The drivers of Bitcoin trading volume in selected emerging countries

Taoufik Bouraoui

The drivers of Bitcoin trading volume in selected emerging countries

Taoufik Bouraoui

Rennes School of Business,

2 Rue Robert d'Arbrissel, 35000 Rennes, France

E-mail: taoufik.bouraoui@rennes-sb.com

The drivers of Bitcoin trading volume in selected emerging countries

Abstract:

While most of the debates about cryptocurrencies are centered on the global Bitcoin market, in this article, we focus on local Bitcoin trading volume in 21 emerging countries. In particular, we attempt to determine the drivers of Bitcoin trading volume in these countries over the period August 1st, 2015 – June 2nd, 2018. Based on VECM and ARDL models, we find evidence of significant relationship between the local Bitcoin trading volume in each country and the associated banking system access, especially in the short-run. Moreover, altcoins (Ethereum, Ripple) prices are shown to affect positively and significantly the local Bitcoin trading volume for most countries in the long-run (VECM results) and the short-run (ARDL results).

Keywords: Bitcoin, cryptocurrencies, banking system access, altcoins, VECM, ARDL.

JEL Classification: C22, C58, G12

I. Introduction

Bitcoin is a cryptocurrency introduced in 2009 by an anonymous person known as Satoshi Nakamoto. The main characteristics of this cryptocurrency is that it is fully decentralized and operates only through its users without any control from central banks or governments. Since its creation, Bitcoin has been the subject of many studies. Most of them conclude for the inefficiency of the Bitcoin market (Urquhart, 2016; Bariviera, 2017; Nadarajah and Chu, 2017) while others argue that it is a speculative bubble (Cheah and Fry, 2015; Cheung et al. 2015). The question raised in this paper is rather about the determinants of the Bitcoin trading volume. Although it was traded at less than 1 USD during the first year after its launching, the average price of Bitcoin reached more than 9000 USD over March 2018, which make it the most expensive and popular among other digital currencies. Several factors have been presented in the literature as variants of the Bitcoin price, such as exchange rates (Wijk, 2013), Bitcoin searches on internet (Kristoufek, 2013; Panagiotidis et al., 2018; Aalborg et al., 2018), Chinese stock market index (Bouoiyour and Selmi, 2014), supply and demand (Ciaian et al., 2016), uncertainty (Bouri et al., 2017; Demir et al., 2018), gold returns (Panagiotidis et al., 2018) and altcoins price (Bouri et al., 2018a; Bouri et al., 2018b; Ji et al., 2019). In this paper, we attempt to explore new factors that may have an impact on Bitcoin trading volume. The aim of this paper is not to focus on Bitcoin price formation, but to present the factors driving the local trading volume within emerging countries. In particular, we investigate whether the local banking system and the price of two competing cryptocurrencies, called also altcoins (Ethereum and Ripple) may affect the trading volume of Bitcoin in a sample of 21 emerging countries. The rationale for choosing these variables is that in some developing economies, the access to financial services through local banking system, (e.g bank accounts, debit card) is not provided to all people, but still restricted to some part of the population. This fact may push these people to use Bitcoin as means of payment. Furthermore, while the Bitcoin is the most recognized and known digital currency, there are several other digital currencies that investors may invest in. Therefore, it is interesting to know how the existence of altcoins will influence the number of traded Bitcoin. Ethereum and Ripple have been selected because they are considered as the most traded cryptocurrencies behind Bitcoin with a daily average market capitalization of approximately $67 billion and $28 billion, respectively, over May 2018[1].

The contribution of this paper is twofold. First, while previous papers analyzed the Bitcoin price globally without distinction between countries, in this paper, we study the local Bitcoin trading volume for each selected country in the sample to determine the variables that may influence it. Second, we introduce new factors as drivers of Bitcoin trading volume. Such factors are suitable for the framework of developing countries, such as the accessibility to banking services, which is limited and may lead people to use other alternatives. Furthermore, the discrepancy in the prices as well as in the transaction time and fees between Bitcoin and other rival cryptocurrencies affect usually the behavior of investors in the way of choosing one cryptocurrency at the detriment of others.

The remainder of the paper is structured as follows. In section 2, we review the literature related to Bitcoin drivers. In section 3, we describe the data and the methodology. Empirical results are discussed in section 4. Finally, section 5 concludes the paper.

II. Literature review

[1] Source *Thomson Reuters Eikon* database.

Since its first trading in late 2010, the price of Bitcoin witnessed a substantial rise and rapid growth associated with higher volatility. Numerous factors have been discussed in the literature to explain the determinants of Bitcoin price.

Wijk (2013) analyzed the relationship between Bitcoin price and economic indicators including exchange rates, stock exchange indices and oil price measures. Using ECM regression, the author finds that the euro-dollar exchange rate, Dow Jones index and WTI oil price have a predictive power in explaining the Bitcoin value in the long-run. Similarly, Bouoiyour and Selmi (2014) used a set of seven economic and financial variables in an attempt to identify the close variants of Bitcoin. Their estimates based on ARDL model reveal that investors 'attractiveness and Shanghai stock market index have the strongest impact on the Bitcoin price and dominates other factors such as the exchange trade ratio, Bitcoin velocity and gold price. Moreover, the authors emphasize the speculative behavior of Bitcoin. The rise in Bitcoin's attractiveness for investors is due, among others, to the low transaction fees. Kim (2017) analyzed Bitcoin quotes in 16 different currencies and found the Bitcoin's transaction cost is lower than that of retail foreign exchange markets. Bid-ask spreads in Bitcoin markets are found to be 2% less than that of retail foreign exchange markets. The author explains this cost advantage by the virtual infrastructure that Bitcoin uses. Ciaian et *al*. (2016) argue that Bitcoin can be considered as any other commodity and, therefore, its price is determined by markets forces of supply and demand. In addition to supply and demand variables, they tested the impact of macro-financial development measured by oil price and the Dow Jones stock market index, and include digital currency specific indicators such as investors 'attractiveness. Based on the results of four regression models, the authors report that fluctuations of Bitcoin price are mainly due to the law of supply and demand and Bitcoin attractiveness for investors and users. However, unlike the findings of Wijk (2013), oil price and Dow Jones index are found to have no significant impact, especially in the long-run.

Kristoufek (2013) demonstrated that changes in Bitcoin price are due to the interest that users show for it, proxied by search queries on *Google Trends* and *Wikipedia*. The author points out not only a strong and positive correlation between variables, but also a bidirectional causality. Likewise, Panagiotidis et *al*. (2018) examined Bitcoin searches on internet through *Google Trends* and *Wikipedia* in a study including twenty other potential factors. They decompose the whole study period ranging from June 2010 to June 2017 to three sub-periods depending on the major events in the history of Bitcoin. Using LASSO regression, their results indicate for the full sample that Bitcoin returns depend mainly on search intensity, economic policy uncertainty and gold returns. However, for the most recent sub-period, Nikkei stock market index, economic policy uncertainty and *Google Trends* are found to have the strongest impact. The increased popularity and public interest for the Bitcoin lead some researchers to investigate the causes of such interest. For instance, Urquhart (2018) attempted to determine whether returns, realized volatility and volume are significant factors for surging investors' attention to Bitcoin. As proxy for investors' attention, the author uses *Google Trends* over the period August 1st, 2010 – July 31st, 2017. Using VAR model, the findings show evidence of unidirectional causality running from realized volatility and volume to the following day investor attention. Aalborg et al. (2018) used the same variables as Urquhart (2018) in attempt to investigate the determinants of return, volatility and trading volume of Bitcoin. Using simple regression models, their results reveal that *Google searches* for Bitcoin as well as the transaction volume in the Bitcoin network have a significant impact on the trading volume. Moreover, the future realized volatility depends mainly on its past values. However, none variable has showed an explanatory power in predicting Bitcoin's returns. Similarly, Blau (2018) tested whether returns, trading activity and especially speculative trading in Bitcoin are driving the unusual level of volatility. Based on GMM model, the findings report that both returns and trading activity have a significant effect, while speculation is not associated to volatility. El Alaoui et al. (2018) examined the Bitcoin price–volume nexus, and through a multifractal detrended cross-correlations analysis, they point out a nonlinear dependency and multifractality between Bitcoin price and trading volume.

