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Exploring the Determinants of Crypto Currencies Price: A Short and Long-Run Analysis

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Research Article

Abstract
Purpose*: This study examines the factors influencing the prices of major cryptocurrencies (Bitcoin, Litecoin, and Ethereum) in both the short and long term. The analyzed variables include the attractiveness of cryptocurrencies, stock market indices, commodity markets, and interactions among cryptocurrencies.*
Method: *We exploited daily data from August 13, 2015, to March 29, 2020. The analysis used a Vector Error Correction Model (VECM) to determine the dynamic relationships among the variables.*
Results: *The findings reveal that in the short term, the value of each cryptocurrency is mainly explained by the value of the two competing cryptocurrencies and the overall cryptocurrency growth index, while the price of gold does not significantly affect any of them. In the long term, the value of all three cryptocurrencies is negatively influenced by their own attractiveness and by the commodity markets.*
Implications*: The results suggest that investors and policymakers should consider both the competitive dynamics among cryptocurrencies and factors from the commodity market when evaluating cryptocurrency prices. This has implications for investment strategies and market regulation.*
Originality: *This research contributes to the existing literature by integrating a comparative analysis of major cryptocurrencies and exploring the influences of competition and commodity markets on their values. By employing a VECM, the study provides an innovative perspective on the short- and long-term interactions among these digital assets.*

Keywords: Cryptocurrency price, determinants, cryptocurrency interdependence, bitcoin, ethereum, Litecoin

1. Introduction

The last few years have seen an explosive growth in Google searches and social media posts about block chain technology and crypto-currency. The main interest in crypto-currency began in 2014, when the price of the most famous crypto-currency, Bitcoin, first climbed to over USD 1,000 per Bitcoin. This exponential growth attracted worldwide attention and became the main topic of FinTech and finance conferences.

Our research is part of the recent branch of literature that deals with the price determinants of cryptocurrencies. Previous studies have focused mainly on the effect of attractiveness on crypto currency prices (Urquhart, 2024, De la Horra et al. 2019, Sovbetov 2018, Kavvadias 2017). Other studies have examined the relationship between crypto currency price changes and various economic and financial factors such as interest rates, stock market indices, exchange rates, and commodities (Jareño et al. 2022, Colon et al. 2021, Wang et al. 2019, Bouoiyour et al. 2018, Klein et al. 2018, Bouri et al. 2018). However,

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recent studies (Katsiampa et al. 2019a, 2019b; Bação et al. 2018; Shi et al. 2020; Qureshi et al. 2020) have addressed the topic of interdependence between different cryptocurrencies.
The existing literature on cryptocurrency prices often focuses on specific factors one by one, often failing to consider the complex interactions between these factors. While numerous studies have focused on Bitcoin due to its dominant position in terms of market capitalization and transaction volume, there is a notable lack of comprehensive analysis that includes other significant cryptocurrencies. This oversight limits our understanding of how the cryptocurrency market operates and how different currencies affect each other.
Furthermore, most prior research tends to concentrate on either short-term or long-term influences separately, without adequately capturing the interplay of these effects. As a result, the existing studies do not provide any information on how various factors can work together over different time frames to influence the value of cryptocurrencies.
To address this gap, this study aims to employ a Vector Error Correction Model (VECM) to analyze the key determinants affecting the values of Bitcoin, Ethereum, and Litecoin. We will examine not just the individual effects of these determinants but also how they interact with each other, capturing both short-term fluctuations and long-term relationships within the cryptocurrency market. This approach will enhance our understanding of the cryptocurrency ecosystem and provide valuable insights for investors, policymakers, and researchers.

2. Literature Review
Since the last decade, empirical literature has been compiled to investigate the determinants of cryptocurrency exchange rates. Some research papers investigated the attractiveness of crypto currencies based on the number of transactions, the number of searches on Google, and the number of tweets. De la Horra et al. (2019) examined bitcoin from a monetary theory perspective and found that the number of transactions explains Bitcoin prices given that a 1% increase in the number of transactions leads to a 0.49% increase in Bitcoin prices. In the short run, the positive and significant coefficient of the number of transactions suggests that there is a demand for Bitcoin as a payment tool; hence, the number of transactions in the Bitcoin economy is positively related to the demand for Bitcoin.
In order to consider the dynamics of the short and long term, Sovbetov (2018) examined the factors that influence the prices of the five most common crypto-currencies (Bitcoin, Ethereum, Dash, Litecoin, and Monero) using the Auto-Regressive Distributed Lag (ARDL) models. The results showed that the transaction volume and the number of Google queries for crypto currencies have a significant long-term impact on Bitcoin, Ethereum, Litcoin, and Monero, while in the short-term, only Bitcoin gained a significant estimate of 0.14%. Kavvadias (2017) used the VECM model to find out if trading volume, Google trends, Volatility Index VIX, Morgan Stanley Capital International (MSCI) word Index and oil price affect the price of bitcoin. In the short term, they found that trading volume and Google Trends (based on Google queries) have a positive impact on bitcoin price, while in the long run, Google Trends has a negative impact on bitcoin price.
Another body of research concentrated on economic and financial variables such as interest rates, stock indices, exchange rates, and commodities. Bouri et al. (2018) used several advanced ARDL models to show the possibility of predicting Bitcoin movements based on price changes in the global commodity index and gold. They found that the MSCI index and the price of gold have a symmetric influence on Bitcoin prices and that past variation in Bitcoin prices significantly and positively determine their own current variations. Klein et al. (2018) used a BEKK-GARCH (Baba, Engle, Kraft, and Kroner-Generalized Auto Regressive Conditional Heteroskedastic) model to analyze and compare the conditional variance properties of Bitcoin and gold. Their results showed that gold plays a significant role in financial markets during market distress, while Bitcoin behaves differently and it is positively correlated with bear markets. Zhu et al. (2017) demonstrate that Bitcoin behaves similarly to gold as a financial asset when the Consumer Price Index (CPI), Dow Jones Industrial Average (DJIA), US dollar price, and Federal Funds Rate (FFR) all have a

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negative long-term influence on Bitcoin price. Jareño et al. (2022) applied the quantile regression approach to show that the risk factor VIX has a negative and statistically significant effect on Bitcoin returns in most time periods and quantiles. Wang et al. (2016) constructed a VECM model to analyze the influence of the stock price index, oil price, and daily trading volume on the Bitcoin price. The results showed that the bitcoin price is negatively related to the oil price. Using ordinary least-squares regression Kavvadias (2017) found that, in the long run, proxies for the global market portfolios Standard and Poor's 500 (SP500) and MSCI have a positive impact on the price of bitcoin.

A more recent set of studies addressed the interdependence between different crypto currencies. Göttfert (2019), for instance, analyzed the existence of a potential relationship between crypto-currency markets. The result of the Johansen test indicated that there was cointegration between four out of five pairs. Bitcoin and EOS (Electro-Optical System) crypto currency were the only pairs that did not have statistically significant cointegration. The result was confirmed by the Engle-Granger test, which also showed that four out of five pairs had a long-term relationship and were cointegrated, with Bitcoin and EOS being the exception. The VECM result suggests that the Bitcoin price has a statistically significant impact on the prices of Bitcoin, Ethereum, Litecoin, and XRP in the long run. Baçao et al. (2018) studied the transmission of information between the most important crypto-currencies such as Bitcoin, Litecoin, Ripple, Ethereum, and Bitcoin using a Vector Auto Regressive (VAR) modelling approach. The results showed that the crypto-currencies are closely related and most of the transmission of information occurs within the day, but a delayed transmission of information is observable. It would seem reasonable to expect that Bitcoin would tend to dominate other crypto-currencies in terms of information transmission, given its dominance in terms of trading volume, market capitalization, and trading volume. Shi et al., (2020) applied the Model "Modified Fuzzy Support Vector Machine" (MFSVM) to analyze the correlations between six crypto-currencies. According to their results, there is a significant positive correlation between the price volatility values of Bitcoin and Litecoin. In addition, the volatility values of Ethereum have a positive correlation with those of Ripple and Stellar. There is also a positive correlation between the volatility values of Ripple and Dash. The evidence suggests that Bitcoin is mainly related to Litecoin, but Ethereum is associated with other crypto-currencies. Qureshi et al., (2020) studied the dynamics of multiscale interdependencies between five major and liquid crypto-currencies (Bitcoin, Ethereum, Ripple, Litecoin, and Bitcoin) using wavelet-based analyses that account for the heterogeneous behavior of crypto-traders and crypto-investors. The results show high levels of dependence from 2016 to 2018 on daily frequency scales. Wavelet coherence results confirm short- and long-term market integration between selected crypto-currency pairs.

