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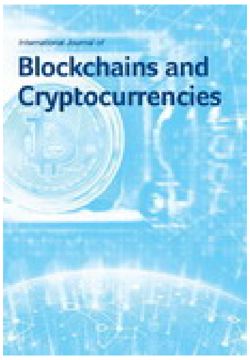

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Cryptocurrency pricing determining factors

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Abstract: Cryptocurrencies have emerged as a popular investment option in recent years. This paper aims to identify and analyse the factors that determine the pricing of cryptocurrencies. The existing problem is the lack of a comprehensive framework for understanding cryptocurrency pricing. The study is necessary to help investors make informed decisions about investing in cryptocurrencies. To examine determinants of cryptocurrency prices, the study used five cryptocurrencies and employs the GMM techniques. The study used multiple variables (coin prices; coins issued per day; difficulty and market capitalisation) to test how they can determine cryptocurrency prices. Findings showed that coins that uses higher hash rate, which has higher difficulty, higher market capitalisation and has lower number of coins that are mined on daily basis, is likely to have its pricing improved over short to medium terms. Overall, this research work provides valuable insights into the factors that determine the pricing of cryptocurrencies.

Keywords: cryptocurrencies; digital currency; Bitcoin; pricing factors; generalised method of moment; GMM; dynamic panel; hash rate; coins issued; market capitalisation; short-run dynamics; long-run dynamics.

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1 Introduction

The race to develop cryptocurrencies valuation and asset pricing methodologies has been highly contested with many divergent views and research findings. The most popular and widely cited Bitcoin valuation methodology was proposed by Chen et al. (2018) who claimed that the important component of Bitcoin pricing entails considering its inelastic money supply as a reward for mining process and transaction costs.

Gourov (2014) concluded that traditional pricing methods do not apply to the cryptocurrencies, while Güring and Grigg (2011) and Chen et al. (2018) concluded that a suitable method to be considered for pricing Bitcoin is through an analysis of the entire coin mining process. However, this pricing methodology has been found to be incomplete as different cryptocurrencies are structured and mined differently – they use different algorithms, some have infinite coins to be issued, whilst others have finite, some have relations to financial institutions and some do not. All these differences make a 'one-size-fits-all' pricing methodology to be inappropriate.

The assertion that Bitcoin prices differ depending from the country of reference cannot be given unqualified support as there is a need to identify factors that universally determine cryptocurrencies prices. It is thus evident that there are no accepted pricing methods for cryptocurrencies as yet. The above gaps in research are a challenge as cryptocurrency trading volumes have grown tremendously over the past few years (Corbet et al., 2017). The concern for South African regulators and other stakeholders is the potential for negative spillover effects when a major negative development takes place within the cryptocurrencies industry.

The objective of the study is to contribute to the cryptocurrency discourse, this will be done by identifying variables that are responsible for the pricing of cryptocurrencies. This is of importance as it will assist in understanding the pricing dynamics of cryptocurrencies. The study in this area is considered important because: first, the cryptocurrencies industry is under-researched mostly in emerging markets like South Africa. Second, the study is relevant for a wide range of stakeholders which includes academicians, legislators and investors. Third, cryptocurrencies are a new field that changes in a great speed, and therefore any attempt to understand it better is welcome.

In examining the determinants of cryptocurrency prices, the study used a panel of five cryptocurrencies and employs the system generalised method of moments (GMMs) techniques. The study used multiple variables (coin prices; coins issued per day; difficulty and market capitalisation) to test how they can determine cryptocurrency prices.

Section 2 of this study discusses the theoretical and empirical literature around cryptocurrency pricing. Section 3 discusses the research tools and methods used in achieving the objective of this study; that is, identifying variables that are responsible for pricing of cryptocurrencies. Section 4 presents the results and lastly, Section 5 concludes the paper and presents recommendations.

