[a]	0.916[a]	0.997	-0.009	3.398	0.089[a]	0.913[a]	0.999	-0.006	3.400
FTSE/JSE TOP40	0.000	0.942[a]	0.984	0.083[a]	3.535	0.000	0.941[a]	1.007	0.085[a]	3.531
Brazil REIT	0.059[c]	0.859[a]	0.945	0.056[d]	4.317	0.060[c]	0.857[a]	0.960	0.058[d]	4.305
Russia REIT	0.056[d]	0.910[a]	0.983	0.033	4.356	0.059[d]	0.907[a]	0.989	0.034	4.352
India REIT	0.059[c]	0.900[a]	0.975	0.034	3.836	0.060[b]	0.897[a]	0.982	0.033	3.835
China REIT	0.042[b]	0.917[a]	0.978	0.039	3.810	0.043[b]	0.922[a]	0.993	0.038	3.801
South A. REIT	0.000	0.957[a]	0.986	0.057[a]	3.677	0.000	0.959[a]	1.000	0.056[a]	3.673
Crude Oil	0.023[d]	0.941[a]	0.996	0.065[a]	4.046	0.020	0.944[a]	1.013	0.064[a]	4.042
Gold	0.021[a]	0.974[a]	0.994	-0.000	2.424	0.021[a]	0.974[a]	0.995	0.000	2.420
Sugar	0.021[b]	0.967[a]	0.997	0.019	3.664	0.023[a]	0.967[a]	1.002	0.017	3.663
CRIX	0.208[a]	0.816[a]	0.998	-0.053	5.401	0.191[a]	0.824[a]	0.992	-0.034	5.412
MSCI EM FX	0.015[c]	0.963[a]	0.992	0.026[c]	0.297	0.014[c]	0.963[a]	1.018	0.026[c]	0.292
MSCI EMI	0.000	0.929[a]	0.980	0.102[a]	2.395	0.000	0.926[a]	1.008	0.105[a]	2.392
MSCI EM REIT	0.024	0.874[a]	0.951	0.105[a]	3.099	0.026	0.874[a]	0.978	0.102[b]	3.096
BCOM	0.031[a]	0.951[a]	0.993	0.023	2.205	0.032[c]	0.950[a]	0.999	0.023	2.201
GBI-EM	0.056[c]	0.859[a]	0.951	0.072[c]	1.603	0.055[c]	0.860[a]	0.970	0.072[c]	1.598

Therefore, motivated by these two classical works, our study adopts the characterization of asymmetry and leverage by Caporin and Costola (2019) to investigate the presence of the two effects in diverse asset classes. More specifically, our study contributes to the literature by exploring asymmetry and/or local leverage in a wider market coverage which spread across six asset classes. Also, the study pioneers the discussion on the return-volatility relationship of a new global market entrant, i.e. cryptocurrencies and conventional emerging economies assets. A novel contribution to this area of research is made as we foremost explore asymmetry and/or local leverage over different time-scales for both individual and aggregate market variables. Additionally, aside from examining volatility clustering in time samples (as put forward by Cont, 2001), our work also shows that clustering is prevalent in time-scale samples.

2.4.5.1 Evidence of asymmetric behaviour

Tables 2.25-2.30 give the estimated parameters of the NGARCH and GJR-GARCH models under the generalized hyperbolic and skew Student's *t* distributed errors. The two distributions are considered for the conditional volatility modelling due to the reason that both offered competitive fits, and were counted among the best four fitting distributions for the market variables at hand (refer, sub-section 2.4.3.1). Over here, the key parameter which interests us is the estimated gamma coefficient γ, that announces the presence of asymmetry in the markets.

With regards to the full sample log-returns (refer, Tables 2.25-2.26), the results point to a situation where a considerable number of the BRICS asset markets recorded positive and highly significant[35] asymmetric coefficient. Yet, four out of the eight

[35] The statistical significance level is marked as "a"0.1%; "b"1%; "c"5%; and "d"10%. These significance levels are applicable for all estimated coefficients reported under the NGARCH and GJR-GARCH models. Besides, in all cases, our analysis is primarily based on the estimated parameters from the fitted model with the lowest BIC value.

cryptocurrency markets witnessed negative γ. Except for NEO which had a weaker significant negative γ under the NGARCH, none of the eight individual cryptocurrencies shows statistical significance. Interestingly, our latter finding does not deviate much from the works of Bouri et al., (2017) and Baur and Dimpfl (2018b), which also reported non-significant asymmetric coefficients of -0.027 and -0.0043 respectively for Bitcoin under separate time samples. In addition to Bitcoin, the latter authors unveiled the absence of significant asymmetry in a number of the cryptocurrencies with negative γ (Ripple, Ethereum, Ethereum Classic, DASH, etc.), but only contradict our results for Litecoin and NEO.

The significant negative γ for the likes of NEO may be interpreted to mean that asymmetry is as a result of the greater effect of positive shocks which increase volatility in relation to negative shocks. This inverted asymmetry may best be accounted for by possible speculative trading strategies, not well-understood price drivers and surges which seem not to follow fundamentals, activities of inexperienced traders, and perhaps pump and dump machinations.

For the aggregate market data, CRIX reveals itself as the only asset that shows non-significant and a negative gamma coefficient. On a broader perspective, the asymmetric behaviour of the cryptocurrencies looks quite unique, relative to the BRICS asset which predominantly exhibits positive gamma coefficients, signifying that the presence of asymmetry is consequential to a larger effect of negative shocks which increase the volatility of the markets with regards to positive shocks. Remarkably, these findings remain consistent under both NGARCH and GJR-GARCH specifications, as well as the two error distributional approximations.

Table 2.27: Estimated NGARCH parameters for the short-run scale returns

	Generalized Hyperbolic					skew Student's t				
	α	β	p	γ	BIC	α	β	p	γ	BIC
Bitcoin	0.397[a]	0.604[a]	1.010	0.021	3.319	0.396[a]	0.603[a]	1.011	0.015	3.315
Litecoin	0.416[a]	0.583[a]	1.005	0.011	4.041	0.418[a]	0.580[a]	0.987	-0.015	4.039
Ripple	0.438[a]	0.561[a]	0.997	-0.004	4.129	0.438[a]	0.561[a]	0.998	-0.001	4.127
Ethereum	0.433[a]	0.526[a]	1.111	0.305	4.533	0.430[a]	0.524[a]	1.200	0.324	4.526
Ethereum Classic	0.551[a]	0.428[a]	1.074	0.190	4.523	0.550[a]	0.427[a]	1.280	0.201	4.514
DASH	0.459[a]	0.536[a]	1.043	0.095	4.339	0.461[a]	0.535[a]	1.054	0.073	4.335
NEO	0.453[a]	0.524[a]	1.088	0.223	4.981	0.453[a]	0.523[a]	1.153	0.228	4.972
ZCASH	0.381[a]	0.562[a]	0.751	-0.383	4.601	0.367[a]	0.564[a]	0.606	-0.429	4.596
BRL/USD	0.282[a]	0.640[a]	1.076	0.307	0.494	0.287[a]	0.636[a]	1.163	0.304	0.490
RUB/USD	0.206[a]	0.762[a]	1.163	0.390	-1.361	0.209[a]	0.757[a]	1.274	0.398	-1.366
INR/USD	0.245[a]	0.705[a]	0.929	-0.402	-1.129	0.258[a]	0.657[a]	0.542	-0.471	-1.133
CNY/USD	0.320[a]	0.674[a]	0.934	-0.121	-2.977	0.323[a]	0.673[a]	0.915	-0.100	-2.981
ZAR/USD	0.266[a]	0.640[a]	0.787	-0.238	0.506	0.267[a]	0.638[a]	0.698	-0.262	0.501
BOVESPA	0.306[c]	0.554[d]	1.196	0.674	1.907	0.304[a]	0.557[b]	1.165	0.674	1.902
MOEX	0.269[a]	0.680[a]	0.994	0.088	1.535	0.266[a]	0.684[a]	1.002	0.067	1.530
NIFTY50	0.302[a]	0.558[a]	1.115	0.450[c]	0.730	0.328[a]	0.530[a]	1.374	0.655[b]	0.723
SSE50	0.287[a]	0.711[a]	0.977	-0.043	1.239	0.285[a]	0.171[a]	0.914	-0.104	1.234
FTSE/JSE TOP40	0.215[c]	0.685[b]	0.869	-0.061	1.321	0.236[a]	0.626[a]	0.469	-0.504	1.316
Brazil REIT	0.350[a]	0.480[a]	1.162	0.665[c]	2.074	0.345[a]	0.487[a]	1.330	0.642[c]	2.069
Russia REIT	0.381[a]	0.573[a]	0.783	-0.343[d]	2.116	0.383[a]	0.588[a]	0.789	-0.234	2.113
India REIT	0.260[a]	0.633[a]	1.049	0.313	1.561	0.261[a]	0.632[a]	1.129	0.302	1.557
China REIT	0.356[a]	0.586[a]	1.049	0.213	1.628	0.357[a]	0.590[a]	1.072	0.160	1.626
South A. REIT	0.361[a]	0.541[a]	0.641	-0.520[a]	1.414	0.349[a]	0.532[a]	0.437	-0.581[b]	1.409
Crude Oil	0.213[a]	0.706[a]	0.613	-0.613[b]	1.760	0.206[a]	0.721[a]	0.456	-0.590[c]	1.754
Gold	0.290[a]	0.600[a]	0.672	-0.436	0.236	0.295[a]	0.589[a]	0.504	-0.482	0.230
Sugar	0.288[a]	0.550[a]	0.924	0.172	1.443	0.290[a]	0.551[a]	0.977	0.173	1.439
CRIX	0.468[a]	0.531[a]	0.996	-0.005	3.203	0.472[a]	0.527[a]	0.999	-0.013	3.198
MSCI EM FX	0.226[a]	0.632[a]	0.883	0.051	-1.902	0.226[a]	0.631[a]	0.908	0.064	-1.907
MSCI EMI	0.234[a]	0.626[a]	0.853	-0.013	-1.881	0.234[a]	0.626[a]	0.872	0.016	-1.885
MSCI EM REIT	0.316[a]	0.581[a]	1.062	0.330	0.857	0.318[a]	0.581[a]	1.146	0.315	0.854
BCOM	0.236[a]	0.558[a]	0.328	-0.932[a]	-0.104	0.237[a]	0.564[a]	0.083	-0.915[b]	-0.108
GBI-EM	0.287[a]	0.588[a]	0.772	-0.207	-0.698	0.287[a]	0.585[a]	0.680	-0.245	-0.702

Table 2.28: Estimated GJR-GARCH parameters for the short-run scale returns

	Generalized Hyperbolic					skew Student's t				
	α	β	p	γ	BIC	α	β	p	γ	BIC
Bitcoin	0.405[a]	0.605[a]	0.999	-0.022	3.319	0.400[a]	0.604[a]	0.996	-0.010	3.315
Litecoin	0.392[a]	0.583[a]	0.999	0.048	4.041	0.400[a]	0.581[a]	1.009	0.036	4.039
Ripple	0.407[a]	0.562[a]	0.998	0.059	4.128	0.404[a]	0.563[a]	1.017	0.063	4.127
Ethereum	0.314[a]	0.555[a]	1.003	0.267	4.534	0.430[a]	0.524[a]	1.198	0.324	4.526
Ethereum Classic	0.401[a]	0.437[a]	1.001	0.327	4.521	0.407[a]	0.438[a]	1.081	0.313	4.513
DASH	0.370[a]	0.536[a]	1.002	0.192	4.337	0.378[a]	0.534[a]	1.053	0.181	4.334
NEO	0.366[a]	0.549[a]	0.998	0.165	4.983	0.368[a]	0.549[a]	1.043	0.163	4.974
ZCASH	0.421[b]	0.614[a]	0.996	-0.078	4.603	0.433[a]	0.622[a]	0.970	-0.112	4.599
BRL/USD	0.257[a]	0.676[a]	0.942	0.018	0.497	0.264[a]	0.675[a]	0.944	0.006	0.493
RUB/USD	0.178[a]	0.786[a]	0.990	0.051	-1.361	0.174[a]	0.785[a]	1.007	0.063	-1.365
INR/USD	0.192[a]	0.710[a]	0.951	0.096	-1.129	0.213[a]	0.711[a]	0.969	0.057	-1.132
CNY/USD	0.373[a]	0.676[a]	1.000	-0.099	-2.977	0.364[a]	0.674[a]	0.976	-0.077	-2.980
ZAR/USD	0.255[a]	0.659[a]	0.917	0.004	0.506	0.257[a]	0.656[a]	0.916	0.005	0.501
BOVESPA	0.245[a]	0.674[a]	0.929	0.020	1.917	0.245[a]	0.674[a]	0.935	0.019	1.912
MOEX	0.371[a]	0.694[a]	0.957	-0.218[b]	1.531	0.367[a]	0.703[a]	0.892	-0.226[c]	1.525

NIFTY50	0.274[a]	0.632[a]	0.916	0.020	0.731	0.270[a]	0.631[a]	**0.925**	0.030	0.726
SSE50	0.308[a]	0.712[a]	0.999	-0.042	1.239	0.316[a]	0.712[a]	**0.982**	-0.058	1.234
FTSE/JSE TOP40	0.098[d]	0.730[a]	0.926	0.196[c]	1.319	0.110[c]	0.729[a]	**0.970**	**0.168[d]**	1.315
Brazil REIT	0.197[a]	0.546[a]	0.881	0.276[b]	2.075	0.196[a]	0.546[a]	**0.963**	**0.281[c]**	2.069
Russia REIT	0.459[a]	0.604[a]	0.985	-0.157	2.118	0.403[a]	0.603[a]	**0.964**	-0.054	2.114
India REIT	0.198[a]	0.653[a]	0.911	0.120	1.563	0.201[a]	0.651[a]	**0.944**	0.117	1.559
China REIT	0.258[a]	0.595[a]	0.951	0.195[d]	1.628	0.294[a]	0.596[a]	**0.986**	0.123	1.623
South A. REIT	0.376[a]	0.627[a]	0.935	-0.136	1.417	0.358[a]	0.634[a]	**0.905**	-0.112	1.413
Crude Oil	0.265[a]	0.775[a]	0.989	-0.102	1.763	0.266[a]	0.776[a]	**0.959**	-0.104	1.759
Gold	0.329[a]	0.629[a]	0.910	-0.096	0.237	0.344[a]	0.631[a]	**0.876**	-0.125	0.232
Sugar	0.244[a]	0.553[a]	0.841	0.087	1.444	0.244[a]	0.554[a]	**0.868**	0.089	1.439
CRIX	0.472[a]	0.531[a]	0.999	-0.007	3.203	0.478[a]	0.527[a]	**0.995**	-0.012	3.198
MSCI EM FX	0.201[a]	0.627[a]	0.856	0.056	-1.903	0.199[a]	0.626[a]	**0.874**	0.061	-1.907
MSCI EMI	0.214[a]	0.623[a]	0.859	0.042	-1.881	0.212[a]	0.622[a]	**0.873**	0.049	-1.886
MSCI EM REIT	0.262[a]	0.592[a]	0.905	0.102	0.858	0.268[a]	0.592[a]	**0.931**	0.090	0.855
BCOM	0.314[a]	0.710[a]	0.930	-0.188[d]	-0.096	0.312[a]	0.708[a]	**0.729**	**-0.184[d]**	-0.100
GBI-EM	0.276[a]	0.599[a]	0.881	0.013	-0.697	0.278[a]	0.600[a]	**0.882**	0.006	-0.702

In addition to the full sample, we also report asymmetry in two chosen time-scales. Estimated parameters for the short- (or intraweek) and long-run (or fortnight to monthly) time-scale samples are displayed in Tables 2.27-2.30. The results from the tables further unveil the continual non-significant asymmetric coefficient behaviour for the cryptocurrency markets. To another notable finding, the significant asymmetric coefficients reported in the full sample for majority of the BRICS markets mainly disappears as one move along the time-scales, thus from the short to long-run scales. Meanwhile, at the latter scale, none of the markets had a significant gamma coefficient. This suggests that the evidence in favour of asymmetry looks more prevalent in the full sample data, particularly for the BRICS assets but tends to dissipate immensely in the short-run scale, and eventually disappears in the long-run scale.

2.4.5.2 Evidence of local leverage

We report the presence of local leverage based on the estimated γ coefficient from the fitted NGARCH model across time and scale samples (refer, Tables 2.25, 2.27, and 2.29). Except for the cryptocurrencies, there is high empirical evidence in the full sample data favouring the presence of local leverage in majority of the BRICS asset markets. The evidence even looks more noticeable in the FX and stock markets, where

a single market each of the former and latter shows otherwise, while the remaining exhibit features of local leverage at a higher significant level of 0.01%.

Table 2.29: Estimated NGARCH parameters for the long-run scale returns

	Generalized Hyperbolic					skew Student's t				
	α	β	p	γ	BIC	α	β	p	γ	BIC
Bitcoin	0.182[a]	0.817[a]	0.967	-0.062	5.091	0.182[a]	0.817[a]	**0.951**	-0.060	5.087
Litecoin	0.219[a]	0.780[a]	0.994	-0.010	5.726	0.217[a]	0.782[a]	**0.988**	-0.014	5.723
Ripple	0.211[a]	0.787[a]	0.989	-0.019	6.092	0.211[a]	0.788[a]	**0.978**	-0.027	6.089
Ethereum	0.190[a]	0.808[a]	0.968	-0.060	5.834	0.190[a]	0.808[a]	**0.950**	-0.060	5.827
Ethereum Classic	0.182[a]	0.814[a]	1.003	0.015	6.141	0.177[a]	0.816[a]	**1.009**	0.020	6.136
DASH	0.201[a]	0.797[a]	0.953	-0.089	5.715	0.200[a]	0.797[a]	**0.926**	-0.089	5.709
NEO	0.166[a]	0.826[a]	0.943	-0.100	6.654	0.167[a]	0.826[a]	**0.924**	-0.088	6.646
ZCASH	0.206[a]	0.793[a]	0.972	-0.053	6.475	0.206[a]	0.792[a]	**0.961**	-0.048	6.467
BRL/USD	0.124[a]	0.857[a]	0.977	-0.006	1.726	0.124[a]	0.856[a]	**0.978**	-0.003	1.722
RUB/USD	0.146[a]	0.847[a]	0.979	-0.027	0.006	0.146[a]	0.847[a]	**0.969**	-0.029	0.001
INR/USD	0.136[a]	0.846[a]	0.986	-0.007	0.257	0.136[a]	0.846[a]	**0.989**	-0.008	0.252
CNY/USD	0.173[a]	0.826[a]	0.996	-0.006	-1.428	0.174[a]	0.825[a]	**0.994**	-0.006	-1.432
ZAR/USD	0.134[a]	0.846[a]	0.957	-0.044	2.082	0.134[a]	0.846[a]	**0.944**	-0.044	2.077
BOVESPA	0.110[a]	0.863[a]	0.958	-0.030	3.243	0.110[a]	0.863[a]	**0.949**	-0.030	3.238
MOEX	0.133[a]	0.854[a]	0.971	-0.032	2.997	0.133[a]	0.854[a]	**0.962**	-0.031	2.992
NIFTY50	0.126[a]	0.839[a]	0.929	-0.070	2.279	0.126[a]	0.839[a]	**0.895**	-0.070	2.275
SSE50	0.131[a]	0.868[a]	1.009	0.020	2.746	0.131[a]	0.868[a]	**1.014**	0.019	2.741
FTSE/JSE TOP40	0.126[a]	0.860[a]	0.951	-0.071	2.846	0.126[a]	0.860[a]	**0.930**	-0.070	2.842
Brazil REIT	0.132[a]	0.831[a]	0.993	0.060	3.595	0.131[a]	0.831[a]	**1.011**	0.061	3.590
Russia REIT	0.134[a]	0.850[a]	1.022	0.074	3.704	0.134[a]	0.850[a]	**1.041**	0.072	3.699
India REIT	0.146[a]	0.831[a]	1.001	0.048	3.407	0.146[a]	0.831[a]	**1.015**	0.047	3.402
China REIT	0.130[a]	0.849[a]	0.953	-0.053	3.180	0.130[a]	0.849[a]	**0.936**	-0.054	3.175
South A. REIT	0.159[a]	0.824[a]	1.021	0.074	3.181	0.159[a]	0.824[a]	**1.042**	0.074	3.176
Crude Oil	0.115[a]	0.879[a]	0.973	-0.042	3.391	0.115[a]	0.880[a]	**0.959**	-0.044	3.386
Gold	0.116[a]	0.861[a]	1.011	0.069	1.908	0.115[a]	0.861[a]	**1.032**	0.069	1.904
Sugar	0.105[a]	0.881[a]	0.978	-0.014	3.061	0.105[a]	0.881[a]	**0.955**	-0.019	3.056
CRIX	0.171[a]	0.826[a]	0.958	-0.079	4.736	0.171[a]	0.827[a]	**0.937**	-0.076	4.731
MSCI EM FX	0.133[a]	0.847[a]	1.012	0.064	-0.324	0.132[a]	0.847[a]	**1.034**	0.067	-0.329
MSCI EMI	0.122[a]	0.858[a]	0.887	0.057	-0.465	0.121[a]	0.859[a]	**1.030**	0.062	-0.469
MSCI EM REIT	0.135[a]	0.843[a]	0.945	-0.065	2.562	0.135[a]	0.842[a]	**0.924**	0.066	2.557
BCOM	0.099[a]	0.890[a]	0.982	-0.014	5.378	0.099[a]	0.890[a]	**0.979**	-0.012	5.373
GBI-EM	0.165[a]	0.816[a]	0.995	0.028	1.011	0.165[a]	0.816[a]	**1.005**	0.029	1.007

Table 2.30: Estimated GJR-GARCH parameters for the long-run scale returns

	Generalized Hyperbolic					skew Student's t				
	α	β	p	γ	BIC	α	β	p	γ	BIC
Bitcoin	0.193[a]	0.817[a]	0.999	-0.022	5.091	0.193[a]	0.816[a]	**0.993**	-0.021	5.088
Litecoin	0.225[a]	0.780[a]	0.999	-0.012	5.726	0.224[a]	0.783[a]	**0.995**	-0.014	5.723
Ripple	0.201[a]	0.809[a]	0.999	-0.026	6.834	0.229[a]	0.790[a]	**0.988**	-0.039	6.088
Ethereum	0.190[a]	0.808[a]	0.968	-0.060	5.834	0.190[a]	0.808[a]	**0.951**	-0.060	5.827
Ethereum Classic	0.174[a]	0.813[a]	0.995	-0.047	6.141	0.168[a]	0.816[a]	**0.998**	0.020	6.136
DASH	0.226[a]	0.797[a]	0.999	-0.047	5.715	0.225[a]	0.797[a]	**0.985**	-0.046	5.710
NEO	0.186[a]	0.826[a]	0.993	-0.036	6.655	0.185[a]	0.826[a]	**0.983**	-0.035	6.646
ZCASH	0.225[a]	0.793[a]	0.999	-0.037	6.475	0.224[a]	0.793[a]	**0.989**	-0.035	6.467
BRL/USD	0.125[a]	0.857[a]	0.980	-0.004	1.726	0.125[a]	0.856[a]	**0.979**	-0.002	1.722

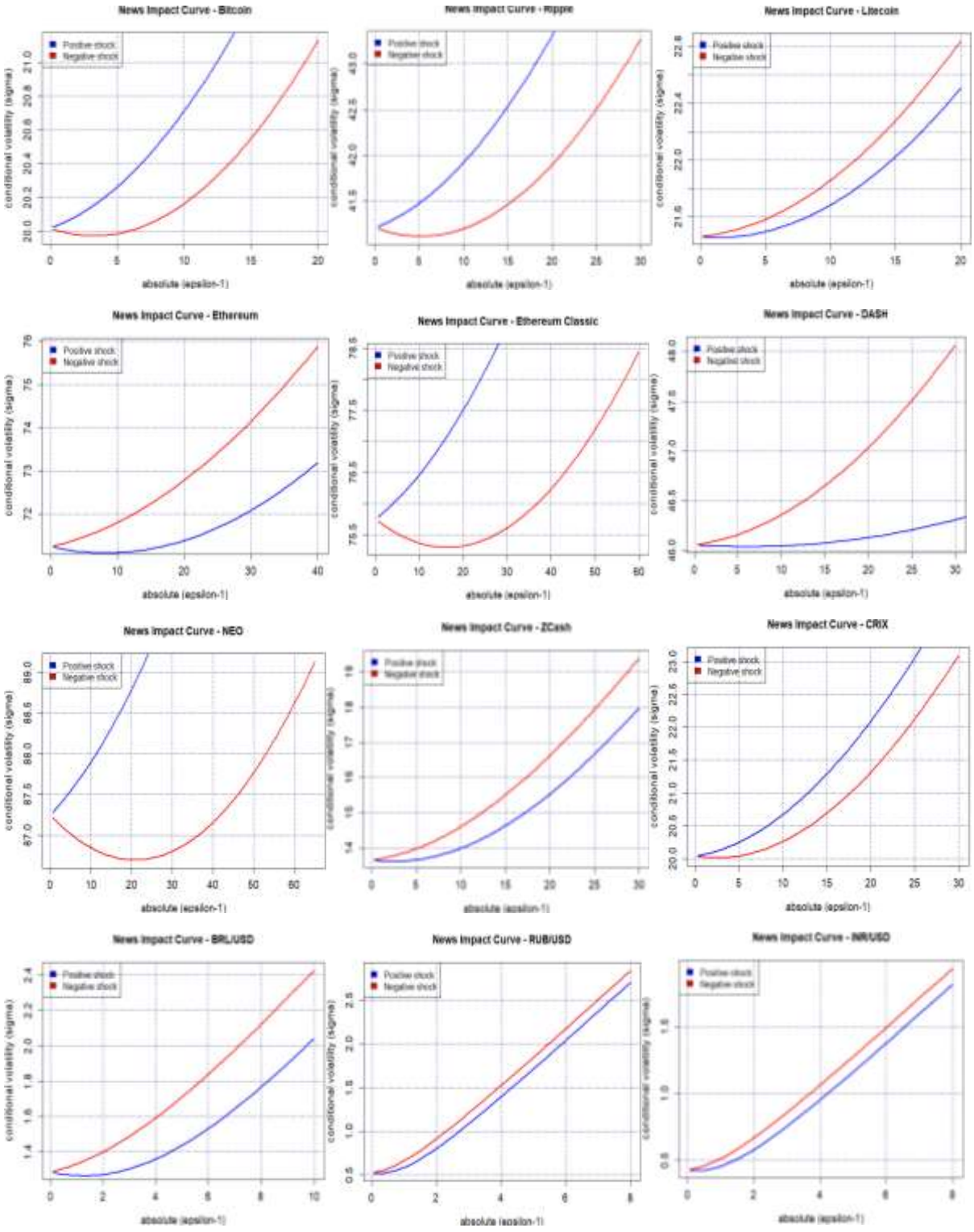
RUB/USD	0.153[a]	0.847[a]	0.992	-0.015	0.006	0.153[a]	0.846[a]	**0.988**	-0.014	0.001
INR/USD	0.128[a]	0.847[a]	0.982	0.015	0.257	0.128[a]	0.847[a]	**0.987**	0.015	0.252
CNY/USD	0.168[a]	0.826[a]	0.999	0.011	-1.428	0.169[a]	0.825[a]	**1.002**	0.010	-1.432
ZAR/USD	0.145[a]	0.845[a]	0.979	-0.023	2.082	0.145[a]	0.846[a]	**0.972**	-0.023	2.077
BOVESPA	0.108[a]	0.863[a]	0.973	0.004	3.243	0.108[a]	0.863[a]	**0.974**	0.004	3.238
MOEX	0.133[a]	0.854[a]	0.987	-0.001	2.997	0.133[a]	0.854[a]	**0.987**	-0.001	2.992
NIFTY50	0.126[a]	0.840[a]	0.965	-0.002	2.280	0.126[a]	0.840[a]	**0.964**	-0.002	2.275
SSE50	0.129[a]	0.869[a]	0.999	0.005	2.746	0.129[a]	0.868[a]	**1.000**	0.004	2.741
FTSE/JSE TOP40	0.137[a]	0.860[a]	0.987	-0.022	2.846	0.136[a]	0.860[a]	**0.981**	-0.019	2.842
Brazil REIT	0.119[a]	0.831[a]	0.963	0.026	3.595	0.118[a]	0.831[a]	**0.970**	0.026	3.590
Russia REIT	0.116[a]	0.852[a]	0.985	0.034	3.704	0.117[a]	0.852[a]	**0.994**	0.033	3.699
India REIT	0.140[a]	0.831[a]	0.978	0.012	3.407	0.141[a]	0.831[a]	**0.981**	0.012	3.402
China REIT	0.141[a]	0.850[a]	0.980	-0.012	3.180	0.140[a]	0.850[a]	**0.973**	-0.021	3.175
South A. REIT	0.152[a]	0.824[a]	0.984	0.015	3.182	0.152[a]	0.824[a]	**0.988**	0.015	3.177
Crude Oil	0.121[a]	0.880[a]	0.995	-0.012	3.391	0.121[a]	0.880[a]	**0.990**	-0.013	3.386
Gold	0.102[a]	0.861[a]	0.977	0.029	1.908	0.102[a]	0.861[a]	**0.985**	0.028	1.904
Sugar	0.109[a]	0.881[a]	0.985	-0.008	3.061	0.110[a]	0.880[a]	**0.983**	-0.009	3.056
CRIX	0.181[a]	0.826[a]	0.999	-0.017	4.736	0.180[a]	0.827[a]	**0.995**	-0.016	4.731
MSCI EM FX	0.127[a]	0.846[a]	0.980	0.014	-0.324	0.126[a]	0.847[a]	**0.985**	0.015	-0.329
MSCI EMI	0.119[a]	0.858[a]	0.980	0.008	-0.464	0.117[a]	0.858[a]	**0.983**	0.010	-0.469
MSCI EM REIT	0.143[a]	0.842[a]	0.977	-0.016	2.562	0.143[a]	0.842[a]	**0.972**	-0.016	2.557
BCOM	0.104[a]	0.890[a]	0.989	-0.010	5.378	0.103[a]	0.890[a]	**0.986**	-0.009	5.373
GBI-EM	0.160[a]	0.816[a]	0.981	0.010	1.012	0.159[a]	0.816[a]	**0.994**	0.011	1.007

Regarding the short-run scale sample, the substantial evidence of local leverage found for the full sample data surprisingly disappears, leaving only two markets with significant levels far lesser than those earlier recorded. Even more surprising, we found no significant evidence supporting the presence of local leverage in the long-run scale for all studied market variables. Based on this latter finding, we could then argue that the cryptocurrencies at this juncture behave almost the same as the BRICS assets when considered for local leverage under the intraweek to monthly frequency samples.

2.4.5.3 Analysis of News Impact Curves

To visualize the functional linkages between shocks to the studied markets and the corresponding impact on the conditional volatility, while every other variable is being held constant, we report the NICs for each market (refer, Fig. 2.14). In illustrating a discernible picture of the effect, we only report the absolute values of the most current shock ε_{t-1}, in order to access the extent to which such shock influences the next future's conditional volatility. As earlier observed, four of the cryptocurrencies

(Bitcoin, Ripple, Ethereum Classic, and NEO) and the assets' weighted market index CRIX are consistently in tune with an inverted asymmetric behaviour, where the impact of positive shocks (blue lines in Fig. 2.14) on the conditional volatility far exceeds the generated impact of the negative shocks (red lines in Fig. 2.14).



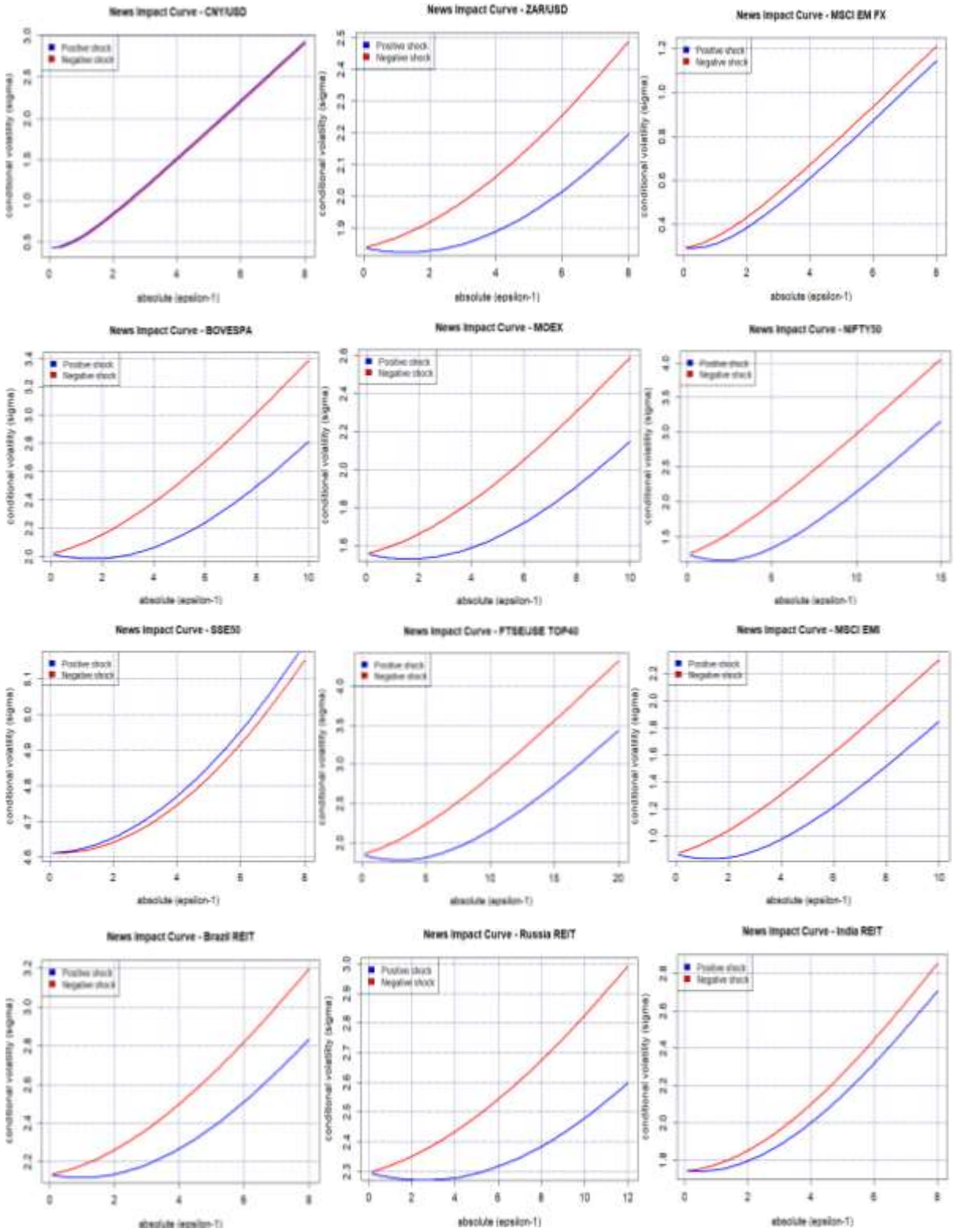


Fig. 2.14: News Impact Curves from the fitted NGARCH-SST model for all six asset classes. *Note: The skew Student's t (SST) error distribution is employed because it recorded an overwhelming number of best fitted model based on the BIC. Also, due to close similarities which do not alter the conclusion, we discard the NIC plots from the GJR-GARCH-SST model.*

Apart from CNY/USD, SSE50, and gold, all the remaining BRICS asset markets revealed asymmetric behaviour, which is primarily as a result of a greater effect emanating from negative shocks on the increase of the conditional volatility relative to the positive shocks. The inverted asymmetry in gold has been attributed to the safe haven characteristics of the asset (see, Baur, 2012). That of the SSE50 equity could best be explained with the leverage and volatility feedback hypotheses. Meanwhile, the inverted asymmetry in the CNY/USD FX market may perhaps be linked to the bilateral base-currency effect[36], and the Chinese Central Bank's usual interventions aimed at halting the weakening yuan currency against the USD. Given that such interventions occur at only one side of the currency pair, asymmetry becomes much plausible. A recent business news item by Reuters[37] gives credence to this practice which may be a cause of the observed asymmetric behaviour in the CNY/USD market.

2.4.5.4 Persistence analysis

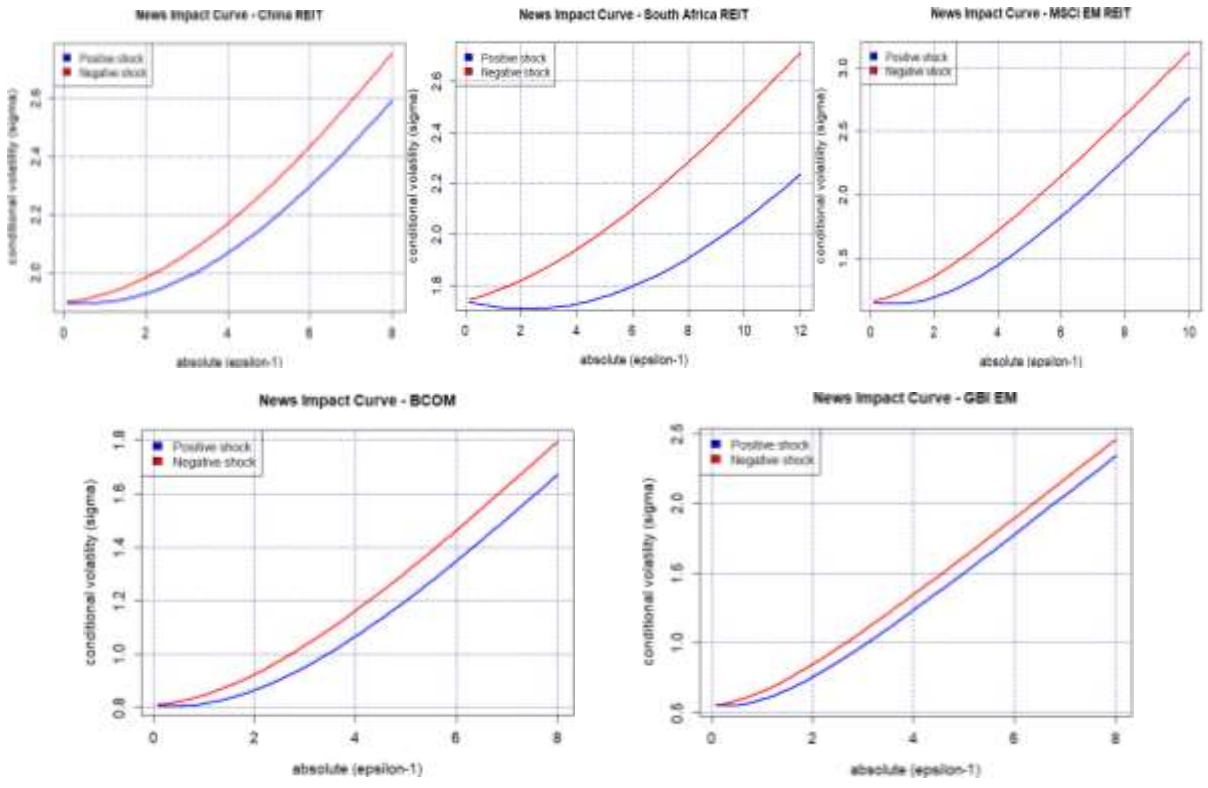
According to Cont (2001), several measures of volatility exhibit positive serial correlation over days, which seems to quantify the fact that high-volatility occurrences tend to cluster in time. One such measure is the persistence parameter P, which numerically estimates the extent of volatility clustering when GARCH-type models are fitted to empirical datasets. For this study, not only do we report volatility clustering over time (as propounded by Cont, 2001), we further consider the clustering behaviour of diverse assets across different time-scales. The general persistence model for the selected conditional volatility models in our case is given by $P = \sum_{j=1}^{q} \alpha_j + \sum_{j=1}^{p} \beta_j + \sum_{j=1}^{q} \gamma_j k$, with $P = \alpha_1 + \beta_1 + \gamma_1 k$ as the simplified version for the first-order specification. The k in the model is the standardized innovations' expected

[36] For extensive explanation of base-currency effect, see Wang and Yang (2009).

[37] Available online at: https://www.reuters.com/article/us-china-markets-yuan-pboc/chinas-central-bank-wont-let-yuan-weaken-past-7-to-the-dollar-sources-idUSKCN1SN0NT, and accessed on June 10, 2019.

value, which is dependent on the (a)symmetric nature of the approximated error (or innovation) distribution. For symmetric distributions, k takes on ½. Also, α and β are the estimated ARCH and GARCH terms from the conditional volatility models.

Tables 2.25-2.26, 2.27-2.28, and 2.29-2.30 display the estimates of the ARCH, GARCH, and persistence parameters, respectively for the full, short-, and long-run data samples. For simplicity, we adopt a self-developed persistence classification, similar to that from the work of Engle and Ng (1993): there is high persistence if $P \geq 0.999$; intermediate persistence if $0.900 \leq P < 0.999$; low persistence if $0.800 \leq P < 0.900$; and very low persistence if $P < 0.800$. The brown-coloured entries of the tables are the favoured persistence estimates based on the BIC's choice of the best fitting model.



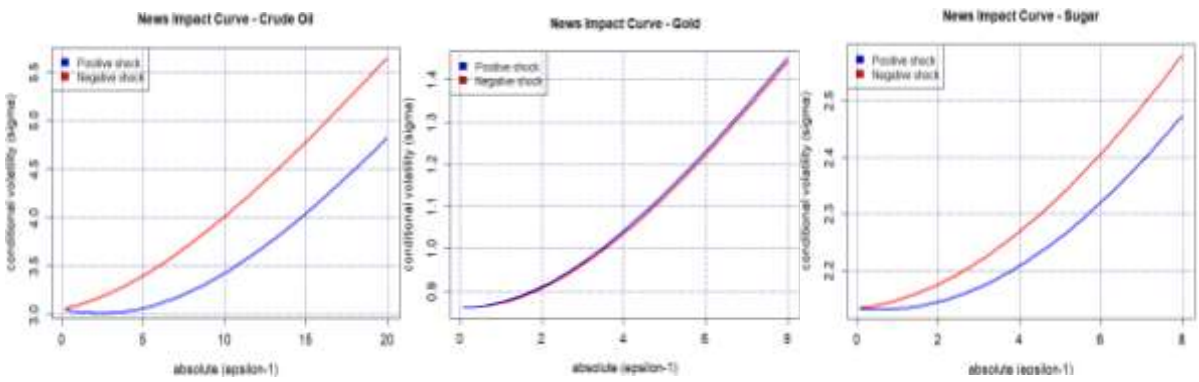


Fig. 2.14 Cont.

The results from the NGARCH model for the full sample data show high-level persistence characteristics for BRICS's REIT (1.116-1.905), stocks (0.972-2.119), and FX (0.942-1.705) markets. On the other side, the cryptocurrencies recorded low (0.817) to high (1.079) persistence values. Comparably, this could be interpreted to mean that the observed volatilities of the BRICS assets tend to highly cluster well than the clustering in the cryptocurrencies. This becomes more pronounced as we consider the aggregate data, where all the BRICS assets had persistence values far greater than 1, with CRIX being the only market showing intermediate persistence (0.992). Although there are few reductions (in magnitude) for the estimated parameter P, especially for the stock and REIT equities, qualitatively the deductions mostly remain the same. Thus, the cryptocurrencies less persist relative to the BRICS markets. More so, we observe that for all data and market specifications, the estimated GARCH parameters are highly significant and show greater dominance over the corresponding ARCH components.

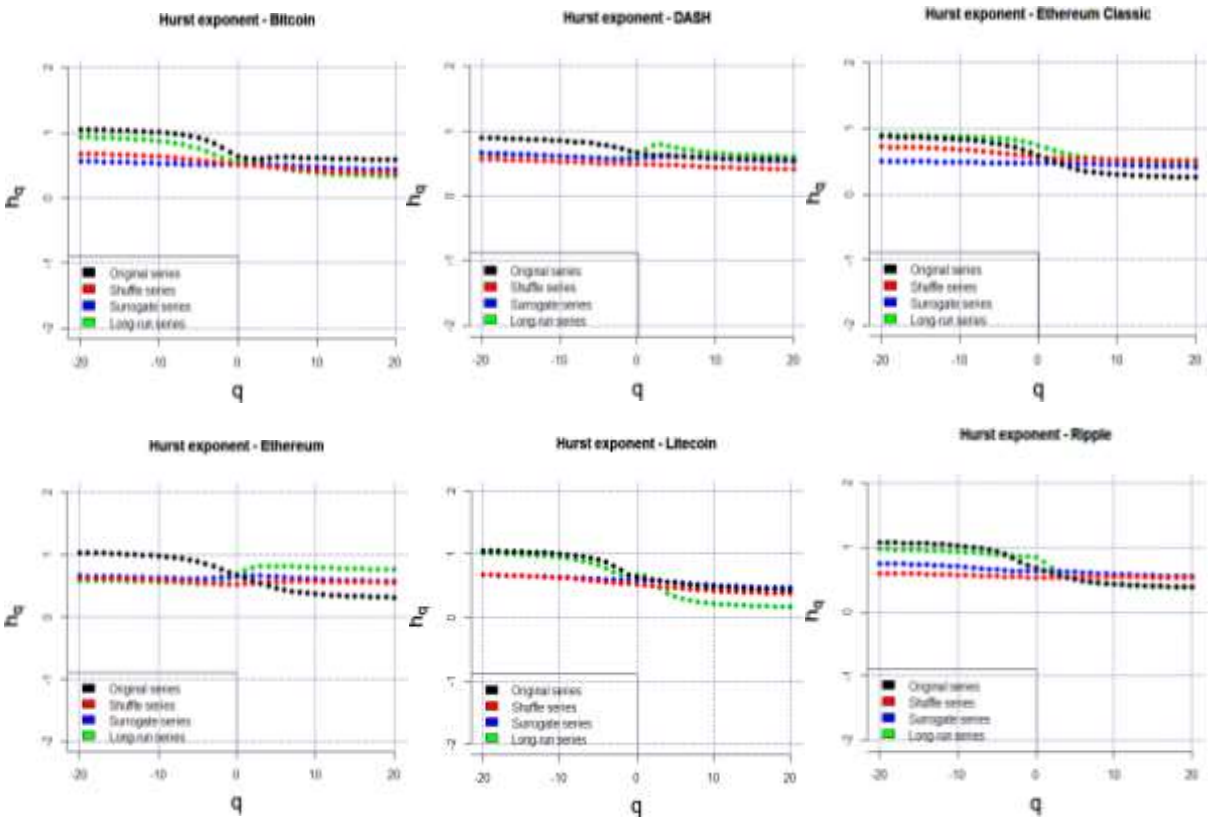
Generally, the persistence parameter P fairly reduces under the time-scale samples, and overly shows descriptionally indifferent characteristics among the various asset classes. For instance, the estimated P of the cryptocurrencies (0.606-1.280), FXs (0.542-1.274), stocks (0.469-1.374), REITs (0.437-1.330), and commodities (0.456-0.977) from the NGARCH under the short-run scale, all exhibit very low to high persistence values. Notably, the results obtained from the GJR-GARCH model for the long-run

sample show a much-related persistence behaviour for the cryptocurrencies (0.951-0.998), BRICS's FXs (0.972-1.002), stocks (0.964-1.000), REITs (0.970-0.994), and commodities (0.983-0.990). For the same data and model specification, it becomes keenly undistinguishable for CRIX, MSCI EM FX, MSCI EMI, MSCI REIT, BCOM, and GBI-EM as the markets respectively recorded persistence values of 0.995, 0.985, 0.983, 0.972, 0.986, and 0.994 (i.e. intermediate persistence). Also, from the short-run estimates, it is revealed that the dominance of the GARCH terms moderately reduces in magnitude, with respect to the associated ARCH terms. However, such reduced dominance remained as a fluke, which is restored under the long-run scale.

2.4.6 Multifractal analysis

Financial asset markets are often marked as a complex dynamical system, from which generated data normally deviate from being in a state of equilibrium. This attribute of financial markets makes it practically impossible to comprehensively describe them with an exponent scale, but instead, the use of mass scaling exponents may largely be required for such task. Although studies on fractal scaling behaviour are now gaining popular attention in the financial literature, more empirical shreds of evidence are warranted to further understand the fractal dynamics of financial and economic time series. The literature in this direction has to extent focused fairly well on international stocks (Rizvi et al., 2014; Hasan and Mohammed, 2015; Bouoiyour et al., 2018; Maganini et al., 2018; Han et al., 2019; etc.) and bilateral foreign currency (Batten et al., 2014; Ning et al., 2018; Feng et al., 2019; etc.), with recent growing interest channeled towards the decade-young financial markets, i.e. cryptocurrencies (da Silva Filho et al., 2018; Takaishi, 2018; Stosic et al., 2019; Derbentsev et al., 2019; etc.). However, empirical studies which compare multifractal characteristics of this new currency market with long-existing assets look rare, yet the works of Al-Yahyaee et al., (2018) and Kristjanpoller and Bouri (2019) are noted.

As the latter works commit to the multifractal behaviour of cryptocurrencies with leading advanced traditional currencies, commodity, and stock indexes, there seems to be no study at this point which explores cryptocurrencies with asset markets of emerging economies. Yet, the behaviour of cryptocurrencies remains important to emerging economies, as authorities in several of these countries are in a dilemma of either to usher in an appropriate framework which is expected to define a functional role for these new global currencies or otherwise. From an empirical setting, the purpose of our study is to investigate the inherent scaling characteristics of the cryptocurrency markets amid diverse emerging asset markets.



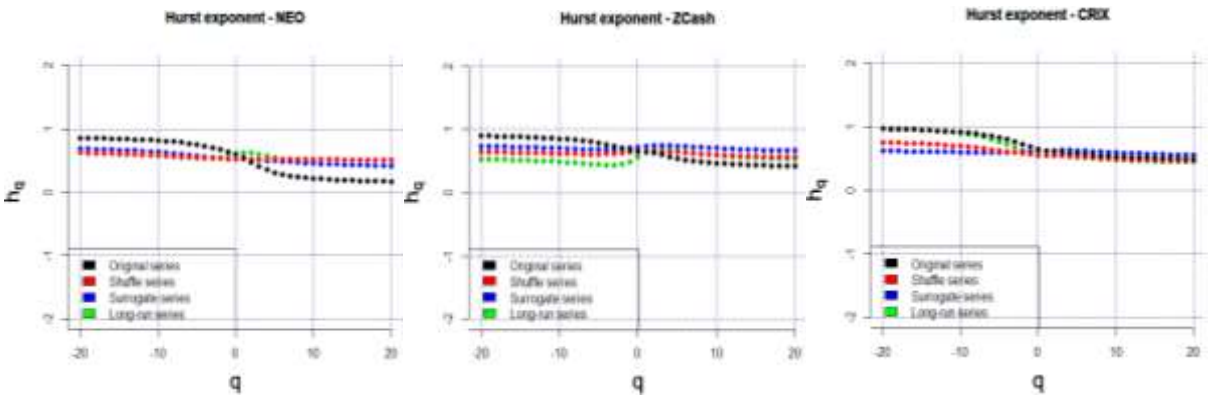


Fig. 2.15: Generalized Hurst exponent h(q) vs q for the short-to-medium-run cryptocurrency series, with corresponding shuffled and surrogated series, and imposed long-run time-scale series.

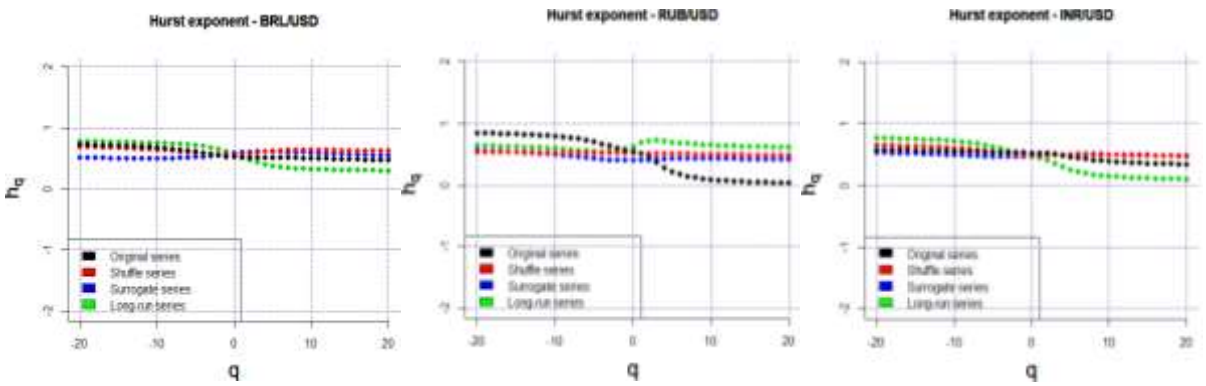
Indeed, our study augments the existing works with three major contributions. The initial additional piece to the literature sterns from the diverse nature of the markets used for the analysis. Our second contribution is rooted in the provision of multifractal characteristics for the log-returns of five different emerging asset classes and the cryptocurrencies under short- and long-run time-scales. Being the first of its kind, such analysis instils a debate to assess which traditional asset(s) of emerging economies do the cryptocurrency market empirically mimic the most. Another Contribution worth pursuing is the evaluation of the level of efficiency of the studied markets over the short- and long-run scales using the MF-DFA-based multifractal estimates.

2.4.6.1 Multifractal characteristics of asset returns

Prior to implementing the MF-DFA approach, we initially weigh in on the task of determining a range of values for q and the time-scale to use. Wary of observing possible hidden scaling behaviour within the log-returns, we choose two distinct time-scales, such that $s < 90$ (short-to-medium-run scale) and $s > 90$ (long-run scale). Similar to Bouoiyour et al., (2018), our work investigates fractal characteristics of the studied markets for the chosen short-to-medium-, and long-run scales over q. The former scale i.e. $s < 90$ is used in our case as a reference or original scale. Observably, the choice of values for the q parameter remains inconclusive in the literature, yet

drawing on the explanation of Maganini et al., (2018), we set q from -20 to 20, related to the works of Kantelhardt et al., (2002) and Lahmiri and Bekiros (2018).

Figs. 2.15-2.19 display plots of the estimated generalized Hurst exponent $h(q)$ for $s<90$ and $s>90$ under different q values (ranging from -20 to 20). At a quick glance of the plots, one could generally observe that the pattern of movements of $h(q)$ for $s<90$ (represented by the black-coloured dash lines) and $s>90$ (green-coloured dash lines) are apparently not stable, but evolve by depending on the range of values for q. Much noticeably, for increasing values of q, $h(q)$ records corresponding decreasing values, signifying clearly that the log-returns of the markets exhibit multifractal behaviour which looks consistent across the two distinct scales. From the plots, where q assumes negative values, it is seen that small fluctuations give higher scaling exponent $h(q)$, while for positive values of q which correspond to large fluctuations, the scaling exponent $h(q)$ display relatively lower values. In congruence with multifractal series, the identified features indicate that the daily returns could best be described by a multitude of scaling exponents $h(q)$, instead of a single exponent.



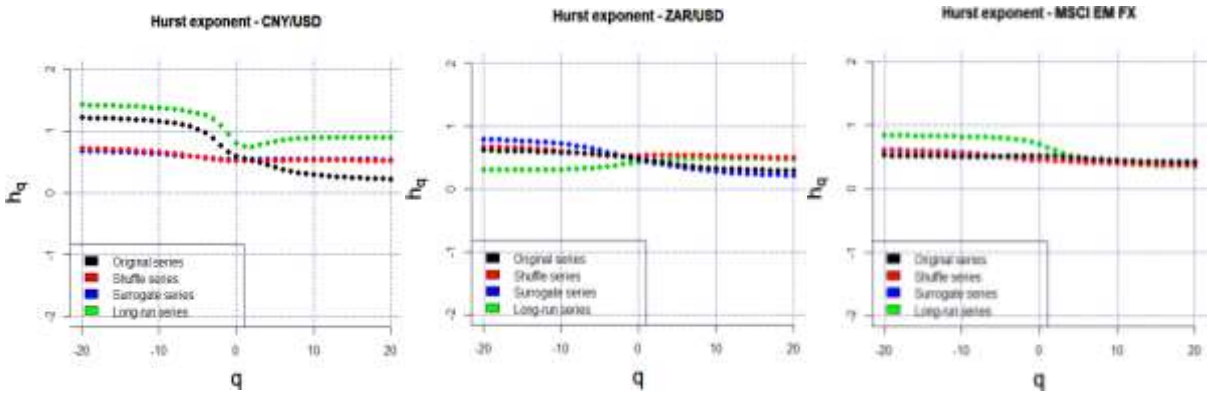


Fig. 2.16: Generalized Hurst exponent h(q) vs q for the short-to-medium-run FX series, with corresponding shuffled and surrogated series, and imposed long-run time-scale series.

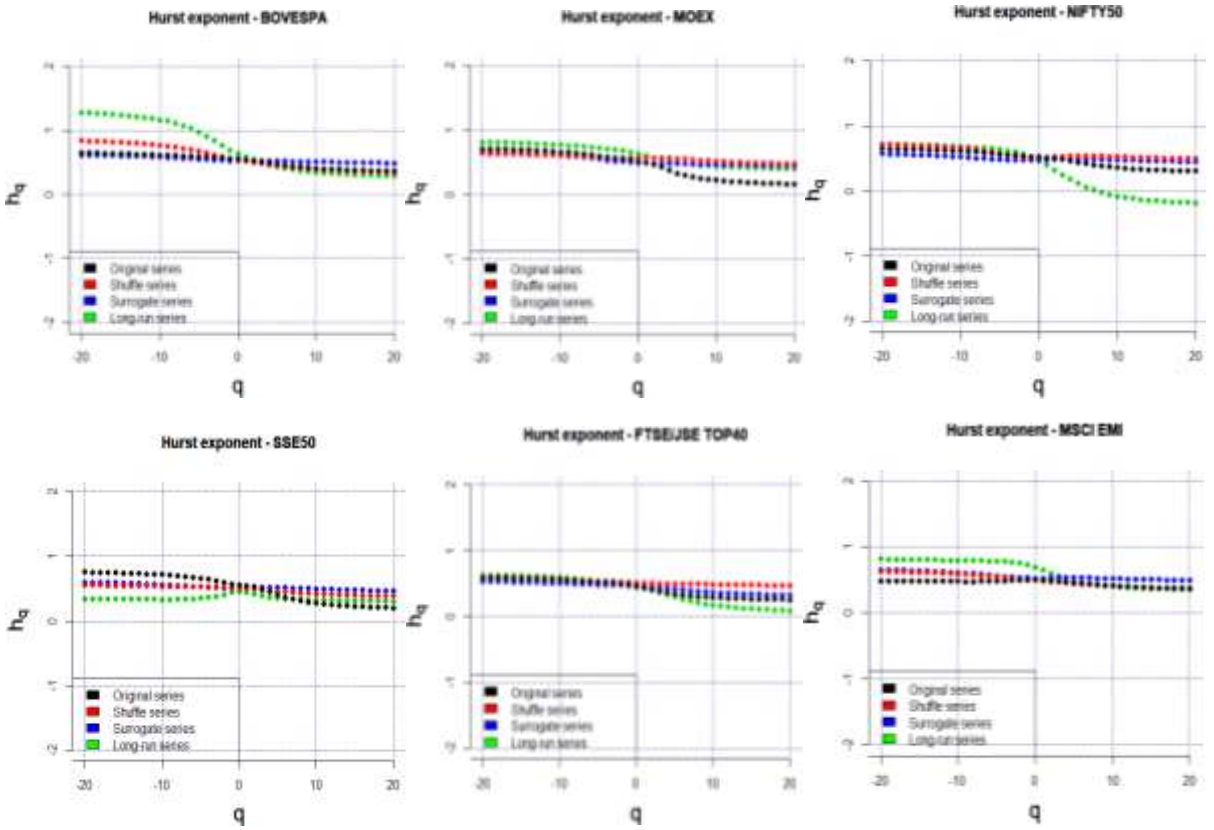
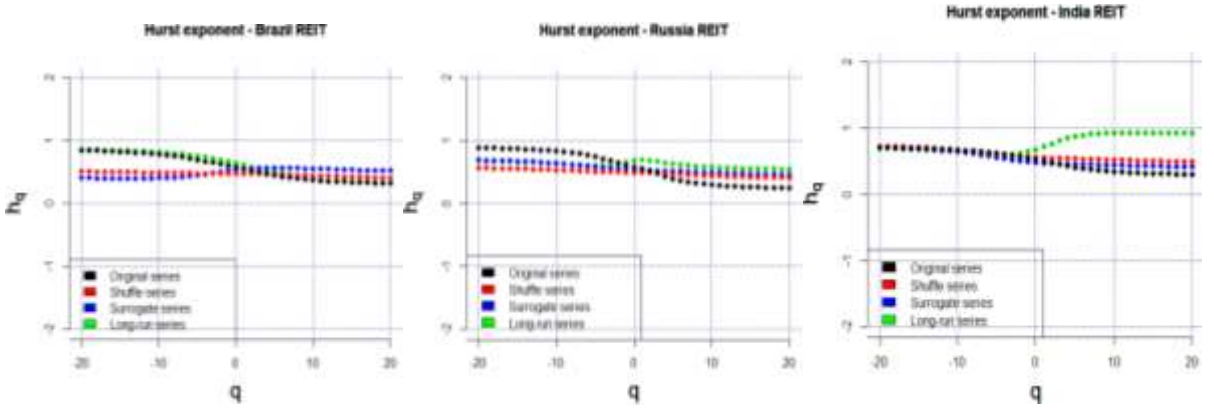


Fig. 2.17: Generalized Hurst exponent h(q) vs q for the short-to-medium-run stock series, with corresponding shuffled and surrogated series, and imposed long-run time-scale series.



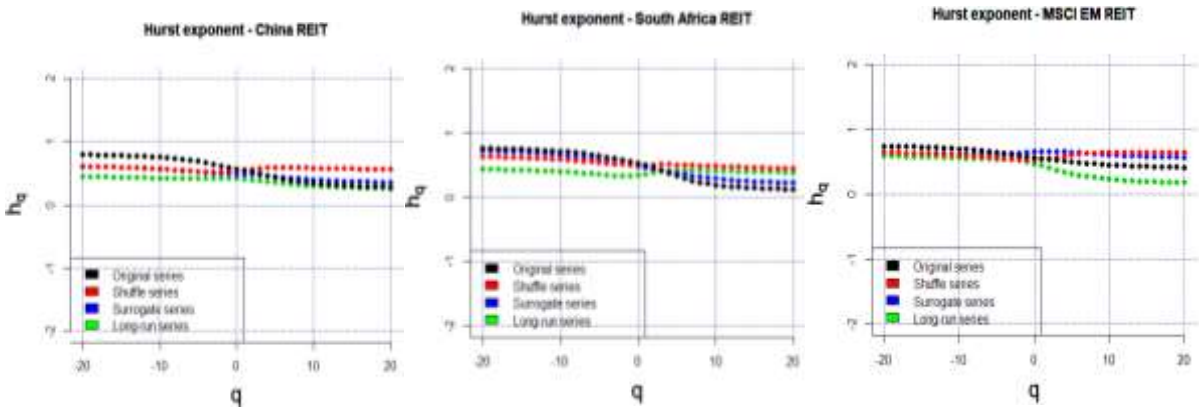


Fig. 2.18: Generalized Hurst exponent h(q) vs q for the short-to-medium-run REIT series, with corresponding shuffled and surrogated series, and imposed long-run time-scale series.