The above detailed studies have a significant gap in that they focus on specific determinants of crypto currency prices separately without considering the interactions between them. Besides most of these researches have been limited to bitcoin and neglect other crypto currencies because bitcoin rank first in terms of price and transaction volume. To address this gap, we will use a VECM to identify the key determinants of three cryptocurrencies: bitcoin, ethereum, and litecoin. This will allow us to capture both short and long-term relationships.

3. Data and methodology

3.1 Data

The data used in this research covers the period from 13 August 2015 to 29 March 2020 (1692 observations). This period was chosen to exclude the health crisis linked to the Coronavirus pandemic and the political crisis resulting from the conflict between Russia and Ukraine. Our goal is to investigate how many economic, financial, political, and attractiveness factors affect the value of three crypto currencies (bitcoin, ethereum, and litecoin). That is, how two groups of variables explain a cryptocurrency's price (the dependent variable)? First, there are internal factors such as trading volume and each cryptocurrency's

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popularity. External factors include commodity prices (gold and oil), the MSCI world index, the Cryptocurrency index (CCI30), the Volatility Index (VIX), and the Geopolitical Risk Index (GPR). The variables used in the analysis and the sources of the data are presented in Table 1.

Table 1: Variables

Variables	Notation	Description	Source
Crypto currency prices	BTC, LTC ETH		bitinfocharts.com
Internal factors			
Attractivity			
Google trends	Google	Normalized number of daily search queries in Google	trends.google.fr
Transaction volume	Trans	Number of crypto currency transactions per day	bitinfocharts.com
External factors			
Raw materials			
Oil Price	Oil	The spot price of a barrel of Crude Oil	Data Stream
Gold Price	Gold	The average price of gold on the main markets	Data Stream
Stock markets			
MSCI world Index	MSCI	A market-capitalization-weighted index of 1,655 stocks from around the world	Data Stream
Crypto Index	CCI30	The 30 largest crypto-currencies per market capitalization	cci30.com
VIX	VIX	A volatility index created by the Chicago Board Options Exchange (CBOE)	Data Stream

3.2 The Vector Error Correction Model (VECM)

In this study, we used the VECM, which is constructed by restricting the behavior of the long-run relationships of the endogenous variables to converge to their cointegrating equilibrium while allowing for a dynamic adjustment in the short run. Because the deviation from long-run equilibrium is gradually corrected through a series of partial short-run adjustments, the cointegration term is stated as the error correction term. The Johansen cointegration tests and estimations are carried out by restricting a VAR model. Suppose that a set of p univariate non-stationary time series $(p \geq 2)$ and integrated of order one, $Y_{it} \sim I(1)$. A vector autoregressive (VAR) model with k lags containing these variables could be set up:

$$Y_t = B_1 Y_{t-1} + B_2 Y_{t-2} + \cdots + B_k Y_{t-k} + \epsilon_t \qquad (1)$$

where Y_t is an $p \times 1$ vector of dependent variables which are integrated of order one, $\mathrm{B}_1 - \mathrm{B}_k$ are $p \times p$ matrices of parameters, ϵ_t denotes an $p \times 1$ vector of innovations with mean 0 and covariance matrix Σ, and is independent identically distributed (i.i.d.) normal over time. The VAR model (with the assumption that all variables in the system are stationary), must be transformed into a VECM to use the Johansen test since VECM releases the data stationarity condition. The VECM contains first difference terms and cointegration relationships:

$$\Delta Y_t = \Pi Y_{t-k} + \sum_{i=1}^{k-1} \Gamma_i \Delta Y_{t-i} + \epsilon_t \quad \text{for } t = 1, \dots, T \qquad (2)$$

where $\Pi = \left[\left(\sum_{j=1}^{k} B_j\right) - I_p\right]$ and $\Gamma_i = -\sum_{j=i+1}^{k} B_j$.

Engle and Granger (1987) prove that if the variables Y_t are $I(1)$, the matrix Π in (2) has a reduced rank $r < p$, where r is the number of linearly independent cointegrating vectors. Accordingly, the long-run cointegrating matrix of Π determines the number of cointegrating vectors. In fact, the Johansen test focuses

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on the examination of coefficient matrix Π defined as the product of α and β, i.e. $\Pi = \alpha\, \beta'$ with β the cointegration vector and α the adjustment (loading) coefficients vector, both of dimension $p \times r$. Hence, if Y_t has cointegration relationship, then, $\beta' Y_{t-1} \sim I(0)$ and formula (2) can be written as follows:

$$\Delta Y_t = \alpha\, \beta'\, Y_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \Delta Y_{t-i} + \mathrm{v} + \epsilon_t \quad \text{for } t = 1, \dots, T \tag{3}$$

Where $\beta' Y_{t-1} = ECT_{t-1}$ is the error correction term, which reflects the long-run equilibrium relationships between variables. The above formula can be thus written as follows:

$$\Delta Y_t = \alpha\, ECT_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \Delta Y_{t-i} + \mathrm{v} + \epsilon_t \quad \text{for } t = 1, \dots, T \tag{4}$$

(4) is the VECM, in which each equation is an Error Correction Model (ECM).

To sum up, there are important elements to be distinguished in the VECM. On one hand, the short-term parameters give the effect on the value of the cryptocurrency due to a change in the previous period in each of the variables used. On the other hand, the cointegrating vectors can be interpreted as the long-term effects of an increase or decrease in internal and external factors on the value of the cryptocurrency. These long-term effects are not instantaneous but rather gradual and persistent over time. It takes some time for the market to adjust to the shock and return to its equilibrium level. It is the cointegration coefficient that determines how quickly the long-run effects will return to their equilibrium levels. In other words, it shows how quickly equilibrium is restored once the model is out of equilibrium. To confirm the existence of long-run equilibrium, the error correction coefficient must be significantly negative. Otherwise, the ECM specification should be rejected. Indeed, the error correction or catch-up mechanism that allows us to move towards the long-run relationship would then move in the opposite direction and away from the long-run target. A small adjustment parameter means that the series does not respond to an equilibrium error and will therefore reach the long-run equilibrium relatively slowly. Moreover, this speed of adjustment refers to impulse response functions that trace the response of a variable to a one-time shock, such as a change in trading volume. The influence of a shock on the current and future values of endogenous variables is traced by an impulse response function.

3.3 Testing for cointegration

Given that all variables are non-stationary at the level, co-integration testing verifies the validity of long-run correlations between variables. If there is co-integration, it signifies that even if the variables are non-stationary at the level, they have a long-run correlation (Johansen 1988). Furthermore, Johansen (1988) recommends two procedures for measuring the number of co-integrated vectors: the Trace test and the Maximum Eigen Value test. The trace test investigates the hypothesis that there is no more than r co-integrating vectors, whereas the Maximum Eigen Value test investigates the hypothesis that there are $r + 1$ co-integrating vectors (Maddala and Kim 1998). Johansen and Juselius (1990) propose that the Maximum Eigen value test is efficient for predicting the number of co-integrating vectors, to indicate the presence of a long-run link between the variables. Besides, the presence of a co-integrated association between the variables influences the choice of either the VAR or VECM models for efficient estimation and forecasting (Hill et al. 2012; Maddala et al. 1998). The Johansen co-integration test is used in this study to determine if the variables are co-integrated and hence the rank of the co-integrating vector.