2 Literature

Cryptocurrency has gained significant attention in recent years due to its potential to disrupt traditional financial systems and revolutionise the way we conduct transactions.

Cryptocurrency operates on decentralised blockchain networks that allow for secure, transparent, and immutable transactions without the need for intermediaries like banks or financial institutions. This technology has numerous applications in various fields, including finance, supply chain management, and healthcare.

Table 1 Seven main approaches to cryptocurrencies pricing from 2010 to 2020

	Main considerations		
No.	*Valuation method*	*Main references*	*Gap identification and comments*
1	Valuation methodology that is based on finite number of coins to be ever produced[1]	Woo et al. (2019)	Altcoins like Bitcoin, Litecoin and Dash have a finite number that will ever be issued at some stage. There are two challenges with this methodology: first, does it mean that the altcoins with an unlimited number of coins to be ever issued does not have value; second, what about the fact that each coin is divisible sometimes thousands of times?
2	Valuation based on energy use and computer power	Chen et al. (2018) and Hayes (2015, 2016b)	Energy use in cryptocurrencies is measured in hash-rates, and it is linked to difficulty retargeting. This is a credible valuation methodology, however, the source of energy[2] is relevant, and this variable must be mixed with other ones like number of coins, difficulty and number of blocks produced per day.
3	Valuation based on media searches (Twitter and Google Searches)	Yasar (2017)	The idea that cryptocurrencies that are not popular in social media platforms might not be appropriately valued is not wholly acceptable. Yasar (2017)[3] included other variables in the model and the pricing output improved.
4	• Artificial neural network (ANN) • RNN, auto-regressive integrated moving average (ARIMA) and long short-term memory (LSTM)	McNally (2016)	The techniques are found to be too technical and require enormous computer-based data manipulation.
5	Valuation based on crypto acceptance and transaction speed	Burniske (2017)	This methodology has limitations as well since Bitcoin is one of the slowest digital currencies in terms of transaction speed, yet it has the highest price per coin.[4]

Notes: [1]the maximum for Bitcoin is 21-million coins.
[2]https://www.reuters.com/technology/ – on the 13 May 2021 Elon Musk announced that Tesla will no longer accept payments in Bitcoin owing to its high use of non-renewable energy. A major price correction took place after the announcement.
[3]adding on Twitter and Google movements she added regulation.
[4]an important consideration for valuing cryptocurrency also entails whether it is able to play a role that it was designed for (Bitcoin was designed mainly as a store of value) rather than transactional altcoin.

Source: Author's own compilation

Table 1 Seven main approaches to cryptocurrencies pricing from 2010 to 2020 (continued)

		Main considerations	
No.	*Valuation method*	*Main references*	*Gap identification and comments*
6	Population-based stochastic optimisation (PSO)	Indera et al. (2017)	PSO is a population-based stochastic optimisation technique based on swarm theory (ST) and evolutionary computation (EC). This methodology is a price prediction exercise rather than a valuation technique.
7	Quantity theory of money (QTM)	EY (2018)	This pricing technique is applicable for digital currencies that are designed to play a role of being a medium of exchange, and is not suitable for those that are designed for other purposes.

Notes: [1]the maximum for Bitcoin is 21-million coins.
[2]https://www.reuters.com/technology/ – on the 13 May 2021 Elon Musk announced that Tesla will no longer accept payments in Bitcoin owing to its high use of non-renewable energy. A major price correction took place after the announcement.
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[4]an important consideration for valuing cryptocurrency also entails whether it is able to play a role that it was designed for (Bitcoin was designed mainly as a store of value) rather than transactional altcoin.

Source: Author's own compilation

Cryptocurrency has the potential to transform various industries by improving transparency, security, and efficiency. While there are still challenges to be addressed, such as regulatory issues and scalability, the growing adoption of cryptocurrency suggests that it will continue to have a significant impact in the years to come. In February 2021, Tesla announced that it had invested $1.5 billion in Bitcoin and planned to accept the cryptocurrency as payment for its products in the future. This news had a significant impact on the price of Bitcoin, which surged to an all-time high of over $58,000.