According to Bouri et *al.* (2017), price fluctuations in the Bitcoin can be attributed to global uncertainty, measured by the common component of the implied volatility index (VIX). They collect the VIX of 14 developed and developing stock markets during the period spanning from March 17, 2011 to October 7, 2016. Based on the estimates of quantile regression model, the authors highlight that uncertainty has a positive and significant impact on Bitcoin returns and conclude that Bitcoin can serve as a hedge against uncertainty. Demir et *al*. (2018) support the findings of Bouri et *al*. (2017). They use the economic policy uncertainty index in the US over the period July 18, 2010 - November 15, 2017 and study the dependency with Bitcoin returns. The results obtained from BGSVAR model as well as quantile regression and OLS model provide evidence of significant relationship between Bitcoin returns and economic policy uncertainty. The authors recommend investors to use information on economic policy uncertainty in their investment decisions related to Bitcoin.

While it is often found that Bitcoin is a bubble (Cheah and Fry, 2015; Cheung et al. 2015), Bouri et al. (2018a) tested this bubbling effect in other altcoins and examined whether they co-bubble simultaneously. The authors selected seven leading cryptocurrencies based on their market capitalizations (Bitcoin, Ripple, Ethereum, Litecoin, Nem, Dash, and Stellar). Over the period August 7, 2015 to December 31, 2017, they find evidence of multiple periods of explosivity for all cryptocurrencies, including Bitcoin. Interestingly, they point out a significant link in the explosive periods between cryptocurrencies. That is, the probability of one cryptocurrency shows a bubbling effect rises with the existence of explosivity in other cryptocurrencies.

Bouri et al. (2018b) extended their study on the same seven leading cryptocurrencies to study henceforth the relationship between trading volume on the one hand, and return and volatility on the other hand. Based on the copula-quantile causality approach, their findings reveal a significant causality from trading volume to return of cryptocurrencies. Whereas, for most cryptocurrencies (4 out of 7), trading volume does not Granger cause volatility.

In the same context, Ji et al. (2019) also found that leading cryptocurrencies (Bitcoin, Ethereum, Ripple, Litecoin, Stellar and Dash) are interconnected through the establishment of return and volatility-connectedness networks. Finally, Nguyen et al. (2019) emphasized the competitive effect that may have the introduction of new altcoins in the cryptocurrency market on Bitcoin. They tested the impact of 62 altcoins on Bitcoin's return and found that these altcoins generated a substantial decrease in the return of Bitcoin.

All the above studies have addressed the Bitcoin's topic from different perspectives. From a perspective of price or trading volume determinants, we contribute to the existing studies by suggesting a new factor that may be appropriate for the variations in trading volume across emerging countries.

III. Data and methodology

Our sample consists of 21 developing countries namely Argentina, Brazil, Chile, Colombia, Dominican Republic, India, Indonesia, Iran, Kenya, Malaysia, Mexico, Morocco, Nigeria, Pakistan, Peru, Philippines, Singapore, South Africa, Tanzania, Thailand and Venezuela. These countries have been selected based on the availability of data. For each selected country, we use weekly data on local Bitcoin trading volume, the price of two altcoins which are Ethereum and Ripple, and the banking system access measured by the proportion of people aged +15 having a debit or credit card. Ethereum and Ripple have been chosen since they are listed as the second and the third respectively (after the Bitcoin) in terms of market capitalization. Moreover, their price data cover the entire study period unlike other cryptocurrencies (Litecoin, EOS, IOTA) which have price data available for shorter period. These data are extracted from *Thomson Reuters Eikon* database and cover the period spanning from August 1st, 2015 to June 2nd, 2018[2].

To analyze the relationship between the above variables, we employ Vector Error Correction Model (VECM) and AutoRegressive Distrubuted Lag Model (ARDL).

VECM is applied when all variables have the same integration order and it exists at least one cointegrating relationship between them. This model provides a convenient way to deal with both short-run and long-run relationships between variables.

We estimate a VECM as follows[3]:

$$\Delta TDG_t = \alpha_0 + \sum_{i=1}^{p} \alpha_{1i} \Delta TDG_{t-i} + \sum_{j=1}^{p} \alpha_{2j} \Delta XRP_{t-j} + \sum_{k=1}^{p} \alpha_{3k} \Delta ETH_{t-k} + \sum_{l=1}^{p} \alpha_{4l} \Delta BKG_{t-l} + \delta_1 ect_{t-1} + \varepsilon_{1t} \quad (1)$$

$$\Delta XRP_t = \beta_0 + \sum_{i=1}^{p} \beta_{1i} \Delta XRP_{t-i} + \sum_{j=1}^{p} \beta_{2j} \Delta TDG_{t-j} + \sum_{k=1}^{p} \beta_{3k} \Delta ETH_{t-k} + \sum_{l=1}^{p} \beta_{4l} \Delta BKG_{t-l} + \delta_2 ect_{t-1} + \varepsilon_{2t} \quad (2)$$

$$\Delta ETH_t = \lambda_0 + \sum_{i=1}^{p} \lambda_{1i} \Delta ETH_{t-i} + \sum_{j=1}^{p} \lambda_{2j} \Delta TDG_{t-j} + \sum_{k=1}^{p} \lambda_{3k} \Delta XRP_{t-k} + \sum_{l=1}^{p} \lambda_{4l} \Delta BKG_{t-l} + \delta_3 ect_{t-1} + \varepsilon_{3t} \quad (3)$$

$$\Delta BKG_t = \theta_0 + \sum_{i=1}^{p} \theta_{1i} \Delta BKG_{t-i} + \sum_{j=1}^{p} \theta_{2j} \Delta TDG_{t-j} + \sum_{k=1}^{p} \theta_{3k} \Delta XRP_{t-k} + \sum_{l=1}^{p} \theta_{4l} \Delta ETH_{t-l} + \delta_4 ect_{t-1} + \varepsilon_{4t} \quad (4)$$

Where Δ is the first-order difference operator, *TDG* denotes the local Bitcoin trading volume, *XRP* is the Ripple price, *ETH* is the Ethereum price, *BKG* is the percentage of people aged

[2] We could not collect data prior to August 1st, 2015 since Ethereum's trading has been started only as from that week.
[3] These equations are based on the assumption that there is one cointegrating relationship between variables.

+15 having a debit or credit card, and *ect* is the error correction term (the residual obtained from the cointegrating equation).

Unlike VECM, the estimation of ARDL does not require the same integration order for variables. In this case, variables are mixture of I(0) and I(1). In general, a four-variable ARDL(p,q,r,s) is given by the following equation:

$$\Delta TDG_t = \alpha_0 + \sum_{i=1}^{p}\alpha_{1i}\Delta TDG_{t-i} + \sum_{j=0}^{q}\alpha_{2j}\Delta XRP_{t-j} + \sum_{k=0}^{r}\alpha_{3k}\Delta ETH_{t-k} + \sum_{l=0}^{s}\alpha_{4l}\Delta BKG_{t-l} + \theta_1 TDG_{t-1} + \theta_2 XRP_{t-1} + \theta_3 ETH_{t-1} + \theta_4 BKG_{t-1} + \varepsilon_t \quad (5)$$

IV. Empirical results

We first examine the stationarity properties of our variables using Augmented Dickey-Fuller (ADF) test. The results are summarized in Table 1.

