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Risk substitution in cryptocurrencies: Evidence from BRICS announcements

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ABSTRACT

We investigate the impact of BRICS regulatory announcements on cryptocurrency volatilities and returns. Results evidence risk substitutions after announcements moving from ETH, XRP and LTC to BTC and vice versa, with BTC having volatility reactions to regulatory announcements that differ from those of other cryptocurrencies. Bootstrap quantile regression indicates a stronger detrimental impact of announcements when BTC is currently manifesting lower volatility and higher daily returns. Robustness checks confirm our findings, as well as evidence that the cryptocurrencies in our sample are considerably more reactive to BRICS announcements than US Fed announcements, suggesting important linkages between emerging markets and cryptocurrencies.

1. Introduction

Since the seminal white paper of Nakamoto (2008), attention toward peer-to-peer electronic transaction systems has grown rapidly. The introduction of Bitcoin challenged the financial system by offering cryptocurrencies as a replacement of legal tender money. Since then, thousands of other cryptocurrencies emerged. As stated by Nakamoto (2008), the objective of cryptocurrencies is to avoid relying on the authority of financial institutions and central banks, while at the same time cutting costs and enhancing safety of transactions and payments. The main tool to achieve such goals is to solve the double-spending problem, through a peer-to-peer distributed blockchain technology, finalized to produce a computational proof of work or stake. All these characteristics encouraged the adoption of cryptocurrencies globally, but at the same time raised concerns about their regulation and risks.

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According to Lyocsa et al. (2020), the main risk of Bitcoin is the absence of a central authority guaranteeing its economic value, as well as the lack of an established methodology to assess its value or to infer future price changes. Therefore, the consensus on cryptocurrencies converges on defining them as speculative assets (e.g., Baur and Dimpfl, 2018; Baur et al., 2018). Nevertheless, despite (or because of) their reputation for being speculative, the literature seeking to identify the determinants of price and volatility movements of cryptocurrencies is rich. These include, but are not limited to, supply and demand forces (Ciaian et al., 2016), the rationale of financial market fundamentals (e.g., Bouoiyour and Selmi, 2015), the irrationality of investors sentiment (Cretarola et al., 2017), social media and investor attention (Li et al., 2021; Shen et al., 2019; Urquhart, 2018), COVID-19 (Conlon and McGee, 2020; Conlon et al., 2020; Goodell and Goutte, 2021a; Goodell and Goutte, 2021b); as well as the regulatory actions-price changes nexus (Auer and Claessens, 2018; Lyocsa et al., 2020).

While cryptocurrencies are often publicly regarded as a homogenous asset class, this view is disputed by several recent papers. For instance Goodell and Goutte (2021b) evidence that Tether behaves very differently from other well-known cryptocurrencies. And so-called 'DeFi tokens' are now being considered by many as a separate asset class (Corbet et al., 2021). In this paper, we contribute to the ongoing interest in the heterogeneity of cryptocurrencies, particularly from the view of investors. We investigate Bitcoin (BTC), Ethereum (ETH), Ripple (XRP) and Litecoin (LTC), in terms of how respective returns and volatility react to Brazilian, Russian, Indian, Chinese, and South African (BRICS) regulatory announcements. Specifically, we study the effect of all publicly available announcements of BRICS regulators with 'neutral' (for instance, defining cryptocurrencies) or 'negative' (for instance, bans or restrictions) connotation from 2015 to 2021.

We focus on leading emerging-market countries since they arguably benefit more from the purposes of cryptocurrencies, coupled with the relatively greater weaknesses of their legal tender and less developed traditional payments and settlement systems. Additionally, BRICS represent one of the largest geopolitical blocks, extending to three continents and with a global increasing economic influence, while relying heavily on the US dollar and international payment systems.[1] Therefore, while exploring the potential of blockchain and cryptocurrencies in reducing BRICS' exposure to foreign currency risks (Aggarwal, 2020), the argument on a common cryptocurrency initiative for BRICS rapidly increased. Finally, BRICS are also especially active in regulating cryptocurrencies (Dulatova and Razak, 2020). BRICS, therefore, are an ideal setting for the purposes of our study.

We selected a subset of cryptocurrencies accordingly to several criterion, including larger market capitalization (largest for BTC, second for ETH, sixth for XRP and thirteenth for LTC at the time of writing[2]), inner differences (the connection with smart contract platforms for ETH, the speed of transactions for XRP and LTC, the connection with traditional payments systems of XRP, not to mention the wide variation of their respective technical bases (Ahelegbey et al., 2021), as well as longer history (dating back to 2009 for BTC, 2011 for LTC, 2012 for XRP and 2015 for ETH). In particular, the longer history allows us to test on all four cryptocurrencies regulatory announcements that were made in 2015–2021.

The effect of macroeconomic news and regulatory announcements on cryptocurrencies has to date been only partially considered (Lyocsa et al., 2020). Additionally, no study either directly focuses on BRICS, or on how announcements spread across cryptocurrencies. According to Bouri et al. (2018), BTC volatility stems from movements in other financial markets, while Corbet et al. (2017) report a strong increase in BTC volatility after announcements. Similarly, Lyocsa et al. (2020) find that both BTC realized variance and its jump components show a similar trend after a broad set of macroeconomic, regulatory and 'hacking' news. Finally, the greater focus on BTC, compared to other cryptocurrencies, does not afford insight into their differences, entailing different responses to events such as regulatory announcements.

We find that the BTC realized volatility increases after both 'neutral' and 'negative' BRICS regulatory announcements. Secondly, the news negatively affecting BTC volatility concomitantly induces an opposite response in other cryptocurrencies, consistent with a 'risk substitution' effect that is unlike the winner-take-all dynamic documented in Gandal and Halaburda (2016). This result is especially strong for ETH and XRP. We also find a stronger increase of BTC volatility at low level of the returns distribution, suggesting that investors seem to wait for (any) news before implementing bigger reactions in relatively quiet periods.

Further, in terms of daily returns, we find negative daily and weekly effects of selected news. While these results corroborate expectations of high sensitivity of cryptocurrencies to regulatory news, we also evidence significant differences in reactions at distinct levels of the return distributions. Results of quantile regression analysis reveal a non-linear impact, evidencing a negative correlation at the 95th percentile.

In summary, we contribute to the literature by empirically showing how BRICS regulatory announcements heterogeneously impact the volatility and returns of differing cryptocurrencies, suggesting a risk substitution effect on volatility. This effect is exploitable by hedging strategies, as long as a similar behavior of returns and an opposed reaction of volatility impacts the risk-return profile of a portfolio of cryptocurrencies. Despite most studies focused on returns, the different impact on volatilities is especially material to investors.

Further, in additional robustness checks, while confirming our findings we also evidence that the cryptocurrencies in our sample are considerably more reactive to BRICS announcements than US Fed announcements, suggesting important linkages between emerging markets and cryptocurrencies.

Finally, since cryptocurrencies' participants, assets, and investments often fall outside regulation, present transparency issues, and seldom operate borderline with country-based laws and supervisors, we explore if, within leading cryptocurrencies, regulatory risk hedging possibilities exist in BRICS countries.

[1] For instance, see https://cointelegraph.com/news/brics-nations-discuss-shared-crypto-to-break-away-from-usd-and-swift

[2] For details, see https://coinmarketcap.com/

Results provide important insights into the nature of cryptocurrencies and important guidance for portfolio management.

The remainder of this paper is organized as follows. Section 2 reviews the literature on macroeconomic news announcements and the models used in this strand of the research. Section 3 shows data sources and our econometric approach. Section 4 describes and discuss the main results. In Section 5 we test the robustness and additional checks of our baseline analysis. Section 6 presents conclusions.

2. Literature review and hypothesis development

The literature on macroeconomic, regulatory, and central banks announcements on asset pricing is rich. It includes, but is not limited to, the stock market perspective (Bernanke and Kuttner, 2005; Bekaert and Engstrom, 2010; Flannery and Protopapadakis, 2015; Naeem and Karim, 2021), the corporate and government bond market (Balduzzi et al., 2001; Beechey and Wright, 2009; Altavilla et al., 2017), as well as commodities (Elder et al., 2012; Chan and Gray, 2018). Faust et al. (2007) investigate co-movements of exchange rates and U.S. foreign term structures post macroeconomic news. They find that strong announcements about economic activity in the U.S. are correlated to short-run appreciation of the dollar. Similarly, Flannery and Protopapadakis (2002) examine the impact of macroeconomic news on stock price returns. By employing a GARCH model on a series of announcements, the authors conclude that CPI, PPI, Monetary Aggregate, Balance of Trade, Employment Report and Housing Starts announcements can be identified as risk factors.

Using high frequency data, Hasan et al. (2021) demonstrate a higher-moment connectedness among Bitcoin, Ethereum and Litecoin, as well as a moderate realized-volatility connectedness for Bitcoin, Litecoin, Ripple and Binance Coin. In a seminal work, Chan and Gray (2018) explore the link between macroeconomic news and jumps in the asset return volatility for commodities. Focusing on the Federal Open Market Committee's (FOMCs) announcements on the target Federal Funds rate, non-farm payroll (NFP), the unemployment rate, and the producer price index (PPI), the authors conclude that all selected news drive volatility jumps. From a bond market perspective, Altavilla et al. (2017), find that macroeconomic news are not strong predictors of variation on bond yields. More precisely, the authors posit that macroeconomic news explain only 10% of the daily variation in bond yields, with a peak of one-third for quarterly bond yields variation.

Nevertheless, insufficient attention has been directed at the role of regulators, central banks and governments on returns and volatility of cryptocurrencies, with most studies focusing on U.S. announcements and just BTC. A notable exception is Corbet et al. (2017) who investigate cryptocurrency reactions to macroeconomic news, finding a different volatility behavior after quantitative easing and monetary policy announcements, especially among minable and non-minable cryptocurrencies. Similarly, Corbet et al. (2018) study the effect of GDP, unemployment, retail sales and durable goods news on BTC returns. Interestingly, they find that announcements related to durable goods and unemployment are statistically significantly correlated with BTC price changes. Surprisingly, announcements on GDP and CPI seem instead uncorrelated.