If a long-run equilibrium exists, the $\Delta Y_{t-i} = 0$, and setting the error tem, ϵ_t, to their expected value of zero will leave $\Pi Y_{t-1} = 0$. So, the test of cointegration between different variables is by looking at the rank of Π via its eigenvalues, denoted hereafter by λ_i. The number of eigenvalues that are distinct from zero

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determines a matrix's rank. The rank of Π will not be statistically different from zero if the variables are not cointegrated, i.e. $\lambda_i = 0$. To determine the cointegration rank r, Johansen (1988, 1991) proposed a sequential probability testing approach. Under the null hypothesis there are at most r cointegration relationships.

$$H_0: rank(\Pi) \leq r \;\; vs \;\; H_1: rank(\Pi) > r$$

There is no cointegration in the particular situation of $r = 0$, hence we must proceed with a stationary VAR model in first differences. However, if $r = p$, we can use a stationary VAR model in levels without any error correction terms. In all other cases ($0 < r < p$), the series are cointegrated. Inferring the number of cointegrating vectors, Johansen and Juselius (1990) propose to use the trace test and maximum eigenvalue statistics, which are expressed as:

$$\lambda_{trace}(r) = -T\sum_{i=r+1}^{p} \ln(1 - \hat{\lambda}_i); \quad \lambda_{max}(r, r+1) = -T\ln(1 - \hat{\lambda}_{r+1})$$

where r the number of cointegrating vectors under the null hypothesis, T is the sample size and λ denotes the eigenvalues. The null hypothesis of at most r cointegrating vectors against the alternative hypothesis of more than r cointegrating vectors is tested by trace statistics. The null hypothesis of r cointegrating vector against the alternative of $r + 1$ is tested by maximizing eigenvalues statistic.

4. Results and discussion

4.1. Descriptive Statistics

Table 2 displays the descriptive statistics for the series under investigation.

Table 2: Descriptive statistics (Series in logarithm)

Variable	Mean	Sd	Min	Max	Skewness	Kurtosis	J-B	Ljung-Box
Bitcoin								
ln BTC	7.8445	1.2805	5.3644	9.8730	-0.4348	1.6578	180.21***	13981***
ln Trans	12.424	0.2774	11.400	13.103	-0.6141	3.2002	109.12***	9499.4**
ln Google	3.3288	0.8787	1.7713	6.4246	0.2087	2.7733	15.894***	13221***
Litecoin								
ln LTC	3.1591	1.4675	0.9917	5.8658	-0.2761	1.5027	179.43***	14054***
ln Trans	9.4922	0.9808	7.6783	12.327	-0.2149	2.0311	79.163***	13389***
ln Google	-0.3297	1.6398	-3.5863	4.8738	-0.2128	1.9017	97.748***	13483***
Ethereum								
ln ETH	4.1624	2.0201	-0.8119	7.2122	-0.7906	2.5052	193.41***	14039***
ln Trans	12.114	1.6015	7.7336	14.115	-0.7860	2.2898	209.64***	13671***
ln Google	1.0179	1.2787	-3.1033	3.9651	-0.5740	3.2202	96.276***	13247***
ln Gold	7.1620	0.0907	6.9590	7.4390	0.4843	3.3933	77.028***	12989***
ln Oil	4.0289	0.2179	3.2304	4.4555	-0.6758	3.4708	144.36***	13778***
ln MSCI	7.5697	0.1218	7.2922	8.2486	8.25e-08	3.1962	27.13***	13855***
ln VIX	2.7085	0.3213	2.2126	4.4150	1.5841	7.3830	2060.8***	13866***
ln CCi30	7.1733	1.5614	4.2670	9.9425	-0.4708	1.7856	166.38***	14067***

Note: *, **, *** shows significance at 10%, 5%, and 1% level, respectively.
J-B denotes for Jaques-Bera normality test.

The study used the Augmented Dickey-Fuller (ADF), Kwiatkowski-Philips-Schimdt-Shin (KPSS), and Philips-Perron (PP) tests to examine the presence of unit roots in the data.

4.2 Stationarity tests for level and first difference variables

Referring to table 2, the three analyzed cryptocurrencies have considerably higher standard deviation than any of the other financial assets examined. Unlike all the other markets, Bitcoin is the only crypto exhibiting a high average return comparable to gold, corroborating with the never seen before rise in Bitcoin prices

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even during the COVID-19 outbreak. Moreover, the kurtosis statistics for commodities are higher than 3, suggesting that their returns are leptokurtic. The JB test statistics show that all series are not normally distributed. Besides, as shown in Table 3, all variables are stationary at first difference at the conventional significance levels.

Table 3: Unit-root tests

Variable	Phillips-Perron		Lag[a]	ADF		KPSS	
	Levels	Difference	ADF	Levels	Difference	Levels	Difference
Bitcoin							
$\ln BTC$	-1.675	-94.219***	2	-1.693	-21.891***	4.3529	0.3145***
$\ln Trans$	0.412	-86.994***	4	-4.783	-35.963***	1.637	0.1106***
$\ln Google$	-2.464	-45.914***	4	-2.262	-27.129***	2.7991	0.0515***
Litecoin							
$ln\ LTC$	-1.2528	-32.435***	3	-1.2362	-27.7413***	3.7519	0.246***
$\ln Trans$	-2.2524	-65.3051***	4	-1.9643	-25.2905***	3.4845	0.0315***
$\ln Google$	-2.0161	-81.256***	3	-1.9005	-25.5778***	3.6293	0.089***
Ethereum							
$\ln ETH$	-1.9359	-32.9170***	2	-1.8400	-32.4429***	3.492	0.5059***
$\ln Trans$	-2.4960	-53.2749***	2	-2.6647	-17.2514***	4.4299	0.4331***
$\ln Google$	-3.0744	-56.2747***	4	-2.4630	-16.702***	2.3730	0.074***
$ln\ Gold$	-0.9960	-41.982***	1	-0.9695	-41.982***	2.8222	0.084***
$ln\ Oil$	-0.7458	-40.747***	1	-0.7370	-40.748***	2.7110	0.396***
$ln\ MSCI$	-2.2325	-29.682***	2	-2.0525	-15.374***	4.4124	0.094***
$ln\ VIX$	-3.4275	-41.937***	3	-3.4012	-41.646***	3.747	0.114***
$ln\ CCi30$	-1.7437	-42.822***	1	-1.7853	-42.497***	3.825	0.521***

Note: [a] To determine the number of lags to include in the ADF test, the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) were employed.
*, **, *** shows significance at 10%, 5%, and 1% level, respectively.

4.3. The Johansen Cointegration Test

We apply the Johansen co-integration test, which is based on the Trace and Maximum Eigen statistics, to determine whether there is a long-run link between the endogenous variables.

Table 4: Johansen Cointegration trace tests

Null Hypothesis	Alternative Hypothesis	Eigenvalue	Trace Statistic	Critical Value (5%)
Bitcoin (restricted constant, 3 lags)				
r=0	r > 0	-	393.07*	244.15
r ≤ 1	r > 1	0.073	263.55*	202.92
r ≤ 2	r > 2	0.052	173.38*	165.58
r ≤ 3	r > 3	0.037	109.14	131.70
Ethereum (No trend, 2 lags)				
r=0	r > 0	-	425.16*	212.67
r ≤ 1	r > 1	0.084	276.63*	175.77
r ≤ 2	r > 2	0.057	177.42*	141.20
r ≤ 3	r > 3	0.044	99.95	109.99
Litecoin : Johansen Cointegration trace test (No trend, 2 lags)				
r=0	r > 0	-	467.46*	212.67
r ≤ 1	r > 1	0.089	309.33*	175.77
r ≤ 2	r > 2	0.068	189.36*	141.20
r ≤ 3	r > 3	0.051	99.35	109.99

The presence of co-integrated vectors also aids in determining whether to adopt a constrained or unconstrained VAR model (i.e. VEC model). The Johansen co-integration test is shown in Table 4. As a

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result, at the 5% level of significance, both the Trace and Maximum-Eigen value tests show the rejection of the null hypothesis of "no co-integrated vectors," demonstrating the presence of a long run link between the variables. Furthermore, both Trace and Maximum-Eigen value tests reveal the presence of three co-integrating equations, which we include into VEC model estimate.