Table 1: Results of ADF unit root test

Variable	Level			1st difference			Integration order
	Model 3	Model 2	Model 1	Model 3	Model 2	Model 1	
ETH	2.25	1.26	-0.72	0.40	0.70	-13.07*	I(1)
XRP	2.36	1.34	-1.16	0.29	0.48	-9.33*	I(1)
Argentina							
TDG	-2.77	0.37	-1.70	0.32	-1.19	-13.22*	I(1)
BKG	1.49	2.27	-0.09	0.52	-0.02	-3.73*	I(1)
Brazil							
TDG	-0.33	5.08(-6.06)**	-	-	-	-	I(0)
BKG	1.32	2.28	0.22	-0.78	0.29	-2.85*	I(1)
Chile							
TDG	-0.35	2.99(-3.45)**	-	-	-	-	I(0)
BKG	1.59	2.55(-2.54)	0.89	-0.05	0.93	-2.88*	I(1)
Colombia							
TDG	2.63	2.42	-0.79	-0.17	0.86	-14.92*	I(1)
BKG	-1.92	1.74	-1.03	1.04	-0.93	-2.46*	I(1)
Dominican Republic							
TDG	2.65	4.19(-4.86)**	-	-	-	-	I(0)
BKG	1.59	2.04	0.20	0.07	0.40	-3.43*	I(1)
India							
TDG	-3.61	3.73(-4.15)**	-	-	-	-	I(0)
BKG	1.67	2.13	-0.08	-0.40	0.09	-2.44*	I(1)
Indonesia							
TDG	-1.22	2.00	-2.79*	-	-	-	I(0)
BKG	-0.61	2.42	-1.22	-2.25	-0.07	-3.18*	I(1)
Iran							
TDG	-0.37	1.71	-0.82	-0.50	0.76	-13.62*	I(1)

BKG	-0.18	2.50	-0.70	0.50	-0.28	-2.41*	I(1)
Kenya							
TDG	-1.51	2.73(-2.92)**	-	-	-	-	I(0)
BKG	-1.85	1.88	-1.45	0.31	-0.34	-2.24*	I(1)
Malaysia							
TDG	-0.95	2.84(-3.36)**	-	-	-	-	I(0)
BKG	1.08	2.40	0.60	-0.73	0.68	-2.28*	I(1)
Mexico							
TDG	-5.61	1.75	-1.48	0.10	-0.56	-11.38*	I(1)
BKG	1.59	2.17	-0.10	0.13	-1.07	-2.53*	I(1)
Morocco							
TDG	-1.41	2.65(-2.98)**	-	-	-	-	I(0)
BKG	-1.68	2.00	-0.38	0.01	-0.27	-2.44*	I(1)
Nigeria							
TDG	0.74	1.56	-0.78	-0.50	0.43	-14.72*	I(1)
BKG	3.81(4.00) (-3.99)***	-	-	-	-	-	I(0)
Pakistan							
TDG	2.69	7.49(-8.41)**	-	-	-	-	I(0)
BKG	0.19	2.80(-2.75)	0.20	0.80	0.55	-2.24*	I(1)
Peru							
TDG	2.07	0.92	0.71	1.28	1.04	-9.61*	I(1)
BKG	0.12	2.26	0.32	2.12	0.41	-2.80*	I(1)
Philippines							
TDG	-3.06	1.42	-1.69	0.23	-0.57	-13.40*	I(1)
BKG	-0.70	2.05	-0.57	-2.17	-0.49	-2.78*	I(1)
Singapore							
TDG	-1.44	6.81(-7.94)**	-	-	-	-	I(0)
BKG	2.15	1.75	1.10	-0.99	1.12	-2.69*	I(1)
South Africa							
TDG	-2.13	0.18	-1.10	-0.34	-0.70	-12.00*	I(1)
BKG	0.81	2.45	1.05	-0.08	0.05	-3.51*	I(1)
Tanzania							
TDG	1.74	4.47(-5.85)**	-	-	-	-	I(1)
BKG	-1.11	2.03	-1.38	1.90	-1.12	-2.21*	I(1)
Thailand							
TDG	-5.57	2.21	-1.32	-0.61	-1.39	-6.77*	I(1)
BKG	-0.38	2.48	-0.51	0.59	-0.28	-2.40*	I(1)
Venezuela							
TDG	1.54	1.65	-0.02	0.02	0.92	-16.51*	I(1)
BKG	-0.64	2.53	-0.47	-0.91	-0.37	-2.68*	I(1)

Notes: Model 1= model without trend and intercept. Model 2= model with intercept. Model 3= model with trend and intercept.

* means that time series is stationary at level or at 1st difference using model 1. The single number is ADF stat.

** means that time series is stationary at level using model 2. The first number indicates that the intercept is significant at 5% level, and the number in parenthesis is for the ADF stat.

*** means that time series is stationary at level using model 3. The first number indicates that the trend is significant at 5% level; the first number in parenthesis indicates that the intercept is significant at 5% level and the second number in parenthesis is for the ADF stat.

Table 1 shows that most of variables are stationary at first difference (I(1)), while some others are found to be stationary at level (I(0)).

IV.1 VECM estimates

In addition to having the same integration order, variables should be cointegrated to be eligible for VECM estimation. To test for cointegration, we use Johansen (1988) test which does not only check whether variables are cointegrated or not, but also determines the number of cointegrating relationships.

Johansen (1988) approach uses two test statistics, namely, Trace statistics and Maximum eigenvalue statistics:

$$\lambda_{Trace}(r) = -T \sum_{i=r+1}^{g} \ln(1 - \hat{\lambda}_i) \qquad (6)$$

$$\lambda_{Max}(r, r+1) = -T.\ln(1 - \hat{\lambda}_{r+1}) \qquad (7)$$

Where r is the number of cointegrating vectors, T is the number of observations, and $\hat{\lambda}_i$ is the estimated eigenvalues.

In conducting Trace and Max-eigenvalue tests, we employ for the ten countries for which variables are I(1) (Argentina, Colombia, Iran, Mexico, Peru, Philippines, South Africa, Tanzania, Thailand and Venezuela) the model assuming no intercept in the short-run equation and no trend in the cointegrating equation. This choice is based on the fact that variables in level do not show any obvious trend while the first difference form appear to fluctuate around zero.

The results of Johansen (1988) test reported in Table 2 reveal the existence of at least one cointegrating relationship for all selected countries. Indeed, for Argentina, Mexico, Philippines, South Africa and Venezuela, only the null hypothesis of no cointegration is rejected at 5% significance level, implying that there exists one cointegrating relationship between variables. However, for Iran, Peru, Tanzania and Thailand, we fail to reject the null hypothesis at the cointegrating ranks “at most 2” and “at most 3”, which suggest the existence of two cointegrating relationships. Finally, for Colombia, we find that trace and maximum eigenvalue and tests provide conflicting results. Lutkepohl et al. (2001) set up a Monte Carlo simulation to compare between maximum eigen value and trace tests and found that trace test outperforms maximum eigen value test. Therefore, we consider only the results of trace test and conclude that there exists one cointegrating relationship for that country.

Table 2: Johansen cointegration test results

Country	H_0 : there is a certain cointegrating rank "r".	Trace statistic	Max-Eigen statistic	r
Argentina	r = 0 r ≤ 1 r ≤ 2 r ≤ 3	90.27(54.07)* 29.94(35.19) 9.37(20.26) 2.34(9.16)	60.32(28.58)* 20.57(22.29) 7.03(15.89) 2.34(9.16)	1
Colombia	r = 0 r ≤ 1 r ≤ 2 r ≤ 3	101.08(54.07)* 39.42(35.19)* 18.64(20.26) 2.72(9.16)	61.66(28.58)* 20.77(22.29) 15.91(15.89)* 2.72(9.16)	2 (Trace) 1 (Max-Eigen)
Iran	r = 0 r ≤ 1 r ≤ 2 r ≤ 3	97.39(54.07)* 46.36(35.19)* 10.45(20.26) 3.66(9.16)	51.02(28.58)* 35.91(22.29)* 6.78(15.89) 3.66(9.16)	2
Mexico	r = 0 r ≤ 1 r ≤ 2 r ≤ 3	89.57(54.07)* 27.45(35.19) 9.73(20.26) 3.67(9.16)	62.12(28.58)* 17.71(22.29) 6.05(15.89) 3.67(9.16)	1
Peru	r = 0 r ≤ 1 r ≤ 2 r ≤ 3	135.20(54.07)* 52.10(35.19)* 16.61(20.26) 4.45(9.16)	83.10(28.58)* 35.48(22.29)* 12.16(15.89) 4.45(9.16)	2
Philippines	r = 0 r ≤ 1 r ≤ 2 r ≤ 3	167.93(54.07)* 27.48(35.19) 15.51(20.26) 4.07(9.16)	110.44(28.58)* 21.97(22.29) 14.44(15.89) 4.07(9.16)	1
South Africa	r = 0 r ≤ 1 r ≤ 2 r ≤ 3	81.36(54.07)* 25.26(35.19) 11.52(20.26) 4.13(9.16)	56.09(28.58)* 13.74(22.29) 7.38(15.89) 4.13(9.16)	1
Tanzania	r = 0 r ≤ 1 r ≤ 2 r ≤ 3	114.12(54.07)* 41.19(35.19)* 18.12(20.26) 2.36(9.16)	72.93(28.58)* 23.06(22.29)* 15.76(15.89) 2.36(9.16)	2
Thailand	r = 0 r ≤ 1 r ≤ 2 r ≤ 3	102.79(54.07)* 41.97(35.19)* 13.43(20.26) 5.64(9.16)	57.81(28.58)* 31.54(22.29)* 7.79(15.89) 5.64(9.16)	2
Venezuela	r = 0 r ≤ 1	87.80(54.07)* 26.97(35.19)	60.83(28.58)* 12.99(22.29)	1

	r ≤ 2	13.97(20.26)	9.17(15.89)	
	r ≤ 3	4.80(9.16)	4.80(9.16)	

Notes: 'r' is the number of cointegrating relationships. Numbers in parentheses are the 5% critical values; * denotes rejection of the null hypothesis at 5% significance level.