Changes on BTC price volatility after macroeconomic news support that BTC represents a concrete medium of exchange (Lyocsa et al., 2020). Consistently, recent studies (e.g., Dahir et al., 2018; Arbaa and Varon, 2019) find a nexus between exchange rate fluctuations in the BRICS economies and investments in cryptocurrencies. Zhou (2018) studies the BTC exchange rate movement and its relationship with global financial markets by applying an EGARCH model. Results suggest that macroeconomic fundamentals and BTC-related events statistically significantly explain the exchange rate of the cryptocurrency. Moreover, the author suggests a nexus between regulatory events affecting BTC and market sentiment, especially in explaining its volatility. Finally, the author finds that BTC is a useful hedge during 'quiet' periods, but not when financial market experience stress conditions.

Lyocsa et al. (2020) investigate the impact of macroeconomic, regulation and 'hacking' news on the volatility of BTC. By employing the daily realized volatility and its jump component, authors find that volatility is much higher than that of other assets, as well as highly persistent. Moreover, news about cryptocurrencies impact the volatility of BTC especially a day before the respective publication in globally recognized newspapers (e.g., *Financial Times*). In line with previous research, Auer and Claessens (2018) confirm the detrimental effect of US regulation on cryptocurrencies as a price factor for BTC.

Nevertheless, our paper is theoretically based on two prevalent streams of research in the asset pricing literature: i) one exploring financial markets determinants of cryptocurrency prices, returns and volatility: ii) another focusing on foreign exchange market forces and announcement effects. However, because of the uncertain nature of cryptoassets (partially and simultaneously meeting the definitions of financial assets, commodities, currencies, or intangibles), the lack of a worldwide accepted classification, and its potential increased adoption in emerging markets, we aim at contributing to the literature on the effects of regulatory announcements on cryptocurrencies in BRICS countries. More precisely, based on the theories showing the connection between announcements, macroeconomic news, and asset pricing, we hypothesize a statistically significant role played by BRICS regulatory announcements in explaining BTC, ETH, XRP and LTC volatility and returns.

Therefore, we formulate the following hypotheses:

H1. *BRICS regulatory announcements negatively affect BTC, ETH, XRP and LTC daily realized volatility*.

H2. *BRICS regulatory announcements negatively affect BTC, ETH, XRP and LTC daily returns*.

We also anticipate that the response between our sampled cryptocurrencies, especially in terms of volatility, should differ. Along with distinct market capitalizations and differing investor attention, ETH, XRP and LTC differ from BTC in several aspects, including technical basis (for instance, the lack of mining of XRP), the degree of connectivity with smart contract platforms (ETH) or traditional payments systems (XRP), and the speed of transactions (XRP and LTC).

The economic usefulness of cryptocurrencies is still a debated issue in the literature. From one perspective, there are many studies exploring the efficiency of their markets (see Al-Yahyaee et al., 2018; Cheah et al., 2018), that conclude with warnings on its limited presence and the potential of asset bubbles (see e.g. Corbet et al., 2017).

Others investigate if cryptocurrencies provide diversification benefits (Bariviera, 2017) and find evidence of volatility clustering. However, to what extent regulatory hedging properties exist within the cryptocurrency's universe is still an open question.

Therefore, by combining the efficiency and diversification theoretical frameworks, we propose the following hypothesis:

H3. *The response of returns and volatility to BRICS regulatory announcements is different between BTC and other cryptocurrencies (ETH, XRP and LTC).*

In this vein, we coin the concept of "risk-substitution effect", inheriting this approach directly from the microeconomic substitution-effect theory. In particular, the latter explains the dynamic of consumer preferences switching to less expensive but qualitatively similar alternatives when products prices rise (at the general level, Sato and Koizumi, 1973; on spillover effects in the non-fungible token, decentralised finance tokens and cryptocurrencies, Karim et al., 2021). From our perspective, cryptocurrency investors act similarly, but from a market side, shifting their preferences to cryptocurrencies other than BTC, in the aftermath of regulatory announcements, may negatively affect BTC return and risks.

3. Data and methodology

3.1. Sample selection

We investigate daily volatility and returns of Bitcoin (BTC), Ethereum (ETH), Litecoin (LTC) and Ripple (XRP) and the way they are affected by announcements of BRICS regulatory authorities. We follow the literature (Lyocsa et al., 2020) by obtaining the BTC (BTC/

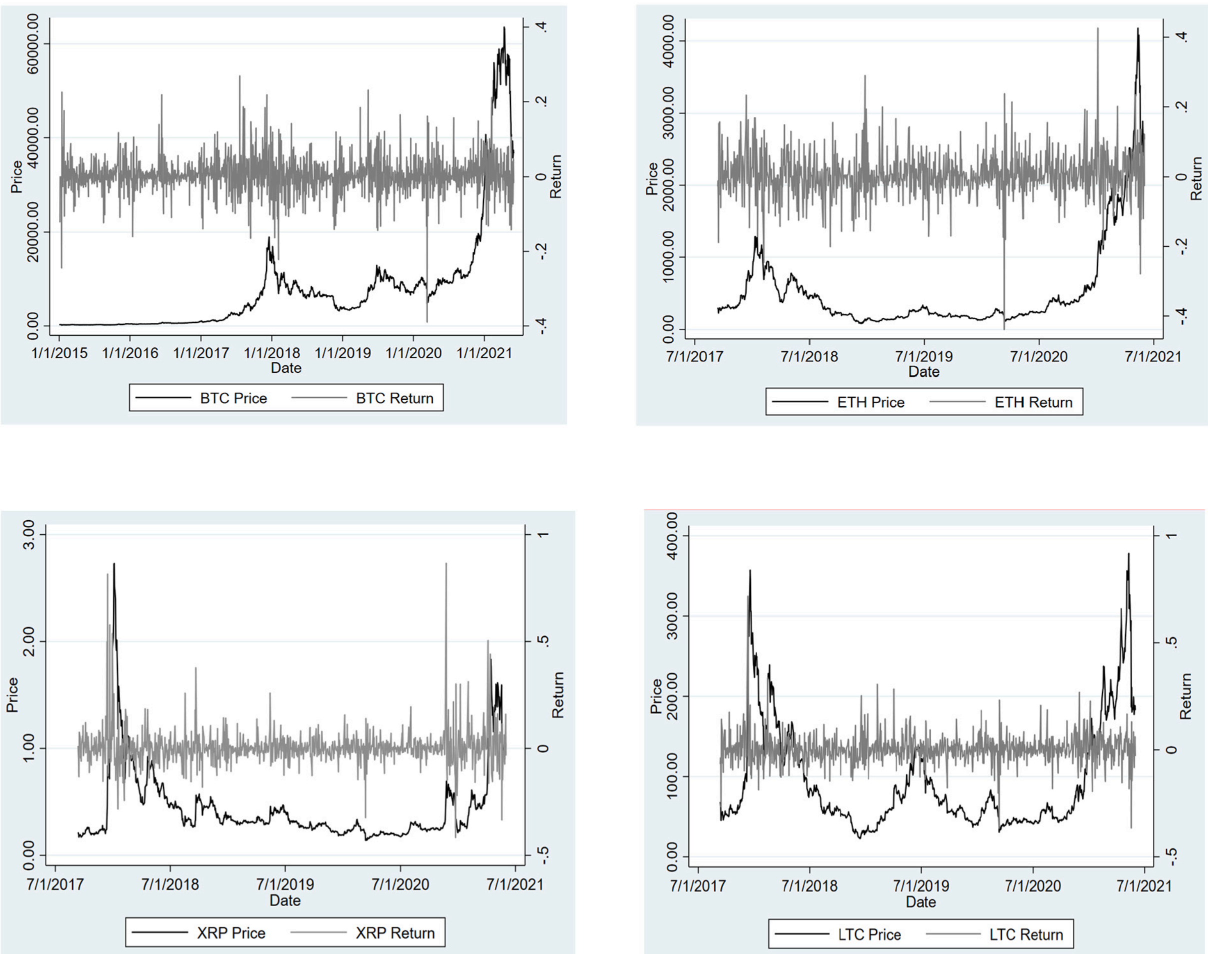

Fig. 1. Prices and returns plot of selected cryptocurrencies.
These figures provide daily prices (left hand scale) and returns (right hand scale) of selected cryptocurrencies from January 2015 to June 2021.

USD), Ethereum (ETH/USD), Litecoin (LTC/USD) and Ripple (XRP/USD) price series volatility collected from the Bitstamp exchange as provided by Thomson Reuters. Benchmarking all cryptocurrencies to the USD allows us to avoid specific BRICS-country currency volatilities and shocks, providing a more accurate measure of the effect of announcements. Specifically, we use all daily data available from January 2015 to June 2021 for the selected cryptocurrencies.

Similarly, we obtain data from macroeconomic indexes (MSCI ACWI, VIX and GOLD), as control variables, directly by Thomson Reuters. And, additionally, we collect all relevant announcements related to cryptocurrencies coming from BRICS countries during the selected period by Bloomberg, Thomson Reuters, and the *Financial Times* (Lyocsa et al., 2020).

Fig. 1 plots price changes (left axis) and daily returns (right axis) of our selected cryptocurrencies. As documented in the existing literature (Lyocsa et al., 2020), BTC prices after an initial period of slow growth, jumped at the end of 2017, in mid-2019, and at the beginning of 2021, while experiencing a more recent downfall. Looking at other cryptocurrencies, price dynamics are different. ETH experienced a first peak slightly later (beginning of 2018) and remained stable until the peak and downfall experienced in the first part of 2021. XRP also achieved a first remarkable peak in early 2018, while the 2021 rally occurred at lower price levels. Finally, LTC shows more similarities than differences with BTC: a peak at the end of 2017, a smaller one in mid-2019, and a 2021 rally of smaller proportions.

