Impact of Public Information Arrivals on Cryptocurrency Market: A Case of Twitter Posts on Ripple

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Public information arrivals and their immediate incorporation in asset price is a key component of semi-strong form of the Efficient Market Hypothesis. In this study, we explore the impact of public information arrivals on cryptocurrency market via Twitter posts. The empirical analysis was conducted through various methods including Kapetanios unit root test, Maki cointegration analysis and Markov regime switching regression analysis. Results indicate that while in bull market positive public information arrivals have a positive influence on Ripple's value; in bear market, however, even if the company releases good news, it does not divert out the Ripple from downward trend.

Keywords: Cryptocurrency, Public Information Arrivals, Semi-Strong Efficiency,
              Ripple, Twitter Posts
JEL Classification: G14, G15, G40, G41

I. INTRODUCTION

Compared to past, social media has completely changed the speed and the way of sharing information. Today, information is rapidly shaping our expectations, plans and life. From finance point of view as well, fast and easy access to information and lower cost of information has increased its impact and engagement on our investment decisions. Therefore, firms also use social media tools often to reach and maybe manage the information-based perceptions as much as individuals do. This new fact gives us chance to examine the impact of information shared on these platforms on asset price.

Cryptocurrency market is very convenient environment to check the influence of public information arrival (PIA). Unlike capital markets where trade is open only for limited time slots per day, cryptocurrency market remains open for trade round the clock, and once new information arrives it is incorporated without waiting for the

trading hours. In this study, we test the semi-strong form of Efficient Market Hypothesis (EMH) or in other words, the impact of PIA on cryptocurrency market through Markov regime switching regression analysis. In a semi-strong efficient market, besides the historical asset price information, current asset price also reflects the publicly available information thus making it impossible for an investor to beat the market with new public information. In this context, test of semi-strong form efficiency can be modeled through event studies in which response of asset price to news announcements is examined. In this regard, we use information posted by the company on Twitter platform to test the impact of news announcements on the asset price. Here it should be noted that as we use the information released by the company on social media, the information essentially is a positive information (see Appendix 1). The research in this field is limited, and this study is an attempt to explore the relationship between PIA and asset price and provide evidence, in support or otherwise to this relationship.

Since the seminal paper of Fama (1970), EMH has been analyzed in detail through various methods. The EMH can be classified under three types of efficiency levels: weak form, semi-strong form and strong form. As discussed in Grossman and Stiglitz (1980), in a perfectly efficient market, there is no reason to trade because obtained information cannot generate abnormal returns since the prices already incorporate this information. Testing of market efficiency is mostly examined for the weak form of EMH, which states that past prices and their patterns are not useful for future price predictions and historical price information cannot generate abnormal returns. As discussed by Fama (1970), in a weak form of EMH asset prices move randomly and the successive price changes (or returns) are independent and identically distributed. This assumption, in fact, forms the basis for random walk hypothesis.

$$f(R_{j,t+1}|\Phi_t) = f(R_{j,t+1}) \tag{1}$$

Equation (1) depicts that conditional and marginal probability distribution of an independent random variable is identical. This approach gives an opportunity and ability to measure the level of efficiency in any asset. By assuming the expected return in security j is constant over time, we can arrive at the following expression:

$$E(\tilde{R}_{j,t+1}|\Phi_t) = E(\tilde{R}_{j,t+1}). \tag{2}$$

Equation (2) states that the mean in the distribution of $R_{j,t+1}$ is not dependent on the information existing at t, Φ_t. Therefore, the examination of stochastic process generating returns would enable an analysis of efficiency of the respective asset price. Based on this approach, current literature mostly examines the departures from random walk, which is the weak form of EMH, through non-parametric (R/S), semi-parametric (GPH) and parametric methods (ARFIMA). However, the test of semi-strong form of efficiency is based on event studies and empirical models are formed to test the reflection of PIA on asset price. In a semi-strong market, the incorporation of the news in asset price is immediate. Therefore, news announcements are the most important determinant in price innovations. As discussed by Soultanaeva (2008), when news announcements affect the investor's expectations, they rollover and consequently prices are corrected accordingly in the market. Because, adjusted expectations are immediately reflected in equilibrium asset prices.

II. LITERATURE REVIEW

As we discussed in introduction, incorporated information is the key determinant of market efficiency. Studies, which test the EMH, however, are mostly based on the correlation-based analysis that use Hurst exponent and its derivatives to examine weak form of efficiency. Mandelbrot's (1972) R/S test and other models (such as DFA of Peng et al., 1994; GPH of Geweke and Porter-Hudak, 1983) are widely used in literature for different financial instruments.