Once variables are found to be cointegrated, we proceed to estimate VECM. In determining the optimal lag length, we refer to Akaike Information Criterion (AIC) which suggest the inclusion of 1 lag (p=1) for Argentina, Colombia, Iran, Mexico, South Africa, Thailand and Venezuela, and 2 lags (p=2) for Peru, Philippines and Tanzania. The results of VECM estimates are given in Table 3.

Table 3: VECM estimation results

Argentina						
Short-run estimates					**Long-run estimates**	
	Dependent variables					
	ΔTDG	*ΔXRP*	*ΔETH*	*ΔBKG*		***CE1*** *Dependent variable: TDG*
ECT1(-1)	-0.10(-2.29)*	0.0011(1.31)	-0.49(-5.27)*	0.01(1.79)	*XRP*	0.37(8.91)*
ΔTDG(-1)	-0.48(-6.56)*	-0.002 (-0.73)	0.23(1.62)	-0.004 (-0.43)		
ΔXRP(-1)	0.30(1.47)	0.61(6.15)*	1.81(1.44)	0.017(1.19)	*ETH*	0.67(10.49)*
ΔETH(-1)	0.01(0.31)	-0.001 (-1.36)	-0.37(-5.43)*	-0.44(-1.81)	*BKG*	-2.88(-1.06)
ΔBKG(-1)	-1.25(-3.41)*	0.20(1.41)	1.29(0.17)	0.96(4.60)*	*C*	1.23(0.66)

Colombia						
Short-run estimates					**Long-run estimates**	
	Dependent variables					
	ΔTDG	*ΔXRP*	*ΔETH*	*ΔBKG*		***CE1*** *Dependent variable: TDG*
ECT1(-1)	-0.01(-1.18)	0.09(1.80)	-0.10(-5.00)*	-0.94 (-6.19)*	*XRP*	0.66(8.18)*
ΔTDG(-1)	-0.19(-2.40)*	-0.01(-0.35)	-0.06(-0.45)	0.56(0.26)		
ΔXRP(-1)	-2.50(-1.09)	0.62(6.39)*	1.84(1.54)	-0.009 (-1.61)	*ETH*	2.77(1.55)
ΔETH(-1)	-0.02(-0.53)	-0.0017 (-1.34)	-0.39(-5.73)*	0.03(1.29)	*BKG*	-1.91(-3.97)*
ΔBKG(-1)	-2.55(-2.42)*	-0.38(-1.52)	-0.31(-1.29)	0.97(6.19)*	*C*	-6.10(-4.01)*

Iran							
Short-run estimates					**Long-run estimates**		
	Dependent variables						
	ΔTDG	*ΔXRP*	*ΔETH*	*ΔBKG*		***CE1*** *Dependent variable: TDG*	***CE2*** *Dependent variable: XRP*
ECT1(-1)	-0.29(-6.65)*	0.01(1.46)	-0.15(-0.45)	0.86(0.06)	*TDG*	-	0.00
ECT2(-1)	0.27(0.70)	-0.27 (-3.14)*	0.46(3.85)*	-0.19 (-3.77)*			
ΔTDG(-1)	-0.03(-0.33)	-0.11(-0.99)	0.17(2.73)*	0.66(0.20)	*XRP*	0.00	-
ΔXRP(-1)	0.21(1.01)	0.61(6.13)*	2.27(1.19)	0.04(0.79)	*ETH*	0.03(4.04)*	-0.01(-1.65)
ΔETH(-1)	0.11(2.35)*	-0.0015	-0.44(-5.57)*	-0.001	*BKG*	-0.55(-1.97)*	0.03(1.06)

		(-1.13)		(-1.17)			
ΔBKG(-1)	-1.27(-2.86)*	0.02(0.78)	0.39(1.38)	0.94(4.19)*	*C*	1.86(1.24)	-0.09(-0.68)

Mexico

Short-run estimates					**Long-run estimates**	
Dependent variables						
	ΔTDG	*ΔXRP*	*ΔETH*	*ΔBKG*		***CE1*** *Dependent variable: TDG*
ECT1(-1)	-0.04(-2.62)*	0.04(2.46)*	-0.36(-5.41)*	0.06(5.02)*	*XRP*	0.72(8.97)*
ΔTDG(-1)	-0.28(-3.49)*	0.03(2.75)*	0.08(0.44)	-0.33 (-1.99)*		
ΔXRP(-1)	0.19(2.29)*	0.60(6.17)*	1.76(1.36)	0.01(1.42)	*ETH*	0.89(9.14)*
ΔETH(-1)	-0.13(-0.46)	-0.0011 (-1.31)	-0.39(-5.80)*	-0.008 (-1.22)	*BKG*	-2.58(-3.47)*
ΔBKG(-1)	-1.03(-2.22)*	0.44(1.66)	1.99(1.74)	0.97(4.98)*	*C*	1.29(3.18)*

Peru

Short-run estimates					**Long-run estimates**		
Dependent variables							
	ΔTDG	*ΔXRP*	*ΔETH*	*ΔBKG*		***CE1*** *Dependent variable: TDG*	***CE2*** *Dependent variable: XRP*
ECT1(-1)	-0.21(-3.00)*	-0.03(-0.49)	0.88(2.84)*	-0.06 (-2.14)*	*TDG*	-	0.00
ECT2(-1)	-0.14(-1.48)	-0.57 (-6.64)*	0.15(0.36)	0.02(7.03)*			
ΔTDG(-1)	-0.25(-2.56)*	-0.37(-0.04)	-0.53(-1.26)	0.11(1.80)	*XRP*	0.00	-
ΔTDG(-2)	-0.01(-0.20)	-0.87(-1.08)	-0.03(-0.09)	1.77(0.44)			
ΔXRP(-1)	0.92(0.56)	1.33(10.84)*	2.79(1.64)	-0.02(-1.38)	*ETH*	0.06(3.37)*	-0.12(-1.15)
ΔXRP(-2)	1.13(1.05)	-0.06(-0.67)	-1.14(-1.47)	0.015(1.33)			
ΔETH(-1)	0.20(2.39)*	-0.0012 (-1.69)	-0.35(-3.88)*	0.002(1.30)	*BKG*	-3.14(-2.78)*	-0.04(-1.84)
ΔETH(-2)	0.01(0.87)	0.007(1.70)	0.33(4.04)*	-0.014 (-1.73)			
ΔBKG(-1)	-2.17(-2.36)*	1.09(1.60)	4.33(0.08)	0.48(4.98)*	*C*	7.17(0.62)	0.94(1.78)
ΔBKG(-2)	-2.55(-1.11)	-0.57(-1.54)	-3.91(-0.41)	0.47(5.03)*			