4.4. VECM Estimates

In this paper, we are interested in three crypto currencies. The error correction models (ECM) for each analyzed crypto currency are as follow:

$$\begin{aligned} \ln BTC_t = {} & \delta_{11}ECT_{1,t-1} + \delta_{12}ECT_{2,t-1} + \delta_{13}ECT_{3,t-1} + \sum_{i=1}^{k} a_1 \,\Delta \ln BTC_{t-i} \\ & + \sum_{i=1}^{k} a_2 \,\Delta \ln LTC_{t-i} + \sum_{i=1}^{k} a_3 \,\Delta \ln ETH_{t-i} + \sum_{i=1}^{k} a_4 \,\Delta \ln Trans_{t-i} \\ & + \sum_{i=1}^{k} a_5 \,\Delta \ln Google_{t-i} + \sum_{i=1}^{k} a_6 \,\Delta \ln Gold_{t-i} + \sum_{i=1}^{k} a_7 \,\Delta \ln Oil_{t-i} \\ & + \sum_{i=1}^{k} a_8 \,\Delta \ln MSCI_{t-i} + \sum_{i=1}^{k} a_9 \,\Delta \ln CCi30_{t-i} + \sum_{i=1}^{k} a_{10} \,\Delta \ln VIX_{t-i} \\ & + \epsilon_{1,t} \end{aligned} \tag{5}$$

$$\begin{aligned} \Delta \ln LTC_t = {} & \delta_{21}ECT_{1,t-1} + \delta_{22}ECT_{2,t-1} + \delta_{23}ECT_{3,t-1} + \sum_{i=1}^{k} b_1 \,\Delta \ln BTC_{t-i} \\ & + \sum_{i=1}^{k} b_2 \,\Delta \ln LTC_{t-i} + \sum_{i=1}^{k} b_3 \,\Delta \ln ETH_{t-i} + \sum_{i=1}^{k} b_4 \,\Delta \ln Trans_{t-i} \\ & + \sum_{i=1}^{k} b_5 \,\Delta \ln Google_{t-i} + \sum_{i=1}^{k} b_6 \,\Delta \ln Gold_{t-i} + \sum_{i=1}^{k} b_7 \,\Delta \ln Oil_{t-i} \\ & + \sum_{i=1}^{k} b_8 \,\Delta \ln MSCI_{t-i} + \sum_{i=1}^{k} b_9 \,\Delta \ln CCi30_{t-i} + \sum_{i=1}^{k} b_{10} \,\Delta \ln VIX_{t-i} \\ & + \epsilon_{2,t} \end{aligned} \tag{6}$$

$$\begin{aligned} \Delta \ln ETH_{ti} = {} & \delta_{31}ECT_{1,t-1} + \delta_{32}ECT_{2,t-1} + \delta_{33}ECT_{3,t-1} + \sum_{i=1}^{k} c_1 \,\Delta \ln BTC_{t-i} \\ & + \sum_{i=1}^{k} c_2 \,\Delta \ln LTC_{t-i} + \sum_{i=1}^{k} c_3 \,\Delta \ln ETH_{t-i} + \sum_{i=1}^{k} c_4 \,\Delta \ln Trans_{t-i} \\ & + \sum_{i=1}^{k} c_5 \,\Delta \ln Google_{t-i} + \sum_{i=1}^{k} c_6 \,\Delta \ln Gold_{t-i} + \sum_{i=1}^{k} c_7 \,\Delta \ln Oil_{t-i} \\ & + \sum_{i=1}^{k} c_8 \,\Delta \ln MSCI_{t-i} + \sum_{i=1}^{k} c_9 \,\Delta \ln CCi30_{t-i} + \sum_{i=1}^{k} c_{10} \,\Delta \ln VIX_{t-i} + \epsilon_{3,t} \end{aligned} \tag{7}$$

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Where ECT_{t-1} is the lagged error correction term departured from the long-run cointegrating relations between the considered variables. It is worth noting that a VECM is basically a VAR in its first difference form with the addition of a vector of cointegrating residuals.
These cointegration (long-run) equations can be formulated as follows:

$$\begin{aligned} ECT_{1,t-1} = \ln BTC_{t-1} - \beta_{1,1} \ln BTC_{t-1} - \beta_{2,1} \ln ETH_{t-1} - \beta_{3,1} \ln Trans_{t-1} \\ - \beta_{4,1} \ln Google_{t-1} - \beta_{5,1} \ln Gold_{t-1} - \beta_{6,1} \ln Oil_{t-1} \\ - \beta_{7,1} \ln MSCI_{t-1} - \beta_{8,1} \ln CCi30_{t-1} - \beta_{9,1} \ln VIX_{t-1} \end{aligned} \quad (8)$$

$$\begin{aligned} ECT_{2,t-1} = \ln LTC_{t-1} - \beta_{1,2} \ln BTC_{t-1} - \beta_{2,2} \ln ETH_{t-1} - \beta_{3,2} \ln Trans_{t-1} \\ - \beta_{4,2} \ln Google_{t-1} - \beta_{5,2} \ln Gold_{t-1} - \beta_{6,2} \ln Oil_{t-1} \\ - \beta_{7,2} \ln MSCI_{t-1} - \beta_{8,2} \ln CCi30_{t-1} - \beta_{9,2} \ln VIX_{t-1} \end{aligned} \quad (9)$$

$$\begin{aligned} ECT_{3,t-1} = \ln ETH_{t-1} - \beta_{1,3} \ln BTC_{t-1} - \beta_{2,3} \ln LTH_{t-1} - \beta_{3,3} \ln Trans_{t-1} \\ - \beta_{4,3} \ln Google_{t-1} - \beta_{5,3} \ln Gold_{t-1} - \beta_{6,3} \ln Oil_{t-1} \\ - \beta_{7,3} \ln MSCI_{t-1} - \beta_{8,3} \ln CCi30_{t-1} - \beta_{9,3} \ln VIX_{t-1} \end{aligned} \quad (10)$$

The estimation results are presented in Tables 5 and 6.

4.5. The attractiveness factor

In the short run, our results show that the coefficients of attractiveness and the number of transactions of bitcoin are statistically significant but with different signs (positive for attractiveness and negative for the number of transactions). This indicates that an increase in the number of searches for the word "bitcoin" in Google leads to an increase in its value by about 1.24%. However, a 1% increase in transaction volume causes bitcoin's price to fall by 1.22% in the short term. This is quite expected given that the closer crypto-currencies get to the public, moving from anonymity to "trendiness" in the daily news, the more their prices will reflect the acceptance of participants. This result is in line with those of Kavvadias (2017) and Shen et al. (2020), indicating a positive and statistically significant relationship between the popularity of Bitcoin measured by the variable "Google Trends" and its price in the short run. These findings allow us to ultimately argue that a higher degree of public recognition or interest in bitcoin increases its market price.
Regrading Ethereum and Litecoin, it appears that, in the short-run, the number of their transactions and attractiveness does not affect their prices. Also, the number of transactions and the Google search volume of these two crypto-currencies, do not affect bitcoin. Interestingly, however, the Google search volume of bitcoin positively affects all three cryptocurrencies and his number of transactions negatively affects the price of ethereum. Indeed, a unit increase in the number of searches for the word bitcoin in Google leads to an increase in the price of bitcoin, ethereum, and litecoin of the order of 0.012, 0.018, and 0.017 units, respectively, while a unit increase in the number of transactions of bitcoin leads to a decrease in the price of bitcoin and ethereum of the order of 0.012 and 0.023 units, respectively. These results can be explained by the fact that Bitcoin is the main cryptocurrency and the market leader, as since its introduction it has continued to be the most used and largest virtual currency in terms of market value and market capitalization. Certain dominance can explain the impact of bitcoin transactions and search volume on Google over other crypto-currencies. The primary reason for comparing altcoins to bitcoin is that their prices are typically measured in bitcoin. Also, most altcoins cannot be purchased directly using currency; instead, the majority of buyers buys bitcoin first and then exchanges it for the altcoin of their choice. In the long run, a permanent 1% increase in the number of searches on Google will imply a permanent appreciation of about 0.78% in the Bitcoin price. However, this effect seems to be larger (in terms of magnitude) than the short-term effect, which might indicate that Bitcoin's popularity is a deterministic component of

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Bitcoin's price in the long run. Similarly, the relationship between Bitcoin's price and its trading volume reverses in the long run and becomes positive and highly significant, indicating a cointegrating relationship. Indeed, a permanent increase of 1% in Bitcoin transaction volume will imply a permanent appreciation of about 0.88% in the Bitcoin price.