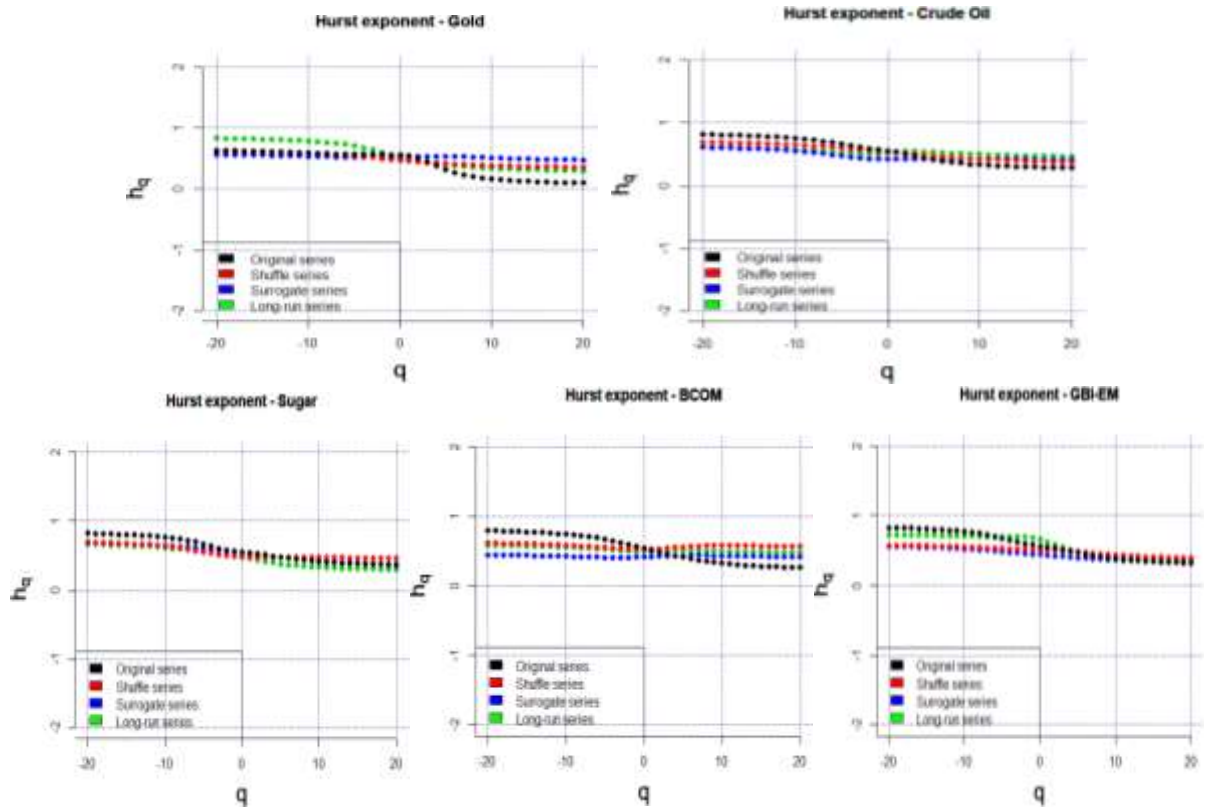


Fig. 2.19: Generalized Hurst exponent h(q) vs q for the short-to-medium-run commodity and government bond series, with corresponding shuffled and surrogated series, and imposed long-run time-scale series.

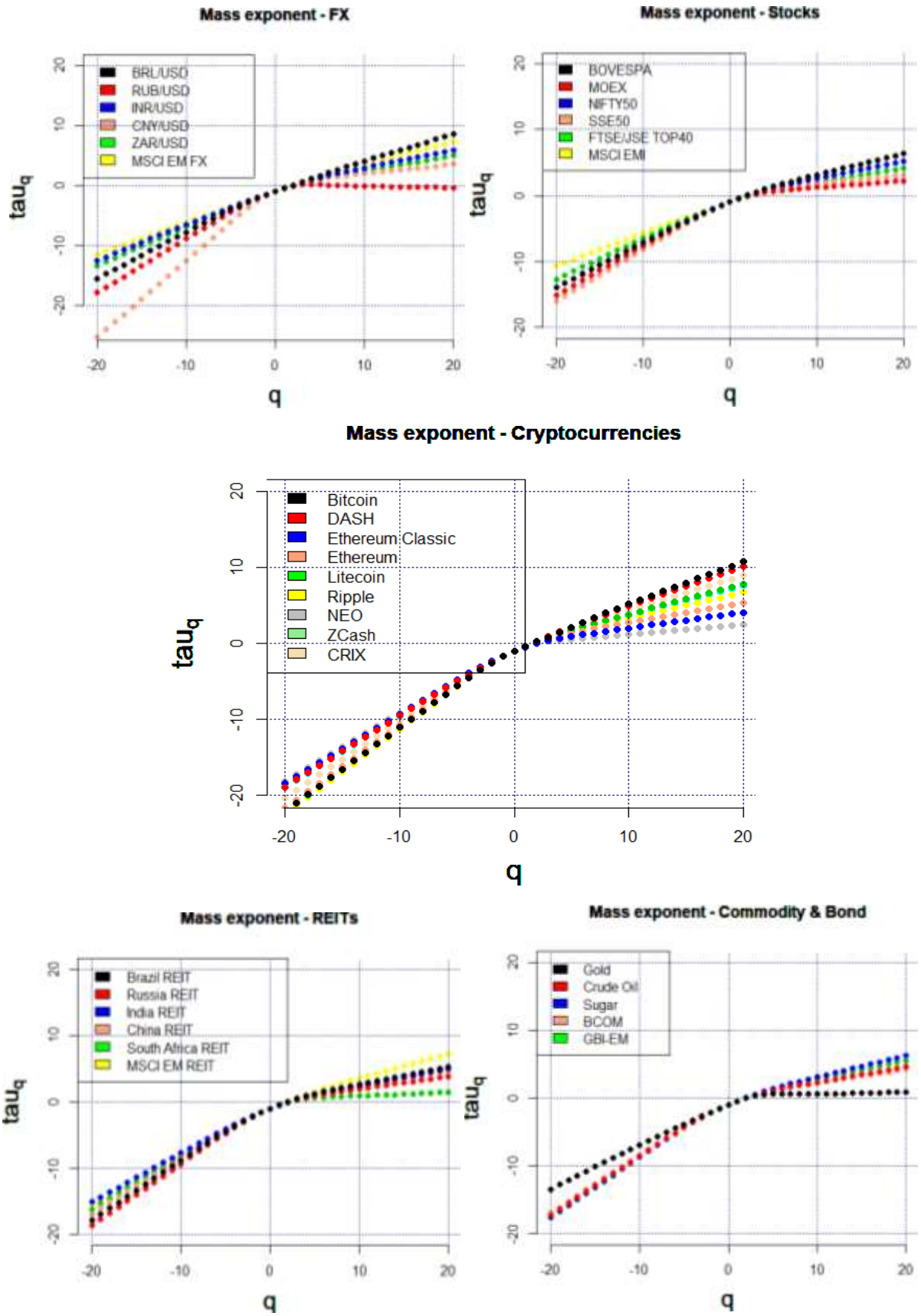


Fig. 2.20: Mass exponent tau(q) vs q for asset classes under the short-to-medium-run time-scale

The decrease in the level of $h(q)$ with respect to q is fairly pronounced in $s<90$ for the cryptocurrencies and the BRICS REITs than could be witnessed under $s>90$. Besides, we also report a graphical representation of the mass exponent function $\tau(q)$ plotted against the values of q under the reference time-scale. The non-linear nature of $\tau(q)$ exhibited by the curves in the plots provide additional indication of multifractal characteristics in all the markets. Otherwise, a linear relationship would have suggested the presence of monofractality. Our results downplay on any attempt to solely use fractals models in capturing the return dynamics of cryptocurrency and the BRICS assets.

Subsequent to detecting evidence against monofractality, we measure the degree of multifractality, thus MF1 and MF2 under $s<90$ and $s>90$. The results of MF1 and MF2, based on Δh and $\Delta\alpha$ respectively are both shown in Tables 2.31 and 2.32. We derive Δh from the difference between the estimated maximum and minimum values of the q parameter. Likewise, $\Delta\alpha$ is the fractal spectrum width obtained from the difference between the estimated maximum and minimum α values. Thus $\Delta h=\max[h(q)]-\min[h(q)]$; and $\Delta\alpha=\max[\alpha]-\min[\alpha]$. The presence of multifractality is only stronger if Δh and/or $\Delta\alpha$ become larger.

From Table 2.31, the four largest cryptocurrency markets (Bitcoin, Ethereum, Ripple, and Litecoin) recorded Δh and $\Delta\alpha$ values ranging from 0.467-0.717 and 0.549-0.826 respectively. The remaining smaller markets (Dash, NEO, Ethereum Classic, Zcash) had a range of values over 0.338-0.687 for Δh and 0.425-0.714 for $\Delta\alpha$. Multifractality manifests stronger in the major cryptocurrency markets relative to the smaller ones. Also, Δh and $\Delta\alpha$ respectively ranges from 0.231-0.989 and 0.309-1.128 for the BRICS FX; 0.283-0.552 and 0.368-0.669 for the stocks; 0.404-0.640 and 0.488-0.763 for the REITs; and 0.460-0.533 and 0.572-0.659 for the commodities. Comparably, evidence of a stronger degree of multifractality is observed for the BRICS FXs, whereas the stocks

had the least degree of detection. More so, closer scrutiny of the range of values for the smaller cryptocurrency markets and the BRICS REITs lead us to conclude of a much alike multifractal behaviour for the two markets. However, from the aggregate market data, BCOM and GBI-EM recorded the highest degree, while MSCI EM REIT continues to trail closely behind CRIX.

From the MF1 and MF2 results for the long-run scale ($s > 90$) in Table 2.32, further remarkable characteristics are noticed. Ironically, the Δh and $\Delta\alpha$ range of values marginally reduces in magnitude for the individual markets, but almost increases for all the aggregate markets except for BCOM and GBI-EM. Akin to the behaviour reported under the short-to-medium-run scale ($s < 90$), the relatively smaller cryptocurrencies and the BRICS REITs trail each other with smaller differences in their values. The results also reveal the relative closeness of the Δh and $\Delta\alpha$ values for the major cryptocurrency markets (0.278-0.849 and 0.356-0.991) and that of the BRICS stocks (0.146-0.983 and 0.161-1.154). Drawing from the results for $s < 90$ and $s > 90$, there is enough evidence in favour of multifractality in the log-returns of all the diverse asset markets, where the degree of manifestation varies across the asset classes.

2.4.6.2 Evidence of market (in)efficiency

We document the (in)efficiency of the markets and its implied ease (or less chance) of predictability based on the relationship between the scaling exponent $h(q)$ and the Hurst exponent. From the MF-DFA's generalized Hurst exponent and the multifractal degree or dimension, different inefficiency measures have been proposed. Not being anyway exhaustive, the measures in the works of Rizvi et al., (2014), Bouoiyour et al., (2018), and Jiang et al., (2019) are noted. For this study, we assume a market is efficient if $|h(2) - 0.5| \leq 0.05$. Intuitively, we prefer to denote an inefficient market index by:

$$Inefficiency\ index(IE) = |h(2) - 0.5| > 0.05 \qquad (2.85)$$

where $h(2)$ is the Hurst exponent H, obtained from the estimated generalized Hurst $h(q)$ when $q = 2$. The extremely lesser the values for the index, the efficient the market would be, else larger index value connotes high-level of inefficiency.

Table 2.31: Multifractality degrees and efficiency ranking under short-to-medium-run scale

	MFI					MF2			Hurst exponent		
	Δh	Δh_{sf}	Δh_{sr}	Δh_c	Ratio	$\Delta\alpha$	$\Delta\alpha_{sf}$	$\Delta\alpha_{sr}$	$h(2)$	IE	Rank
Bitcoin	0.467	0.299	0.129	0.274	0.916	0.549	0.393	0.216	0.5992	0.0992	23
Litecoin	0.619	0.297	0.205	0.323	1.090	0.717	0.398	0.297	0.5948	0.0948	22
Ripple	0.692	0.068	0.199	0.624	9.159	0.793	0.126	0.291	0.6019	0.1019	24
Ethereum	0.717	0.096	0.087	0.648	6.761	0.826	0.135	0.168	0.5812	0.0812	20
Ethereum Classic	0.620	0.213	0.089	0.407	1.909	0.714	0.284	0.155	0.4876	**0.0124**	04
DASH	0.338	0.153	0.128	0.189	1.235	0.425	0.231	0.234	0.6280	0.1280	25
NEO	0.687	0.117	0.266	0.570	4.882	0.782	0.189	0.365	0.4763	**0.0237**	12
ZCASH	0.475	0.091	0.081	0.390	4.282	0.568	0.170	0.157	0.6304	0.1304	26
BRL/USD	0.251	0.127	0.112	0.183	1.437	0.341	0.178	0.146	0.5165	**0.0165**	06
RUB/USD	0.815	0.059	0.154	0.756	12.92	0.950	0.109	0.239	0.4573	**0.0427**	18
INR/USD	0.231	0.179	0.065	0.167	0.934	0.309	0.258	0.131	0.5235	**0.0235**	11
CNY/USD	0.989	0.206	0.142	0.789	3.838	1.128	0.286	0.218	0.5269	**0.0269**	14
ZAR/USD	0.322	0.179	0.569	0.214	1.195	0.398	0.293	0.701	0.4507	**0.0493**	19
BOVESPA	0.283	0.493	0.129	0.216	0.438	0.368	0.619	0.205	0.5229	**0.0229**	09
MOEX	0.548	0.160	0.204	0.388	2.419	0.661	0.241	0.282	0.4629	**0.0371**	16
NIFTY50	0.343	0.216	0.121	0.213	0.985	0.435	0.306	0.218	0.5047	**0.0047**	03
SSE50	0.552	0.169	0.137	0.383	2.266	0.669	0.237	0.228	0.5270	**0.0270**	15
FTSE/JSE TOP40	0.330	0.127	0.208	0.203	1.600	0.409	0.192	0.295	0.4107	0.0893	21
Brazil REIT	0.526	0.097	0.165	0.429	4.409	0.642	0.169	0.219	0.5264	**0.0264**	13
Russia REIT	0.640	0.157	0.234	0.483	3.079	0.745	0.232	0.329	0.5128	**0.0128**	05
India REIT	0.404	0.237	0.292	0.196	0.828	0.488	0.333	0.397	0.4817	**0.0183**	07
China REIT	0.511	0.088	0.251	0.462	5.273	0.611	0.137	0.343	0.5232	**0.0232**	10
South A. REIT	0.637	0.187	0.501	0.453	2.426	0.763	0.287	0.637	0.4653	**0.0347**	16
Crude Oil	0.533	0.316	0.197	0.217	0.688	0.648	0.412	0.281	0.5039	**0.0039**	01
Gold	0.525	0.279	0.089	0.342	1.227	0.659	0.361	0.167	0.5044	**0.0044**	02
Sugar	0.460	0.241	0.314	0.223	0.928	0.572	0.339	0.417	0.5207	**0.0207**	08
CRIX	0.473	0.293	0.077	0.186	0.636	0.571	0.395	0.143	0.6039	0.1039	06
MSCI EM FX	0.115	0.226	0.186	0.136	0.603	0.182	0.311	0.260	0.5140	**0.0140**	02
MSCI EMI	0.132	0.253	0.164	0.161	0.637	0.185	0.333	0.253	0.4911	**0.0089**	01
MSCI EM REIT	0.329	0.120	0.094	0.325	0.271	0.419	0.167	0.148	0.5382	**0.0382**	05
BCOM	0.535	0.088	0.039	0.486	5.537	0.657	0.126	0.094	0.4860	**0.0140**	03
GBI-EM	0.507	0.186	0.230	0.321	1.728	0.629	0.267	0.317	0.5368	**0.0368**	04

The results of the Hurst exponent, IE, and the efficiency rank of each market under $s < 90$ are shown in the last three columns of Table 2.31. The red-coloured entries are IE values far below or equal to 0.05, which reasonably signifies market efficiency. From the results, the returns of all the BRICS markets (except for FTSE/JSE TOP40) follow a Wiener process or are seen to be drawn from a memoryless stochastic process,

implying evidence of relatively high informational flow intensity. On the other hand, the four major cryptocurrency markets show persistence characteristics which contradicts the weak form of the efficient market hypothesis (EMH). These informational flow inefficiencies of the latter markets provide an opportunity for probable excessive exploitation by speculative market agents. However, such exploitation would be reduced or disincentivized as two of the relatively smaller cryptocurrency markets (Ethereum Classic and NEO) ranked well for efficiency.

To our surprise, the values of the inefficiency index become exceedingly larger from the 0.05 threshold for majority of the BRICS markets under the long-run scale (refer Table 2.32). Except for the commodities, none of the asset classes ranks better for efficiency. The persistence characteristics of the cryptocurrencies manifest clearly under the long-run scale. This contrast the findings from the study of Omane-Adjepong et al., (2019), which reports informational flow efficiency for five of the cryptocurrency markets (Bitcoin, Ethereum, Ripple, Litecoin, and Dash) under a long-run scale. Perhaps, the (in)efficiency of the markets changes or evolves with varying time-scales. Similar to the cryptocurrencies, all markets of the BRICS REITs also exhibit return characteristics which do not follow a memoryless stochastic process. The large inefficiency values for several of the markets, especially the cryptocurrencies and REITs connote common evidence of long-term correlated daily returns and the easiness for predictability. With the ease of predictability and it implied low intensity of informational flow, a greater chance exists for speculative manipulations through for instance trend trading which could be used as a tool to explore the markets of abnormal profits.

2.4.6.3 Sources of the multifractal features

The two main origins of multifractality in a given time series data are mostly attributed to the inherent temporal correlation and/or heavy taildness distributional properties of the series. Over here, we investigate to unveil which of the above-

mentioned sources, if present, looks more prevalent to the detected multifractal characteristics of the studied markets. Before our investigation, we computed scaling exponents $h(q)$ for a randomly shuffled and surrogated[38] log-returns based on the original series under $s<90$ and $s>90$. We then average respectively over the values of the 1000 randomly shuffled and surrogated return series. It is imperative knowing that any exercise aimed at shuffling a series for a higher number of runs collapses long-range correlations structure, while the same distribution of events within the series is preserved. More so, from the constructed phase-randomized surrogated return series, possible non-normal features of the series eventually become weakened.

In a situation where the curve of the scaling exponents $h(q)$ for the shuffled series departs quite wider from the corresponding original series, a conclusion is reached by attributing the source of multifractality to the presence of long-range correlations, instead of heavy tail distributions. The converse remains valid as well. Besides, we also computed the fractal spectrum and scaling exponent widths for the shuffled ($\Delta\alpha_{sf}$ and Δh_{sf}) and surrogated ($\Delta\alpha_{sr}$ and Δh_{sr}) series. A reduction in the values of $\Delta\alpha_{sf}$ and $\Delta\alpha_{sr}$ relative to $\Delta\alpha$; and Δh_{sf} and Δh_{sr} relative to Δh signals that the detected multifractal behaviour could be accounted for by the presence of heavy tail distributional features and long-range correlations. We further distinguish between the two sources using a ratio given by: $Ratio(R)=\Delta h_c/\Delta h_{sf}$, where Δh_c denotes a correlation-induced scaling exponent and Δh_{sf} is the width of the exponent for the shuffled series. The long-range correlations account more for multifractality if $R\geq 1$, else fat tail distributions become the dominant source.

Table 2.32: Multifractality degrees and efficiency ranking under long-run scale

	MFI					MF2			Hurst exponent		
	Δh	Δh_{sf}	Δh_{sr}	Δh_c	Ratio	$\Delta\alpha$	$\Delta\alpha_{sf}$	$\Delta\alpha_{sr}$	$h(2)$	IE	Rank
Bitcoin	0.596	0.343	0.084	0.260	0.758	0.713	0.447	0.133	0.5612	0.0612	06

[38] The number of surrogate and random shuffling is set to 1000 runs each.

Litecoin	0.849	0.190	0.201	0.685	3.615	0.991	0.226	0.258	0.5724	0.0724	09
Ripple	0.593	0.497	0.275	0.296	0.595	0.684	0.655	0.339	0.6817	0.1817	20
Ethereum	0.278	0.260	0.625	0.440	1.694	0.356	0.345	0.728	0.7897	0.2897	26
Ethereum Classic	0.433	0.293	0.119	0.172	0.589	0.513	0.388	0.156	0.6586	0.1586	17
DASH	0.212	0.369	0.750	0.394	1.068	0.284	0.451	0.899	0.7772	0.2772	25
NEO	0.218	0.270	0.542	0.208	0.771	0.314	0.337	0.640	0.6233	0.1233	16
ZCASH	0.253	0.233	0.539	0.317	1.360	0.317	0.317	0.645	0.6852	0.1852	21
BRL/USD	0.478	0.261	0.832	0.366	1.403	0.543	0.355	0.998	0.4774	**0.0226**	01
RUB/USD	0.182	0.767	0.280	0.743	0.969	0.236	0.937	0.335	0.7185	0.2185	22
INR/USD	0.669	0.487	0.738	0.187	0.384	0.776	0.572	0.903	0.4070	0.0930	12
CNY/USD	0.677	0.397	0.238	0.553	1.392	0.731	0.556	0.326	0.7458	0.2458	23
ZAR/USD	0.187	0.200	0.048	0.287	1.430	0.245	0.256	0.081	0.4602	**0.0398**	02
BOVESPA	0.983	0.132	0.417	0.969	7.332	1.154	0.189	0.565	0.5451	**0.0451**	03
MOEX	0.412	0.493	0.105	0.082	0.165	0.503	0.594	0.164	0.5665	0.0665	08
NIFTY50	0.902	0.325	0.268	0.580	1.785	1.061	0.406	0.354	0.3287	0.1713	18
SSE50	0.146	0.132	0.172	0.246	1.857	0.161	0.175	0.223	0.4108	0.0892	11
FTSE/JSE TOP40	0.541	0.413	0.287	0.139	0.337	0.664	0.553	0.418	0.4020	0.0980	13
Brazil REIT	0.461	0.192	0.736	0.321	1.671	0.542	0.234	0.861	0.5783	0.0783	10
Russia REIT	0.144	0.464	0.572	0.376	0.809	0.223	0.550	0.686	0.6811	0.1811	19
India REIT	0.321	0.231	0.115	0.456	1.977	0.408	0.331	0.152	0.7629	0.2629	24
China REIT	0.189	0.337	0.116	0.175	0.519	0.266	0.431	0.138	0.3993	0.1007	14
South A. REIT	0.107	0.132	0.316	0.139	1.048	0.148	0.158	0.410	0.3808	0.1192	15
Crude Oil	0.152	0.288	0.323	0.185	0.643	0.236	0.377	0.438	0.5478	**0.0478**	05
Gold	0.534	0.085	0.357	0.451	5.283	0.631	0.185	0.431	0.4545	**0.0455**	04
Sugar	0.368	0.097	0.219	0.272	2.816	0.452	0.182	0.303	0.4339	0.0661	07
CRIX	0.531	0.424	0.102	0.122	0.288	0.648	0.546	0.144	0.5471	**0.0471**	02
MSCI EM FX	0.488	0.468	0.279	0.149	0.318	0.568	0.574	0.369	0.6046	0.1046	06
MSCI EMI	0.461	0.238	0.357	0.673	2.823	0.539	0.305	0.422	0.5983	0.0983	05
MSCI EM REIT	0.410	0.089	0.368	0.341	3.816	0.505	0.153	0.153	0.4083	0.0917	04
BCOM	0.106	0.199	0.107	0.189	0.945	0.164	0.256	0.146	0.4949	**0.0051**	01
GBI-EM	0.377	0.092	0.124	0.460	4.978	0.457	0.132	0.205	0.5831	0.0831	03

Figs. 2.15 to 2.19 show the $h(q)$ curves for the shuffled, surrogated, and their associated original return series for $s < 90$[39]. For all the market returns, there are visible departures of the shuffled- and surrogated-based curves from the curve of the original series. This indicates that broad probability densities and temporal correlations jointly explain the multifractal behaviour of the markets. The evidence is strongly corroborated in both time-scales where the values of Δh far exceed Δh_{sf} and Δh_{sr} for almost all the markets (refer, Tables 2.31 and 2.32). Likewise, the estimated values for $\Delta\alpha_{sf}$ and $\Delta\alpha_{sr}$ reduces substantially when compared to $\Delta\alpha$. In other words, the

[39] Note well that the shuffled and surrogate curves for $s > 90$ (long-run scale) series are not reported. We mainly focused our graphical representation on the reference scale $s < 90$. However, Tables 2.31-32 give estimates to that effect for both scales.

degree of multifractality for the shuffled and surrogated return series is relatively smaller than that of the corresponding original return series under $s < 90$ and $s > 90$. Interestingly, while the multifractal behaviour of the individual markets under $s < 90$ looks much to be accounted for by the hidden long-range correlation structure, the evidence in the aggregate markets could best be explained by the featured heavy tail distributions. This conclusion is reached based on the computed ratio, where $R < 1$ for only 7 out of the 26 individual markets, and 4 out of the 6 aggregate markets. Besides, the fat taildness of the markets, especially the cryptocurrency market becomes apparently pronounced at the long-run scale where 4 of its 8 assets (Bitcoin, Ripple, Ethereum Classic, and NEO) had *R* values far below 1. Noticeably, Bitcoin, INR/USD, crude oil, CRIX, and MSCI EM FX consistently recorded $R < 1$, suggestive that the market information of the mentioned assets may best be captured by non-normal or heavy tail distributions, with far-reaching implications for risk computation, volatility modelling, and forecasting.

2.4.7 Herding behaviour

Using the cross-sectional absolute standard deviation approach, we report a possible non-linear relationship between the extent of return dispersions with regards to the ensemble market return. The presence (or absence) of herd behaviour during up (down) market periods are also explored using the cross-sectional standard deviation. To investigate these phenomena, we construct a market portfolio for 8 leading cryptocurrencies[40] and the traditional foreign currency and stock markets of the emerging economies within the G20[41] setup. The source and criteria for the selection of the cryptocurrencies are outlined in sub-section 2.3.1. The use of the other well-

[40] Unlike Vidal-Tomás et al., (2019), Calderón (2018), and da Gama Silva et al., (2019), we discarded the inclusion of several currencies due to the fact that most of these currencies are truly illiquid and contribute nothing (or very less) in the portfolio market. One such event is recorded in this study where Bitcoin alone nearly weighted 100% based on the global minimum-variance portfolio construction strategy (refer, *Appendix 2.A8*). Therefore, similar to Bouri et al., (2019), our use of a relatively smaller number of markets which are much liquid is not misplaced.

[41] For the list of the countries, see www.ifrs.org/groups/emerging-economies-group/#members

known traditional emerging markets (eg. REITs, bond, etc.) is discarded as a result of researchers' inaccessibility to reliable market data. The 10 emerging FX and stock data are obtained from Bloomberg. All the market variables span 29.10.2016-07.06.2019 and are sourced in the United States dollars. Owing to the non-weekend trading nature of the conventional markets, we cleaned the data to synchronize with each other. The daily prices are put into percentage log-returns by simply finding the logged differences: $r_t = [In(P_t) - In(P_{t-1})]*100$.

In determining a strategy to compute the ensemble market returns, we employ an equally-weighted portfolio as done by Vidal-Tomás et al., (2019), and the global minimum-variance (GMV) portfolio construction approach. This is done to test the sensitivity of our detection with regards to empirical portfolio construction strategies. The equally-weighted portfolio is obtained using the expression:

$$r_t = \frac{1}{N}\sum_{i=1}^{N} r_{i,t} \tag{2.86}$$

where $r_{m,t}$ is the overall market return at time t; $r_{i,t}$ represents the daily log-returns of each market from a unique asset class; and N gives the number of markets in the class.

Drawing from the selected portfolio of risky assets, the global minimum-variance portfolio strategy minimizes the variance of the daily returns in an objective function stated as:

$$\min \; w_t^{'} \sum_t w_t, \quad s.t. \; I\, w_t^{'} = 1 \tag{2.87}$$

Here, w_t denote N×1 vector of weights, where the optimal portfolio weights[42] are expressed as $\left(\sum_t^{-1} I\right) \div \left(I^{'} \sum_t^{-1} I\right)$. Also, I is a vector of the values of ones with dimension N×1; and lastly, $\sum_t$ represents a covariance matrix of a square order, i.e. N×N. In addition to the full sample return data, we also examine for herding activities in four

[42] Refer to *Appendices 2.A6-2.A8* for graphical representations of the assigned weights.

different time samples. The full sample returns series is disaggregated into four sub-samples using a time interval of approximately 150 trading days (i.e. averagely semi-annual intervals).

Table 2.33: Time sample OLS regression estimates for $CSSD_{m,t}$ at 5% extremes

Panel A	Equally-weighted portfolios				
10.2016-06.2019	a	γ_1	γ_2	AIC	RSE
Cryptocurrency	6.736 (0.325)*	19.29 (1.967)*	30.94 (2.319)*	3569.6	7.260
Emerging FX	0.503 (0.076)*	2.626 (0.467)*	5.521 (0.467)*	2547.1	1.843
Emerging Stock	1.686 (0.346)*	19.43 (2.278)*	7.989 (2.015)	4449.6	8.424
	Global minimum-variance portfolios				
Cryptocurrency	5.637 (0.264)*	18.01 (1.582)*	17.85 (1.739)*	4112.0	6.433
Emerging FX	0.496 (0.011)*	0.169 (0.076)**	0.142 (0.076)***	146.7	0.271
Emerging Stock	1.657 (0.042)*	3.248 (0.267)*	2.612 (0.238)*	1808.4	1.022
Panel B	Equally-weighted portfolios				
10.2016-06.2017	a	γ_1	γ_2	AIC	RSE
Cryptocurrency	9.487 (0.725)*	39.18 (4.009)*	26.33 (4.468)*	1133.9	8.817
Emerging FX	0.703 (0.219)*	6.222 (1.353)*	18.56 (1.353)*	759.0	2.671
Emerging Stock	1.526 (1.183)	58.74 (7.290)*	8.028 (6.542)	1287.7	14.390
	Global minimum-variance portfolios				
Cryptocurrency	8.654 (0.819)*	47.02 (5.051)*	21.63 (4.532)*	1172.5	9.968
Emerging FX	0.496 (0.021)*	-0.035 (0.114)	0.188 (0.127)	15.2	0.250
Emerging Stock	1.193 (0.068)*	7.033 (0.422)*	1.845 (0.422)*	392.9	0.833
Panel C	Equally-weighted portfolios				
07.2017-02.2018	a	γ_1	γ_2	AIC	RSE
Cryptocurrency	6.968 (0.527)*	2.533 (2.998)	43.00 (3.846)*	1095.9	6.599
Emerging FX	0.395 (0.015)*	0.161 (0.075)**	0.120 (0.082)	-92.3	0.180
Emerging Stock	1.584 (0.255)*	13.07 (1.321)*	8.507 (1.608)*	854.5	3.175
	Global minimum-variance portfolios				
Cryptocurrency	4.684 (0.271)*	4.846 (1.398)*	6.971 (1.527)*	873.1	3.360
Emerging FX	0.396 (0.015)*	0.180 (0.092)***	0.073 (0.083)	-89.6	0.182
Emerging Stock	1.512 (0.904)***	2.438 (5.699)	41.00 (4.683)*	1272.1	11.250
Panel D	Equally-weighted portfolios				
03.2018-10.2018	a	γ_1	γ_2	AIC	RSE
Cryptocurrency	3.881 (6.802)	19.90 (4.796)*	27.26 (18.74)	1875.3	8.359
Emerging FX	0.905 (0.547)	5.367 (3.048)***	22.92 (3.048)*	1067.9	6.704
Emerging Stock	2.392 (0.250)*	18.57 (1.272)*	4.691 (1.548)*	816.5	3.056
	Global minimum-variance portfolios				
Cryptocurrency	3.548 (0.198)*	0.306 (1.101)	-0.755 (1.101)	742.2	2.423
Emerging FX	0.745 (0.072)*	5.139 (0.369)*	3.112 (0.449)*	420.4	0.886
Emerging Stock	1.600 (0.138)*	9.144 (0.770)*	4.993 (0.858)*	627.5	1.693
Panel E	Equally-weighted portfolios				
11.2018-06.2019	a	γ_1	γ_2	AIC	RSE

Cryptocurrency	3.304 (0.210)*	0.205 (1.237)	3.018 (1.110)*	670.3	2.438
Emerging FX	0.499 (0.143)*	5.191 (0.695)*	1.593 (0.972)	560.5	1.665
Emerging Stock	1.968 (0.133)*	10.50 (0.788)*	2.015 (0.788)**	540.4	1.553
		Global minimum-variance portfolios			
Cryptocurrency	3.948 (0.389)*	-0.883 (2.658)	5.034 (2.310)**	850.3	4.555
Emerging FX	0.465 (0.022)*	0.086 (0.115)	0.178 (0.115)	17.3	0.253
Emerging Stock	1.629 (0.473)*	4.806 (2.787)***	17.93 (2.502)*	904.3	5.494

Note: The standard errors associated with the estimated regression coefficients are reported in brackets; and the statistical significance level is marked as "*"1%; "**" 5%; and "***"10%. RSE represents the residual standard error of the fitted regression, and AIC is the well-known Akaike information criterion. The estimations are based on the ordinary least squares (OLS) approach.

Table 2.33 displays the estimated coefficients of the CSSD-based regression which is employed to distinguish between extreme market conditions. From the table, the γ_1 and γ_2 coefficients associated respectively with the down-, and up-market periods are almost non-negative for all the three asset classes under the two portfolio construction strategies. Though the cryptocurrency market recorded a negative value each for γ_1 and γ_2 at two different time samples (refer, Panels D and E of Table 2.33), the estimated coefficients are highly insignificant. We observe the same for the emerging FX market in Panel B of the same table. Not only do we notice significant anti-herding behaviour during the up-, and down-markets for the full sample data, but the evidence against it (anti-herding) is overly missing in the time-varying data samples as well. This could perhaps be interpreted to mean that the extreme price or return variations observed at the tail-end of the ensemble market return distribution cannot be attributed to activities of herding.

Also, the results of the CSAD-based OLS regression from equation (2.82) are shown in Table 2.34. As robustness to the OLS estimations, we analyze herding at different quantile distributions[43] (refer, Table 2.35). Owing to our small time-samples, we associate up- and down-markets with the 25th and 75th quantiles and compares the conditional-median QR to the OLS results. Though not new, QR has rarely been

[43] Quantile regression (QR) does not assume normality, which is rarely applicable for financial variables and is less sensitive to outliers and structural breaks that often account for non-linear structures in asset returns.

applied to quantify herding in cryptocurrencies. To further incorporate the possibility of realizing non-stable regression estimates over moving time-intervals, we augment our herding analysis with a time-varying version of the OLS[44], using a rolling-window of size 80[45]. From the tables, the estimated γ_2 coefficient of the OLS is negative for all three asset classes but appears significant for only the stock under the full-sample. Except for the cryptocurrency, the QR estimations report negative and nonsignificant γ_2 for the aggregate sample. However, under the sub-sample estimations, the OLS detected a significant herding behaviour for the cryptocurrency and stock markets over 29.10.2016-30.06.2017; the FX and stock for 01.03.2018-31.10.2018; and all asset classes over 01.11.2018-07.06.2019. From the QR results, significant herding is recorded for the cryptocurrencies and stocks over the period 29.10.2016-30.06.2017; and for the stocks at 01.03.2018-31.10.2018.

Notably, the slight difference between the OLS and QR results may be attributed to perhaps the location measure used for the return dispersion relationships. As also observed by Calderón (2018) and da Gama Silva et al., (2019), the high variation patterns may have shredded evidence of herding behaviour in the full-sample, only to be unveiled in the sub-samples, and further corroborated by the rolling-window estimations (refer, *Appendix A.29*). From the γ_2 rolling-window *t*-statistics, we could observe significant time-varying herd trading which manifests strongly in the stock market. Although the cryptocurrencies witnessed a lengthy period of anti-herding, traces of herding activity mark periods from 19.10.2017-20.02.2018, 02.10.2018-12.11.2018, and 13.11.2018-17.01.2019, of which the herd effect of the former two periods appears weak and nonsignificant. Besides, the duration of significant herding in the FX market lasted for fewer days but varied with time.

[44] Earlier studies by Stavroyiannis and Babalos, (2017) and Bouri et al., (2019) applied such method.

[45] Considering the length of our data-sample, we believe a window-size of 80 is not too short (long) to induce large (overly smooth) variations of the regression estimates. For more insight of the approach, see Su and Hwang (2009).

Considering periods of up- and down-market, we observe evidence of significant herding behaviour at quantile 0.75 for the cryptocurrencies and stocks over 29.10.2016-30.06.2017; while at the same period, the stocks recorded a significant value of -0.090 under quantile 0.25. γ_2 is found significant for the stock market at quantile 0.75 over the periods 01.03.2018-31.10.2018 and 01.11.2018-07.06.2019. Interestingly, the symmetric and asymmetric herding behaviour of the cryptocurrency market coincides with the 2017 price surges and the declaration of the currency by the Japanese Payment Services Act as legal tender. This indicates that investors of the market do not only herd during down-market, or more so, exclusively respond to bad news (as found by Vidal-Tomás et al., 2019), but besides, they react to good news. Naïve and ill-informed traders who imitate experienced colleagues, as well as others who fear of missing out on prospective higher returns may mostly trigger such reactions.

Table 2.34: Time sample OLS regression estimates for $CSAD_{m,t}$

Panel A	Equally-weighted portfolios				
10.2016-06.2019	a	γ_1	γ_2	AIC	RSE
Cryptocurrency	2.203 (0.309)*	0.748 (0.026)*	0.040 (0.020)**	3276.0	5.486
Emerging FX	0.284 (0.014)*	0.941 (0.010)*	0.053 (0.010)*	379.4	0.326
Emerging Stock	0.325 (0.033)*	1.026 (0.006)*	-0.015 (0.006)*	1458.7	0.773
	Global minimum-variance portfolios				
Cryptocurrency	2.181 (0.256)*	0.735 (0.027)*	-0.010 (0.021)	3803.1	5.026
Emerging FX	0.441 (0.015)*	0.317 (0.057)*	-0.063 (0.040)	122.5	0.266
Emerging Stock	0.734 (0.037)*	0.747 (0.019)*	-0.025 (0.013)***	1213.4	0.635
Panel B	Equally-weighted portfolios				
10.2016-06.2017	a	γ_1	γ_2	AIC	RSE
Cryptocurrency	4.737 (0.640)*	0.804 (0.045)*	-0.057 (0.037)	1041.1	6.559
Emerging FX	0.165 (0.032)*	0.962 (0.012)*	0.040 (0.011)*	140.3	0.372
Emerging Stock	0.220 (0.059)*	1.026 (0.012)*	-0.019 (0.012)	328.5	0.678
	Global minimum-variance portfolios				
Cryptocurrency	5.304 (0.587)*	0.834 (0.048)*	-0.157 (0.043)*	1022.8	6.188
Emerging FX	0.426 (0.028)*	0.415 (0.115)*	-0.072 (0.080)	4.779	0.242
Emerging Stock	0.393 (0.044)*	0.670 (0.020)*	-0.072 (0.016)*	162.4	0.400
Panel C	Equally-weighted portfolios				
07.2017-02.2018	a	γ_1	γ_2	AIC	RSE
Cryptocurrency	2.047 (0.444)*	0.564 (0.036)*	0.178 (0.027)*	931.4	4.009
Emerging FX	0.358 (0.020)*	0.212 (0.070)*	0.048 (0.049)	-97.4	0.177
Emerging Stock	0.294 (0.047)*	0.999 (0.012)*	-0.013 (0.011)	269.4	0.539

	Global minimum-variance portfolios				
Cryptocurrency	2.861 (0.336)*	0.358 (0.040)*	0.055 (0.028)**	832.4	2.970
Emerging FX	0.359 (0.020)*	0.233 (0.081)*	0.061 (0.057)	-95.6	0.178
Emerging Stock	0.414 (0.051)*	0.962 (0.026)*	0.086 (0.026)	284.8	0.565
Panel D	Equally-weighted portfolios				
03.2018-10.2018	a	γ_1	γ_2	AIC	RSE
Cryptocurrency	-1.578 (0.367)*	1.029 (0.030)*	-0.049 (0.030)	915.0	4.158
Emerging FX	0.159 (0.036)*	0.924 (0.010)*	0.084 (0.010)*	178.6	0.416
Emerging Stock	0.708 (0.104)*	0.904 (0.029)*	-0.101 (0.026)*	477.8	1.060
	Global minimum-variance portfolios				
Cryptocurrency	2.979 (0.271)*	0.206 (0.073)*	0.037 (0.050)	734.7	2.367
Emerging FX	0.307 (0.032)*	0.782 (0.020)*	-0.036 (0.017)**	122.1	0.349
Emerging Stock	0.389 (0.074)*	0.877 (0.024)*	-0.042 (0.019)**	364.3	0.744
Panel E	Equally-weighted portfolios				
11.2018-06.2019	a	γ_1	γ_2	AIC	RSE
Cryptocurrency	2.236 (0.282)*	0.288 (0.052)*	0.071 (0.034)**	644.4	2.228
Emerging FX	0.223 (0.030)*	0.908 (0.032)*	-0.080 (0.031)**	92.3	0.328
Emerging Stock	0.665 (0.097)*	0.811 (0.037)*	-0.096 (0.029)*	357.8	0.824
	Global minimum-variance portfolios				
Cryptocurrency	1.933 (0.355)*	0.578 (0.060)*	-0.101 (0.049)**	766.9	3.410
Emerging FX	0.430 (0.030)*	0.236 (0.114)**	0.007 (0.080)	15.9	0.251
Emerging Stock	0.629 (0.072)*	1.001 (0.022)*	0.065 (0.021)*	348.7	0.798

Note: The standard errors associated with the estimated regression coefficients are reported in brackets; and the statistical significance level is marked as "*"1%; "**" 5%; and "***"10%. RSE represents the residual standard error of the fitted regression, and AIC is the well-known Akaike information criterion. The estimations are based on the ordinary least squares (OLS) approach.

Table 2.35: Time sample QR regression estimates for $CSAD_{m,t}$

Panel A	Equally-weighted portfolios								
	tau=0.25			tau=0.50			tau=0.75		
29.10.2016-07.06.2019	a	γ_1	γ_2	a	γ_1	γ_2	a	γ_1	γ_2
Cryptocurrency	0.731*	0.344*	0.107*	1.127*	0.546*	0.102**	1.897*	0.791*	0.033*
Emerging FX	0.193*	0.627*	0.068	0.259*	0.961*	0.042	0.426*	0.972*	0.029
Emerging Stock	0.070	0.702*	-0.031	0.193***	0.843*	-0.062	0.409*	0.989*	-0.003
	GMV portfolios								
Cryptocurrency	0.819*	0.296*	0.081*	1.165*	0.508*	0.073***	1.712*	0.759*	-0.006
Emerging FX	0.286*	0.215*	0.038	0.398*	0.206*	-0.008	0.518*	0.396*	-0.112
Emerging Stock	0.283*	0.532*	0.019	0.483*	0.609*	-0.031	0.648*	0.701*	-0.015
Panel B	Equally-weighted portfolios								
	tau=0.25			tau=0.50			tau=0.75		
29.10.2016-30.06.2017	a	γ_1	γ_2	a	γ_1	γ_2	a	γ_1	γ_2
Cryptocurrency	0.704*	0.693*	-0.057	1.594*	0.755*	**-0.061****	3.388*	0.803*	-0.032
Emerging FX	0.009*	0.957*	0.033	0.187*	0.966*	0.040**	0.334*	0.978*	0.025***
Emerging Stock	-0.130	0.875*	-0.120	0.041	0.911*	-0.083	0.349	0.992*	-0.001
	GMV portfolios								
Cryptocurrency	1.237*	0.615*	-0.060	2.065*	0.812*	**-0.174****	3.859*	0.790*	**-0.182***
Emerging FX	0.302*	0.327**	-0.053	0.397*	0.335*	-0.010	0.507*	0.290	-0.037
Emerging Stock	0.306*	0.552*	**-0.090****	0.415*	0.642*	**-0.073***	0.611*	0.678*	**-0.082****

Panel C	Equally-weighted portfolios								
	tau=0.25			tau=0.50			tau=0.75		
01.07.2017-28.02.2018	a	γ_1	γ_2	a	γ_1	γ_2	a	γ_1	γ_2
Cryptocurrency	0.990*	0.400*	0.154*	2.001*	0.533*	0.177*	3.450*	0.649*	0.175*
Emerging FX	0.245*	0.143*	0.069***	0.323*	0.176**	0.118***	0.444*	0.222***	0.071
Emerging Stock	0.015	0.757*	-0.074	0.096***	0.914*	-0.060	0.371*	0.963*	-0.008
	GMV portfolios								
Cryptocurrency	1.563*	0.257*	0.080**	2.472*	0.290*	0.108*	3.679*	0.419*	0.120
Emerging FX	0.243*	0.148*	0.071**	0.327*	0.136	0.151***	0.452*	0.177	0.106
Emerging Stock	0.048	0.792*	0.164*	0.275*	0.845*	0.154*	0.463*	0.905*	0.092***
Panel D	Equally-weighted portfolios								
	tau=0.25			tau=0.50			tau=0.75		
01.03.2018-31.10.2018	a	γ_1	γ_2	a	γ_1	γ_2	a	γ_1	γ_2
Cryptocurrency	-2.946*	0.848**	-0.163	-0.118	-0.478	0.891	0.299	0.943***	-0.066
Emerging FX	-0.015	0.866*	0.117	0.160	0.933*	0.077	0.460**	0.923*	0.084
Emerging Stock	0.127	0.724*	-0.038	0.447*	0.816*	**-0.101****	0.843*	0.881*	**-0.125***
	GMV portfolios								
Cryptocurrency	1.124*	0.099**	-0.042	1.760*	0.145*	0.051	2.498*	0.261***	0.118
Emerging FX	0.143*	0.668*	0.001	0.278*	0.775*	-0.028	0.479*	0.820*	-0.053
Emerging Stock	0.236**	0.667*	-0.026	0.412*	0.897*	-0.034	0.746*	0.902*	-0.026
Panel E	Equally-weighted portfolios								
	tau=0.25			tau=0.50			tau=0.75		
01.11.2018-07.06.2019	a	γ_1	γ_2	a	γ_1	γ_2	a	γ_1	γ_2
Cryptocurrency	0.641*	0.187*	0.019	1.258*	0.220*	0.058***	1.884*	0.323*	0.101***
Emerging FX	0.190*	0.632*	-0.026	0.257*	0.832*	-0.044	0.351*	0.965*	-0.045
Emerging Stock	0.309*	0.562*	-0.045	0.590*	0.593*	-0.065	0.724*	0.807*	**-0.109****
	GMV portfolios								
Cryptocurrency	0.871*	0.165*	0.031	1.131*	0.278*	0.032	1.431*	0.757*	-0.133
Emerging FX	0.301*	0.096***	0.087**	0.405*	-0.013	0.079	0.499*	0.302	-0.050
Emerging Stock	0.131	0.720*	0.143	0.306*	0.948*	0.072	0.667***	0.979*	0.036

Statistical significance:""1%; "**"5%; and "***"10%.*

Like Bouri et al., (2019) and da Gama Silva et al., (2019), our detection of herd effect is dependent on the time samples. Such evidence of time-dependent herd effect could be explained from the view that rational investors do not make static decisions over time, but vary their stands towards the market. Also, the presence of herding in the emerging markets may be linked to the low intensity of informational flow, frequent price variations, and the existence of amateur investors. Similarly, the herd effect in the cryptocurrency could mostly be attributed to its price surges and expected high returns, as well as the activities of inexperienced or uninformed traders who merely follow the crowd. Moreover, we argued that the presence of herd effect in the markets does not just increase an investor's risk, but renders the markets inefficient and

reduces the possibility of diversification benefits, owing to the fact that individual traders downplay their own beliefs and unique trading strategies to merely follow others or herd on the market performance.

In summary, our study through the CSSD and CSAD measures have unveiled (anti-) herding behaviour for the cryptocurrency and two distinct traditional emerging asset markets. Highlights from the study's results are as follows: (i) Significant herding looks more pronounced in the emerging stock and cryptocurrency markets, especially when considered under the GMV; (ii) Like Bouri et al., (2019), evidence of time-dependent herding is documented, signalling the rationality of investors of these markets in-terms of making trading decisions over-time; (iii) Owing to the absence of significant herding behaviour, the rational asset-pricing model is best used to explain the extreme price variations at the tail distribution of the FX market; and (iv) Comparatively, the behavioural characteristics of the cryptocurrency market are qualitatively less distinctive from that of the stocks. Altogether, our results hold important implications for investors, risk managers, and regulatory agencies in emerging economies. Thus, herd trading does not just increase investors' risk but in addition, renders the markets inefficient and reduces the possibility of diversification benefits since individual traders downplay their unique trading strategies to follow other colleagues or herd on the prevailing market performance. This phenomenon fuels speculative trading that culminate to heighten market uncertainty and instability. Meanwhile, the potential common drivers that induce herding in these markets remain a subject for future research.

2.5 Concluding remarks

As the uncertainties surrounding existing conventional financial markets continue to deepen due to a multiplicity of factors, the introduction of a new global market in the form of digital currencies a decade ago has gradually been embraced not only by the

enthusiastic libertarian public, but among heterogeneous groups of users. The machine-driven currency market triumphs on powerful blockchain technology to facilitate a decentralized peer-to-peer simple cash payment network. Although the new currency market has received intense criticisms such as being less transparent, its avoidance of supervision and interference, mainly by financial intermediaries, as well as the recent evolution of the market in the global space remains laudable, and as a result, courted immense global attention. Aside its originally introduced role or identity as a monetary instrument, which is also upheld in a Japanese Payment Services Act (article 2, paragraph 5), other economies through their regulatory agencies view it otherwise. For instance, in the United States, it is classified as property by the Internal Revenue Service, and as tradable commodities by the Commodity Futures Trading Commission, but the Exchange Traded Funds (ETF) of Bitcoin, the largest and most liquid cryptocurrency was rejected by the country's Security and Exchange Commission (SEC). In the same way as the United States SEC, several regulatory agencies, including monetary authorities and the general investor community are still unsure of the kind of financial instrument that characterizes cryptocurrencies, therefore, raising the issue of an identity crisis.

Weighing in on this, our study have attempted to chart a path which empirically assesses the functional form and nature of the digital currency market vis-à-vis existing emerging markets, proxied mainly by the BRICS and other emerging economies within the G20 (excluding Saudi Arabia). Using the historical price movement of the markets, a range of statistical and financial characteristics are compared. To mention few, the price or return distribution, stochastic and chaotic signals (randomness vs. chaoticity), fractality, asymmetry and local leverage, and herding characteristics are documented. From the empirical perspective, the cryptocurrencies bear the least resemblance to the traditional currencies of the emerging market economies. The collective results indicate that the characteristics of the two latter markets have very little in common. Our findings unveil a currency

market which fairly mimics, as at now, the inherent market characteristics of emerging market equities.

Even though our results do not look overly exhaustive, the study being the first of its kind to contextualize the evolving characteristics of cryptocurrencies has set sailed to provoke a continual debate on the appropriate designation of the new currencies, not only through the use of historical price changes, but to involve other market quantities and subject the currencies to standard scrutiny of demand for and supply of money, and other examinations that question the ideals of neoclassical economics, relative to those of the traditional currencies of specific economies.

We envisage that such important pool of literature could form one of the readily available sources from which regulators, especially of emerging market economies may tap to inform their decisions on the future of digital currencies, in the wake of the increasing demand for electronic commerce and the digitalization of national and global economies

CHAPTER 3

Dynamic Co-variation and Diversification with Applications to Cryptocurrencies and other Financial Assets

"Africa is one continent, one people and one nation" ***Kwame Nkrumah***

3.1 Introduction

Among the immediate upsets from the last global financial crisis were the decline in asset prices and investment returns, a continual heightened uncertainty, and an increase in the correlation between mainstream financial assets. The aftershocks of the crisis prompted the investor community to somewhat lessen their dependence on traditional assets, and to instead explore alternative investment opportunities. Risk managers and the general investor community reeling themselves from these shocks, in 2009, launched Bitcoin as a digital currency, which subsequently garnered immense traction to culminate into a new asset class known as cryptocurrency.

In the seminal work by Nakamota (2008), cryptocurrency, pioneered by Bitcoin was foremost introduced as an innovative channel to transact electronic payments under a fully decentralised peer-to-peer system without recourse to financial institutions. This explanation places cryptocurrency to contend with the functional roles of fiat currency, yet critics like Yermack (2014) argues against the former's maturity to perform the functions of the latter.

Meanwhile, despite concerns of anonymity, which could breed fraudulent transactions, money laundering, high level of insecurity, and issues of instability, the rapid growth of the cryptocurrency market has courted unbridled widespread interest by the general populace, in the financial media, among regulators, and investors alike. As a medium of exchange, many users are attracted to its lower costs of transaction,

lack of financial intermediaries and central bank controls, non-existence of bilateral base exchange rate effect, as well as inflation, and the tendency of providing a global platform for instant cash transfers via foreign and local remittances. Perhaps, these factors partially account for the surge in price, trading volume, market size, and the number of usable digital currencies. For instance, from the end of 2015 to 2018, the price of Bitcoin skyrocketed from approximately 430 to 3,829 US dollars, while its corresponding market capitalisation increased from 6.4 to 66 billion. At the same period, the number of cryptocurrencies jumped almost four-folds from over 500 to a little around 2000, with overall capitalisation rising from 7.0 to 130.1 billion US dollars (refer, https://coinmarketcap.com/).

In parallel, the mammoth attention towards the new currency market has sparked increased research interest in the price and other observed market quantities of cryptocurrency. Baur et al., (2018b) disclosed that Bitcoin is largely used now as a speculative investment asset, than a currency. Affirming the concluding remark by Baur et al., (2018b), Aslanidis et al., (2019) sounded even more sceptical on the suitability of Bitcoin to function as a store of value. Earlier, Bouri et al., (2017) found a diversifier role for Bitcoin, while Corbet et al., (2018) extended such role to cover Ripple and Litecoin. Bouri et al., (2020a), established diversification and hedge roles of Bitcoin and other major virtual currencies against advanced equity markets. Pavković et al., (2019) detected a very weak correlation between cryptocurrencies and key equities on the European market and further found Bitcoin and Ripple to be good diversifiers for most of the observed equities. Aside from reporting evidence of a decoupled cryptocurrency market from other financial markets, extensive investment benefits of the new currencies are now mushrooming in few empirical studies (see, Kostika and Laopodis, 2019; Shahzad et al., 2020; Stensås et al., 2019; Symitsi and Chalvatzis, 2019; Urquhart and Zhang, 2019; Wang et al., 2019; etc.). However, the analyses from the existing works have so far failed to investigate, exclusively,

probable investment benefits of the cryptocurrency asset in an emerging market setting.

Our study strives to fill the knowledge gap by providing fresh insight into the dynamic linkages between cryptocurrencies and emerging financial asset markets and assesses the kind of investment opportunities that prevail to the advantage of the heterogeneous group of emerging market investors. The contribution of our work to literature is multifarious. Firstly, we examine the extent of conditional correlation and co-movement structure between the cryptocurrency market and equities and foreign exchange rates of 10 giant emerging economies, using the dynamic conditional correlation (DCC), asymmetric DCC, and the rolling-window wavelet correlation (RWWC) techniques. Even though the RWWC technique is not new, it has rarely been applied in cryptocurrency research. Hence, we believe its combination with the time-varying symmetric and asymmetric conditional correlation approaches offers relevant contribution to the analysis, as issues of nonlinearity, regime shift, and extreme price changes are well-captured. Secondly, from a wavelet correlation matrix, we construct a frequency-based diversification ranking of the markets to better inform investment decisions of scale-conscious traders. Thirdly, we assess the risk-adjusted performance in varying time periods, and along trading time-scales of multi-asset portfolios comprising two leading cryptocurrencies and regional groups of emerging assets, under the naïve and mean-variance frameworks. Fourth, we assess the extent to which major cryptocurrency news headlines or events influence the latter's relatedness with other markets. Finally, drawing on few of the literature gaps identified by Corbet et al., (2019), and juxtaposing such vacuums in our context, we explore plausible economic capabilities of Bitcoin and Ripple to an emerging market investor[46]. Thus, we provide answers as to whether each or both mega-size digital currencies, which

[46] We scaled down to conduct our analysis on only Bitcoin and Ripple, owing to the reason that most of the digital currencies are mere clones of Bitcoin, except for Ripple. Hence, they behave much common. Therefore, we discared the clones of Bitcoin to include Ripple and the former for further anal

has been the epicentre of cryptocurrency-related research offer any benefit during periods where emerging markets wanders in distress.

The remainder of the chapter is organised as follows: Section 3.2 review in detail, the literature on correlation, co-movement, and investability of cryptocurrencies vis-à-vis other assets. Section 3.3 explains the pool of econometric techniques employed. Section 3.4 presents preliminary results, while Sections 3.5-3.6 give expanded analyses of the main results. Finally, Section 3.7 concludes the chapter.

3.2 Review of related literature

Brière et al., (2015) pronounced the correlation between Bitcoin and other assets as remarkably low and found through the mean-variance spanning tests that Bitcoin investment does not only provides greater diversification benefits but its inclusion, even in the least amount, dramatically improve the risk-return trade-off of well-diversified portfolios. Nonetheless, in a caution statement, the authors recounted that such low correlations reflect during the bullish period and do not cover periods of market stress. They also push for care to be taken when interpreting their diversification results because the analysis captured the early-stage behaviour of the markets. Affirming the results of Brière et al., (2015), Baumöhl (2019) also projected the diversification role of Bitcoin and argued that other cryptocurrencies could better perform such a role. Baur et al., (2018a) studied the statistical properties of Bitcoin to unveil that it is uncorrelated with existing asset classes under different market conditions. Corbet et al., (2018) identified a diversifier role for cryptocurrencies, which they emphasize would benefit investors with short-term trading preferences and additionally showed a highly related currency market that remained isolated from traditional financial and economic assets.

Employing daily and weekly data (07.2011-12.2015) within a dynamic conditional correlation (DCC) modelling perspective, Bouri et al., (2017) found Bitcoin as an effective diversifier, but serves as a poor hedge instrument for major international stocks, bonds, gold, the US dollar index, oil, and the general commodity index. Mensi et al., (2018) used the cross-wavelet spectrum and wavelet coherency approach to establish a frequency-dependent co-movement between Bitcoin and Islamic equity returns, which they claim vary across countries. The results detailed better benefits of hedging, emanating from diversifying into Bitcoin and Islamic equities in the short-run. Kajtazi and Moro (2019) evaluated the benefits of including Bitcoin in well-diversified portfolios of US, European, and Chinese assets. Their finding has it that Bitcoin's inclusion improves the portfolio performance with regards to investment returns but tends to increase the risk of the portfolio.

In providing empirical evidence for the role of Bitcoin, Stensås et al., (2019) used the DCC model to find that Bitcoin best serves as a hedging tool for investors in the BRICS (Brazil, Russia, India, China, and South Africa), but only acts as a diversifier for investors in advanced countries, and global commodities. Employing 30 developed and developing equities, with 973 cryptocurrency assets, Wang et al., (2019) found that, in most of the cases, the cryptocurrency market behaved more as a safe haven but not a hedge, contrasting the findings by Stensås et al., (2019). Kang et al., (2019a) investigated hedging and diversification capabilities of Bitcoin and gold returns (26.07.2010-25.10.2017) with the DCC and wavelet coherence approaches. The wavelet results indicated a high level of correlation for the pair over 2012-2015 at specific frequency bands. However, the DCC estimations unveiled significant lower and negative correlations during 2014-2016, thereby giving opportunity for improved diversification rewards in the time-domain. Using variants of the DCC-GARCH modelling approach, Guesmi et al., (2019) analysed the properties of Bitcoin to conclude that it stands to offer investment benefits to investors. A noteworthy result from their study shows that hedging strategies comprising oil, gold, emerging stock

markets, and Bitcoin reduce substantially a portfolio's risk, in relation to the risk of a portfolio involving oil, gold, and emerging stocks only. Similar to its investment prospects, Kang et al., (2019b) used an extended version of the DCC model to reach a conclusion that Bitcoin offers an effective safe haven option for US investors.

Urquhart and Zhang (2019) investigated the relationship between Bitcoin and six major world fiat currencies (AUD, CAD, CHF, EUR, GBP, and JPY against USD) and found using the (asymmetric) dynamic conditional correlation (DCC and ADCC) that negative and positive correlations characterise the pairs of market, indicative that Bitcoin could act as a diversifier and hedge for international investors. Symitsi and Chalvatzis (2019) used four portfolio construction strategies to assess the economic gains of adding Bitcoin to portfolios of diverse asset classes and a well-diversified portfolio. Their results point to greater diversification rewards, especially for Bitcoin-commodity portfolio. Platanakis and Urquhart (2019a) examined potential diversification gains of including Bitcoin in a traditional stock-bond portfolio, to observe that the out-of-sample gains appear consistent over all the portfolio construction strategies, and varied levels of risk aversion. Shahzad et al., (2020) divulged two distinct functions (safe haven and hedge characteristics) of Bitcoin to the benefit of Canadian investors. Further, Bouri et al., (2020a) showed through the DCC and regression approaches that aside from Bitcoin, other major cryptocurrencies (like Ethereum, Ripple, Litecoin, and Stellar) could act as effective diversifiers and hedges, especially for Asia-Pacific and Japanese equities.

Aslanidis et al., (2019) adopted the generalised DCC model to assess the conditional correlation dynamics among the daily log-returns (21.05.2014-27.09.2018) of Bitcoin, Dash, Monero, and Ripple, against selected traditional assets (S&P500 Composite, S&P500 US Treasury bond 7-10Y, and gold bullion LBM). Among others, their results revealed that the cryptocurrency market is detached from the behaviour of the traditional financial markets. Kostika and Laopodis (2019) examined the short- and

long-run dynamic relationships between six cryptocurrencies (Bitcoin, Ethereum, Ripple, Dash, Stellar, and Monero) and leading bilateral exchange rates (Euro, Japanese Yen, British Pound, and the Chinese Yuan vs. US dollar), as well as international equities (DAX, S&P500, DJIA, CAC, FTSE, NIKKEI, Hang Seng, and Shanghai). Using the DCC-GARCH-type models, their results document weak interactive relationships among the cryptocurrencies, and further show the suitability for their inclusion in global investment portfolios. Pavković et al., (2019) proved with the DCC and wavelet-based correlation techniques that Bitcoin and Ripple offer substantial diversification gains for European traders.

Based on a static low-level positive correlation value for pairs of four most liquid cryptocurrencies (Bitcoin, Litecoin, Ripple, and Dash), Platanakis et al., (2018) postulate meaningful diversification opportunities, and constructed naïve (1/N) and optimal (Markowitz) portfolios for the four assets to assess their performance. From the results, not much difference in performance was found between the two portfolio diversification techniques, however, the authors favoured the naïve diversification over the optimal diversification. Using the same assets with preliminary lower positive correlation results, Platanakis and Urquhart (2019b) extended the work by Platanakis et al., (2018) with a third portfolio construction method (i.e. The Advanced Black-Litterman model) with variance-based constraints that accounts for errors. Concerning the out-of-sample risk-adjusted returns and lower risks, the latter approach outperformed the naïve and Markowitz diversifications. From a data sample covering 01.01.2015-31.12.2017 of the largest 500 cryptocurrencies, Brauneis and Mestel (2019) assessed risk-return benefits of diversified digital currency portfolios in the Markowitz mean-variance framework. Concerning estimations of the Sharpe ratio and certainty equivalent returns, the naïve diversified portfolio is reported to have outclassed the mean-variance optimal portfolios. Liu (2019), whose work examined the investability prospects in the cryptocurrency market, reached a

similar conclusion. The author's results affirmed the superiority of the naive portfolio under the Sharpe ratio criterion.

Mensi et al., (2019a) in a time-frequency domain examined co-movement between Bitcoin and five major cryptocurrencies, and also explore their diversification performance under three portfolio strategies. The results unmask leading relationships for Bitcoin-Dash, Bitcoin-Monero, and Bitcoin-Ripple, and argued in favour of a mixed portfolio, which is projected to offer better diversification gains for investors. Drawing their findings from a fitted IGARCH(1, 1)-DCC(1, 1) model, Kumar and Anandarao (2019) observed moderate return co-movement among four cryptocurrencies (Bitcoin, Ethereum, Ripple, and Litecoin), and also, provided evidence of persistent correlation with the wavelet coherency measure. With daily exchange rates of Bitcoin, Ethereum, Litecoin, and Dashcoin (07.08.2015-24.03.2018), Kumar and Ajaz (2019) examined short- to medium-run co-movement structure of the mentioned assets using wavelet-based correlation methods, and report of moderate to high correlations across the scales. The authors then discounted potential diversification benefits of a cryptocurrency portfolio, with an explanation that such investment looks risky since their results indicate that prices of the currencies are largely driven by Bitcoin. To a similar finding, Katsiampa (2019) found evidence of time-varying conditional correlations for the daily returns of Bitcoin and Ethereum, and ascribe that positive correlations seem stronger around the period of September 2017. Building on Katsiampa's (2019) work, Katsiampa et al., (2019b) concluded that the intra-day returns of eight cryptocurrencies display time-varying and highly positive conditional correlations. Ferreira and Pereira (2019) used the Detrended Cross-Correlation Analysis technique to identify evidence of contagion effect and showed that the returns of Bitcoin and 10 other leading cryptocurrencies are strongly integrated now than in the past. Based on their findings, the authors cautioned on the riskiness of investing in portfolios involving several cryptocurrencies.

Worthy of mentioning from the above review is a derived consensus from the dearth of the empirical literature, which elucidates the isolation of cryptocurrency market from mainstream financial assets. However, as the paucity of studies identified cryptocurrency as an effective diversifier (mainly through the use of Bitcoin), and in few cases as a hedge and/or safe haven tool for advanced assets, with correspondingly diverse investment advantages for European traders (Pavković et al., 2019), US/Canadian investors (Brière et al., 2015; Bouri et al., 2020a; Shahzad et al., 2020), and other investors worldwide (Bouri et al., 2017; Kajtazi and Moro, 2019; Urquhart and Zhang, 2019; etc), such opportunities have nearly been overlooked for emerging market investors. Therefore, using time- and frequency-varying estimation techniques, our study enriches the narrative by examining, in the lens of an emerging market trader, the kinds of investment benefits that characterise two of the leading global digital currencies (Bitcoin and Ripple).