On the other hand, a good amount of research, which explore the influence of PIA, is available in the literature. In one of the early studies, Friedman et al. (1984) use future market as information provider proxy and find that the spot market gives signals that assets evolve towards strong form informational efficiency regardless whether future market exist or not. In a different study, French and Roll (1986) report that PIA have a very fast incorporation in price and do not allow anyone to take the advantage on this information in trading. In one of the seminal papers, Berry and Howe (1994) develop a proxy measure for public information and investigate the impact of this news on stock market. According to their findings, while public information has an influence on trading volume it is not associated with the price volatility. In a similar study, Mitchell and Mulherin (1994) explore the link between number of news announcements and trading volume and stock returns. Although they found a significant relationship between the two, authors state that news announcements cannot account for the day-

of-the-week seasonality in market activity. Engle et al. (2011) use more than three million firm specific news to examine the impact on stock price. Results show that while asset price incorporates the public information contemporaneously, for private information it takes longer time. Byström (2016) examine stock market volatility and news volume relationship by using Google News and conclude that these two variables are strongly related in both English and Chinese. Soultanaeva (2008) investigate the similar linkage in Baltic state stock markets and state that there is a weak relationship between political risks and stock market volatility in countries analyzed. Todorova and Souček (2014) show that overnight information flow leads better out-of-sample results in Australian stock market. Jiang et al. (2011) employ a simple regime-switching model to explain informed state in Treasury market. They show that intraday patterns of probability of informed estimation display meaningful results in accordance with scheduled arrival of public information and probability of informed estimates have very high correlation with public information shocks. Malinowska (2010) explores the price adjustment process against the PIA, and states that prices slowly respond to public information arrivals and good news is followed by positive returns. Yin and Zhao (2013) investigate the dynamic relation between information based trading and daily risk-returns. Results show that rather than the systematic risk, PIA are closely associated with unsystematic risk. Unlike the studies so far discussed, Herath and Maier (2015) examine the informational efficiency in real estate market and reach mixed results. Ranaldo (2008) depicts that type of news bulletin is important in the influence of PIA on price discovery, liquidity position and transaction-cost. He also states that even if the market expose to some extreme news, limit order traders still keep market liquid. Clements et al. (2015) develop a model for volatility and impact of PIA and find that while overnight news provide better in-sample fit, forecast accuracy remain inferior. Hautsch et al. (2011) analyze the impact of macroeconomic news on volatility and quote adjustments. According to their findings news have a positive effect on conditional variance components.

There is also a great deal of interest in literature regarding the impact of PIA on foreign exchange rates. Neely (2011) investigates the influence of macroeconomic announcements on foreign exchange volatility. Results shows that US based news cause more volatility than foreign news. In a similar paper, Cai et al. (2001) discuss the conditional variance characterization of dollar-yen currency rate in 1998 through high frequency data and shows that while news in fundamentals are significant on volatility, order flow has more important effect on it. Likewise, Chang and Taylor

(2003) examine the link between DEM/$ volatility and news announcements by classifying the news under different categories. Results demonstrate that triggered jumps in volatility by PIA are extended by traders approximately 15 minutes. Eddelbüttel and McCurdy (1998) also exhibits the linkage between PIA and conditional variance of DEM/$. According to authors during the periods of statements of market participants spot exchange rates display higher fluctuations. Frömmel et al. (2008) use order flow and public news as a proxy of private information and public information respectively, to explain exchange rate volatility. Results show that size of the order flows matter in the accounting for fluctuations. Melvin and Yin (2000) examine the volatility reaction of DEM/$ and Yen/$ by using Reuters Market Headline News. According to the results, higher than normal public information causes more than the normal quoting activity and fluctuation in currency rates. For the influence of macroeconomic variables on $/€ volatility, Laakkonen (2007) uses Flexible Fourier Form method. The author concludes that conflicting news and bad news have greater impact on volatility. Unlike other studies, Chaboud et al. (2004) use Electronic Broking Service database to explore the effect of US macroeconomic data release on foreign exchange rates and volumes. Authors state that conditional mean of exchange rates respond to data release very quick. As for the volume, it is seen that public information release increment in volume. In one of the recent papers, Kim et al. (2014) inspect the influence of scheduled and unscheduled information arrivals on conditional volatility and volume of USD/AUD. They conclude that data releases before and after Australian business hours, which is mostly related to the offshore money market news, dominates volatility of this exchange rate.