Table 5: Results of the short-run VECM models

	$\Delta \ln BTC$	$\Delta \ln ETH$	$\Delta \ln LTC$
$\boldsymbol{ECT_{1,t-1}}$	-0.0089***	-0.0121***	-0.0083***
$\boldsymbol{ECT_{2,t-1}}$	0.0027***	-0.0078**	-0.0030***
$\boldsymbol{ECT_{3,t-1}}$	0.00238***	0.0016	0.0054***
$\Delta \ln BTC$	0.0635**	-0.1817***	-0.1533***
$\Delta \ln ETH$	-0.1321***	0.1523***	-0.1253***
$\Delta \ln LTC$	-0.999***	-0.1084***	0.1347***
$\Delta \ln Trans$	-0.0122*	-0.0076	0.0057
$\Delta \ln Google$	0.0124**	0.004	0.0008
$\Delta \ln Oil$	0.1305	0.1407	0.1455
$\Delta \ln Gold$	-0.0628*	-0.0475	0.0191
$\Delta \ln MSCI$	-0.0971***	-0.0078	-0.0484
$\Delta \ln CCi30$	0.5145***	0.5783***	0.5175***
$\Delta \ln VIX$	-0.0286***	-0.0194	-0.0178
R^2	0,3537	0.2403	0.2419
RMSE	0,2686	0.45672	0.040681
Chi2	910,152***	529.6237***	534.0839***
Note: *, **, *** shows significance at 10%, 5%, and 1% level, respectively.			

Recall that, in this sense, transaction volume is a proxy for demand for this cryptocurrency. This result is in line with Li and Wang (2017) and Ciaian et al. (2016), who found that the transaction volume has a significant and negative impact on the price of bitcoin. The result can be explained by the fact that as the attention to crypto currency increases; the demand also increases, leading to an increase in price. This is in line with our expectations, especially for a financial asset without underlying fundamentals like crypto-currencies, considering that speculation dominates the dynamics of this market. Also, on December 17, 2017, the daily volume of Bitcoin trading reached 405507 transactions. This had the immediate effect of inflating the price of Bitcoin by nearly 5% in 24 hours to an all-time high of $19783.

Table 6: Results of the long-run VECM models

	$\ln BTC$		$\ln ETH$		$\ln LTC$	
	$\boldsymbol{ECT_{1,t-1}}$	Std. Err	$\boldsymbol{ECT_{1,t-1}}$	Std. Err	$\boldsymbol{ECT_{1,t-1}}$	Std. Err
$\Delta \ln Trans$	-0,8846***	0,1461	-0,3484***	0,0677	-1.1322***	0.1167
$\Delta \ln Google$	-0,7803***	0,9214	-0,7749***	0,0570	-0,1858**	0.0893
$\Delta \ln Oil$	-0,9913*	0,5203	-2.1054***	0,4865	-1.9223***	0,5768
$\Delta \ln Gold$	-1,3133***	0,2734	-1,6029***	0,2485	-0.8518***	0,3025
$\Delta \ln MSCI$	-2,5798***	0,7173	3.3945***	0,5164	3.2981***	0,6507
$\Delta \ln CCi30$	-0,0069	0,0403	-0,3703***	0,0867	-0,1432**	0,0839
$\Delta \ln VIX$	-0,7230***	0,1059	-0,2453***	0,1034	0,2902***	0,1189
Note: *, **, *** shows significance at 10%, 5%, and 1% level, respectively.						

Regarding the crypto currencies ethereum and litecoin, our results show that in the long run, the relation reverses and becomes significant and positive, indicating a positive cointegration relationship between the price of ethereum and litecoin and their trading volume and number of searches on Google. Indeed, a permanent increase of 1% in the volume of ethereum transactions and in the number of searches for the word ethereum in Google will imply a permanent appreciation of about 0.34% and 0.77%, respectively, of the price of ethereum. Similarly, a permanent increase of 1% in the volume of litecoin transactions and the

number of Google searches for the word litecoin will imply a permanent appreciation of about 1.34% and 0.18%, respectively, in the price of litecoin.
Regarding the impact of the number of transactions and the search volume in Google of each crypto currency on the other two in the long term, the results show that all coefficients are significant. Indeed, a unit increases in the number of transactions on ethereum leads to an increase in the price of bitcoin (0.3484) and a decrease in the price of litecoin (0.6507). However, a 1% increase in the number of transactions of litecoin leads to a decrease in the price of bitcoin (2.6934) and ethereum (0.5718). A 1% increase in the number of Google searches for ethereum results in a decrease in the price of bitcoin (0.7039) and litecoin (1.5650). However, a 1% increase in the number of Google searches for litecoin results in an increase in the price of bitcoin (2.7537) and a decrease in the price of ethereum (0.0691). Our results are in line with the empirical literature. De la Horra et al. (2019) show that the number of transactions plays an important role in the formation of Bitcoin demand in the long run, a 1% increase in the number of transactions leads to a 0.49% increase in Bitcoin prices.

4.6. Competition between crypto-currencies

Our results do not support the existence of a long-term relationship between the three crypto-currencies and indicate the absence of a (long-term) cointegrating relationship between the three major crypto-currencies. Indeed, the error correction terms are both non-negative coefficients, although they have a significant p-value. A short-run causal relationship between bitcoin and its two major competitors is, however, evident in the first lag with coefficients of -0.13 and -0.99, respectively. In the short term, our results also show that a 1% increase in the price of bitcoin and litecoin leads to a decrease in the value of ethereum by 18.17% and 10.84%, respectively. Similarly, a 1% increase in the price of bitcoin and ethereum leads to a decrease in the value of litecoin of 15.33% and 12.53%, respectively. Our results corroborate the findings of Baçao et al. (2018) that crypto-currencies (Bitcoin, Ethereum, Ripple, Litecoin, and Bitcoin Cash) were indeed closely related in the short term and that the majority of information transmissions between these crypto-currencies had taken place within one day. Let us now analyze our results in detail and recall that in interpreting the long-run relationships of the VECM model, the signs must be reversed. The second column of Table 6 presents the results of the long-run cointegration relationship between ethereum and the rest of the explanatory variables. Despite the absence of a long-run relationship between the three cryptocurrencies in the three cointegration equations, the results indicate that the number of bitcoin transactions positively affects the price of ethereum. This interesting result implies that an increase in the volume of bitcoin transactions seems to draw attention to the other cryptocurrencies, and the value of ethereum increases as a result. However, this cointegration relationship shows that the number of searches for the word bitcoin in Google significantly but negatively affects the price of ethereum. Thus, there seems to be a long-term negative equilibrium relationship between ethereum and the attractiveness of Bitcoin.