3.3 Research methods

We adopt a range of empirical modelling strategies to assess the level of linkages among the markets. On one hand, the DCC and the ADCC models are used to quantify time-varying dynamic conditional symmetric and asymmetric correlation of pairs of market returns. Under the second approach, we decomposed the aggregate return series into time-scale constituents to explore risk-adjusted performance of scale-dependent diversified portfolios. Third, a bivariate wavelet correlation in a moving window context is employed. The procedure for each approach is explained in the subsequent subsections.

3.3.1 Time-varying conditional correlation approaches

Employing Engle's (2002) dynamic conditional correlation (DCC) model, with the asymmetric dynamic conditional correlation (ADCC) version by Cappiello et al., (2006), we estimate nexuses between the cryptocurrency market and assets of

emerging economies. For purposes of observing separate dynamic behaviours for Bitcoin and Ripple versus each emerging market asset, the DCC and ADCC models are estimated in a bivariate setting, hence avoiding the possibility of obtaining unreliable estimates, and the issues of computing complexities that prevails in modelling higher dimensions.

Let us consider r_t to be a k x 1 vector of our asset return realizations, where r_t is computed as percentage log changes of the daily closing prices. We set out an autoregressive process of order one, AR(1) for r_t to capture the autocorrelation within the return series, and assumes that $r_t|\Im_{t-1}$, where $\Im_{t-1}$ denotes the information set available at time t–1. Then:

$$r_t = \mu + \phi r_{t-1} + \varepsilon_t \tag{3.10}$$

$$\varepsilon_t = H_t^{1/2} z_t \tag{3.11}$$

Here, ε_t is a vector of residuals for the conditional mean equation, H_t represent the conditional variance-covariance matrix of r_t, and z_t is an i.i.d sequence of random errors given in a vector form. Next, a covariance stationary univariate GARCH-type process is specified to model the conditional variance of the DCC. Weighing on the observation by Engle and Shepherd (2008), we introduce asymmetry into the GARCH specification for the variance process. The nonlinear asymmetric GARCH [NAGARCH(1, 1)] of Engle and Ng (1993) which has capabilities of capturing asymmetry and/or local leverage (Caporin and Costola, 2019) as well as volatility clustering in the return series is used, and defined as:

$$h_{i,t} = \omega + \alpha\left(\varepsilon + \gamma\sqrt{h_{t-1}}\right)^2 + \beta h_{t-1} \tag{3.12}$$

where $h_{i,t}$ denote the conditional variance of the ith asset at time t, $\omega_1 > 0, \beta_1 \geq 0$, $\alpha_1 \geq 0$, and for covariance stationary, $\alpha_1 + \beta_1 + 0.5\gamma_1 < 1$.

In the second stage of the DCC modelling protocol, we express H_t as follows:

$$H_t = D_t P_t D_t \tag{3.13}$$

where from eqn (3.13), H_t is the covariance matrix, while P_t represent a k x k symmetric matrix of conditional correlations. D_t defines the diagonal matrix of time-varying conditional standard deviations, given by:

$$D_t = diag\left(h_{1,t}^{1/2},...,h_{n,t}^{1/2}\right) \tag{3.14}$$

The matrix P_t that contains the time-varying conditional correlation is written as:

$$P_t = \left(diag\, Q_t\right)^{-1/2} Q_t \left(diag\, Q_t\right)^{1/2} \tag{3.15}$$

given that,

$$Q_t = \left[q_{ij,t}\right] = \left(1-\theta_1-\theta_2\right)\overline{Q} + \theta_1 z_t z_{t-1}^{|} + \theta_2 Q_{t-1} \tag{3.16}$$

where Q_t gives the variance-covariance matrix of the standardized errors or residuals $z_t = \left(z_{i,t},...,z_{k,t}\right)$. $\overline{Q} = E\left(z_t z_t^{|}\right)$ is a k x k unconditional correlation matrix of z_t, and the unknown parameters θ_1 and θ_2 are positive scalars that satisfy the boundary condition $\theta_1 + \theta_2 < 1$, in order to allow positivity of the Q_t matrix. The symmetric DCC estimator between asset markets i and j is computed as:

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}\, q_{jj,t}}} \tag{3.17}$$

Building on the DCC of Engle (2002), Cappiello et al., (2006) introduced the ADCC, which incorporate asymmetries in the time-varying dynamic conditional correlations. They proposed a modification of the dynamic correlation evolution in eqn (3.16) as:

$$D_t = \left(\overline{Q} - A^{|}\overline{Q}A - B^{|}\overline{Q}B - G^{|}\overline{W}G\right) + G^{|}n_{t-1}n_{t-1}^{|}G + A^{|}z_{t-1}z_{t-1}^{|}A + B^{|}Q_{t-1}B \tag{3.18}$$

where A, B, and G denote k x k parameter matrices, $n_t = I\left[z_t < 0\right] \circ z_t$, and $\overline{W} = E[n_t n_t^{|}]$. Cappiello et al., (2006) refer eqn (3.18) as the asymmetric DCC given that the matrix parameters A, B, and G are substituted with scalars. To handle extreme movements of

the return distribution, we estimate the innovations of the conditional correlation models with the multivariate *t* distribution.

3.3.2 Wavelet decomposition

Unlike the DCC and ADCC models which offers flexibilities in quantifying nexuses between asset markets in the time domain settings, with limited investment options, the wavelet decomposition and correlation approaches provide a lean way to observe heterogeneous nexuses under diverse time-scales, with hindsight of different investment opportunities[47].

Specifically, a wavelet decomposition allows for the disaggregation of aggregated time series or return realisations into frequency (or time-scale) constituents. Such decomposition could be performed under either a Continuous Wavelet Transform (CWT) or the Discrete Wavelet Transform (DWT). While the latter works better for return series with definite range, the former is applicable for series defined over the real axis. Further, clearer distinction (Percival and Walden, 2000; Whitcher et al., 2000) and superiority (Fernández-Macho, 2012) of the Orthonormal or Maximal Overlap DWT (MODWT) over the conventional DWT are expatiated.

Following Fernández-Macho (2012), Ranta (2013), and Polanco-Martínez et al., (2018), we employ the MODWT, which draws on a multiresolution dynamic to decompose our asset (portfolio) return series into wavelet scales using the least asymmetric wavelet filter (LA), initially introduced in the work by Daubechies (1992). The LA(8) filter is widely preferred among practitioners perhaps due to the underlying reason that it gives estimated wavelet coefficients that are (less or) uncorrelated over the time-scales, and answers to the phenomenon of boundary conditions (Cornish et al., 2005).

[47] For comparative advantages of frequency-based correlation approaches, see Ftiti et al., (2015).

The expression $J = \log_2(N)$ is used in specifying the highest decomposition level, which in our case, becomes approximately a maximum level of 10 for Ripple and its basket of emerging assets (N = 1411), and 11 for that of Bitcoin (N = 1479). For higher Js, Fernández-Macho (2012) argues that the number of feasible wavelet coefficients tends critically small. Hence, in both specifications, we choose $j = 7$ to obtain seven non-zero wavelet and one scaling coefficients, given respectively as $\tilde{w}_{1,t}, \tilde{w}_{2,t}, ..., \tilde{w}_{7,t}$ and $\tilde{v}_{7,t}$.

It is imperative knowing that the time-scale of the derived wavelet constituents $\tilde{w}_{j,t}$ is dependent on the chosen level for the transformation. Also, the MODWT's structure is marked with the use of approximately suitable bandpass filters, having passband within the frequency interval $[2^{-(j+1)}, 2^{-j})$ for the scale levels $j = 1, ..., J$. The accuracy of the approximation is better enhanced as the size of the wavelet filter increases. By inverting the frequency range to get a time period, and further multiplying it by the approximate time units, i.e Δt, the resultant equivalent time periods are given by $[2^j, 2^{j+1}]\ \Delta t$ days for scale levels $j = 1, ..., J$ (Whitcher et al., 2000). Therefore, for our daily return series, the scale λ_j (where, $j = 1, ..., J$) of the obtained wavelet coefficients correspond to day periods of 2~4 (D1 - intraweek scale), 4~8 (D2 - weekly scale), 8~16 (D3 - fortnight scale), 16~32 (D4 - monthly scale), 32~64 (D5 - monthly to quarterly scale), 64~128 (D6 - quarterly to biannual scale), and 128 ~256 (D7 - biannual scale).

3.3.3 Bivariate rolling-window wavelet correlation method

An overriding edge of the wavelet correlation method is its ability to allow for multidimensional analysis, under which the strength of the correlation structure between assets markets are assessed in time and frequency domains. To analyse the level of linkages among the return series, the MODWT wavelet correlation, incorporation of a rolling-window is used to report temporal correlation patterns

across the time-scales. Based on the work by Gençay et al., (2002), we outline the MODWT wavelet covariance estimator at scale $\lambda_j \equiv 2^{j-1}$ as:

$$\tilde{\sigma}_X^2(\lambda_j) = \frac{1}{\tilde{N}_j} \sum_{t=L_j-1}^{N-1} \tilde{W}_{j,t}^2 \tag{3.19}$$

where $L_j = (2^j - 1)(L-1) + 1$ denote the length of the scale λ_j wavelet filter, $\tilde{w}_{j,t}$ represent the jth-level MODWT wavelet coefficients of the pairs of return series, and $\tilde{N}_j = N - L_j + 1$ gives the number of coefficients that are not affected by the boundary. Since the concept of covariance is not applicable for univariate return series (Ranta, 2013), we define the MODWT-based unbiased estimator of the wavelet correlation (WC), introduced by Gençay et al., (2002) as:

$$\tilde{\rho}_{XY} = \frac{\operatorname{cov}\left(\tilde{W}_{X,j,t}, \tilde{W}_{Y,j,t}\right)}{\left(\operatorname{var}\left(\tilde{W}_{X,j,t}\right)\operatorname{var}\left(\tilde{W}_{Y,j,t}\right)\right)^{1/2}} = \frac{\tilde{\gamma}_{XY}(\lambda_j)}{\tilde{\sigma}_X(\lambda_j)\tilde{\sigma}_Y(\lambda_j)} \tag{3.20}$$

Here, $\tilde{\gamma}_{XY}(\lambda_j)$ represent the unbiased estimator of the wavelet covariance for the wavelet constituents $\tilde{W}_{X,j,t}$ and $\tilde{W}_{Y,j,t}$ involving the pair of distinct series, and $\tilde{\sigma}_X^2(\lambda_j)$ and $\tilde{\sigma}_Y^2(\lambda_j)$ denote unbiased measures of the wavelet variances for X and Y at scale λ_j. In simple words, Whitcher et al., (2000), described the WC as a nonlinear function of wavelet covariance and two variances.

The confidence interval (CI) for WC is constructed based on the approach by Whitcher et al., (2000). Of particular interest, an approximate $100(1-2p)\%$ CI that captures non-spurious WC for pairs of returns series is deduced as:

$$\left[\tanh\left\{h\left[\tilde{\rho}_{XY}(\lambda_j)\right] - \frac{\Phi^{-1}(1-p)}{\left(\tilde{N}_j - 3\right)^{1/2}}\right\}, \tanh\left\{h\left[\tilde{\rho}_{XY}(\lambda_j)\right] + \frac{\Phi^{-1}(1-p)}{\left(\tilde{N}_j - 3\right)^{1/2}}\right\}\right] \tag{3.21}$$

where the function $h\left(\tilde{\rho}_{XY}\right)=\tanh^{-1}\left(\tilde{\rho}_{XY}\right)$ describes Fisher's z-transformation, while the number of estimated wavelet coefficients that correspond to a particular scale is given by $\tilde{N}_j$.

Like Polanco-Martínez et al., (2018), we choose to estimate the pairwise rolling-window wavelet correlation (RWWC) at $J=4$, instead of the maximum levels of $J=\log_2(N=1411)\approx 10$ and $J=\log_2(N=1479)\approx 11$, because the selected size of the window ($w=250$ return realisations) induces a substantial decrease in the derived maximum level. Although the 250 rolling-window size (which corresponds to a trading year) feasibly allow correlation estimates under five wavelet scales D1, …,D5 (N-w number of windows), we performed our analysis using the initial four scales, i.e. the intraweek (smaller day-band) to the monthly (medium) time-scales. As done in the work by Benhmad (2013) and currently by Polanco-Martínez et al., (2018), we rolled forward the return realisations one at a time, and centred such movement on time t, to compute the pairwise RWWC.

3.4 Data and preliminary results

After screening a universe of cryptocurrencies, we only focused on the most liquid currencies with over 10 billion US dollars market capitalisation (as of 05.03.2019[48]), and on those with lengthier data, commencing around 2013. In such regard, data[49] on Bitcoin and Ripple are chosen for our analysis. In addition, we considered stocks (BOVESPA, NIFTY50, MOEX, SSE50, BIST30, FTSE/JSE TOP40, KOSPI200, Indonesian-JCI, MEXBOL, and MERVAL) and bilateral foreign currencies (forex or

[48] The date format is given by dd.mm.year

[49] The cryptocurrency data was obtained from https://coinmarketcap.com/ on 05.03.2019. We later updated it on 07.06.2019 to reflect current price movement.

FX) of emerging economies within the G20[50] setup, except for Saudi Arabia, which for purposes of data inconsistency[51] was ruled-out from the study. For uniformity, we sourced all market data in US dollars. The data spans 29.04.2013-07.06.2019, and was cleaned to synchronize with each other.

3.4.1 Unconditional rolling-window correlation results

Table 3.10 presents descriptive statistical measures of the pairwise unconditional correlations between the daily log-return of Bitcoin/Ripple and the emerging stock, as well as the forex markets. Differing from previous empirical works which report static correlations (through standard correlation methods) in the cryptocurrency literature (Brière et al., 2015; Baur et al., 2018a; Baumöhl (2019); Kajtazi and Moro, 2019; Kostika and Laopodis, 2019; etc.) as part of their analysis, we consider, rather, a measure of relationship that incorporates time variations due to the frequent price fluctuations of the market. In such regard, a rolling-window Pearson correlation is applied with two window sizes, w = 125 and w = 250 days (or return realisations), corresponding respectively to biannual and annual trading periods. We compute rolling-window correlations using the expression (N–w+1), and by rolling forward one day (or realisation) at a time with a centred option (similar to Polanco-Martínez, 2019), hence, downplaying on the standard methods which only compute a global measure.

Table 3.10: Unconditional pairwise rolling-window correlations

	125-day rolling-window				250-day rolling-window			
	Min	Max	Mean	SD	Min	Max	Mean	SD
Panel A: Bitcoin vs. Emerging foreign currencies								
Bitcoin-Argentina Peso	-0.198	0.202	-0.012	0.079	-0.134	0.087	-0.013	0.041
Bitcoin-Brazilian Real	-0.250	0.298	-0.005	0.101	-0.132	0.173	-0.014	0.061
Bitcoin-Mexican Peso	-0.229	0.212	-0.040	0.086	-0.146	0.058	-0.046	0.041
Bitcoin-Russian Rubble	-0.164	0.161	0.003	0.078	-0.117	0.104	0.008	0.051
Bitcoin-South African Rand	-0.254	0.191	-0.016	0.095	-0.176	0.129	-0.021	0.076

[50] Refer, www.ifrs.org/groups/emerging-economies-group/#members for a complete list of the countries

[51] The equity data is sourced from Bloomberg database terminal

Bitcoin-Turkish Lira	-0.155	0.233	0.001	0.086	-0.120	0.105	0.002	0.054
Bitcoin-Chinese Yuan	-0.200	0.238	0.003	0.100	-0.126	0.135	0.000	0.064
Bitcoin-South Korean Won	-0.281	0.244	0.020	0.115	-0.144	0.206	0.017	0.088
Bitcoin-Indian Rupee	-0.178	0.210	0.030	0.092	-0.096	0.134	0.032	0.061
Bitcoin-Indonesian Rupiah	-0.171	0.174	0.009	0.066	-0.111	0.133	0.005	0.050
Panel B: Ripple vs. Emerging foreign currencies								
Ripple-Argentina Peso	-0.173	0.252	0.038	0.078	-0.077	0.166	0.027	0.041
Ripple-Brazilian Real	-0.218	0.230	0.028	0.079	-0.140	0.162	0.022	0.054
Ripple-Mexican Peso	-0.194	0.208	-0.016	0.082	-0.138	0.066	-0.022	0.039
Ripple-Russian Rubble	-0.146	0.218	0.010	0.081	-0.131	0.182	-0.005	0.062
Ripple -South Africa Rand	-0.271	0.291	0.005	0.133	-0.153	0.242	-0.009	0.102
Ripple-Turkish Lira	-0.205	0.169	-0.009	0.082	-0.144	0.106	-0.007	0.064
Ripple-Chinese Yuan	-0.256	0.148	0.012	0.063	-0.088	0.116	0.016	0.040
Ripple-South Korean Won	-0.243	0.308	0.050	0.128	-0.121	0.254	0.048	0.101
Ripple-Indian Rupee	-0.157	0.270	0.044	0.093	-0.160	0.190	0.039	0.071
Ripple-Indonesian Rupiah	-0.214	0.194	0.060	0.076	-0.118	0.145	0.054	0.053
Panel C: Bitcoin vs. Emerging stock markets								
Bitcoin-MERVAL	-0.168	0.270	0.055	0.067	-0.031	0.173	0.058	0.043
Bitcoin-BOVESPA	-0.233	0.231	0.045	0.088	-0.028	0.141	0.040	0.039
Bitcoin-MEXBOL	-0.236	0.278	-0.016	0.115	-0.155	0.106	-0.018	0.070
Bitcoin-MOEX	-0.297	0.269	0.045	0.123	-0.168	0.120	0.045	0.093
Bitcoin-FTSE/JSE TOP40	-0.225	0.200	0.006	0.088	-0.149	0.120	0.006	0.063
Bitcoin-BIST30	-0.153	0.289	0.033	0.091	-0.086	0.167	0.032	0.062
Bitcoin-SSE50	-0.353	0.227	-0.020	0.141	-0.202	0.138	-0.030	0.085
Bitcoin-KOSPI200	-0.244	0.231	0.005	0.657	-0.147	0.131	0.003	0.063
Bitcoin-NIFTY50	-0.172	0.179	-0.000	0.084	-0.133	0.657	0.657	0.657
Bitcoin-Jakarta Stock Index	-0.274	0.154	0.015	0.085	-0.162	0.106	0.015	0.055
Panel D: Ripple vs. Emerging stock markets								
Ripple-MERVAL	-0.087	0.236	0.057	0.067	-0.062	0.173	0.055	0.045
Ripple-BOVESPA	-0.221	0.178	0.043	0.081	-0.137	0.156	0.045	0.056
Ripple-MEXBOL	-0.165	0.309	0.022	0.103	-0.107	0.152	0.015	0.064
Ripple-MOEX	-0.217	0.330	0.008	0.124	-0.181	0.255	0.006	0.089
Ripple-FTSE/JSE TOP40	-0.240	0.300	0.014	0.141	-0.159	0.247	0.005	0.110
Ripple-BIST30	-0.276	0.190	-0.026	0.085	-0.165	0.123	-0.023	0.063
Ripple-SSE50	-0.284	0.303	0.004	0.130	-0.192	0.213	-0.006	0.077
Ripple-KOSPI200	-0.183	0.395	0.066	0.137	-0.116	0.277	0.067	0.097
Ripple-NIFTY50	-0.221	0.253	0.010	0.093	-0.142	0.147	0.005	0.068
Ripple-Jakarta Stock Index	-0.117	0.310	0.070	0.087	-0.079	0.194	0.064	0.064

Note: Min, Max, Mean and SD denote the minimum, maximum, average and standard deviation of the Pearson's unconditional correlation coefficients based on a 125-day (biannual) and 250-day (annual) rolling-window estimations.

From the average correlation measures in Table 3.10, it is evidential that Bitcoin and Ripple are weakly correlated with emerging assets, irrespective of the window size of the correlation approach. The magnitude of the average correlations is slightly smaller

for Bitcoin and its pairs than Ripple. A similar pattern is observed for the FXs relative to the stocks. Consistently, the relationship between Bitcoin and the Latin America FXs does not only appears weak but also negatively correlated under both window sizes. Though not overly widened, the variability measure depicts that the estimated correlations are not static but instead time-variant.

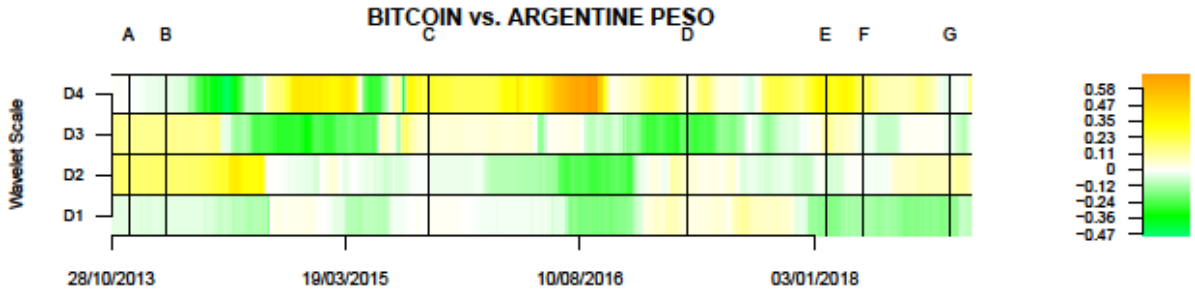
Generally, we describe the correlations for (Bitcoin-) Ripple-emerging stocks and (Bitcoin-) Ripple-emerging FXs as mostly positive, but extremely weak, as also found by Kostika and Laopodis (2019) for some major advanced assets and six virtual currencies, yet contrasting the fairly high correlated Bitcoin-US assets (Kajtazi and Moro, 2019). These average correlation patterns signal opportunities for expected diversification gains. Nonetheless, the existence of such gains is further probed with robust modelling approaches. Thus, it is known that the rolling-window Pearson method gives an account of the stability of estimated correlation coefficients with time, however, the imposition of linear relationship coupled with its weak powers against non-normally distributed prices, as well as non-linear dynamics like regime shifts, volatility clustering, and extreme price movement – which are common features of financial market returns, limit the usefulness of the method. In the perspective of heterogeneous groups from the investor community, the average analysis holds little relevance, hence our motivation to examine inter-market relatedness using other time-varying approaches and at four different investment horizons.

3.5 Evidence from time-varying dynamic conditional correlation

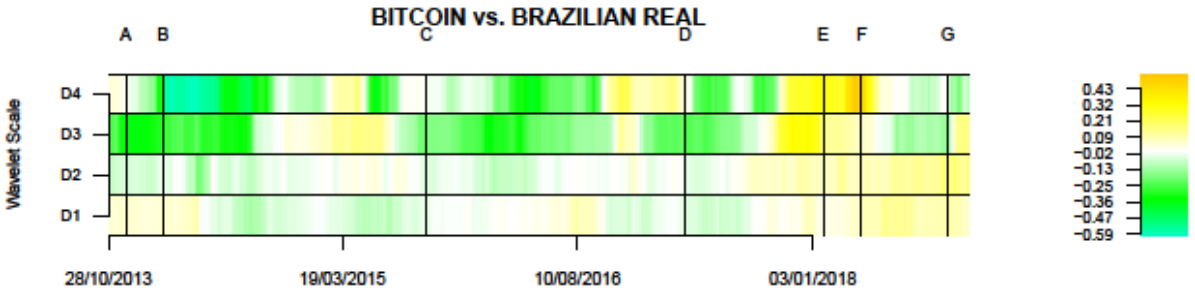
The dynamic conditional correlations for the pairs of markets involving Bitcoin-emerging FXs, Bitcoin-emerging stocks, Ripple-emerging FXs, and Ripple-emerging stocks are respectively displayed in *Appendices 3.A1-3.A2*, *3.A3-3.A4*, *3.B1-3.B*2, and *3.B3-3.B4*. For brevity, we only focus our interest on the extracted pairwise conditional

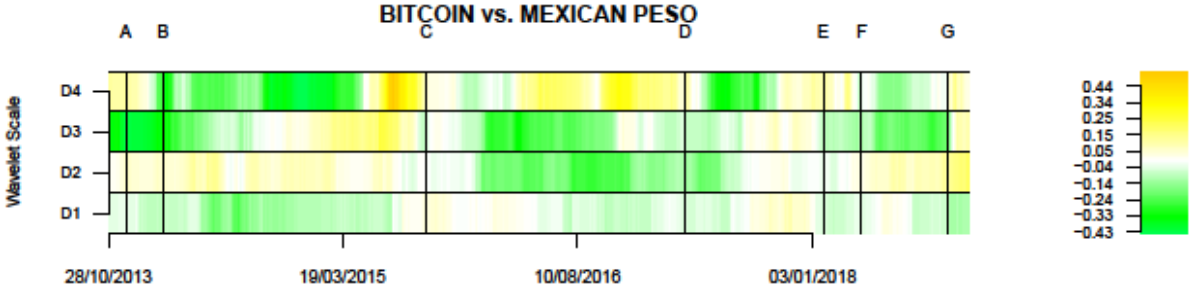
correlations. However, our diagnostic checks confirm appropriateness for majority of the fits[52].

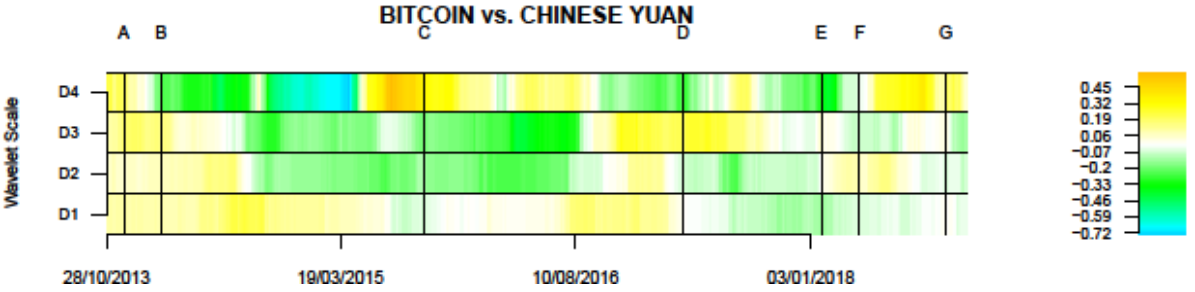
Observably, the pairwise conditional correlations vary over the time sample. Similar to the classical unconditional correlations, the DCC and ADCC re-affirm evidence of weak time-varying pairwise linkages, which largely swings within the positive region – suggestive of a situation where investors are required to oftentimes adjust assets in their investment baskets in order to maximise diversification gains. Meanwhile, few of the pairs (Bitcoin-Lira, Bitcoin-Rupiah, Bitcoin-Rand, Bitcoin-Nifty50, Bitcoin-Mexbol, and Ripple-Bist30) consistently recorded negative relationships. To a slight extent, the level of linkages between each of the two cryptocurrencies and the emerging assets differs. For instance, while markets like Bitcoin-Lira, Bitcoin-Rupiah among others are predominantly negative related, a reverse relationship is witnessed between Ripple and such markets under both the DCC and ADCC approaches. Perhaps, both assets, i.e. Bitcoin and Ripple could somehow serve different roles in an emerging market, apart from their much-trumpeted roles in advanced markets (Bouri et al., 2017; Bouri et al., 2020a; Urquhart and Zhang, 2019; etc.).

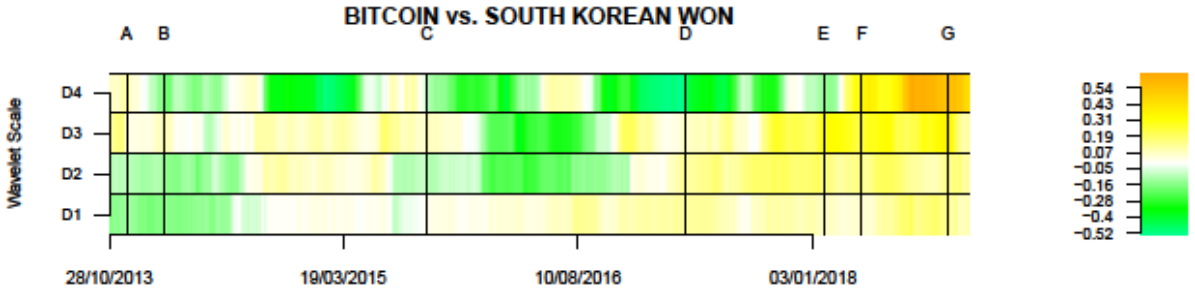


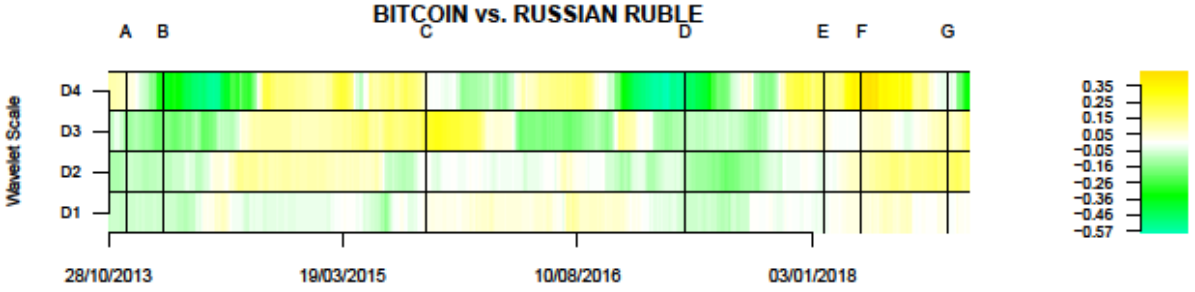
[52] Estimation codes (R statistical software scripts) and coefficients are readily accessible from authors.


BITCOIN vs. BRAZILIAN REAL
A B C D E F G
Wavelet Scale
D4 D3 D2 D1
28/10/2013 19/03/2015 10/08/2016 03/01/2018
0.43 0.32 0.21 0.09 −0.02 −0.13 −0.25 −0.36 −0.47 −0.59


BITCOIN vs. MEXICAN PESO
A B C D E F G
Wavelet Scale
D4 D3 D2 D1
28/10/2013 19/03/2015 10/08/2016 03/01/2018
0.44 0.34 0.25 0.15 0.05 −0.04 −0.14 −0.24 −0.33 −0.43


BITCOIN vs. CHINESE YUAN
A B C D E F G
Wavelet Scale
D4 D3 D2 D1
28/10/2013 19/03/2015 10/08/2016 03/01/2018
0.45 0.32 0.19 0.06 −0.07 −0.2 −0.33 −0.46 −0.59 −0.72


BITCOIN vs. SOUTH KOREAN WON
A B C D E F G
Wavelet Scale
D4 D3 D2 D1
28/10/2013 19/03/2015 10/08/2016 03/01/2018
0.54 0.43 0.31 0.19 0.07 −0.05 −0.16 −0.28 −0.4 −0.52


BITCOIN vs. RUSSIAN RUBLE
A B C D E F G
Wavelet Scale
D4 D3 D2 D1
28/10/2013 19/03/2015 10/08/2016 03/01/2018
0.35 0.25 0.15 0.05 −0.05 −0.16 −0.26 −0.36 −0.46 −0.57

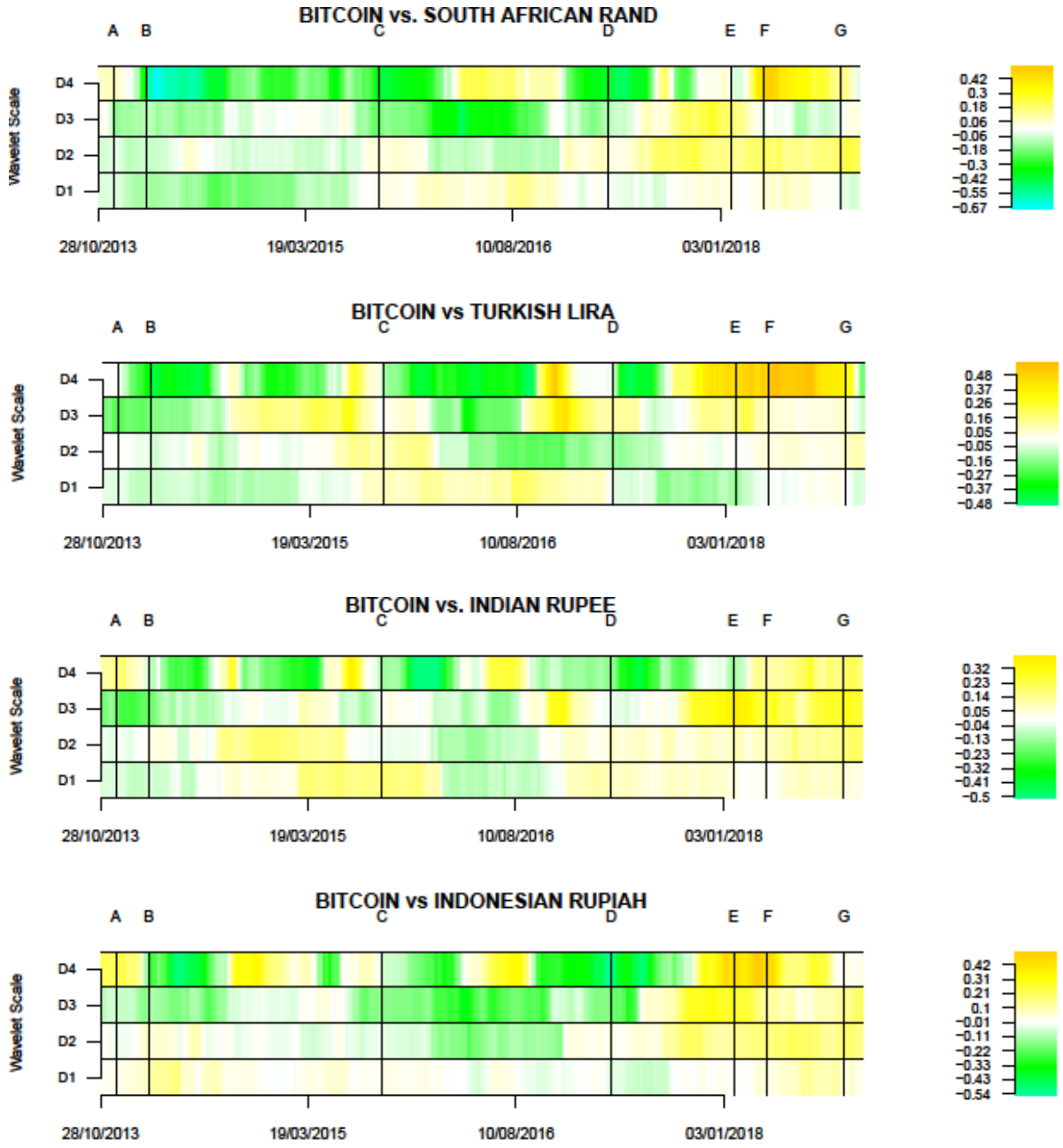


Fig. 3.10: Pairwise rolling-window wavelet correlation (with 250 window size) for **Bitcoin vs Emerging FXs**. *Note: The strength of correlation for the pairs is displayed by the heat map colours, ranging from weak to high (blue, cyan, green, white, yellow, orange, and red respectively), where red and blue signal respectively highest and lowest correlation coefficients within a 95% confidence interval (CI) for the wavelet scales D1,…,D4. We assess whether major events in the evolution of the cryptocurrency market influence the latter's interaction with other assets, by specifying few of such occurrences: China's Central Bank outlaws digital currency for financial institutions (label A), Mt Gox hack (label B), CFTC classified Bitcoin as tradable commodity (label C), Japanese Payment Services Act declared cryptocurrencies as legal payment method (label D), Coincheck hack (label E), MEPs votes in favour of cryptocurrency (label F), and a ruling by ECJ to exempt Bitcoin from VAT (label F).*

Importantly, we also observe that the size of the estimates marginally increases as we account for asymmetry in the conditional correlations. Thus, in most cases, the ADCCs

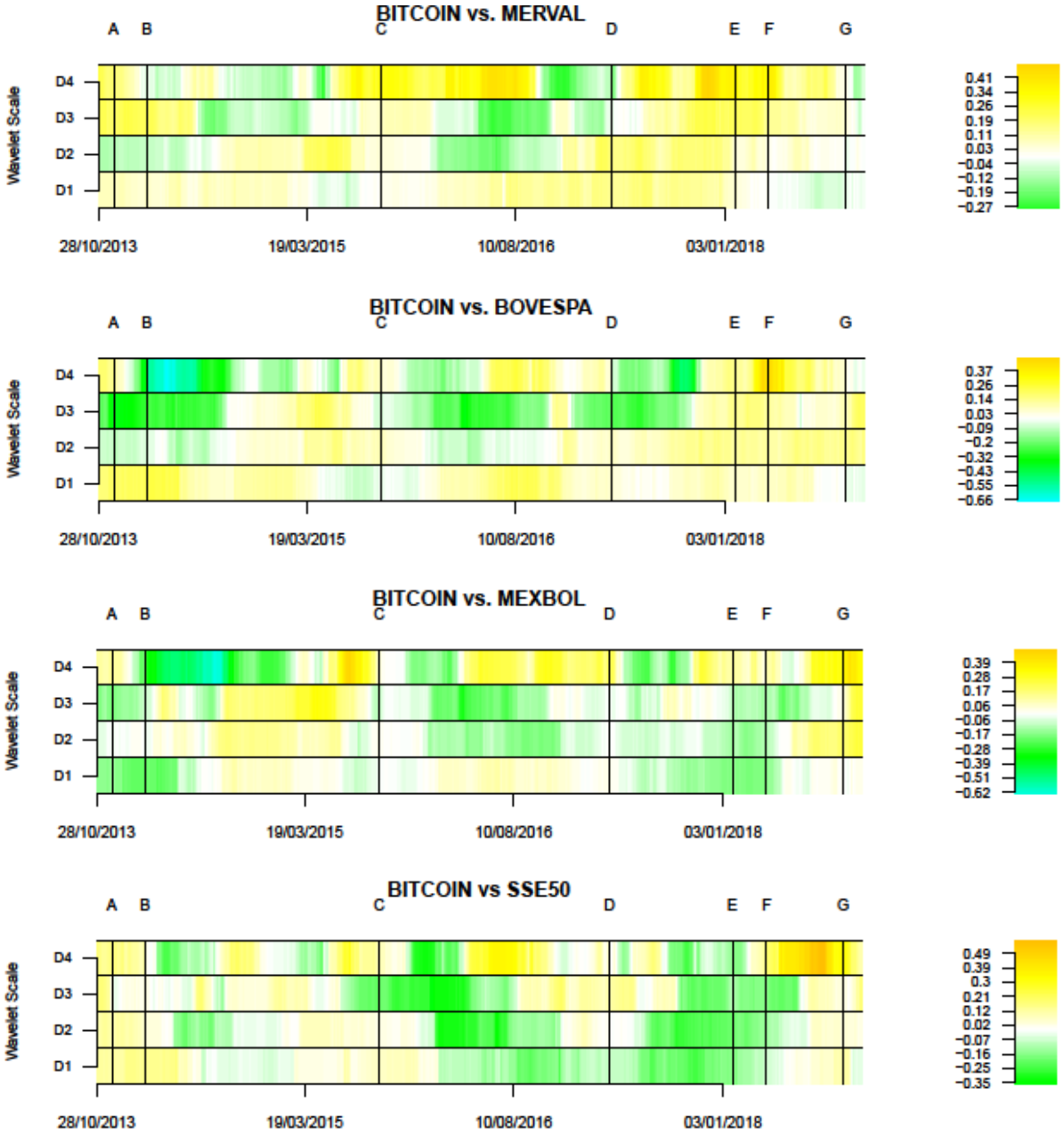
are a little higher than the DCCs. It is further evident that the correlation between Bitcoin/Ripple and the stocks increases in smaller quantities over time, relative to the FXs, however, such pattern is not dominant but localised for a few pairs. From the results, there is no clear homogeneous relationship for the market pairs, common to any group from the emerging economies. This may sound counter-intuitive since we had earlier pronounced a negative relationship and its implication thereon for Bitcoin and the Latin American FXs. Nonetheless, by means of the limitations of the standard correlation approach, we relax such initial pronouncement in replacement of the DCC and ADCC's analyses.

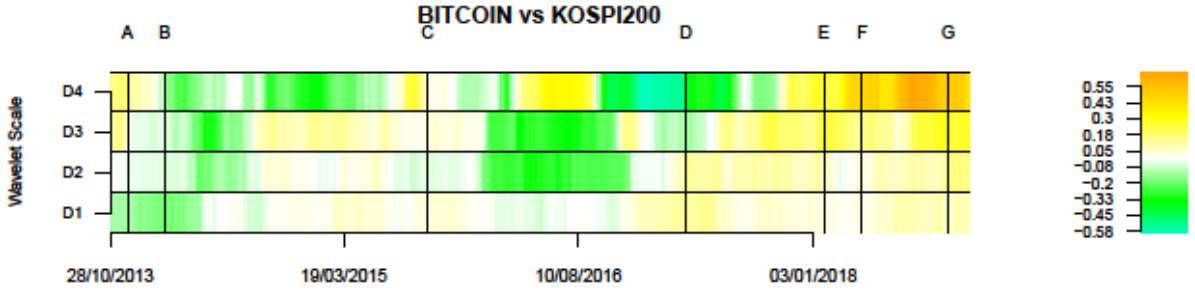
Another result worth mentioning is that the pattern of correlation increases substantially between each of the cryptocurrencies and the East Asian assets, around somewhere close to the initial announcement of sanctions (in March 2018) by President Donald J. Trump, as part of the US-China trade war. These increases in correlations are much conspicuous for Bitcoin-Yuan, Bitcoin-Won, Bitcoin-SSE50, Bitcoin-KOSPI200, Ripple-Yuan, Ripple-Won, and Ripple-SSE50 – indicative of contagion effects.

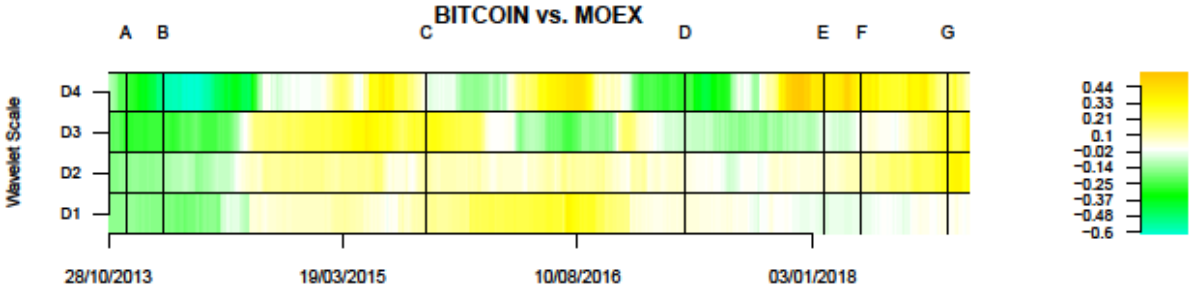
Like Aslanidis et al., (2019), Guesmi et al., (2019), Kostika and Laopodis (2019), and Urquhart and Zhang, (2019), we also document a weak relationship between cryptocurrencies and traditional financial assets in the time domain. Our result only differs in the sense that it exclusively focuses on cryptocurrency-emerging asset linkages, from which the pair is found in our analysis as mainly detached. Also, drawing on the time pattern of the correlations, we surmise and test that (refer, Section 3.7) cryptocurrencies (Bitcoin and Ripple) stand to offer more than the role of a diversifier for emerging market traders.

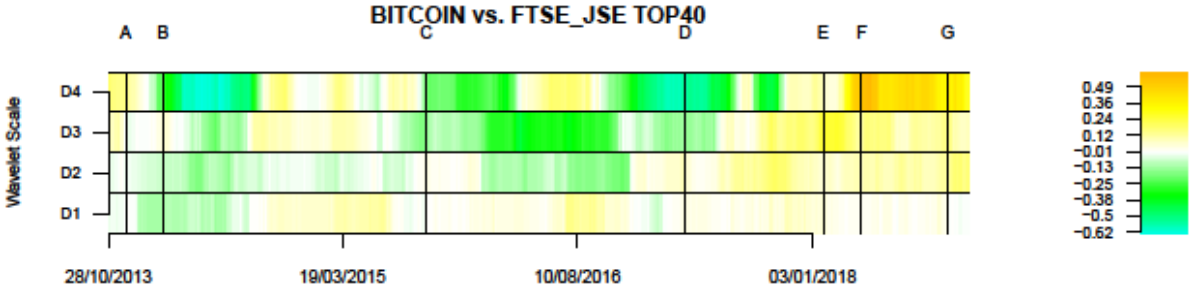
3.6 Time-frequency analysis

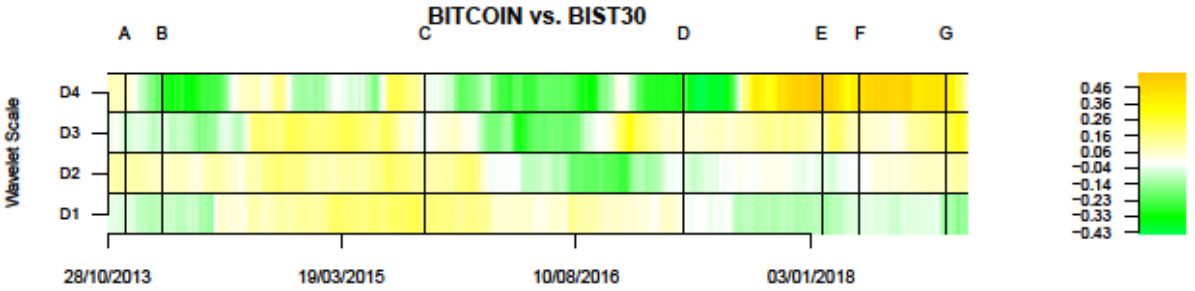
Undoubtedly, the two-dimensional DCC and ADCC analyses provide limited investment opportunities to investors, as both give the extent to which markets are correlated over sample time periods. However, to complement such efforts, we perform correlation analysis along both time and frequency (scale) dimensions. Our time-frequency-based analysis stems from the RWWC method, described in sub-section 3.3.3.

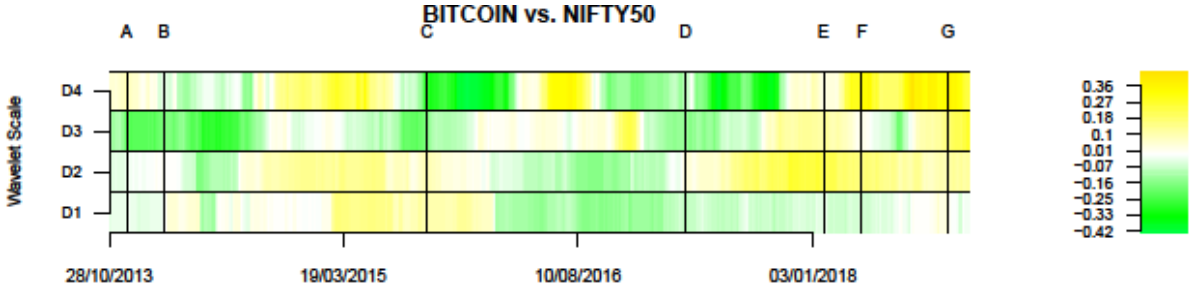



BITCOIN vs KOSPI200
A B C D E F G
Wavelet Scale
D4 D3 D2 D1
28/10/2013 19/03/2015 10/08/2016 03/01/2018
0.55 0.43 0.3 0.18 0.05 −0.08 −0.2 −0.33 −0.45 −0.58


BITCOIN vs. MOEX
A B C D E F G
Wavelet Scale
D4 D3 D2 D1
28/10/2013 19/03/2015 10/08/2016 03/01/2018
0.44 0.33 0.21 0.1 −0.02 −0.14 −0.25 −0.37 −0.48 −0.6


BITCOIN vs. FTSE_JSE TOP40
A B C D E F G
Wavelet Scale
D4 D3 D2 D1
28/10/2013 19/03/2015 10/08/2016 03/01/2018
0.49 0.36 0.24 0.12 −0.01 −0.13 −0.25 −0.38 −0.5 −0.62


BITCOIN vs. BIST30
A B C D E F G
Wavelet Scale
D4 D3 D2 D1
28/10/2013 19/03/2015 10/08/2016 03/01/2018
0.46 0.36 0.26 0.16 0.06 −0.04 −0.14 −0.23 −0.33 −0.43


BITCOIN vs. NIFTY50
A B C D E F G
Wavelet Scale
D4 D3 D2 D1
28/10/2013 19/03/2015 10/08/2016 03/01/2018
0.36 0.27 0.18 0.1 0.01 −0.07 −0.16 −0.25 −0.33 −0.42

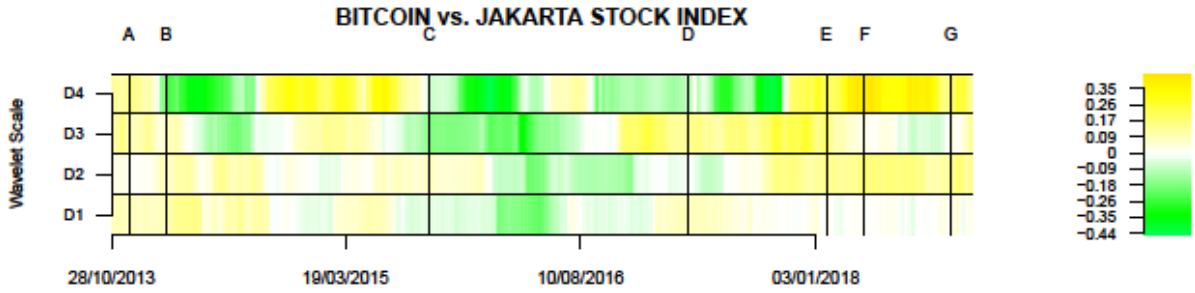


Fig. 3.11: Pairwise rolling-window wavelet correlation (with 250 window size) for **Bitcoin vs Emerging Stocks**. *Note: the strength of correlation for the pairs is displayed by the heat map colours, ranging from weak to high (blue, cyan, green, white, yellow, orange, and red respectively), where red and blues signal respectively highest and lowest correlation coefficients within a 95% confidence interval (CI) for the wavelet scales D1,…,D4. We assess whether major events in the evolution of the cryptocurrency market influence the latter's interaction with other assets, by specifying few of such occurrences: China's Central Bank outlaws digital currency for financial institutions (label A), Mt Gox hack (label B), CFTC classified Bitcoin as tradable commodity (label C), Japanese Payment Services Act declared cryptocurrencies as legal payment method (label D), Coincheck hack (label E), MEPs votes in favour of cryptocurrency (label F), and a ruling by ECJ to exempt Bitcoin from VAT (label F).*

3.6.1 Diversification ranking based on wavelet correlation matrix

Prior to the RWWC analysis, we constructed a wavelet correlation matrix[53] involving regional groupings of the emerging markets and the digital currencies. Extracted correlation coefficients for market pairs were then used to build a diversification ranking table. Our results (refer, *Appendices C1-C8*) show that under each regional market, the pairs having either Bitcoin or Ripple consistently ranked best for purposes of diversification prospects. Thus, minimum positive and negative correlation values, similar to the standard Pearson's and (A)DCC's results are found for the pairs.

On the other hand, moderate to almost perfect correlations are mostly recorded for market pairs comprising the emerging assets only. This may be interpreted to mean that the inclusion of Bitcoin and Ripple in an emerging assets basket promises of offering better investment opportunities. However, since the connectedness of emerging assets is much researched (Guesmi and Nguyen, 2011; Eiling and Gerard, 2015; Zivkov et al., 2018; etc.), we shall not carry further investigation on the subject.

[53] We followed the method and computational approach of Polanco-Martínez and Fernández-Macho (2014).

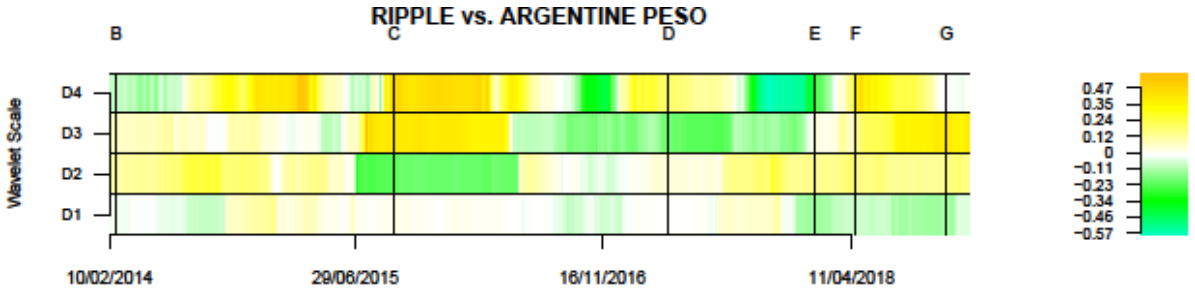
Yet, we employ an advanced technique, in the form of a moving window wavelet correlation, to examine temporal variations within the wavelet correlations to be estimated for market pairs of Bitcoin/Ripple and each emerging asset.

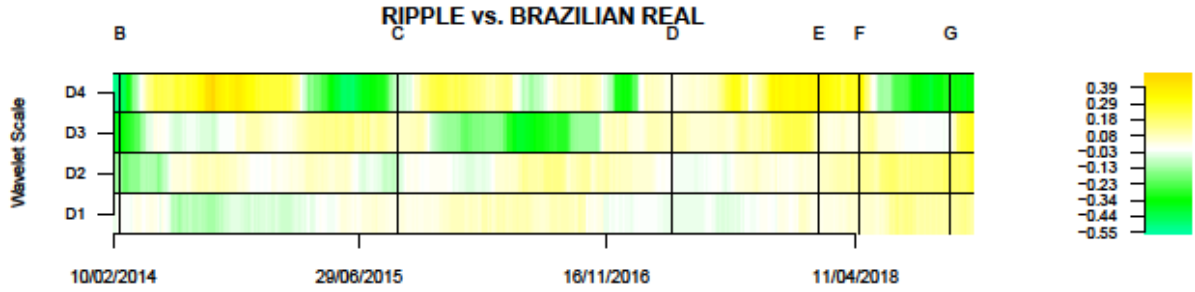
3.6.2 Pairwise correlations in time-frequency domain

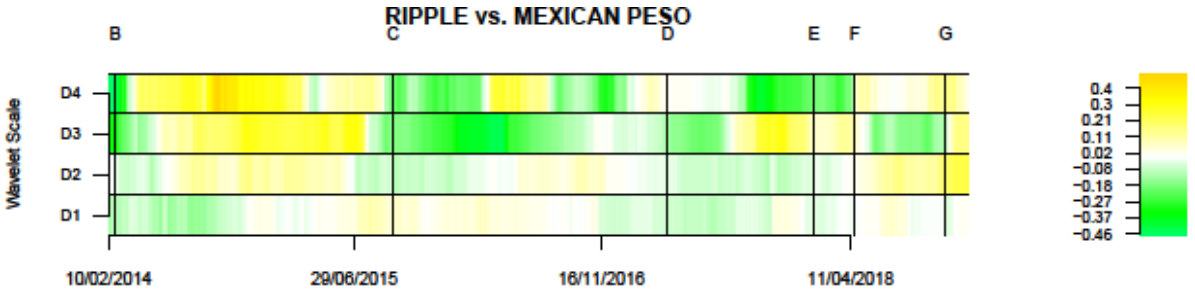
The RWWC results for the market pairs are presented in Figs. 3.10-3.13. Compared to the weakly correlated markets under the static unconditional correlation and time-varying conditional correlation approaches, the RWWC, in general, estimates weak to lower-moderate correlations that toggle between positive and negative coefficients across the time-scales. The dimension of estimations could best explain the discrepancy of the values between the RWWC and the time-domain approaches. More so, our wavelet correlation matrix is based on a technique, which does not consider temporal changes in the computation of the correlation coefficients, hence, the disparity in results with the RWWC is understandable.

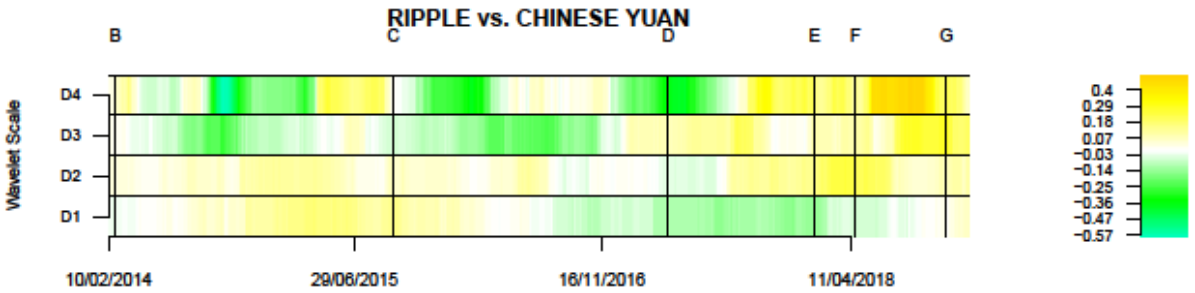
The estimated RWWC coefficients range from -0.72 to 0.58 for Bitcoin-emerging FXs, -0.66 to 0.55 for Bitcoin-emerging stocks, -0.70 to 0.62 for Ripple-emerging FXs, and -0.64 to 0.75 for Ripple-emerging stocks. This correlation pattern visibly depicts that, relatively, Ripple is fairly linked to the emerging assets than could be witnessed for Bitcoin. Distinguishably, such evidence of linkages manifests strongly for Ripple-emerging stocks, followed by Ripple-emerging FXs. The difference in the connectedness of the two cryptocurrencies with the emerging market assets comes at no surprise because irrespective of Bitcoin and Ripple being respectively the first and third largest cryptocurrency markets, both operate on independent trading platforms (Omane-Adjepong and Alagidede, 2019). Noticeably, to a large extent, the evidence of dominantly weak, amid purloins of lower-moderate correlation zones for the pairs are not confined to a particular scale and/or time, but instead, vary along the dimensions.

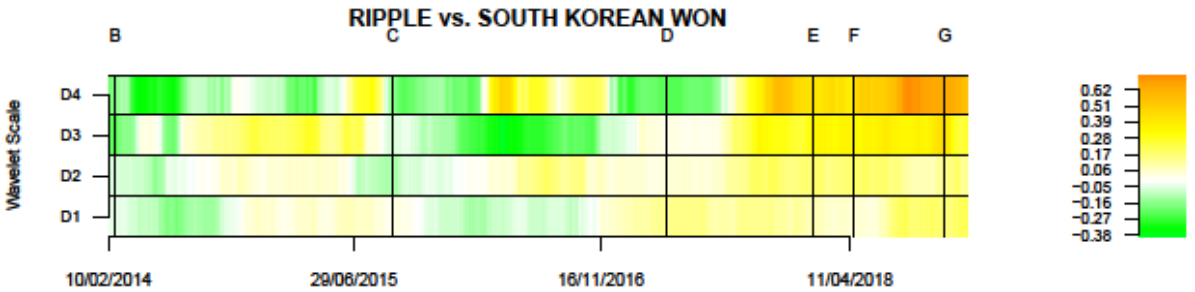
This largely gives indication of interactive markets that could be readily explored under diverse trading horizons for investment gains.











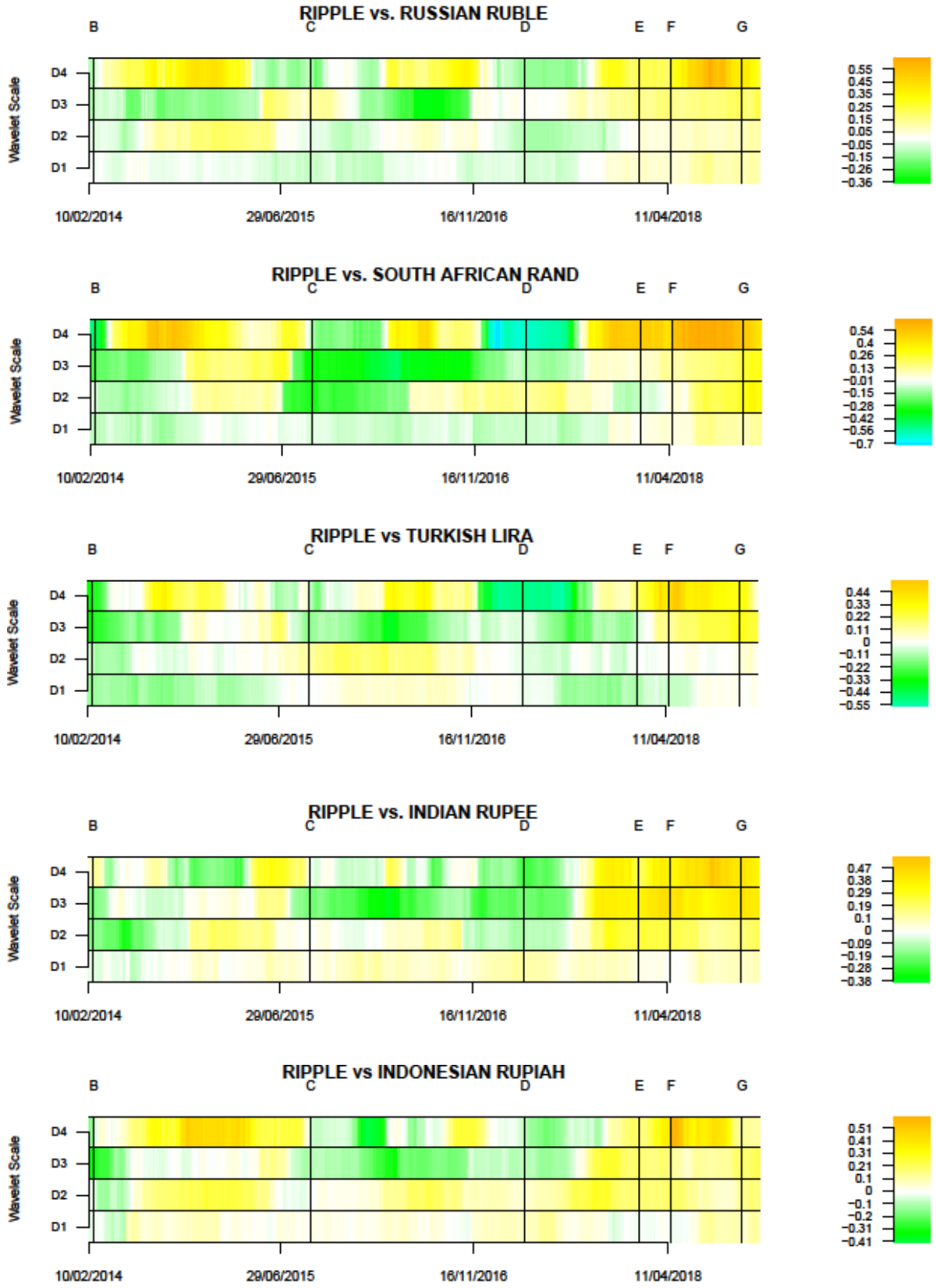
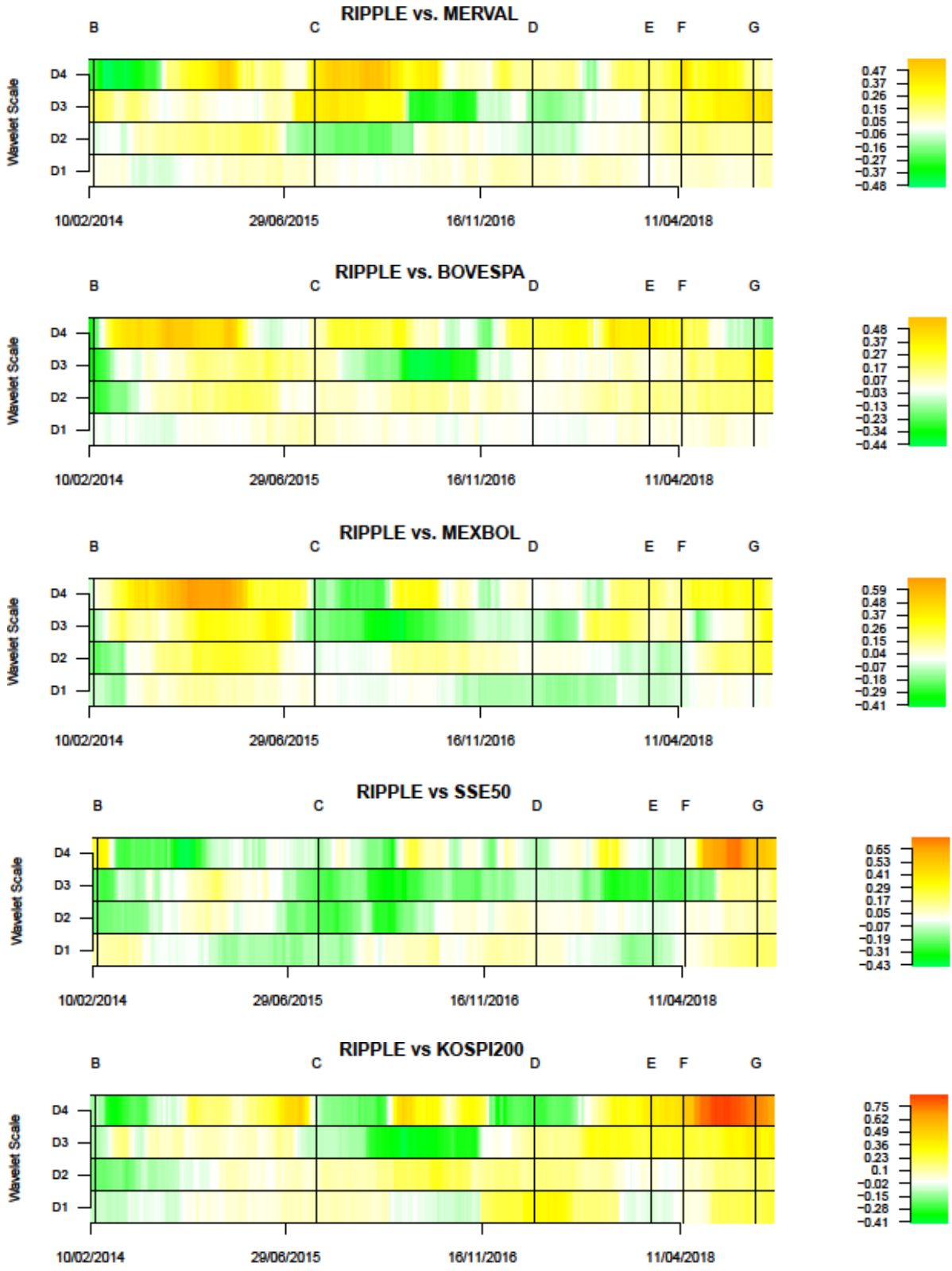


Fig. 3.12: Pairwise rolling-window wavelet correlation (with 250 window size) for **Ripple vs. Emerging FXs**. *Note: the strength of correlation for the pairs is displayed by the heat map colours, ranging from weak to high (blue, cyan, green, white, yellow, orange, and red respectively), where red and blues signal respectively highest and lowest correlation coefficients within a 95% confidence interval (CI) for the wavelet scales D1,…,D4. We assess whether major events in the evolution of the cryptocurrency market influence the latter's interaction*

with other assets, by specifying few of such occurrences: Mt Gox hack (label B), CFTC classified Bitcoin as tradable commodity (label C), Japanese Payment Services Act declared cryptocurrencies as legal payment method (label D), Coincheck hack (label E), MEPs votes in favour of cryptocurrency (label F), and a ruling by ECJ to exempt Bitcoin from VAT (label F).