3.2. Realized volatility and daily returns

Initially, our investigation involves the use of the daily realized volatility. Specifically, the realized volatility, with pricing data provided by Thomson Reuters, is calculated as the standard realized variance estimator in the following annualized form:

$$RV_t^{(m,s)} = 252 \times \sum_{j=1}^{m} r_{t,j}^{2.}$$

where returns are calculated as follows: $r_{t,j} = 100 \times (P_{t,j} - P_{t,j-1}) / P_{t,j-1}$ is the j^{th} daily return for day t, and m represents the number of daily returns. However, the variance of cryptocurrencies prices assumes extreme values, characterized by prominent levels of kurtosis, and right skewness (Lyocsa et al., 2020; Aalborg et al., 2019). Therefore, we address this issue by taking the natural logarithm of the cryptocurrency's variance. Moreover, we additionally run our model by using the weekly volatility series computed as the weekly mean value of the daily realized volatility (Lyocsa et al., 2020).

$$\mathrm{R_d} = (\mathrm{LnP_d} - \mathrm{LnP_{d-1}})$$

where R_d is the return for day d, and P_d is the price. Again, in the robustness section we rerun the baseline model by calculating the weekly return as the weekly average value of the daily price changes.

Table 1
Event data.

Countries	Event data	Event description	Authority
Brazil	November 16, 2017	Warn of the risks derived from storing and negotiating virtual currencies and reiteration that these currencies are neither issued nor guaranteed by any monetary authority	BACEN
	January 12, 2018	Cryptocurrencies cannot be classified as financial assets for the purposes of the provisions of article 2 (V) of CVM Instruction 555/14, and for this reason its direct acquisition by regulated investment funds is not allowed.	CVM
Russia	May 7, 2019	Publishing a document on cryptocurrency taxes in the country.	SDFRB
	December 1, 2020	Passage of an amendments providing for the recognition of cryptocurrency as an "asset" and set out its taxation accordingly	State DUMA
	February 1, 2018	India Finance Minister states that India does not recognise BTC as legal tender and will instead encourage blockchain technology in payment systems.	Finance Minster
	April 6, 2018	Central Bank Ban on the sale or purchase of cryptocurrency for entities regulated by RBI.	RBI
India	February 17, 2019	Petition has been filed by Internet and Mobile Association of India with the Supreme Court of India challenging the legality of cryptocurrencies and seeking a direction or order restraining their transaction.	Mobile Association of India
	March 4, 2020	The Supreme Court of India passed the verdict, revoking the RBI ban on cryptocurrency trade.	Supreme Court
	February 6, 2021	The government is exploring the creation of a state-backed digital currency issued by the Reserve Bank of India, while banning private ones like bitcoin.	Indian government
	September 4, 2017	Initial Coin Offerings (ICOs) is completely banned.	All government institutions
China	October 14, 2017	Proposal of government digital asset different from BTC.	PBOC
	July 6, 2018	Withdrawn of 88 virtual currency trading platforms from the market.	PBOC
	May 18, 2021	Ban of financial payment institutions from cryptocurrency business.	PBOC
South Africa	May 22, 2018	BTC has been classified as intangible asset.	South African Revenue Service

This table shows the BRICS cryptocurrencies-related selected news during the period of interest (January 2015 – June 2021), a description of the news, and the respective authority.

3.3. BRICS regulatory announcements

BRICS countries are increasingly trying to regulate and scale the use of cryptocurrencies as concrete virtual currencies (Dulatova and Razak, 2020). Literature on the effects of announcements on institutional intervention and volatility of cryptocurrencies is focused on the United States. To fill this gap, we follow Lyocsa et al. (2020) by selecting Bloomberg, Thomson Reuters, and Financial Times publicly available news on BRICS regulatory intervention on cryptocurrencies, synchronized in the UTC time zone.

According to recent studies (Auer and Claessens, 2018), cryptocurrencies are strongly affected by news related to possible regulatory actions and cybercrime events. Therefore, we control for such events in two ways: i) we collect all key dates and times of BRICS regulatory-related news; ii) then we include these in our model as two dummy variables. These are assigned '1' for the respective day and its one-day lag (to capture for potential early knowledge of the news), and for distinguishing the originating country. Specifically, after the collection process, we obtain 14 news items for the period January 2015–June 2021 which may be classified as 'negative' or 'neutral' with reference to cryptocurrencies. More precisely, we classified 'negative' or 'neutral' news all announcements aimed at banning and warning cryptocurrencies use/trading (negative news) or simply classifying their fiscal regime and accountability frameworks (neutral news, as opposed to a previous lack of direct regulation). Table 1 shows the complete list of the analyzed event items.

However, since our focus is on BRICS announcements, it is possible that other confounding factors may affect our results. Therefore, in the robustness check section, we repeat our analysis by including exogenous regulatory announcements (i.e. US), to check if our results are confirmed.

3.4. Methodology

Our empirical strategy is composed of two-steps. Firstly, like previous research (Lyocsa et al., 2020; Zhu et al., 2021; Goodell et al., 2022), we empirically investigate the effect of BRICS regulatory news on volatility and returns of BTC, ETH, LTC and XRP. We do this using the heteroskedasticity and autocorrelation consistent (HAC) variance-covariance matrices robust regression estimator of Newey and West (1987), which addresses serial correlations (Newey and West, 1994).

Thus, we test the following two equations:

1) $Vol_{i,t} = c + \beta_1 Vol_{-1} + \beta_2 BRICS_t + \beta_3 BRICS_{t\text{-}1} + \beta_4 ' X_{i,t} + \varepsilon_{it.}$
2) $Ret_{i,t} = c + \beta_1 BRICS_t + \beta_3 BRICS_{t\text{-}1} + \beta_4 ' X_{i,t} + \varepsilon_{it.}$

where dependent variables are represented by each cryptocurrency (i) daily volatility (*Vol*) and return (*Ret*), respectively, at time t. Vol_{t-1} is the lagged value of volatility for cryptocurrency i at time t-1, included to capture the autoregressive statistical nature of daily cryptocurrency movements (Lyocsa et al., 2020). $BRICS_t$ and $BRICS_{t\text{-}1}$ represent the two dummies on regulatory announcements, at the date of the news (t) and one day earlier (t-1). $X_{i,t}$ is a vector of a macroeconomic indexes: the MSCI ACWI (*MSCI*) daily volatility, the gold volatility (*GOLD*) the VIX volatility (*VIX*) at time t, capturing financial conditions worldwide that are empirically found to be statistically associated to cryptocurrencies price returns and volatility (Lyocsa et al., 2020). Finally, ε represents the error term.

Besides recent findings show the usefulness of four-factor models in explaining cryptocurrencies anomalies (Shahzad et al., 2021a, 2021b), our research question is more focused on the effect of news on their risk and return patterns. Therefore, we argue that by following previous similar contributions (Lyocsa et al., 2020) and using an heteroskedasticity and autocorrelation consistent (HAC) variance-covariance matrices robust regression estimator, as well as by controlling for additional macroeconomic indexes, we adopt a coherent methodological and identification strategy for the purposes of this paper.

Secondly, we are interested in testing if BRICS regulatory announcements affect cryptocurrencies return volatility differently, based on the quantile level of the distribution of the dependent variables. As stated by Baur and Dimpfl (2018), the significance of volatility drivers differs across quantiles of cryptocurrency volatility and return distributions. Specifically, Baur and Dimpfl (2018) emphasize a strong persistence of high-level volatility compared to low-level of volatility. Therefore, we follow previous research (Balcilar et al., 2017) by performing a non-parametric quantile-in-causality approach with bootstrap standard errors, to robustly address this issue. Again, as in Baur and Dimpfl (2018), we use the quantile regression model because of its computational benefits and robustness compared to alternative strategies (i.e. GARCH or realized volatility models), finally providing a more accurate estimation of results.

4. Empirical results

4.1. Sample characteristics

Sample characteristics are graphically represented in Fig. 1, while descriptive statistics are shown in Table 2.

As shown in Table 2, BTC, ETH, XRP and LTC have volatilities of 0.023%, 0.016%, 0.046% and 0.033% respectively. These figures, turned into annualized volatilities (daily values times the square root of 252 trading days of a year), show values of 36.5%, 25.5%, 73%, and 52% respectively. In comparison, volatility proxies for MSCI and gold are lower (0.013% and 0.015%, respectively), with only the VIX achieving higher levels (0.034%), but with a much smaller standard deviation (in the range 0.02%–0.05%, compared to values between 0.17% and 0.37% for cryptocurrencies).

We therefore confirm that cryptocurrency volatilities are on average higher than those of traditional asset classes such as commodities, equities, and foreign exchange rates. As in Bollerslev et al. (2018), the average annualized volatility for commodities is about

Table 2
Descriptive statistics.

Variable	Mean	S.D.	Min.	Max.	Skewness	Kurtosis
BTC_Vol	0.0233	0.1740	−0.2092	0.3194	0.016	1.54
ETH_Vol	0.0168	0.3072	−3.979	0.4401	−5.420	4.81
XRP_Vol	0.0460	0.3713	−2.373	0.9675	−2.671	1.504
LTC_Vol	0.0337	0.2618	−2.249	0.7723	−2.701	2.031
BTC_Ret	0.0039	0.0464	−0.3898	0.2692	−0.078	10.001
ETH_Ret	0.0043	0.0645	−0.4376	0.4263	0.099	8.628
XRP_Ret	0.0047	0.0863	−0.4167	0.8656	2.822	26.64
LTC_Ret	0.0038	0.0712	−0.36707	0.7176	1.424	17.774
MSCI_Vol	0.0130	0.0255	0.1017	0.182	0.880	2.471
GOLD_Vol	0.0151	0.0162	0.1300	0.1794	0.201	1.481
VIX_Vol	0.0336	0.0506	0.2709	0.4468	1.055	2.833

This table illustrates descriptive statistics for daily returns of selected indexes over the period January 2015 – June 2021, as well as for volatility proxies obtained from MSCI, gold and VIX.