Philippines

Short-run estimates					**Long-run estimates**	
Dependent variables						
	ΔTDG	*ΔXRP*	*ΔETH*	*ΔBKG*		***CE1*** *Dependent variable: TDG*
ECT1(-1)	-0.06(-3.41)*	-0.004(-8.30)*	0.16(2.09)*	-0.13(-1.64)	*XRP*	0.44(1.98)*
ΔTDG(-1)	-0.49(-5.90)*	-0.75(-0.26)	-0.09(-0.60)	-0.28(-0.50)		
ΔTDG(-2)	-0.22(-2.64)*	-0.24(-0.86)	-0.04(-0.28)	-0.32(-0.56)	*ETH*	1.27(6.67)*
ΔXRP(-1)	0.52(2.14)*	1.52(2.12)*	3.17(1.71)	0.016(1.64)		
ΔXRP(-2)	1.14(0.45)	-0.12(-1.41)	-0.67(-1.46)	-0.06(-1.38)	*BKG*	-0.55(-3.67)*
ΔETH(-1)	0.03(0.65)	-0.0018 (-1.04)	-0.40(-4.20)*	-0.017 (-1.49)		
ΔETH(-2)	-0.15(-0.32)	0.008(1.32)	0.30(3.58)*	0.07(1.23)	*C*	-2.27(-3.99)*
ΔBKG(-1)	-1.17(-2.39)*	-0.34(-0.74)	1.51(0.20)	0.28(3.03)*		
ΔBKG(-2)	2.55(0.33)	0.32(0.25)	1.18(0.44)	0.65(5.22)*		

South Africa

Short-run estimates					**Long-run estimates**	
Dependent variables						
	ΔTDG	*ΔXRP*	*ΔETH*	*ΔBKG*		***CE1*** *Dependent variable: TDG*

ECT1(-1)	-0.003(-0.70)	0.12(2.84)*	-0.008(-4.80)*	0.17(5.36)*	*XRP*	0.71(2.12)*	
ΔTDG(-1)	-0.13(-1.61)	-2.50(-0.31)	-0.012(-0.37)	-0.22(-0.37)			
ΔXRP(-1)	0.39(2.12)*	0.62(6.50)*	2.00(1.05)	0.009(1.25)	*ETH*	0.22(1.71)	
ΔETH(-1)	-0.05(-0.34)	-0.011 (-1.71)	-0.42(-6.07)*	-0.002 (-1.20)	*BKG*	-1.37(-1.09)	
ΔBKG(-1)	-1.08(-2.44)*	0.22(0.94)	1.32(0.13)	0.96(5.38)	*C*	6.96(3.03)*	
Tanzania							
Short-run estimates					**Long-run estimates**		
Dependent variables							
	ΔTDG	*ΔXRP*	*ΔETH*	*ΔBKG*		***CE1*** *Dependent variable: TDG*	***CE2*** *Dependent variable: XRP*
ECT1(-1)	-0.34(-3.15)*	-0.07(-1.28)	0.58(2.11)*	-0.06(-0.69)	*TDG*	-	0.00
ECT2(-1)	-0.22(-1.23)	-0.61 (-6.71)*	0.12(2.59)*	0.01(2.35)*			
ΔTDG(-1)	-0.31(-2.61)*	0.24(0.41)	-4.04(-1.36)	0.13(1.38)	*XRP*	0.00	-
ΔTDG(-2)	-0.14(-1.47)	0.15(0.48)	-0.18(-1.07)	0.32(0.38)			
ΔXRP(-1)	1.34(1.20)	1.37(4.02)*	3.07(1.40)	-0.09(-1.39)	*ETH*	0.02(0.95)	-0.0011(-1.11)
ΔXRP(-2)	1.25(0.60)	-0.06(-0.66)	-0.85(-1.64)	0.004(1.28)			
ΔETH(-1)	0.80(1.04)	-0.17(-1.81)	-0.39(-3.64)*	0.0012(1.45)	*BKG*	-1.52(-2.76)*	-0.03(-1.13)
ΔETH(-2)	0.03(0.85)	0.07(1.08)	0.32(3.40)*	-0.03(-1.10)			
ΔBKG(-1)	-1.70(-3.30)*	0.33(1.52)	-1.95(-0.21)	0.45(4.09)*	*C*	-1.89(-1.97)*	0.33(1.05)
ΔBKG(-2)	-1.12(-2.33)*	-0.15(-1.18)	-3.02(-1.09)	0.52(4.79)*			
Thailand							
Short-run estimates					**Long-run estimates**		
Dependent variables							
	ΔTDG	*ΔXRP*	*ΔETH*	*ΔBKG*		***CE1*** *Dependent variable: TDG*	***CE2*** *Dependent variable: XRP*
ECT1(-1)	-0.30(-6.30)*	-0.15(-0.06)	-0.14(-1.91)	-0.01(-0.34)			
ECT2(-1)	0.007(1.64)	-0.25 (-3.06)*	0.16(4.61)*	-0.07 (-3.52)*	*TDG*	-	0.00
ΔTDG(-1)	-0.08(-0.95)	1.25(0.17)	0.08(2.37)*	-0.09 (-2.05)*	*XRP*	0.00	-
ΔXRP(-1)	-2.32(-1.76)	0.63(6.71)*	2.10(1.52)	0.014(0.65)	*ETH*	0.25(6.48)*	-0.0013(-1.80)
ΔETH(-1)	0.08(2.19)*	-0.11(-1.67)	-0.41(-5.68)*	-0.04(-1.10)	*BKG*	-0.04(-3.01)*	0.55(0.99)
ΔBKG(-1)	-0.66(-2.41)*	-0.02(-0.28)	1.74(1.43)	0.95(5.12)*	*C*	-2.53(-2.09)*	-0.15(-0.69)
Venezuela							
Short-run estimates					**Long-run estimates**		
Dependent variables							
	ΔTDG	*ΔXRP*	*ΔETH*	*ΔBKG*		***CE1*** *Dependent variable: TDG*	
ECT1(-1)	-0.05(-2.48)*	-0.04 (-2.89)*	0.016(2.57)*	-0.009 (-3.55)*	*XRP*	0.29(8.30)*	
ΔTDG(-1)	-0.31(-3.91)*	2.74(0.14)	-0.08(-1.09)	0.99(0.31)			
ΔXRP(-1)	-3.70(-0.93)	0.60(6.55)*	2.17(1.55)	-0.03(-1.89)	*ETH*	1.15(7.41)*	
ΔETH(-1)	-0.44(-0.62)	-0.12(-1.75)	-0.45(-6.36)*	0.94(0.55)	*BKG*	-0.81(-2.58)*	
ΔBKG(-1)	-2.85(-2.67)*	0.04(0.48)	1.28(1.03)	0.94(5.55)*	*C*	-1.05(-2.56)*	

Notes: CE: cointegrating equation. C: constant. ECT: error correction term. Numbers in parentheses are t-statistics; * indicates significance at 5% level.

The results show that for all countries, the banking system access has a negative and significant impact on local Bitcoin trading volume, especially in the short-run. That is, the less people have payment cards, the more they use Bitcoin. In this case, Bitcoin is used mainly as a payment instrument. Indeed, the access to banking sector in these markets, in particular Colombia and Venezuela is relatively restricted so that only few people can hold a credit or debit card. The emergence of new digital currency as Bitcoin can help skipping unfair financial and banking practices in these regions by allowing people to make use of decentralized currency system without any aid from their economic and governmental system. Therefore, Bitcoin constitutes a great opportunity for them to conduct financial transactions.

In the long-run, this relationship tends to disappear in Argentina and South Africa since the decision of buying or selling Bitcoin in the long-run may be influenced by several other factors, other than presented in our model.

Moreover, the negative relationship between banking system access and Bitcoin trading volume appears to run in both directions for Mexico and Thailand meaning that the use of Bitcoin as a payment tool may lead people in these countries to disclaim holding traditional banking cards.

We also find, for 9 out of 10 countries, that Ethereum and/or Ripple price affects positively and significantly Bitcoin trading volume, particularly in the long-run where the effect is more highlighted than in the short-run. These results confirm the findings of Ji et al. (2019) who demonstrate that the cryptocurrency Litecoin has a significant effect on Bitcoin in the transmission role of return and volatility spillovers. Table 3 shows that the strongest dependency is recorded for Philippines where 1% increase in the price of Ethereum is associated with 1.27% rise in the Bitcoin trade volume; while Venezuela reports the smallest effect (+0.29%) lead by 1% increase in the Ripple price. In fact, Bitcoin and altcoins as Ethereum and Ripple are considered as substitutes because they are competing on the same market share, indicating that when the price of one altcoin increases, its demand declines. As a result, users move towards another digital currency such as Bitcoin, generating a rise in the trade volume. These results are in line with those of Gandal and Halaburda (2016) who provide evidence of a substitution effect between Bitcoin and a competing digital currency (Litecoin) as they find a strong and positive correlation between them.