The announcement by Tesla highlights the role of corporate adoption and mainstream acceptance as a key determinant of cryptocurrency pricing. In this case, Tesla's investment in Bitcoin signalled to the market that cryptocurrencies were gaining acceptance among mainstream companies and institutions, which led to a surge in demand and increased the price of Bitcoin. Furthermore, Tesla's investment in Bitcoin also highlighted the potential for cryptocurrencies to be used as a hedge against inflation and currency devaluation. With concerns about inflation on the rise, more investors may look into cryptocurrencies as a way to protect their wealth and diversify their portfolios, which could further increase demand and drive-up prices.

There is a difference between valuing and pricing an asset. Valuation on one hand is generally expressed as an intrinsic value and is driven by the nature of cashflows that are forecasted from existing assets, the growth in those cash flows, the risks associated with those cash flows and the quality of growth. Pricing on the other hand is driven by a different set of factors: first, by mood and momentum which are largely driven by behavioural factors; second, by incremental information which includes news stories, rumours, gossip and how it measures up relative to expectations; third, by liquidity and trading ease of and asset; and last, by group thinking which is expressed as herd mentality (Damodaran, 2012). The literature review conducted by the researcher informed a decision regarding studying the pricing of cryptocurrencies rather than their valuation.

Table 1 grouped together different cryptocurrencies pricing techniques and came up with seven main pricing themes. However, most importantly, the table points out weaknesses in each of the presented pricing technique as a strategy to identify gaps in knowledge that the current research will attempt to address.

Based on the number of cryptocurrencies pricing techniques and valuation methods that have been presented above, the one that has a great deal of rationale is the one that was developed by Chen et al. (2018) and Hayes (2015, 2016b).

The gap that has been identified with the above valuation techniques is that none of them proposes a methodology that combines variables that associated with cryptocurrencies (coins issued units per day, hash rate, difficulty, blocks per day) with other relevant economic variables (i.e., gold and ten-year treasury bill) at the same time. Hayes (2015) used four of the variables listed at the R-squared was 70%, but that model was only applicable to Bitcoin. EY (2018) and Indera et al. (2017) proposed a method that categorises cryptocurrencies according to certain criteria and develop a pricing technique that is tailor-made for each category. Despite the rationale for this technique, it is expected that it will cause confusion as other practitioners would want to use a technique that favours their circumstance against another one.[1]

3 Methodology

3.1 Data collection

Cryptocurrency related data (coin prices; coins issued per day; difficulty and market capitalisation) was obtained from CoinMarketCap Database. In examining the determinants of cryptocurrency prices, the study used a panel of five cryptocurrencies (Bitcoin; Ethereum; Dash; Litecoin and Dogecoin) for a five-year period (1 January 2016) to (31 December 2020).

The study considered daily observations (Gourieroux and Hencic, 2014; Chu et al., 2015). Following previous studies, the dependent variable is the natural logarithm of cryptocurrency prices (Chan et al., 2017; Kaya, 2018) and the explanatory variables drawn from literature include cryptocurrency related variables such as coins issued which measured the number of coins issued per day; difficulty which is a measure of how hard it is to find a hash that meets the protocol-designated requirement; coin market capitalisation (which coin price multiplied by the total number of coins issued). In line with relevant previous research this studies included gold and MSCI as control variables (Dyhrberg, 2016).

This study employed the dynamic panel regression methodology to determine the factors that influence the pricing of cryptocurrencies. The method allowed for the analysis of lagged dependent variable effects on the current price and also included cross sectional effects (Biørn, 2016). The study employed the system generalised method of moments (GMM) estimation techniques developed by Blundell and Bond (1998). This method has the power to overcome heteroscedastic and endogeneity problems in estimation (Mohanty et al., 2018; Vengesai and Kwenda, 2020; Hayes, 2015). The dependent variable to be explained by the model is cryptocurrency prices and the explanatory variables are cryptocurrency related data such as difficulty[2], number of coins issued per day, market capitalisation and gold and MSCI were also used as other control variables.