25.40%, for equities of 20.60%, and foreign exchange of 10.30%. This corroborates the higher risk profile of cryptocurrencies if compared to other assets (Lyocsa et al., 2020). In terms of daily returns, BTC, ETH, XRP and LTC take the values of 0.0039, 0.0043, 0.0047, and 0.0038 respectively.

To initially measure co-movements across BTC, ETH, XRP, and LTC, we calculate their static and dynamic correlations by estimating pairwise correlation (Table 3, Panel A) and estimating a DCC MGARCH model (Table 3, Panels B and C). The DCC MGARCH model provides an econometric setting that guarantees the positive definiteness of the variance-covariance matrix of the return distribution, thus providing a stronger estimation for conditional correlations (Tse and Tsui, 2002).

We find that the stronger univariate correlation appears between LTC and ETH (0.77), followed by the BTC and ETH (0.73). This is confirmed by the DCC model, showing a dynamic correlation of 0.948 between LTC and ETH and of 0.918 between BTC and ETH.

Looking at the DCC results in Panel C, we find that the higher conditional variance reactions (α) happen in XRP (1.171), followed by ETH (0.796), LTC (0.497) and BTC (0.373). However, as expected, the higher persistence of conditional variance appears to be in BTC, thus reflecting a longer duration of impact news for BTC. Therefore, we confirm previous findings (Wang and Ngene, 2020) about strong daily return connectedness and conditional variance co-movements. However, our research question requires a stronger and more accurate econometric strategy, provided in the following section.

4.2. Newey and west estimator results

Table 4 shows the results of our baseline modeling. Looking at our variables of interest, we find an average positive and statistically

Table 3
Univariate and dynamic correlation.

Panel A: Univariate correlation					
	Index	1	2	3	4
1	BTC_Ret	1			
2	ETH_Ret	0.7301*	1		
3	XRP_Ret	0.4373*	0.5520*	1	
4	LTC_Ret	0.6986*	0.7681*	0.5056*	1
Panel B: DCC MGARCH results					
Index		Corr.			
BTC-ETH		0.918***			
BTC-XRP		0.797***			
BTC-LTC		0.915***			
ETH-XRP		0.852***			
ETH-LTC		0.948***			
XRP-LTC		0.884***			
Adj.					
Lambda1		0.0532***			
Lambda2		0.921***			
Panel C: DCC MGARCH model					
Index	ω		α	β	
BTC_Ret	0.00528**		0.373***	0.615***	
ETH_Ret	0.00387***		0.796***	0.00432	
XRP_Ret	0.00147***		1.171***	0.244***	
LTC_Ret	0.00419***		0.497***	0.0625	

This table reports unconditional correlations, DCC MGARCH, and DCC GARCH models of daily returns between BTC, ETH, XRP and LTC over the period of interest (January 2015–June 2021). The ω, α, and β represent the constant, the ARCH and GARCH term respectively. Significance codes: *** express significance at the 0.999 level, ** at 0.99, * at 0.95.

significant correlation of the BRICS announcements on BTC volatility. Most importantly, since announcements may occur at different hours/days worldwide, we interpret BRICS announcements and their lags as aggregately as an individual announcement (Lyocsa et al., 2020).

We find that, combining current and lagged dummies for each announcement, the volatility effect is positive on BTC for Brazil, Russia, China and South Africa. In contrast, the outcome is negative for all other cryptocurrencies in Brazil, and for ETH in South Africa. The strongest effects arise in South Africa (0.0009), where the news revolved around the classification of most cryptocurrencies as intangibles. In summary, with some nuance, and some instances of insufficient statistical significance, for BTC announcements from most BRICS countries generate an increase in volatility, whereas for other cryptocurrencies in our sample, especially ETH, the result is the opposite.

As in Gandal and Halaburda (2016), cryptocurrencies appear prone to a substitution effect when investors perceive that a portfolio reallocation provides advantages. Our findings corroborate this possible mechanism from a volatility perspective, suggesting that BRICS regulatory announcements affect respective cryptocurrencies differently, especially distinguishing BTC from ETH, XRP and LTC.

Next, we examine returns. Table 5 reports the baseline model applied to returns. As shown in Table 5, results are that, in the case of South Africa, announcements impact negatively the returns of all cryptocurrencies. We do not find any statistically significant relationship for India and China, while Russian announcements produce a positive response on ETH. For Brazil, the outcome is more diverse: positive for all cryptocurrencies except for ETH, where we find a negative response.

Therefore, while our results for volatility document a substitution effect, daily returns are more homogeneously (or sparsely) affected by BRICS regulatory announcements. This latter result is consistent with positive co-movements across cryptocurrency daily returns, consistent with (Auer and Claessens, 2018).[3]

4.3. Quantile regression results

The second step in our empirical strategy involves bootstrap quantile regression, which provides a simultaneous-quantile regression that estimates bootstrapped standard errors of the entire variance–covariance matrix. Specifically, quantile regression allows us to assess if the correlation between BRICS regulatory announcements and cryptocurrency volatility or returns changes at different levels of the respective volatility or return distribution. Results are provided in Table 6.

In Panel A (B), we show the impact of announcements on the 5th, 25th, 50th and 95th percentiles of the BTC and ETH (XRP, LTC) volatility distributions. Interestingly, our results confirm previous findings (Lyocsa et al., 2020), showing a higher detrimental effect of announcements on BTC volatility at lower levels of the volatility distribution.

As with the Newey-West estimation results, the most impacting news are those originating in Brazil and South Africa. Moreover, the coefficient decreases as the level of the BTC volatility distribution increases. We interpret these results by considering any regulatory change announcement as a ‘fear’ signal during quiet (low volatility) times. Therefore, BTC traders appear to be highly concerned about any possible cryptocurrency-related news when the return is experiencing relatively low volatility periods. On the contrary, when BTC is experiencing high daily return changes, the impact of regulatory announcements is significantly less.

Specifically, we find that a negative response of volatilities is present for BTC at the highest percentiles for all BRICS except China. In the case of ETH, the negative relationship occurs initially at the 50th percentile for Brazil and across all percentiles for South Africa. However, India manifests positive coefficients at the 5th and 95th percentiles. For XRP, the negative association is documented at the 50th percentile for both Brazil and South Africa. Finally, for LTC, the negative impact is statistically significant at the 25% percentile for Brazil and China, and from the 50th percentile for South Africa. As in the case of ETH, for LTC the response is positive in India at the 5th percentile.

Looking at the risk substitution effect in the other cryptocurrencies, Table 6 confirms the Newey-West results on the negative effect of announcements on ETH, XRP and LTC volatility. Most importantly, we underline that the negative effect on ETH, XRP and LTC increases at a higher level of volatility distribution. Therefore, the results of the bootstrap quantile regression suggest the possibility for traders and short-term investors of short-term hedging strategies with cryptocurrencies other than BTC after BRICS regulatory announcements.

Table 7 shows the result of the bootstrap quantile regression applied on daily returns, where Panel A is dedicated to BTC and ETH and Panel B to XRP and LTC.

Results show a negative and statistically significant correlation between all BRICS news and BTC returns at the 95th percentile of the distribution. Results are stronger for Brazil (with positive significant coefficients from the 5th to the 50th percentile) and South Africa (with negative coefficients significant since the 25th percentile), intermediate for Russia and India (positive association at the 5th percentile and negative at the 95th) and weaker for China (only negative at the 95th percentile). Altogether, the detrimental effect of BRICS regulatory announcements increases at higher levels of the return distributions.

Considering other cryptocurrencies, the negative association at the highest percentile holds for XRP, and in most countries for ETH (India excluded) and LTC (India and China excluded). A positive association is found for ETH up to the 25th percentile in Brazil, up to the 50th percentile in Russia and only at the 5th percentile in China. For XRP, a positive association is present only in Brazil at the 5th and 25th percentiles. Finally, for LTC Brazil again induced a positive response of returns at the 5th and 25th percentiles, whereas in Russia it remains limited to the 5th percentile.

[3] Goodell and Goutte (2021b) evidence that Tether is an exception to this.

Table 4
Newey-West estimator: cryptocurrencies daily realized volatility.

	BTC_Vol	ETH_Vol	XRP_Vol	LTC_Vol
Variables	(I)	(II)	(III)	(IV)
Dependent var. (−1)	0.999***	0.985***	0.965***	0.929***
	(0.000684)	(0.00733)	(0.0195)	(0.0372)
Brazilian	0.0001	−0.0220***	−0.0312***	−0.0688**
	(0.0001)	(0.00662)	(0.0117)	(0.0272)
Russian	0.000345*	0.00119	0.0112	0.00466
	(0.000206)	(0.000821)	(0.00801)	(0.00516)
Indian	−0.000763	0.000938	0.00399	0.00566
	(0.000595)	(0.00434)	(0.00446)	(0.00562)
Chinese	0.000459	0.0238	−0.00461	−0.0246
	(0.000430)	(0.0197)	(0.00713)	(0.0221)
South African	0.000927***	−0.00420***	0.00126	−0.000468
	(0.000199)	(0.00135)	(0.00324)	(0.00198)
Brazilian (−1)	0.000278***	−0.0223***	−0.0341***	−0.0690**
	(6.45e-05)	(0.00667)	(0.0119)	(0.0277)
Russian (−1)	0.000273	−0.00129	0.00819	0.00674
	(0.000205)	(0.00148)	(0.00623)	(0.00576)
Indian (−1)	−0.00124	0.000724	0.00451	0.00603
	(0.00111)	(0.00422)	(0.00469)	(0.00576)
Chinese (−1)	0.000560**	0.0189	−0.00980	−0.0194
	(0.000281)	(0.0154)	(0.00730)	(0.0183)
South African (−1)	0.000947***	−0.00490***	0.00140	−0.000451
	(0.000204)	(0.00131)	(0.00306)	(0.00171)
MSCI_Vol	0.0810***	−0.141	−0.694	−1.123
	(0.0181)	(0.133)	(0.617)	(0.866)
GOLD_Vol	−0.00393	0.258***	0.342***	0.759**
	(0.00725)	(0.0679)	(0.113)	(0.306)
VIX_Vol	−0.0388***	0.0639	0.312	0.506
	(0.00869)	(0.0627)	(0.289)	(0.409)
Observations	1672	952	1007	964

This table reports the estimates of the Newey-West (1994) model during the period 2015–2021. The dependent variable is the daily realized volatility of BTC (BTC_Vol), ETH (ETH_Vol), XRP (XRP_Vol) and LTC (LTC_Vol). The variables of interest are: the Brazilian, Russian, Indian, Chinese, and South African announcements and their lagged values (see Table 2). Newey-West standard errors (SE) are reported in parentheses. The superscripts ***, **, and * denote coefficients statistically different from zero at the 1%, 5%, and 10% levels, respectively, in two-tailed tests.