In the short-run, the causality between Ethereum and Bitcoin trading volume in Iran and Thailand, and between Ripple and Bitcoin trading volume in Mexico is found to be running in both directions implying that altcoins prices are also impacted by Bitcoin volume. Indeed, since Bitcoin is the leading cryptocurrency, most of altcoins are generally influenced by its price's trend. Furthermore, Bitcoin serves as a medium of exchange between several cryptocurrencies indicating that most of major altcoins prices are expressed in terms of Bitcoin price. These results corroborate those of Ciaian et al. (2018) who reveal that Bitcoin price affects significantly the value of 15 altcoins in the short-run.

The estimates of error correction term resulting from long-run equations where *TDG* is the dependent variable are negative and statistically significant for all selected countries, apart from Colombia and South Africa. These coefficients range between -0.04 for Mexico and -0.34 for Tanzania, which means that when variables incur a shock and are no longer in equilibrium, only 4% and 34% of that disequilibrium is corrected within one week[4] for Mexico and Tanzania, respectively. This implies a slow adjustment and convergence toward the long-run equilibrium.

With regards to the relationship between altcoins, neither of Ethereum and Ripple have shown an explaining power on the other in the long-run as well as in the short-run, since both of them are considered as equal substitutes without any dominant effect. These results do not corroborate those of Bouri et al. (2018) since they considered a larger set of cryptocurrencies

[4] Because we have weekly data.

(Bitcoin, Ripple, Ethereum, Litecoin, Nem, Dash, and Stellar) and find evidence of interaction between them over bubble periods.

Similarly, both Ethereum and Ripple seem to be not linked to the banking system access in the short-run. This finding may be explained by the fact that these altcoins are not recognizable as payment instruments worldwide. Therefore, they cannot be considered as an alternative to holding bank accounts in local baking institution.

IV.2 ARDL estimates

For variables with a mixed integration order (I(0) and I(1)), the appropriate model to analyze the relationship between them is ARDL. The estimation of ARDL model requires, first, checking for cointegration through the bounds test developed by Pesaran et *al*. (2001). This test uses the Wald or *F*-statistic in testing the null hypothesis of no cointegration; H_0: $\theta_1 = \theta_2 = \theta_3 = \theta_4$ against the alternative hypothesis; H_1: $\theta_1 \neq \theta_2 \neq \theta_3 \neq \theta_4$; where θ_1, θ_2, θ_3 and θ_4 are the long-run parameters given in equation (5).

The calculated F-statistics for the bounds test are presented in Table 4.

Table 4: Results of bounds test

Estimated model: *TDG = f(TDG, XRP, ETH, BKG)*			
Country	**Selected model [a]**	**F-statistic**	**Cointegration results: Are variables cointegrated?**
Brazil	ARDL (2,0,0,1)	10.293*	Yes
Chile	ARDL (3,1,1,1)	3.767*	Yes
Dominican Republic	ARDL (2,2,2,1)	5.564*	Yes
India	ARDL (5,0,0,0)	4.527*	Yes
Indonesia	ARDL (7,0,1,6)	3.757*	Yes
Kenya	ARDL (5,0,0,0)	1.482	No
Malaysia	ARDL (3,0,1,5)	1.906	No
Morocco	ARDL (3,0,0,0)	2.482	No
Nigeria	ARDL (3,1,0,0)	2.256	No
Pakistan	ARDL (1,0,0,1)	18.460*	Yes
Singapore	ARDL (3,5,2,5)	4.980*	Yes
Critical values at 5% significance level: Lower bound = 2.79 Upper bound = 3.67			

Notes: * indicates significance at 5% level. ARDL models are estimated using case 2: Restricted intercept and no trend. [a] :optimal lag length is based on AIC criterion. K = number of regressors = 3.

For Brazil, Chile, Dominican Republic, India, Indonesia, Pakistan and Singapore, the null hypothesis of no cointegration is rejected as the F-statistics lie above the upper bound of the critical value, suggesting an evidence of cointegration between variables. However, we fail to reject the null hypothesis for Kenya, Malaysia, Morocco and Nigeria as the F-statistics are less than the lower bound of the critical value, indicating that variables are not cointegrated.

ARDL approach procedure suggest the estimation of a long-run relationship as well as a short-run relationship for variables that are found to be cointegrated. However, in the absence of cointegration, the relationship between variables is modeled using equation (5) which estimates simultaneously the short-run and the long-run coefficients in a single equation. The results of ARDL estimates for cointegrated and non-cointegrated variables are summarized in Table 5 and Table 6, respectively.

Table 5: ARDL estimation results (cointegrated variables)

Long-run estimates Dependent variable: ***TDG***							
Explanatory variables	**Brazil**	**Chile**	**Dominican Republic**	**India**	**Indonesia**	**Pakistan**	**Singapore**
XRP	-1.37 (-1.07)	1.11(0.37)	1.44(1.90)	3.86(0.45)	1.42(0.70)	-2.41 (-1.12)	-1.92 (-0.82)
ETH	0.03(0.56)	-0.02 (-0.85)	-0.02 (-1.78)	-0.19 (-1.16)	-0.04 (-0.71)	0.08(2.72)*	0.11(1.12)
BKG	-1.32 (-2.04)*	2.98 (2.35)*	1.94 (1.97)*	-1.64 (-1.98)*	1.78 (2.59)*	2.41 (3.78)*	1.26 (2.04)*
C	4.76(1.31)	-3.87 (-2.18)*	-2.97 (-1.64)	3.64(1.77)	-4.40 (-1.40)	-7.28 (-1.91)	-1.06 (-1.22)
Short-run estimates Dependent variable: ***ΔTDG***							
Explanatory variables	**Brazil** ARDL (1,0,0,0) [a]	**Chile** ARDL (2,0,0,0)	**Dominican Republic** ARDL (1,1,1,0)	**India** ARDL (4,0,0,0)	**Indonesia** ARDL (6,0,0,5)	**Pakistan** ARDL (0,0,0,0)	**Singapore** ARDL (2,4,1,4)
ΔTDG(-1)	0.20(2.48)*	-0.07 (-0.73)	-0.19 (-2.14)*	0.08(0.90)	-0.13 (-1.18)	-	-0.38 (-4.42)*
ΔTDG(-2)	-	-0.17 (-2.21)*	-	-0.07 (-0.78)	0.17(1.57)	-	-0.35 (-4.73)*
ΔTDG(-3)	-	-	-	0.22 (2.61)*	0.08(0.79)	-	-
ΔTDG(-4)	-	-	-	0.11(1.39)	0.10(1.03)	-	-
ΔTDG(-5)	-	-	-	-	0.24(2.51)*	-	-

ΔTDG(-6)	-	-	-	-	0.58(5.90)*	-	-
ΔXRP	-2.43 (-1.07)	-2.33 (-0.33)	1.62(2.69)*	1.52(0.45)	1.86(0.70)	-1.89 (-1.11)	1.67(3.35)*
ΔXRP(-1)	-	-	1.46(2.90)*	-	-	-	1.35(2.87)*
ΔXRP(-2)	-	-	-	-	-	-	0.77(3.86)*
ΔXRP(-3)	-	-	-	-	-	-	1.41(0.98)
ΔXRP(-4)	-	-	-	-	-	-	2.16(1.56)
ΔETH	0.02(0.57)	-0.01 (-0.93)	0.02(0.13)	-0.07 (-1.14)	0.01(2.22)*	0.06(2.62)*	0.09(2.82)*
ΔETH(-1)	-	-	0.01(1.70)	-	-	-	0.06(1.28)
ΔBKG	-1.12 (-2.42)*	1.60 (1.98)*	2.13 (2.81)*	-2.49 (-2.95)*	0.80 (1.99)*	1.41 (2.66)*	1.54 (5.15)*
ΔBKG(-1)	-	-	-	-	1.48 (2.56)*	-	-2.56 (-6.21)*
ΔBKG(-2)	-	-	-	-	-1.23 (-2.40)*	-	1.84 (0.84)
ΔBKG(-3)	-	-	-	-	1.01 (1.98)*	-	-2.38 (-1.01)
ΔBKG(-4)	-	-	-	-	-1.21 (-2.03)*	-	1.07 (1.71)
ΔBKG(-5)	-	-	-	-	1.02 (2.03)*	-	-
ECT(-1)	-0.58 (-7.27)*	-0.43 (-4.40)*	-0.44 (-5.38)*	-0.39 (-4.82)*	-0.42 (-4.42)*	-0.78 (-9.74)*	-0.41 (-5.06)*

Notes: C: constant. ECT: error correction term. Numbers in parentheses are t-statistics; * indicates significance at 5% level. [a] the selected model is based on variables at level. Therefore, when we move from variables at level to variables at first difference, the number of lags is reduced by 1.