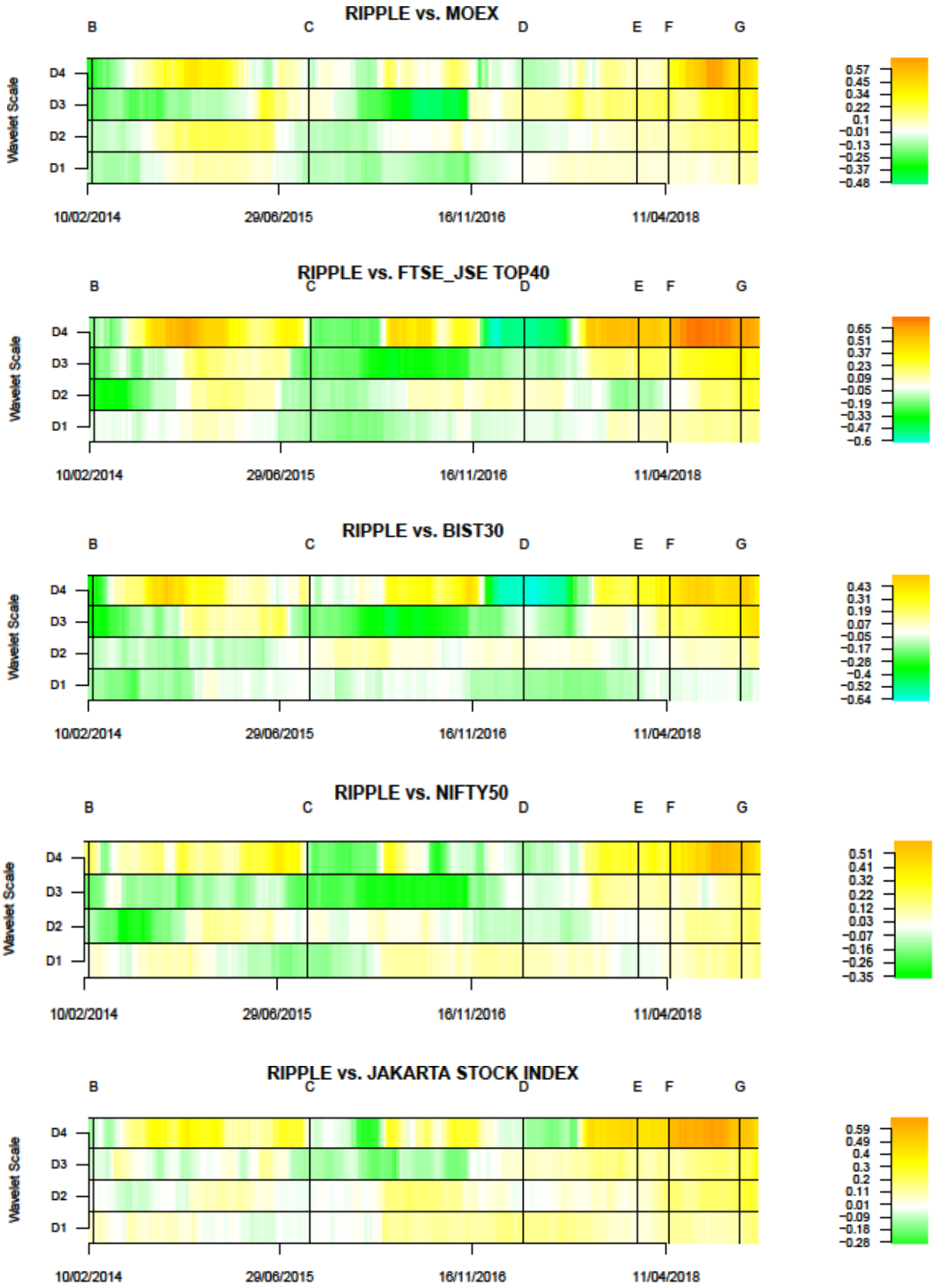


Fig. 3.13: Pairwise rolling-window wavelet correlation (with 250 window size) for **Ripple vs. Emerging Stocks**. *Note: the strength of correlation for the pairs is displayed by the heat map colours, ranging from weak to high (blue, cyan, green, white, yellow, orange, and red respectively), where red and blues signal respectively highest and lowest correlation coefficients within a 95% confidence interval (CI) for the wavelet scales D1,…,D4. We assess whether major events in the evolution of the cryptocurrency market influence the latter's interaction*

with other assets, by specifying few of such occurrences: Mt Gox hack (label B), CFTC classified Bitcoin as tradable commodity (label C), Japanese Payment Services Act declared cryptocurrencies as legal payment method (label D), Coincheck hack (label E), MEPs votes in favour of cryptocurrency (label F), and a ruling by ECJ to exempt Bitcoin from VAT (label F).

Interestingly, few isles of moderately high degree of correlations, in some way, coincide with the events labelled C, F, and G, along the monthly scale. Perhaps, aside from macroeconomic factors that often influence market correlation at higher scales (or lower frequencies) as argued by Zhou (2012), the occurrence of favourable events (or good news), in our case, partly account for the very short changes in the co-movement of markets at intermediate time-scales.

For the co-movement dynamics of Bitcoin and the emerging assets, minimum level of coefficients are noted, especially for Bitcoin-Mexican Peso (-0.43 to 0.44), Bitcoin-Lira (-0.48 to 0.48), Bitcoin-Merval (-0.27 to 0.41), Bitcoin-SSE50 (-0.35 to 0.49), Bitcoin-Nifty50 (-0.42 to 0.36), Bitcoin-Jakarta Stock Index (-0.44 to 0.35), and Bitcoin-Bist30 (-0.43 to 0.46), while Bitcoin-Won (-0.52 to 0.54) and Bitcoin-KOSPI200 (-0.58 to 0.55) show minimum to moderate level correlations. Moreover, weaker correlations with coefficients nearer to zero (see, white-coloured zones) sporadically mark the time and frequency movements of each pair. These zones evidentially confirm that the RWWCs are not much distinct from our wavelet correlation matrix results, as well as the low-level correlations reported under the time-domain approaches.

Furthermore, we noticed that several of the Ripple constituted pairs, particularly, Ripplke-KOSPI200 (-0.41 to 0.75), Ripple-FTSE/JSE (-0.61 to 0.65), and Ripple-SSE50 (-0.43 to 0.65) exhibit smaller chains of moderate correlations. Nonetheless, such correlation pattern is intermittently disrupted with zones having correlation coefficients of zero (Ripple-Argentina Peso, Ripple-Lira, Ripple-Rupee, and Ripple-Rupiah) or closer to the zero mark.

Altogether, empirical evidence from the moving window pairwise analysis reveals that Bitcoin and Ripple are not well-linked for now, to emerging market assets. Generally, we found situations where fewer zones with moderate correlation values define relationship for the pairs, however, lesser extent correlations, which swings from lower-moderate to weaker zones with coefficients nearer to zero mostly characterise the asset pairs. With the benefit of hindsight, we contest that not only does the cryptocurrency market detach itself from advanced markets (Corbet et al., 2018; Kang et al., 2019a,b; Kostika and Laopodis, 2019; Pavković et al., 2019; etc.), but from our analysis, it has also not coupled well with asset market of emerging economies. Apparently, this low-level relatedness at different trading time-scales holds important implications for heterogeneous investors, as they require such opportunities to maximize returns on investment.

3.6.3 Portfolio performance analysis

Using the Generalised Sharpe Ratio (GSR) of Hodges (1998), we conduct an analysis to assess the risk-adjusted performance of multi-asset diversified portfolios, constituting cryptocurrencies and emerging assets. The analysis is performed over yearly time-samples and across different trading scales, obtained by means of the wavelet decomposition in sub-section 3.3.2. Two broad-spectrum portfolios with several scenarios are considered: (i) multi-asset equally-weighted portfolio; and (ii) multi-asset global minimum-variance (GMV) portfolio[54]. From the multi-task scenarios, we initially constructed aggregate portfolio series, which were subsequently disaggregated into time-samples in order to factor variations in our risk-adjusted performance measure. To incorporate the interest of scale-conscious investors, the aggregate portfolios are also decomposed into seven scale components,

[54] For current readings on portfolio construction strategies, see Platanakis et al., (2018); Symitsi and Chalvatzis (2019); and Liu (2019).

where, as earlier specified the synthesised portfolio series correspond to D1 (2~4), D2 (4~8),…,D7 (128~256) day bands.

With regard to the limitation of the commonly used standard Sharpe Ratio (SR), the GSR, which is based on a mean-variance-skewness framework, is favoured in this study. The GSR approach is practically suitable because most financial return distributions are skewed and non-normal, thereby appealing to investors with preferences for higher moments. It is expressed as: $SR * \sqrt{1 + b(skew/3)SR}$, where, like Zakamouline and Koekebakker (2009), we adopt $|SR|$ in our computation. More so, the risk-free rate is deduced from a corresponding 3-month T-Bill series of the United States (Source: https://fred.stlouisfed.org/search?st=t-bill). Obviously, the GSR measure depends on the skewness value, the CARA utility coefficient (with b set to one), and the SR.

Table 3.11: Time-domain risk-adjusted diversified portfolio performance measures

	Aggregate measures			Time-domain sub-sample measures						
				Y1	Y2	Y3	Y4	Y5	Y6	Y7
				Equally-weighted portfolio						
	Exp	SD	GSR	GSR	GSR	GSR	GSR	GSR	GSR	GSR
Bitcoin-Ripple	0.315	6.054	**0.0513**	0.1679	0.0442	0.0534	0.0702	0.2575	0.1143	0.0973
CC-Latin America	0.051	1.732	0.0252	0.1618	0.0595	0.1030	0.0631	0.2610	0.1489	0.0460
CC-Africa/Europe	0.052	1.707	0.0258	0.1549	0.0825	0.0968	0.0671	0.2644	0.1454	0.0956
CC-East Asia	0.108	2.078	0.0489	**0.1740**	0.0345	0.0670	0.0613	**0.2784**	0.1354	0.0896
CC-South Asia	0.107	2.066	0.0485	0.1539	0.0279	0.0749	0.0765	0.2702	0.1252	0.0979
Bitcoin-Latin America	0.003	1.187	0.0036	0.0607	0.0843	0.0683	0.0688	0.1856	0.1493	0.0497
Bitcoin-Africa/Europe	0.004	1.183	0.0021	0.0554	**0.1140**	0.0577	0.0733	0.1885	0.1493	0.1228
Bitcoin-East Asia	0.056	1.174	0.0419	0.1198	0.0586	0.0033	0.0876	0.2396	**0.1550**	0.1298
Bitcoin-South Asia	0.050	1.174	0.0366	0.0587	0.0427	0.0172	**0.1130**	0.2239	0.1360	**0.1476**
Ripple-Latin America	0.014	1.618	0.0043	0.1009	0.0317	0.1347	0.0262	0.2152	0.1423	0.0881
Ripple-Africa/Europe	0.015	1.590	0.0047	0.0885	0.0588	**0.1355**	0.0297	0.2187	0.1376	0.0350
Ripple-East Asia	0.068	1.931	0.0320	0.1178	0.0033	0.1148	0.0008	0.2333	0.1307	0.0168
Ripple-South Asia	0.067	1.912	0.0315	0.0891	0.0117	0.1278	0.0206	0.2245	0.1166	0.0265
				Global minimum-variance portfolio						
Bitcoin-Ripple	0.308	5.087	0.0594	0.2164	0.0773	0.0100	0.1106	**0.2303**	0.1172	**0.1424**
CC-Latin America	-0.060	0.620	0.1066	0.0707	0.1651	0.1454	0.0874	0.0041	0.1510	0.1090
CC-Africa/Europe	-0.046	0.801	0.0657	0.0004	0.1492	0.1089	0.0040	0.0213	0.1112	0.0517
CC-East Asia	-0.008	0.218	0.0715	**0.2233**	0.1076	0.0959	0.1303	0.0823	0.1271	0.1261
CC-South Asia	-0.017	0.395	0.0601	0.0799	0.0299	0.0652	0.0189	0.0331	0.1468	0.0398

Bitcoin-Latin America	-0.063	0.617	0.1105	0.1100	**0.1663**	0.1428	0.0866	0.0042	**0.1528**	0.1184
Bitcoin-Africa/Europe	-0.048	0.795	0.0687	0.0571	0.1479	0.1068	0.0037	0.0151	0.1113	0.0550
Bitcoin-East Asia	-0.007	0.214	0.0668	0.1988	0.1075	0.0961	0.1303	0.0837	0.1277	0.1446
Bitcoin-South Asia	-0.022	0.402	0.0604	0.1348	0.0299	0.0720	0.0060	0.0735	0.1453	0.0266
Ripple-Latin America	-0.066	0.627	**0.1136**	0.1325	0.1499	**0.1515**	0.0948	0.0150	0.1407	0.1336
Ripple-Africa/Europe	-0.049	0.844	0.0728	0.0667	0.1381	0.1164	0.0297	0.0117	0.1039	0.0718
Ripple-East Asia	-0.009	0.219	0.0740	0.1826	0.1023	0.0983	**0.1339**	0.0765	0.1240	0.1317
Ripple-South Asia	-0.018	0.396	0.0630	0.0904	0.0579	0.0433	0.0237	0.0206	0.1426	0.0490

Note: CC denotes cryptocurrency, Exp is expected portfolio return, and SD is the associated standard deviation. The regional markets comprise both stocks and FXs of the groups, as specified in Section 3.4. For instance, *CC-Latin America* is a diversified portfolio containing the two cryptocurrencies and Latin America's stocks and FXs.

Table 3.12: Frequency risk-adjusted diversified portfolio performance measures

	D1	D2	D3	D4	D5	D6	D7
	Equally-weighted portfolio						
	GSR	GSR	GSR	GSR	GSR	GSR	GSR
Bitcoin-Ripple	0.0017	0.0024	0.0036	0.0042	0.0055	0.0075	0.0098
CC-Latin America	0.0061	0.0084	0.0122	0.0149	0.0205	0.0273	0.0383
CC-Africa/Europe	0.0063	0.0084	0.0124	0.0149	0.0201	0.0276	0.0378
CC-East Asia	0.0051	0.0071	0.0107	0.0123	0.0163	0.0218	0.0286
CC-South Asia	0.0051	0.0071	0.0108	0.0122	0.0164	0.0230	0.0293
Bitcoin-Latin America	0.0083	0.0118	0.0164	**0.0239**	**0.0328**	0.0372	0.0530
Bitcoin-Africa/Europe	**0.0085**	0.0118	0.0159	0.0225	0.0325	0.0420	**0.0560**
Bitcoin-East Asia	0.0082	**0.0124**	0.0175	**0.0239**	0.0306	0.0395	0.0462
Bitcoin-South Asia	0.0083	0.0120	**0.0177**	0.0229	0.0300	**0.0438**	0.0501
Ripple-Latin America	0.0068	0.0088	0.0124	0.0151	0.0222	0.0290	0.0398
Ripple-Africa/Europe	0.0069	0.0089	0.0129	0.0149	0.0219	0.0296	0.0387
Ripple-East Asia	0.0056	0.0074	0.0112	0.0122	0.0177	0.0227	0.0293
Ripple-South Asia	0.0057	0.0075	0.0114	0.0120	0.0178	0.0245	0.0291
	Global minimum-variance						
Bitcoin-Ripple	0.0019	0.0029	0.0043	0.0056	0.0065	0.0088	0.0128
CC-Latin America	0.0160	0.0233	0.0346	0.0559	0.0660	0.0859	0.1588
CC-Africa/Europe	0.0126	0.0175	0.0265	0.0395	0.0610	0.0754	0.1023
CC-East Asia	**0.0459**	**0.0674**	**0.0995**	**0.1360**	**0.2256**	**0.2496**	0.2397
CC-South Asia	0.0245	0.0367	0.0624	0.0761	0.1057	0.1680	**0.2868**
Bitcoin-Latin America	0.0153	0.0225	0.0329	0.0536	0.0629	0.0827	0.1548
Bitcoin-Africa/Europe	0.0121	0.0168	0.0255	0.0384	0.0592	0.0723	0.0959
Bitcoin-East Asia	0.0448	0.0658	0.0972	0.1331	0.2199	0.2394	0.2400
Bitcoin-South Asia	0.0237	0.0323	0.0531	0.0679	0.0851	0.1334	0.2097
Ripple-Latin America	0.0157	0.0231	0.0340	0.0564	0.0645	0.0886	0.1521
Ripple-Africa/Europe	0.0125	0.0173	0.0262	0.0390	0.0614	0.0759	0.0977
Ripple-East Asia	**0.0459**	0.0671	0.0993	0.1355	0.2243	0.2488	0.2383
Ripple-South Asia	0.0245	0.0366	0.0622	0.0758	0.1044	0.1667	0.2742

Note: CC denotes cryptocurrency, Exp is expected portfolio return, and SD is the associated standard deviation. The regional markets comprise both stocks and FXs of the groups, as specified in Section 3.4. For instance, *CC-Latin America* is a diversified portfolio containing the two cryptocurrencies and Latin America's stocks and FXs.

Table 3.11 presents results of the GSR scores for all the diversified portfolios over the yearly sub-samples, namely Y1,…,Y7, which match respectively to 2013,…,2019. The beginning three columns display the expected returns, standard deviations, and the GSRs of the aggregate portfolios. As could be observed, the Bitcoin-emerging asset portfolios invariably exhibit the lowest risk. Moreover, the best portfolio performance in the time-samples for the equally-weighted model is produced by (a) the cryptocurrencies and East Asian assets for 2013, (b) Bitcoin and Africa/European assets for 2014, (c) Ripple and Africa/European assets for 2015, (d) Bitcoin and South Asian assets for 2016, (e) cryptocurrencies and East Asia assets for 2017, (f) Bitcoin and East Asian assets for 2018, and (g) Bitcoin and South Asian assets for 2019. Apart from Y1, a different set of portfolios are adjudged best under the GMV model. Contrary to Platanakis et al., (2018) and Liu (2019), in our context, the minimum-variance portfolios outperform the equally-weighted portfolios. We also note that in four out of the seven cases, the equally-weighted Bitcoin portfolios perform better over the time-samples than the portfolios involving Ripple or both cryptocurrencies. On the other side, the performance of the GMV portfolios varies throughout the sub-samples, hence unveiling the inadequacy of computing portfolio performance with static measures.

Somehow similar to Symitsi and Chalvatzis (2019), higher Sharpe Ratio performance is observed for the equally-weighted Bitcoin portfolios across the frequency bands (refer, Table 3.12). However, the GMV portfolio, which is made up of the two leading cryptocurrencies and the East Asian assets (stocks and FXs) show consistency in performance. Perhaps, since Bitcoin and Ripple are not clones to each other, and sometimes differ in their dynamic properties, their joint inclusion in an East Asian basket of investment stand a chance to increasing diversification benefits.

3.7 Hedge and safe haven capabilities of cryptocurrencies

Besides the evidence of weak positive linkages, with denouement of an increase in diversification prospects, can Bitcoin/Ripple serve as a hedge and/or safe haven tool(s) for emerging assets? We provide empirical answers by first, invoking Baur and Lucey's (2010) explanation of a diversifier, hedge, and safe haven instrument. The authors termed an asset to be a diversifier if it's relationship with another asset or portfolio is positive on the average (but not perfectly correlated). An asset that exhibits negative correlation on the average or shows no correlation with another asset or portfolio is best described as a hedge instrument. A safe haven status is conferred on an asset that is uncorrelated or displays negative correlation with another asset or portfolio during periods of market stress or turmoil.

By extending the above definitions to differentiate between the intensity of their usefulness in a financial system, Baur and McDermott (2010) described an asset as a strong (weak) hedge if it is negatively correlated (uncorrelated) with another asset or portfolio on the average. Additionally, an asset could serve as a strong (weak) safe haven if such asset is negatively correlated (uncorrelated) with another asset or portfolio, especially in times of turmoil or down-market. From these testable definitions, we examine Bitcoin's/Ripple's potential investment roles against extreme movements in the return distribution of emerging stocks and FX markets. Motivated by the approach of Ratner and Chiu (2013), we extracted the estimated pairwise DCC coefficients between Bitcoin/Ripple and each emerging asset, as distinct time series, denoted by DCC_t. The extracted DCC_t is regressed on dummies as follows:

$$DCC_t = m_0 + m_1 D\left(r_{asset} q_{10}\right) + m_2 D\left(r_{asset} q_5\right) + m_3 D\left(r_{asset} q_1\right) + \varepsilon_t \qquad (3.22)$$

where the dummy variable D mark movements in the return distribution of the emerging assets at the tail ends, represented by the 10th, 5th, and 1st quantiles. r_{asset} denote the corresponding return series of each emerging asset, and ε_t captures the disturbances of the regression model. Bitcoin/Ripple performs a diversifier role

against movements in any of the emerging asset if m_0 is non-negative and statistically significant; a strong (weak) hedge if m_0 is significantly negative (zero); a strong (weak) safe haven if the regression coefficients m_1, m_2, m_3 are significantly negative (insignificantly different from zero). Though, not quite new, the approach has less been applied in the cryptocurrency literature (except for similar works by Bouri et al., 2017; Bouri et al., 2020a; Shahzad et al., 2020; and Stensås et al., 2019; Stensås et al., 2019; and Wang et al., 2019). Different from the others, our work explores the capabilities of Bitcoin and Ripple against the extreme downside movement of the return distributions for an extensive coverage of emerging assets.

Table 3.13: Estimation of cryptocurrencies emergent role in emerging asset markets

	Panel A: Bitcoin vs. emerging FX market				**Panel B: Ripple vs. emerging FX market**			
		1%	5%	10%		1%	5%	10%
	$H(m_0)$	m_3	m_2	m_1	$H(m_0)$	m_3	m_2	m_1
Argentina Peso	8.3e-03^{A}	-1.3e-08	-1.4e-08	2.9e-09	8.2e-03^{A}	-8.3e-08	-4.7e-08	2.5e-08
Brazilian Real	-0.01581^{A}	0.00138	-0.00059	0.00023	2.2e-02^{A}	7.6e-08	-2.5e-09	3.8e-08
Mexican Peso	-0.04253^{A}	0.00157	0.00197	-0.00393	-0.01578^{A}	-0.00382	-0.00071	0.00085
Russian Rubble	2.3e-02^{A}	9.9e-09	6.3e-08^{B}	4.6e-08^{A}	1.4e-02^{A}	-5.4e-08^{B}	-9.6e-09	-2.1e-09
South A. Rand	-1.5e-02^{A}	-7.0e-08	-3.5e-08	5.0e-10	0.02713^{A}	-0.01010	-0.00777	0.00950^{B}
Turkish Lira	-6.2e-04^{A}	4.7e-08^{A}	3.8e-09	-1.5e-10	6.8e-03^{A}	2.9e-08^{B}	-2.2e-09	6.6e-09
Chinese Yuan	-1.9e-02^{A}	8.8e-09	-6.3e-08^{A}	2.0e-08^{B}	1.1e-02^{A}	6.4e-09	9.9e-09^{A}	-3.1e-10
South K. Won	0.01161^{A}	-0.00062	-0.00577	0.00382	0.04291^{A}	0.00050	-0.00981	-0.00301
Indian Rupee	0.01079^{A}	0.00283	-0.00927^{B}	-0.00598^{C}	0.02039^{A}	-0.01128	-0.00564	-0.00079
Indon. Rupiah	-1.6e-03^{A}	-1.8e-08	-3.5e-08^{A}	-6.7e-09	4.2e-02^{A}	-5.7e-08^{A}	-1.5e-08	-9.4e-09
	Panel C: Bitcoin vs. emerging stock market				**Panel C: Ripple vs. emerging stock market**			
		1%	5%	10%		1%	5%	10%
	$H(m_0)$	m_3	m_2	m_1	$H(m_0)$	m_3	m_2	m_1
Merval	6.0e-02^{A}	-1.8e-08^{B}	6.7e-09	3.7e-11	5.3e-02^{A}	-1.1e-07^{B}	1.1e-08	3.4e-08
Bovespa	0.02068^{A}	0.00007	-0.00053	0.00089	0.03302^{A}	0.00194	0.00163	0.00061
Mexbol	-0.04230^{A}	0.00669	-0.00361	0.00238	5.0e-03^{A}	1.4e-07	-1.3e-07	-2.3e-07^{B}
Moex	5.4e-02^{A}	9.7e-03	2.0e-04	-9.7e-05	0.00081	-0.00544	0.00263	-0.01013^{A}
FTSE/JSE TOP40	2.4e-02^{A}	-4.2e-08	-1.3e-08	1.4e-08	0.01441^{A}	-0.01623	-0.00695	0.02189^{A}
BIST30	3.3e-02^{A}	1.2e-07^{C}	-3.1e-08	6.9e-09	-2.3e-02^{A}	1.9e-08	-1.9e-08	8.2e-09
SSE50	0.00273^{B}	-0.00865	0.00528	-0.00107	0.02010^{A}	-0.00922	-0.00920	0.00799
KOSPI200	3.5e-02^{A}	1.3e-06	2.6e-07	3.9e-07	0.05715^{A}	0.00077	0.01128	0.00556
NIFTY50	-3.1e-03^{A}	-2.0e-07	8.1e-08	1.0e-07	-0.01943^{A}	0.00150	-0.00218	-0.00672
Jak. Stock Index	0.02062^{A}	-0.00310	-0.00290	0.00340^{C}	6.3e-02^{A}	-1.6e-07^{A}	-8.2e-08^{B}	1.8e-08

Notes: This table presents the estimation results from Eq. (3.22). 'A', 'B', and 'C 'indicate statistical significance levels at 1% , 5% and 10% respectively. In $H(m_0)$, *H* stands for hedge, while m_0 is an estimated coefficient.

The results in Panel A of Table 3.13 reveal that Bitcoin acts more as a strong hedge that an effective diversifier, as the estimated m_0 coefficient is negative and statistically significant for majority of the foreign currency rates. This signifies that in times of unfavourable bilateral currency rate market conditions, Bitcoin can play an effective role to reduce such currency market risk. We found strong safe haven capabilities for Bitcoin against movements in the return distribution of the Chinese Yuan (in the 5% quantile), Indian Rupee (in the 5% and 10% quantiles), and the Indonesian Rupiah (in the 5% quantile). The result suggests that during adverse market periods in the government-backed Asia currencies, there is a high preference to hold on to Bitcoin. This phenomenon may be explained by the not yet central bank controlled, lack of monetary policy schemes, and the decentralise characteristics of Bitcoin, which appeal more to investors who distrust financial institutions, especially during crisis in the mainstream financial system. Moreover, as argued by Baur et al., (2018b), Bitcoin can best function to provide temporal refuge to a rapidly depreciating fiat currency.

Contrary to Bitcoin, the evidence in Panel B of Table 3.13 indicates that Ripple is no more than an effective diversifier for almost all the merging FXs, except for the Mexican Peso. Similar to Bitcoin, Ripple also acts as a strong safe haven for the Indonesian Rupiah, and additionally for the Russian Rubble, both in the 1% quantile. However, the safe haven role of Bitcoin and Ripple should be interpreted with caution because both asset markets are relatively not much liquid now, and highly volatile, compared to other traditional safe haven contenders like gold and major fiat currencies.

Further, the results in Panels C and D of Table 3.13 show that Bitcoin and Ripple could substantially serve as effective diversifiers against extreme movements in giant emerging equities. This gives emerging market investors the edge to consider the inclusion of Bitcoin and/or Ripple in their equity portfolios. Aside from the Indian

stock (NIFTY50), our finding contradicts that of Stensås et al., (2019), which found Bitcoin as a hedge tool for the Russian (MICEX10), South Korean (KOSPI), and the Brazilian (IBRX) stock markets. Perhaps, the use of different proxies for the equities may account for the dissimilarities in both results. Evidently, the safe haven capabilities of Ripple is enhanced as it is observed as a strong safe haven instrument for Merval (in the 1% quantile), Mexbol (in the 10% quantile), Moex (in the 10% quantile), and the Jakarta Stock Index (in the 1% and 5% quantiles).

Summing up, we provide highlights of the main findings: (i) The results suggest that Bitcoin/Ripple could play multiple economic roles in an emerging market setting; (ii) We found that the benefits of Bitcoin/Ripple do not only vary across the emerging market assets, but likewise, the country-specific assets, and that of the regional groupings; and (iii) Observably, there are differences in the economic capabilities of Bitcoin and Ripple, which ought to be benefited by emerging market investors. Thus, our findings may provide informed avenues for investors to offset forex and equity investment losses with Bitcoin and/or Ripple. Analysing the benefits of each of the two cryptocurrencies, independently from one another, addresses the research gap of Corbet et al., (2019), which calls for researchers to "*Evaluate the benefits of cryptocurrencies separately, and not as one large asset class*". ". Hence, our results tend to support the argument that cryptocurrencies are not homogeneous investable assets.

3.8 Conclusions

Despite the decade-old existence, cryptocurrency has gradually emerged as the youngest alternative global asset class, which appeals to the general populace due to its numerous distinctive characteristics. This unbridled interest is similarly evident in the recent increasing research works in multidisciplinary areas involving cryptocurrency. Regardless of such growing research attention, there is still a dearth in the literature concerning the extent of interrelatedness and economic benefits of

cryptocurrencies, in the midst of emerging assets. Employing a time-varying version of the standard Pearson's method, the (asymmetric) dynamic conditional correlation, and a rolling-window wavelet correlation, we examine linkages between two leading cryptocurrencies and diverse emerging assets (FXs and equities), and further assess economic roles of the digital assets.

Our correlation analyses document lesser extent linkages, in time and frequency dimensions, for the cryptocurrency-emerging asset pairs. Evidently, weak to lower-moderate positive and negative correlations characterised the pairs, indicative of a barely coupled markets. This finding augments the existing studies (Corbet et al., 2018; Aslanidis et al. 2019; Pavković et al., 2019; Kostika and Laopodis, 2019; etc.), which mostly report a detached cryptocurrency market from advanced traditional markets. Further to this, we found that major cryptocurrency events (news headlines) exert piffling influence on the observed level of pairwise market relatedness. This perhaps suggests that emerging market assets remain, largely, insensitive to major news about the cryptocurrency market.

The weak positive and negative correlations motivate testing to assess whether Bitcoin/Ripple could serve more than a potential diversifier. Based on the extracted dynamic conditional correlations and a dummy variable regression model, we found that the economic benefits of Bitcoin/Ripple are multifaceted, but differ for the two digital currencies, and vary across the regional and country-specific assets. Specifically, Bitcoin/Ripple could function well as a diversifier and offer capabilities to reduce downside risk in emerging equities and foreign currency rates during turmoil or market downturn. This implies that emerging market investors with exposures to high equity and/or forex market(s) risk could benefit from holding positions in Bitcoin and/or Ripple during periods of such heightened uncertainties. On the other hand, governments of emerging economies should widely open up to explore potential economic role(s) of cryptocurrency assets, especially as Bitcoin and

Ripple have shown capabilities of acting as safe haven against downward movements in some fiat currencies, and regulate them as such.

In addition to the above, a multi-asset portfolio analysis, involving the cryptocurrencies and the regional emerging assets is provided, with implication thereof. We believe our study would inspire further debate on the economic roles of several cryptocurrencies in an emerging and frontier market settings, with the use of even wider market coverage.

CHAPTER 4

Interdependence and Spillovers between Cryptocurrencies and Emerging Financial Assets

"As Africans, we need to share common recognition that all of us stand to lose if we fail to transform our continent" ***Thabo Mbeki;*** *"Africa is poor because its investors and its creditors are unspeakably rich"* ***Naomi Klein***

4.1 Introduction

Amid the scepticism about their fundamental values and lack of proper financial and monetary regulatory system, the decade-old digital currencies, i.e. cryptocurrencies have evolved to become apparently a new global financial asset (Baur et al., 2018b; Corbet et al., 2019) widely embraced by sections of the general investor community. For instance, the number of users, worldwide, of Coinbase only, a leading cryptocurrency exchange is currently a little above 30 million, and holds over 150 billion US dollars in trade since its inauguration in mid-2012 (refer, https://www.coinbase.com). The exponential growth in the price, volume, and market size of cryptocurrencies[55], and the rising hope of cashing out bounty returns, perhaps drive the widespread interest in the new currency market.

To position cryptocurrency in mainstream finance and project it as a stable and viable investment asset class, a plethora of recent empirical research has tended to focus on investigating the level of interdependence, as well as shock transmissions, first, among

[55] Barely two years (10.12.2015 - 11.01.2018), the price of the leading cryptocurrency, i.e. Bitcoin increased significantly from 415.41 to 13,515 US dollars (representing approximately 3,153%) with a corresponding market cap moving swiftly from 6 to 229 billion US dollars (denoting a change of 3,593%). Similar increasing pattern for the same period is also observed for Ethereum (the second largest cryptocurrency), which witnessed a change in price from 0.86 to 1,201 US dollars, with an associated market cap from 64 million to 116 billion US dollars (refer, https://www.coinmarket.com). This substantial growth and the expected high reward for holding a cryptocurrency asset is very unlikely to be realised in other financial assets markets, hence creating an alternative investment opportunity for international investors, albeit high risk.

cryptocurrency assets, and second, between cryptocurrencies and long-existing financial assets and economic conditions (see, Kurka, 2017; Bouri et al., 2018; Corbet et al., 2018; Koutmos, 2018; Trabelsi, 2018; Gillaizeau et al., 2019; Jang et al., 2019; Ji et al., 2019a; Ji et al., 2019b; Kumar and Anandarao, 2019; etc.). Not only do studies on interactions and movement of shocks between asset markets remain important to ensuring financial system stability, but it is also further believed that identifying shock transmission channels has far-reaching consequences for asset allocation, hedging strategies, and portfolio management (Al-Yahyaee et al., 2019; Ji et al., 2019a), which when well-considered culminate to better inform investment decisions of traders and fund managers.

Moreover, understanding the interdependence and spillover behaviour between the nascent cryptocurrencies and other assets, especially emerging assets is a phenomenon of utmost significance. For example, assessing potential spillover effects of the cryptocurrency market on traditional financial asset markets would perhaps enable policymakers to adequately regulate the environment to curtail undesirable inter-market shocks, which may have the tendency to destabilize conventional financial system. Also, in situations of weak interactions, investors can employ portfolio diversification schemes to maximize return on investment. Although, empirical research on spillovers of the new currency market has sprung up lately, there exist the need for more studies since the existing ones have mostly focused on the dynamics within the cryptocurrency market (Antonakakis et al., 2019; Canh et al., 2019; Omane-Adjepong and Alagidede, 2019; Zięba et al., 2019; etc.), and also between cryptocurrencies and fewer traditional assets, mainly selected from the developed markets (Jang et al., 2019; Kurka, 2019; Liu and Serletis, 2019; Qarni et al., 2019; etc.).

In the above context, we pose the following questions: *Is there any form of interlinkages between returns and volatilities of the most liquid cryptocurrencies and emerging assets? Are such causal relationships time-dependent?* More specifically, are there return and

volatility shocks that spill from cryptocurrencies to diverse emerging asset classes of country-specific and regional groupings, and vice versa?

Motivated by the dearth of literature to provide insight into these research questions, our study augments the discussion to include these unexplored avenues and makes the following salient contributions. First, we investigate the nature of cross-market interrelatedness and risk spillovers using the non-linear causality test of Diks and Panchenko (2005, 2006), the rolling-window method of Hill (2007), and the spillover index approach developed by Diebold and Yilmaz (2012, 2014, 2016). We believe the use of these refined empirical methods would help to unearth fresh and robust findings that have relevant implications for market participants. Second, differing from previous studies, the current work considers in addition to two leading cryptocurrencies, an extensive asset of 10 giant emerging economies[56], drawn from 4 geographical regions, hence making our analysis more informative. Lastly, a unique contribution is chartered by examining the sensitivity of risk spillovers to major news events or occurrences in the evolution of the cryptocurrency market.

Excerpts from our main results show a weak and time-invariant level of interlinkages or causal relationships between each of the two studied cryptocurrencies and the emerging assets. Regarding spillover transmissions, we found Bitcoin and Ripple to be mostly net receivers than emitters of shocks. The results further reveal that major news reports about the cryptocurrency market apparently exert influence on the spillover behaviour among the markets.

The ensuing sections of the chapter are structured in the following way: Section 4.2 provides in detail, a review of relevant empirical studies on the subject matter. Section 4.3 discusses the methods employed for the study. Section 4.4 presents the data and

[56] A total of 20 emerging assets from different asset classes (forex and stock) belonging to emerging economies within the composition of the G20 (except Saudi Arabia) are included in our analysis.

preliminary results, while extended results and discussions are offered under Section 4.5. Finally, Section 4.6 concludes.

4.2 Related literature

In spite of its decade-long existence, until the last two years, empirical work in the field of cryptocurrency research overlooked the relevance of examining risk spillovers of the new market entrant. The paucity of evidence in the literature is epitomized in a systematic survey on return and volatility spillovers conducted by Kyriazis (2019). The author identified 11 empirical studies that formed the basis for his investigation. In complementing Kyriazis' (2019), we summarise their review and extend the literature review to include (in the best of our knowledge) all the 34 published research articles on the subject so far. *Could this emergent research interest be as a result of the pronouncement by certain central banks and regulators that, the cryptocurrency market is too small to influence monetary policies and existing financial system?* Out of the 34, 25 were published online in 2019 alone. For better interrogation of the issues, the strand of the existing studies is reviewed under three dimensions: (i) spillovers among markets within the cryptocurrency family; (ii) cross-market spillover analysis of cryptocurrency and traditional markets; and (iii) articles that combine (ii) and (iii) in a single study.

Koutmos (2018) examines return and volatility interdependencies among 18 largest cryptocurrency markets with data from 07.08.2015 - 17.07.2018[57]. Among the sampled coin markets, Bitcoin is adjudged by the researcher as the dominant transmitter of return and volatility shocks. Using a multivariate GARCH model, i.e., IGARCH(1, 1)-DCC(1, 1), and covering the period from 15.08.2015 - 18.01.2018, their study found significant volatility spillover which moves from Bitcoin to Litecoin and Ethereum. Applying the Granger causality test and a BEKK-MAGARCH approach, Tu and Xue

[57] Date format: dd.mm.yyyy

(2019) investigate effect of the bifurcation of the Bitcoin market (into Bitcoin and Bitcoin Cash) on its interlinkages with Litecoin. Two periods are considered: prior- (28.04.2013 - 31.07.2017) and post-bifurcation (01.08.2017 - 31.07.2018). their results detail that, prior to bifurcation, return and volatility spillovers run from Bitcoin to Litecoin, whereas shock transmission is reversed, thus from Litecoin to Bitcoin, in the era of post-bifurcation. Elsewhere, Bação et al., (2018) provide evidence to suggest that, with respect to shock transmissions, a mega-cap cryptocurrency with large trading volume like Bitcoin does not automatically dominate the cryptocurrency universe. By considering data (01.05.2013 - 14.03.2018) on 5 cryptocurrencies (Bitcoin, Litecoin, Ethereum, Ripple, and Bitcoin Cash) in a VAR system of modelling, the authors identified the direction of information transmission to had mainly run from other supposedly lesser coin markets, especially Litecoin to Bitcoin.

In agreement with Bação et al., (2018), Yi et al., (2018) assert and offer empirical evidence to show that spillover effect has less to do with the size of a particular market. This conclusion was reached based on a volatility connectedness analysis of 52 cryptocurrencies, using aa LASSO-VAR process. The results of their study reveal the likelihood of volatility shocks emitting from mega- to small-cap cryptocurrencies, while the reverse is also observed in some cases. Employing daily data (08.09.2015 - 04.01.2019) on Bitcoin, Ethereum, Ripple, Litecoin, and Stellar in a VAR-SVAR Granger causality framework, and under a Student's *t* copula, Huynh (2019) unveils Bitcoin as a spillover effect recipient, while a propagator role is defined for Ethereum. Ji et al., (2019a) used the spillover measure by Diebold and Yilmaz (2012, 2016) to assess shock transmission across 6 major cryptocurrencies and found Litecoin and Bitcoin to be emitters of return and shocks to the remaining markets. In a study designed to answer the question, "Shock transmission in the cryptocurrency market. Is Bitcoin the most influential?", Zięba et al., (2019) document that the price of Bitcoin does not affect and is not also affected by price shift in other cryptocurrencies. Litecoin

and Dogecoin are reported to be the most influential markets which affect majority of the other markets.

Furthermore, Antonakakis et al., (2019) explore shock transmission channels among 9 most liquid cryptocurrencies (with data spanning 07.08.2015 - 31.05.2018) by employing a TVP-FAVAR modelling approach. A key result from their findings reads, "*… Bitcoin still influences the cryptocurrency market substantially, we note that, recently, Ethereum has become the number one net transmitting cryptocurrency*". Canh et al., (2019) found evidence of structural breaks and detailed higher volatility spillovers among 7 selected cryptocurrency markets. Specifically, aside from the markets being strongly correlated, causality effects are reported to run among the large cryptocurrencies. Providing analysis along transitory and permanent causalities, Bouri et al., (2020b) concluded that causal relationships among the unexpected volatility ("volatility surprise") of 8 studied cryptocurrencies do not necessarily emanate from Bitcoin, over short horizons, and further found transitory shocks to dominate the causality across smaller cryptocurrencies over long horizons. To another set of the extant literature (Katsiampa et al., 2019a; Omane-Adjepong and Alagidede, 2019; and Sifat et al., 2019), evidence of feedback informational linkages with no clearer domineering propagator (or receiver) of shocks is reported.

Dong et al., (2019) investigate asymmetric effect of volatility spillovers among 6 different Bitcoin exchange rate markets based on the MS-VAR model. From the results, the USD followed by the Euro Bitcoin markets came up as the largest net emitters of volatility spillovers. Similarly, Gillaizeau et al., (2019) contend that Bitcoin-USD exchange rate market possesses net predictive power, while the Bitcoin-Euro market is designated as a net receiver of spillovers. In a different twist, Giudici and Pagnottoni (2019), Ji et al., (2019c), and Kliber and Włosik (2019) examine interlinkages and spillovers across varied cryptocurrency platforms. The latter authors found evidence in favour of closely related exchanges, especially for the large exchanges.

Regarding spillover transmissions, Giudici and Pagnottoni (2019) identified Bitfinex and Gemini as leading exchanges, whereas Coinbase is declared a market leader by Ji et al., (2019c).

Another important strand of the literature is pathed in the direction of analyzing interlinkages and shock transmission dynamics between cryptocurrencies and traditional financial markets. The maiden paper in this area of research documents extremely low-level of connectedness between Bitcoin and other markets (Euro/USD, JPY/USD, crude oil, S&P500, and US 2-yr T-note), but instead found a substantial amount of shocks emitted from Bitcoin to global gold market (Kurka, 2017). Erdas and Caglar (2018) establish a causal link running from Bitcoin to S&P500 when they studied possible asymmetric causal linkages between Bitcoin and 5 different markets, namely, Brent oil, gold, S&P500, USD, and BIST100. Symitsi and Chalvatzis (2018) investigate return and volatility shock spillovers of Bitcoin with S&P Global Clean Energy Index, MSCI World Energy Index, and MSCI World Information Technology Index (22.08.2011 - 15.02.2018), using a VAR(1)-AGARCH model and surprisingly found directional asymmetric shock spillovers between Bitcoin and the energy stock indices. Using a Smooth Transition VAR GARCH-in-mean process, Bouri et al., (2018) examine spillovers between markets from 4 asset classes (MSCI Emerging market, MSCI World, MSCI China, S&P GSCI energy, S&P GSCI commodity, US 10-yr Treasury yields, and one ounce of gold) and Bitcoin during bear and bull market periods. They concluded that Bitcoin is not completely isolated from traditional markets, and further indicated that, in both market conditions, Bitcoin receives more volatility shocks than it transmits.

Ji et al., (2019b) employ a time-varying entropy-based and a minimum spanning tree technique to explore information spillovers between a pool of energy, agricultural, and metal commodities, and 5 major cryptocurrencies (Bitcoin, Ethereum, Ripple, Litecoin, and Stellar). Their results indicate that energy and agricultural commodity

markets remained important movers of spillovers; cryptocurrencies occupy the mid-range; while the metal market reacts the least to informational spillover flow in the network. In a related study, Mensi et al., (2019b) analyze the asymmetric volatility interrelatedness of precious metals (gold, silver, platinum, and palladium) with Bitcoin, and report among others that, risk spillovers are time-variant and sensitive to slowdowns in economic and political occurrences. Palladium is found to be the largest net transmitter, followed by gold, while Bitcoin placed itself as a net recipient of spillovers. Concerning asymmetry in semi-volatility transmission, Bitcoin showed high prospects as a propagator of net positive spillover. Further to the above, interesting conclusions are reached by Qarni et al., (2019), Jang et al., (2019), and Kang et al., (2019b), as they studied spillover behaviour between Bitcoin and US dominated financial markets. Particularly, the last two groups of authors identified (asymmetric)causal interdependency for Bitcoin and their other studied markets.

Our final set of empirical studies (Milunovich, 2018; Trabelsi, 2018; and Liu and Serletis, 2018) detail the level of interrelatedness and spillovers among cryptocurrencies, and between cryptocurrencies and diverse traditional markets. For instance, Trabelsi (2018) uses the spillover index construction procedure (of Diebold and Yilmax, 2012) along with a spectral representation of variance decomposition networks to unveil no significant spillover effects for 4 cryptocurrency markets (Bitcoin, Ethereum, Ripple, and Litecoin) with commodities (gold, Brent oil), forex (Euro/USD, USD/JPY, GBP/USD, USD/CAD, and USD/CHF), and stock index (S&P500, FTSE100, NASDAQ, Hang Seng, and Nikkei225). The author concludes that "*… cryptocurrencies are real independent financial instruments that pose no danger to financial system stability*". Further results have it that Bitcoin emits more shocks to other cryptocurrencies, but conversely, it appears to be the most influenced or absorber of shocks from the remaining cryptocurrencies.

Highlights from the reviewed works above bring to our attention that the dominance of Bitcoin as the most liquid cryptocurrency (with mega-cap and high trade volumes) does not necessarily position it as a defacto lead market of risk spillover. In anything, its influence as a lead propagator of shocks is fiercely contended by other cryptocurrencies. Moreover, the literature on interlinkages and spillovers among cryptocurrencies and other markets warrants more empirical studies, as there seems to be no consensus in the findings of the few existing studies. Whereas Trabelsi (2018) places cryptocurrencies as independent financial instruments with no apparent risk spillover effects or danger to other markets, Bouri et al., (2018) tend to suggest that, the cryptocurrency market is not completely detached from traditional markets. Except for studies by Malhota and Gupta (2019) and Vardar and Aydogan (2019), which respectively considered 5 Asian stocks and few Turkish assets, the literature has failed to include wider coverage of traditional emerging asset classes in the narrative. Although the recent work of Dahir and Mahat (2019) is acknowledged, the authors' choice to add S&P500 and VIX to BRICS equities defeat any purpose to exclusively quantify the extent of risk spillovers among emerging assets and cryptocurrencies. We, therefore, augment the literature by employing different techniques to examine interrelatedness and risk spillovers between a pool of diverse emerging asset markets with the nascent cryptocurrency market. Unlike the majority of the previous studies, which only considered Bitcoin, we include in our analysis, Ripple which is not a clone of the former but remains one of its fierce competitors.

4.3 Empirical methodology

The modelling approaches adopted in this study are described in this section. The level of return and volatility informational interlinkages for pairs of markets are detailed using Diks and Panchenko's (2005, 2006), as well as Hill's (2007) causality methods. Prior to that, we derived conditional volatility return series for each market, from a univariate ARFIMA-GJRGARCH process. Further, static and dynamic

directional and total spillover indexes are constructed based on the novel methodology in the work of Diebold and Yilmaz (2012, 2014, 2016).

4.3.1 Specification of conditional volatility models

In practice, several univariate volatility models are used to explain variations in return distributions of financial variables. However, our aim is not to compare performances across these models, but to generate conditional volatility return series from one of such popularly used models. First, we denote continuously compounded return series as:

$$r = 100 * \left[In(P_t) - In(P_{t-1}) \right] \tag{4.10}$$

where P_t and P_{t-1} are the close of day prices for the current and previous days respectively. We proposed to model the marginal distribution of each asset returns with ARFIMA(1, *d*, 1)-GJRGARCH(1, 1) process, under skewed Student's *t* (SST) innovations – which we believe could well-explained extreme movements and other financial properties of the assets.

The mean equation of the process reads as follows:

$$\phi_1(L)(1-L)^d(r_t - \mu) = \theta_1(L)\varepsilon_t \tag{4.11}$$

where r_t is the returns, L gives the lag operator, ϕ_1 and θ_1 are the parameters to be estimated, and d represent the differencing parameter. We favoured the ARFIMA(1, *d*, 1) process due to its ability to capture short and long-run dependencies between return realizations. Specifically, the short-run effect is observed with the AR(1) component of the process, where d is set to zero. On the other hand, the long-run effect is captured by the fractional differencing parameter.

Furthermore, we considered the Glosten-Jagannathan-Runkle GARCH, i.e., the GJRGARCH of Glosten et al., (1993), which flexibly accounts for a range of stylized

facts (like volatility clustering, asymmetric volatility effect, among others) in financial assets to model the variance equation. The GJRGARCH(1, 1) component is express as:

$$\sigma_t^2 = \omega + \left[\alpha_1 + \gamma I(\varepsilon_{t-1} < 0)\right]\varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \qquad (4.12)$$

where the gamma parameter, γ describes the asymmetric volatility effect, $I(\bullet)$ is an indicator function; and $\omega > 0$, $\alpha \geq 0$, $\beta \geq 0$, and $\gamma \geq 0$ remains as sufficient conditions to achieve positivity of the conditional variances. Altogether, the wide variety of stylized facts that could be accounted for by the ARFIMA(1, *d*, 1)-GJRGARCH(1, 1) process with the SST innovations makes its application to our diverse assets classes more appropriate.

4.3.2 Testing for non-linear interdependence

There is a growing number of empirical works that argue and tend to suggest that the relationship between economic and financial variables is largely non-linear. In addition to the above, the use of linear models to mainly examine interlinkages among financial assets has been heavily criticized, owing to the reason that asset markets are part of a dynamical financial system that appears to be characterized by non-linearities. To address the limitations of linear models such as the frequently favoured standard Granger causality, Baek and Brock (1992) initially developed a non-linear version of the test, which was later modified by Hiemstra and Jones (1994). However, the latter's non-linear causality test is flawed with high rejection rates of the null hypothesis, when indeed the test shows otherwise. In mitigating this flaw, Diks and Panchenko (2005, 2006) introduced the nonparametric DP test in a bivariate setting. Ever since its introduction, the DP test for non-linear Granger causality has witnessed wide-level multidisciplinary applications and is described in the work of Diks and Wolski (2016) as consistent and robust against other range of alternatives.

In this study, we have applied the DP test to investigate return and volatility interdependencies between pairs of the studied assets, thus Bitcoin (Ripple) vs

selected emerging assets. Aside from the works done by Omane-Adjepong and Alagidede (2019) and Kang et al., (2019b), the DP test has rarely been used in empirical researches in the area of cryptocurrency finance. The description of the DP test approach is presented in the lines that follow. Let us consider X_t and Y_t as a pair of stationary and dependent time series. Let us assume $F_{X,t}$ and $F_{Y,t}$ denote respectively the information sets of past realizations of X_t and Y_t, before time $t-1$, while '~' is taken to symbolize the equivalence in distribution, then the time series X_t Granger-causes series Y_t provided that for $k \geq 1$:

$$\left(Y_{t+1},...,Y_{t+k}\right)\left|\left(F_{X,t},F_{Y,t}\right)\sim\left(Y_{t+1},...,Y_{t+k}\right)\right|F_{X,t} \tag{4.13}$$

where, k gives the forecasting horizon. Let the delay vectors $X_t^{l_r}=\left(X_{t-l_r+1},...,X_t\right)$ and $Y_t^{l_s}=\left(Y_{t-l_s+1},...,Y_t\right)$, where $\left(l_r,l_s\geq 1\right)$. The DP method allows for testing conditional independence using a determinate number of lags, thus l_r and l_s under a null hypothesis which reads:

$$H_0: Y_{t+1}\left|\left(X_t^{l_r};Y_t^{l_s}\right)\sim Y_{t+1}\right|Y_t^{l_s} \tag{4.14}$$

Considering a strictly stationary bivariate series, the null hypothesis in Eqn (4.14) is basically an assertion about the invariant distribution of the $\left(l_r+l_s+1\right)$-dimensional vector $Q_t=\left(X_t^{l_r},Y_t^{l_s},Z_t\right)$, where vector $Z_t=Y_{t+1}$. For notational compatibility and ease of presentation, we discard the time index to set $Q=\left(X,Y,Z\right)$, and $l_r=l_s=1$, with $k=1$ and assume that the variables X, Y, and Z in Q are continuous random variables. The null hypothesis is Eqn (4.14) can be reframed in a joint probability function $f_{X,Y,Z}(x,y,z)$ with its marginal satisfying the understated condition:

$$\frac{f_{X,Y,Z}(x,y,z)}{f_Y(y)}=\frac{f_{X,Y}(x,y)}{f_Y(y)}*\frac{f_{Y,Z}(y,z)}{f_Y(y)} \tag{4.15}$$

where, for each determinate value of y, the variables X and Z are independent conditionally on $Y=y$. Hence, under the reformulated null hypothesis, Diks and Panchenko (2006) employed a weight function $g(x,y,z)=f_Y^2(y)$ and delineated that:

$$q \equiv E\left[f_{X,Y,Z}(X,Y,Z) f_Y(Y) - f_{X,Y}(X,Y) f_{Y,Z}(Y,Z)\right] = 0 \tag{4.16}$$

The authors further deduced a natural estimator of q, and expressed it as:

$$T_n(\varepsilon_n) = \frac{(2\varepsilon_n)^{-d_X - 2d_Y - d_Z}}{n(n-1)(n-2)} * \sum_i \left[\sum_{k,k\neq i} \sum_{j,j\neq i} (I_{ik}^{XYZ} I_{ij}^{Y} - I_{ik}^{XY} I_{ij}^{YZ}) \right] \tag{4.17}$$

Here, $I(\bullet)$ denote an indicator function, where $I_{ij}^{Q} = I\left(\left\|Q_i - Q_j\right\| < \varepsilon_n\right)$ and ε_n is the bandwidth parameter which depends on the sample at hand, if a consistent test result is required. Through the representation of the local density estimators of a d_Q-variate random vector Q at Q_i ;

$$\hat{f}_Q(Q_i) = \frac{(2\varepsilon_n)^{-d_Q}}{n-1} * \sum_{j,j\neq i} I_{ij}^{Q} \tag{4.18}$$

the test statistic $T_n(\varepsilon_n)$ of the DP test simplifies to:

$$T_n(\varepsilon_n) = \frac{(n-1)}{n(n-2)} * \sum_i \left(\hat{f}_{X,Y,Z}(X_i,Y_i,Z_i) \hat{f}_Y(Y_i) - \hat{f}_{X,Y}(X_i,Y_i) \hat{f}_{Y,Z}(Y_i,Z_i) \right) \tag{4.19}$$

For $d_X = d_Y = d_Z = 1$, if $\varepsilon_n = Cn^{-\beta}$ for $(c > 0, \beta \in (0.25, 0.67))$, then Diks and Panchenko (2006) showed that $T_n(\varepsilon_n)$ converges in distribution to the standard normal

$$\sqrt{n} * \frac{\left(T_n(\varepsilon_n) - q\right)}{S_n} \xrightarrow{d} N(0,1) \tag{4.20}$$

where the asymptotic variance of $T_n(\bullet)$ is denoted by S_n.

4.3.3 Hill's causality approach

As earlier mentioned, it is well-known that most variables generated in the financial markets are complex dynamical systems that are unlikely to be in equilibrium, but rather manifest non-linearities such as regime shifts, non-stationarity, extreme fluctuations, intermittency, among several others. This is predominantly observed for high-frequency data (e.g. intraday and daily data), collected over a longer time span. Unarguably, extreme price volatility has remained an evidential feature that engulfs cryptocurrencies and most emerging financial assets. Wary of this phenomenon, in

addition to the DP test for non-linear Granger causality, we extend our findings to include a rolling-window non-causality analysis.

Generalizing the standard Granger causality, Hill (2007) proposed a simple but efficient sequential multi-step ahead non-causality method in trivariate VAR models, which may be used to characterize a causality chain. A causal chain is anticipated to allows for multi-horizon causation delays. Meaning, non-causation periods may be followed by causation. Practically, the approach is designed for non-linear causality chains (or non-linear Granger causality linkages) in the perspective of linear parametric restrictions. This unique property of Hill's (2007) non-causality test makes it use much plausible in our study due to the extremely volatile nature of the markets under consideration. The method is based on the specification of a vector autoregressive (VAR) process of order p at horizon h, simply put, a (p, h)-autoregression, expressed as:

$$W_{t+h} = \alpha + \sum_{k=1}^{p} \pi_k^{(h)} W_{t+1-k} + \mu_{t+h}^{(h)} \qquad (4.21)$$

Here W_t is taken as an m-vector stationary process, with $m \geq 2$, and $\pi_k^{(h)}$ are matrix-valued coefficients based on non-linear recursive representations. α denote the constant term, and μ_t follow a zero-mean $(m \times 1)$-vector white noise process, having a non-singular covariance matrix given by $\Omega = [\mu_t, \mu_t^{|}]$.

With reference to Theorem 2.1 of Hill (2007), causality is observed at any horizon, say h, if and only if such causality exists at horizon one. In this study, we simplify Hill's trivariate procedure in a bivariate framework. In so doing, we assume $W_t = (C_t^{|}, E_t^{|})^{|}$ is now a 2-vector process with a stationary autoregressive representation. The variables C_t and E_t are respectively the returns at time t for Bitcoin or Ripple and each of our chosen emerging assets. We, therefore, test to show that E does not linearly cause C at one-step ahead if and only if the CE-block $\pi_{CE,1}^{(h)} = 0$ for $k = 1$. According to Hill (2007),

a simple Wald test under zero parameter linear restrictions is all that may be needed to test for a one-step-ahead non-causality. However, due to the shortcomings of the Wald-type test in small finite samples, the authors devised a standard and parametric bootstrap approach for simulating small sample probability values[58]. This approach is adopted in our non-causality test procedure.

4.3.4 Measuring return and volatility spillovers

The methodological procedure employed for estimating the degree of return and volatility risk spillovers under both static and time dynamic settings follow the spillover index approach of Diebold and Yilmaz (2012, 2014, 2016), hereafter DY. The DY approach is rooted in a generalized forecast-error variance decomposition (GFEVD), specified under a VAR system that eliminates any possible dependence stemming from the ordering of the variables in the system. Recently, empirical studies on cryptocurrencies have used this spillover framework to either measure shock spillovers among cryptocurrencies (Koutmos, 2018; Yi et al., 2018; Dong et al., 2019; Gillaizeau et al., 2019; Giudici and Pagnottoni, 2019) or between cryptocurrencies and other traditional assets (Corbet et al., 2018; Trabelsi, 2018; Kurka, 2019; Qarni et al., 2019). However, none of these mushrooming papers that used the DY approach reports exclusively on potential pairwise spillovers transmitted from cryptocurrencies to diverse emerging assets and vice versa. In this regard, we adopt the DY's modelling procedure to address this gap.

Let us assume the return or volatility return series X_t follows a covariance-stationary N-variable p^{th}-order VAR process, expressed as:

[58] Notes: The optimal VAR order selection is based on the AIC. A 250 window size is chosen for the rolling-window non-causality test, which is rolled forward one at a time. We set the number of bootstrap replications to 5000, and run the test using a GAUSS code (GAUSS 20) accessible at: http://jbhill.web.unc.edu/software/.

$$X_t = \sum_{i=1}^{p} \Phi_i X_{t-i} + \varepsilon_t \qquad (4.22)$$

where in our case we considered 11 variables, comprising Bitcoin or Ripple and 10 each of emerging equities at one hand, and emerging forex at the other hand, notationally represented as $X_t = (X_{1,t},...,X_{11,t})'$ – thus, (11 × 11) random vector of endogenous variables. Φ_i denote (11 × 11) autoregressive parameter matrices, and ε_t is the disturbances which are assumed to be independent and identically distributed with $\varepsilon_t \sim (0, \sum)$.

Given that the VAR(p) process is covariance-stationary, we express the moving average component of the process by:

$$X_t = \sum_{i=1}^{\infty} \tau_i \varepsilon_{t-i} \qquad (4.23)$$

where the (11 × 11) parameter matrices τ_i are based on the recursion $\tau_i = \Phi_1 \tau_{i-1} + \Phi_2 \tau_{i-2} + ... + \Phi_p \tau_{i-p}$, with τ_0 taken to be a (11 × 11) identity matrix, and $\tau_i = 0$ for $\tau_i < 0$. The flexibility of the generalized variance decomposition has to do with its ability to allow analysts to assess the proportion of the H-step ahead error variance in forecasting say X_i that is attributed to shocks in X_j, $\forall j \neq i$, for each i (Diebold and Yilmax, 2012). Meaning, shocks in the system of variables could be separated to unveil the proportion of error variance in forecasting for instance Bitcoin due to shocks in say Bovespa, Merval, FTSE/JSE TOP40, Mexbol, Ruble/USD and so on. Under such procedure, asset markets that transmit (receive) shock to (from) the system are easily identified.