The third cointegration relationship (Table 6) shows that, unlike ethereum, the number of transactions in bitcoin negatively affects the price of litecoin, and the number of Google searches for the word bitcoin positively affects the price of litecoin. This can be explained by the different characteristics that distinguish Litecoin and Ethereum. Litecoin is a lighter version of Bitcoin as it allows for faster transactions and lower transaction fees, so it is aimed at fast digital payments, whereas Ethereum serves a totally different purpose. Therefore, when interest in crypto currencies and the number of bitcoin transactions increases, investors are advised not to invest in litecoin since it is strongly inspired by Bitcoin technology and has almost the same characteristics, but to invest in ethereum, which can be a safe haven for bitcoin. Overall, the VECM results suggest that the Bitcoin price does not have a statistically significant impact on Ethereum and Litecoin

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prices in the long run, and vice versa. The results are not consistent with previous studies on cointegration between crypto-currencies by Leung and Nguyen (2018), Ciaian et al. (2018), and Van den Broek (2018). According to our results, crypto-currencies seem to interact in the short run but not in the long run. This result contradicts our expectations as well as the findings of previous empirical work and can be explained by the fact that the long-run relationship does indeed exist between cryptocurrencies, but in an indirect way. Indeed, as an example, the price of ethereum seems to be strongly and positively impacted by the volume of transactions in Bitcoin, but negatively and significantly affected by the popularity of Bitcoin. Thus, the price of Bictoin does not directly affect the price of Ethereum since the two crypto-currencies (occupying the top two places in the crypto-currency rankings in terms of capitalization and sharing the characteristics inherent to most crypto-currencies) are fundamentally different in terms of their objectives and therefore address two different types of customers (consumers and investors). Bitcoin is a direct and viable alternative to fiat currency (cash in particular) and the traditional banking system. While Ether, like Bitcoin, can be used for peer-to-peer transactions and has a monetary value, But Ethereum, as thought and intended by its creator, Vitalik Buterin, is much broader in its conception. Indeed, Ether is rather a way to operate the Ethereum platform, created to develop decentralized applications (DApps) based on "smart contracts." While the Bitcoin blockchain is only used for transactional purposes, the Ethereum blockchain hosts mostly applications. This analysis allows us to advance the existing complementarity between Bitcoin and Ethereum, especially since they can operate on the same blockchain. This is confirmed by the reversal of the evolution of transaction volume in favor of Ethereum from July 2017 onwards, where, for the first time, Ethereum transaction volume exceeds Bitcoin transaction volume. This is quite understandable, given that Ethereum was unknown, unlike Bitcoin. However, investors' interest in blockchain technology is growing following some international political and economic events that gave rise to financial crises such as tensions between China and the US. These events have contributed to the development of blockchain startups and the growth of investments in Ethereum at the expense of Bitcoin. As for Litecoin, and unlike Ethereum, it is one of the first "copies" of bitcoin, but the two cryptocurrencies are stored on completely separate blockchains, so they are two very distinct currencies. Bitcoin and Litecoin are direct competitors serving the same type of consumer. This explains the significant and negative impact of Bictoin's transaction volume on the Litecoin price. However, being less known than Bitcoin, Bitcoin's popularity helps to make its competitors known at the same time.

Finally, an interesting fact is the coefficient of the CCi30 index, which seems to affect the prices of the three cryptocurrencies very strongly in the short term. Indeed, a 1% increase in this index causes bitcoin's price to rise by more than 51%, Ethereum's by 64%, and Litecoin's price by more than 56%. This makes perfect sense given that the CCi30 is an index designed to measure the overall growth of the blockchain sector by tracking the 30 largest crypto-currencies by market capitalization, and bitcoin, dominates that list to this day. Even more interesting is that this large short-term effect persists over the long term only for Litecoin and Ethereum, but becomes insignificant for Bitcoin. This result is of great importance as it confirms once again the superiority and independence of Bitcoin over its two biggest competitors in the long run. Indeed, Bitcoin can be the source of transmitting shocks and volatility to the rest of the cryptocurrency market without being a receiver of them.

4.7. Crypto currencies versus Gold and oil

Our results show, interestingly, that in the short term, gold is uncorrelated with the three crypto currencies studied. However, they seem to benefit from the long-term price evolution of gold. This result is highly significant, as it reveals that crypto currencies are independent of gold movements and are thus an effective hedge for investors, but only in the short term. This result is in line with Pala et al. (2019), who confirmed that among the underlying assets, gold provides a better hedge against bitcoin. In the long run, a 1% increase in the price of gold will increase the prices of bitcoin, ethereum, and litecoin by about .99%, 2.10%, and 1.92%, respectively. On the other hand, the price of oil has a statistically significant and negative effect on

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the price of bitcoin in the short term, unlike gold. In other words, a 1% increase in the price of oil will decrease the price of bitcoin by about 0.06%. The value of bitcoin is sensitive to oil price movements in the short term. This result is also confirmed over the long term, but this time it is for the three crypto currencies where a 1% change in the price of oil increases the value of bitcoin, ethereum, and litecoin by more than 1.3%, 1.6%, and 0.8%. Our results are in line with Das and Kannadhasan (2018), who showed that crude oil prices and uncertainty are the most relevant factors influencing Bitcoin returns. We can confirm that, in the short term, bitcoin, ethereum, and litecoin can be used as hedges against oil.

4.8. Impulse–response functions for VECMs

We can estimate and interpret impulse response functions (IRFs) to know how the price of a crypto-currency reacts to shocks or innovations (impulses) of the different factors studied through graphical representations for a maximum horizon of 25 days. A shock to variable I can directly affect this variable, but it is also transmitted to all the other variables through the dynamic structure of the VAR.

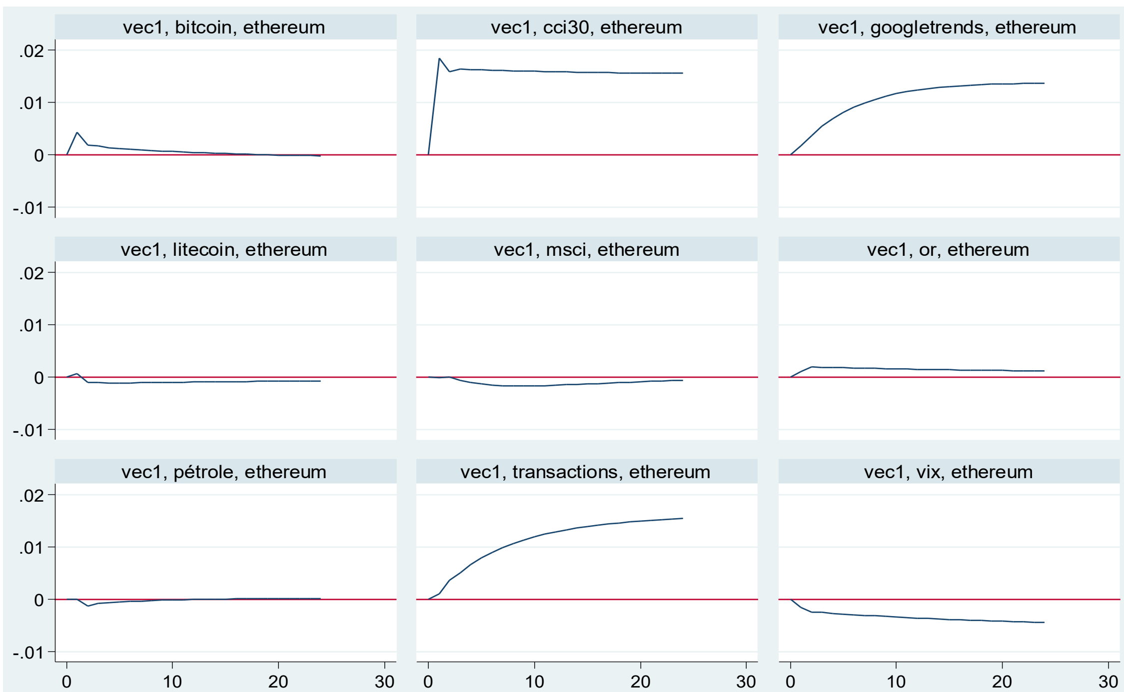

Fig 1. Generalized Impulse Responses of ETH to one S.d. Shock

These graphical representations (Figures 1, 2, and 3) confirm our previous results and lead to the following conclusions: First of all, the magnitude of the reaction of each crypto currency is roughly equivalent for these two main competitors and very close to zero. Indeed, a shock to the average price of each crypto currency has a temporary effect on the price of competing crypto currencies. The charts also indicate that a shock to the three indicators (CCI30, transaction volume, and attractiveness) has a permanent positive effect on the average price of each cryptocurrency, but that a shock to the average price of gold has only a temporary effect on the price of crypto-currencies. Regarding the MSCI index, its shock effect varies from one crypto currency to another. Indeed, a shock to this index has a permanent positive impact on the price of bitcoin and litecoin but a transient negative impact on the price of ethereum. This is unsurprising given that bitcoin and litecoin are the two most similar currencies, with litecoin heavily influenced by bitcoin. The only negative effect is that of the VIX index, since a shock to the price of the latter negatively affects the price of all three crypto currencies.