Table 6: ARDL estimation results (non-cointegrated variables)

Dependent variable: ***ΔTDG***				
Explanatory variables	**Kenya** ARDL (4,0,0,0)[a]	**Malaysia** ARDL (2,0,0,4)	**Morocco** ARDL (2,0,0,0)	**Nigeria** ARDL (2,0,0,0)
ΔTDG(-1)	-0.39(-4.16)*	-0.25(-2.75)*	-0.35(-3.20)*	-0.14(-1.73)
ΔTDG(-2)	-0.20(-2.09)*	-0.16(-1.87)	-0.24(-2.58)*	0.16(1.91)
ΔTDG(-3)	-0.15(-1.68)	-	-	-
ΔTDG(-4)	-0.19(-2.34)*	-	-	-
ΔXRP	-1.92(-0.89)	2.01(0.69)	-0.45(-0.07)	-2.81(-0.52)
ΔETH	0.01(0.63)	0.05(0.57)	-0.01(-0.16)	0.32(1.30)
ΔBKG	2.04(2.09)*	-2.89(-2.71)*	1.33(2.78)*	1.02(2.73)*
ΔBKG(-1)	-	1.95(1.57)	-	-
ΔBKG(-2)	-	-1.66(-0.29)	-	-
ΔBKG(-3)	-	-4.34(-0.75)	-	-
ΔBKG(-4)	-	-2.31(-1.83)	-	-
TDG(-1)	-0.17(-2.57)*	-0.12(-1.99)*	-0.36(-3.43)*	-0.11(-3.07)*
XRP(-1)	-1.92(-0.89)	2.01(0.69)	-0.45(-0.07)	1.08(1.35)
ETH(-1)	0.01(0.63)	-0.06(-1.42)	-0.01(-0.16)	0.32(1.30)
BKG(-1)	2.04(2.09)*	-1.07(-2.54)*	1.33(2.78)*	1.02(2.73)*
C	-5.90(-0.91)	-4.62(-2.49)*	-2.35(-0.57)	-3.37(-2.71)*

Notes: C: constant. Numbers in parentheses are t-statistics; * indicates significance at 5% level. [a] the selected model is based on variables at level. Therefore, when we move from variables at level to variables at first difference, the number of lags is reduced by 1.

We note that the banking system access has a significant impact on local Bitcoin trading volume for all selected countries in both the long-run and the short-run. While the effect is negative for Brazil, India and Malaysia; it is positive for the remaining countries. This positive relationship may be explained by the fact that although people own bank accounts, they prefer using Bitcoin in their payments. Indeed, the conventional banking system works through a pull system, which requires a third party to accomplish transactions. However, the Bitcoin does not require any intermediary to facilitate the transactions and interactions between two parties. Moreover, with Bitcoin, transactions are faster and processing fees are cheaper than traditional banking system. Although Bitcoin is not recognized as legal currency in some countries (Morocco, Pakistan) and restricted in other countries (India, Indonesia), people use it in the black market especially for their international purchases or sales.

Table 5 shows also a positive and significant relationship between Ethereum and/or Ripple price and Bitcoin trading volume. In the short-run, an increase of 1% in the Ethereum price rises the local Bitcoin trading volume in Indonesia, Pakistan and Singapore by 0.01%, 0.06% and 0.09% respectively; whereas a 1% increase in the Ripple price generates an increment in the Bitcoin trading volume by 1.62% and 1.67% in Dominican Republic and Singapore, respectively. However, for the remaining countries, we find that Bitcoin volume, in both the long-run and the short-run, does not exhibit a significant relationship with neither Ethereum nor Ripple. Although Bitcoin is the most expensive currency relative to other altcoins, it continues to dominate the cryptocurrency market, as it is the most valuable, liquid and popular. These factors constitute a major advantage for Bitcoin and make its price insensitive to the price of other cryptocurrencies. These results are consistent with the findings of Osterrieder et al. (2017) who show that Bitcoin price is not correlated with Ripple (correlation coefficient =0.183).

Regarding variables that have been found cointegrated (Table 5), the coefficient of *ECT(-1)* is negative and significant for all selected countries. These coefficients indicate how quickly variables converge to the long-run equilibrium. For instance, Pakistan records the highest speed of adjustment (78%) toward the long-run relationship following a deviation from equilibrium.

V. Conclusion

Since its creation in 2009, several debates have discussed Bitcoin and its close drivers. While most of these discussions were centered on the worldwide market for Bitcoin, in this paper, we focused on local Bitcoin trading volume for each country in a sample containing 21 emerging countries. Specifically, we attempted to investigate whether banking system access and altcoins (Ethereum and Ripple) may have an effect on Bitcoin trading volume. To do so, we used VECM and ARDL models. Overall, our results reveal that banking system access is shown to affect significantly the local Bitcoin trading volume for all selected countries. VECM results show that the effect is negative and occurs mainly in the short-run; while with ARDL results, we find that the effect is negative for some countries and positive for others, and is highlighted in the both the short-run and the long-run. Indeed, holding bank accounts and a debit/credit card still restricted in some developing countries, which lead people to use a new decentralized system working without any government or central bank's authority as a substitute. Two policy implications may emerge. First, if central banks believe that Bitcoin may constitute a threat for their conventional banking system since a shadow economy may arise from the use of this cryptocurrency in several illicit activities such as money laundering. In this case, they have to restrict people from using this digital money by giving them more opportunities and access to use financial and banking services, through, for instance, lighting the rules or the criteria for owning a bank account. Second, the move towards a new digital system me be viewed by central banks as a new trend in the finance industry. In such a situation, they have to adjust their offers and adopt the technology in their products. For instance, bank of England and Sweden's central bank expressed interest in launching their own digital currency as a substitute for their current money. In Mexico and Thailand, the causality between banking system access and Bitcoin trading volume is found to be running in both directions. The negative impact of Bitcoin on banking system access is explained by the fact that the use of Bitcoin as a payment instrument may lead people in these countries to waive owning conventional banking cards.

Moreover, for most countries, we demonstrate a positive and significant relationship between Ethereum and/or Ripple price and Bitcoin trading volume in the long-run (VECM results) and the short-run (ARDL results). This is due to the substitution effect, which states that an increase in altcoins prices will encourage consumers to search for alternative substitutes (Bitcoin). VECM findings indicate that this relationship is bidirectional in Iran, Thailand and Mexico, suggesting that altcoins prices are also impacted by Bitcoin volume.

There are several influential factors, which affect the Bitcoin price and its trading volume. However, due to its decentralized nature, drawing up an exhaustive list of these factors is inconceivable. Nevertheless, as Bitcoin works mainly through the blockchain technology, it would be interesting to investigate the technological and technical factors behind it in order to predict better its movement.

References

Aalborg, H.A., P. Molnár, and J.E. de Vries. 2018. "What can explain the price, volatility and trading volume of Bitcoin?". *Finance Research Letters (in press)*, https://doi.org/10.1016/j.frl.2018.08.010

Bariviera, A.F. 2017. "The inefficiency of Bitcoin revisited: A dynamic approach". *Economics Letters* 161, 1-4.

Blau, B.M. 2018. "Price dynamics and speculative trading in Bitcoin". *Research in International Business and Finance* 43, 15-21.