Corresponding to increasing interest in cryptocurrency in media, there has been a great deal of interest in literature as well. The most recent studies can be summarized as follows: to study its future evaluations Cocco et al. (2017) present an agent-based artificial cryptocurrency market, which includes random traders and chartists. Valstad and Vagstad (2014) measure the risk of Bitcoin and traditional assets (Gold and Euro/USD exchange rate) through volatility modeling. They state that Bitcoin is far more risky than other two assets. Gandal and Hałaburda (2014) investigate impact of network effects in cryptocurrency market and state that without arbitrage opportunities multiple exchanges can coexist in equilibrium. Jahani et al. (2018) state that succeeds in the cryptocurrency ecosystem depends on information availability and higher level of technical innovation availability for these currencies. Stråle Johansson and Tjernström (2014) conclude that information demand is a significant variable with a

positive impact on Bitcoin volatility. Corbet et al. (2017) depicts that monetary policy decisions taken by FED on interest rates has a significant impact on the volatility of Bitcoin. In a similar paper Eross et al. (2017) report that volume, bid-ask spread and volatility are main intraday dynamics of Bitcoin.

III. METHODOLOGY

As discussed by Krolzig (1998), Markov regime switching vector autoregressive model (MRS-VAR) is one of the members of models which characterize a non-linear data generating process and derived from basic finite order vector autoregressive model (VAR) model. For a given time series vector y_t, VAR (p) can be shown as below:

$$y_t = v + \beta_1 y_{t-1} + \beta_p y_{t-p} + u_t \tag{3}$$

If y_t is has regime shifts the model given above might not be the precise VAR model. By considering the regime shifts, the appropriate model estimation can be conducted under MRS-VAR model. Since in the new case data generating process of y_t depends on unobservable regime variable s_t, the most general form of m regime MRS-VAR model can be written as below:

$$y_t = \begin{cases} v_1 + \beta_{11} y_{t-1} + \cdots + \beta_{p1} y_{t-p} + \Sigma_1^{1/2} u_t, & if \ s_t = 1 \\ \quad\quad\quad\quad\quad\quad . \\ \quad\quad\quad\quad\quad\quad . \\ \quad\quad\quad\quad\quad\quad . \\ v_m + \beta_{1m} y_{t-1} + \cdots + \beta_{pm} y_{t-p} + \Sigma_m^{1/2} u_t, & if \ s_t = m, \end{cases} \tag{4}$$

where $u_t \sim NID(0, I_K)$.

Likewise, as explained by Kim et al. (2008), for the time series y_t, Gaussian regime-switching regression model can be shown as below:

$$y_t = x_t' \beta_{s_t} + \sigma_{s_t} u_t \tag{5}$$

where, $u_t \sim i.i.d$ N(0,1) and y_t is scalar. As for x_t, it is a $(k \times 1)$ vector of the explanatory variables. As discussed above s_t is the regime variable and for number of the regimes, N, $i = 1, 2, ..., N$. The regime variable s_t is unobserved and follow a first-order Markov chain with the given transition probabilities below:

$$P(s_t = i | s_{t-1} = j, z_t) = P_{ij}(z_t) \tag{6}$$

IV. EMPIRICAL ANALYSIS

In empirical analysis of the paper we analyze if new and relevant information in cryptocurrency market is capitalized as described by EMH. Variables used in this study are the logarithmic prices of following cryptocurrency: Bitcoin, Ethereum, Litecoin and Ripple. Selection of the variables is based on the highest market capitalization criteria as of Jan 14, 2018. The period we analyze is between Aug 07, 2015 and Jan 13, 2018. The data on closing prices with daily frequency has been obtained from www.coinmarketcap.com. Modeling framework of the econometrical discussions covers various unit root tests, Maki cointegration analysis and Markov regime switching regression analysis. Empirical models have been executed through E-views, Matlab and Gauss softwares. In econometrical analysis, first we model the long-term relationship between Bitcoin and other cryptocurrencies, if any, and in case this relationship exists then we filter the effect of Bitcoin on respective cryptocurrency through FMOLS model to attain a pure series which has innovations driven by other variables in the market including PIA. Finally, we investigate whether new information has a significant effect on cryptocurrency value under different regimes, bull and bear periods. For the news effect, we assign a dummy variable, which represents the Twitter posts of the company and takes the value of 1 in posting day and 0 for other days. As can be seen in Appendix 1, Twitter posts can be classified as good news in terms of public information arrivals. Therefore, in fact, the analyzed PIA is a positive PIA about the company. Behavior of variables can be seen in Figure 1.

Having I(1) series, that is stationary in first difference, is a preliminary requirement in cointegration analysis to examine the long-term relationship. As discussed by Brooks (2014) financial time series are mostly non-stationary, that is, have unit root, I(1). However, residual of linear combination of these variables might be I(0) meaning that the set of these series forms a stationary equilibrium, that is cointegrated and move together in long run even if they deviate from each other in short run. In order to check

the level of stationarity of our variables, we implement three different unit root tests, which are conventional methods and a relatively new approach which takes structural breaks into account. Results are presented in Table 1.