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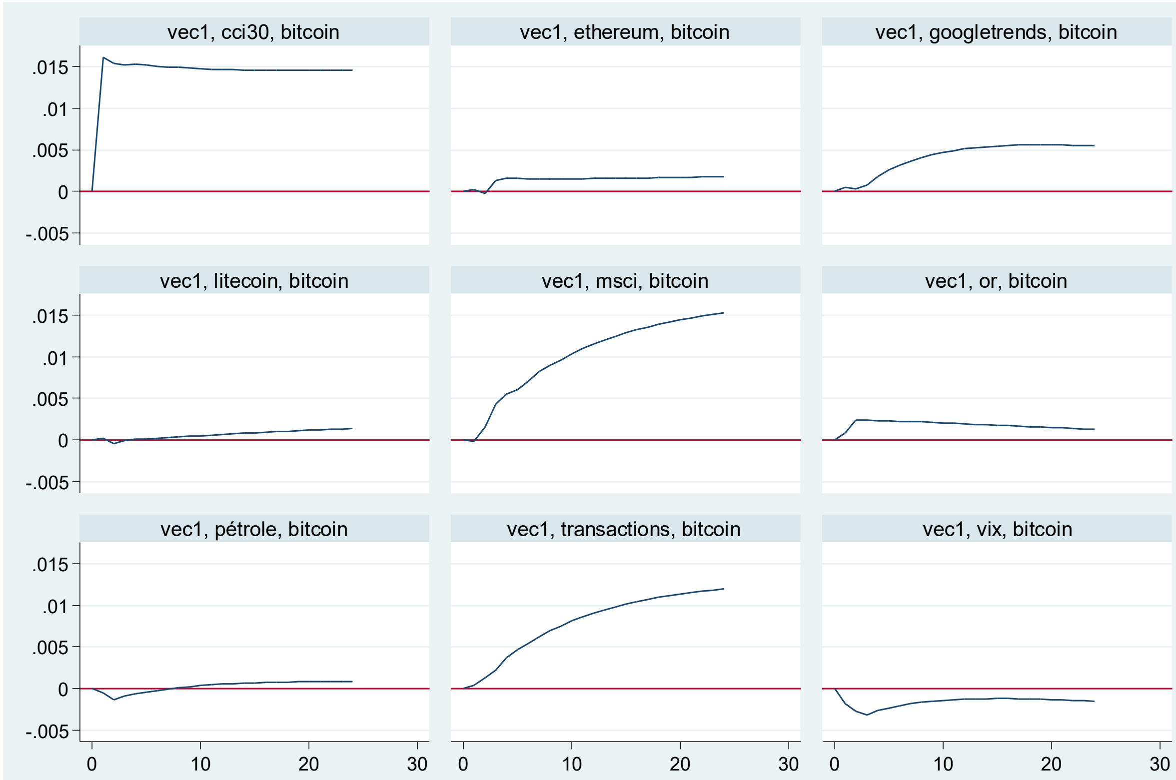

Fig. 2 Generalized Impulse Responses of BTC to one S.d. Shock

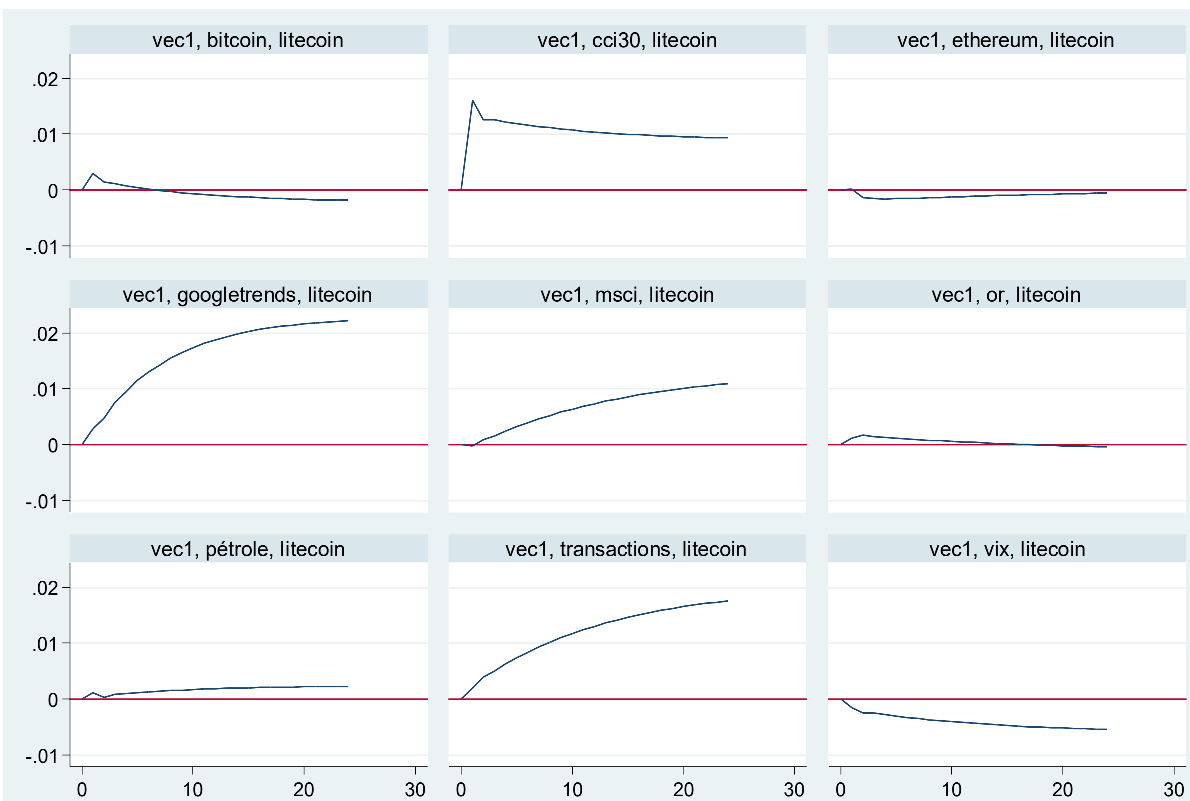

Fig. 3 Generalized Impulse Responses of LTC to one S.d. Shock

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4.9. Granger Causality Test Based on VEC Model

VECM may check for the presence of Granger causality in three ways. The first short-run Granger causality test, the partial F-statistic, may be used to analyze the significance of the sum of lagged differences in explanatory variables. Second, the t-statistic-based significance of the $ECT_{i,t-1}$ coefficient may be used to measure long-run Granger causality. Third, by examining the joint hypothesis using the Wald test, which acts as a long-run causality test for the individual variables, the strong Granger causality, which shows a joint significance of both sources (short- and long-run), may be proven.