Bouoiyour, J., and R. Selmi. 2014. "What Bitcoin looks like?" *MPRA Working Paper* No. 58091, Munich, http://mpra.ub.uni-muenchen.de/58091/

Bouri, E., R. Gupta, A.K. Tiwari, and D. Roubaud. 2017. 'Does Bitcoin hedge global uncertainty? Evidence from wavelet-based quantile-in-quantile regressions". *Finance Research Letters* 23, 87 – 95.

Bouri, E., S.J.H. Shahzad, and D. Roubaud. 2018a. "Co-explosivity in the cryptocurrency market". *Finance Research Letters (in press)*, https://doi.org/10.1016/j.frl.2018.07.005

Bouri, E., C.K.M. Lau, B. Lucey, and D. Roubaud. 2018b. "Trading volume and the predictability of return and volatility in the cryptocurrency market". *Finance Research Letters (in press)*, https://doi.org/10.1016/j.frl.2018.08.015

Cheah, E.T., and J. Fry. 2015. "Speculative bubbles in Bitcoin markets? An empirical investigation into the fundamental value of Bitcoin". *Economics Letters* 130, 32-36.

Cheung, A., J.J. Su, and E. Roca. 2015. "Crypto-currency bubbles: An application of the Phillips-Shi-Yu (2013) methodology on Mt. Gox Bitcoin prices". *Applied Economics* 47, 2348–2358.

Ciaian, P., M. Rajcaniova, and D. Kancs. 2016. “The economics of Bitcoin price formation”. *Applied Economics* 48, 1799-1815.

Ciaian, P., M. Rajcaniova, and D. Kancs. 2018. “Virtual relationships: Short- and long-run evidence from Bitcoin and altcoin markets”. *Journal of International Financial Markets, Institutions & Money* 52, 173-195.

Demir, E., G. Gozgor, C.K.M. Lau, and S.A. Vigne. 2018. “Does economic policy uncertainty predict the Bitcoin returns? An empirical investigation”. *Finance Research Letters* 26, 145-149.

El Alaoui, M., E. Bouri, and D. Roubaud. 2018. “Bitcoin price–volume: A multifractal cross-correlation approach”. *Finance Research Letters (in press)*, https://doi.org/10.1016/j.frl.2018.12.011

Gandal, N., and H. Halaburda. 2016. “Can We Predict the Winner in a Market with Network Effects? Competition in Cryptocurrency Market”. *Games* 7, 1-21.

Ji, Q., E. Bouri, C.K.M. Lau, and D. Roubaud. 2019. “Dynamic connectedness and integration in cryptocurrency markets”. *International Review of Financial Analysis* 63, 257-272. https://doi.org/10.1016/j.irfa.2018.12.002

Johansen, S. 1988. “Statistical Analysis for Cointegration Vectors.” *Journal of Economic Dynamics and Control* 12, 231–254.

Kim, T. 2017. “On the transaction cost of Bitcoin”. *Finance Research Letters*, 23, 300–305. http://doi.org/10.1016/J.FRL.2017.07.014

Kristoufek, L. 2013. “BitCoin meets Google Trends and Wikipedia: Quantifying the relationship between phenomena of the Internet era”. *Scientific Reports* volume 3, Article number: 3415 doi:10.1038/srep03415

Lutkepohl, H., P. Saikkonen, and C. Trenkler. 2001. “Maximum eigenvalue versus trace tests for the cointegrating rank of a VAR process”. *The Econometrics Journal* 4, 287-310.

Nadarajah, S., and J. Chu. 2017. “On the inefficiency of Bitcoin”. *Economics Letters* 150, 6-9.

Nguyena, T.V.H., B. T. Nguyen, T. C. Nguyen, and Q. Q. Nguyen. 2019. “Bitcoin return: Impacts from the introduction of new altcoins”. *Research in International Business and Finance* 48, 420-425.

Osterrieder, J., J. Lorenz, and M. Strika. 2017. “Bitcoin and cryptocurrencies – not for the faint-hearted”. *International Finance and Banking* 4, 56-94.

Panagiotidis, T., T. Stengos, and O. Vravosinos. 2018. “On the determinants of Bitcoin returns: A LASSO approach”. *Finance Research Letters*, *(in press)* https://doi.org/10.1016/j.frl.2018.03.016

Pesaran, M. H., Y. Shin, and R.J. Smith. 2001. “Bounds testing approaches to the analysis of level relationships”. *Journal of Applied Economics* 16, 289–326.

Urquhart, A. 2016. “The inefficiency of Bitcoin”. *Economics Letters* 148, 80-82.

Urquhart, A. 2018. “What causes the attention of Bitcoin?”. *Economics Letters* 166, 40-44.

Wijk, D. V. 2013. “What can be expected from the BitCoin?” *Working Paper* No. 345986. Rotterdam: Erasmus, Rotterdam Universiteit.

Appendix

Table 7 : Descriptive Statistics

		Obs.	Mean	Median	Std. Dev.	Skewness	Kurtosis
ETH		149	199.27	13.05	297.23	1.66	5.22
XRP		149	0.22	0.01	0.41	3.02	14.51
Argentina	**TDG**	149	62.23	46.66	47.62	1.08	3.48
	BKG	149	46.63	46.69	1.47	-0.08	1.94
Brazil	**TDG**	149	88.55	73.21	57.03	3.86	26.71
	BKG	149	52.80	52.33	1.67	0.40	1.61
Chile	**TDG**	149	26.35	21.86	16.25	2.421	12.21
	BKG	149	52.15	52.21	0.69	-0.36	2.25
Colombia	**TDG**	149	113.56	106.16	72.95	0.62	2.68
	BKG	149	30.51	31.29	1.51	-0.47	1.60
Dominican Republic	**TDG**	118	7.55	8.51	5.19	0.61	3.34
	BKG	149	20.31	20.00	2.08	0.39	1.91
India	**TDG**	149	231.72	226.46	111.39	1.72	8.39
	BKG	149	22.48	21.90	1.80	0.60	1.94
Indonesia	**TDG**	140	4.14	1.47	7.07	3.26	14.56
	BKG	149	26.57	27.10	1.75	-0.51	1.77
Iran	**TDG**	139	17.32	7.55	27.71	4.74	35.90
	BKG	149	49.84	50.97	8.42	0.11	2.16
Kenya	**TDG**	149	66.69	63.20	30.10	0.80	3.31
	BKG	149	34.34	35.18	1.93	-0.67	1.89
Malaysia	**TDG**	149	182.94	157.50	111.52	2.51	10.29
	BKG	149	45.13	45.61	1.47	-0.74	2.27
Mexico	**TDG**	149	83.24	84.40	43.26	0.70	3.50
	BKG	149	27.23	27.19	0.92	0.27	1.99
Morocco	**TDG**	123	16.78	13.69	13.79	1.66	6.86
	BKG	149	23.092	23.29	1.23	-0.48	1.95
Nigeria	**TDG**	147	456.07	406.73	458.49	0.68	2.36
	BKG	149	34.68	34.82	0.74	-0.13	1.68
Pakistan	**TDG**	149	73.63	71.41	38.56	4.72	43.10
	BKG	149	3.97	3.95	0.50	0.02	2.02
Peru	**TDG**	149	27.57	23.22	18.01	1.72	6.17
	BKG	149	21.00	20.92	0.76	0.11	1.64
Philippines	**TDG**	149	48.11	37.75	40.12	2.57	14.09

	BKG	149	22.13	22.34	0.72	-0.37	1.71
Singapore	**TDG**	149	41.30	35.85	24.52	2.43	12.09
	BKG	149	88.56	88.18	0.94	0.36	1.59
South Africa	**TDG**	149	588.96	309.61	531.73	1.04	3.05
	BKG	149	52.18	52.22	0.97	-0.14	1.71
Tanzania	**TDG**	135	3.08	2.38	2.94	1.85	8.14
	BKG	149	10.63	10.40	1.00	0.24	1.53
Thailand	**TDG**	149	211.75	200.47	111.69	0.63	3.15
	BKG	149	40.41	40.11	3.96	0.56	2.52
Venezuela	**TDG**	149	265.73	266.81	188.78	0.36	2.29
	BKG	149	38.46	38.22	1.67	0.60	2.80