3.2 Preliminary tests

3.2.1 The panel unit root test

Prior to estimating the models, the panels were tested for unit root. Both the first-generation tests and the second-generation tests were applied. The first-generation tests used included the Levin, Lin and Chu; Im, Pesaran and Shin; ADF Fisher and PP Fisher tests. The null hypothesis in panels contain a unit root. The second-generation tests conducted are the Bai and NG PANIC and the Pesaran (2007) CIPS tests. The Traditional tests (first generation) use pooled panels and assume cross-sectional independence, and ignoring panel dynamics. The second-generation tests assume cross-sectional dependence and take into account cross-sectional dynamics. However, the estimation technique used differences all variables in estimating the models; hence non-stationarity was not a problem in this analysis since the variables containing unit root are stationary at first difference.

3.3 Model specification

3.3.1 General panel model

Panel data models provide information on heterogeneous individual behaviour across individuals over time. Pane data and panel models have both time-series dimensions and cross-sectional dimension. According to Hsiao et al. (1999), panel data models have generally three approaches namely fixed effect, random effects and independently pooled panels. The error term distribution determines whether a fixed or a random effect is most appropriate. The error term is assumed to vary non-stochastically over the cross section or time dimension and the random effects assumes that the error term varies stochastically hence requiring a special variance matrix treatment. However, due to the presence of endogeneity and other unique characteristics of financial data, these models normally fall short and the need to employ advanced models. According to Hayes (2015) a standard static panel model can be specified as follows:

$$\begin{aligned} &Y_{it} = \beta_0 + \beta_x X_{it} + \varepsilon_{it} \\ &\text{with } i = 1, \ldots, N; t = 1, \ldots, T \end{aligned} \tag{1}$$

where Y_{it} is the dependent variable, β_0 is the intercept, β_x is a $(Kx1)$ vector, the slopes independent of i and t are model and ε_{it} is an error term

To examine the factors that drive cryptocurrency pricing this study extended the general panel model [equation (1)] to a dynamic panel model setting. A dynamic panel model includes a lagged dependent variable as one of the independent variables. In this section the focus dependent variable is cryptocurrency price (hence a lag of coin prices was included as one of the explanatory variables). Financial asset pricing is dynamic, future prices may depend on past prices; the current price of an asset is the best estimate of its value. The inclusion of the lagged cryptocurrency price helps to explain the impact of historical coin price behaviour on current coin value. The lagged dependent variable captures the historical trends. Moreover, lagged dependent variables helps to reduce autocorrelation that may arise from model misspecifications; capture price dynamics over time and helps to deal with the problem of endogeneity and nickel bias in fixed effects. Above all, a dynamic panel data model allows partial adjustment mechanism modelling (Baum, 2001). In line with Bhattarai (2019), a dynamic panel model with fixed effects is generally given by:

$$Y_{it} = \beta_0 + \gamma Y_{it-1} + \beta_x X_{it} + \eta_i + \varepsilon_{it} \tag{2}$$

where Y_{it} is the dependent variable, Y_{it-1} is the lagged dependent variable, γ coefficient of the lagged dependent variable, η_i is a fixed effect, β_0 is the intercept, β_x is a ($Kx1$) vector, the slopes independent of i and t are model, ε_{it} is an error term. $\varepsilon_{it} \sim N(0, \sigma_\varepsilon^2)$ is a random disturbance and assuming $\sigma_\varepsilon^2 > 0, \in (\varepsilon_{it}, \varepsilon_{js}) = 0$.