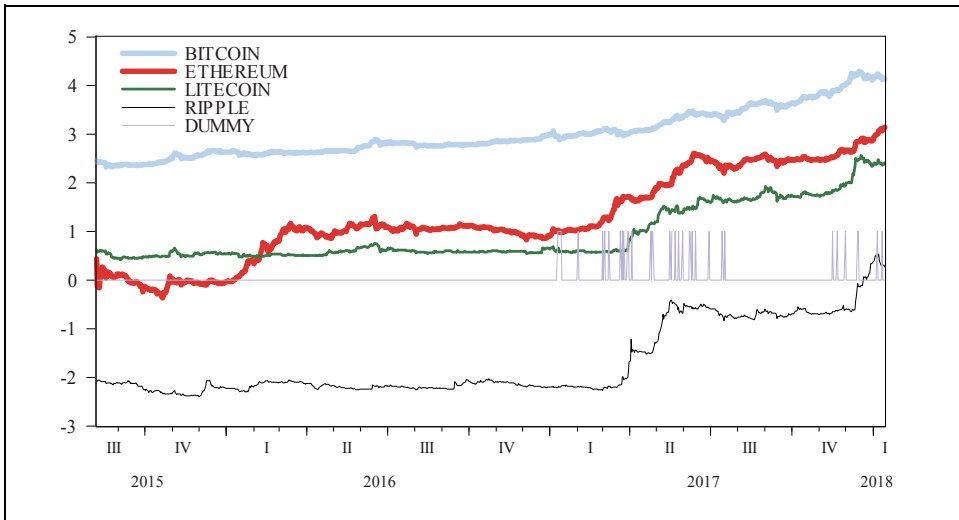Figure 1. Log-price of Variables and Dummy Variable for Ripple

Table 1. Kapetanios (2005) Structural Break Unit Root Test

	Bitcoin	Ethereum	Litecoin	Ripple
	-6.9091	-6.2815	-8.1074	-6.5521
	158	76	261	117
Kapetanios	359	163	318	404
	517	315	601	549
	763	580	763	600
	841	650	840	801
KPSS Test	3.4022	3.2633	2.8993	2.8190
	[0.4630]	[0.4630]	[0.4630]	[0.4630]
ADF Test	1.4770	0.7740	1.6376	1.2877
	[-2.8646]	[-2.8646]	[-2.8646]	[-2.8646]

Critical value of Kapetanios test is – 7.39 at 99% confidence level.

As results indicate, except for Litecoin, all variables are stationary in first difference, I(1), meaning that they might have a long-run relationship if residuals of their linear combinations are stationary. That is why we investigate this likely long-run equilibrium relationship through Maki (2012) cointegration analysis as shown below, which allows

unknown number of breaks with a comparatively low computational burden. By following the original study of Maki (2012), we estimate four different models, which are Level Shift, Level Shift with Trend, Regime Shifts and finally Regime Shifts with Trend. The model is quite robust and residual-based model and assumes that the unspecified number of breaks in equilibrium relationship is less than or equal to the maximum number of breaks. Results of Maki (2012) cointegration analysis are presented in Table 2.

Table 2. Maki Cointegration Test Results

Model		Model 0: Level Shift	Model 1: Level Shift with Trend	Model 2: Regime Shifts	Model 3: Regime Shifts and Trend
Bitcoin / Ethereum	Test Statistic	-5.6611	-3.2549	-5.6024	-5.2979
	Critical Value	(−5.426)	(−5.699)	(−6.357)	(−7.414)
	Breaks	50	52	63	48
		254	102	113	511
		305	148	267	557
		350	267	539	779
		587	691	587	841
Bitcoin / Ripple	Test Statistic	-6.2869	-6.6961	-6.8024	-7.5482
	Critical Value	(−5.426)	(−5.699)	(−6.357)	(−7.414)
	Breaks	604	604	405	522
		664	658	604	604
		737	709	650	709
		793	773	759	780
		844	818	844	845

Critical values are given in parenthesis.

Findings indicate that under each model we reject the null hypothesis of no cointegration only for Bitcoin and Ripple relationship. For other two variables, the null hypothesis is accepted in Model 1, Model 2 or Model 3. It means that we cannot obtain the cointegration relationship for these two groups of variables. On the other hand, Bitcoin and Ripple has a statistically significant long-run equilibrium relationship at 95% confidence level even in the presence of structural breaks. Following the determination of cointegration between Bitcoin and Ripple, we can state that even if there are departures from the equilibrium model in short-run, these two variables move together in long-run. According to Model 3, breaks are intensifying in the second half of the period we analyze.