Table 7: Granger Causality Test Based on VEC Models

	$\Delta \ln BTC$	$\Delta \ln ETH$	$\Delta \ln LTC$	$\Delta \ln Trans$	$\Delta \ln Google$	$\Delta \ln Oil$	$\Delta \ln Gold$	$\Delta \ln MSCI$	$\Delta \ln CCi30$	$\Delta \ln VIX$
Bitcoin Equation										
$\Delta \ln BTC$	-	29.25***	33.59***	6.37*	5.58	5.97	0.48	14.68***	1.02	6.22
$\Delta \ln ETH$	67.83***	-	38.08***	0.29	0.20	0.30	11.46***	0.39	2.58	0.94
$\Delta \ln LTC$	25.53***	18.04***	-	3.33	0.54	3.82	3.52	1.80	2.57	1.05
$\Delta \ln Trans$	4.43	5.89	2.50	-	0.88	2.07	1.59	5.91	3.00	7.83**
$\Delta \ln Google$	9.28**	4.22	4.36	52.34***	-	2.12	4.19	2.90	1.95	6.58*
$\Delta \ln Oil$	5.64	1.39	0.19	1.54	0.16	-	7.86**	20.34***	9.97***	2.86
$\Delta \ln Gold$	4.52	1.90	3.46	2.91	0.66	2.89	-	10.09***	5.16	8.50**
$\Delta \ln MSCI$	11.35***	2.10	2.87	9.30**	3.16	2.48	4.66	-	1.97	0.33
$\Delta \ln CCi30$	670.92***	361.1***	347.0***	12.70***	8.43**	9.29**	4.71	3.90	-	1.37
$\Delta \ln VIX$	7.91**	1.92	9.21	8.68**	12.57***	10.2***	4.60	9.72**	12.66***	-
Ethereum Equation										
$\Delta \ln BTC$		30.30***	28.56***	1.45	0.10	1.94	1.30	6.19**	0.26	6.3**
$\Delta \ln ETH$	64.88***		42.04***	3.57	12.92***	0.62	10.7***	0.32	2.52	0.13
$\Delta \ln LTC$	25.98***	16.31***		2.93	1.86	1.03	4.76*	1.40	0.96	0.32
$\Delta \ln Trans$	3.13	0.85	1.29		43.45***	2.58	0.08	0.83	3.30	3.99
$\Delta \ln Google$	0.38	1.88	0.00	23.35***		0.28	0.59	0.94	0.92	0.00
$\Delta \ln Oil$	4.18	1.25	0.05	1.23	0.71	-	7.59	4.42	9.7***	0.77
$\Delta \ln Gold$	4.98*	2.64	1.51	0.82	0.42	1.02	-	1.62	4.49	2.77
$\Delta \ln MSCI$	6.90*	0.94	1.35	5.46*	1.31	0.62	0.95	-	1.30	0.01
$\Delta \ln CCi30$	680.1***	371.6***	358.0***	6.65*	0.83	9.1***	4.68*	0.31	-	1.23
$\Delta \ln VIX$	5.20*	1.47	1.36	7.97*	2.51	5.7**	3.33	12.09***	6.40**	-
Litecoin Equation										
$\Delta \ln BTC$		28.72***	24.48***	3.31	5.69**	1.73	1.13	6.33*	0.13	6.25**
$\Delta \ln ETH$	61.56***		40.20***	2.75	0.62	0.68	11.7***	0.84	2.76	0.09
$\Delta \ln LTC$	29.09***	17.42***		3.04	4.54	0.69	4.56	2.23	3.27	0.76
$\Delta \ln Trans$	0.62	2.25	1.09	-	17.6***	1.71	2.56	0.48	0.82	2.95
$\Delta \ln Google$	0.62	0.00	0.00	1.21	-	0.81	0.91	3.14	4.12	5.39*
$\Delta \ln Oil$	4.45	1.44	0.01	0.27	1.79	-	7.04**	4.20	10.24***	0.70
$\Delta \ln Gold$	4.60	2.42	1.31	0.18	0.25	1.04	-	1.80	4.00	3.07
$\Delta \ln MSCI$	6.82**	0.92	0.95	0.88	0.26	0.91	0.68	-	0.88	0.05
$\Delta \ln CCi30$	678.4***	367.94***	358.2***	3.59	1.60	8.9***	4.43	0.31	-	1.24
$\Delta \ln VIX$	6.19**	1.85	1.937	1.41	1.62	6.60**	3.29	13.55***	6.78**	-

Note: *, **, *** shows significance at 10%, 5%, and 1% level, respectively.

The results of the short-run test of the bitcoin model presented in Table 6 first indicate a two-way causality between the three crypto-currencies. However, there is a unidirectional causality running from Google trends, VIX, and CCi30 to bitcoin. However, this causality has not been verified for Ethereum and Litecoin. In the short term, we also verify a bidirectional causal relationship between Bitcoin and MSCI, which is, again, not verified for the other two crypto-currencies. An interesting fact is the lack of a causal relationship between each cryptocurrency and commodities (gold and oil). In the long run, the significant coefficients of the ECM (Table 7) indicate the existence of causal relationships for all equations except gold, oil, and VIX. Regarding the results of the bitcoin, ethereum and litecoin models presented in table 7, we note bidirectional causality between the three crypto-currencies and a unidirectional causality running from CCi30 to these two crypto-currencies in the short run. In the long run and contrary to the bitcoin model, the significant coefficients of the ECT indicate the absence of causality for the two competing crypto currencies. At this point, we have several important results: First, the value of the three crypto-currencies is mainly affected in the short term by the competing crypto-currencies and the CCI30 index. Secondly,

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ethereum and litecoin have the same determinants in the short term and almost in the long term as the only difference is the MSCI index equation. Another interesting fact is the lack of a causal relationship between each crypto-currency and the price of gold in the short and long term. Finally, the number of transactions does not cause any crypto currency, while the number of Google searches causes just bitcoin, and even the MSCI and VIX index prices only cause the price of bitcoin in the short term.

5. Conclusion

This article aims to provide empirical evidence on cryptocurrency, which may be viewed as the emergence of new digital currencies that are closely linked to a decentralized electronic payment system. The original goal of cryptocurrencies was to serve as a payment function comparable to cash; however, it also serves as an investment asset. This dual function has been critical to their success. In this essay, we specifically look at the factors that might affect the price formation of three main crypto currencies (Bitcoin, Litecoin, and Ethereum) and the drivers of their success in the short and long term. We also paid close attention to the interconnectedness and competitiveness among cryptocurrencies. In this regard, it is worthwhile to note that there is still no clear theory defining how cryptos should be valued because, by definition, they provide no dividends, cash flows, or earnings. We opted to do an exploratory empirical investigation instead because there were no obvious conventional valuation techniques. More specifically, the method used here is based on examining both supply-side and demand-side factors.

Our results indicate first, that in the short term, the value of any of each cryptocurrency is largely determined by its two competitors. While the overall performance of the crypto market raises their prices, the negative relationship between the major currencies confirms their competition. At the same time, because it is still a relatively untrustworthy newcomer, this technology is not fully integrated with traditional stock markets and the macroeconomy. Indeed, in line with prior research, all three currencies are independent of commodity markets. In the long term, we find that one of the key variables driving cryptocurrency values is their popularity. We observed that when the number of individuals searching for them on Google grows, cryptos' prices tend to rise. There is also some evidence that demand from users' transactional demands drives increasing prices, confirming the relationship between the payment and investing functions of cryptocurrencies. Finally, we discover that Ethereum and Litecoin share the same short- and long-term drivers. To some extent, these findings appear to reflect and corroborate Bitcoin's uniqueness, as well as possibly explaining its higher performance.

In summary, our results indicate that crypto-currencies can be considered as risk-hedging assets only in the short run. For oil, Bitcoin proves to be an effective risk hedge compared to oil, as both assets show a negative and statistically significant relationship in the short run. The other two crypto currencies, litcoin and ethereum, are independent of oil movements in the short term. In the long term, only Ethereum maintains its independence from oil. Again, the specificity of this crypto-currency makes it insensitive to market shocks and makes it an interesting alternative to bitcoin, which is considered the leader of crypto-currencies worldwide.

Finally, our findings considerably widen understanding of cryptocurrencies and their potential. Indeed, finance is crucial in wars in general, but the Russia-Ukraine conflict is the first serious conflict in which cryptocurrencies play a key role, after worries about Russian players' ability to use bitcoin to circumvent sanctions. Crypto supporters, on the other hand, argue that crypto contributes to the destabilization of Moscow's autocratic system by providing an alternative to the Russian currency, encouraging capital flight from Russia.

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Appendix

Abbreviations

ADF:	Augmented Dickey-Fuller
AIC:	Akaike Information Criterion
ARDL:	Auto-Regressive Distributed Lag
BEKK-GARCH:	Baba, Engle, Kraft, and Kroner-Generalized Auto Regressive Conditional Heteroskedastic
BIC:	Bayesian Information Criterion
CCI30:	Cryptocurrency index
CPI:	Consumer Price Index
DJIA:	Dow Jones Industrial Average
ECM:	Error Correction Model
EOS:	Electro-Optical System
FFR:	Federal Funds Rate
GPR:	Geo-Political Risk
IID:	independent identically distributed
KPSS:	Kwiatkowski-Philips-Schimdt-Shin
MFSVM:	Modified Fuzzy Support Vector Machine
PP:	Philips-Perron
SP500:	Standard and Poor's 500
VAR:	Vector Auto Regressive
VECM:	Vector Error Correction Model
VIX:	Volatility Index

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