We interpret these results again as a 'fear signal' reaction among short-term traders and investors. Specifically, when cryptocurrencies are performing well in terms of daily returns, negative or neutral announcements cause a drop in prices, which results in a pronounced negative return.

Our results confirm previous findings (Lyocsa et al., 2020) and extend the literature on the impact of regulatory announcements of BRICS on financial markets and cryptoassets. Specifically, we find a strong negative impact on BTC volatility and returns, filling the gap on the existing heterogeneity across other cryptocurrencies market profiles. We interpret this result as a "risk-substitution effect", where investors function as consumers shifting their preferences to cryptocurrencies (ETH, XRP and LTC) not immediately affected by regulatory announcements. Most importantly, since this effect seems to appear only on the volatility side, our results shed light on regulatory risk-hedging properties for BRICS investors, during a relatively extended period of analysis that includes the COVID-19 shock. Finally, evidence from our quantile regression indicates consistency with investors' herding behavior in cryptocurrencies (Bouri et al., 2019), showing that the size of the impact of cryptocurrencies news changes according to the specific BTC, ETH, XRP and LTC good or bad performance.

5. Additional tests and robustness checks

In this section, we report results of a set of robustness tests to check the consistency of our results. Firstly, we apply Newey-West testing of our baseline assumptions on weekly (instead of daily) volatility and returns of BTC, ETH, XRP and LTC. This additional testing allows for checking the following issues: i) the persistency of the effects of BRICS regulatory announcements; ii) the consistency of our baseline results in a smaller frequency setting.

As in Aalborg et al. (2019), we compute weekly volatility and returns as the 5-day average of daily volatilities, and then taking its natural logarithm transformation (Lyocsa et al., 2020; Aalborg et al., 2019). Table 8 shows these results, confirming the positive and statistically significant association between BRICS announcements and cryptocurrency return volatility. This relationship shows again a positive response for BTC (except in India), with a negative outcome recorded for ETH in Brazil and for XRP in both Brazil and South Africa. Shifting from daily to weekly data, Table 8 shows the different 'persistence' of BRICS announcements on cryptocurrency volatility. At the same time, Table 8 highlights results consistent with an interpretation of a risk substitution effect, as reflected for daily data in our baseline models.

Table 5
Newey-West estimator: cryptocurrencies daily returns.

	BTC_Ret	ETH_Ret	XRP_Ret	LTC_Ret
Variables	(I)	(II)	(III)	(IV)
Brazilian	0.0710***	−0.0134**	0.0713***	0.0985***
	(0.00241)	(0.00599)	(0.00902)	(0.00899)
Russian	−0.00382	0.00196	−0.0252	−0.00965
	(0.0221)	(0.0422)	(0.0328)	(0.0167)
Indian	0.0276	0.0169	−0.0330	−0.00462
	(0.0489)	(0.0438)	(0.0356)	(0.0426)
Chinese	−0.0340	0.00275	−0.0400	−0.0282
	(0.0299)	(0.00945)	(0.0469)	(0.0623)
South African	−0.0497***	−0.0777***	−0.0554***	−0.0446***
	(0.00234)	(0.00436)	(0.00495)	(0.00449)
Brazilian (−1)	−0.0266***	−0.00317	−0.0267***	−0.0590***
	(0.00236)	(0.00593)	(0.00890)	(0.00889)
Russian (−1)	0.0103	0.0111**	−0.0554	0.00426
	(0.0116)	(0.00492)	(0.0566)	(0.0136)
Indian (−1)	0.00540	−0.00648	0.00523	0.00142
	(0.00877)	(0.0267)	(0.0171)	(0.0241)
Chinese (−1)	−0.0365	−0.0729	−0.107	−0.107
	(0.0340)	(0.0661)	(0.0757)	(0.0829)
South African (−1)	−0.0613***	−0.0976***	−0.0710***	−0.0707***
	(0.00239)	(0.00444)	(0.00504)	(0.00452)
MSCI_Vol	0.373	0.937*	1.106	1.231**
	(0.305)	(0.517)	(0.741)	(0.572)
GOLD_Vol	−0.0542	0.125	0.251	0.221
	(0.0817)	(0.308)	(0.335)	(0.373)
VIX_Vol	−0.176	−0.392	−0.500	−0.582**
	(0.157)	(0.261)	(0.362)	(0.291)
Observations	1672	976	1032	989

This table reports the estimates of the Newey-West (1994) model during the period 2015–2021. The dependent variable is the daily return of BTC (BTC_Ret), ETH (ETH_Ret), XRP (XRP_Ret) and LTC (LTC_Ret). The variables of interest are: the Brazilian, Russian, Indian, Chinese, and South African announcement and their lagged values (see Table 2). Newey-West standard errors (SE) are reported in parentheses. The superscripts ***, **, and * denote coefficients statistically different from zero at the 1%, 5%, and 10% levels, respectively, in two-tailed tests.

Table 9 shows the Newey-West estimator results in the case of returns on a weekly basis. We find statistically significant outcome across all cryptocurrencies for Brazil, China, and South Africa. The South African and Chinese announcements are negatively correlated to all cryptocurrencies, whereas, surprisingly, Brazilian announcements engender a positive correlation. We interpret these results that short-term investors may change their expectations after ‘neutral’ announcements (as in the Brazilian case) compared to ‘negative’ ones (that show more consistency between daily and weekly frequency).

Additionally, we rerun our baseline regressions by using a simpler OLS model. Results are disclosed in Table 10 for volatility and Table 11 for returns. Results are qualitatively similar to our previous findings, which were based on a more elaborate econometric approach. In detail, volatilities are positively impacted for all countries in the case of BTC (except India), whereas a negative association is found in Brazil for other cryptocurrencies. In the case of returns, again Brazil and South Africa provide the strongest statistical significance: a negative association is always present in the latter, whereas the former sees positive coefficients for BTC and XRP and negative ones for ETH and LTC.

Finally, we redo our baseline model by including US most relevant actions and news on cryptocurrencies. We do this to further check the consistency of our findings, considering and comparative results from previous research focusing on this country. Specifically, the selected events include: i) the 20th of May 2020 FED announcement on “taking further steps on cryptocurrencies regulation and development”; ii) the 20th of July 2020 interpretative letter of the OCC on cryptocurrencies; iii) the 13th of February 2018 definition of Initial Coin Offerings (ICOs) as Money Services Businesses (MSBs); and iv) the 1st of January 2018 cryptocurrency taxation requirement. Results are provided in Tables 12 (volatility) and 13 (returns). (See Table 13.)

We find that US news increased only the volatility of BTC, leaving other cryptocurrencies, as well as returns, unaffected. This additional test does not dispute our previous evidence, as volatilities are always impacted positively for BTC (except in India). In contrast to the results of US announcements, Brazilian announcements induced a negative response in all other cryptocurrencies. In terms of returns, South African announcements are negatively correlated with all cryptocurrencies, while Brazilian announcements are positively associated with BTC, XRP and LTC and negatively with ETH. Interestingly, a positive association is found for ETH in the case of Russian announcements.

Taken together, our results are robust under different methodologies and additional tests, consistent with a risk substitution mechanism from ETH, XRP and LTC to BTC daily volatility after BRICS cryptocurrencies-related announcements. Regarding returns, rather than volatilities, we do not identify a similar effect. Results show a homogenous negative effect across all cryptocurrencies, consistent with their widely acknowledged strong co-movement relationship. Moreover, our results corroborate previous research

Table 6
Bootstrapped S.E. quantile regression: cryptocurrencies daily realized volatility.