Following the detection of long-run equilibrium relationship in the log prices of Bitcoin and Ripple in Table 3, we also present some evidence that return volatility of

these two variables have an interaction. Here in this analysis, first, by running a FIGARCH (1.d.1) model for both variables, we have obtained volatility series of Bitcoin and Ripple and tested the causality for these series. As it is expected, the direction of the causality indicates that fluctuations in Bitcoin returns is the Granger-Cause the return volatility of Ripple at 95% confidence level. The FIGARCH (1.d.1) volatility modeling results can be seen in Appendix 2.

Table 3. Granger Causality for Volatility

Null Hypothesis			Lag Selection Criteria			F statistic
			AIC	SC	HQ	
v_Bitcoin	↛	v_Ripple	-20.66	-20.65	-20.65	2.64935**
			-22.03	-21.99	-22.01	
			-22.11	-22.06	-22.09	
v_Ripple	↛	v_Bitcoin	-22.14*	-22.06*	-22.11*	0.63054
			-22.13	-22.03	-22.09	
			-22.13	-22.01	-22.09	

↛ states the null hypothesis of no Granger causality between two series.
** denotes the significance at 95% confidence level.

In order to be able to identify the effect of Bitcoin price over Ripple price, we ran three models for the estimation of single cointegrating vector: Fully Modified OLS (FMOLS), Canonical Cointegrating Regression (CCR), and Dynamic OLS (DOLS). The purpose to employ these methods is to attain value and sign of the cointegrating regressor, Bitcoin, on the dependent variable, Ripple. Phillips and Hansen (1990) propose FMOLS model for the optimal estimation of cointegrating regressions. In order to explain the serial correlation effects and endogeneity in the regressor, the method modifies the Ordinary Least Square (OLS) method. Dynamic OLS of Saikkonen (1992) and Stock and Watson (1993), and Canonical Cointegrating Regression (CCR) of Park (1992) are closely related to FMOLS model. Results are presented in Table 4.

Table 4. FMOLS, DOLS and CCR Results

	FMOLS	DOLS	CCR
c	-5.9607***	-5.9542***	-5.9609***
	(0.1739)	(0.1755	(0.1742)
Bitcoin	1.4241***	1.4214***	1.4242***
	(0.0571)	(0.0579)	(0.0573)
R^2	0.8258	0.8256	0.8258

*** denotes the significance at 99% confidence level. Standard errors are in parenthesis.

According to the results, the Bitcoin price has a statistically significant effect on Ripple price in the period of study. Under all models, it has seen that changes in Bitcoin positively affect Ripple's price. For a one percent increase (decrease) in Bitcoin yields a 1.4 percent rise (decline) in Ripple price is observed. According to the goodness of fit statistic (R^2), the explanatory power of model is also quite high under each estimation. It means that models fit the data well. The R^2 obtained states that 83% of the changes occurring in the price of Ripple can be explained by the Bitcoin's price information. Residuals of these models, which are the difference between the actual value of Ripple and the value fitted by the models, can be considered as the components of variation that is unexplained by the fitted model. So the residuals of above models might be related to any other parameter in the market such as the determinants of idiosyncratic risk of Ripple. Here in this section, we attempt to explain the character of residuals through the PIA about Ripple. Out of three models, we use only the residuals of FMOLS model as the other two models are also very close to it. Residuals of FMOLS Model and dummy variable for PIA can be seen in Figure 2.

Figure 2: Residuals of FMOLS Model (Left) and Ripple Official Announcements (Right)
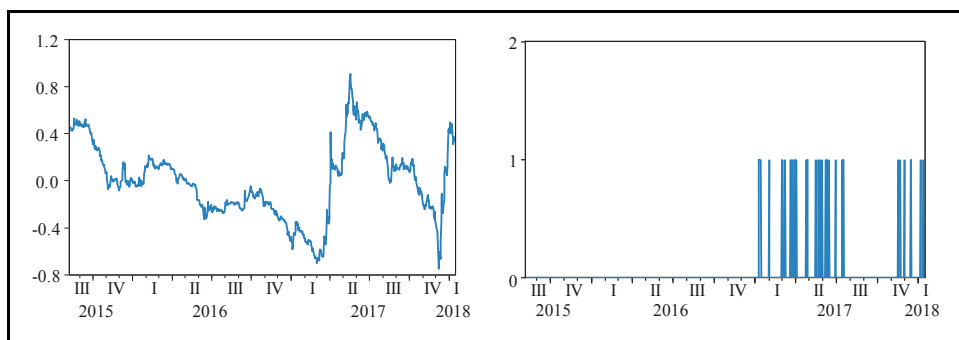
Following the prediction of residuals of FMOLS, we run our final model: Markov regime switching regression analysis. As stated by Kim et al. (2008) financial time series are identified by parameter instability. This feature of financial variables can be modeled in time-varying parameter models such as regime switching regression. Because, these models allow parameters to move discretely between regimes and switching is controlled by an unobserved state variable. In our model, residuals of FMOLS model is taken as the dependent variable and PIA (Ripple's official twitter announcements) is used as the independent variable. Accordingly, the impact of news