In a nutshell, asset market j's share of contribution to asset market i's H-step-ahead generalised forecast-error variance is given by (Diebold and Yilmax, 2012; 2016):

$$\theta_{ij}^{g}(H)=\frac{\sigma_{jj}^{-1}\sum_{h=0}^{H-1}\left(e_i^{|}\tau_h\,\Sigma\,e_j\right)^2}{\sum_{h=0}^{H-1}\left(e_j^{|}\tau_h\,\Sigma\,\tau_h^{|}e_i\right)} \tag{4.24}$$

where Σ represent the variance matrix for the vector of errors ε, σ_{jj} denote the standard deviation of ε_j, and the term e_i describes the selection vector, which has its ith element to be ones and zeros otherwise. The resultant gives a (11 × 11) matrix written as $\theta(H)=[\theta_{ij}]_{ij=1,2,\ldots,11}$. The own-market shock contributions are represented by the entries in the main diagonal of the $\theta(H)$ matrix, while the off-diagonal entries yield directional contributions[59]. Given the circumstances that the shocks generated are not orthogonal, it follows that the sum of the forecast error variance contributions by own-market and that of the cross-market cannot assume one: $\sum_{j=1}^{N}\theta_{ij}^{g}(H)\neq 1$. Therefore, each entry of the variance contributions is normalized by the row sum:

$$\tilde{\theta}_{ij}^{g}(H)=\frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N}\theta_{ij}^{g}(H)} \tag{4.25}$$

Following through, we now have $\sum_{j=1}^{N}\tilde{\theta}_{ij}^{g}(H)=1$ and $\sum_{i,j=1}^{N}\tilde{\theta}_{ij}^{g}(H)=N$, where in our perspective, we operate under a 11-market system.

The total spillover index (TSI), also dubbed as system-wide connectedness quantifies the average contribution of shocks across all the 11 studied markets to the total forecast-error variance. It is computed as the ratio of the off-diagonal entries of matrix $\theta(H)$ to the sum of all its elements:

$$S^{g}(H)=\frac{\sum_{\substack{i,j=1\\ i\neq j}}^{N}\tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N}\tilde{\theta}_{ij}^{g}(H)}\times 100=\frac{\sum_{\substack{i,j=1\\ i\neq j}}^{N}\tilde{\theta}_{ij}^{g}(H)}{N}\times 100 \tag{4.26}$$

[59] For a schematic tabular construction, readers are referred to (Diebold and Yilmax, 2014).

In addition to the TSI, we determine the extent of directional spillover between the markets. Thus, the directional shock spillovers received by asset market *i* from all the remaining asset market *j*, where $j \neq i$ is computed using the expression:

$$S_{i\leftarrow j}^{g}(H)=\frac{\sum_{\substack{j=1\\ j\neq i}}^{N}\tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N}\tilde{\theta}_{ij}^{g}(H)}\times 100=\frac{\sum_{\substack{j=1\\ j\neq i}}^{N}\tilde{\theta}_{ij}^{g}(H)}{N}\times 100 \tag{4.27}$$

On the other hand, the directional shock spillovers transmitted by asset market *i* to all the remaining markets *j*, in the system, where $i \neq j$, is deduced as:

$$S_{i\rightarrow j}^{g}(H)=\frac{\sum_{\substack{j=1\\ j\neq i}}^{N}\tilde{\theta}_{ji}^{g}(H)}{\sum_{i,j=1}^{N}\tilde{\theta}_{ji}^{g}(H)}\times 100=\frac{\sum_{\substack{j=1\\ j\neq i}}^{N}\tilde{\theta}_{ji}^{g}(H)}{N}\times 100 \tag{4.28}$$

For each market, we also measure the gross spillovers transmitted to, and likewise, received from, all other markets in the system. This is termed as net directional spillover. The net spillover from the *i* to *j* markets $(i \neq j)$ is simply the difference of the results between Eqns (4.28) and (4.27):

$$S_{i}^{g}(H)=S_{i\rightarrow j}^{g}(H)-S_{i\leftarrow j}^{g}(H) \tag{4.29}$$

Finally, we compute a net pairwise directional spillover to measure the intensity of influence between pairs of the markets. Here, the net pairwise spillover between market pair *i* and *j* is obtained as the difference of the shocks transmitted from either *i* to *j* or *j* to *i* respectively:

$$S_{ij}^{g}(H)=\frac{\tilde{\theta}_{ji}^{g}(H)-\tilde{\theta}_{ij}^{g}(H)}{N}\times 100 \tag{4.30}$$

$$S_{ji}^{g}(H)=\frac{\tilde{\theta}_{ij}^{g}(H)-\tilde{\theta}_{ji}^{g}(H)}{N}\times 100 \tag{4.31}$$

From the foregoing, given any pairs of markets, the net pairwise spillover measure derived from Eqn (4.30) or (4.31) could easily be used to determine which particular market dominates the other, with respect to shock transmissions.

4.4 Data and preliminary analysis

We conduct our analysis using daily stock and bilateral foreign currency (forex) data of 10 giant emerging economies from the G20, i.e. Brazil (Bovespa and Real/USD), Russia (MOEX, Ruble/USD), India (NIFTY50, Rupee/USD), China (SSE50, Yuan/USD), South Africa (FTSE/JSE TOP40, Rand/USD), Argentina (Merval, Argentine Peso/USD), Mexico (Mexbol, Mexican Peso/USD), Turkey (BIST30, Lira/USD), South Korea (KOSPI200, Won/USD), and Indonesia (Jakarta Stock Index, Rupiah/USD)[60]. The dataset was obtained from Bloomberg's database terminal and covers the period from 12.08.2013 - 07.06.2019.

The same period of data coverage on two leading cryptocurrencies is considered. Data on Bitcoin and Ripple exchanges are derived from CoinMarketCap at www.coinmarketcap.com. Our choice to include only these two digital assets, screened from a universe of cryptocurrencies is premised on the issue of liquidity and availability of lengthier time series data. More importantly, we found favour in Bitcoin and Ripple because aside from the earlier mentioned screening criteria, both digital currency markets operate independently (on different trading platforms), unlike most cryptocurrencies which are mere clones of Bitcoin. For consistency purposes, the dataset from the three asset classes are sourced in US dollars and well-cleaned to match with each other with respect to the timestamp of the time series realizations.

Table 4.10: Summary measures

	Panel A: Raw return series				**Panel B: Volatility return series**			
	Mean	Std. Dev	Kurtosis	Skewness	Mean	Std. Dev	Kurtosis	Skewness

[60] The stock and forex of Saudi Arabia are excluded due to our inability to obtain reliable dataset.

Bitcoin	0.3064	5.2026	14.277	0.4704	4.8404	2.5902	11.949	2.1714
Ripple	0.3228	9.1907	31.131	2.5424	7.6920	6.1636	22.242	3.5202
Argentina Peso	-0.1480	1.2981	231.91	-11.116	0.7479	1.1675	61.031	6.2879
Brazilian Real	-0.0374	1.0473	6.085	-0.1031	1.0190	0.2627	4.901	1.0534
Mexican Peso	-0.0309	0.7698	12.010	-0.9535	0.7500	0.2422	12.924	2.2380
Russian Ruble	-0.0480	1.2526	19.430	-0.3407	1.0612	0.6949	19.796	3.4156
South A. Rand	-0.0293	1.0291	5.049	-0.2536	1.0130	0.2462	1.765	0.7700
Turkish Lira	-0.0786	1.0793	33.501	-1.8448	0.9472	0.4849	50.058	5.8547
Chinese Yuan	-0.0086	0.2211	10.236	-0.2713	0.2026	0.1021	5.712	1.1796
South K. Won	-0.0042	0.5364	5.317	-0.1663	0.5298	0.1165	2.114	0.1165
Indian Rupee	-0.0087	0.4473	10.887	-0.3683	0.4119	0.1631	22.667	3.6833
Indo. Rupiah	-0.0228	0.5471	8.422	0.5471	0.5033	0.2549	7.922	1.7326
Merval	0.0131	2.5495	22.968	-1.8060	2.4363	1.1192	32.063	4.2078
Bovespa	0.0097	2.1137	7.500	-0.2031	2.0779	0.4896	16.020	2.3724
Mexbol	-0.0296	1.3536	7.418	-0.5113	1.2947	0.4939	17.046	2.8032
Moex	0.0000	1.8229	11.127	-0.5395	1.6974	0.6480	9.270	1.9941
FTSE/JSE TOP40	-0.0076	1.5320	4.512	-0.3050	1.4982	0.3948	4.094	1.0340
BIST30	-0.0565	2.1292	8.781	-0.6440	2.0649	0.5178	15.239	2.6766
SSE50	0.0283	1.6512	9.651	-0.3938	1.5466	0.7817	7.940	1.8202
KOSPI200	0.0027	1.1051	5.090	-0.3443	1.0988	0.1520	2.855	0.6602
NIFTY50	0.0442	1.1848	9.810	-0.2775	1.1240	0.3891	16.461	2.9634
Jak. Stock Index	-0.0018	1.1982	6.670	-0.2951	1.1374	0.3963	5.728	1.2755

Table 4.11: TNN test results

	Panel A: Raw return series			**Panel B: Volatility return series**		
	lag 2	**lag 5**	**lag 10**	**lag 2**	**lag 5**	**lag 10**
Bitcoin	8.17[0.000]	3.50[0.000]	3.07[0.000]	1.75[0.093]	1.48[0.018]	2.59[0.000]
Ripple	7.56[0.000]	4.95[0.000]	5.10[0.000]	3.24[0.002]	3.88[0.000]	5.30[0.000]
Argentine Peso	6.94[0.000]	3.73[0.000]	2.24[0.000]	3.89[0.000]	1.51[0.013]	0.56[1.000]
Brazilian Real	3.61[0.001]	1.73[0.001]	1.65[0.000]	1.68[0.109]	1.32[0.067]	1.12[0.118]
Mexican Peso	5.86[0.000]	3.37[0.000]	1.87[0.000]	**1.45[0.183]**	**0.78[0.864]**	5.05[0.000]
Russian Ruble	15.5[0.000]	9.31[0.000]	5.01[0.000]	2.00[0.052]	3.86[0.000]	6.82[0.000]
South A. Rand	4.26[0.000]	2.04[0.000]	1.81[0.000]	1.13[0.339]	**0.79[0.854]**	**0.89[0.883]**
Turkish Lira	22.1[0.000]	9.08[0.000]	3.85[0.000]	19.5[0.000]	25.8[0.000]	6.18[0.000]
Chinese Yuan	3.90[0.000]	2.04[0.000]	1.58[0.000]	**1.33[0.230]**	**0.62[0.983]**	**0.66[1.000]**
South K. Won	1.59[0.135]	1.13[0.254]	1.56[0.000]	**1.35[0.222]**	**0.79[0.852]**	**0.57[1.000]**
Indian Rupee	2.96[0.004]	6.41[0.000]	2.50[0.000]	6.37[0.000]	9.76[0.000]	2.71[0.000]
Indo. Rupiah	9.81[0.000]	5.19[0.000]	3.01[0.000]	1.93[0.061]	2.49[0.000]	2.67[0.000]
Merval	2.42[0.018]	2.77[0.000]	1.61[0.000]	**0.52[0.820]**	1.31[0.075]	0.99[0.532]
Bovespa	2.08[0.043]	1.22[0.140]	1.49[0.000]	**0.85[0.540]**	**0.74[0.913]**	**0.89[0.888]**
Mexbol	4.69[0.000]	3.93[0.000]	2.27[0.000]	7.52[0.000]	2.10[0.000]	3.82[0.000]
Moex	6.10[0.000]	3.45[0.000]	2.53[0.000]	**1.67[0.113]**	2.85[0.000]	1.53[0.000]
FTSE/JSE TOP40	3.44[0.001]	1.86[0.000]	2.08[0.000]	3.76[0.000]	1.52[0.012]	1.39[0.000]
BIST30	6.64[0.000]	2.20[0.000]	1.72[0.000]	3.66[0.001]	4.03[0.000]	4.50[0.000]
SSE50	4.82[0.000]	5.16[0.000]	3.85[0.000]	**1.68[0.110]**	2.50[0.000]	2.65[0.000]
KOSPI200	1.86[0.073]	1.57[0.008]	1.23[0.013]	**0.55[0.799]**	**0.65[0.972]**	**1.03[0.364]**
NIFTY50	3.78[0.000]	3.96[0.000]	2.37[0.000]	**0.90[0.503]**	4.08[0.000]	3.78[0.000]
Jak. Stock Index	**0.97[0.451]**	3.20[0.000]	2.27[0.000]	2.86[0.006]	2.04[0.000]	1.35[0.000]

Basic summary measures for the log-returns and volatility series[61] of the asset classes are presented in *Panels A* and *B* of Table 4.10. As would be expected, the average daily returns of Bitcoin and Ripple far exceeds that of the equities and the non-positive returns of the forex. Turning focus to the standard deviation which measures variations (or volatility) within the series, we found that the two cryptocurrencies are highly volatile (showing values not nearer to, or below one), followed by the equities, while the forex show relatively lower risk. The high kurtosis values for all the assets signals that the distribution of the log-returns and the corresponding volatility series are much peaked and have fatter tails – a feature that is contrary to the characteristics of a normally distributed series. Additional evidence of asymmetric probability distribution is observed from the skewness results, which shows extremely higher skewness values for several of the assets.

4.5 Empirical results

Static and rolling-window causality test results for pairs of markets are discussed under sub-sections 4.5.1 and 4.5.2 respectively. Likewise, empirical results on global and dynamic spillover measures between cryptocurrencies and a different set of emerging assets are offered in sub-section 4.5.3.

4.5.1 Non-linear time-sample causality

As a precursory step to conducting the pairwise non-linear causality test, we employed the Teräsvirta Neural Network (TNN) approach to test the null hypothesis of a linear series against a non-linear alternative at different lag lengths[62]. As could be visualized in Table 4.11, the null hypothesis is mostly rejected (with zero probability values), suggestive of substantial evidence showing that the asset markets are

[61] As earlier stated, the volatility series is derived from an ARFIMA-GJRGARCH process. For brevity, the parametric estimations of the process are only available on review request.

[62] For detail readings of the methodology, see Teräsvirta et al., (1993).

generally characterized by a non-linear structure. This finding strongly motivates our choice to examine the extent of interlinkages among the markets using the non-linear causality test method of Diks and Panchenko (2005, 2006).

In our next step, we provide a report on the non-linear causality test results conducted by choosing a lag length of 2, i.e. $l_s = l_r = 2$ [63], and following the bandwidth adaptation and other test protocols of Diks and Panchenko (2006). In so doing, we applied the non-linear DP test to first, a simple VAR model filtered residual series, and second, an ARFIMA-GJRGARCH filtered VAR residual series[64]. Both specifications are conducted for the full sample (SI) and two sub-samples that mark the pre-2017 (SII) and during/post-2017 market evolution of the cryptocurrency market. Whereas the pre-2017 price development shows almost a flat level growth, the succeeding time periods witnessed fluctuating price growth with high peaks mostly around the last quarter of 2017. The rationale is to examine the extent of influences exerted by the two periods, if any, – with regards to causal linkages between cryptocurrencies and other financial assets. Under which of these price regimes do causal linkages manifest?

In the financial context, we interpret a uni-directional causality to mean that changes in asset *i* is likely to cause changes in asset *j*. Also, we confer a strong interlinkage between asset *i* and *j* if there exists a significant bi-directional causality. Meaning, information in asset *i* can to some extent be used to forecast asset *j* and/or vice versa, should there be a causal link. These phenomena may have implications for portfolio allocation, as well as optimization strategies geared towards profit maximization.

[63] According to Diks and Panchenko (2005), the DP test statistic is progressively conservative for increasing lag lengths, hence the authors claimed that the risk of rejecting the null hypothesis becomes small. Therefore, observing causal linkages at $l_s = l_r = 2$ only is not misplaced.

[64] Prior to the VAR modelling, the residuals from the ARFIMA-GJRGARCH process were standardised.

Table 4.12: Non-linear causality between Bitcoin and Emerging Assets

Bitcoin vs. Emerging Foreign Exchange Rates

Panel A1: VAR-filtered return residuals

Direction	SI	SII	SIII
BTC ≠> ARG	0.75(0.228)	-0.08(0.532)	-0.87(0.808)
BTC ≠> BRL	-1.62(0.948)	-0.44(0.670)	-0.48(0.684)
BTC ≠> MEX	-0.12(0.548)	0.73(0.232)	-0.65(0.741)
BTC ≠> RUB	-1.87(0.969)	-2.03(0.979)	-0.00(0.502)
BTC ≠> LIRA	-1.07(0.857)	-0.77(0.779)	0.01(0.495)
BTC ≠> ZAR	-1.78(0.962)	-2.10(0.982)	0.20(0.420)
BTC ≠> CNY	-0.02(0.509)	-0.61(0.730)	-1.13(0.871)
BTC ≠> WON	-1.55(0.939)	-1.18(0.880)	-0.61(0.728)
BTC ≠> INR	-0.03(0.512)	0.14(0.443)	-0.78(0.781)
BTC ≠> RUP	-2.80(0.997)	0.59(0.279)	-1.69(0.954)
ARG ≠> BTC	-0.51(0.694)	-1.21(0.886)	-2.57(0.995)
BRL ≠> BTC	-0.89(0.813)	-0.44(0.670)	0.30(0.383)
MEX ≠> BTC	-0.71(0.761)	0.55(0.290)	-1.88(0.970)
RUB ≠> BTC	-2.54(0.995)	-0.54(0.706)	-0.73(0.768)
LIRA ≠> BTC	0.99(0.162)	0.96(0.167)	-1.10(0.865)
ZAR ≠> BTC	-1.67(0.952)	-1.97(0.975)	0.12(0.454)
CNY ≠> BTC	0.19(0.425)	-0.80(0.787)	0.77(0.222)
WON≠> BTC	-0.61(0.730)	0.19(0.423)	0.28(0.389)
INR ≠> BTC	-0.17(0.567)	**1.93(0.027)**	-1.90(0.971)
RUP ≠> BTC	-1.57(0.941)	0.45(0.327)	-0.45(0.673)

Panel A2: VAR-GJRGARCH-filtered residuals

Direction	SI	SII	SIII
BTC ≠> ARG	**1.78(0.038)**	0.69(0.245)	0.64(0.262)
BTC ≠> BRL	-0.18(0.572)	-0.12(0.547)	-0.34(0.634)
BTC ≠> MEX	**1.68(0.046)**	0.94(0.173)	**1.40(0.081)**
BTC ≠> RUB	-0.79(0.786)	-0.65(0.731)	0.33(0.369)
BTC ≠> LIRA	-0.95(0.828)	-0.83(0.796)	-0.74(0.772)
BTC ≠> ZAR	-0.78(0.781)	-1.16(0.876)	0.13(0.448)
BTC ≠> CNY	0.21(0.416)	-0.28(0.611)	-1.21(0.888)
BTC ≠> WON	-1.04(0.851)	-1.01(0.843)	-0.76(0.776)
BTC ≠> INR	-0.23(0.589)	-0.40(0.657)	-1.25(0.895)
BTC ≠> RUP	-0.46(0.675)	-0.10(0.539)	-0.13(0.552)
ARG ≠> BTC	1.13(0.130)	0.79(0.215)	-0.21(0.584)
BRL ≠> BTC	-0.07(0.530)	0.47(0.318)	-0.92(0.821)
MEX ≠> BTC	-1.16(0.878)	-1.10(0.865)	0.21(0.416)
RUB ≠> BTC	-1.37(0.914)	-0.47(0.682)	-1.53(0.937)
LIRA≠> BTC	**1.32(0.093)**	0.93(0.177)	0.10(0.459)
ZAR ≠> BTC	0.50(0.307)	-0.59(0.721)	-0.18(0.572)
CNY ≠> BTC	-0.21(0.584)	-0.53(0.703)	-0.30(0.619)
WON≠>BTC	0.11(0.455)	0.79(0.214)	-0.61(0.727)
INR ≠> BTC	0.02(0.493)	0.63(0.264)	-0.49(0.689)
RUP ≠> BTC	-0.59(0.724)	-0.51(0.696)	-0.77(0.780)

Bitcoin vs. Emerging Equities

Panel B1: VAR-filtered return residuals

Direction	SI	SII	SIII
BTC ≠> MERV	0.34(0.368)	1.26(0.104)	-0.83(0.796)
BTC ≠> BOV	-1.33(0.909)	0.43(0.334)	-0.72(0.764)
BTC ≠> MEXB	-0.12(0.548)	0.73(0.232)	-0.65(0.741)
BTC ≠> MOEX	-2.53(0.994)	-1.32(0.906)	-2.02(0.978)
BTC ≠> BIST	-0.04(0.514)	0.44(0.328)	0.69(0.246)
BTC ≠> JSE	-0.55(0.708)	-1.08(0.861)	0.28(0.391)
BTC ≠> SSE	0.66(0.255)	1.36(0.086)	-0.53(0.701)
BTC ≠> KOSP	0.10(0.462)	0.58(0.280)	-1.58(0.943)
BTC ≠> NIFT	-0.34(0.634)	0.75(0.227)	-0.05(0.519)
BTC ≠> JAK	-1.58(0.943)	0.41(0.339)	-0.22(0.588)
MERV ≠> BTC	0.09(0.466)	**1.48(0.070)**	-1.75(0.960)
BOV ≠> BTC	-0.23(0.589)	1.17(0.122)	-2.65(0.996)
MEXB ≠> BTC	-0.71(0.761)	0.55(0.290)	-1.88(0.970)
MOEX≠> BTC	-1.08(0.859)	0.05(0.480)	0.48(0.316)
BIST ≠> BTC	-0.46(0.678)	0.73(0.234)	-1.74(0.959)
JSE ≠> BTC	-0.56(0.711)	0.34(0.366)	-0.48(0.684)
SSE ≠> BTC	-0.69(0.753)	-0.03(0.510)	-1.51(0.934)
KOSP ≠> BTC	-1.39(0.918)	-0.76(0.777)	-0.00(0.501)
NIFT ≠> BTC	-1.01(0.844)	0.27(0.394)	-1.14(0.873)
JAK ≠> BTC	-0.92(0.822)	-0.38(0.648)	0.12(0.451)

Panel B2: VAR-GJRGARCH-filtered residuals

Direction	SI	SII	SIII
BTC ≠>MERV	0.39(0.349)	0.74(0.230)	-0.67(0.747)
BTC ≠> BOV	-0.61(0.729)	-0.04(0.517)	0.32(0.374)
BTC ≠>MEXB	0.71(0.240)	**1.54(0.062)**	-0.00(0.500)
BTC ≠>MOEX	-1.37(0.915)	-0.06(0.525)	-0.85(0.801)
BTC ≠>BIST	-1.15(0.561)	-0.04(0.515)	-0.29(0.614)
BTC ≠>JSE	-2.02(0.978)	-0.42(0.662)	0.02(0.492)
BTC ≠>SSE	0.01(0.494)	0.12(0.451)	-1.28(0.900)
BTC ≠>KOSP	0.39(0.349)	0.49(0.311)	-0.34(0.634)
BTC ≠>NIFT	-0.40(0.657)	-0.20(0.579)	0.46(0.321)
BTC ≠>JAK	-1.03(0.848)	-0.37(0.642)	-0.84(0.799)
MERV≠> BTC	0.34(0.366)	0.42(0.337)	0.06(0.475)
BOV ≠> BTC	0.40(0.344)	**1.38(0.083)**	-0.46(0.679)
MEXB≠> BTC	0.20(0.422)	0.77(0.222)	-0.83(0.798)
MOEX≠>BTC	-0.72(0.764)	-0.25(0.600)	-0.07(0.529)
BIST ≠> BTC	-0.80(0.787)	-0.48(0.683)	-1.22(0.889)
JSE ≠> BTC	0.32(0.376)	-0.34(0.634)	0.89(0.188)
SSE ≠> BTC	-0.31(0.621)	-0.18(0.571)	-0.16(0.564)
KOSP≠> BTC	0.43(0.333)	0.68(0.248)	0.54(0.296)
NIFT ≠> BTC	-0.15(0.560)	0.78(0.219)	-1.00(0.842)
JAK ≠> BTC	-0.06(0.523)	-1.05(0.854)	1.27(0.101)

Table 4.13: Non-linear causality between Ripple and Emerging Assets

Ripple vs. Emerging Foreign Exchange Rates

Panel A1: VAR-filtered return residuals

Direction	SI	SII	SIII
XRP ≠> ARG	-0.97(0.834)	-2.11(0.983)	-0.99(0.840)
XRP ≠> BRL	-0.61(0.946)	-1.46(0.928)	-0.07(0.527)
XRP ≠> MEX	0.99(0.160)	**1.28(0.099)**	-0.12(0.549)
XRP ≠> RUB	-0.76(0.776)	-1.46(0.928)	0.03(0.488)

Panel A2: VAR-GJRGARCH-filtered residuals

Direction	SI	SII	SIII
XRP ≠> ARG	-0.99(0.838)	-1.10(0.863)	-0.34(0.634)
XRP ≠> BRL	0.69(0.244)	0.55(0.292)	1.02(0.153)
XRP ≠> MEX	0.86(0.196)	0.59(0.278)	-0.09(0.534)
XRP ≠> RUB	-0.68(0.752)	-0.24(0.596)	0.47(0.320)

XRP ≠> LIRA	0.59(0.276)	-0.94(0.825)	1.06(0.146)	XRP ≠> LIRA	0.11(0.456)	0.19(0.425)	-0.15(0.561)
XRP ≠> ZAR	-0.33(0.630)	-0.91(0.817)	0.16(0.436)	XRP ≠> ZAR	0.72(0.236)	0.25(0.400)	0.82(0.208)
XRP ≠> CNY	-1.75(0.960)	-2.23(0.987)	-1.13(0.871)	XRP ≠> CNY	-0.75(0.772)	-1.05(0.853)	0.32(0.373)
XRP ≠> WON	-0.48(0.685)	-0.62(0.733)	0.13(0.448)	XRP ≠>WON	-0.60(0.727)	-1.09(0.862)	0.09(0.463)
XRP ≠> INR	**1.52(0.064)**	**1.81(0.036)**	-0.16(0.565)	XRP ≠> INR	0.10(0.459)	-0.69(0.756)	-0.30(0.619)
XRP ≠> RUP	0.12(0.451)	1.16(0.123)	-0.12(0.546)	XRP ≠> RUP	-0.19(0.575)	0.46(0.322)	-0.67(0.750)
ARG ≠> XRP	0.07(0.471)	-1.53(0.937)	-0.09(0.534)	ARG ≠> XRP	-0.35(0.638)	-0.15(0.559)	-1.09(0.862)
BRL ≠> XRP	-0.94(0.826)	0.14(0.444)	-0.77(0.778)	BRL ≠> XRP	0.161(0.436)	0.66(0.256)	-1.32(0.906)
MEX ≠> XRP	-0.20(0.577)	**1.34(0.090)**	-1.04(0.850)	MEX ≠> XRP	-0.48(0.685)	-1.70(0.956)	-0.60(0.726)
RUB ≠> XRP	-1.74(0.959)	-0.03(0.511)	-2.04(0.979)	RUB ≠> XRP	-0.80(0.787)	-0.55(0.710)	-0.53(0.703)
LIRA ≠> XRP	0.09(0.465	**1.40(0.081)**	-0.14(0.554)	LIRA≠> XRP	-0.23(0.591)	0.21(0.417)	0.01(0.497)
ZAR ≠> XRP	-0.45(0.673)	-0.28(0.612)	0.77(0.219)	ZAR ≠> XRP	-1.23(0.890)	-1.26(0.895)	0.42(0.336)
CNY ≠> XRP	-1.28(0.900)	-2.00(0.977)	-0.26(0.604)	CNY ≠> XRP	-0.56(0.711)	-2.09(0.982)	**1.44(0.075)**
WON ≠> XRP	-1.10(0.865)	-1.16(0.877)	0.16(0.438)	WON≠>XRP	0.41(0.342)	-0.13(0.550)	-0.40(0.655)
INR ≠> XRP	**1.61(0.054)**	**2.03(0.021)**	-0.05(0.518)	INR ≠> XRP	1.12(0.131)	1.00(0.159)	0.11(0.455)
RUP ≠> XRP	-1.01(0.845)	0.08(0.467)	-0.62(0.734)	RUP ≠> XRP	-1.68(0.954)	-1.01(0.844)	-1.62(0.947)

Ripple vs. Emerging Equities

Panel B1: VAR-filtered return residuals				Panel B2: VAR-GJRGARCH-filtered residuals			
Direction	**SI**	**SII**	**SIII**	**Direction**	**SI**	**SII**	**SIII**
XRP ≠> MERV	-0.40(0.654)	0.06(0.475)	-0.34(0.634)	XRP≠>MERV	-0.07(0.529)	-0.57(0.714)	-0.17(0.567)
XRP ≠> BOV	-0.83(0.797)	-1.50(0.933)	1.25(0.107)	XRP ≠> BOV	-1.07(0.857)	-0.95(0.830)	0.59(0.279)
XRP ≠> MEXB	0.99(0.160)	**1.28(0.099)**	-0.12(0.549)	XRP≠>MEXB	0.24(0.404)	0.49(0.314)	**4.32(0.000)**
XRP ≠> MOEX	-0.20(0.581)	0.19(0.425)	-0.18(0.571)	XRP≠>MOEX	-0.14(0.556)	0.44(0.331)	0.49(0.311)
XRP ≠> BIST	0.34(0.368)	0.82(0.205)	0.62(0.267)	XRP ≠> BIST	0.77(0.220)	0.78(0.217)	0.70(0.241)
XRP ≠> JSE	0.60(0.273)	0.69(0.247)	0.40(0.344)	XRP ≠> JSE	-0.93(0.824)	-0.54(0.706)	-0.07(0.529)
XRP ≠> SSE	1.06(0.146)	**1.76(0.039)**	0.16(0.436)	XRP ≠> SSE	-0.22(0.585)	1.09(0.139)	-0.70(0.758)
XRP ≠> KOSP	0.33(0.372)	0.13(0.450)	0.42(0.339)	XRP ≠>KOSP	0.02(0.492)	1.09(0.137)	-0.29(0.615)
XRP ≠> NIFT	1.08(0.140)	**1.71(0.043)**	-0.11(0.542)	XRP ≠>NIFT	-0.69(0.754)	-0.47(0.682)	-0.28(0.611)
XRP ≠> JAK	0.27(0.394)	0.38(0.351)	1.15(0.126)	XRP ≠> JAK	-0.37(0.000)	-0.50(0.691)	-0.09(0.537)
MERV≠> XRP	-0.38(0.647)	0.21(0.417)	-0.76(0.778)	MERV≠>XRP	0.04(0.484)	-0.27(0.606)	-0.12(0.546)
BOV ≠> XRP	-0.43(0.667)	1.01(0.156)	-0.14(0.557)	BOV ≠> XRP	-0.56(0.714)	0.47(0.321)	-0.43(0.665)
MEXB≠> XRP	-0.20(0.577)	**1.34(0.089)**	-1.04(0.850)	MEXB≠>XRP	-0.84(0.799)	0.49(0.312)	0.66(0.254)
MOEX≠>XRP	-0.09(0.535)	0.97(0.166)	0.17(0.432)	MOEX≠>XRP	-0.95(0.828)	-0.27(0.605)	-0.21(0.584)
BIST ≠> XRP	0.87(0.192)	**2.09(0.018)**	-1.54(0.938)	BIST ≠> XRP	-0.37(0.645)	0.46(0.322)	-0.79(0.785)
JSE ≠> XRP	0.72(0.236)	0.10(0.462)	0.85(0.198)	JSE ≠> XRP	1.19(0.117)	0.73(0.234)	**1.37(0.085)**
SSE ≠> XRP	1.16(0.124)	**1.59(0.056)**	-0.16(0.563)	SSE ≠> XRP	0.56(0.289)	0.61(0.270)	0.98(0.163)
KOSP≠> XRP	0.50(0.308)	0.80(0.211)	-0.10(0.540)	KOSP≠>XRP	0.78(0.218)	0.96(0.169)	-0.75(0.775)
NIFT ≠> XRP	1.27(0.102)	**2.42(0.008)**	0.29(0.386)	NIFT≠>XRP	**1.87(0.031)**	**1.77(0.039)**	-0.11(0.542)
JAK ≠> XRP	**1.44(0.075)**	0.12(0.454)	**1.29(0.099)**	JAK ≠> XRP	0.35(0.363)	-0.94(0.827)	**1.91(0.028)**

Notes: For Tables 4.12 - 4.13, the arrow "≠>" or "<≠" represents the non-causality null hypothesis. The entries *a*(*b*) give the test statistics and the associated probability values in parenthesis. Symbols SI, SII, and SII denote sample periods, where SI (full sample), SII (pre-2017 price development of the cryptocurrency market), and SIII (during/post-2017 price development of the cryptocurrency market) span 12.08.2013 - 07.06.2019, 12.08.2013 - 30.12.2016, and 03.01.2017 - 07.06.2019 respectively.

Tables 4.12 - 4.13 display the estimated results of the DP test[65]. As shown in the tables, we failed in most of the cases to reject the null hypothesis of non-causality for pairs of the asset markets. Thus, with high probability test values departing even from the 10% significance level, one cannot reject the non-causality null hypothesis, for the VAR filtered residual series and the ARFIMA-GJRGARCH filtered VAR residual series under the respective samples. The results depict that there is not enough evidence in

[65] For full form of the abbreviated market variables, see *Table 4.A1*.

favour of a non-linear dependence relationship between pairs of the markets. Generally, we observe evidence against non-linear price transmission. Put in other words, the price of Bitcoin and Ripple does not, for now, influence significantly the price movement of emerging assets, while the reverse also holds the same. Most importantly, the pattern of the results manifests to us that the detected lack of causation can be attributed neither to volatility effects nor to the partition of the decade-long market evolution of the digital currencies into sample periods that correspond to stable and volatile regimes.

That notwithstanding, we identified a handful of statistically significant uni-directional linkages for Bitcoin-Argentine Peso (in SI), Bitcoin-Mexican Peso (in SI and SIII), Turkish Lira-Bitcoin (in SI), Bitcoin-Mexbol and Bovespa-Bitcoin (both in SII) under the ARFIMA-GJRGARCH filtered residual process. Similarly, for the VAR filtered residuals, we also found one-way non-linear causation running from the Indian Rupee to Bitcoin (at 5% significance level) and Merval to Bitcoin (at 10% significance level), all in sample SII (refer, Table 4.12). Comparatively, the number of significant relationships increases slightly for pairs involving Ripple and the emerging assets. For instance, from the results in Table 4.13, strong significant feedback relationships are found for Ripple-Indian Rupee, Ripple-SSE50, and Ripple-NIFTY50, whereas weak feedback linkages characterize Ripple-Mexican Peso and Ripple-Mexbol. Although there exists a very minimal level of interrelatedness, the findings presupposed that, relatively, Ripple shows prospects of future interactions with emerging assets.

4.5.2 Rolling-Window causality analysis

It is common knowledge that causality tests are sometimes sensitive to data samples. As a result of such occurrences, both hidden and/or unhidden features in a given data may at times obstruct evidence of (non)causation. Although the analysis in the

previous section is based on different time samples, it is instructive to mention that aside from the imposed dating for the samples, the detected causality pattern does not vary within each sample, but instead remain static. In hindsight, a sole analysis of a global causality test measure may not be well enough to explain market interrelationships, which often evolves with time.

Therefore, we report a dynamic causality test results conducted over a fixed length rolling-window, with a size set to 250 (approximately a trading year)[66]. For each window, a bootstrap test of non-causality is performed using the log-returns based on a VAR modelling process. We collate the frequency of rejecting the non-causation null at a 5% significance level and computed the rolling-window rejection rate as the ratio of the computed number of rejections to the overall number of windows. A smaller count or frequency could be interpreted to mean, failing to reject the non-causation null hypothesis more frequently, with the implication, that evidence of causal linkages occurs in a smaller proportion of the overall number of windows.

Table 4.14: RW rejection rates involving Bitcoin and Emerging market assets

Panel A: Bitcoin vs. FXs				Panel B: Bitcoin vs. Stocks			
Direction	**SI**	**SII**	**SIII**	**Direction**	**SI**	**SII**	**SIII**
BTC ≠> ARG	17.8% (207)	10.9% (63)	10.5% (35)	BTC≠>MERV	02.9% (34)	04.0% (23)	03.3% (11)
BTC ≠> BRL	02.0% (23)	02.6% (15)	03.4% (11)	BTC≠>BOV	04.4% (51)	05.9% (34)	03.3% (11)
BTC ≠> MEX	03.4% (40)	06.7% (39)	00.0% (00)	BTC≠>MEXB	06.7% (78)	11.4% (66)	00.3% (01)
BTC ≠> RUB	01.5 % (17)	02.9% (17)	00.0% (00)	BTC≠>MOEX	13.7% (159)	12.8% (74)	03.0% (10)
BTC ≠> LIRA	01.1% (13)	00.9% (05)	00.0% (00)	BTC≠>BIST	02.7% (31)	04.3% (25)	00.0% (00)
BTC ≠> ZAR	00.9% (10)	01.9% (11)	00.0% (00)	BTC≠>JSE	07.9% (92)	04.0% (23)	00.3% (01)
BTC ≠> CNY	15.4% (179)	25.0% (145)	09.3% (31)	BTC≠>SSE	14.6% (170)	24.4% (141)	06.0% (23)
BTC ≠> WON	03.7% (43)	05.4% (31)	00.9% (03)	BTC≠>KOSP	07.1% (83)	07.1% (41)	00.3% (01)
BTC ≠> INR	03.5% (41)	05.9% (34)	02.1% (07)	BTC≠>NIFT	03.3% (38)	00.0% (00)	04.2% (14)
BTC ≠> RUP	08.3% (96)	03.5% (20)	00.0% (00)	BTC≠>JAK	02.5% (29)	03.5% (20)	00.0% (00)
ARG ≠> BTC	17.9% (208)	35.9% (208)	00.0% (00)	MERV≠>BTC	02.2% (26)	04.3% (25)	00.0% (00)
BRL ≠> BTC	01.6% (19)	02.8% (16)	00.9% (03)	BOV ≠> BTC	10.5% (122)	14.9% (86)	06.6% (22)
MEX ≠> BTC	14.0% (163)	05.4% (31)	26.0% (87)	MEXB ≠>BTC	07.9% (92)	11.1% (64)	06.9% (23)
RUB ≠> BTC	13.0% (151)	19.0% (110)	11.1% (37)	MOEX≠>BTC	08.6% (100)	11.9% (69)	06.9% (23)
LIRA≠> BTC	15.5% (180)	03.8% (22)	44.3% (148)	BIST ≠> BTC	06.8% (79)	02.1% (12)	18.0% (60)
ZAR ≠> BTC	05.2% (60)	04.0% (23)	11.1% (37)	JSE ≠> BTC	09.0% (105)	13.0% (75)	09.0% (30)
CNY ≠> BTC	08.9% (103)	12.3% (71)	03.3% (11)	SSE ≠> BTC	13.9% (162)	27.1% (157)	00.0% (00)
WON≠>BTC	07.8% (91)	01.2% (10)	18.0% (60)	KOSP≠> BTC	02.7% (31)	03.5% (20)	00.0% (00)
INR ≠> BTC	07.8% (91)	00.5% (03)	22.5% (75)	NIFT ≠> BTC	03.6% (42)	04.7% (27)	03.3% (11)

[66] The chosen specification generates a total of 1,162 windows for sample SI, 579 for sample SII, and 334 for sample SIII.

RUP ≠> BTC	10.2% (119)	10.4% (60)	06.3% (21)	JAK ≠> BTC	09.0% (105)	13.0% (75)	00.3% (01)

Table 4.15: RW rejection rates involving Ripple and Emerging market assets returns

Panel A: Ripple vs. FXs				Panel B: Ripple vs. Stocks			
Direction	**SI**	**SII**	**SIII**	**Direction**	**SI**	**SII**	**SIII**
XRP ≠> ARG	33.6% (390)	38.5% (223)	46.1% (154)	XRP≠>MERV	07.7% (89)	11.4% (66)	04.2% (14)
XRP ≠> BRL	14.8% (172)	00.0% (00)	12.9% (43)	XRP ≠> BOV	17.6% (205)	00.0% (00)	13.5% (45)
XRP ≠> MEX	02.0% (23)	01.2% (07)	04.8% (16)	XRP ≠>MEXB	02.7% (31)	03.5% (20)	03.0% (10)
XRP ≠> RUB	06.8% (79)	09.5% (55)	07.2% (24)	XRP≠>MOEX	08.5% (99)	10.9% (63)	05.1% (17)
XRP ≠> LIRA	05.5% (64)	00.2% (01)	01.5% (05)	XRP ≠> BIST	09.0% (105)	17.3% (100)	00.6% (02)
XRP ≠> ZAR	07.4% (86)	04.3% (25)	18.3% (61)	XRP ≠> JSE	17.3% (201)	09.8% (57)	42.5% (142)
XRP ≠> CNY	18.4% (214)	36.1% (209)	01.5% (05)	XRP ≠> SSE	24.3% (282)	23.8% (138)	38.3% (128)
XRP ≠> WON	01.3% (15)	02.6% (15)	00.0% (00)	XRP ≠> KOSP	04.8% (58)	05.4% (31)	07.2% (24)
XRP ≠> INR	16.5% (192)	02.8% (16)	20.4% (68)	XRP ≠> NIFT	12.0% (139)	24.0% (139)	00.0% (00)
XRP ≠> RUP	06.2% (72)	10.9% (63)	01.2% (123)	XRP ≠> JAK	02.2% (26)	02.6% (15)	00.0% (00)
ARG ≠> XRP	06.3% (73)	11.2% (65)	02.4% (08)	MERV≠>XRP	04.6% (53)	01.4% (08)	11.4% (38)
BRL ≠> XRP	02.8% (33)	00.2% (01)	07.5% (25)	BOV ≠> XRP	06.0% (70)	04.0% (23)	00.3% (01)
MEX ≠> XRP	02.5% (29)	02.2% (13)	04.8% (16)	MEXB≠>XRP	05.1% (59)	02.6% (15)	09.0% (30)
RUB ≠> XRP	16.3% (189)	24.7% (143)	10.8% (36)	MOEX≠>XRP	10.2% (119)	10.9% (63)	07.5% (25)
LIRA≠> XRP	16.3% (189)	00.0% (00)	54.2% (181)	BIST ≠> XRP	16.3% (189)	00.0% (00)	54.5% (182)
ZAR ≠> XRP	30.3% (352)	00.5% (03)	50.9% (170)	JSE ≠> XRP	05.2% (60)	00.0% (00)	18.0% (60)
CNY ≠>XRP	00.2% (02)	00.2% (01)	00.0% (00)	SSE ≠> XRP	12.5% (145)	24.7% (143)	00.0% (00)
WON≠>XRP	10.0% (116)	02.6% (15)	29.0% (97)	KOSP ≠>XRP	07.1% (83)	04.1% (24)	01.8% (06)
INR ≠> XRP	16.9% (196)	16.6% (96)	29.9% (100)	NIFT ≠> XRP	17.6% (205)	26.9% (156)	02.7% (09)
RUP ≠> XRP	14.2% (165)	11.7% (68)	26.0% (87)	JAK ≠> XRP	05.9% (69)	11.7% (68)	00.0% (00)

Notes: For Tables 4.14 - 4.15, the arrow "≠>" or "<≠" represents the non-causality null hypothesis. For the entries *a%(b)*, a% gives the rejection rates of the null and b is the count (or frequency) of rejections in a given window. Symbols SI, SII, and SII denote sample periods, where SI (full sample), SII (pre-2017 price development of the cryptocurrency market), and SIII (during/post-2017 price development of the cryptocurrency market) span 12.08.2013 - 07.06.2019, 12.08.2013 - 30.12.2016, and 03.01.2017 - 07.06.2019 respectively.

Tables 4.14 and 4.15 provide empirical results of the rolling-window non-causality test for the market pairs. Evidence from all the three data samples indicates that the rolling-window rejection rates of the non-causality null hypothesis between Bitcoin (Ripple) and the emerging equities or forex (and vice versa) remained quite smaller. This signifies that causal linkages for the pairs are currently, at a very weak stage, implying that changes in the price of Bitcoin or Ripple less triggers changes in the price movements of emerging assets. A prominent pattern of the results reveals that the detected evidence of non-causality does not manifest solely for a particular market period or regime and is indifferent to country-specific and the regional markets.

As found from the DP test results, the pairwise causal relationship for Ripple and the emerging assets fairly increases, compared to that of Bitcoin. Specifically, a substantial number of zero or near to zero percent rejection rates of the null (signifying no or weak

causal linkages) are mostly identified for pairs involving Bitcoin than Ripple. Whereas the Bitcoin pairs recorded rejection rates as high as 25% (Bitcoin-Chinese Yuan), 35.9% (Argentine Peso-Bitcoin), 27.1% (SSE50-Bitcoin), and 24.4% (Bitcoin-SSE50), three of the Ripple constituted pairs had rejection rates a little above 50% (Turkish Lira-Ripple, South Africa's Rand-Ripple, BIST30-Ripple) and more double-digit rejection rates. This could be interpreted to imply that, relative to Ripple, the price movement of the Bitcoin market is less affected, and has minimal influence on price changes of emerging assets.

4.5.3 Spillover dynamics between cryptocurrencies and emerging markets

Throughout this section, we present empirical results and analysis to shed more light on the topical issue pertaining to return and volatility shock spillovers between cryptocurrencies (proxy by Bitcoin and Ripple) and selected emerging assets. Results of the static, as well as dynamic total and directional spillovers, are discussed.

Table 4.16: Total and directional spillovers between Bitcoin and Emerging market FXs

Panel A: Raw return spillover

	BTC	ARG	BRL	MEX	RUB	LIRA	ZAR	CNY	WON	INR	RUP	From others
BTC	98.9	0.10	0.12	0.15	0.13	0.11	0.00	0.10	0.03	0.05	0.31	**1.10**
ARG	0.05	98.4	0.50	0.22	0.00	0.43	0.02	0.07	0.00	0.05	0.20	**1.54**
BRL	0.08	0.13	99.2	0.06	0.07	0.00	0.01	0.32	0.01	0.03	0.04	**0.75**
MEX	0.01	0.05	1.03	98.5	0.00	0.14	0.00	0.01	0.04	0.16	0.02	**1.46**
RUB	0.01	0.03	0.14	0.04	98.4	0.22	0.03	0.21	0.17	0.01	0.71	**1.57**
LIRA	0.03	0.05	0.21	0.04	0.01	99.5	0.01	0.08	0.02	0.01	0.05	**0.51**
ZAR	0.02	0.02	0.20	0.02	0.04	0.68	98.5	0.05	0.00	0.33	0.16	**1.52**
CNY	0.01	0.02	0.06	0.00	0.00	0.02	0.04	99.5	0.34	0.06	0.01	**0.56**
WON	0.02	0.07	0.09	0.08	0.03	0.02	1.21	0.19	98.2	0.01	0.06	**1.78**
INR	0.06	0.05	0.25	0.27	0.00	0.03	0.00	0.03	0.49	97.4	1.44	**2.62**
RUP	0.02	0.03	0.06	0.36	0.00	0.02	0.55	0.01	0.61	0.14	98.2	**1.80**
To others	**0.31**	**0.55**	**2.66**	**1.24**	**0.28**	**1.67**	**1.87**	**1.07**	**1.71**	**0.85**	**3.00**	**15.2**
All	**99.2**	**98.9**	**101.9**	**99.7**	**98.7**	**101.2**	**100.4**	**100.6**	**99.9**	**98.3**	**101.2**	**TSI = 1.38%**
Net spillover	**-0.79**	**-0.99**	**1.91**	**-0.22**	**-1.29**	**1.16**	**0.35**	**0.51**	**-0.07**	**-1.77**	**1.20**	

Panel B: Volatility return spillover

	BTC	ARG	BRL	MEX	RUB	LIRA	ZAR	CNY	WON	INR	RUP	From others
BTC	79.2	0.17	0.27	1.28	0.98	0.53	0.06	3.82	13.2	0.38	0.16	**20.9**
ARG	0.28	73.7	0.26	0.85	0.19	2.43	20.2	0.16	1.43	0.17	0.29	**26.3**
BRL	4.18	0.24	80.4	4.48	1.57	0.75	0.41	3.28	4.16	0.49	0.08	**19.6**
MEX	0.05	0.64	0.38	89.6	0.03	0.61	1.21	0.20	6.16	1.06	0.01	**10.4**
RUB	3.42	0.12	1.10	1.52	79.8	0.50	3.18	0.38	4.84	4.52	0.59	**20.2**
LIRA	0.07	0.27	0.40	0.18	0.03	97.0	0.48	0.22	0.68	0.16	0.47	**2.96**
ZAR	0.05	0.10	2.02	4.51	1.61	1.09	76.4	2.41	8.72	2.40	0.69	**23.6**

CNY	0.24	0.20	0.09	2.59	1.33	3.29	0.25	89.8	0.42	1.54	0.24	**10.2**
WON	1.35	0.55	3.49	2.34	1.67	0.82	0.30	1.93	80.9	6.63	0.05	**19.1**
INR	0.18	0.41	0.24	2.95	0.03	3.22	0.20	2.51	3.94	85.8	0.56	**14.2**
RUP	0.19	0.23	3.72	7.86	0.01	0.72	2.39	0.20	3.45	16.0	65.3	**34.8**
To others	**10.0**	**2.93**	**12.0**	**28.6**	**7.45**	**14.0**	**28.7**	**15.1**	**47.0**	**33.4**	**3.14**	**202.3**
All	**89.2**	**76.6**	**92.4**	**118.2**	**87.3**	**111.0**	**105.1**	**104.9**	**127.9**	**119.2**	**68.4**	**TSI = 18.39%**
Net spillover	**-10.9**	**-23.4**	**-7.60**	**18.2**	**-12.8**	**11.00**	**5.10**	**4.90**	**27.9**	**19.2**	**-31.7**	

Table 4.17: Total and directional spillovers between Bitcoin and Emerging market stocks

Panel A: Raw return spillover

	BTC	MER	BOV	MEB	MOX	BIST	JSE	SSE	KOSP	NFT	JAK	From others
BTC	98.5	0.05	0.60	0.04	0.13	0.23	0.03	0.04	0.00	0.07	0.31	**1.50**
MER	0.00	99.7	0.02	0.00	0.01	0.04	0.00	0.01	0.01	0.00	0.17	**0.26**
BOV	0.15	0.32	98.4	0.27	0.06	0.01	0.10	0.03	0.05	0.02	0.14	**1.15**
MEB	0.20	0.18	0.01	99.0	0.00	0.01	0.09	0.01	0.49	0.02	0.02	**1.03**
MOX	0.01	0.45	0.51	1.44	97.1	0.17	0.04	0.02	0.06	0.18	0.02	**2.90**
BIST	0.13	0.13	0.37	0.67	0.02	98.5	0.00	0.08	0.03	0.03	0.01	**1.47**
JSE	0.01	0.42	0.43	2.70	0.14	0.02	95.7	0.08	0.43	0.05	0.02	**4.30**
SSE	0.01	0.10	0.05	0.38	0.06	0.05	0.18	98.9	0.23	0.02	0.02	**1.10**
KOSP	0.00	0.39	0.29	0.43	0.00	0.24	2.28	0.18	95.5	0.47	0.24	**4.52**
NFT	0.19	0.35	0.08	2.04	0.06	0.13	0.01	0.34	0.02	95.8	0.95	**4.17**
JAK	0.02	0.99	0.08	2.35	0.00	0.14	0.16	0.26	0.02	0.00	96.0	**4.02**
To others	**0.72**	**3.38**	**2.44**	**10.3**	**0.48**	**1.04**	**2.89**	**1.05**	**1.34**	**0.86**	**1.90**	**26.4**
All	**99.2**	**100.1**	**100.8**	**109.3**	**97.6**	**99.5**	**98.6**	**99.9**	**96.8**	**96.7**	**97.9**	**TSI = 2.40%**
Net spillover	**-0.07**	**3.12**	**1.29**	**9.27**	**-2.42**	**-0.43**	**-1.41**	**-0.05**	**-3.18**	**-3.31**	**-0.19**	

Panel B: Volatility return spillover

	BTC	MER	BOV	MEB	MOX	BIST	JSE	SSE	KOSP	NFT	JAK	From others
BTC	81.1	0.10	0.38	0.32	0.01	1.41	3.53	0.27	1.85	3.12	7.92	**18.9**
MER	0.08	79.0	3.03	0.87	0.19	4.66	1.06	1.67	0.04	8.36	1.03	**21.0**
BOV	3.42	1.04	89.1	0.47	0.05	0.95	0.20	1.49	0.93	2.20	0.19	**10.9**
MEB	2.12	0.73	0.89	70.5	0.58	0.18	6.14	3.49	14.1	1.34	0.02	**29.6**
MOX	0.40	2.62	1.62	1.64	67.4	0.08	0.88	11.6	3.88	3.80	6.00	**32.5**
BIST	0.84	0.18	0.13	1.09	0.38	88.5	1.41	0.05	1.14	3.05	2.78	**11.1**
JSE	0.78	1.99	9.15	3.62	0.19	1.71	52.1	10.3	7.62	11.3	1.19	**47.9**
SSE	1.20	8.22	1.93	1.65	3.48	1.01	3.87	78.4	0.11	0.07	0.05	**21.6**
KOSP	0.15	2.64	8.98	0.47	0.70	0.04	0.03	3.53	77.7	2.86	2.97	**22.3**
NFT	0.86	1.13	0.08	12.4	1.55	1.27	8.72	1.61	3.41	64.8	4.18	**35.2**
JAK	1.17	4.24	0.60	3.08	1.35	6.57	10.7	2.42	6.82	0.32	62.7	**37.3**
To others	**11.0**	**22.9**	**26.8**	**25.6**	**8.48**	**17.9**	**36.5**	**36.4**	**39.9**	**36.4**	**26.3**	**288.3**
All	**92.1**	**101.9**	**116.9**	**96.1**	**75.9**	**106.4**	**88.6**	**114.8**	**117.6**	**101.2**	**89.0**	**TSI = 26.2%**
Net spillover	**-7.90**	**1.90**	**15.9**	**-4.00**	**-24.0**	**6.80**	**-11.4**	**14.8**	**17.6**	**1.20**	**-11.0**	

4.5.3.1 Static spillover results

Tables 4.16 - 4.19 present summary results of the full sample's total, directional, and net spillover measures among the studied asset markets. As displayed in the tables, the markets generally exhibit, averagely, a very weak level of transmissions. For instance, the total return spillover index reveals that, on average, only 1.38%, 2.40%, 1.40%, and 2.39% of the 60-day ahead return forecast error variance in the overall markets, respectively for Bitcoin and emerging forex, Bitcoin and emerging equities,

Ripple and emerging forex, and Ripple and emerging equities could be attributed to transmissions, whereas the respective differences (i.e. 98.62%, 97.60%, 98.60%, and 97.61%) may arise from the individual asset's own shocks rather spillovers across the markets under consideration. This contrasts the nearly 50% return spillover index reported by Dahir and Mahat (2019). The extreme discrepancy of the latter's result comes as no surprise because the nine markets of the authors comprise of not only Bitcoin and emerging equities, but in addition, S&P500 and the volatility index (VIX) of the Chicago Board Options Exchange. Hence, their result does not explicitly reflect a total spillover measure of markets inclusive of cryptocurrency and emerging equities only.

On the other hand, we realized that the total volatility spillover measures for the markets outrageously exceeded the indexes of the total return spillovers. Comparably, the total volatility spillover index for either Bitcoin- or Ripple-emerging equity constituted market pool is greater than the markets involving the emerging forex and each of the two cryptocurrencies. Relative to Ripple and the emerging assets, the results also manifest that the total spillover measure for volatility, with regards to Bitcoin and the emerging assets, is slightly higher than the former.

Table 4.18: Total and directional spillovers between Ripple and Emerging market Forex

Panel A: Raw return spillover

	XRP	ARG	BRL	MEX	RUB	LIRA	ZAR	CNY	WON	INR	RUP	From others
XRP	98.7	0.04	0.12	0.01	0.00	0.46	0.13	0.09	0.02	0.35	0.04	**1.26**
ARG	0.07	98.4	0.50	0.22	0.00	0.43	0.02	0.07	0.00	0.05	0.20	**1.56**
BRL	0.01	0.13	99.3	0.07	0.06	0.00	0.01	0.32	0.01	0.03	0.04	**0.68**
MEX	0.02	0.05	1.03	98.5	0.00	0.14	0.00	0.00	0.04	0.16	0.02	**1.46**
RUB	0.00	0.03	0.14	0.03	98.4	0.22	0.03	0.22	0.18	0.01	0.71	**1.57**
LIRA	0.00	0.05	0.21	0.05	0.01	99.5	0.01	0.08	0.02	0.01	0.05	**0.49**
ZAR	0.00	0.02	0.20	0.02	0.04	0.68	98.5	0.04	0.00	0.33	0.15	**1.48**
CNY	0.00	0.02	0.06	0.00	0.00	0.02	0.04	99.5	0.33	0.06	0.01	**0.54**
WON	0.06	0.07	0.09	0.09	0.03	0.03	1.21	0.19	98.2	0.01	0.05	**1.83**
INR	0.03	0.05	0.26	0.26	0.00	0.03	0.00	0.04	0.50	97.4	1.45	**2.62**
RUP	0.03	0.07	0.06	0.36	0.03	0.02	0.55	0.01	0.60	0.14	98.2	**1.87**
To others	**0.22**	**0.53**	**2.67**	**1.11**	**0.17**	**2.03**	**2.00**	**1.06**	**1.70**	**1.02**	**2.72**	**15.4**
All	**98.9**	**98.9**	**102.0**	**99.6**	**98.7**	**101.5**	**100.5**	**100.6**	**99.9**	**98.4**	**100.9**	**TSI = 1.40%**
Net spillover	**-1.04**	**-1.03**	**1.99**	**-0.35**	**-1.40**	**1.54**	**0.52**	**0.52**	**-0.13**	**-1.60**	**0.85**	

Panel B: Volatility return spillover

	XRP	ARG	BRL	MEX	RUB	LIRA	ZAR	CNY	WON	INR	RUP	From others
XRP	94.7	0.25	0.90	0.04	0.26	0.18	0.02	0.74	1.69	1.08	0.12	**5.28**
ARG	0.76	74.0	0.30	0.92	0.25	2.55	19.3	0.23	1.31	0.20	0.24	**26.1**
BRL	1.45	0.21	81.9	4.37	2.40	0.43	0.41	3.35	4.63	0.76	0.08	**18.1**
MEX	0.56	0.59	0.37	89.7	0.03	0.58	1.38	0.18	5.68	0.95	0.01	**10.3**
RUB	0.30	0.11	1.72	1.18	83.4	0.78	2.65	0.27	4.44	4.70	0.46	**16.6**
LIRA	0.13	0.25	0.44	0.21	0.01	96.9	0.45	0.21	0.65	0.20	0.53	**3.08**
ZAR	0.63	0.13	1.90	4.51	1.57	1.03	75.3	2.56	9.24	2.58	0.57	**24.7**
CNY	0.87	0.21	0.11	2.45	1.15	3.43	0.21	89.7	0.40	1.33	0.17	**10.3**
WON	2.55	0.44	4.42	2.56	2.01	0.93	0.11	1.71	78.9	6.30	0.04	**21.1**
INR	3.06	0.32	0.40	3.01	0.03	3.08	0.20	2.35	3.21	83.9	0.47	**16.1**
RUP	3.65	0.15	3.44	7.89	0.02	0.63	1.97	0.15	2.72	15.0	64.4	**35.6**
To others	**14.0**	**2.66**	**14.0**	**27.1**	**7.73**	**13.6**	**26.7**	**11.8**	**34.0**	**33.1**	**2.69**	**187.4**
All	**108.7**	**76.7**	**95.9**	**116.8**	**91.1**	**110.5**	**102.0**	**101.5**	**112.9**	**117.0**	**67.1**	**TSI = 17.0%**
Net spillover	**8.72**	**-23.4**	**-4.10**	**16.8**	**-8.87**	**10.5**	**2.00**	**1.50**	**12.9**	**17.0**	**-32.9**	

Table 4.19: Total and directional spillovers between Ripple and Emerging market stocks

Panel A: Raw return spillover

	XRP	MER	BOV	MEB	MOX	BIST	JSE	SSE	KOSP	NFT	JAK	From others
XRP	98.3	0.01	0.04	0.01	0.02	0.70	0.11	0.01	0.04	0.32	0.41	**1.67**
MER	0.02	99.7	0.02	0.00	0.01	0.04	0.00	0.01	0.01	0.00	0.17	**0.28**
BOV	0.03	0.31	98.5	0.29	0.05	0.01	0.10	0.03	0.52	0.02	0.14	**1.50**
MEB	0.10	0.19	0.02	99.1	0.00	0.01	0.09	0.01	0.46	0.02	0.02	**0.92**
MOX	0.02	0.46	0.05	1.45	97.1	0.17	0.04	0.02	0.06	0.18	0.02	**2.47**
BIST	0.01	0.14	0.39	0.63	0.02	98.7	0.00	0.08	0.03	0.03	0.01	**1.34**
JSE	0.04	0.43	0.43	2.71	0.14	0.02	95.6	0.08	0.45	0.06	0.01	**4.37**
SSE	0.00	0.10	0.05	0.39	0.06	0.05	0.18	98.9	0.23	0.02	0.02	**1.10**
KOSP	0.05	0.41	0.29	0.42	0.00	0.23	2.27	0.19	95.4	0.46	0.23	**4.55**
NFT	0.01	0.38	0.09	1.97	0.07	0.13	0.01	0.35	0.02	96.0	0.96	**3.99**
JAK	0.05	1.02	0.08	2.32	0.00	0.14	0.16	0.26	0.02	0.00	96.0	**4.05**
To others	**0.33**	**3.45**	**1.46**	**10.2**	**0.37**	**1.50**	**2.96**	**1.04**	**1.84**	**1.11**	**1.99**	**26.2**
All	**98.6**	**103.2**	**100.0**	**109.3**	**97.5**	**100.2**	**98.6**	**99.9**	**97.2**	**97.1**	**98.0**	**TSI = 2.39%**
Net spillover	**-1.34**	**3.17**	**-0.04**	**9.28**	**-2.10**	**0.16**	**-1.41**	**-0.06**	**-2.71**	**-2.88**	**-2.06**	

Panel B: Volatility return spillover

	XRP	MER	BOV	MEB	MOX	BIST	JSE	SSE	KOSP	NFT	JAK	From others
XRP	93.4	0.16	0.71	0.57	0.23	0.87	0.16	0.77	1.88	0.81	0.41	**6.57**
MER	0.11	79.0	3.08	0.82	0.19	4.48	1.04	1.70	0.03	8.55	1.04	**21.0**
BOV	0.58	0.93	91.2	0.54	0.06	1.54	0.05	1.54	0.62	2.97	0.00	**8.83**
MEB	0.68	0.69	1.31	72.1	0.60	0.35	6.51	3.45	12.3	1.71	0.27	**27.9**
MOX	0.52	2.59	1.93	1.60	68.1	0.12	0.89	11.6	3.34	4.29	5.05	**31.9**
BIST	0.31	0.20	0.05	1.23	0.38	89.9	1.27	0.58	1.52	2.57	2.01	**10.1**
JSE	0.05	1.92	9.81	3.65	0.19	1.51	52.1	10.3	6.96	12.0	1.53	**47.9**
SSE	0.07	8.15	2.36	1.46	3.49	0.77	4.18	79.3	0.03	0.07	0.12	**20.7**
KOSP	0.70	2.66	9.47	0.46	0.67	0.04	0.03	3.49	76.2	2.96	3.31	**23.8**
NFT	0.12	1.07	0.13	12.9	1.60	1.01	9.09	1.65	3.04	64.7	4.66	**35.3**
JAK	0.87	4.12	0.68	3.42	1.43	5.74	11.3	2.54	6.54	0.20	63.1	**36.8**
To others	**4.01**	**22.5**	**29.5**	**26.7**	**8.84**	**16.4**	**34.5**	**37.6**	**36.3**	**36.1**	**18.4**	**270.8**
All	**97.4**	**101.5**	**120.7**	**98.8**	**98.7**	**106.3**	**86.6**	**116.9**	**112.5**	**100.8**	**81.5**	**TSI = 24.6%**
Net spillover	**-2.56**	**1.50**	**20.7**	**-1.20**	**-23.1**	**6.30**	**-13.4**	**16.9**	**12.5**	**0.80**	**-18.4**	

From Table 4.16, the gross directional volatility spillover contribution from the Bitcoin market to the 60-day ahead forecast error variance of the emerging forex is 10%, while the latter also explains 20.9% of the 60-day ahead forecast error variance of Bitcoin's returns. Out of the total index of 20.9%, we noticed that the returns of the South

Korean Won and that of the Chinese Yuan accounted respectively for 13.2% and 3.82% of the forecast error variance of Bitcoin's market volatility, whereas the South African Rand market had the least contribution (0.06%). Conversely, innovation to Bitcoin's market returns explains, relatively, a sizeable portion of the forecast error variance of the returns in the Brazilian Real (4.18%), Russian Rubble (3.42%), and the South Korean Won (1.35%) markets.