Panel A: BTC and ETH								
	BTC_Vol				ETH_Vol			
Variables	P0.05	P0.25	P0.5	P0.95	P0.05	P0.25	P0.5	P0.95
Dependent var. (−1)	0.997***	0.999***	1.000***	1.000***	1.017***	1.009***	0.995***	0.833***
	(0.00337)	(0.000172)	(0.000168)	(0.000893)	(0.00335)	(0.00417)	(0.00369)	(0.186)
Brazilian	0.00202***	0.000458***	9.46e-05***	−0.00125***	0.0179***	0.00473	−0.0177***	−0.256
	(0.000225)	(2.82e-05)	(2.43e-05)	(0.000111)	(0.00530)	(0.00612)	(0.00520)	(0.262)
Russian	0.000860	0.000377**	0.000556*	−0.000609**	0.000513	−0.000111	0.000791	−0.00437
	(0.000842)	(0.000172)	(0.000295)	(0.000263)	(0.000613)	(0.00262)	(0.00363)	(0.00410)
Indian	−0.000933	−0.000327	−0.000380	−0.000899**	0.000105	−0.000410	−1.21e-05	0.00462
	(0.00116)	(0.00162)	(0.00103)	(0.000405)	(0.000563)	(0.000806)	(0.00161)	(0.00291)
Chinese	0.00195***	0.000627	0.000276	0.000176	0.000390	−6.87e-05	0.000219	0.0590
	(0.000591)	(0.00103)	(0.000818)	(0.000648)	(0.174)	(0.166)	(0.156)	(0.193)
South African	0.00329***	0.000572***	0.000157***	−0.000486***	−0.000228*	−0.00101***	−0.00165***	−0.00698**
	(0.000782)	(4.82e-05)	(2.49e-05)	(9.39e-05)	(0.000117)	(0.000291)	(0.000391)	(0.00331)
Brazilian (−1)	0.00223***	0.000641***	0.000277***	−0.00105***	0.0174***	0.00411	−0.0185***	−0.259
	(0.000231)	(2.86e-05)	(2.40e-05)	(0.000108)	(0.00533)	(0.00617)	(0.00525)	(0.265)
Russian (−1)	0.000725	0.000377	0.000434*	−0.000692**	0.000531	−9.83e-05	0.000545	−0.00391
	(0.000976)	(0.000230)	(0.000236)	(0.000333)	(0.00338)	(0.00197)	(0.000692)	(0.0162)
Indian (−1)	−0.00353*	−0.000297	−0.000381	−0.000656	0.000471*	−4.68e-05	8.79e-05	0.00555**
	(0.00204)	(0.00272)	(0.00134)	(0.000465)	(0.000281)	(0.00110)	(0.00332)	(0.00280)
Chinese (−1)	0.00233***	0.000900	0.000549	4.66e-05	0.000412	−5.70e-05	0.000214	−0.00673
	(0.000385)	(0.000635)	(0.000420)	(0.000194)	(0.0581)	(0.0569)	(0.0950)	(0.0489)
South African (−1)	0.00332***	0.000574***	0.000157***	−0.000466***	−0.000582***	−0.00137***	−0.00207***	−0.00833*
	(0.000795)	(4.88e-05)	(2.53e-05)	(9.68e-05)	(0.000117)	(0.000280)	(0.000379)	(0.00436)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1672	1672	1672	1672	951	951	951	951
Panel B: XRP and LTC								
	XRP_Vol				LTC_Vol			
Variables	P0.05	P0.25	P0.5	P0.95	P0.05	P0.25	P0.5	P0.95
Dependent var. (−1)	1.007***	1.002***	0.999***	0.905***	1.022***	1.000***	0.996***	0.789***
	(0.00205)	(0.000649)	(0.00117)	(0.0436)	(0.00800)	(0.00317)	(0.00364)	(0.0369)
Brazilian	0.00823***	0.00222***	−0.00190*	−0.117***	0.0169**	−0.00710**	−0.0125***	−0.236***
	(0.00212)	(0.000579)	(0.00112)	(0.0455)	(0.00824)	(0.00319)	(0.00332)	(0.0382)
Russian	0.000291	−4.07e-05	0.00295	0.00746	−3.71e-05	−0.000940	−0.000137	−0.00196
	(0.00820)	(0.00782)	(0.00917)	(0.00721)	(0.000172)	(0.000573)	(0.00120)	(0.00520)
Indian	0.000215	0.000303	0.00114	−0.00202	0.00140*	−4.93e-05	0.000342	−0.00108
	(0.000656)	(0.000913)	(0.000864)	(0.00311)	(0.000782)	(0.00131)	(0.00148)	(0.00409)
Chinese	−4.06e-05	0.000610	0.000215	−0.000945	−0.000549	−0.0223**	−0.000153	−0.00451
	(0.00223)	(0.00166)	(0.0103)	(0.0339)	(0.00531)	(0.0110)	(0.0148)	(0.0858)
South African	0.000258***	3.46e-05	−0.000549***	−0.00845**	0.00102***	0.000114	−0.00115***	−0.0125***
	(5.09e-05)	(8.44e-05)	(7.55e-05)	(0.00378)	(0.000220)	(0.000138)	(0.000273)	(0.00122)
Brazilian (−1)	0.00564***	−0.000364	−0.00450***	−0.120***	0.0179**	−0.00633**	−0.0117***	−0.238***
	(0.00213)	(0.000582)	(0.00112)	(0.0457)	(0.00833)	(0.00323)	(0.00337)	(0.0386)
Russian (−1)	0.000279	−5.46e-05	0.00246	−0.000388	−1.22e-05	−0.000139	0.000503	−0.00221
	(0.00151)	(0.00130)	(0.00370)	(0.00429)	(0.00277)	(0.00223)	(0.00174)	(0.00438)
Indian (−1)	0.000175	0.000299	0.000770	−0.00194	0.00138	2.04e-05	0.000942	0.000264
	(0.00176)	(0.00160)	(0.00188)	(0.00456)	(0.00113)	(0.00168)	(0.00180)	(0.00574)
Chinese (−1)	−0.000121	0.000689	0.000329	−0.00126	0.000671	−0.00515*	−0.000238	−0.00300
	(0.00314)	(0.00213)	(0.00190)	(0.0601)	(0.00563)	(0.00272)	(0.00590)	(0.0839)
South African (−1)	0.000657***	0.000433***	−0.000164**	−0.00839**	0.00159***	0.000603***	−0.000671**	−0.0128***
	(4.96e-05)	(8.23e-05)	(7.50e-05)	(0.00371)	(0.000246)	(0.000142)	(0.000261)	(0.00133)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1007	1007	1007	1007	964	964	964	964

This table reports the estimates of the bootstrap quantile regression model during the period 2015–2021. The dependent variable is the daily realized volatility of BTC (BTC_Vol), ETH (ETH_Vol) (Panel A), XRP (XRP_Vol) and LTC (LTC_Vol) (Panel B) at the 0.05, 0.25, 0.5, and 0.95 percentile levels. The variables of interest are: the Brazilian, Russian, Indian, Chinese, and South African announcement and their lagged values (see Table 2). Bootstrapped standard errors (SE) are reported in parentheses. The superscripts ***, **, and * denote coefficients statistically different from zero at the 1%, 5%, and 10% levels, respectively, in two-tailed tests.

Table 7
Bootstrapped S.E. quantile regression: cryptocurrencies daily returns.

Panel A: BTC and ETH

	BTC_Ret				ETH_Ret			
Variables	P 0.05	P 0.25	P 0.5	P 0.95	P 0.05	P 0.25	P 0.5	P 0.95
Brazilian	0.149***	0.0913***	0.0728***	−0.0151**	0.0995***	0.0201***	−0.00601	−0.137***
	(0.00626)	(0.00282)	(0.00200)	(0.00664)	(0.0197)	(0.00538)	(0.00368)	(0.0168)
Russian	0.0136	−0.0312	0.00736	−0.0482**	0.0316	−0.0358	−0.0286	−0.0230
	(0.0375)	(0.0334)	(0.0255)	(0.0228)	(0.0211)	(0.0382)	(0.0712)	(0.0602)
Indian	−0.0396	−0.00942	−0.00316	0.131	0.0258	0.00314	0.00324	0.107
	(0.0677)	(0.0795)	(0.0788)	(0.0830)	(0.0363)	(0.0336)	(0.0544)	(0.105)
Chinese	−0.0608	−0.000657	−0.0193	−0.0709***	0.0959***	0.0157	0.00910	−0.0667***
	(0.0659)	(0.0620)	(0.0333)	(0.00645)	(0.0164)	(0.0120)	(0.0151)	(0.0184)
South African	0.0226**	−0.0344***	−0.0509***	−0.124***	0.0192	−0.0480***	−0.0748***	−0.196***
	(0.00977)	(0.00219)	(0.00113)	(0.00701)	(0.0132)	(0.00431)	(0.00302)	(0.0122)
Brazilian (−1)	0.0515***	−0.00647**	−0.0249***	−0.112***	0.109***	0.0303***	0.00411	−0.127***
	(0.00611)	(0.00279)	(0.00195)	(0.00655)	(0.0195)	(0.00536)	(0.00365)	(0.0166)
Russian (−1)	0.0605***	0.00253	0.0211	−0.0585***	0.102***	0.0345***	0.0150***	−0.0669***
	(0.0191)	(0.0174)	(0.0156)	(0.0129)	(0.0110)	(0.00453)	(0.00378)	(0.0227)
Indian (−1)	0.0560***	0.0177	0.00208	−0.0491***	0.00709	0.0114	0.00410	−0.0519
	(0.0124)	(0.0123)	(0.0151)	(0.0125)	(0.0498)	(0.0469)	(0.0321)	(0.0448)
Chinese (−1)	−0.0809	−0.0113	−0.0300	−0.0525	−0.199	−0.0255	−0.0516	−0.0814
	(0.0583)	(0.0692)	(0.0639)	(0.0512)	(0.130)	(0.140)	(0.0902)	(0.0699)
South African (−1)	0.0109	−0.0462***	−0.0626***	−0.135***	−0.000909	−0.0679***	−0.0948***	−0.216***
	(0.0100)	(0.00221)	(0.00118)	(0.00713)	(0.0134)	(0.00435)	(0.00308)	(0.0124)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1672	1672	1672	1672	976	976	976	976

Panel B: XRP and LTC

	XRP_Ret				LCT_Ret			
Variables	P 0.05	P 0.25	P 0.5	P 0.95	P 0.05	P 0.25	P 0.5	P 0.95
Brazilian	0.147***	0.111***	0.0729***	−0.0451*	0.131***	0.0880***	0.0388***	−0.0924***
	(0.00486)	(0.00563)	(0.0112)	(0.0245)	(0.00720)	(0.00532)	(0.00764)	(0.0306)
Russian	−0.00965	−0.0122	0.000491	−0.113***	−0.0549	−0.0169	0.00768	−0.117**
	(0.0201)	(0.0275)	(0.0300)	(0.0221)	(0.0539)	(0.0491)	(0.0423)	(0.0460)
Indian	−0.00558	−0.0110	0.0354	0.0160	0.0110	−0.00290	−0.0278	−0.0440
	(0.0651)	(0.0835)	(0.0766)	(0.0519)	(0.0606)	(0.0487)	(0.0415)	(0.0424)
Chinese	0.0362	0.00542	0.00659	−0.0593	0.0298	−0.00430	−0.0233	−0.0813*
	(0.120)	(0.0962)	(0.0854)	(0.0643)	(0.0830)	(0.0748)	(0.0609)	(0.0458)
South African	−0.00827**	−0.0409***	−0.0669***	−0.139***	−0.0191***	−0.0519***	−0.0786***	−0.153***
	(0.00375)	(0.00155)	(0.00438)	(0.0112)	(0.00644)	(0.00380)	(0.00493)	(0.0176)
Brazilian (−1)	−0.0107**	−0.0461***	−0.0845***	−0.202***	0.0326***	−0.0104*	−0.0591***	−0.189***
	(0.00482)	(0.00554)	(0.0110)	(0.0242)	(0.00717)	(0.00529)	(0.00758)	(0.0304)
Russian (−1)	0.0230*	0.00728	−0.00276	−0.0867***	−0.135	0.0122	−0.0105	−0.0985
	(0.0123)	(0.0168)	(0.0183)	(0.0315)	(0.0851)	(0.101)	(0.0682)	(0.0710)
Indian (−1)	0.0198	0.0186	−0.00335	−0.0383	0.0334	0.0235	−0.00161	−0.0915***
	(0.0376)	(0.0243)	(0.0235)	(0.0237)	(0.0285)	(0.0221)	(0.0134)	(0.0248)
Chinese (−1)	−0.0495	−0.0852	−0.0516	−0.0562	−0.0652	−0.109	−0.0264	−0.0977
	(0.116)	(0.122)	(0.0766)	(0.0941)	(0.143)	(0.133)	(0.0960)	(0.0863)
South African (−1)	−0.0345***	−0.0671***	−0.0929***	−0.164***	−0.0351***	−0.0677***	−0.0940***	−0.167***
	(0.00381)	(0.00154)	(0.00449)	(0.0113)	(0.00653)	(0.00385)	(0.00499)	(0.0177)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	989	989	989	989	1032	1032	1032	1032