announcements on the value of Ripple is examined. As we discussed, the Markov regime switching regression analysis allows us to investigate this influence under different regimes. As can be seen in Table 5, we obtained two different coefficients for the public information arrivals.

Table 5. Markov Regime Switching Regression Results

Regimes	Expected Durations	Transition Probabilities		Variables	Coefficients
Regime 1	161 days	Regime 1	Regime 2	C	-0.0953** (0.0448)
		0.99	0.01	PIA	-0.2877*** (0.0112)
Regime 2	306 days	Regime 1	Regime 2	C	0.2508*** (0.0456)
		0.01	0.99	PIA	0.2019*** (0.0093)

*** and ** denote the significance at 99% and 95% confidence level, respectively.

Results indicate that Regime 1 displays the features of bear market and Regime 2 seems as bull market, where the bull and bear market terms are used to define upward and downward movement of trend of the variables, respectively. The graph presented in Appendix 3 supplements the description of the regimes. According to the coefficients of public information arrivals, while in bull markets PIA significantly and positively influences Ripple price, in bear markets, although the coefficient is significant due to its sign we can say that Twitter announcements cannot divert out the Ripple from downward trend. Most likely, in a bear period, the value of the Ripple is driven by other determinants and its price strongly depends on the main downward trend. Therefore, even if the company announces good news about their cryptocurrency, it cannot provide an alteration to the perception of investors corresponding to the trend. The power governing the market might also be herd psychology, which leads to investors in the market to follow the trend.
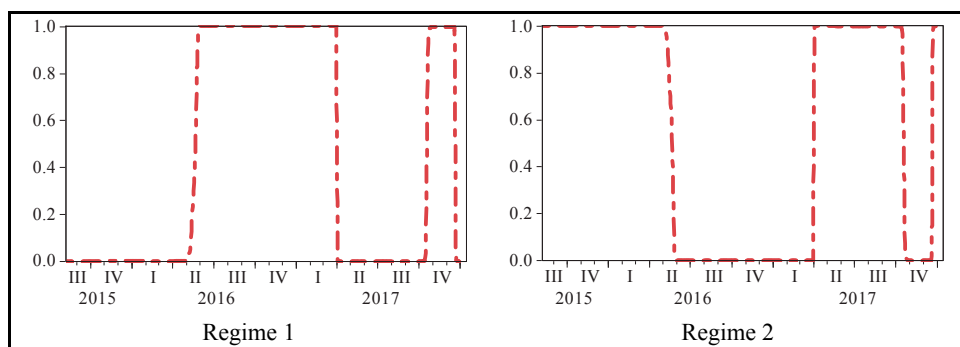
Figure 3. Smoothed Regime Probabilities

Table 4 also presents the expected duration of each regime. According to the results, the bull regime is longer than the bear regime in average duration. It means that market is more likely to remain in the bull regime. Transition probabilities show that each regime is quite persistent. Because, the probabilities to remain in each regime is 99%. The smoothed regime probabilities are presented in Figure 3.

As the cryptocurrency market is quite new, it is obvious that many things have not settled yet and still there is a wild volatility in the market. This high volatility is one of the reasons for the antagonists of cryptocurrency, who protest against any move to substitute fiat money with cryptocurrencies. However, corresponding regulations in this market relevant to information sharing policy would provide more stability, and lowered volatility would convince antagonists to revise their concerns about the long-term stability of cryptocurrency, and its ability to act as a store of value. Our results indicate that since the market is still immature and inefficient, even positive public information arrivals do not divert asset prices out from a bearish trend caused by market turbulence. By means of the required regulations, however, the impact of any event such as insider trading and misleading information (already seen a couple of times in the market) would be minimized and it would bring more stability.