Regarding the net-directional spillovers, we found that the highest spillover moves from the volatility of the South Korean Won to the volatilities of the remaining markets (27.9%), while the lowest spillover moves from volatilities of the other markets to the volatility of Indonesian's Rupiah (-31.7%), Argentine's Peso (-23.4%), Russian Rubble (-12.8%), and Bitcoin (-10.9%) respectively. Notably, the negative net-directional return and volatility spillover measures recorded consistently for Bitcoin is suggestive that, in general, the market is a net recipient of return and volatility shocks.

Turing focus to Table 4.17, although the overall markets, on average, are loosely reactive to each other, we realized that, in terms of return spillovers, the Latin American equities, i.e. Merval and Mexbol ranked high as the main contributors to the other markets, while Bitcoin exerts lesser influence. Pertaining to *Panel B* of Table 4.17, we observe that volatility shocks emanating from the Asian equity markets (KOSPI200, SSE50, and NIFTY50) are adjudged the most influential in connection with contributions to other markets' volatility (39.9%, 36.4%, and respectively). Thus, the estimated 17.6% net-directional volatility spillover index is relatively enough to make KOSPI200 the largest shock transmitter, whereas the net value of -7.90% is all that is needed to ensure Bitcoin remains a net absorber of volatility shocks.

As found for Bitcoin, the Ripple market, in whole, also explains a trivial portion of the forecast error variance of the emerging assets returns. With emphasis on the estimated

return spillovers (shown in *Panel A* of Tables 4.18 - 4.19), it could be viewed that innovations to Ripple's market returns less influence returns of other markets than it is influenced by those markets. However, unlike Bitcoin, Ripple ranks 5th as a dominant contributor to volatility shock transmission. Intriguingly, the gross directional volatility spillovers emitted (received) to (from) the other markets amounted to 14.0% (5.28%), hence making Ripple a net propagator of shocks (with an estimated net value of 8.72%). More so, a specific look at the results shows that the volatility of Ripple accounts for a little over 9.0% of volatility in three of the Asian markets, namely, the Indonesian Rupiah (3.65%), Indian Rupee (3.06%), and South Korean Won (2.55%).

Furthermore, with the recorded values of -7.90% and -2.56%, in net terms, we deduced that the inherent volatilities of Bitcoin and Ripple respectively contribute far lesser volatilities in emerging equity markets. This simply connotes that the two digital asset markets look more susceptible to absorbing volatility shocks that emanate from emerging equities. Nonetheless, the volatility spillover characteristics disposed of by Ripple tend to suggest that the market has higher prospects of somewhat driving volatility shocks in emerging forex markets, albeit the averagely weak spillover interactions.

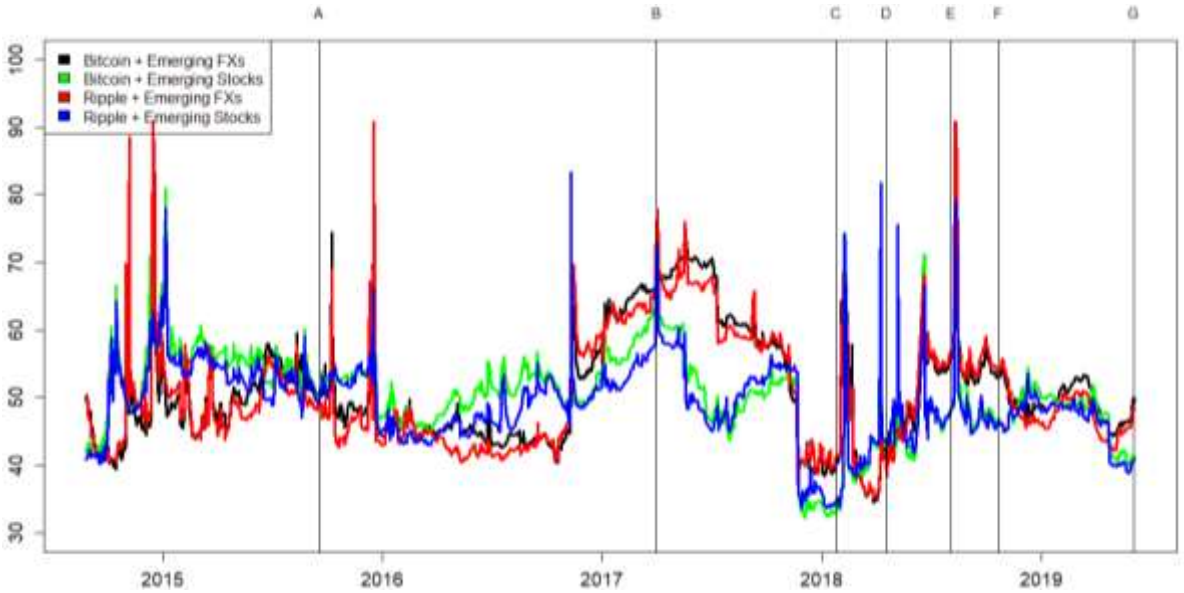
4.5.3.2 Rolling-Window total spillover analysis

Taking into consideration the market evolution of cryptocurrencies and the high level of uncertainties that characterized emerging asset markets, it is most unlikely for a static measure to capture secular and/or abrupt fluctuating spillover movements within the chosen sample period. More so, under static estimations, relevant spillover patterns may be concealed, resulting in misleading implications. To downplay on the issues raised, we estimate a dynamic return and volatility spillover using a 250-day rolling-window sample and estimate from each window a 60-day ahead forecast.

At a quick glance, one could easily designate the total return [refer, Fig. 4.10(a)] and total volatility [refer, Fig. 4.10(b)] spillovers among the markets as time-varying. Observably, the total return spillover index ranges between 5% and 12%, while the total volatility spillover index fluctuates between 30% and 70% with visibly high spikes. Compared to the static estimates of (1.38 - 2.40)% for the returns, and (17.0 - 26.2)% for the volatility, we found now that both return and volatility spillover indexes increased substantially with time. This increased pattern of spillover effect connotes that, irrespective of the low-level price connectedness, volatility shocks to any of the markets have a higher chance of spilling to the remaining markets.



(a) Rolling-Window Total Return Spillover Index



(b) Rolling-Window Total Volatility Spillover Index

Fig. 4.10: Rolling-Window Total Spillover Index: (a) Return; (b) Volatility.
Notes: The thin vertical black lines are associated with major news events of the cryptocurrency market. The dates and specific occurrences that match labels A to G are outlined as follows: (A) US CFTC declared bitcoin as a commodity: 17.09.2015; (B) Japan declaration of virtual currencies as legal tender: 01.04.2017; (C) Coincheck, a Japanese exchange lost close to 500 million US dollars to hackers: 26.01.2018; (D) European parliament votes in favour of virtual currencies: 19.04.2018; (E) Designating cryptocurrency as "scam" by JP Morgan's CEO – Jamie Dimon: 04.08.2018; (F) ECJ ruled to exempt Bitcoin and other virtual currencies from value-added tax in the European Union: 22.10.2018; (G) Reserve Bank of India deny bill to ban digital currencies: 04.06.2019.

Further scrutiny of the spillover plots shows that the differently constituted markets involving cryptocurrency and the emerging assets move quite closely. However, the variations in the level of movement for the volatility spillover index is more pronounced and has several significant jumps, relative to the steady growth movement of the return spillover index. In both plots, there is a noticeable sharp spike at the beginning of 2016, which incidentally coincides with the unprecedented network rate of Bitcoin that was reported to have exceeded one exahash per second[67].

Markedly, the estimated values of the total volatility spillover witnessed an increasing trend from late 2014 to 2015 and later exhibited relatively steady growth with sharp increases and decreases until 2016. The level of the values then decreased from early 2016 but subsequently changed cause to achieve a slow upward movement around mid-2016. An upward trend is viewed from the beginning of 2017 to somewhere in the third quarter of the same year, from which the spillover index significantly fell to its lowest value in the early part of 2018. Thereafter, the spillover values seem to have been increasing at a marginal rate. The observed behaviour of the spillover index somehow mimics, in general, the market price development of the cryptocurrency assets. For instance, after a remarkable market boom in 2017 for most cryptocurrencies, prices generally fell by higher margins, mainly from January to February 2018. Even the price of Bitcoin, the largest cryptocurrency, was

[67] Accessed on January 5, 2020 at: https://bitcoinist.com/bitcoin-hash-rate-exceeds-1-ehs-for-the-first-time/

approximately halved from an all-time high of 18,851.61 with a market cap of 315 billion in 18.12.2017 to 8,478.64 with a cap of 142 billion US dollars as of 10.02.2018 (refer, https://coinmarketcap.com/currencies/bitcoin/). On this backdrop, we surmise that the boom and burst periods of the cryptocurrency market have higher tendencies of influencing volatility shocks in emerging asset markets, irrespective of the current low-level market linkages.

Another relevant result worth mentioning is that the total return spillover index is by way very less sensitive to major cryptocurrency events, as opposed to the volatility spillover index. Specifically, the US Commodities Futures Trading Commission's (CFTC) declaration of Bitcoin as a tradable commodity led to a sharp increase in volatility spillover. Interestingly, a slow upward trend is witnessed in the level of the volatility spillover just after the Swiss city of Zug and a bunch of European Union countries accepted (on 03.05.2016) to use Bitcoin for government payment services. In another finding, conspicuously high spikes are recorded around August 2016 where the unfortunate event, which saw the hacking of Bitfinex on 02.08.2016, occurred. Contrary to the findings of Koutmos (2018) and Dahir and Mahat (2019), the occurrence of this particular negative event had substantial influences on the time evolution of the volatility spillovers, while movements in the level of the return spillovers rather look insensitive – the mentioned authors reported a reverse of this finding. The difference in our results from theirs could arise from the sample period and the kind of markets used for the spillover analysis.

Similarly, the hacking of Coincheck, the largest cryptocurrency exchange in Japan also led to a slow upward trend in January 2018, with visibly high spikes in February of the same year, which clashes with the 20.02.2018 launching of the oil-backed "Petro" by the Central Bank of Venezuela. Except for major events such as the rejection of Bitcoin's ETFs by the US Security and Exchange Commission (on 22.08.2018), and the ruling to exempt Bitcoin and other virtual currencies from value-added tax, which

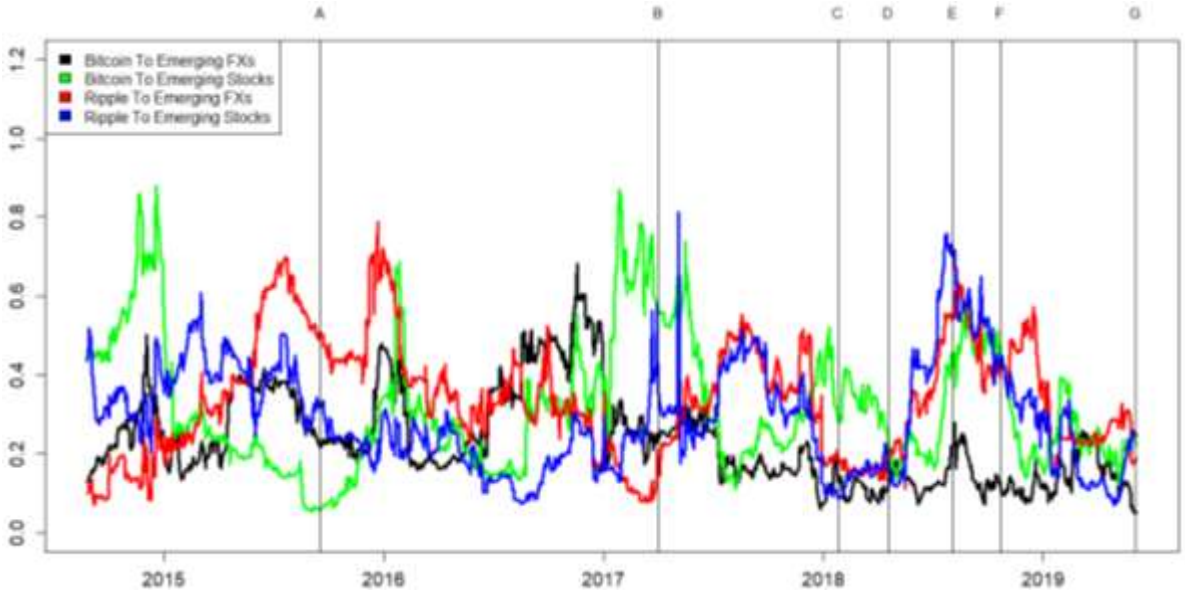
resulted to a slow downward trend in volatility spillover, events like Japan's declaration of cryptocurrencies as legal tender, votes casted in favour of Bitcoin by the EU parliament, and the pronouncement of cryptocurrency as "scam" by JP Morgan's Jamie Dimon, collectively coincided with different magnitude of positive volatility spillover spikes. In addition, the Reserve Bank of India's denial to ban cryptocurrencies was met with mixed reactions, as volatility spillovers involving Bitcoin (or Ripple) and the constituted emerging forex markets slightly increased, while that of the emerging equities recorded a fall in spillover. Like Koutmos (2018), our result is suggestive that both positive and negative major cryptocurrency events appear to influence, to a certain level, spillovers in emerging asset markets. Additionally, our finding indicates that positive major occurrences exhibit high chances of increasing the rate of volatility spillovers than negative events. Importantly, we noticed that, return spillovers hardly respond to both positive and negative events (or news reports).

4.5.3.3 Rolling-Window gross directional spillover analysis

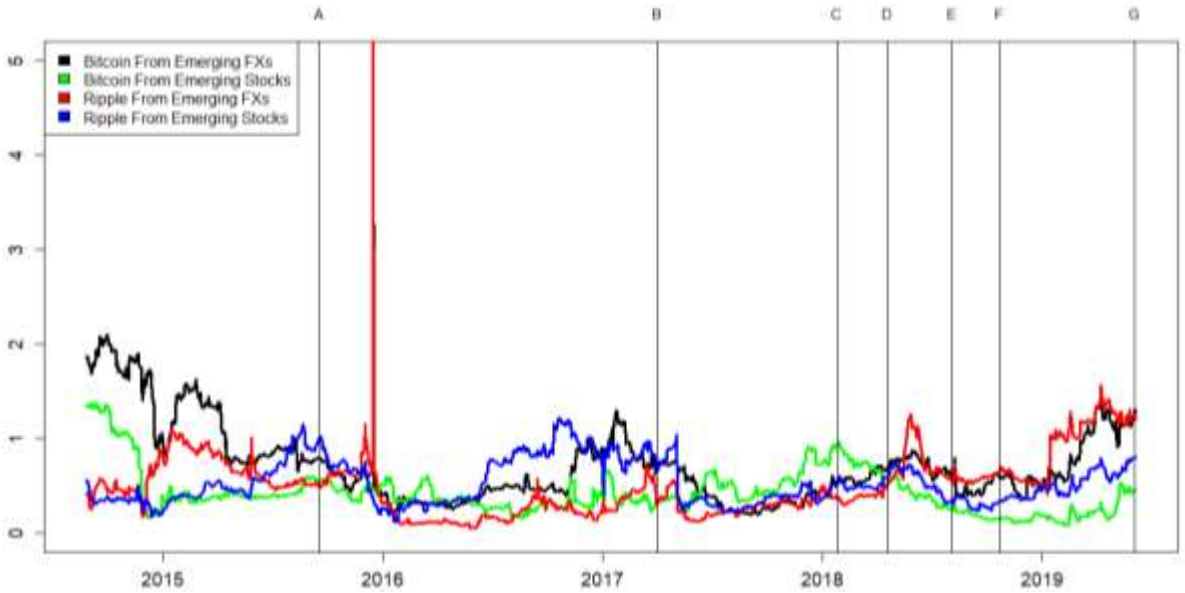
Under this sub-section, we provide results and analysis of the gross directional return and volatility spillovers, first, from Bitcoin or Ripple to the emerging assets, and second, spillovers transmitted from emerging assets to either Bitcoin or Ripple over time. Whereas Figs. 4.11(*a* and *c*) display respectively a rolling-window gross directional returns and volatility spillovers that emanate from each cryptocurrency (Bitcoin or Ripple) to either the emerging stock or forex markets, Figs. 4.11(*b* and *d*) give plots of return and volatility directional spillover running from the respective emerging asset classes to Bitcoin or Ripple.

The gross directional spillovers in Figs. 4.11(*a* and *b*) for the returns show that the directional spillovers moving from Bitcoin (Ripple) to the emerging assets look volatile and ranges (0.10 - 0.80)%, a little above the measures obtained under the static

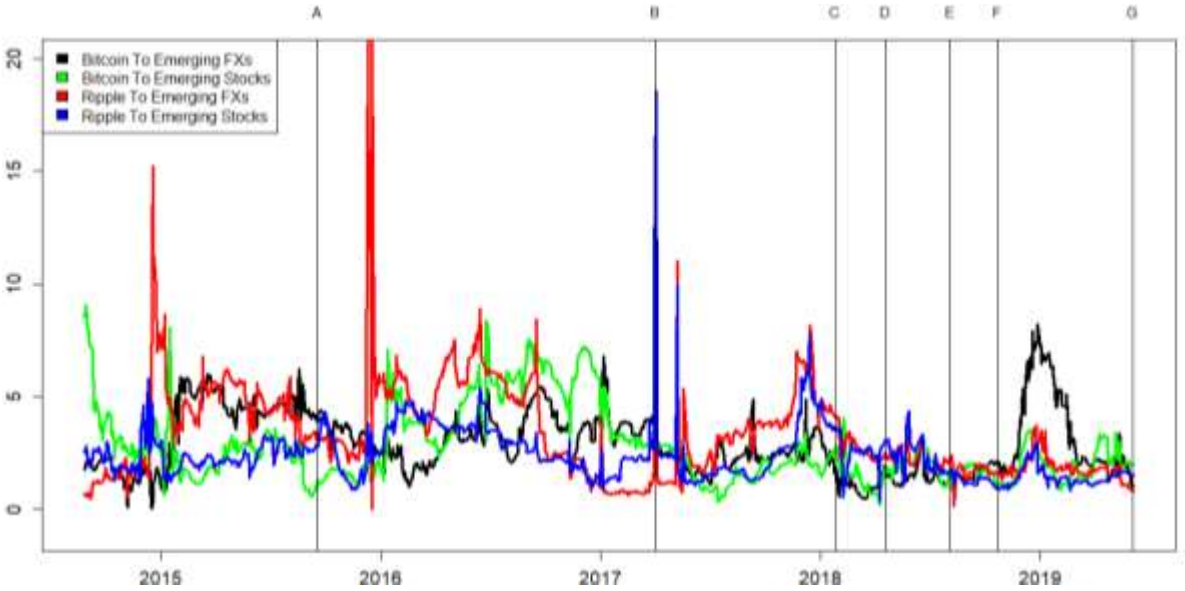
estimations. On the other hand, the directional spillover plots that display the degree of transmission from the stocks (or forex) to each of the cryptocurrency market moves in tandem and ranges from 0.20% to 2.0%. Compared to the returns, the gross directional volatility spillovers [see, Figs. 4.11(*c* and *d*)], in terms of magnitude, are quite higher and occasionally marked with sharp peaks. While the volatility spillovers from the cryptocurrencies oscillate around 0.10% to 0.80%, the spillovers from the emerging assets closely range between (1.50 - 0.82)%.



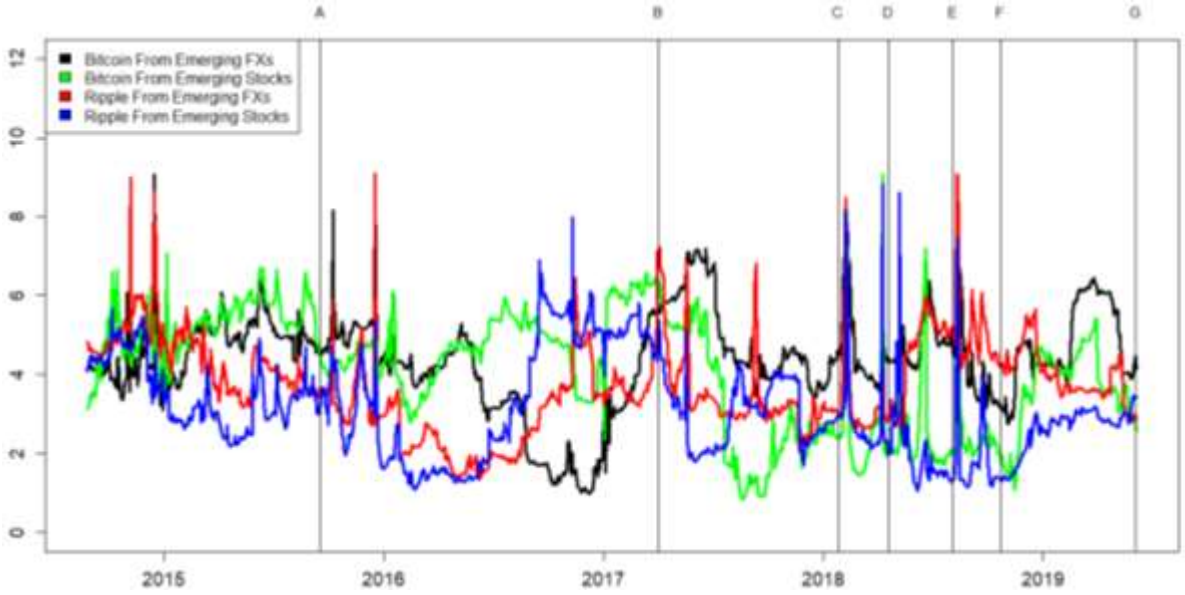
(a) Return Spillover from Bitcoin (Ripple) To Emerging Assets



(b) Return Spillover From Emerging Assets to Bitcoin (Ripple)



(c) Volatility Return Spillover from Bitcoin (Ripple) To Emerging Assets



(d) Volatility Return Spillover From Emerging Assets to Bitcoin (Ripple)

Fig. 4.11: Rolling-Window Directional Spillover Index.

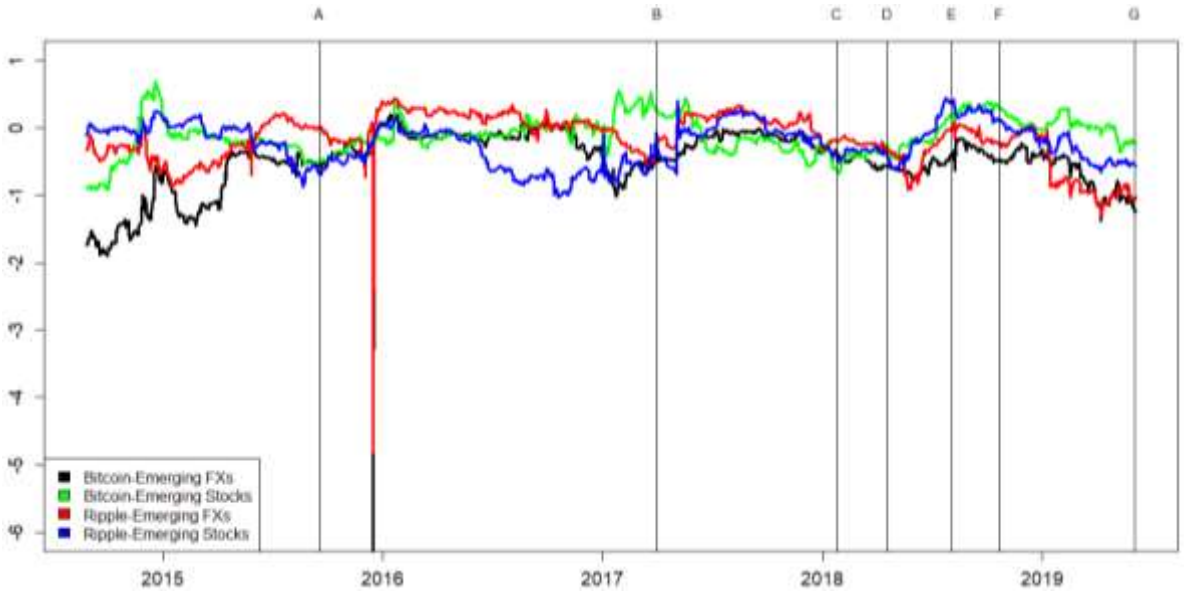
Notes: The thin vertical black lines are associated with major news events of the cryptocurrency market. The dates and specific occurrences that match labels A to G are outlined as follows: (A) US CFTC declared bitcoin as a commodity: 17.09.2015; (B) Japan declaration of virtual currencies as legal tender: 01.04.2017; (C) Coincheck, a Japanese exchange lost close to 500 million US dollars to hackers: 26.01.2018; (D) European parliament votes in favour of virtual currencies: 19.04.2018; (E) Designating cryptocurrency as "scam" by JP Morgan's CEO – Jamie Dimon: 04.08.2018; (F) ECJ ruled to exempt Bitcoin and other virtual currencies from value-added tax in the European Union: 22.10.2018; (G) Reserve Bank of India deny bill to ban digital currencies: 04.06.2019.

We further observe from the graphical display of both return and volatility directional spillovers that, consistently, there are high spikes at the beginning of 2016, and immediately after the first quarter of 2017. These detected abrupt spikes quadrate respectively with the Bitfinex hack and the acceptance of cryptocurrencies as legal

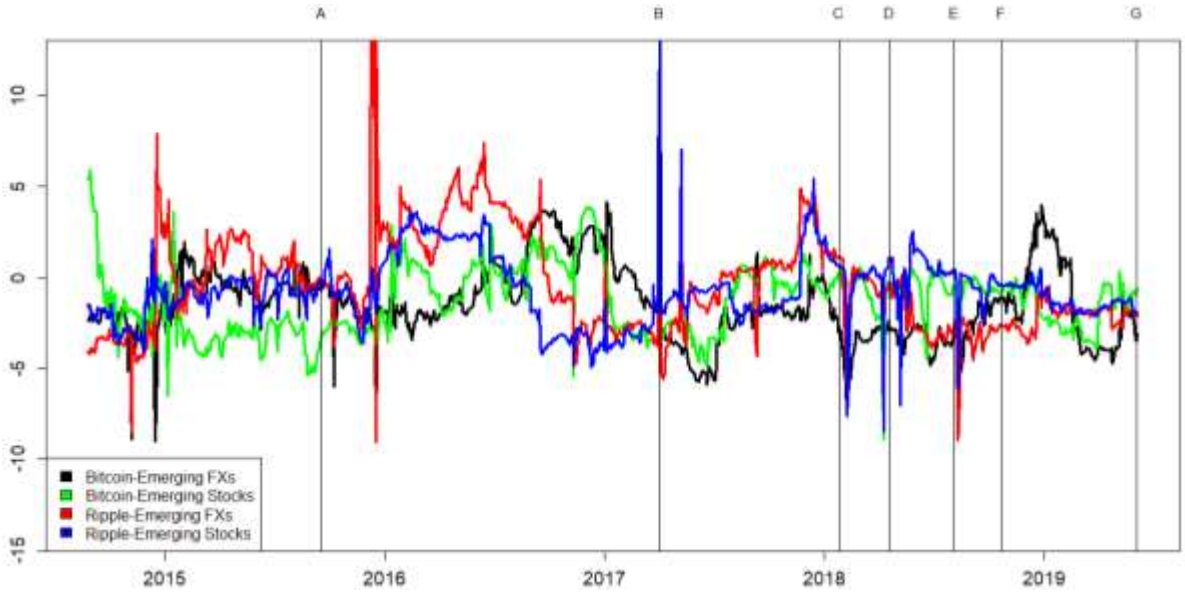
tender by Japan. The results re-affirm the previous finding in the sense that major events of the cryptocurrency market remain influential to the spillover behaviour between emerging assets and cryptocurrencies.

4.5.3.4 *Rolling-Window net directional spillover analysis*

Results of the net-directional spillovers obtained through Eqn (4.29) and the pairwise net-directional spillovers from Eqn (4.30 or 4.31), for both return and volatility, are presented and discussed under this sub-section. Figs. 4.12(*a* and *b*) correspond to the former, while *Appendices 4.A1*, 4.*A2*, *4.B1*, and *4.B2* show plots of the latter. Moreover, of greater interest to us are the net-directional spillovers of Bitcoin and Ripple, hence, we report results on the net contributions of these two assets.



(a) Return Net Spillover



(b) Volatility Return Net Spillover

Fig. 4.12: Rolling-Window Net Spillover Index; (a) Return; (b) Volatility.
Notes: The thin vertical black lines are associated with major news events of the cryptocurrency market. The dates and specific occurrences that match labels A to G are outlined as follows: (A) US CFTC declared bitcoin as a commodity: 17.09.2015; (B) Japan declaration of virtual currencies as legal tender: 01.04.2017; (C) Coincheck, a Japanese exchange lost close to 500 million US dollars to hackers: 26.01.2018; (D) European parliament votes in favour of virtual currencies: 19.04.2018; (E) Designating cryptocurrency as "scam" by JP Morgan's CEO – Jamie Dimon: 04.08.2018; (F) ECJ ruled to exempt Bitcoin and other virtual currencies from value-added tax in the European Union: 22.10.2018; (G) Reserve Bank of India deny bill to ban digital currencies: 04.06.2019.

The net-directional spillovers for the returns [Fig. 4.12(*a*)] move closely together along the time axis and have a substantial portion of their values below zero. Meaning, Bitcoin and Ripple are mostly net recipients of return shocks. Of the two, Bitcoin became a pronounced net recipient of shocks from the emerging equities between late 2014 to mid-2015. However, in few cases along the time intervals, the two cryptocurrency assets are crowned as net propagators of return shocks. More so, it could be visualized from Fig. 4.12(*b*) that the estimated net-directional spillovers for the volatility of Bitcoin and Ripple fluctuate between -5.0% and +5.0%, with few up and downward spikes which coincide with several major events that occurred within the time evolution of the cryptocurrency market. The plots conspicuously indicate that almost half of the volatility spillover values are either below or above the zero lines and are distributed fairly across the sample time intervals. This latter spillover pattern

unveils the swinging dual roles of Bitcoin and Ripple as net transmitters of volatility shocks at one time, and net absorbers of shocks at another time.

We further report results of the pairwise directional return and volatility spillovers occasioned by the net contributions of either Bitcoin or Ripple to each of the emerging assets. As shown in *Appendices 4.A1-4.A2* and *4.B1-4.B2*, the pairwise net spillover values for both return and volatility generally fluctuate over time and exhibit several peaks that could be traced to major events of the cryptocurrency markets. For almost all the plots, the pairwise net directional spillovers toggle between positive and negative values across the time span and mostly oscillate around the zero marks, suggestive of weak pairwise spillover transmissions. However, relative to the return spillovers, the volatility spillover values are in terms of magnitude, slightly higher. The results show no consistent direction of spillover that characterizes the cryptocurrency and emerging market pairs, rather, we found evidence in favour of a weak bidirectional (positive and negative) time-varying spillover transmissions. That is, the flapping positive and negative pairwise spillover values indicate to us that Bitcoin and Ripple are net propagators and receivers of return and volatility shocks "to" and "from" the individual emerging assets, although such transmissions, for now, remain at low levels.

4.5.3.5 Robustness checks

To ensure whether the results detailed above are not by mere chance or fluke, we further explore return and volatility spillovers by varying the forecast horizon and the size for our rolling-window analysis. The plots in *Appendix 4.C1* display the resultant total return and volatility spillovers at two window sizes, w=125 (close to semi-annual) and w=160 (eight months), and for different forecast horizons, i.e., h=10 days (or

fortnight) and h=20 (one month)[68]. A simple scrutiny of these plots leads one to conclude that altering the forecast step size and the rolling-window period does not substantially distort the observed patterns of the spillover index. Thus, a direct comparison of the plots in Fig. 410 and *Appendix 4.C1* gives an indication that the time movement of the estimated spillover index, though not identical in terms of magnitude, fairly mimics each other. Therefore, our results remained unchanged, qualitatively, and are less sensitive to the choice of forecast horizons and window sizes.

4.6 Conclusions

The emergence of cryptocurrencies has been trumpeted as one recent disruptive innovation in the financial system. Like emerging asset markets, the new digital currencies promise of mellowing higher returns on investment, but sceptics argue that both markets are highly volatile and risky. By applying a set of refined modelling approaches, this study investigates the extent and pattern of causal relationships and possible risk spillovers between these asset classes under different time samples.

Our results are summarised as follows. First, weaker causal linkages with few feedback relationships are documented for the market pairs. The revealed pattern of (non)causation is found to be insensitive to time and also to the dissected regimes that mark the price evolution of the cryptocurrency market. Second, we found evidence to support a weak but time-dependent pairwise shock transmission, where the duality in the role for Bitcoin and Ripple manifested. Thus, both markets became, mostly, net recipients at one hand, and on a few occasions, net propagators, albeit weak spillover patterns. Meaning, the cryptocurrency market is less influenced and has very little effect on emerging asset markets. This implies that Bitcoin and Ripple, for now, pose

[68] The gross and net (pairwise) direction spillover plots are not reported, just to conserve space. They are readily available upon review request.

a trivial danger to emerging assets, and vice versa. Third, the results unveil to us that, major cryptocurrency news reports (or headlines) exert influences, to some extent, on the total, gross-, and net(pairwise)-directional volatility spillovers among the markets – thus, mainly causing pronounced abrupt spikes in the movement pattern of the spillover index. Further to this, we found the volatility spillover to be more reactive to positive news than negative news. On the other hand, the return spillover looks less responsive to cryptocurrency news items.

Based on our findings pertaining to the current intensity of risk spillover and interrelatedness between cryptocurrency and emerging asset classes, investors and asset managers could hold such information in relevance to portfolio diversification and investment risk management. Besides, the results could act as early signals to policymakers of emerging economies to vary policies geared towards regulating the cryptocurrency market, in order to prevent adverse effects that could spill from the volatility of the new currency market to destabilize financial assets of emerging market economies.

CHAPTER 5

General Conclusion

"A dream doesn't become reality through magic; it takes sweat, determination and hard work"

Colin L. Powell

5.1 Introduction

This chapter brings closure to the thesis. It recounts, concisely, the essence and rationale that set this work into motion. Next, we summarize salient points and review major contributions with conclusions for each sub-theme of the thesis. This is followed by a general conclusion with implications and recommendations. Lastly, we provide related areas that require further research attention.

5.2 Encapsulation of the Thesis

The essays have been generally focused on the evolving statistical and financial behaviour of the youngest global market entrant, i.e., cryptocurrencies, in relation to traditional markets of emerging economies. We began by recognizing that cryptocurrency is on the vogue since its introduction about a decade ago. The new digital currency, which was pioneered by Bitcoin is the first and most successful FinTech creation that uses blockchain to document and decentralise the ownership of ledgers and transactions when earlier attempts in the 1990s by libertarian cryptographers had become unsuccessful. It triumphs on cryptographic algorithms, and had widely been reported in the media and by the academic community as a revolution in the financial ecosystem due to pseudonymity, portability, decentralization, divisibility, low transaction cost, fast and non-expensive money transfer scheme, among others, albeit in the face of scepticism and cynicism. Upon all its trumpeted potentials and rapid development, cryptocurrency is challenged with an identity crisis. This has become a heated debate among the general public, whose

standpoints are mainly ill-informed and at times driven by the verbiage churned out by the even less informed financial press. Even in the academic space, no consensus has been reached, and less is known about the evolving characteristics of the new digital currency. So, therefore, the questions remain: *Is cryptocurrency indeed money or a financial asset gaining traction because of its investment prospects? Can it offer a run alternative to the existing currency system? Does its exponential growth pose dangers to the financial system?*

The thesis explored the features of cryptocurrencies and compared the results to first, fiat currencies of emerging economies, and second, other traditional asset classes. Though the earlier design was to serve a monetary purpose (see, Nakamoto, 2008), it is unsure whether cryptocurrency is money, commodity, an investment instrument, or a hybrid of the mentioned classes. We posit that cryptocurrency can best be designated by knowing much about its evolving characteristics. This viewpoint is shared by the European Central Bank via a released paper in 2012, i.e. ECB (2012) and Bjerg (2016), who in a similar way based their definition and classification of the new currency on the currency's own structure and observed characteristics. In their paper, the ECB issued a caveat that their standpoint might change in future as a result of the evolving characteristics of the currency. On this backdrop, it is only hoped that studies in this direction would provide enough features of the new currency, which consequentially could be used as reference materials to appropriately class or designate the currency into the mainstream financial ecosystem.

Further to the above, we examined whether the cryptocurrency market couples (or decouples) with long-existing emerging financial markets, and later determined the economic benefits of the former. More so, using a set of refined empirical methodologies, we investigated the degree of interdependence and shock spillovers between the new currency market and other asset markets to evaluate the level of risk. The thrust of such analysis was to assess the threat posed by the rapid development

of cryptocurrencies on emerging markets, which are often tagged with high price or value instability.

5.3 Summary of major contributions

Weighing into the topical issue that has received less research attention in the academic space and rather dominated public debates, we examined through the evolving empirical characteristics to shed more light on whether cryptocurrency is a currency, commodity, an investment vehicle, or otherwise. We situated cryptocurrency in an emerging market economy setting and first compared its observed statistical and financial characteristics to traditional emerging market currencies and other well-known assets; second, examined relatedness and economic benefits; and third, investigated the level of interdependence and shock spillovers. These broad themes are organised respectively into three empirical essays.

The first essay sought to designate, or class cryptocurrency based on its market behaviour, relative to financial markets of emerging economies. If it is indeed a currency, then we expected cryptocurrency to bear a high resemblance, in characteristics, to emerging market currencies. Under this essay, five sub-themes were developed and analysed with summaries of their salient findings couched under sub-sections 5.31-5.3.5. At the time of writing, a paper had been published in peer-reviewed journal whiles others are at various stages of publication consideration.

The second assay, which attempted to examine how well (or otherwise) the cryptocurrency market couples or decouples with emerging financial markets, has its abridgement of major results presented in sub-section 5.3.6. An extracted article is published online.

Brief results of the last empirical essay on risk spillovers are provided in sub-section 5.3.7. Unlike the few pieces of existing studies that are mainly challenged with a limited scope and analysis, our essays employed a pool of refined methodologies and dived deep through the lens of emerging market economies to contextualise and empirical provide answers to the gaped questions arising from the rapid evolution of cryptocurrencies. Important fallouts from the essays, implications and conclusions, and possible areas for extensions are presented in the next (sub-)sections.

5.3.1 Distribution of returns in cryptocurrencies and emerging markets

Several empirical studies have fitted different statistical distributions to financial variables collected over short frequency intervals with varying successes. As some merely follow existing works to assume a single best fitting distribution, others fit popular distributions without recourse to the empirical features of the data at hand. Using a large pool of parametric distributions, we explored the functional form and distributional properties of the daily log-returns of cryptocurrency exchange rate vis-à-vis traditional markets of emerging economies, proxied by BRICS. In all, 1,280 candidate parametric fits are assessed for statistical adequacies, with the implied usage for risk measurement, economic modelling and forecasting. The results show that, despite the different formations of the markets, in majority of the cases, distributions with complex parameterization, thus the skew generalized *t*, skew Student's *t*, generalized hyperbolic, and the skew *t* recorded the highest number of best fits as they well-captured variations in the data. Besides, the distribution densities of the cryptocurrencies largely show relatively steep towering peaks with less fat tails, which slightly distinguish the functional form of the former from the other markets. From the value-at-risk and expected-shortfall results, we unveil a very high level of tail risk for the cryptocurrencies, while the BRICS equities and FX market respectively show moderate and relatively lower risk. This finding accentuates the immaturity and exceedingly speculative sort of instrument that characterises cryptocurrencies.

Generally, the findings reveal that the new digital currencies show quite lesser resemblance features and risk characteristics to the BRICS FX, but instead, display some distributional properties that are in a way similar to the BRICS equities, albeit not identical, hence a different class of financial instrument.

5.3.2 Chaoticity versus stochasticity: financial markets conundrum

The theory of chaos has long existed but its application to econophysics dates back about a little over four decades ago. From the theoretical standpoint, economic and financial models could possibly be designed even in chaotic regimes, however, apart from the substantial evidence in the literature that supports the presence of non-linearity in the realizations of variables over time, not much is known about chaos, especially for the nascent cryptocurrency and most assets of emerging market economies. In this study, the probabilistic or chaotic features that characterize leading cryptocurrencies and those of mainstream BRICS assets are examined under two important time dimensions (i.e. time and frequency domains). Specifically, the result has it that chaos is absent in the daily log-returns of all asset classes when considered under the full and intraweek time frames. Nonetheless, except for the conventional commodities, stronger evidence against stochastic signal is observed for almost all the markets at the weekly scale, with implied ease of predictability. In general, we found not many unique dissimilarities for the markets, particularly, the dynamic properties of the BRICS stocks and the new currencies trail closer. Both markets are often characterised by large frequent price fluctuations and interactive traders with rising expectation for higher returns. Perhaps, this could be a common ground for such observed dynamic behaviour in their price structure. The novelty of the result indicates that the complex dynamic behaviour of cryptocurrencies is descriptionally indistinguishable to a large extent from the traditional BRICS assets, unlike the weak and decoupled markets documented under several correlation studies.

5.3.3 Asymmetry and leverage in asset markets

In another phenomenon to ascertain the nature of the decentralised digital currencies, we investigated asymmetry and local leverage behaviour in individual and aggregate markets of leading cryptocurrencies and compared such characteristics to monetary and other traditional assets of emerging market economies. Generally different from the cryptocurrencies, the results show diffuse evidence of asymmetry and a significant presence of local leverage in the emerging markets. New findings indicate that mega-size cryptocurrencies like Bitcoin and Ripple exhibit return-volatility behaviour whereby volatility changes in their markets increase rather by a response to positive shocks than by a response to negative shocks of the same magnitude. Besides, the closely similar behaviour of the gold market to the latter fuels the argument that Bitcoin is a commodity money which acts as complement or substitute to gold and other commodity monies. The intuitions gleaned from the results are of useful relevance to policymakers, regulators, and practitioners. For instance, understanding the return-volatility profile of the markets may help investors to position themselves better through the adoption of effective hedging and diversification strategies. Also, knowing the volatility dynamics may inform decisions of policymakers as they continue to appreciate the unique riskiness of cryptocurrencies.

5.3.4 Multifractal analysis and market (in)efficiency

The main rationale that underscores an efficient market, is that, all new relevant information should immediately be factored to reflect in the current price formation process. In such circumstances, arbitrage opportunities seem impossible, yet, the efficiency of financial markets has been a subject of intense debate. The purpose of the study was to investigate the inherent scaling characteristics of cryptocurrency and examine the (in)efficiency of the market against those of emerging financial markets. Our results show that the dynamics in the price changes of the markets could not be explained by a single scaling exponent, but rather, a multifractal structure. Further,

drawing on the relationship between the scaling exponent and the Hurst exponent, we constructed an inefficiency index to rank the markets under different frequency domain. Regarding the short- to medium-run, the cryptocurrencies, specifically the mega-size currencies (Ripple, Bitcoin, Litecoin, and Ethereum) respectively recorded larger indexes, connoting evidence of high-level market inefficiency with implied ease of predictability, whereas the BRICS markets led by the commodities showed smaller values that fall outside the inefficiency rage, rendering them reasonably efficient. Interestingly, all the asset classes except the commodities, in the long-run deviate, largely, from a memoryless stochastic process, signalling low intensity of informational flow and its implication for speculative trading strategy which may be adopted to "beat" the market.

5.3.5 Do investors of cryptocurrency and emerging markets herd?

Investors' behavioural biases in the fast embryonic cryptocurrency market relative to traditional currency and stock markets of 10 emerging economies within the G20 are studied through herding. Our results reference significant symmetric crowd and imitation trading, which is dependent on time for all markets. Additionally, we report asymmetric herd behaviour, particularly, in the stock and cryptocurrency markets, indicative that traders of these markets react collectively to extreme return movement with implied high risk and consequences for market informational efficiency.

5.3.6 Dynamic co-movement and economic role of cryptocurrencies

The aftermaths of the 2008/9 global financial crisis market higher uncertainties and substantial increases in the correlation of mainstream asset markets worldwide. It is believed that the introduction of cryptocurrency was a move to usher in a new financial instrument rooted on a decentralise system to provide a lean alternative to the government-controlled ecosystem and break, to an extent, the long chain of financial intermediaries. However, in spite of its decade of existence, the evolving

relationship and economic potentials of cryptocurrencies are less explored, even the few works in this direction are often based on a two-dimensional analysis, and the ones designed on the three-dimensional analysis are mostly static modelling approaches. In view of the above, this study, through refined time- and frequency-varying techniques, examined the extent of linkages between leading cryptocurrencies and diverse traditional assets of emerging economies. Using variants of the multivariate conditional heteroscedasticity models and a dummy, we assessed the economic potential, each for Bitcoin and Ripple, from the perspective of an emerging market investor. The results, from both time and frequency analyses indicate that these mega-size cryptocurrency assets have not yet coupled with the emerging assets, as weaker to lower-moderate correlations characterise movements of the pairs. Additionally, our results unveil a multifaceted economic benefit of Bitcoin and Ripple, however, this varies across emerging asset classes (forex and equities), country-specific assets, and regional emerging market groupings. The findings hold some implications for investors, regarding portfolio diversification and risk management.

5.3.7 Cryptocurrency versus other assets: Interdependence and shock transmission

In this final essay, we applied a set of measures to examine the extent of cross-market interdependencies and risk spillovers between leading cryptocurrencies and emerging markets. Results from the causality approaches show substantial evidence of non-causation with few instances of unidirectional and feedback linkages. Highlights from the spillover measures indicate weak and apparently no significant differences in the dynamic pairwise spillover movements for the returns and volatilities of the markets, over time. Further, new evidence emerges that the volatility spillovers react more abruptly to major cryptocurrency positive news events, albeit low-magnitude, while the return spillover appears insensitive to such news. Our findings suggest that cryptocurrency, is currently less influenced and has little effect on emerging markets. This synchronizes with the standpoint of several central

authorities, which claim, based on the low transaction volumes, that cryptocurrency does it pose any systemic threat, for now, to the stability of traditional financial system. However, the time-varying pattern of the spillovers and the responsiveness to cryptocurrency news reports raises uncertainty regarding the intensity of the markets' future interaction and possible danger, which should be of concern to economic managers and regulators in emerging economies.

5.4 Concluding remarks and recommendations

Using the empirical findings from the essays, we generally conclude the study by digesting the conundrums identified in the opening chapter and provide a comprehensible path of analysis with recommendations where needed.

We begin with the first set of questions: *Does cryptocurrency fulfil the functional role of money? Can it become a well-established national currency?* From an empirical standpoint, Bitcoin and the altcoin cryptocurrencies bear a very minimal resemblance, in characteristics, to fiat currencies of emerging economies. Instead, they behave, in some few cases to emerging market security assets (mostly equities), and in particular instances, commodity money like gold. We interpret the disposed empirical findings to mean that cryptocurrency at this point, is less recognised through the lens of emerging market economies to be classified as real money, but largely for other derived financial purposes. Therefore, in this direction, cryptocurrency could be viewed partially as money, albeit less active and very weak, perhaps due to extremely low transaction volumes (especially for the altcoins); and as a store of value-like tool that is far yet to mature, hence our observed results. In a subtle analogy, cryptocurrency within the perspective of an emerging economy may be designated as a unique item that shares features of a real currency, security (like stock), and commodity money (like gold), therefor dubbed a "trinity hybrid" financial instrument currently functioning more as an alternative investment vehicle for emerging market

investors (see, Stensås et al., 2019). Owing to the lack of oversight by a central authority and the pseudonymous nature of the transaction (which is the utmost distinctive hallmark), it is highly unlikely for cryptocurrency to become a national currency, as in our understanding, central banks would not accept to superintend over a currency regime that they cannot administer their logistics, and control the supply of money, ledgers, among needful monetary policy operations – *what then will be the use of the central authority under such high risk adventure?* Against the backdrop of this insight and weighing on the challenges of the new currency (which are to be expected for a new financial instrument), we envisage a future for cryptocurrency under the ambit of the private sector and recommend legislation to perhaps recognise it for micropayments, a complement to commodity money like gold to store value, and allowed to be traded as securities. It should be noted that even if the long-awaited central bank fiat digital currencies are to be operationalized (as reported by Barontini and Holden, 2019), they cannot entirely replace cryptocurrencies to meet the future demand for electronics cash and investment alternative, because the latter's niche is based on decentralisation and pseudonymity, which places advantage to the public instead of a few financial intermediaries who make unspeakable profits. In such phenomenon, we are hopeful that cryptocurrencies would gradually be fully integrated and coexist to complement the sovereign-backed cash and digital currencies (and not thwarted because of its disruptive competitiveness to mainstream financial system), albeit the paradox of multiple currency regime, which may require an appropriate legislative framework to usher in the supposedly new financial ecosystem.

Second: *Is cryptocurrency currently coupling (or otherwise) with mainstream asset markets? Can it offer any economic benefits?* Based on our empirical findings from the two- and three-dimensional analyses, we conclude that Bitcoin and even the largest long-lived altcoin cryptocurrencies have not in many ways coupled with traditional asset markets of emerging economies. The evidence shows an extremely weak relatedness

and as a result position cryptocurrency for gains emanating from effective diversification schemes, which may be to the advantage of heterogeneous groups of emerging market investors. In a subsequent development, we found multifaceted economic benefits of cryptocurrency in times where assets of emerging economies wander in distress, but in a word of caution, expectations of these capabilities are to be carefully measured owing to the fact that the new currency has not yet fully-fledged. In summing up, the prospects of cryptocurrencies to serve as effective diversifiers, hedge tools, and in rare cases as safe haven instruments underscores the diffused relevance of the new currencies to emerging economies despite the warnings by some governments acting through their central banks to discourage people from holding positions in the currencies. Meaning, regardless, of not being streamlined, emerging market investors may seize the opportunity and make gains from the observed economic virtues of cryptocurrencies, especially in periods of market downturn (or turmoil). Therefore, from what have been learnt so far, we believe the featured capabilities of cryptocurrencies could somehow be maximised to offset the downside risk of emerging market assets in a diversified economy where digital currencies are perhaps formalised to well-enhance their full potentials.

Third: *Does cryptocurrency's exponential growth poses any threat to existing financial system of emerging economies?* As of now, our empirical evidence reveals that cryptocurrency is less influenced and has little effect on conventional markets of emerging economies, and as such, exert less danger on financial system stability. However, governments and monetary authorities should thread cautiously, as cryptocurrency is still in its incipient, and perhaps might not remain so in the coming years if it is to be widely adopted by the enthusiastic libertarian general public, as projected in several studies. This wide-level adoption would contribute to strengthening cryptocurrency's value and propels it to be a more disruptive competitor which may, perhaps, impact well on existing system. If this increasing adoption and usage are to be on a consistent basis, then the popularly held notion by economic authorities that the cryptocurrency

market is relatively too small to make a meaningful impact in an economy due to its minimal transaction volumes per day should be re-looked in the near future. In a released document by GLR (2018) on the regulation of cryptocurrency around the globe, most of these economic managers, largely from emerging and less developed economies, posited that they do not foresee the new digital currencies posing any systemic danger or threat. Perhaps, this could have informed their decision to remain "cold" and adopt a wait and see posture on the future of cryptocurrencies. However, in light of the insights gleaned, this viewpoint needs to be gradually relaxed as cryptocurrencies may not continue to run trivial impacts in the coming years if adoption levels soar.

In a general concluding remark, we do admit that some economies are less exposed to the rapid development of the diversity in electronic cash payments and the digital money system, though the introduction of cryptocurrencies (a special kind of digital currency) in the last decade has gained attention worldwide. This slow pace may have to change to meet the emerging demand for electronic commerce and online cash payments. The use of cryptographic algorithms to document and decentralise financial transactions and the ledger of ownership has resulted in a paradigm shift in the financial ecosystem, yet, the distributional consequences and economic benefits across economies and among heterogeneous groups of market participants are primarily asymmetric. These skewed distributional consequences could even widen for most emerging economies. This is because of the lack of universal electricity access and frequent power outages to mine cryptocurrencies, electronic gadget and internet services that do not come affordable, remote suburbs without widespread and inadequate telecommunication infrastructure, and the challenge of computer illiteracy. Nonetheless, a national currency should be accessible to all but not sections of the privilege elite community. Therefore, we reiterate that, cryptocurrency is unlikely to become a national currency, however, to explore and maximise its economic potentials in economies like emerging market ones, we recommend that it

should be allowed to offer an alternative in the financial ecosystem under the watch of the private sector as means to exchange goods and services, and facilitate transactions of diverse forms. This may provide a recalibrated diversified financial system, inclusive of the libertarian market participants with appropriate legislation and regulation put in place for a well-functioning ecosystem. We are optimistic that with proper legislative and regulatory framework coming into being, the dangers of cyber security and money laundering, which critics hold against cryptocurrencies without acknowledging that these issues remain a general threat to even well-established financial instruments, would be highly reduced. In our view, cryptocurrencies may have a bright future under the private sector with the coming into being of correct support systems needed to instil confidence in the general public, as other impeding setbacks are gradually faced off. Although the use of digital currencies is restricted to smaller niches, we envisage that this may gradually change as knowledge of information, communication, and technology (ICT) is diffused, telecommunication infrastructure advances and become affordable, and more reliable energy mix are sourced to provide uninterrupted power to all at competitive rates.

It is, therefore, our hope that the insights from this empirical study provoke a new debate to open the doors for governments of emerging market economies to respond to the increasing demand for a digital financial system, given that several sectors of most economies are fast becoming virtual or digitalised with prospects for expanded and sustainable economic growth.

5.5 Areas for further research

Even though some important hidden features had largely been unearthed, our essays considered a limited number of characteristics. Therefore, given the short existence of Bitcoin and the altcoin cryptocurrencies, one may argue that the digital currencies have not matured enough, and for that matter, even the detected characteristics may

be just evidence of early or temporal evolutionary stage findings, hence not entirely conclusive. Owing to the above, we spotlight further related works to cover, in addition to ours, other relevant but much broader economic, financial, and statistical characteristics of the digital currencies as they still evolve, and match them against other existing financial instruments to reveal, perhaps more hidden (dis)similarities. Aside from the empirical analysis of their exchange rate data, we believe future studies on the role of cryptocurrencies in the monetary system is critical. Perhaps, subjecting cryptocurrencies to standard analysis of demand for, and supply of money, and non-standard criteria that questions the fundamental logic of neoclassical economics would provide a lot of exciting research trajectories.

Second, as more actual or reliable real-time transaction data of Bitcoin and the altcoins' distributed ledgers become widely available through transaction networks, though sensitive and very difficult to access but not impossible (as revealed by Kondor et al., 2014), a study to probe, comprehensively, the hands-on functional role(s) (and a realistic number and kinds of users) of these digital currencies in different economic zones or jurisdictions would be required. Analysis of cryptocurrency exchange rate data and the general public or users' action toward it may culminate to better inform what cryptocurrency actually is or has become in an economy or a particular jurisdictional community, and also project a more accurate adoption rate. Also worth investigating is the inherent fundamental characteristics (if any) that perhaps drive the new currency's value and the examination of the market structure of cryptocurrency exchanges vs other rival exchanges (like stock market). Holistically, the market microstructure of this new financial instrument (cryptocurrency) requires intensive research.

Another important dimension that requires further probing is the use of other advanced robust econometrics and statistical methodologies amid a larger pool of emerging and even the inclusion of frontier economies' fiat currencies and assets to

re-affirm or uncover new insights on the studied themes under different data frequencies (e.g. intraday, daily and diverse time-scales). Such works could examine the relatedness and influences of cryptocurrency with relevant (micro)macroeconomic and/or financial variables, of typical example, economic policy uncertainty indexes. On the premise that cryptocurrency is still in its early evolutionary stages, studies that evaluate shock spillover dynamics in several dimensions to alert the possible dangers of the new digital currency market on mainstream financial system are warranted. More importantly, we call for future studies to re-examine the correlation structure, economic benefits and the spillover dynamics of cryptocurrencies against traditional assets, measured from the onset, crisis duration, and the post-crisis period of the novel coronavirus pandemic. *Do cryptocurrencies offer refuge to global and/or national assets in such times? Does the crisis influence the usage, relationship, and shock spillover transmissions between cryptocurrencies and other asset markets?* Empirical investigations in this direction would provide unique contributions to the literature.