This table reports the estimates of the bootstrap quantile regression model during the period 2015–2021. The dependent variable is the daily return of BTC (BTC_Ret), ETH (ETH_Ret) (Panel A), XRP (XRP_Ret) and LTC (LTC_Ret) (Panel B) at the 0.05, 0.25, 0.5, and 0.95 percentile levels. The variables of interest are: the Brazilian, Russian, Indian, Chinese, and South African announcement and their lagged values (see Table 2). Bootstrapped standard errors (SE) are reported in parentheses. The superscripts ***, **, and * denote coefficients statistically different from zero at the 1%, 5%, and 10% levels, respectively, in two-tailed tests.

Table 8
Newey-West estimator: cryptocurrencies weekly realized volatility.

	BTC_Vol	ETH_Vol	XRP_Vol	LTC_Vol
Variables	(I)	(II)	(III)	(IV)
Dependent var. (−1)	0.998***	0.961***	0.843***	0.825***
	(0.00123)	(0.0224)	(0.0859)	(0.127)
Brazilian	0.000152*	−0.0489*	−0.00374**	−0.00189
	(8.32e-05)	(0.0254)	(0.00186)	(0.00233)
Russian	0.000172	−0.00158	0.000882	−0.00119
	(0.000323)	(0.00247)	(0.00133)	(0.00143)
Indian	0.000131	0.00131	−0.00171	−0.00152
	(0.000192)	(0.00283)	(0.00112)	(0.00148)
Chinese	0.00138**	0.403	−0.0156	−0.00482
	(0.000657)	(0.324)	(0.0121)	(0.00393)
South African	0.000962***	0.00416	−0.00144*	−0.00132
	(0.000287)	(0.00424)	(0.000813)	(0.000921)
Brazilian (−1)	0.000172**	−0.0491*	−0.00370**	−0.00186
	(8.39e-05)	(0.0255)	(0.00184)	(0.00230)
Russian (−1)	0.00140**	0.0133	−0.0125	0.000620
	(0.000571)	(0.00898)	(0.0106)	(0.00122)
Indian (−1)	−0.00582	0.0101	−0.00137	−0.00198
	(0.00448)	(0.00975)	(0.00110)	(0.00159)
Chinese (−1)	−0.000786	−0.0134	−0.00208	−0.000476
	(0.000816)	(0.0133)	(0.00129)	(0.000875)
South African (−1)	0.000982***	0.00403	−0.00140*	−0.00129
	(0.000293)	(0.00416)	(0.000802)	(0.000892)
Controls	Yes	Yes	Yes	Yes
Observations	1672	976	1032	989

This table reports the estimates of the Newey-West (1994) model during the period 2015–2021. The dependent variable is the weekly realized volatility of BTC (BTC_Vol), ETH (ETH_Vol), XRP (XRP_Vol) and LTC (LTC_Vol). The variables of interest are: the Brazilian, Russian, Indian, Chinese, and South African announcement and their lagged values (see Table 2). Newey-West standard errors (SE) are reported in parentheses. The superscripts ***, **, and * denote coefficients statistically different from zero at the 1%, 5%, and 10% levels, respectively, in two-tailed tests.

Table 9
Newey-West estimator: cryptocurrencies weekly returns.

	BTC_Ret	ETH_Ret	XRP_Ret	LTC_Ret
Variables	(I)	(II)	(III)	(IV)
Brazilian	0.0272***	0.0144***	0.00651	0.0141**
	(0.00175)	(0.00387)	(0.00683)	(0.00617)
Russian	0.00471	0.0216	−0.0228	0.00116
	(0.0260)	(0.0173)	(0.0170)	(0.0145)
Indian	−0.00345	−0.00277	−0.0137	−0.0119
	(0.0149)	(0.0117)	(0.0146)	(0.0180)
Chinese	−0.0125	−0.0149	−0.0259*	−0.0247
	(0.0111)	(0.0145)	(0.0133)	(0.0156)
South African	−0.0200***	−0.0287***	−0.0197***	−0.0235***
	(0.00180)	(0.00314)	(0.00374)	(0.00328)
Brazilian (−1)	0.0274***	0.0146***	0.00678	0.0144**
	(0.00171)	(0.00383)	(0.00674)	(0.00611)
Russian (−1)	0.00551	−0.0126	−0.0196	−0.0147
	(0.0250)	(0.0177)	(0.0156)	(0.0212)
Indian (−1)	0.00150	0.00146	−0.000482	−0.0124
	(0.0164)	(0.0148)	(0.0200)	(0.0179)
Chinese (−1)	−0.0185**	−0.0229**	−0.0325***	−0.0313***
	(0.00884)	(0.0107)	(0.00893)	(0.0121)
South African (−1)	−0.0199***	−0.0285***	−0.0195***	−0.0231***
	(0.00184)	(0.00320)	(0.00380)	(0.00331)
Controls	Yes	Yes	Yes	Yes
Observations	1672	976	1032	989

This table reports the estimates of the Newey-West (1994) model during the period 2015–2021. The dependent variable is the weekly return of BTC (BTC_Ret), ETH (ETH_Ret), XRP (XRP_Ret) and LTC (LTC_Ret). The variables of interest are: the Brazilian, Russian, Indian, Chinese, and South African announcement and their lagged values (see Table 2). Newey-West standard errors (SE) are reported in parentheses. The superscripts ***, **, and * denote coefficients statistically different from zero at the 1%, 5%, and 10% levels, respectively, in two-tailed tests.

Table 10
OLS estimator: cryptocurrencies daily realized volatility.

	BTC_Vol	ETH_Vol	XRP_Vol	LTC_Vol
Variables	(I)	(II)	(III)	(IV)
Dependent var. (−1)	0.999***	0.832***	0.965***	0.929***
	(0.000462)	(0.108)	(0.0192)	(0.0313)
Brazilian	6.33e-05	−0.191*	−0.0312***	−0.0688***
	(3.91e-05)	(0.109)	(0.0111)	(0.0226)
Russian	0.000352**	0.0142	0.0112	0.00466
	(0.000168)	(0.0130)	(0.00806)	(0.00438)
Indian	−0.000728	0.0192	0.00399	0.00566
	(0.000530)	(0.0167)	(0.00438)	(0.00505)
Chinese	0.000486	0.0451	−0.00461	−0.0246
	(0.000412)	(0.0620)	(0.00701)	(0.0219)
South African	0.000934***	0.0226	0.00126	−0.000468
	(0.000127)	(0.0183)	(0.00315)	(0.00158)
Brazilian (−1)	0.000264***	−0.194*	−0.0341***	−0.0690***
	(3.92e-05)	(0.111)	(0.0113)	(0.0230)
Russian (−1)	0.000277	0.0127	0.00819	0.00674
	(0.000175)	(0.0128)	(0.00621)	(0.00509)
Indian (−1)	−0.00117	0.0192	0.00451	0.00603
	(0.00100)	(0.0169)	(0.00464)	(0.00521)
Chinese (−1)	0.000588**	0.0153	−0.00980	−0.0194
	(0.000282)	(0.0397)	(0.00715)	(0.0180)
South African (−1)	0.000954***	0.0208	0.00140	−0.000451
	(0.000129)	(0.0173)	(0.00297)	(0.00134)
Controls	Yes	Yes	Yes	Yes
Observations	1672	952	1007	964

This table reports the estimates of the OLS model during the period 2015–2021. The dependent variable is the daily realized volatility of BTC (BTC_Vol), ETH (ETH_Vol), XRP (XRP_Vol) and LTC (LTC_Vol). The variables of interest are: the Brazilian, Russian, Indian, Chinese, and South African announcement and their lagged values (see Table 2). Robust standard errors (SE) are reported in parentheses. The superscripts ***, **, and * denote coefficients statistically different from zero at the 1%, 5%, and 10% levels, respectively, in two-tailed tests.

Table 11
OLS estimator: cryptocurrencies daily returns.