V. CONCLUSION

The most important element of market efficiency is the public information arrivals because the theory states that the asset price incorporates all information in an efficient market. In this study, we explore the effect of news announcements on the value of cryptocurrency. Official Twitter announcements have been used as a proxy for public

information arrivals. Empirical analyses were conducted for four cryptocurrencies: Bitcoin, Ethereum, Litecoin and Ripple to examine their long-term relationship and causality. As unit root test results indicate the stationarity of all variables in the first difference, we examined the possible long-run relationship in those currencies through Maki (2012) cointegration analysis. Results show that only Ripple and Bitcoin are cointegrated under four different models proposed by Maki (2012). Following the determination of cointegrated variables, in order to estimate a single cointegrating vector in this relationship we employed FMOLS, DOLS and CCR models. All the models have exhibited similar results, which indicate that as an independent variable Bitcoin has a statistically significant effect on Ripple with coefficient 1.4. It means that one unit increase in Bitcoin price causes 1.4 unit rise in the value of Ripple, or vice versa. By using official Twitter announcements of Ripple as an independent variable, we attempt to explain the residuals of FMOLS model, which is the unexplained portion in Ripple prices, through Markov regime switching regression analysis. Here, our intention is to see the influence of public information arrival in Ripple price. Results are examined under two regimes: bull and bear markets. According to the findings while in bull market public information arrivals have a positive effect on Ripple, in bear market Twitter announcements of Ripple do not have sufficient power to divert out the Ripple from the downward trend.

APPENDIX 1. TWITTER POSTS OF RIPPLE

Jan 09, 2017	India's Axis Bank to Launch Ripple Payments http://bit.ly/2i9QqaO
Jan 10, 2017	Bitstamp is announcing trading of @Ripple's #XRP today! Full trading is going to be available on January 17 http://bit.ly/XRPTrading .
Jan 11, 2017	Axis Bank Pulls Ripple Into X-Border Payments Efforts (2)The Bitstamp exchange is launching new markets for Ripple's XRP digital asset
Jan 12, 2017	.@Bitstamp, one of the world's leading digital asset exchanges, will launch trading of XRP.
Jan 13, 2017	National Bank of Abu Dhabi: First Middle East Bank to Use Ripple for Cross-Border Payments
Feb 01, 2017	National Bank of Abu Dhabi: First Middle East Bank to Use Ripple for Cross-Border Payments
Mar 01, 2017	Excited to announce 47 banks in Japan are transferring money in real-time on #Ripple – next stop, commercialization!
Mar 03, 2017	"Ripple is lowering the cost of transactions between banks and other financial institutions through its global settlement network." : Harvard Biz Review
Mar 08, 2017	We're happy to see France is bringing banking into the 21st century with #blockchain.
Mar 21, 2017	.@daranda speaks w/ @joymacknight on @TheBanker's TechTalks about how Ripple's DLT will improve cross-border pymnts.
Mar 23, 2017	This week I met banks and regulators in Saudi Arabia, Qatar, UAE - lot of interest in the emerging @Ripple Network as a regional platform!
Mar 25, 2017	Happy to be partnering with @Ripple to launch #XRP support and leverage the transaction scalability of RCL
Mar 29, 2017	For the second time in one month, the SEC has denied a #bitcoin company's request to list and trade the asset.
Mar 30, 2017	Proud to welcome MUFG to Ripple's growing number of customers moving actual money across borders.
Apr 03, 2017	Now over 50 banks in Japan are transferring money in real-time on #Ripple (up from 47 last month!).
Apr 24, 2017	Banks have come together to launch the Japanese Consortium for cross border & domestic payments powered by #Ripple.
Apr 26, 2017	Ripple announces 10 new bank clients; 75+ banks are now using Ripple's ledger. #bankchain! https://yhoo.it/2oJJtR6 @YahooFinance
Apr 27, 2017	.@Akbank is the 1stTurkish bank to adopt #blockchain & model for others who want to make faster cross-border payment :Ten New Customers Join Ripple's Global Payment Network
May 16, 2017	A pleasure to meet with Bank Indonesia about expanding Ripple. Here receiving a gift of raw uncut bills from the Head of Payments
May 18, 2017	#XRP will be listed on these six new exchanges- @bitso, @coinone_info, @bitbank_inc, @Satoshi_Citadel, @QUOINE_SG and @sbigroup.
May 19, 2017	#XRP now paired with EUR, USD, JPY and CAD on @krakenfx.
May 22, 2017	Did you know? Payments with #XRP process in a mere 4 seconds, as opposed to Bitcoin, which can take more than an hour #xrpthestandard
May 26, 2017	We have real customers touching real production systems. We're the only company you can say that about in our space." @bgarlinghouse : Bitcoin rival Ripple is suddenly sitting on many billions of dollars worth of currency