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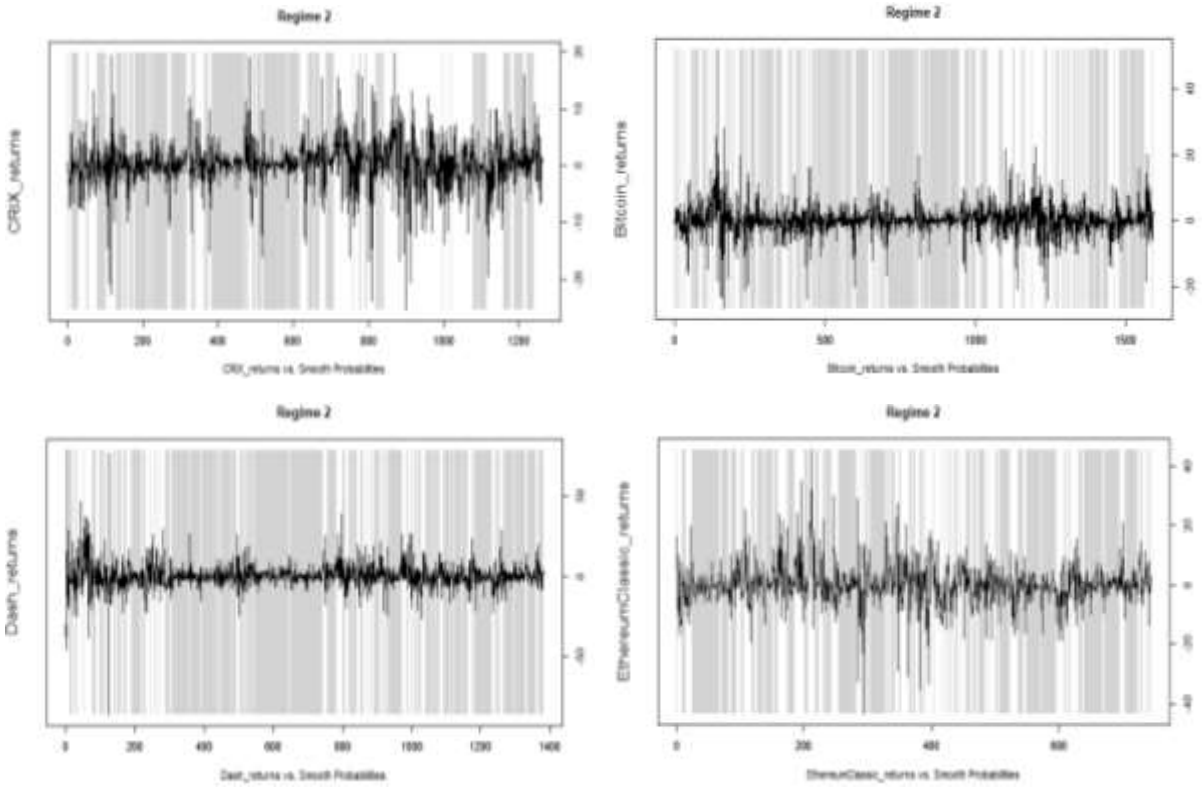
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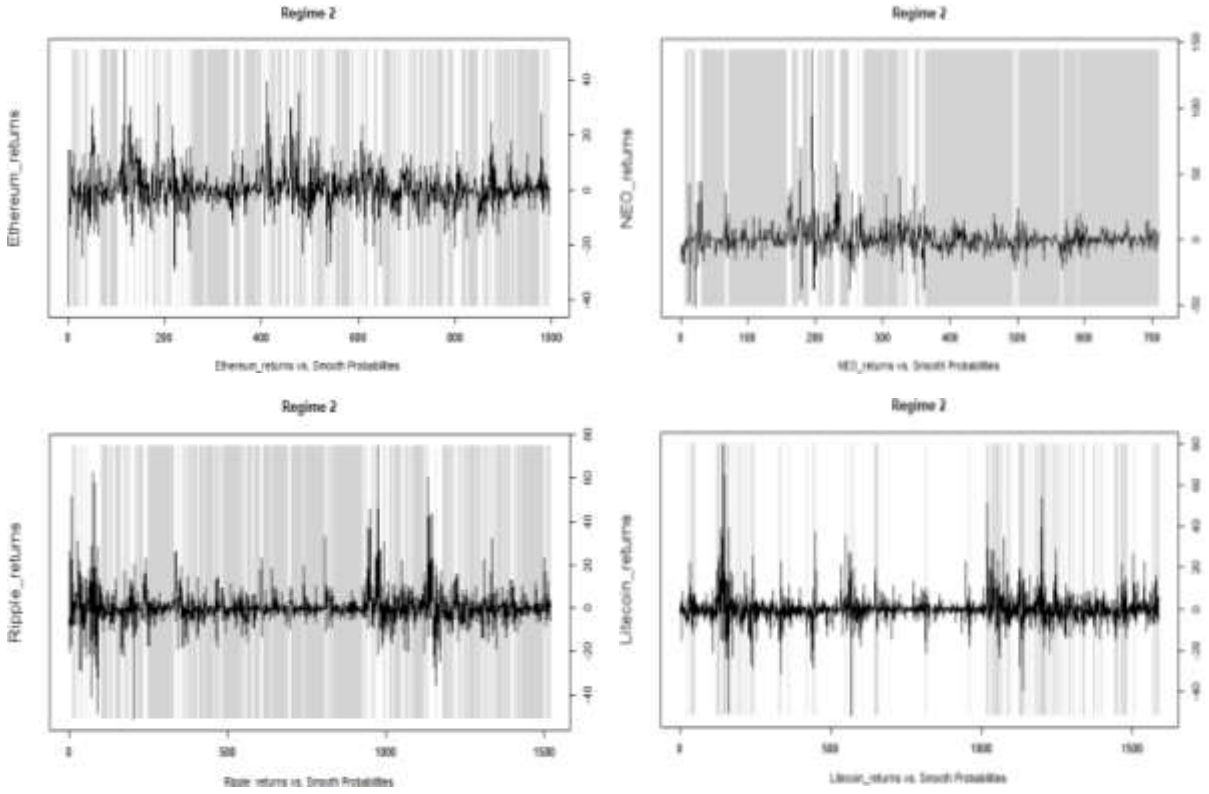
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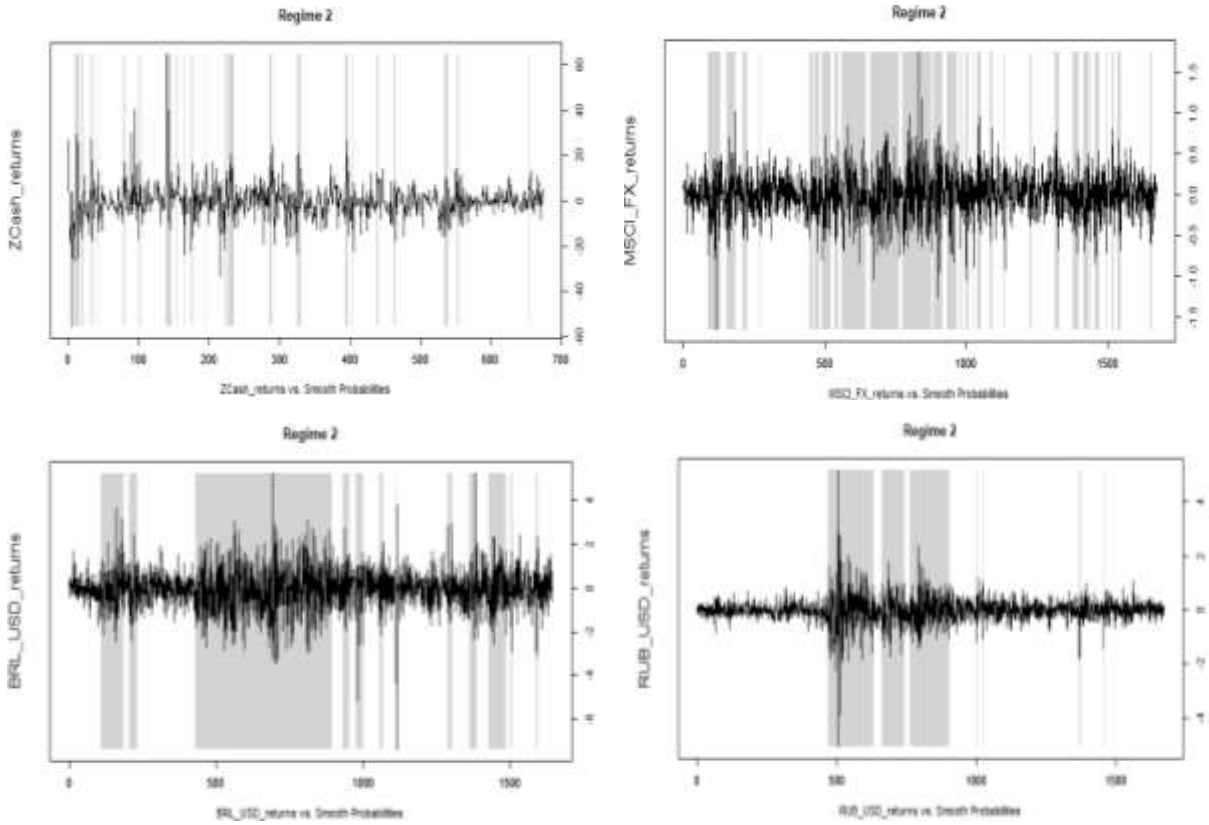
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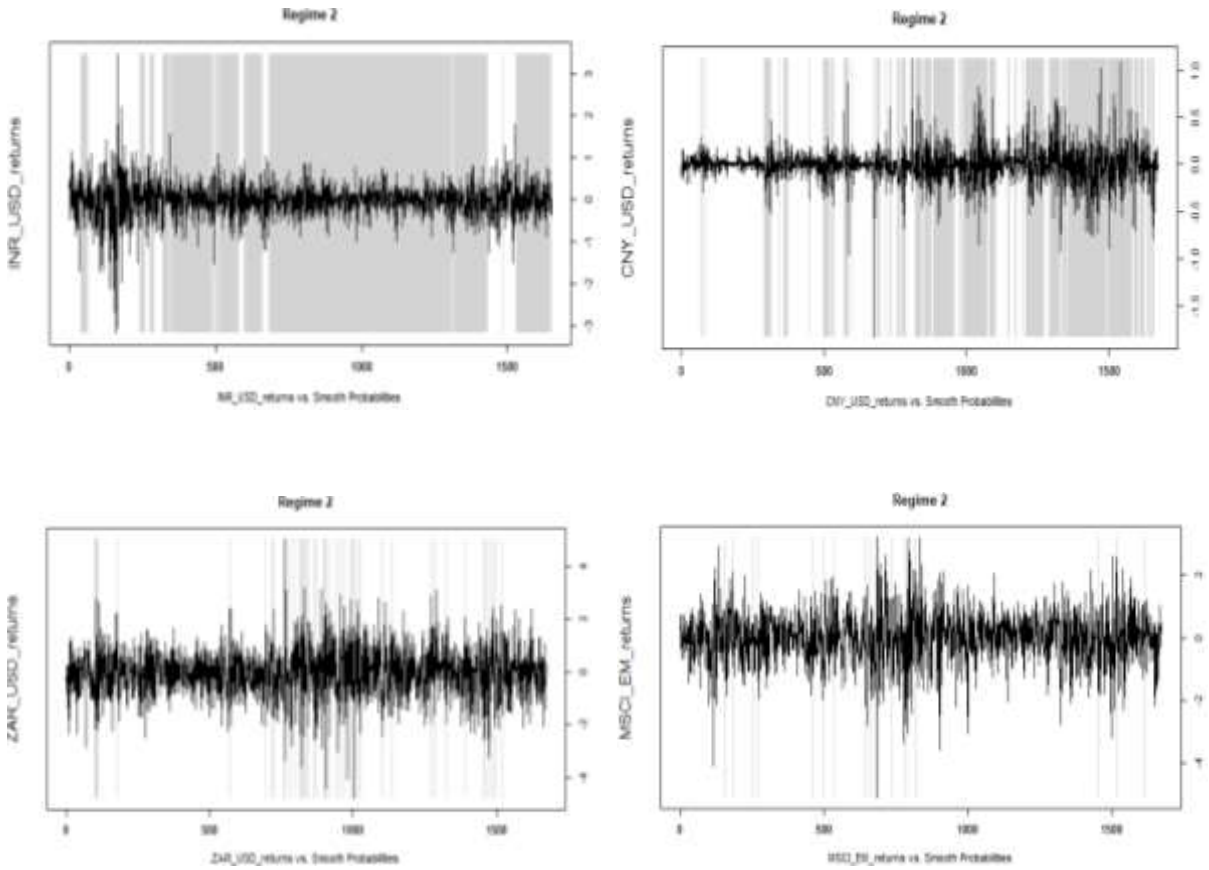
Appendices



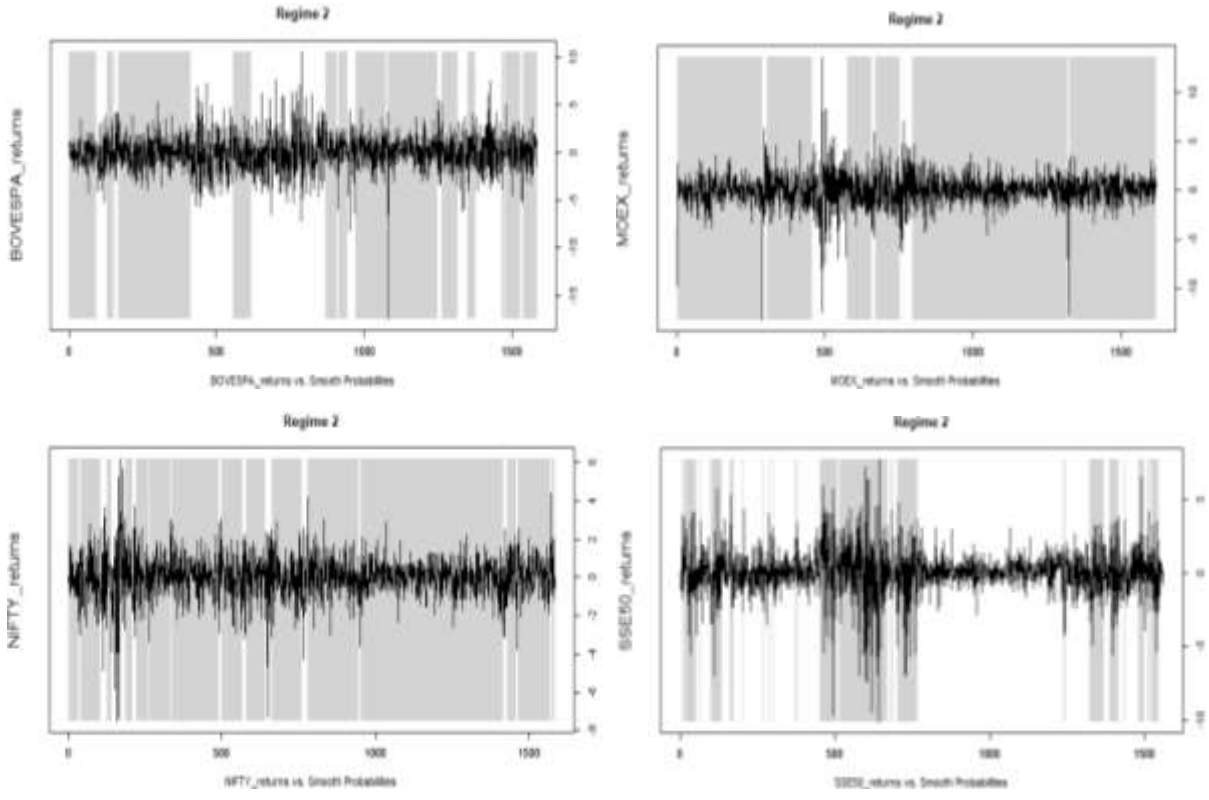


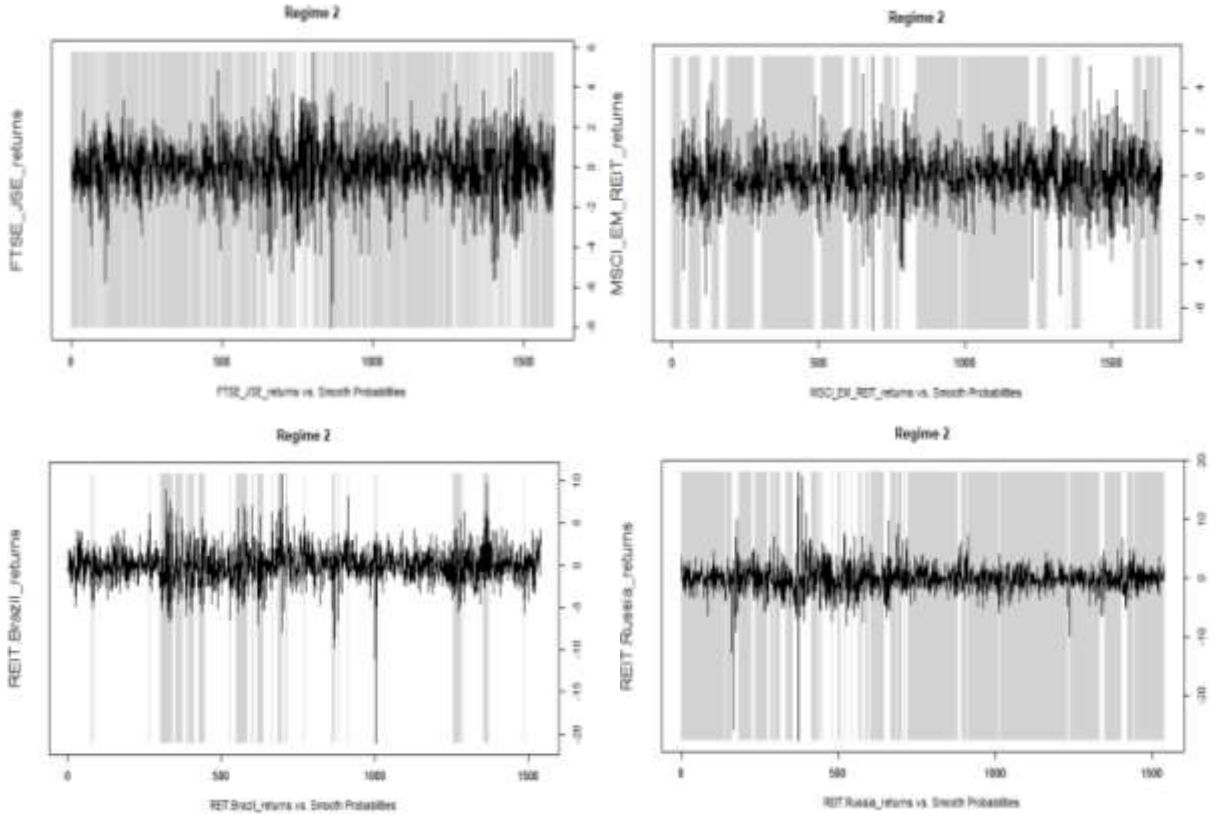
Appendix 2.A1: Graphical plots of regime probabilities vs. daily log-returns



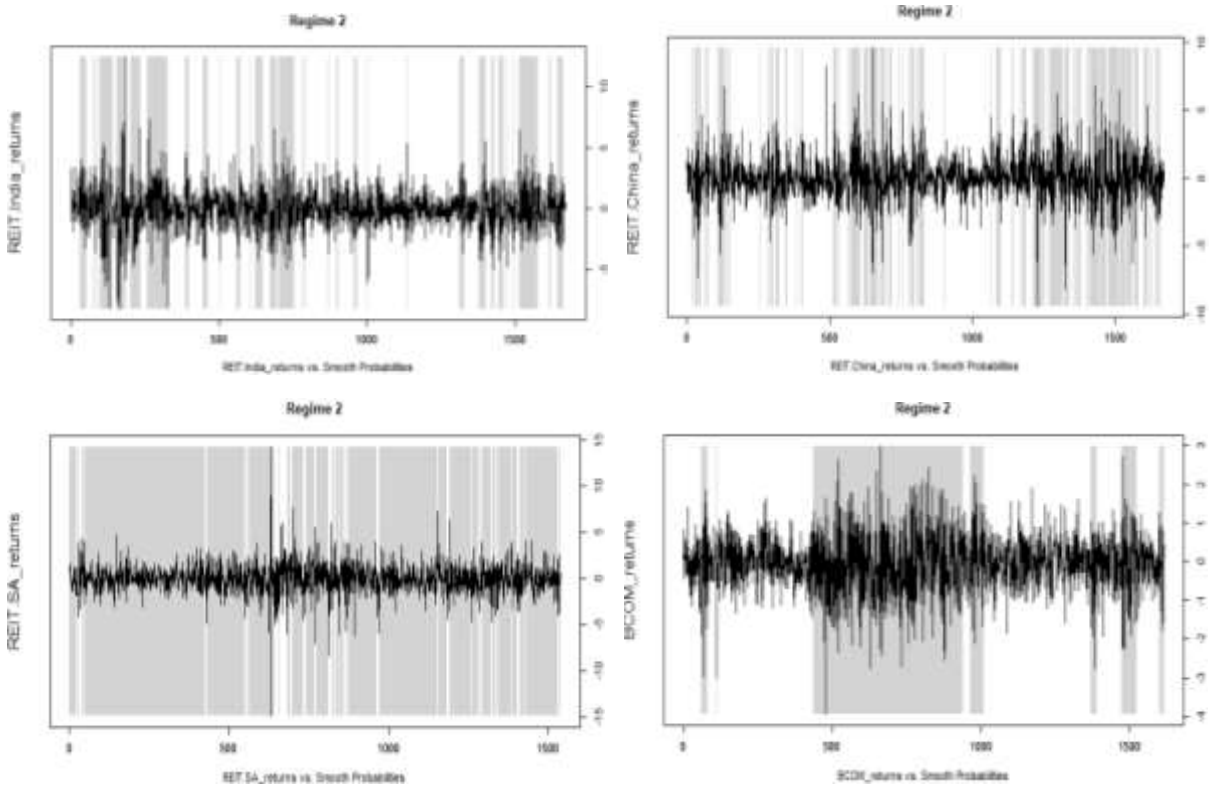


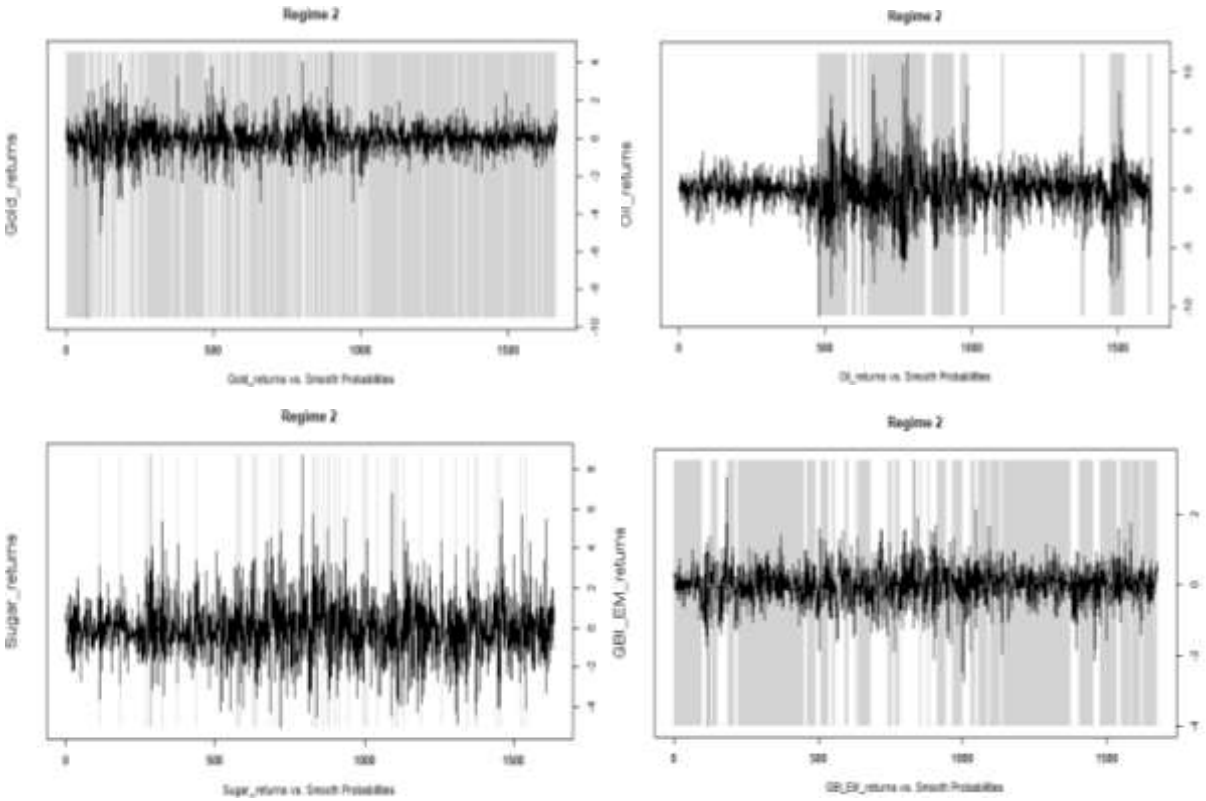
Appendix 2.A1 Cont.



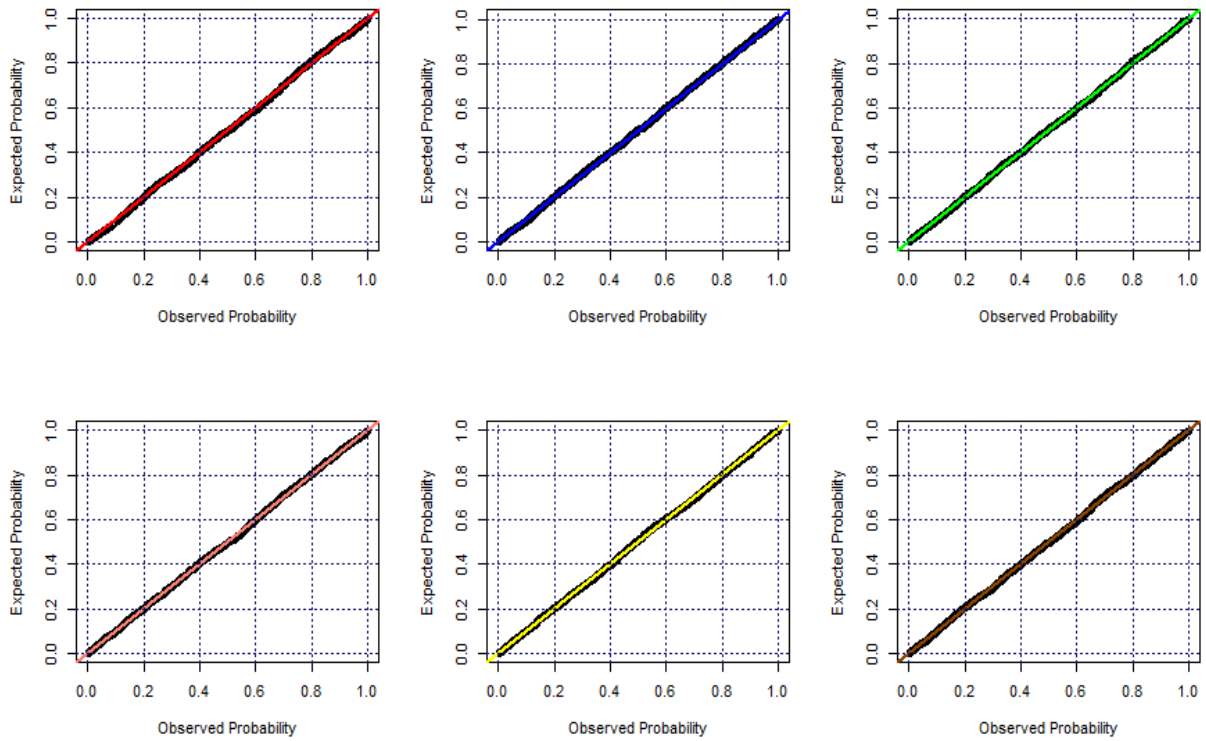


Appendix 2.A1 Cont

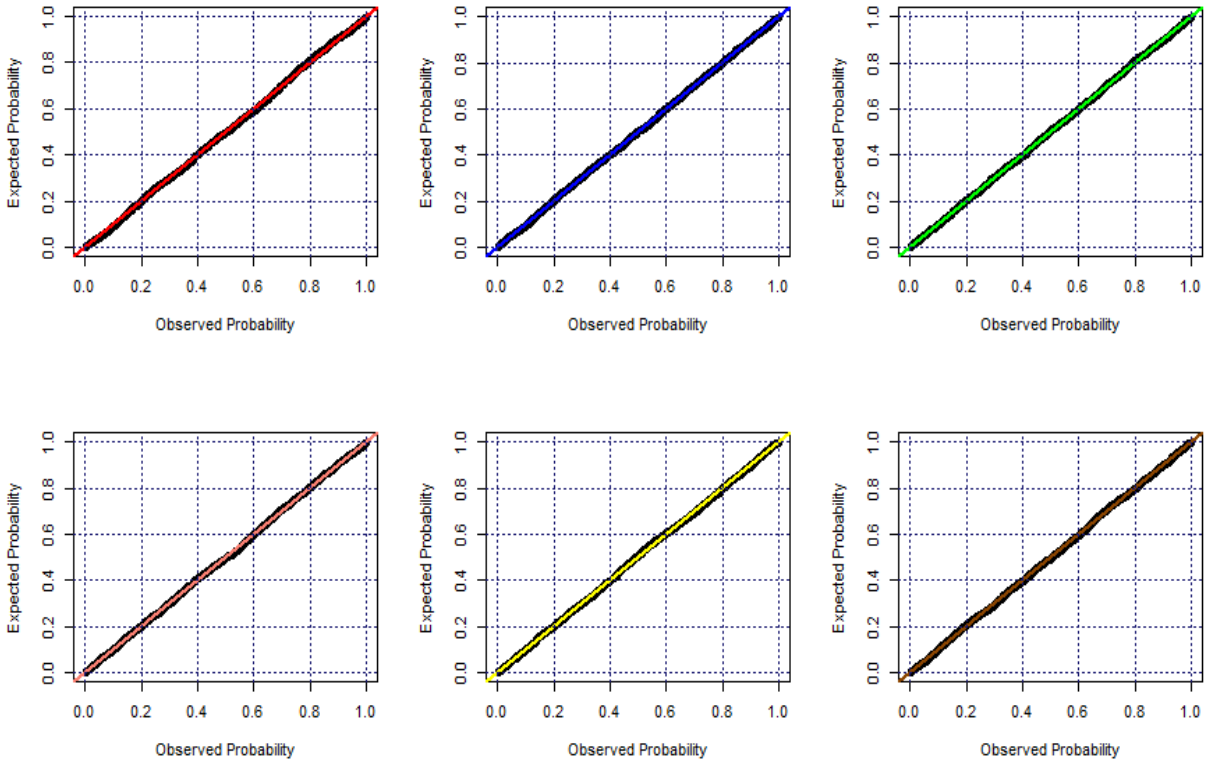




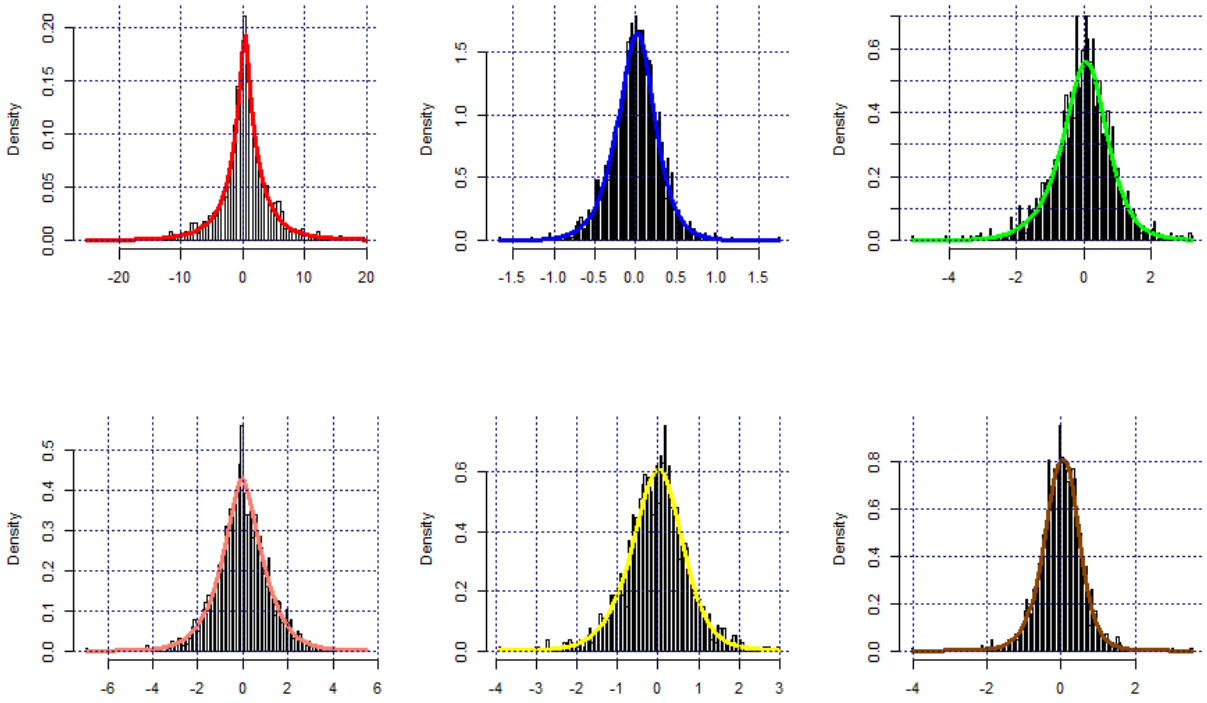
Appendix 2.A1 Cont.



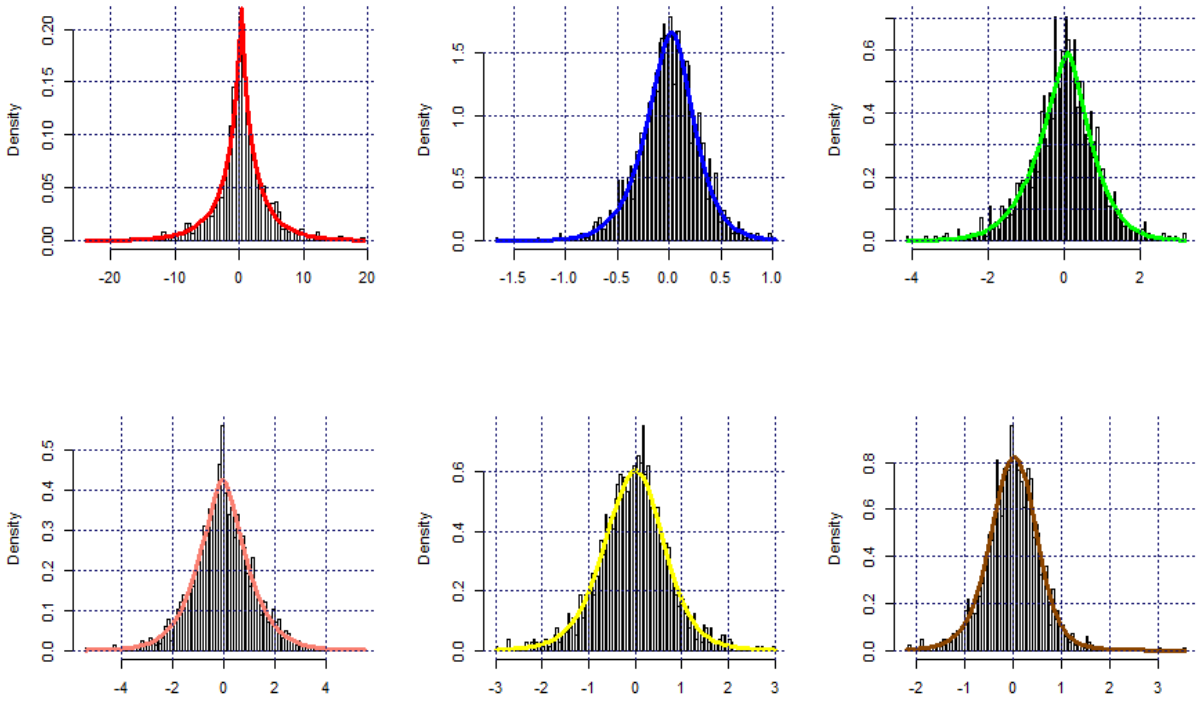
Appendix 2.A2: P-P graphical representation of the most appropriate fitting distributions for the shuffled log-returns. *Note: CRIX (first row, left), MSCI EM FX (first row, middle), MSCI EMI (first row, right), MSCI EM REIT (second row, left), BCOM (second row, middle), and GBI-EM (second row, right) asset classes.*



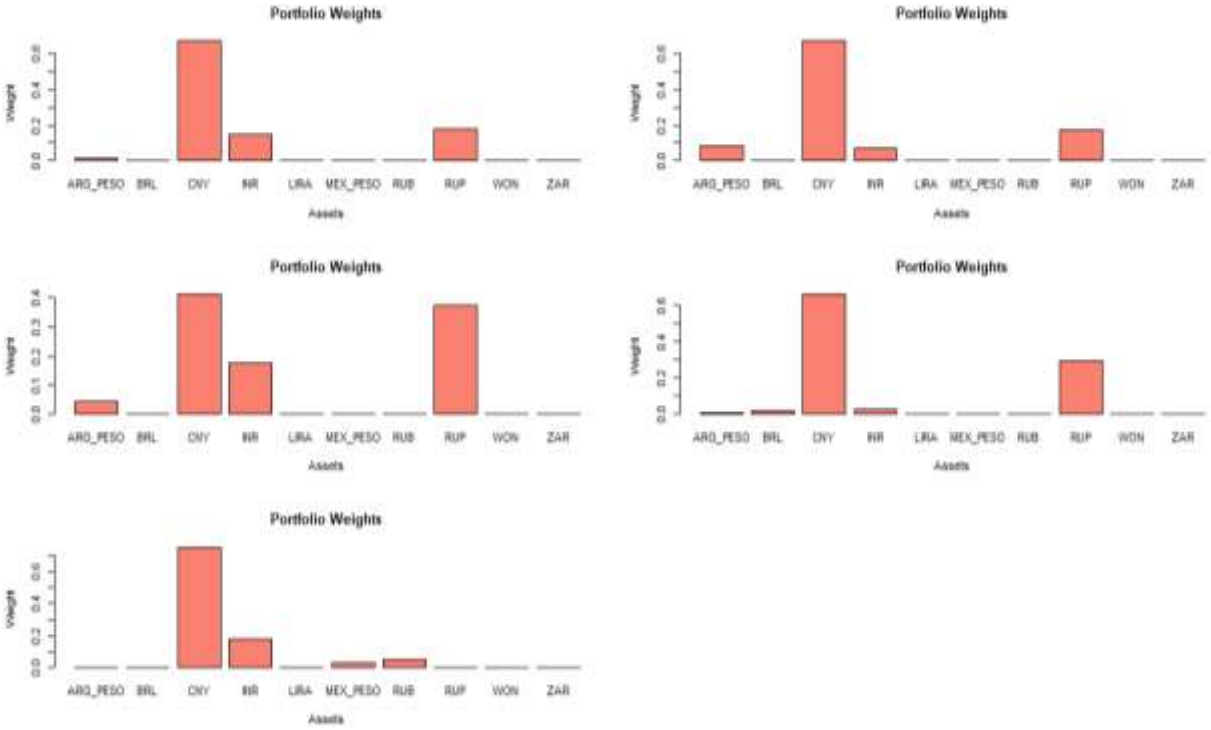
Appendix 2.A3: P-P graphical representation of the most appropriate fitting distributions for the outlier-adjusted log-returns. *Note: CRIX (first row, left), MSCI EM FX (first row, middle), MSCI EMI (first row, right), MSCI EM REIT (second row, left), BCOM (second row, middle), and GBI-EM (second row, right) asset classes.*



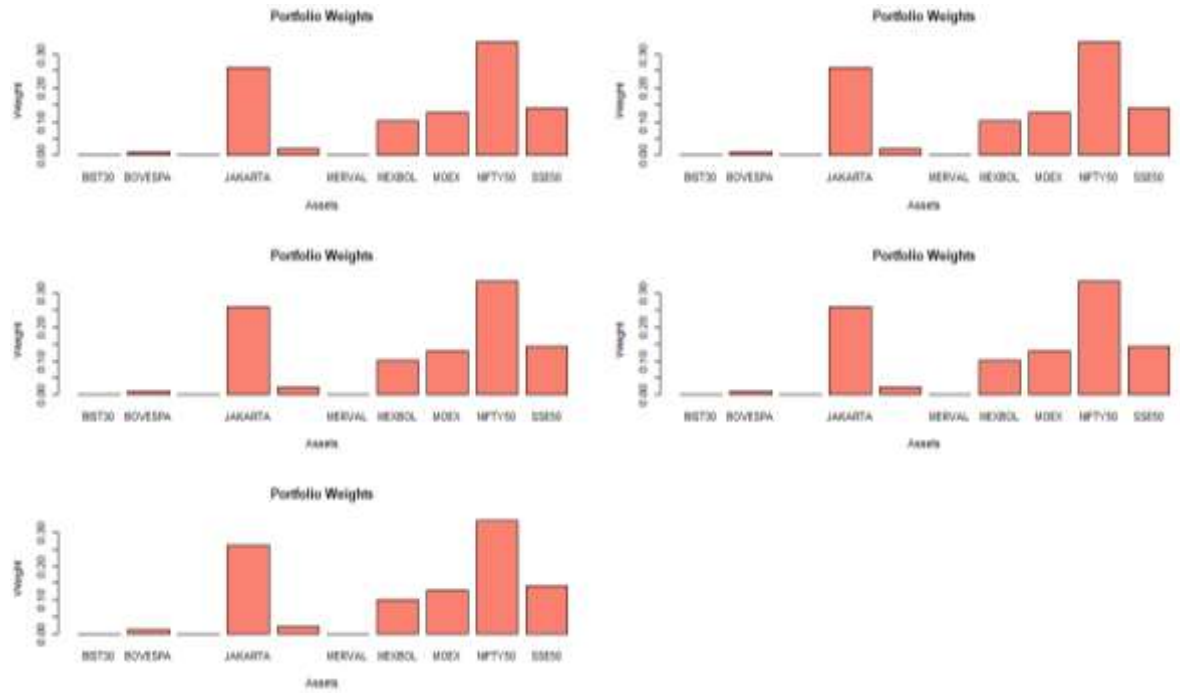
Appendix 2.A4: Actual frequencies with superimposed best fitting distribution density for the shuffled log-returns. *Note: CRIX (first row, left), MSCI EM FX (first row, middle), MSCI EMI (first row, right), MSCI EM REIT (second row, left), BCOM (second row, middle), and GBI-EM (second row, right) asset classes.*



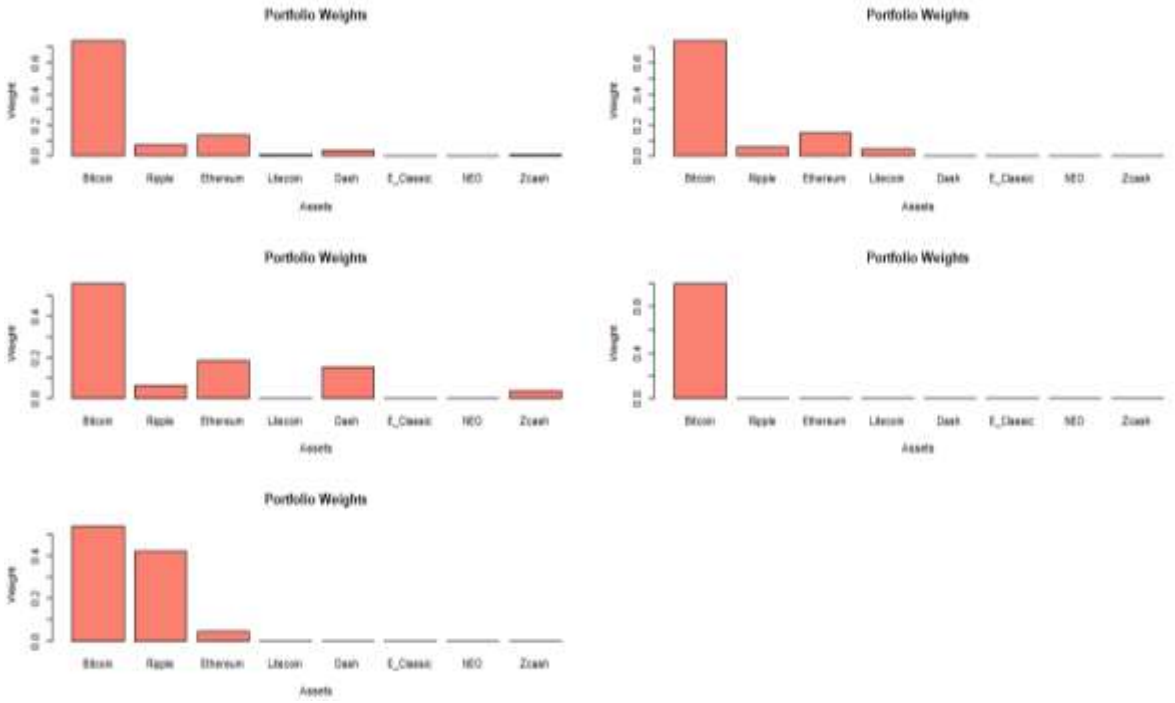
Appendix 2.A5: Actual frequencies with superimposed best fitting distribution density for the outlier-adjusted log-returns. *Note: CRIX (first row, left), MSCI EM FX (first row, middle), MSCI EMI (first row, right), MSCI EM REIT (second row, left), BCOM (second row, middle), and GBI-EM (second row, right) asset classes.*



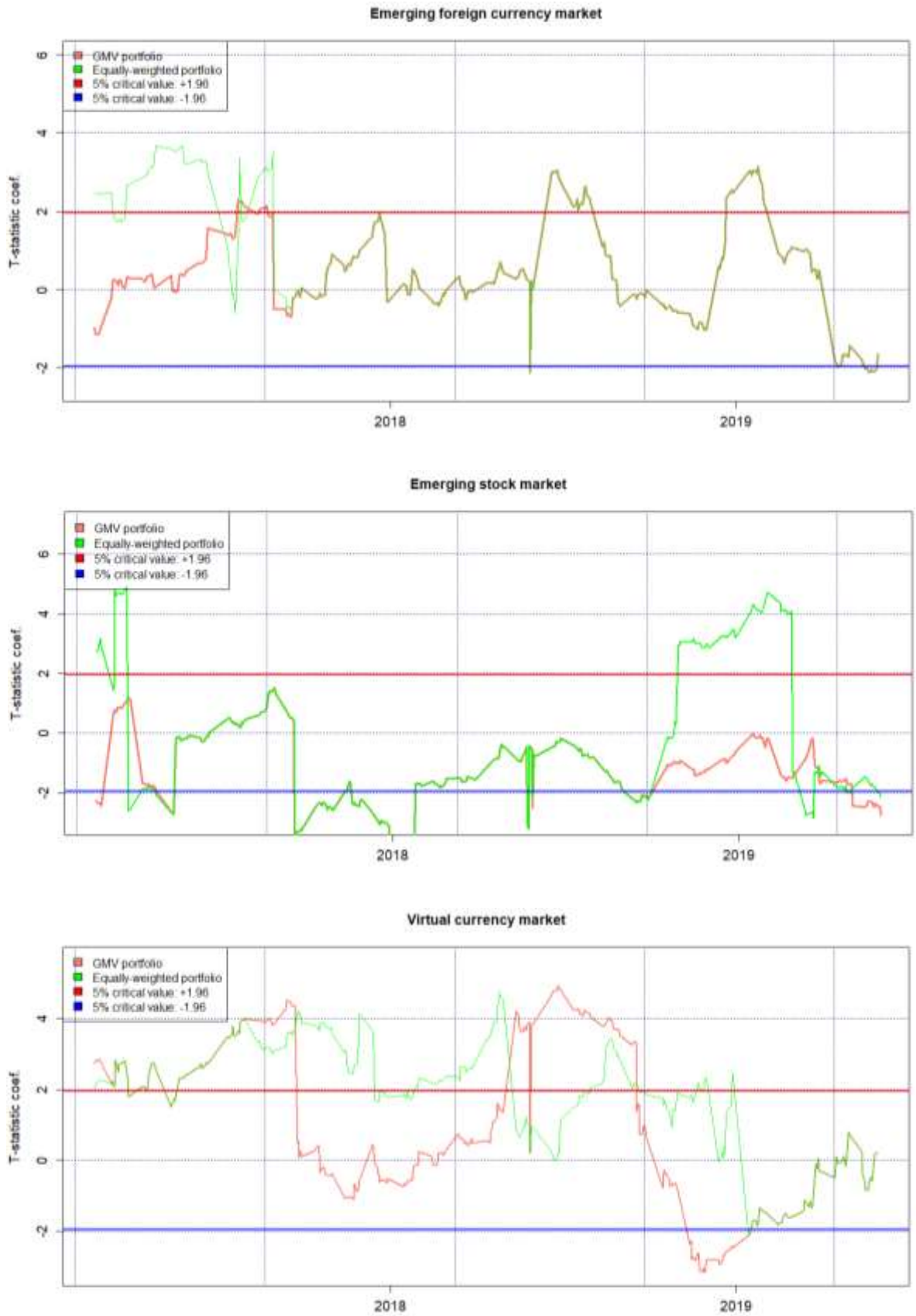
Appendix 2.A6: Portfolio weights for the emerging FX time series samples. *Note: The GMV-based portfolio weights are obtained for October 2016-June 2019 (first row, left), October 2016-June 2017 (first row, right), July 2017-February 2018 (second row, left), March 2018-Oct 2018 (second row, right), and November 2018-June 2019 (third row, left) data samples.*



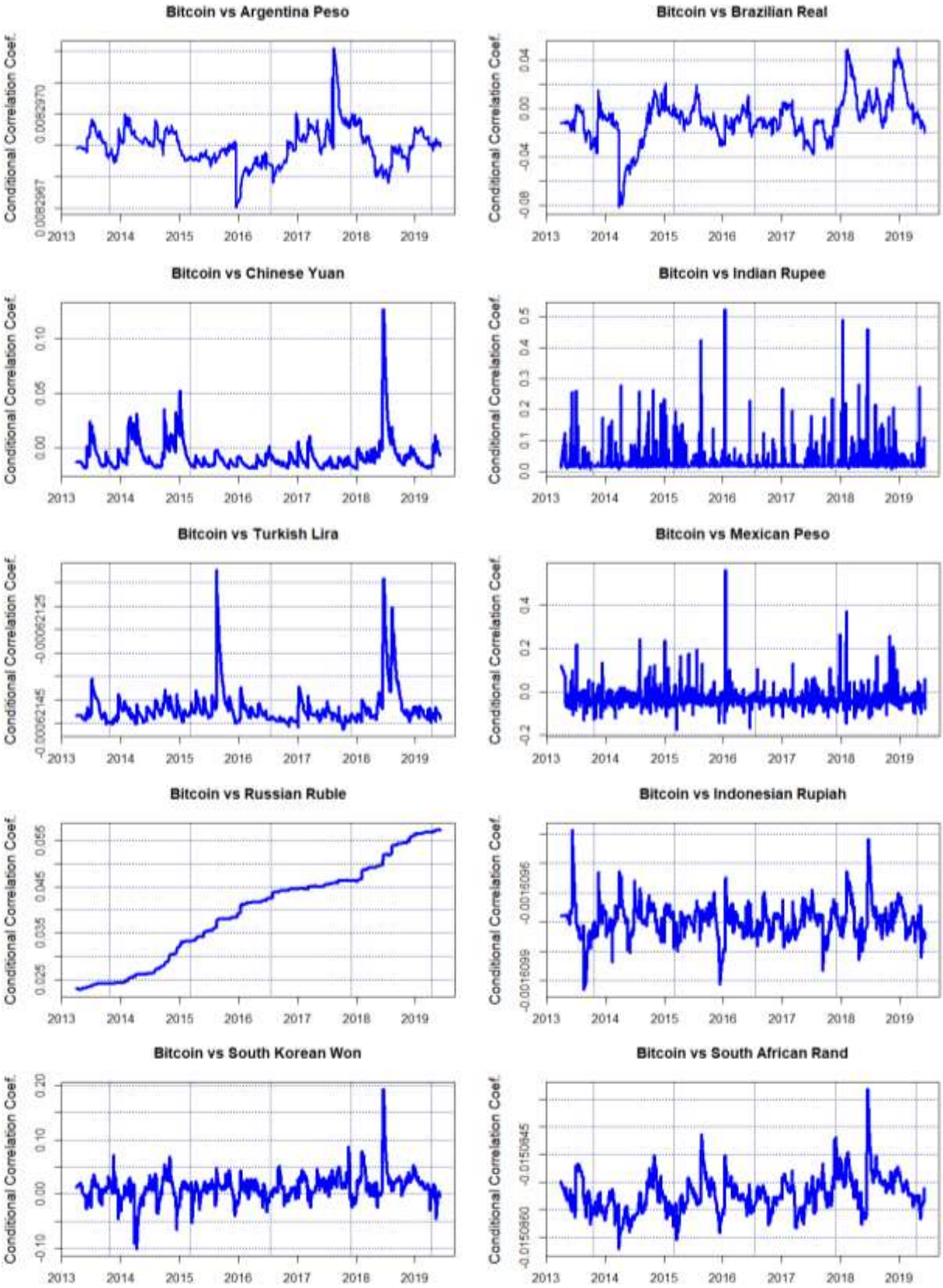
Appendix 2.A7: Portfolio weights for the selected emerging stock time series samples. *Note: The GMV-based portfolio weights are obtained for October 2016-June 2019 (first row, left), October 2016-June 2017 (first row, right), July 2017-February 2018 (second row, left), March 2018-Oct 2018 (second row, right), and November 2018-June 2019 (third row, left) data samples.*



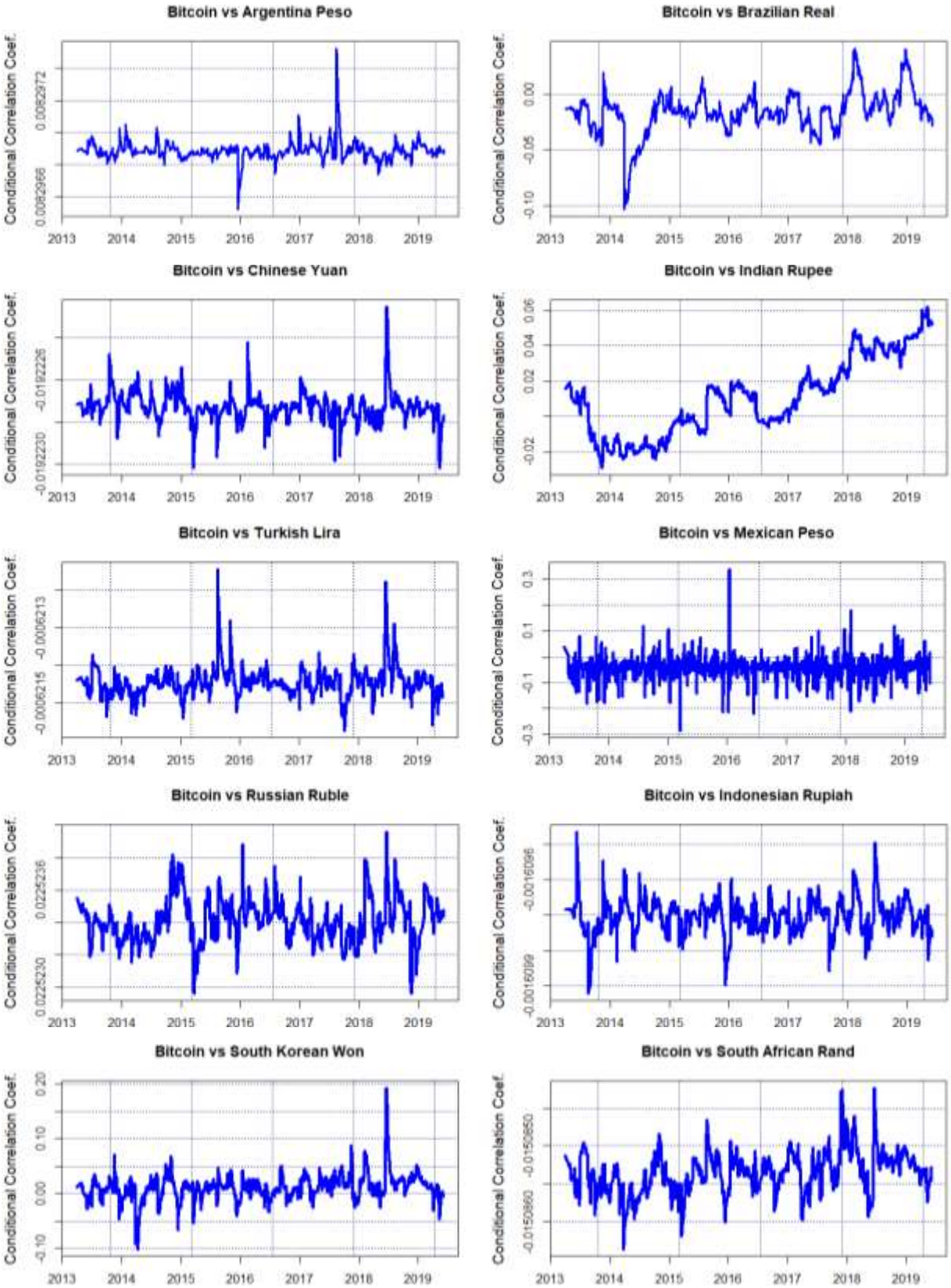
Appendix 2.A8: Portfolio weights for the cryptocurrency time series samples. *The GMV-based portfolio weights are obtained for October 2016-June 2019 (first row, left), October 2016-June 2017 (first row, right), July 2017-February 2018 (second row, left), March 2018-Oct 2018 (second row, right), and November 2018-June 2019 (third row, left) data samples.*



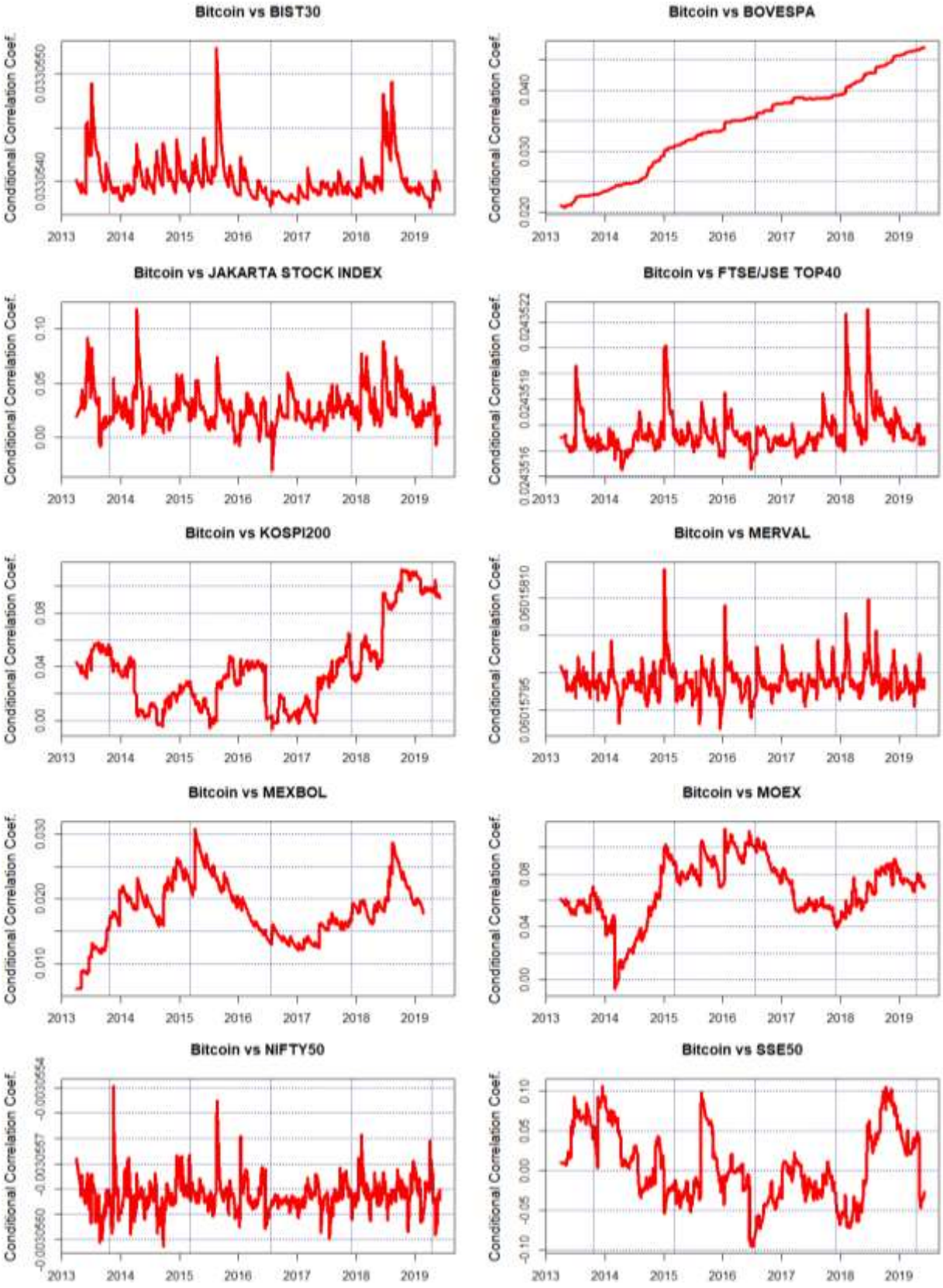
Appendix A.29: Evolution of γ_2 coefficient based on 80-day rolling window OLS estimation



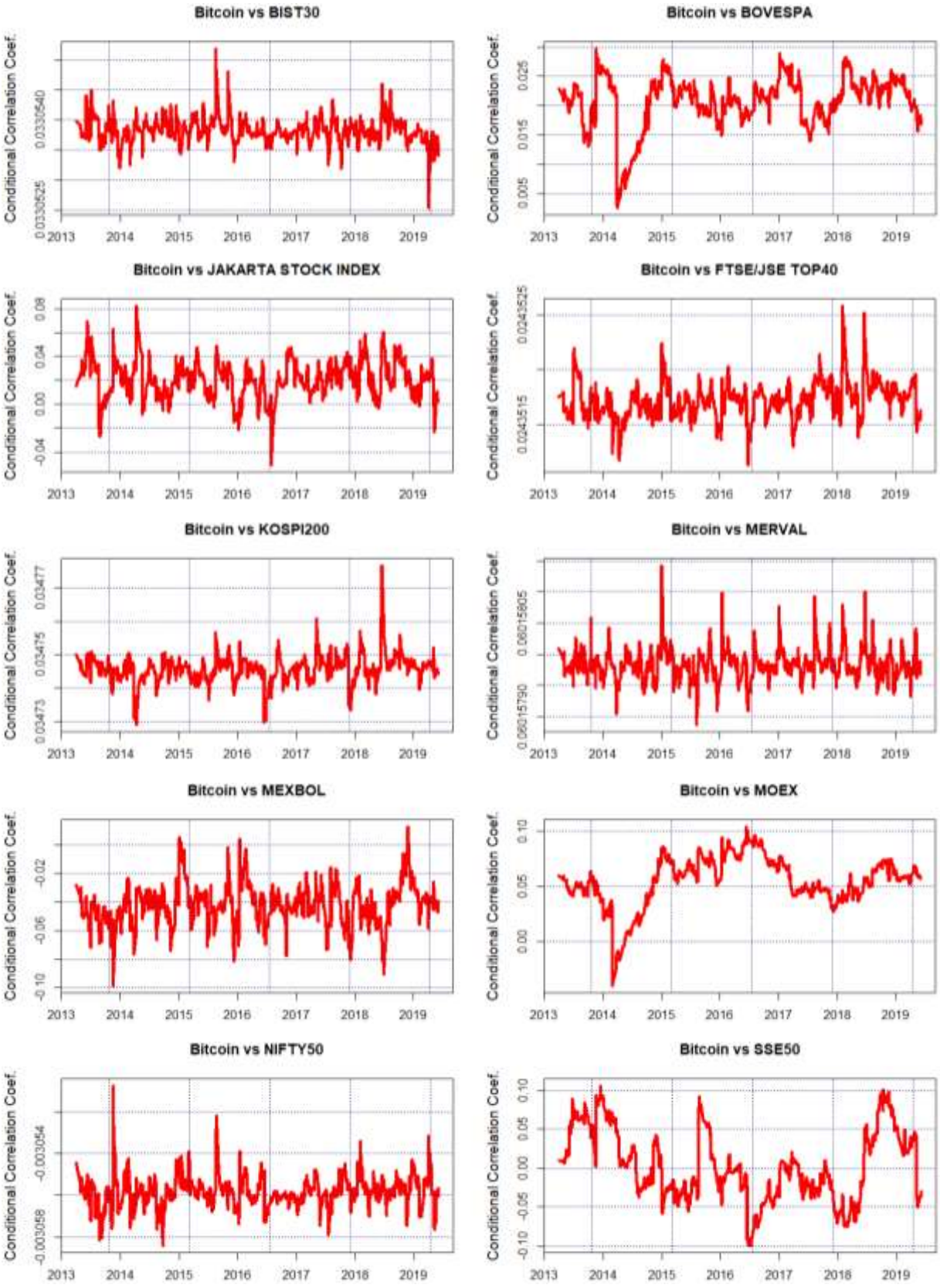
Appendix 3.A1: Conditional correlation plots of Bitcoin vs FXs based on ADCC-AR(1)-NAGARCH(1,1) model



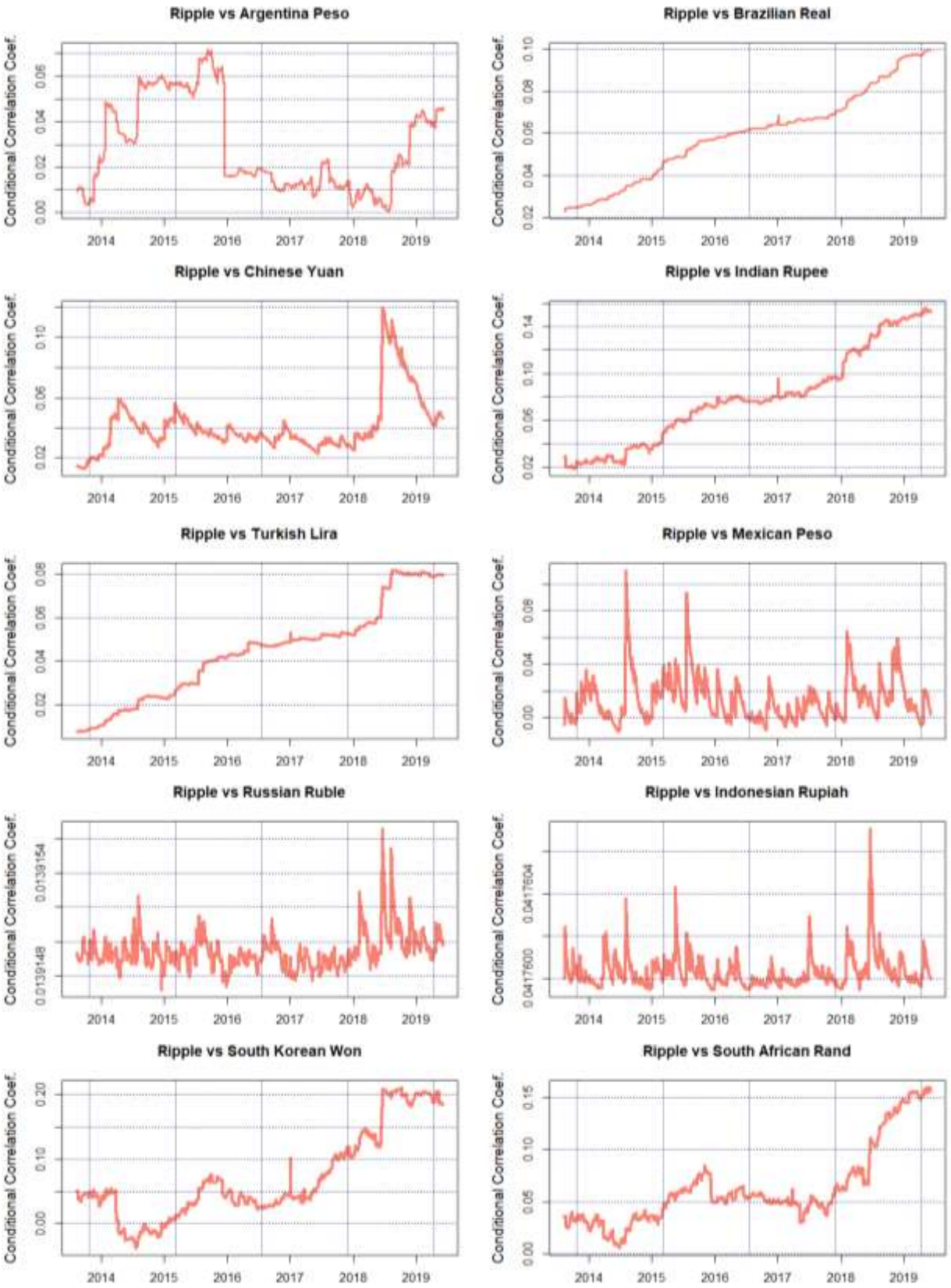
Appendix 3.A2: Conditional correlation plots of Bitcoin vs FXs based on DCC-AR(1)-NAGARCH(1,1) model



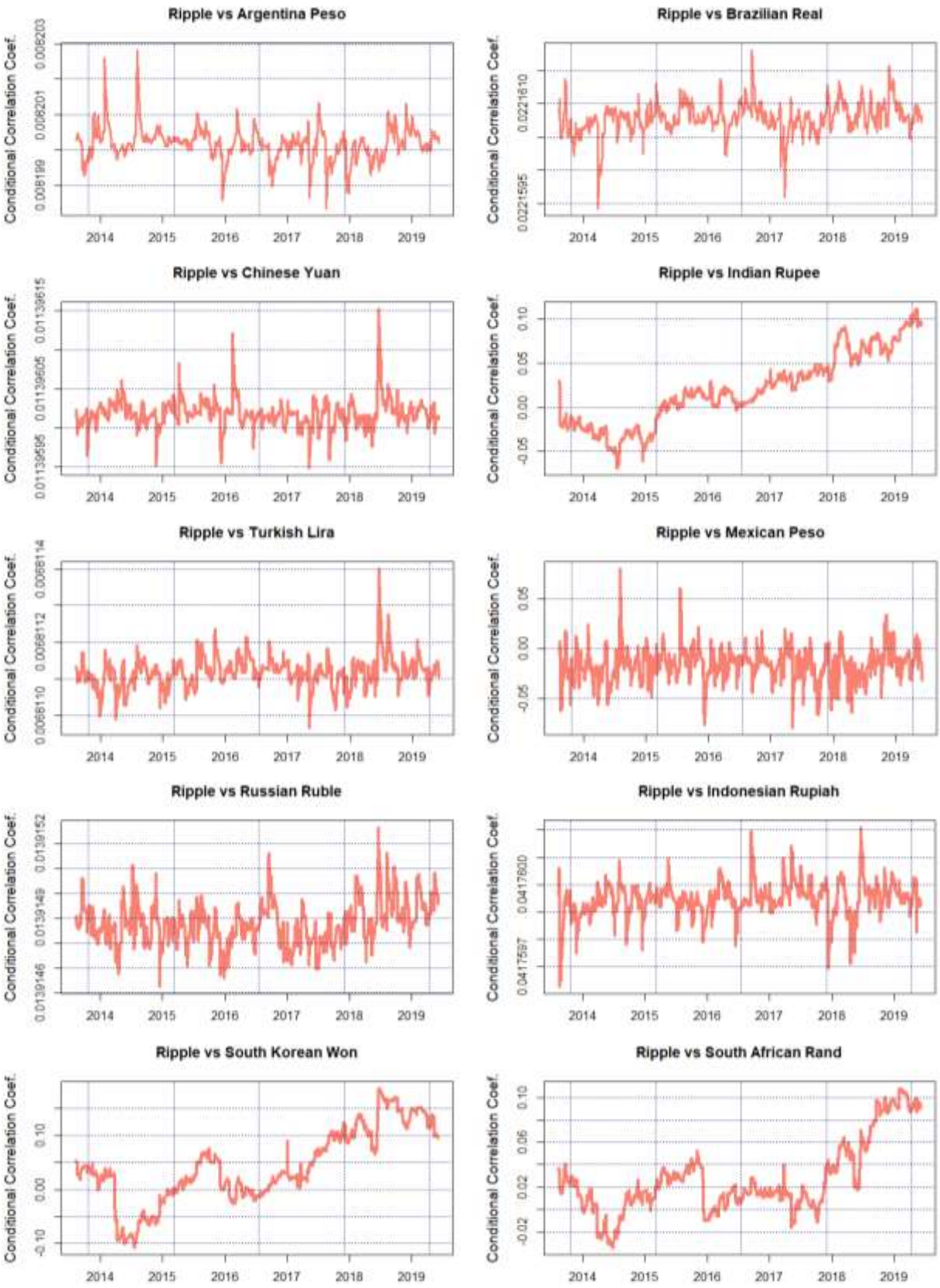
Appendix 3.A3: Conditional correlation plots of Bitcoin vs Stocks based on ADCC-AR(1)-NAGARCH(1,1) model