	BTC_Ret	ETH_Ret	XRP_Ret	LTC_Ret
Variables	(I)	(II)	(III)	(IV)
Brazilian	0.0710***	−0.0134**	0.0713***	0.0985***
	(0.00245)	(0.00582)	(0.00822)	(0.00772)
Russian	−0.00382	0.00196	−0.0252	−0.00965
	(0.0220)	(0.0418)	(0.0324)	(0.0162)
Indian	0.0276	0.0169	−0.0330	−0.00462
	(0.0490)	(0.0440)	(0.0359)	(0.0428)
Chinese	−0.0340	0.00275	−0.0400	−0.0282
	(0.0299)	(0.00937)	(0.0468)	(0.0618)
South African	−0.0497***	−0.0777***	−0.0554***	−0.0446***
	(0.00235)	(0.00437)	(0.00481)	(0.00444)
Brazilian (−1)	−0.0266***	−0.00317	−0.0267***	−0.0590***
	(0.00240)	(0.00576)	(0.00810)	(0.00764)
Russian (−1)	0.0103	0.0111**	−0.0554	0.00426
	(0.0118)	(0.00500)	(0.0568)	(0.0138)
Indian (−1)	0.00540	−0.00648	0.00523	0.00142
	(0.00885)	(0.0271)	(0.0173)	(0.0241)
Chinese (−1)	−0.0365	−0.0729	−0.107	−0.107
	(0.0340)	(0.0662)	(0.0757)	(0.0831)
South African (−1)	−0.0613***	−0.0976***	−0.0710***	−0.0707***
	(0.00240)	(0.00446)	(0.00491)	(0.00449)
Controls	Yes	Yes	Yes	Yes
Observations	1672	952	1007	964

This table reports the estimates of the Newey-West (1994) model during the period 2015–2021. The dependent variable is the daily return of BTC (BTC_Ret), ETH (ETH_Ret), XRP (XRP_Ret) and LTC (LTC_Ret). The variables of interest are: the Brazilian, Russian, Indian, Chinese, and South African announcement and their lagged values (see Table 2). Robust standard errors (SE) are reported in parentheses. The superscripts ***, **, and * denote coefficients statistically different from zero at the 1%, 5%, and 10% levels, respectively, in two-tailed tests.

Table 12
Newey-West estimator: cryptocurrencies daily realized volatility BRICS vs US news.

Variables	BTC_Vol (I)	ETH_Vol (II)	XRP_Vol (III)	LTC_Vol (IV)
Dependent var. (−1)	0.999***	0.832***	0.965***	0.934***
	(0.000772)	(0.102)	(0.0195)	(0.0300)
US	0.000507**	−0.00625	0.00129	0.0786
	(0.000239)	(0.00398)	(0.00834)	(0.0644)
Brazilian	6.55e-05	−0.191*	−0.0312***	−0.0643***
	(6.50e-05)	(0.104)	(0.0118)	(0.0219)
Russian	0.000357**	0.0141	0.0112	0.00489
	(0.000172)	(0.0129)	(0.00801)	(0.00468)
Indian	−0.000724	0.0192	0.00401	0.00586
	(0.000532)	(0.0163)	(0.00443)	(0.00511)
Chinese	0.000490	0.0450	−0.00458	−0.0228
	(0.000418)	(0.0610)	(0.00714)	(0.0208)
South African	0.000936***	0.0225	0.00128	−4.53e-05
	(0.000215)	(0.0176)	(0.00322)	(0.00205)
US (−1)	0.000246*	−0.00555	0.00178	0.0562
	(0.000146)	(0.00425)	(0.00951)	(0.0474)
Brazilian (−1)	0.000267***	−0.194*	−0.0340***	−0.0644***
	(6.51e-05)	(0.105)	(0.0120)	(0.0223)
Russian (−1)	0.000282	0.0126	0.00821	0.00697
	(0.000178)	(0.0127)	(0.00621)	(0.00524)
Indian (−1)	−0.00117	0.0191	0.00453	0.00622
	(0.00100)	(0.0165)	(0.00467)	(0.00524)
Chinese (−1)	0.000592**	0.0152	−0.00978	−0.0175
	(0.000291)	(0.0378)	(0.00731)	(0.0168)
South African (−1)	0.000956***	0.0207	0.00141	1.21e-05
	(0.000219)	(0.0167)	(0.00303)	(0.00184)
Controls	Yes	Yes	Yes	Yes
Observations	1672	952	1007	964

This table reports the estimates of the Newey-West (1994) model during the period 2015–2021 by controlling for US regulatory news. The dependent variable is the daily realized volatility of BTC (BTC_Vol), ETH (ETH_Vol), XRP (XRP_Vol) and LTC (LTC_Vol). The variables of interest are: the US, the Brazilian, Russian, Indian, Chinese, and South African announcement, and their lagged values (see Table 2). Robust standard errors (SE) are reported in parentheses. The superscripts ***, **, and * denote coefficients statistically different from zero at the 1%, 5%, and 10% levels, respectively, in two-tailed tests.

(Gandal and Halaburda, 2016) in suggesting that, after BRICS regulatory announcements, cryptocurrency investors increase their confidence in alternatives to BTC (as ETH, XRP and LTC). At the same time, we document a potential risk-hedging opportunity for investors after regulatory announcements, by shifting from BTC to ETH, XRP and LTC.

6. Conclusions

We investigate the daily volatility and returns of Bitcoin (BTC), Ethereum (ETH), Ripple (XRP) and Litecoin (LTC) in the aftermath of regulatory announcements originating in Brazil, Russia, India, China, and South Africa (BRICS), as well as their co-movements. Results confirm existing literature by showing strong univariate and dynamic correlations of daily returns across cryptocurrencies, as well as higher daily realized volatilities during periods of interest compared to traditional asset classes. Additionally, we document a higher persistence of BTC conditional variance when compared to other cryptocurrencies.

Further, our results are consistent with a risk substitution effect from ETH, XRP and LTC to BTC daily volatility after BRICS regulatory announcements on cryptocurrencies. Specifically, our evidence suggests that both ‘neutral’ or ‘negative’ announcements produce two opposite effects: i) an increase of BTC volatility; and ii) a decrease of ETH, XRP and LTC volatility. This finding is especially strong during periods of low volatility. As we find through quantile regression, strong and negative correlations between BRICS announcements and BTC volatility hold especially at lower levels of the return distribution. On the other side, ETH, XRP and LTC seem to differ in terms of the response of their volatility, suggesting a potential risk hedging property toward the behavior of BTC.

In contrast to our results for volatility, regarding returns, our results highlight similar negative impacts of BRICS cryptocurrency-related regulatory announcements on BTC, ETH, XRP and LTC. Moreover, the higher the point in the daily return distribution, the stronger this detrimental effect of BRICS regulatory announcements. In short, it is not with respect to returns that BTC differs, but with respect to volatility.

Further, in additional robustness checks, we show that the cryptocurrencies in our sample are considerably more reactive to BRICS

Table 13
Newey-West estimator: cryptocurrencies daily returns BRICS vs US news.

	BTC_Ret	ETH_Ret	XRP_Ret	LTC_Ret
Variables	(I)	(II)	(III)	(IV)
US	−0.0183	−0.00176	0.00411	−0.0191
	(0.0213)	(0.0241)	(0.0206)	(0.0272)
Brazilian	0.0710***	−0.0133**	0.0712***	0.0983***
	(0.00241)	(0.00597)	(0.00905)	(0.00902)
Russian	−0.00391	0.00201	−0.0252	−0.00976
	(0.0222)	(0.0422)	(0.0328)	(0.0167)
Indian	0.0276	0.0170	−0.0331	−0.00473
	(0.0489)	(0.0439)	(0.0357)	(0.0427)
Chinese	−0.0340	0.00280	−0.0401	−0.0283
	(0.0299)	(0.00949)	(0.0470)	(0.0624)
South African	−0.0498***	−0.0777***	−0.0555***	−0.0447***
	(0.00234)	(0.00436)	(0.00495)	(0.00450)
US (−1)	0.00346	0.00786	−0.0162	0.00451
	(0.0181)	(0.0275)	(0.0234)	(0.0281)
Brazilian (−1)	−0.0266***	−0.00311	−0.0268***	−0.0591***
	(0.00236)	(0.00591)	(0.00892)	(0.00892)
Russian (−1)	0.0102	0.0111**	−0.0555	0.00415
	(0.0116)	(0.00492)	(0.0567)	(0.0137)
Indian (−1)	0.00532	−0.00643	0.00514	0.00131
	(0.00878)	(0.0268)	(0.0171)	(0.0241)
Chinese (−1)	−0.0366	−0.0729	−0.108	−0.108
	(0.0340)	(0.0661)	(0.0757)	(0.0830)
South African (−1)	−0.0614***	−0.0976***	−0.0710***	−0.0708***
	(0.00239)	(0.00444)	(0.00504)	(0.00454)
Controls	Yes	Yes	Yes	Yes
Observations	1672	976	1032	989

This table reports the estimates of the Newey-West (1994) model during the period 2015–2021 by controlling for US regulatory news. The dependent variable is the daily return of BTC (BTC_Vol), ETH (ETH_Vol), XRP (XRP_Vol) and LTC (LTC_Vol). The variables of interest are: the US, the Brazilian, Russian, Indian, Chinese, and South African announcement, and their lagged values (see Table 2). Robust standard errors (SE) are reported in parentheses. The superscripts ***, **, and * denote coefficients statistically different from zero at the 1%, 5%, and 10% levels, respectively, in two-tailed tests.

announcements than US Fed announcements. This suggests important linkages between emerging markets and cryptocurrencies. Results provide important insights into the nature of cryptocurrencies and important guidance for portfolio management.

Altogether, our results reveal a different reaction of BTC volatility to BRICS regulatory announcements compared to other cryptocurrencies. This is consistent with heterogeneity among cryptocurrencies as to the impact of investor reaction to the 'fear signaling' embedded in regulatory announcements. Our findings suggest potential hedging, in terms of risk substitution, by strategically allocating resources on cryptocurrencies other than BTC after BRICS regulatory announcements.

As usual, our results are subjected to some limitations that call for further useful research. For example, effects present in different geographical areas or considering various levels of economic and financial development could furtherly investigate the robustness of our results.

Additionally, it could be interesting to extend the sample of cryptocurrencies to investigate if other potential risk-hedging opportunities exist, also with reference to other assets, for instance those traditionally considered safe-havens.

Finally, future research could test our assumptions by including environmental regulatory announcements, to understand how volatility and returns of cryptocurrencies is affected in connection with their specific exposure to issues related to energy consumption and emissions.

Author declaration

The authors assert that this work is an equal collaboration and is not under consideration elsewhere.

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