APPENDIX 1. Continued

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May 30, 2017	"The top five biggest currencies—Ethereum, Ripple, Litecoin, Dash, and Monero—now account for 20 percent of the market." #xrpthestandard
Jun 07, 2017	#XRP is now one of 4 cryptocurrencies in investor Tim Enneking's blue chips asset category.
Jun 08, 2017	#GPSG convened in Tokyo this week to discuss the Ripple Network Rulebook, joined by the Japan Bank Consortium to explore network expansion.
Jun 10, 2017	Last month we announced 10 more customers. Interested in who we're working with?: Santander, UniCredit, UBS, ReiseBank, CIBC, National Bank of Abu Dhabi (NBAD), and ATB Financial are among the latest banks to adopt Ripple to improve their cross-border payments.
Jun 14, 2017	#Ripple has "advantages over other cryptocurrencies" like speed, certainty of settlement & low cost @FXstreetNews
Jun 29, 2017	Did you know? @Ripple #xrp processes more transactions than #bitcoin and #ethereum combined - at 1/100th the cost per tx. #UnderstandTheTech
Jul 14, 2017	#XRP Ledger reaching new heights
Jul 17, 2017	The #XRP Ledger ecosystem has expanded to 55 validator nodes, an increase of 120% since May
Nov 16, 2017	We're excited to announce @ AmericanExpress joined RippleNet! Instant payments are now live between the US - UK!
Nov 21, 2017	Ripple is growing and with the appointment of @benlawsky as a new board member and @ronxwill as our new CFO, we're on a path to accelerate adoption of blockchain and digital assets in the years ahead.
Nov 30, 2017	Delighted we were shortlisted for the @FT Future of FinTech Impact Award at the #FTBanking Summit. Here's @daranda and @delatinne accepting the trophy from @patrickjenkins_
Dec 14, 2017	The Japan Bank Consortium launched a Ripple pilot with two large Korean banks - the first time money moves from Japan to Korea over RippleNet.(2) SBI Ripple Asia CEO @OKITATakashi appeared on @Nikkei Morning Plus today and demonstrated Japan Bank Consortium's new payments app powered by @Ripple's blockchain technology, which enables real-time payments using a phone number or QR code. #IOV #BlockchainTechnology
Dec 15, 2017	The Japan Bank Consortium and representatives from two major Korean banks come together to launch a new pilot on #RippleNet!
Jan 05, 2018	3 of the top 5 global money transfer companies plan to use XRP in payment flows in 2018. Even more in the pipeline.
Jan 11, 2018	Ripple and MoneyGram test XRP currency transfers --- We're excited to announce our new partnership with

APPENDIX 2. FIGARCH MODEL FOR VARIABLES

	Ripple	Bitcoin
c (μ)	-0.0018**	0.0011***
	(0.0008)	(0.0004)
c (σ^2) $\times 10^4$	0.4737	0.0376
	(0.4611)	(0.0237)
d	0.7551***	0.8036***
	(0.2484)	(0.1085)
α	0.5822	0.2335**
	(0.3983)	(0.0977)
β	0.6918***	0.8074***
	(0.2464)	(0.0621)

APPENDIX 3. REGIME 2 AND LOG PRICE OF RIPPLE

Figure 1. Log-price of Variables and Dummy Variable for Ripple
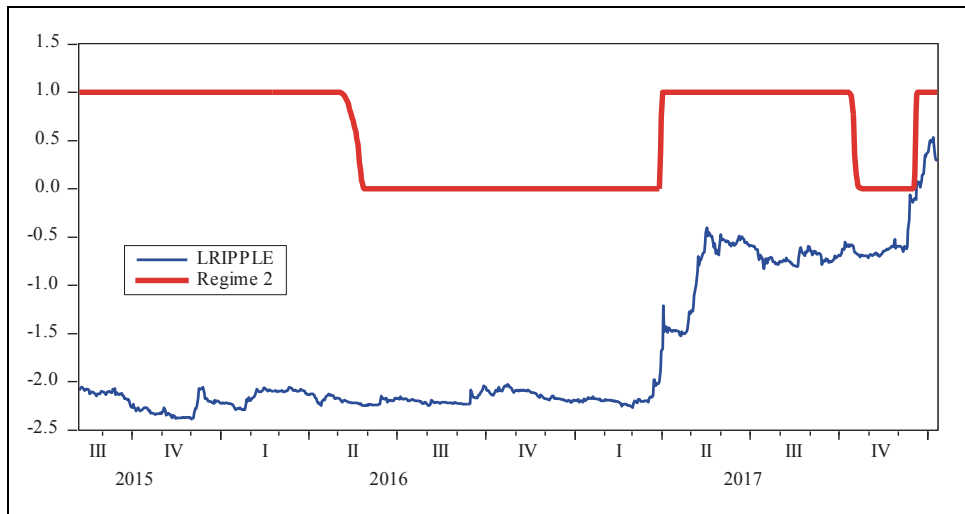
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