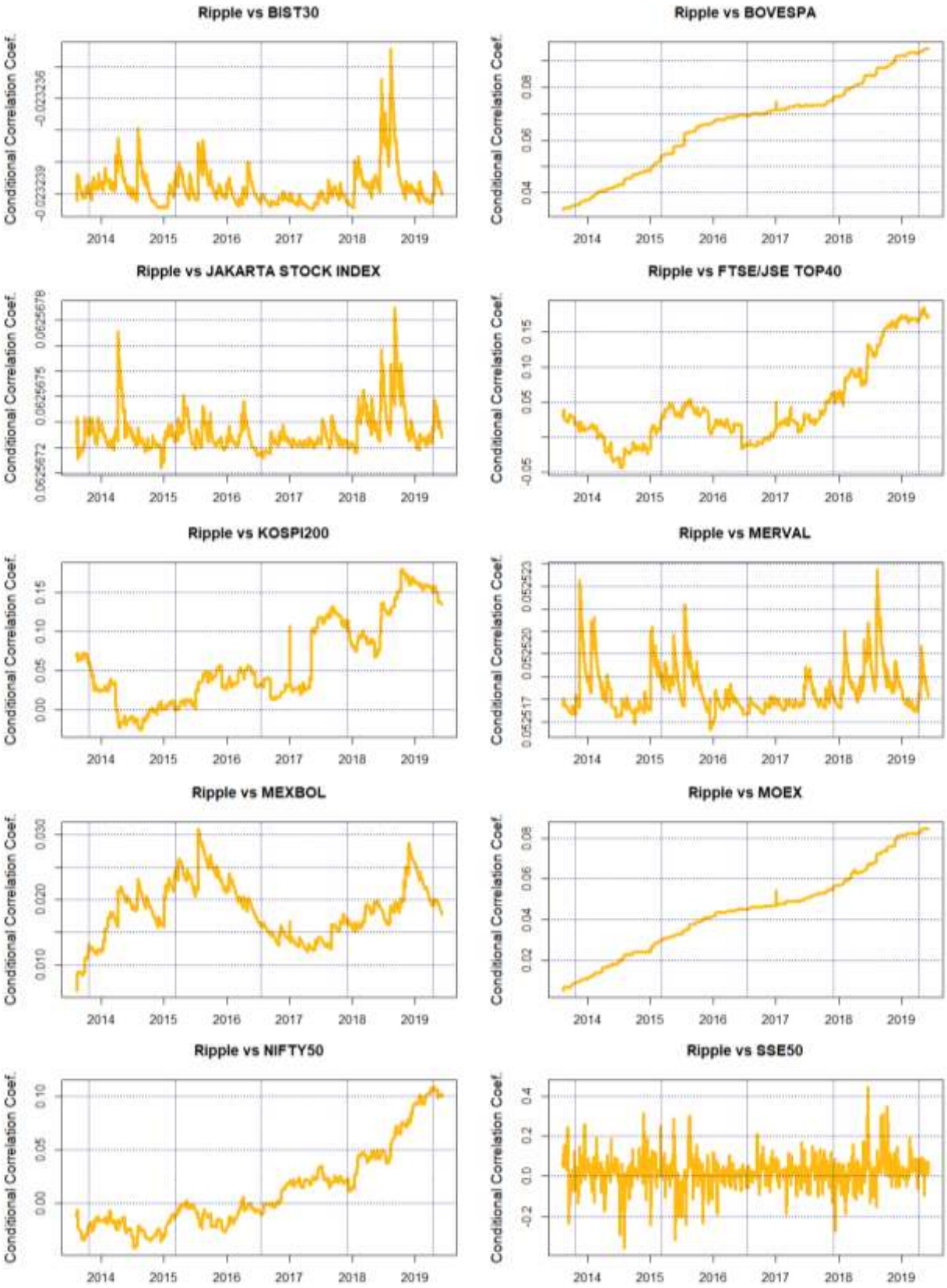
Appendix 3.A4: Conditional correlation plots of Bitcoin vs Stocks based on DCC-AR(1)-NAGARCH(1,1) model



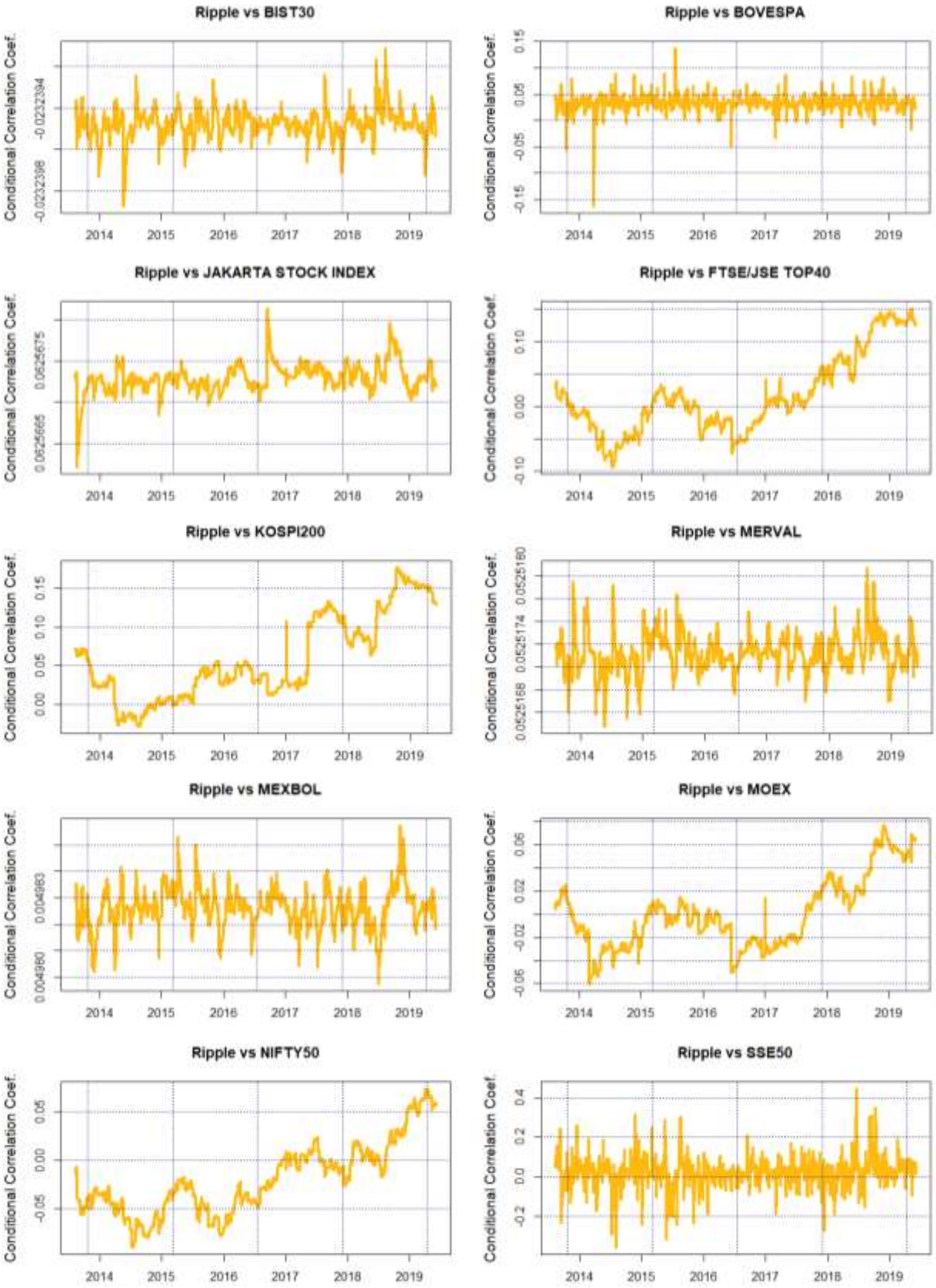
Appendix 3.B1: Conditional correlation plots of Ripple vs FXs based on ADCC-AR(1)-NAGARCH(1,1) model



Appendix 3.B2: Conditional correlation plots of Ripple vs FXs based on DCC-AR(1)-NAGARCH(1,1) model



Appendix 3.B3: Conditional correlation plots of Ripple vs Stocks based on ADCC-AR(1)-NAGARCH(1,1) model



Appendix 3.B4: Conditional correlation plots of Ripple vs Stocks based on DCC-AR(1)-NAGARCH(1,1) model

Appendix 3.C1: Time-scale correlation ranking of Bitcoin and Latin American assets

Rank	D1	D2	D3	D4	D5	D6	D7
1	BTC-MEX	BTC-MPES	BTC-BRL	BTC-BRL	BTC-MPES	BTC-BOV	BTC-MEX
	[-0.05]	**[-0 02]**	**[-0.09]**	**[-0.04]**	**[-0.16]**	**[-0.15]**	**[-0.16]**
2	BTC-MPES	BTC-BRL	BTC-MPES	BTC-BOV	BTC-BRL	BTC-BRL	BTC-BOV
	[-0.04]	**[0.01]**	**[-0.09]**	**[-0.02]**	**[-0.13]**	**[-0.13]**	**[-0.16]**
3	BTC-APES	BTC-MER	BTC-BOV	APES-MPES	BTC-MEX	BTC-MEX	BTC-MPES
	[-0.03]	**[0.01]**	**[-0.06]**	**[0.00]**	**[-0.12]**	**[-0.07]**	**[-0.13]**
4	BTC-BRL	BTC-APES	BTC-MEX	BTC-MPES	BTC-BOV	BTCMPES	BTC-APES
	[0.02]	**[0.02]**	**[-0.01]**	**[0.01]**	**[-0.06]**	**[-0.06]**	**[-0.04]**
5	BTC-MER	BTC-MER	BTC-APES	BTC-MEX	BTC-APES	BTC-MER	APES-BRL
	[0.05]	**[0.02]**	**[0.01]**	**[0.04]**	**[-0.03]**	**[0.06]**	**[0.05]**
6	APES-MEX	BTC-BOV	APES-MPES	APES-BOV	BTC-MER	BTC-APES	BTC-MER
	[0.05]	**[0.04]**	**[0.05]**	**[0.06]**	**[0.03]**	**[0.18]**	**[0.08]**
7	APES-BRL	APES-MEX	BTC-MER	APES-MPES	APES-MEX	APES-BRL	BTC-BRL
	[0.05]	**[0.07]**	**[0.06]**	**[0.07]**	**[0.15]**	**[0.39]**	**[0.14]**
8	APES-BOV	APES-MPES	APES-MEX	APES-BRL	APESMPES	BRL-MER	APES-BOV
	[0.06]	**[0.08]**	**[0.09]**	**[0.10]**	**[0.17]**	**[0.46]**	**[0.23]**
9	BTC-BOV	APES-BOV	APES-BOV	BTC-MER	MPES-MER	APES-BOV	BRL-MER
	[0.08]	**[0.09]**	**[0.17]**	**[0.11]**	**[0.23]**	**[0.47]**	**[0.28]**
10	APES-MPES	APES-BRL	APES-BRL	BTC-MER	APES-BOV	MPES-MER	BRL-MPES
	[0.09]	**[0.10]**	**[0.19]**	**[0.14]**	**[0.28]**	**[0.47]**	**[0.31]**
11	MPES-MER	MPES-BRL	MPES-MER	BRL-MER	MER-MEX	APES-MEX	APES-MPES
	[0.27]	**[0.28]**	**[0.24]**	**[0.26]**	**[0.30]**	**[0.53]**	**[0.34]**
12	BRL-MER	BRL-MER	MER-MEX	MPES-MER	BRL-MER	APES-MPES	APES-MPES
	[0.30]	**[0.35]**	**[0.33]**	**[0.27]**	**[0.38]**	**[0.57]**	**[0.38]**
13	MER-MEX	MER-MEX	BRL-MER	BRC-MEX	APES-BRL	BRL-MPES	BRL-MER
	[0.30]	**[0.38]**	**[0.40]**	**[0.31]**	**[0.38]**	**[0.58]**	**[0.40]**
14	BRL-MEX	BRL-MEX	BRL-MEX	BRL-MPES	MPES-BOV	MER-MEX	BRL-MEX
	[0.33]	**[0.42]**	**[0.45]**	**[0.34]**	**[0.40]**	**[0.60]**	**[0.45]**
15	MER-BOV	MPES-BOV	MER-BOV	MER-MEX	BRL-MPES	BRL-MEX	MER-BOV
	[0.38]	**[0.44]**	**[0.46]**	**[0.38]**	**[0.41]**	**[0.63]**	**[0.54]**
16	MPES-BOV	MER-BOV	BRL-MPES	MER-BOV	MER-BOV	MER-BOV	BOV-MEX
	[0.40]	**[0.45]**	**[0.49]**	**[0.39]**	**[0.44]**	**[0.64]**	**[0.58]**
17	APES-MER	BRL-MPES	MPES-BOV	APES-MER	APES-MER	APES-MER	MPES-MER
	[0.44]	**[0.45]**	**[0.51]**	**[0.42]**	**[0.45]**	**[0.66]**	**[0.59]**
18	BOV-MEX	APES-MEX	APES-MER	MPES-BOV	BRL-MEX	MPES-BOV	MER-MEX
	[0.44]	**[0.45]**	**[0.59]**	**[0.44]**	**[0.45]**	**[0.69]**	**[0.61]**
19	BRL-MPES	BOV-MEX	BOV-MEX	BOV-MEX	BOV-MEX	BOV-MEX	APES-MEX
	[0.50]	**[0.53]**	**[0.60]**	**[0.54]**	**[0.48]**	**[0.79]**	**[0.80]**
20	MPES-MEX	MPES-MEX	BRL-BOV	BRL-BOV	BRL-BOV	BRL-BOV	BRL-BOV
	[0.50]	**[0.70]**	**[0.78]**	**[0.78]**	**[0.83]**	**[0.85]**	**[0.83]**
21	BRL-BOV	BRL-BOV	MPES-MEX	MPES-MEX	MPES-MEX	MPES-MEX	MPES-MEX
	[0.62]	**[0.74]**	**[0.81]**	**[0.79]**	**[0.87]**	**[0.90]**	**[0.97]**

Note: For Tables C1-C8, the rankings are based on a wavelet correlation matrix estimation. The ranks are associated with the degree of correlation between the assets, ranging from rank 1 or highest rank (for the lowest correlation value) to the lowest rank (for the highest correlation value). The respective correlation coefficients are placed below the pairs in square bracket. In cases where there is tie in the estimated coefficients under a time-scale, the subsequent scales' coefficients are used to split such tie. In that case, the pair with the smallest coefficient in the subsequent scale(s) is given a higher rank in the tie scale. The preceding scale(s) coefficients are used to split ties at the 128~256 day band. BTC (Bitcoin); MPES (Mexican Peso); APES (Argentine Peso); BRL (Brazilian Real); BOV (Bovespa); MER (Merval); MEX (Mexbol).

Appendix 3.C2: Time-scale correlation ranking of Bitcoin and African-European assets

Rank	D1	D2	D3	D4	D5	D6	D7
1	BTC-LIRA	BTC-LIRA	BTC-ZAR	BTC-ZAR	BTC-MOEX	BTC-MOEX	BTC-ZAR
	[-0.03]	**[0.01]**	**[-0.05]**	**[-0.06]**	**[-0.17]**	**[0.00]**	**[-0.35]**
2	BTC-ZAR	BTC-JSE	BTC-JSE	BTC-MOEX	BTC-RUB	BTC-BIST	BTC-BIST
	[-0.02]	**[0.01]**	**[0.00]**	**[0.00]**	**[-0.03]**	**[0.01]**	**[-0.31]**
3	BTC-BIST	BTC-RUB	BTC-LIRA	BTC-JSE	BTC-JSE	BTC-RUB	BTC-JSE
	[-0.02]	**[0.02]**	**[0.01]**	**[0.02]**	**[0.05]**	**[0.04]**	**[-0.25]**
4	BTC-RUB	BTC-ZAR	BTC-RUB	BTC-RUB	BTC-ZAR	BTC-ZAR	LIRAMOEX
	[0.00]	**[0.04]**	**[0.04]**	**[0.03]**	**[0.06]**	**[0.05]**	**[-0.20]**
5	BTC-JSE	BTC-MOEX	BTC-MOEX	BTC-LIRA	BTC-BIST	BTC-BIST	BTC-LIRA
	[0.02]	**[0.05]**	**[0.04]**	**[0.04]**	**[0.12]**	**[0.09]**	**[-0.05]**
6	BTC-MOEX	BTC-BIST	BTC-BIST	BTC-BIST	BTC-LIRA	BTC-JSE	BTC-MOEX
	[0.10]	**[0.06]**	**[0. 06]**	**[0.07]**	**[0.16]**	**[0.10]**	**[0.07]**
7	LIRA-MOEX	LIRA-MOEX	LIRA-RUB	LIRA-MOEX	LIRA-JSE	LIRA-MOEX	LIRA-RUB
	[0.21]	**[0.18]**	**[0.28]**	**[0.33]**	**[0.27]**	**[0.34]**	**[0.11]**
8	RUB-BIST	LIRA-RUB	LIRA-MOEX	LIRA-RUB	LIRA-MOEX	BIST-MOEX	LIRA-JSE
	[0.23]	**[0.23]**	**[0.28]**	**[0.33]**	**[0.30]**	**[0.40]**	**[0.11]**
9	ZAR-MOEX	RUB-BIST	RUB-BIST	RUB-BIST	ZAR-MOEX	LIRA-RUB	BTC-RUB
	[0.24]	**[0.23]**	**[0.34]**	**[0.41]**	**[0.33]**	**[0.43]**	**[0.70]**
10	RUB-JSE	LIRA-JSE	ZAR-RUB	LIRA-JSE	LIRA-RUB	ZAR-MOEX	BIST-MOEX
	[0.24]	**[0.26]**	**[0.35]**	**[0.42]**	**[0.36]**	**[0.43]**	**[0 21]**
11	LIRA-JSE	BIST-MOEX	LIRA-JSE	BIST-MOEX	RUB-BIST	RUB-BIST	ZAR-LIRA
	[0.28]	**[0.30]**	**[0.37]**	**[0.43]**	**[0.38]**	**[0. 45]**	**[0.25]**
12	LIRA-RUB	ZAR-MOEX	ZAR-MOEX	ZAR-MOEX	BIST-MOEX	ZAR-RUB	RUB-BIST
	[0.31]	**[0.32]**	**[0.41]**	**[0.44]**	**[0.41]**	**[0.45]**	**[0.35]**
13	LIRA-RUB	ZAR-BIST	BIST-MOEX	ZAR-RUB	ZAR-LIRA	LIRA-JSE	ZAR-MOEX
	[0.31]	**[0.36]**	**[0.42]**	**[0.45]**	**[0.41]**	**[0.58]**	**[0.42]**
14	ZAR-BIST	ZAR-RUB	RUB-JSE	ZAR-LIRA	JSE-BIST	RUB-JSE	ZAR-RUB
	[0.31]	**[0.38]**	**[0.42]**	**[0.50]**	**[0.41]**	**[0.59]**	**[0.48]**
15	ZAR-RUB	ZAR-LIRA	ZAR-LIRA	RUB-JSE	RUB-JSE	ZAR-LIRA	JSE-BIST
	[0.38]	**[0.38]**	**[0.43]**	**[0.51]**	**[0.45]**	**[0.65]**	**[0.60]**
16	JSE-BIST	RUB-JSE	ZAR-BIST	ZAR-BIST	ZAR-LIRA	JSE-MOEX	ZAR-BIST
	[0.40]	**[0.39]**	**[0.51]**	**[0.53]**	**[0.47]**	**[0.66]**	**[0.62]**
17	JSE-MOEX	JSE-BIST	JSE-MOEX	JSE-BIST	ZAR-BIST	ZAR-BIST	RUB-JSE
	[0.43]	**[0.41]**	**[0.55]**	**[0.54]**	**[0.49]**	**[0.72]**	**[0.65]**
18	ZAR-JSE	JSE-MOEX	JSE-BIST	JSE-MOEX	JSE-MOEX	JSE-BIST	JSE-MOEX
	[0.49]	**[0.50]**	**[0.58]**	**[0.57]**	**[0.58]**	**[0.77]**	**[0.67]**
19	ZAR-LIRA	ZAR-JSE	LIRA-BIST	RUB-MOEX	ZAR-JSE	ZAR-JSE	LIRA-BIST
	[0.55]	**[0.66]**	**[0.74]**	**[0.78]**	**[0.68]**	**[0.81]**	**[0.74]**
20	RUB-MOEX	RUB-MOEX	RUB-MOEX	LIRA-BIST	RUB-MOEX	RUB-MOEX	LIRA-BIST
	[0.61]	**[0.72]**	**[0.79]**	**[0.80]**	**[0.71]**	**[0.82]**	**[0.88]**
21	LIRA-BIST	LIRA-MOEX	ZAR-JSE	ZAR-JSE	LIRA-BIST	LIRA-BIST	RUB-MOEX
	[0. 61]	**[0.74]**	**[0.80]**	**[0.82]**	**[0.82]**	**[0.83]**	**[0.91]**

Note: BTC (Bitcoin); LIRA (Turkish Lira); ZAR (South Africa Rand); RUB (Russian Rubble); BIST (BIST30); JSE (FTSE/JSE TOP40); MOEX (MOEX).

Appendix 3.C3: Time-scale correlation ranking of Bitcoin and East Asian assets

Rank	D1	D2	D3	D4	D5	D6	D7
1	BTC-CNY	BTC-CNY	BTC-CNY	BTC-WON	BTC-CNY	BTC-WON	BTC-CNY
	[0.01]	**[-0.05]**	**[-0.02]**	**[-0.06]**	**[-0.19]**	**[-0.01]**	**[-0.23]**
2	BTC-WON	BTC-SSE	BTC-SSE	BTC-SSE	BTC-WON	BTC-SSE	BTC-WON
	[0.02]	**[0.00]**	**[-0.01]**	**[-0.02]**	**[-0.17]**	**[-0.01]**	**[-0.04]**

3	BTC-SSE	BTC-KOSP	BTC-KOSP	BTC-KOSP	BTC-KOSP	BTC-CNY	BTC-KOSP
	[0.00]	[0.01]	[0.07]	[0.06]	[-0.13]	[0.01]	[0.13]
4	BTC-KOSP	BTC-KOSP	BTC-WON	BTC-SSE	BTC-SSE	BTC-KOSP	WON-SSE
	[0.00]	[0.01]	[0.08]	[0.06]	[-0.04]	[0.04]	[0.42]
5	WON-SSE	WON-SSE	WON-SSE	WON-SSE	WON-SSE	CNY-SSE	CNY-SSE
	[0.13]	[0.20]	[0.23]	[0.20]	[0.22]	[0.40]	[0.44]
6	CNY-SSE	CNY-SSE	CNY-SSE	CNY-SSE	CNY-WON	CNY-WON	CNY-WON
	[0.21]	[0.25]	[0.25]	[0.3]	[0.27]	[0.48]	[0.5]
7	CNY-KOSP	SSE-KOSP	CNY-KOSP	CNY-KOSP	CNY-KOSP	CNY-KOSP	CNY-KOSP
	[0.24]	[0.26]	[0. 31]	[0.33]	[0. 33]	[0.52]	[-0.51]
8	SSE-KOSP	CNY-KOSP	SSE-KOSP	SSE-KOSP	CNY-SSE	WON-SSE	BTC-SSE
	[0.25]	[0.29]	[0.38]	[0.33]	[0.37]	[0.58]	[-0.52]
9	CNY-WON	CNY-WON	CNY-WON	CNY-WON	SSE-KOSP	SSE-KOSP	SSE-KOSP
	[0.36]	[0.42]	[0. 40]	[0.39]	[0.39]	[0.62]	[0.62]
10	WON-KOSP	WON-KOSP	WON-KOSP	WON-KOSP	WON-KOSP	WON-KOSP	WON-KOSP
	[0.47]	[0.63]	[0.75]	[0.76]	[0.70]	[0. 82]	[0.94]

Note: BTC (Bitcoin); CNY (Chinese Yuan); WON (South Korean Won); SSE (SSE50); KOSP (KOSPI200).

Appendix 3.C4: Time-scale correlation ranking of Bitcoin and South Asian assets

Rank	D1	D2	D3	D4	D5	D6	D7
1	BTC-NTY	BTC-RUP	BTC-NTY	BTC-INR	BTC-RUP	BTC-JSI	BTC-INR
	[-0.02]	[0.01]	[-0.03]	[0.00]	[-0.13]	[-0.04]	[-0.27]
2	BTC-INR	BTC-NTY	BTC-RUP	BTC-NTY	BTC-JSI	BTC-INR	BTC-NTY
	[0.00]	[0.04]	[-0.03]	[0.03]	[-0.07]	[0.07]	[-0.10]
3	BTC-RUP	BTC-INR	BTC-INR	BTC-RUP	BTC-INR	BTC-RUP	BTC-RUP
	[0.02]	[0.04]	[0.01]	[0.05]	[-0.06]	[0.09]	[0.01]
4	BTC-JSI	BTC-JSI	BTC-JSI	BTC-JSI	BTC-NTY	BTC-NTY	RUP-NTY
	[0.03]	[0.04]	[0.05]	[0. 07]	[0.05]	[0.18]	[0.03]
5	RUP-NTY	RUP-NTY	RUP-NTY	RUP-NTY	INR-JSI	INR-RUP	BTC-JSI
	[0.11]	[0.34]	[0.37]	[0.48]	[0.55]	[0.4]	[0.06]
6	INR-JSI	INR-JSI	INR-JSI	INR-RUP	RUP-NTY	INR-JSI	NTY-JSI
	[0.14]	[0.36]	[0.38]	[0.51]	[0.55]	[0.43]	[0.24]
7	INR-RUP	INR-RUP	INR-RUP	INR-JSI	NTY-JSI	RUP-NTY	INR-RUP
	[0.29]	[044]	[0.42]	[0.57]	[0.57]	[0.44]	[0.35]
8	NTY-JSI	NTY-JSI	NTY-JSI	NTY-JSI	INR-RUP	NTY-JSI	INR-JSI
	[0.32]	[0.49]	[0.52]	[0.62]	[0.6]	[0.51]	[0. 45]
9	RUP-JSI	RUP-JSI	RUP-JSI	INR-NTY	INR-NTY	INR-NTY	INR-NTY
	[0.37]	[0.54]	[0.66]	[0.75]	[0. 78]	[0.79]	[0.81]
10	INR-NTY	INR-NTY	INR-NTY	RUP-JSI	RUP-JSI	RUP-JSI	RUP-JSI
	[0.48]	[0.63]	[0.68]	[0.83]	[0.82]	[0.90]	[0.86]

Note: BTC (Bitcoin); NTY (NIFTY50); INR (Indian Rupee); RUP (Indonesian Rupiah); JSI (Jakarta Stock Index).

Appendix 3.C5: Time-scale correlation ranking of Ripple and Latin American assets

Rank	D1	D2	D3	D4	D5	D6	D7
1	XRP-MEX	XRP-MER	XRP-MPES	XRP-MPES	XRP-MPES	XRP-MPES	XRP-BOV
	[-0.04]	[0.01]	[-0.03]	[-0.06]	[-0.21]	[-0.21]	[-0.45]
2	XRP-MPES	XRP-MPES	XRP-BRL	XRP-BRL	XRP-MEX	XRP-MEX	XRP-BRL
	[-0.03]	[0.02]	[-0.02]	[-0.04]	[-0.06]	[-0.06]	[-0.36]
3	XRP-APES	XRP-BRL	XRP-BOV	APES-MEX	XRP-APES	XRP-APES	XRP-MER
	[-0.01]	[0.03]	[-0.01]	[0.00]	[-0.02]	[-0.02]	[-0.20]
4	XRP-BRL	XRP-MEX	XRP-MEX	XRP-APES	XRP-BRL	XRP-BRL	XRP-APES
	[0.01]	[0. 03]	[0.01]	[0.06]	[0.00]	[0.00]	[-0.16]

5	XRP-BOV	XRP-BOV	APES-MPES	APES-BOV	XRP-BOV	XRP-BOV	APES-BRL
	[0.01]	**[0.04]**	**[0.06]**	**[0.06]**	**[0.11]**	**[0.11]**	**[0.05]**
6	XRP-MER	XRP-APES	APES-MEX	APES-MPES	XRP-MEX	XRP-MER	APES-BOV
	[0.05]	**[0.04]**	**[0.09]**	**[0.07]**	**[0.12]**	**[0.12]**	**[0.26]**
7	APES-MEX	APES-MEX	XRP-APES	XRP-MEX	APES-MEX	APES-MEX	BRL-MPES
	[0.05]	**[0.07]**	**[0.12]**	**[0.09]**	**[0.14]**	**[0.14]**	**[0.28]**
8	APES-BRL	APES-MPES	XRP-MER	XRP-MER	APES-MPES	APES-MPES	BRL-MER
	[0.05]	**[0. 09]**	**[0.15]**	**[0.10]**	**[0.17]**	**[0.17]**	**[0.29]**
9	APES-BOV	APES-BOV	APES-BOV	APES-BRL	MPES-MER	MPES-MER	XRP-MEX
	[0.06]	**[0.09]**	**[0.18]**	**[0.10]**	**[0.24]**	**[0.24]**	**[0.33]**
10	APES-MPES	APES-BRL	APES-BRL	XRP-BOV	APES-BOV	APES-BOV	APES-MEX
	[0.09]	**[0.10]**	**[0.20]**	**[0.11]**	**[0.27]**	**[0.27]**	**[0.37]**
11	MPES-MES	MPES-BOV	MPES-MER	MPES-MER	MER-MEX	MER-MEX	BRL-MEX
	[0.27]	**[0.29]**	**[0.25]**	**[0.23]**	**[0.30]**	**[0.30]**	**[0.39]**
12	BRL-MER	BRL-MER	MER-MEX	BRL-MER	APES-BRL	APES-BRL	MPES-BOV
	[0.30]	**[0.36]**	**[0.35]**	**[0.26]**	**[0.38]**	**[0.38]**	**[0.39]**
13	MER-MEX	MER-MEX	BRL-MER	BRL-MPES	BRL-MER	BRL-MER	APES-MPES
	[0.31]	**[0.39]**	**[0.41]**	**[0.32]**	**[0.38]**	**[0.38]**	**[0.40]**
14	BRL-MEX	BRL-MEX	BRL-MEX	BRL-MEX	MPES-BOV	MPES-BOV	XRP-MPES
	[0.33]	**[0.43]**	**[0.46]**	**[0.32]**	**[0.40]**	**[0.40]**	**[0.42]**
15	MER-BOV	MPES-BOV	MER-BOV	MER-MEX	BRL-MPES	BRL-MPES	MER-BOV
	[0.38]	**[0.44]**	**[0.46]**	**[0.36]**	**[0.41]**	**[0.41]**	**[0.49]**
16	MPES-BOV	BRL-MPES	MER-BOV	MER-BOV	MER-BOV	MER-BOV	BOV-MEX
	[0.40]	**[0.45]**	**[0.47]**	**[0.37]**	**[0.43]**	**[0.43]**	**[0.52]**
17	APES-MER	MER-BOV	MPES-BOV	MPES-BOV	BRL-MEX	BRL-MEX	MER-MEX
	[0.44]	**[0.46]**	**[0.50]**	**[0.41]**	**[0.44]**	**[0.44]**	**[0.55]**
18	BOV-MEX	APES-MER	BOV-MEX	APES-MER	APES - MER	APES-MER	MPES-MER
	[0.45]	**[0.46]**	**[0.59]**	**[0.43]**	**[0.45]**	**[0.45]**	**[0.56]**
19	BRL-MPES	BOV-MEX	APES-MEX	BOV-MEX	BOV-MEX	BOV-MEX	BRL-BOV
	[0.50]	**[0.54]**	**[0.60]**	**[0.53]**	**[0.48]**	**[0.48]**	**[0.84]**
20	MPES-MEX	MPES-MEX	BRL-BOV	BRL-BOV	BRL-BOV	BRL-BOV	APES-MER
	[0.52]	**[0.71]**	**[0.79]**	**[0.79]**	**[0.83]**	**[0.85]**	**[0.89]**
21	BRL-BOV	BRL-BOV	MPES-MEX	MPES-MEX	MPES-MEX	MPES-MEX	MPES-MEX
	[0.62]	**[0.75]**	**[0.81]**	**[0.79]**	**[0.87]**	**[0.91]**	**[0.98]**

Note: XRP (Ripple); MPES (Mexican Peso); APES (Argentine Peso); BRL (Brazilian Real); BOV (Bovespa); MER (Merval); MEX (Mexbol).

Appendix 3.C6: Time-scale correlation ranking of Ripple and African-European assets

Rank	D1	D2	D3	D4	D5	D6	D7
1	XRP-BIST	XRP-RUB	XRP ZAR	XRP-ZAR	XRP-MOEX	XRP-MOEX	XRP-MOEX
	[-0.08]	**[-0.02]**	**[-0.05]**	**[-0.05]**	**[0.00]**	**[-0.14]**	**[-0.54]**
2	XRP-LIRA	XRP-BIST	XRP-BIST	XRP-LIRA	XRP-BIST	XRP-RUB	XRP-RUB
	[-0.05]	**[0.00]**	**[-0.04]**	**[-0.04]**	**[0.08]**	**[-0.12]**	**[-0.25]**
3	XRP-ZAR	XRP-LIRA	XRP-RUB	XRP-BIST	XRP-RUB	XRP-JSE	XRP-JSE
	[-0.02]	**[0.01]**	**[-0.02]**	**[0.01]**	**[0.10]**	**[-0.04]**	**[-0.25]**
4	XRP-MOEX	XRP-RUB	XRP-LIRA	XRP-MOEX	XRP-LIRA	XRP-BIST	LIRA-MOEX
	[-0.01]	**[0.03]**	**[-0.01]**	**[0.03]**	**[0.12]**	**[0.05]**	**[-0.25]**
5	XRP-RUB	XRP-ZAR	XRP-MOEX	XRP-RUB	XRP-ZAR	XRP-ZAR	XRP-ZAR
	[-0.01]	**[0.04]**	**[-0.01]**	**[0.08]**	**[0.17]**	**[0.10]**	**[-0.06]**
6	XRP-JSE	XR-MOEX	XRP-JSE	XRP-JSE	XRP-JSE	XRP-LIRA	LIRA-RUB
	[0.00]	**[0.04]**	**[-0.01]**	**[0.10]**	**[0.21]**	**[0.17]**	**[0.12]**
7	LIRA-MOEX	LIRA-MOEX	LIRA-RUB	LIRA-MOEX	LIRA-JSE	LIRA-MOEX	LIRA-JSE
	[0.21]	**[0.18]**	**[0.27]**	**[0.31]**	**[0.3]**	**[0.36]**	**[0.13]**
8	RUB-BIST	LIRA-RUB	LIRA-MOEX	LIRA-RUB	LIRA-MOEX	BIST-MOEX	ZAR-LIRA
	[0.24]	**[0.22]**	**[0.28]**	**[0.32]**	**[0.31]**	**[0.42]**	**[0.21]**

9	ZAR-MOEX	RUB-BIST	RUB-BIST	RUB-BIST	ZAR-MOEX	LIRA-RUB	XRP-BIST
	[0.25]	**[0.24]**	**[0.34]**	**[0.40]**	**[0.33]**	**[0.43]**	**[0.25]**
10	RUB-JSE	LIRA-JSE	ZAR-RUB	LIRA-JSE	LIRA-RUB	ZAR-RUB	ZAR-MOEX
	[0.25]	**[0.25]**	**[0.34]**	**[0.41]**	**[0.36]**	**[0.46]**	**[0.31]**
11	LIRA-JSE	BIST-MOEX	LIRA-JSE	BIST-MOEX	RUB-BIST	RUB-BIST	ZAR-MOEX
	[0.27]	**[0.31]**	**[0.36]**	**[0.41]**	**[0.39]**	**[0.46]**	**[0.45]**
12	BIST-MOEX	ZAR-MOEX	ZAR-MOEX	ZAR-MOEX	ZAR-RUB	ZAR-MOEX	ZAR-RUB
	[0.30]	**[0.34]**	**[0.40]**	**[0.43]**	**[0.40]**	**[0.49]**	**[0.53]**
13	LIRA-RUB	ZAR-BIST	BIST-MOEX	ZAR-RUB	BIST-MOEX	LIRA-JSE	RUB-BIST
	[0.31]	**[0.37]**	**[0.41]**	**[0.45]**	**[0.43]**	**[0.59]**	**[0.55]**
14	ZAR-BIST	ZAR-RUB	ZAR-LIRA	ZAR-LIRA	JSE-BIST	RUB-JSR	XRP-LIRA
	[0.34]	**[0.38]**	**[0.42]**	**[0.49]**	**[0.44]**	**[0.60]**	**[0.59]**
15	ZAR-RUB	ZAR-LIRA	RUB-JSE	RUB-JSE	RUB-JSE	ZAR-LIRA	ZAR-BIST
	[0.39]	**[0.38]**	**[0.42]**	**[0.50]**	**[0.45]**	**[0.65]**	**[0.63]**
16	JSE-BIST	RUB-JSE	ZAR-BIST	JSE-BIST	ZAR-LIRA	JSE-MOEX	JSE-BIST
	[0.39]	**[0.40]**	**[0.51]**	**[0.52]**	**[0.46]**	**[0.70]**	**[0.65]**
17	JSE-MIEX	JSE-BIST	JSE-MOEX	ZAR-BIST	ZAR-BIST	ZAR-BIST	JSE-MOEX
	[0.42]	**[0.40]**	**[0.54]**	**[0.52]**	**[0.49]**	**[0.73]**	**[0.69]**
18	ZAR-JSE	JSE-MOEX	JSE-BIST	JSE-MOEX	JSE-MOEX	JSE-BIST	LIRA-BIST
	[0.50]	**[0.50]**	**[0.56]**	**[0.56]**	**[0.57]**	**[0.79]**	**[0.74]**
19	ZAR-LIRA	ZAR-JSE	LIRA-BIST	RUB-MOEX	ZAR-JSE	ZAR-JSE	RUB-JSE
	[0.55]	**[0.68]**	**[0.76]**	**[0.78]**	**[0.70]**	**[0.82]**	**[0.74]**
20	RUB-MOEX	RUB-MOEX	RUB-MOEX	LIRA-BIST	RUB-MOEX	LIRA-BIST	RUB-MOEX
	[0.62]	**[0.72]**	**[0.80]**	**[0.80]**	**[0.71]**	**[0.83]**	**[0.89]**
21	LIRA-BIST	LIRA-BIST	ZAR-JSE	ZAR-JSE	LIRA-BIST	RUB-MOEX	ZAR-JSE
	[0.62]	**[0.75]**	**[0.81]**	**[0.83]**	**[0.82]**	**[0.84]**	**[0.91]**

Note: XRP (Ripple); LIRA (Turkish Lira); ZAR (South Africa Rand); RUB (Russian Rubble); BIST (BIST30); JSE (FTSE/JSE TOP40); MOEX (MOEX).

Appendix 3.C7: Time-scale correlation ranking of Ripple and East Asian assets

Rank	D1	D2	D3	D4	D5	D6	D7
1	XRP-CNY	XRP-SSE	XRP-SSE	XRP-CNY	XRP-CNY	XRP-WON	XRP-SSE
	[-0.02]	**[-0.03]**	**[-0.09]**	**[0.02]**	**[-0.20]**	**[-0.05]**	**[-0.18]**
2	XRP-SSE	XRP-KOSP	XRP-CNY	XRP-SSE	XRP-SSE	XRP-KOSP	XRP-CNY
	[0.02]	**[0.05]**	**[0.04]**	**[0.04]**	**[0.02]**	**[0.02]**	**[-0.15]**
3	XRP-WON	XRP-WON	XRP-WON	XRP-WON	XRP-KOSP	XRP-CNY	XRP-WON
	[0.05]	**[0.06]**	**[0.05]**	**[0.04]**	**[0.09]**	**[0.06]**	**[0.06]**
4	XRP-KOSP	XRP-CNY	XRP-KOSP	XRP-KOSP	XRP-WON	XRP-SSE	XRP-KOSP
	[0.07]	**[0.07]**	**[0.06]**	**[0.07]**	**[0.13]**	**[0.19]**	**[0.12]**
5	WON-SSE	WON-SSE	WON-SSE	WON-SSE	WON-SSE	CNY-SSE	WON-SSE
	[0.12]	**[0.20]**	**[0.21]**	**[0.20]**	**[0.22]**	**[0.41]**	**[0.37]**
6	CNY-SSE	SSE-KOSP	CNY-SSE	CNY-SSE	CNY-WON	CNY-WON	CNY-SSE
	[0.21]	**[0.24]**	**[0.25]**	**[0.31]**	**[0.27]**	**[0.48]**	**[0.38]**
7	CNY-KOSP	CNY-SSE	CNY-KOSP	CNY-KOSP	CNY-KOSP	CNY-KOSP	CNY-WON
	[0.24]	**[0.25]**	**[0.31]**	**[0.33]**	**[0.33]**	**[0.52]**	**[0.51]**
8	SSE-KOSP	CNY-KOSP	SSE-KOSP	SSE-KOSP	CNY-SSE	WON-SSE	CNY-KOSP
	[0.25]	**[0.29]**	**[0.36]**	**[0.33]**	**[0.39]**	**[0.58]**	**[0.52]**
9	CNY-WON	CNY-WON	CNY-WON	CNY-WON	SSE-KOSP	SSE-KOSP	SSE-KOSP
	[0.36]	**[0.42]**	**[0.41]**	**[0.39]**	**[0.39]**	**[0.62]**	**[0.58]**
10	WON-KOSP	WON-KOSP	WON-KOSP	WON-KOSP	WON-KOSP	WON-KOSP	WON-KOSP
	[0.47]	**[0.64]**	**[0.74]**	**[0.76]**	**[0.70]**	**[0.82]**	**[0.94]**

Note: XRP (Ripple); CNY (Chinese Yuan); WON (South Korean Won); SSE (SSE50); KOSP (KOSPI200).

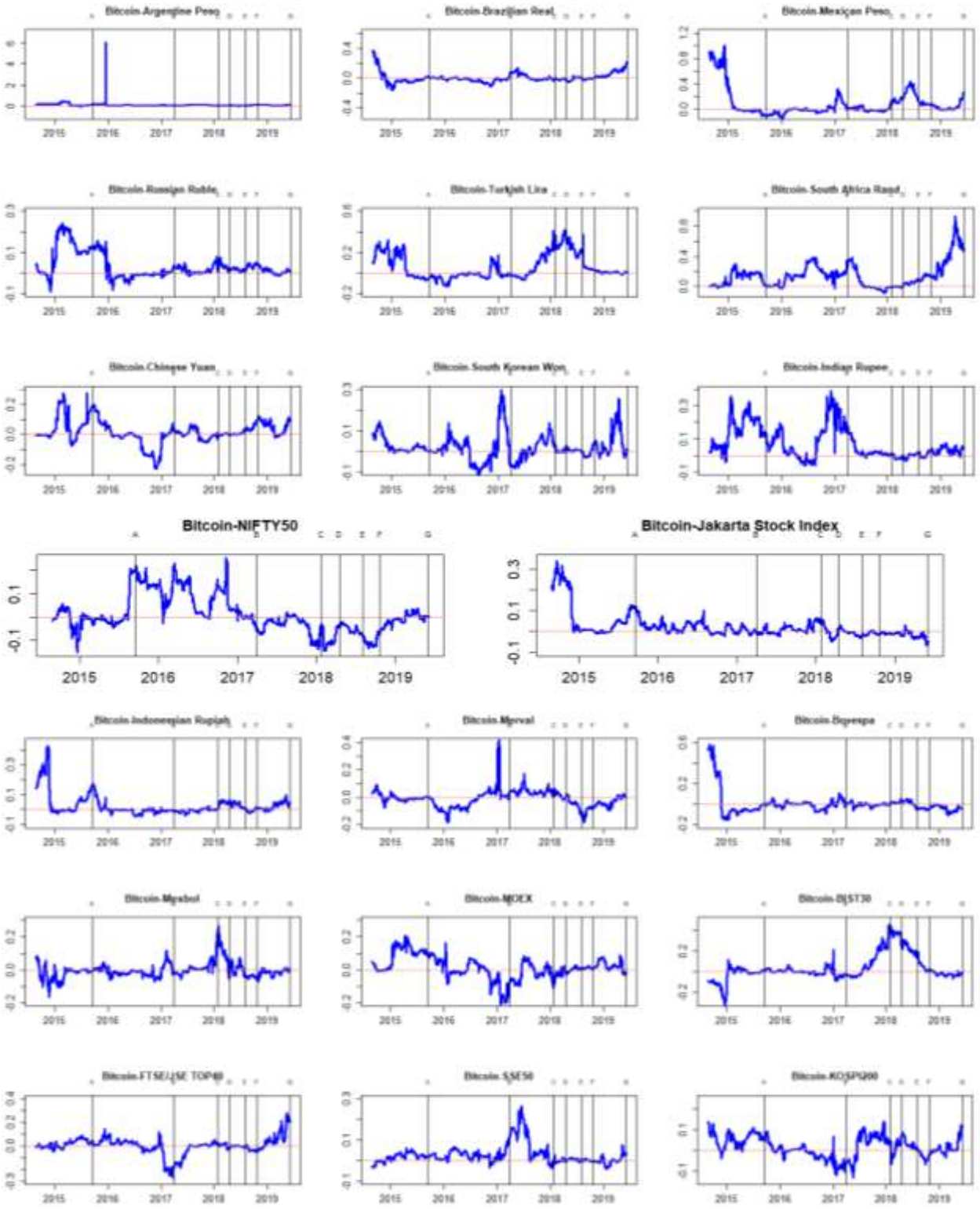
Appendix 3.C8: Time-scale correlation ranking of Ripple and South Asian assets

Rank	D1	D2	D3	D4	D5	D6	D7
1	XRP-RUP	XRP-NTY	XRP-NTY	XRP-RUP	XRP-INR	XRP-INR	RUP-NTY
	[0.00]	**[-0.02]**	**[-0.07]**	**[0.04]**	**[-0.09]**	**[-0.09]**	**[0.09]**
2	XRP-NTY	XRP-INR	XRP-RUP	XRP-INR	XRP-INR	XRP-NTY	XRP-NTY
	[0.02]	**[0.01]**	**[-0.05]**	**[0.07]**	**[-0.06]**	**[-0. 03]**	**[0.19]**
3	XRP-INR	XRP-JSI	XRP-JSI	XRP-JSI	XRP-RUP	XRP-JSI	XRP-RUP
	[0.02]	**[0.04]**	**[-0.01]**	**[0.10]**	**[-0.02]**	**[0.08]**	**[0.20]**
4	XRP-JSI	XRP-RUP	XRP-JSI	XRP-NTY	XRP-JSI	XRP-RUP	XRP-JSI
	[0.06]	**[0.06]**	**[0.02]**	**[0.11]**	**[0.03]**	**[0.11]**	**[0.27]**
5	INTR-JSI	RUP-NTY	RUP-NTY	RUP-NTY	RUP-NTY	INR-RUP	NTY-JSI
	[0.15]	**[0.34]**	**[0.38]**	**[0.41]**	**[0.53]**	**[0.5]**	**[0.27]**
6	RUP-NTY	INR-JSI	INR-JSI	INR-RUP	NTY-JSI	INR-JSI	INR-RUP
	[0.16]	**[0.39]**	**[0.40]**	**[0.46]**	**[0.57]**	**[0.50]**	**[0.39]**
7	NTY-JSI	INR-RUP	INR-RUP	INR-JSI	INR-RUP	RUP-NTY	INR-JSI
	[0.33]	**[0.45]**	**[0.47]**	**[0.50]**	**[0.60]**	**[0.54]**	**[0.45]**
8	INR-RUP	NTY-JSI	NTY-JSI	NTY-JSI	INR-JSI	NTY-JSI	XRP-INR
	[0.34]	**[0.48]**	**[0.48]**	**[0.57]**	**[0.60]**	**[0.59]**	**[0.46]**
9	RUP-JSI	RUP-JSI	INR-NTY	INR-NTY	INR-NTY	INR-NTY	INR-NTY
	[0.39]	**[0.55]**	**[0.66]**	**[0.72]**	**[0.79]**	**[0.79]**	**[0.81]**
10	INR-NTY	INR-NTY	RUP-JSI	RUP-JSI	RUP-JSI	RUP-JSI	RUP-JSI
	[0.47]	**[0.62]**	**[0.68]**	**[0.80]**	**[0.82]**	**[0.90]**	**[0.92]**

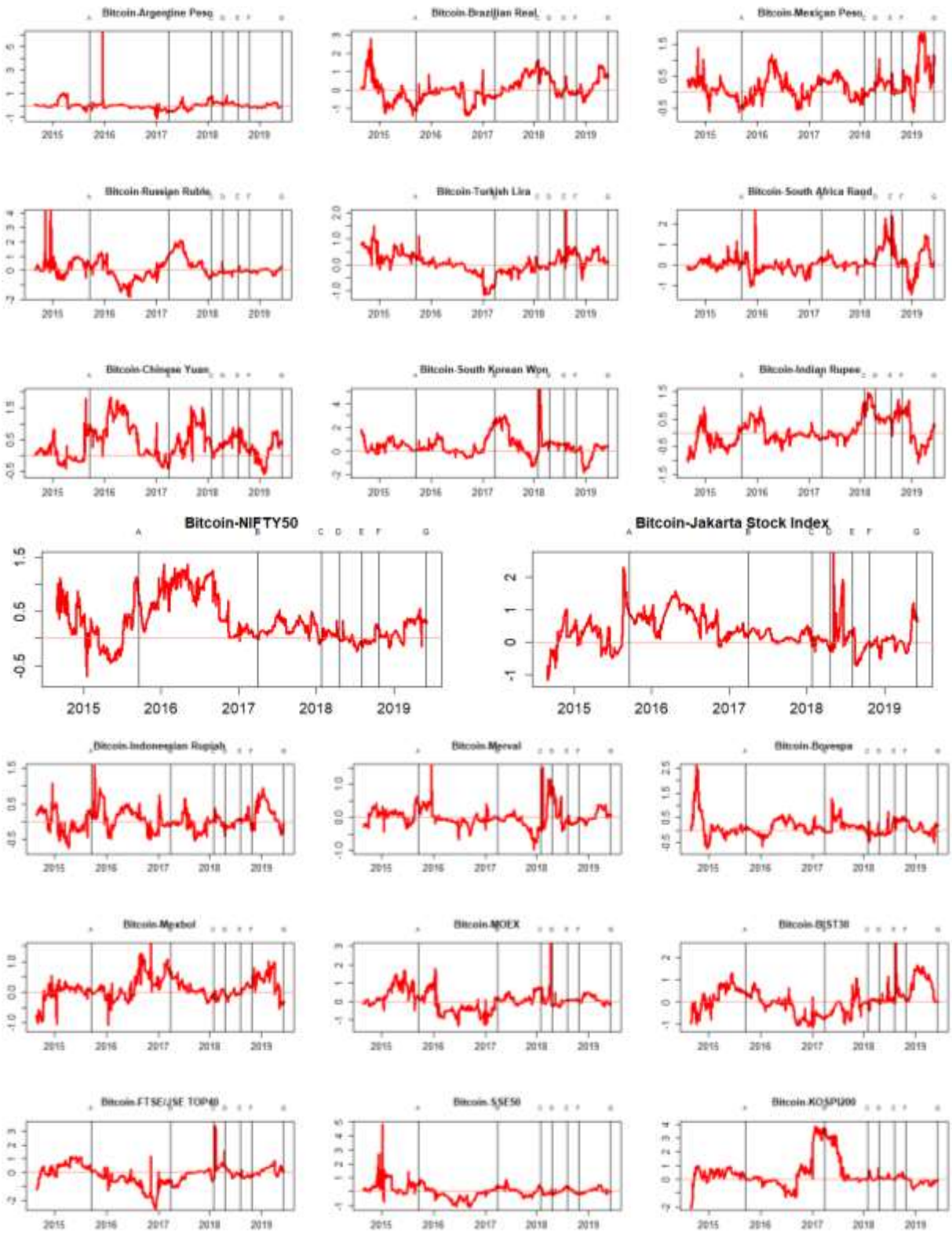
Note: XRP (Ripple); NTY (NIFTY50); INR (Indian Rupee); RUP (Indonesian Rupiah); JSI (Jakarta Stock Index).

Table 4.A1: Full form of abbreviated market variables

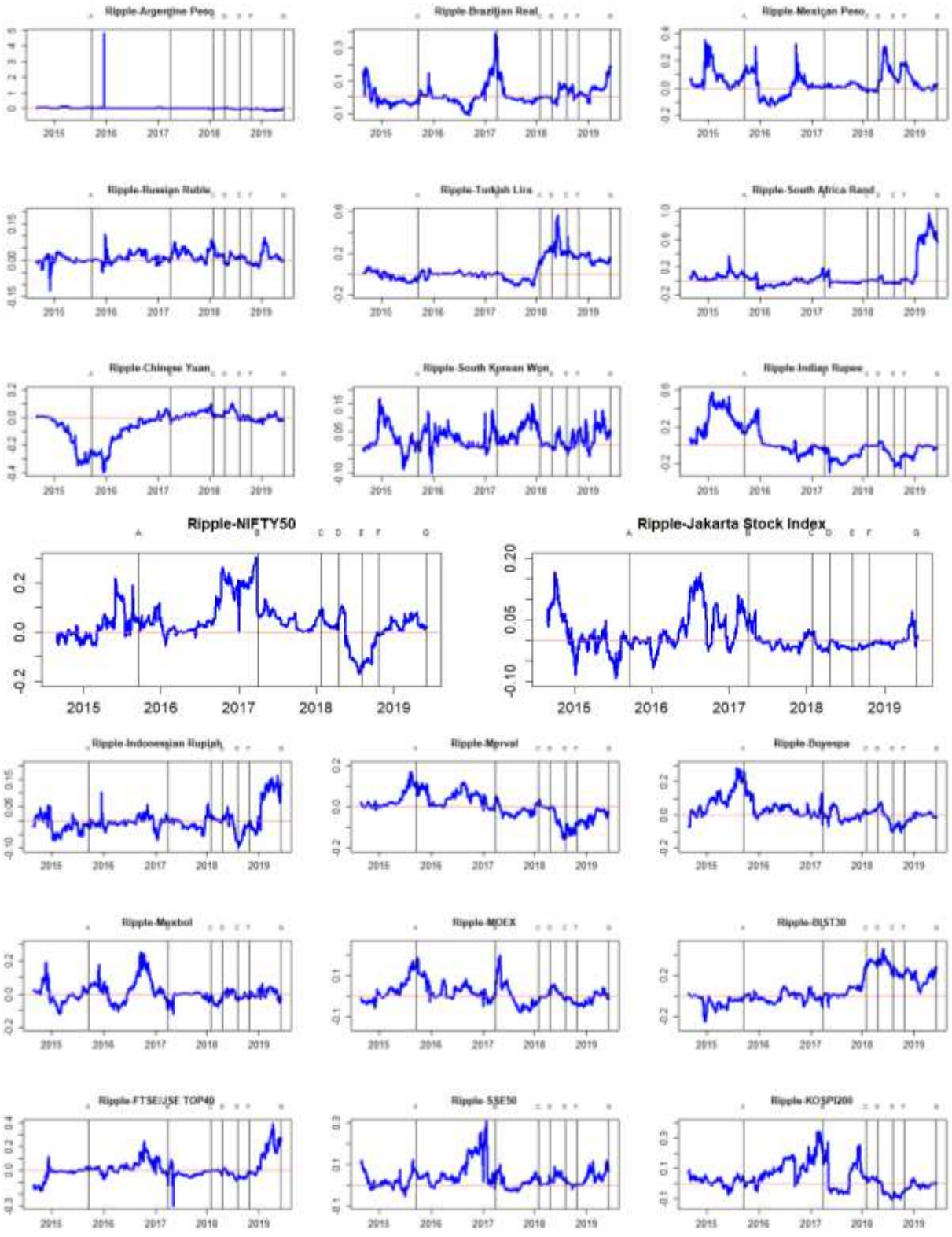
Variable	Full form	Variable	Full form
BTC	Bitcoin	RUP	Indonesian Rupiah/USD
XRP	Ripple	MERV	Merval
ARG	Argentine Peso/USD	BOV	Bovespa
BRL	Brazilian Real/USD	MEXB	Mexbol
MEX	Mexican Peso/USD	MOEX	MOEX
RUB	Russian Ruble/USD	BIST	BIST30
LIRA	Turkish Lira/USD	JSE	FTSE/JSE TOP40
ZAR	South African Rand/USD	SSE	SSE50
CNY	Chinese Yuan/USD	KOSP	KOSPI200
WON	South Korean Won/USD	NIFT	NIFTY50
INR	Indian Rupee/USD	JAK	Jakarta Stock Index



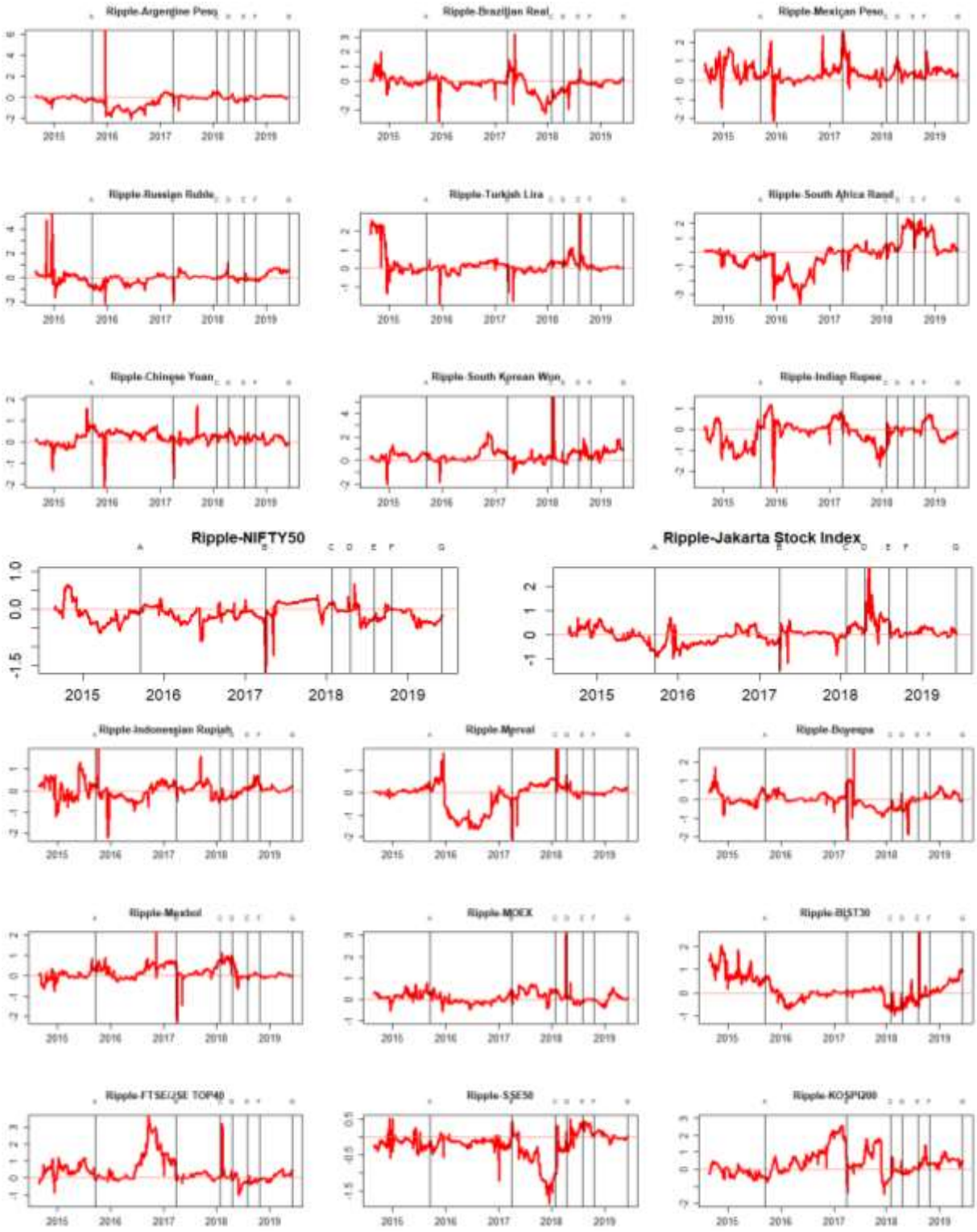
Appendix 4.A1: Bitcoin-Emerging assets rolling-window pairwise net-directional return spillover index



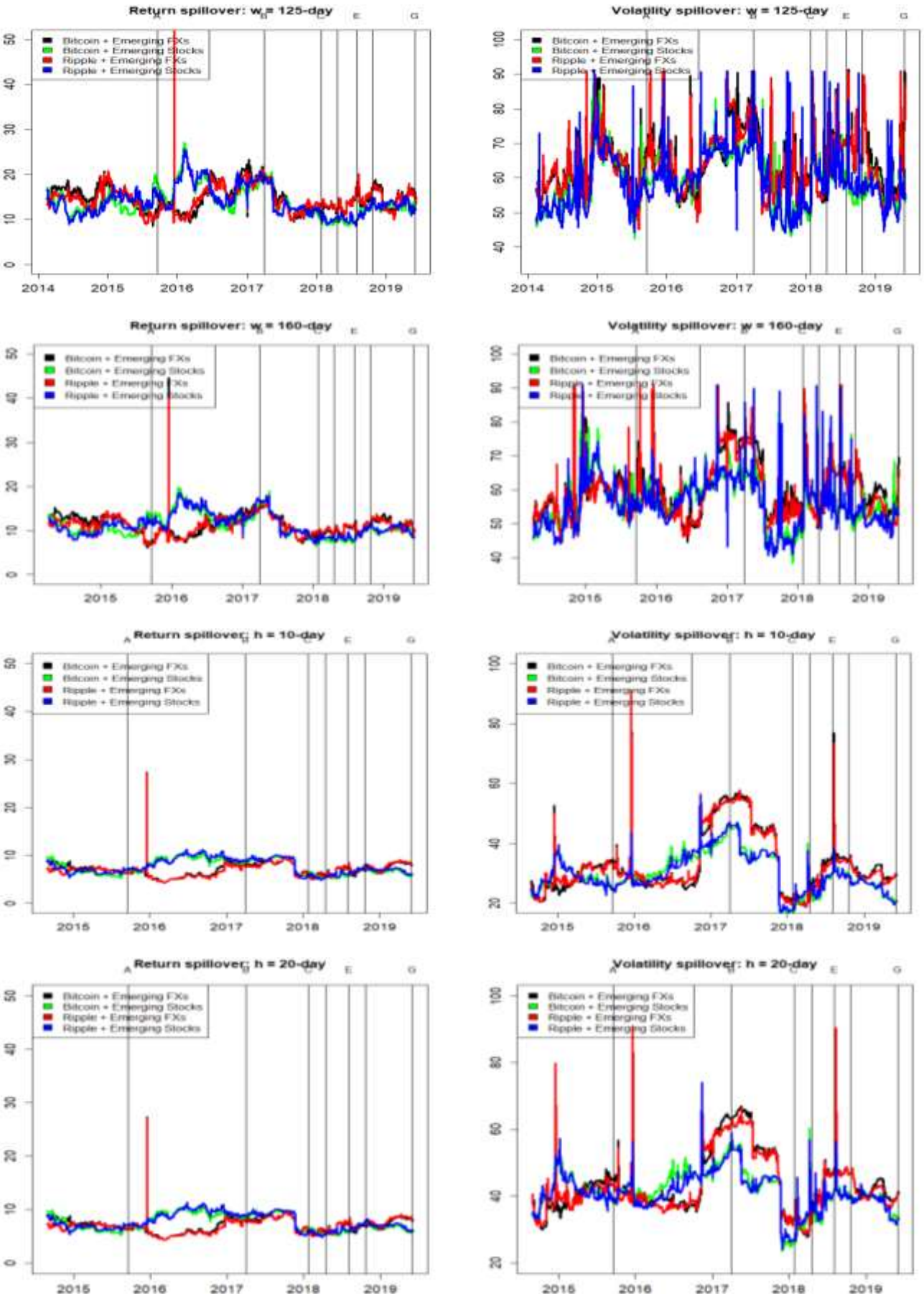
Appendix 4.A2: Bitcoin-Emerging assets rolling-window pairwise net-directional volatility return spillover index.



Appendix 4.B1: Ripple-Emerging assets rolling-window pairwise net-directional return spillover index



Appendix 4.B2: Ripple-Emerging assets rolling-window pairwise net-directional volatility return spillover index.



Appendix 4.C1: Rolling-window total return and volatility spillover index