Equation (1) was extended to a dynamic-panel model by adding a lag of cryptocurrency price as one of the explanatory variables. Using the variables suggested by Hayes (2015), specifically, the model estimated takes the form of equations (3) and (4) below:

$$\ln(P_{it}) = \beta_0 + \gamma \ln(P_{it-1}) + \beta_x \ln(X_{it}) + \varepsilon_{it} \tag{3}$$

where $\ln(P_{it})$ is the natural logarithm of each coin's price at time t. In this case, X_{it} represents the endogenous and exogenous explanatory variables that could influence the pricing of cryptocurrencies. These are difficulty (*diff*); coins issued (CI); coin market capitalisation; gold and MSCI. Empirically the estimation will be as follows:

$$\begin{aligned}\ln(P_{it}) = \beta_0 + \gamma \ln(P_{it-1}) + \beta_1 \ln(Difficulty)_{it} + \beta_2 \ln(Coins\ issued)_{it} \\ + \beta_3 \ln(Market\ Cap)_{it} + \beta_4 \ln(Gold)_{it} + \beta_5 \ln(MSCI_{it}) + \mu_{it}\end{aligned} \tag{4}$$

This study is unique in that it focused on a panel data rather than an individual cryptocurrency.

3.3.2 Model estimation: estimation technique

The two step system GMM technique was used to estimate equation (4). Using traditional estimation methodologies to estimate the dynamic panel model may cause several econometric problems – to mention a few, the cryptocurrency related independent variables-level of difficulty and number of coins issued are assumed to be endogenous; causality may run in both directions – from coin price to cryptocurrency related factors (difficulty and coins issues) and from cryptocurrency related factors to coin, and there is a possibility of correlation between these explanatory variables with the error-term. The addition of the lagged coin price as one of the explanatory variables give rise to autocorrelation.

According to Antoniou et al. (2008) μ_{it} in equation (4) is not directly observable and may correlate with other independent variables thus the pooling method is non-efficient. Taking the first differences to do away with the time-invariant fixed effects, the ordinary least squares (OLS) technique will still be inefficient because of the correlation of $\Delta\ln(P_{it})$ (the change in the dependent variable) from differencing ($\ln(P_{it}) - \ln(P_{it-1})$) and $\Delta\varepsilon_{it}$ the change in the error term from ($e_{i,t} - e_{i,t-1}$) as shown below:

$$\Delta \ln \left(P_{it} \right) = \beta_0 + \Delta \gamma \ln \left(P_{it-1} \right) + \Delta \beta_x \ln \left(X_{it} \right) + \Delta \varepsilon_{it} \quad (5)$$

By definition $\ln(P_{it-1})$ may be correlated with the fixed effect in the error term giving rise to dynamic panel bias (Nickel, 1981). The correlation between the idiosyncratic error term and the explanatory variable violates the necessary conditions of the classic OLS and makes its estimates. Noting that this study employed a panel of five cryptocurrencies, heterogeneity is inevitable, which cannot be handled by the OLS. The fixed effect model can be employed to overcome the inconsistency of the OLS in a heterogeneous panel; however, the fixed effect estimator cannot handle endogeneity problems that arise from endogenous explanatory variables, possible measurement errors, possible bi-directional causation and omitted variables (Muñoz, 2013). The fixed effect estimators are grounded on strict exogeneity notion. The introduction of the lagged dependent variable $\ln(P_{it-1})$ in our model violates the strict exogeneity supposition presenting endogeneity. Consequently, there are inconsistencies and inefficiencies. The Anderson and Hsiao (1982) instrumental variables (IV) technique can be employed to control for endogeneity. Nonetheless, the IV methodology does not use all the moment conditions, instrument selection is difficulty and may be biased.

The dynamic bias and auto-correlation introduced by a dynamic model cannot be solved using the traditional techniques and the IV method. Hence, a need to introduce stochastic variation into the model; the system GMM attest to it being the most appropriate estimation technique in the presence of endogenous explanatory variables, serial correlation and heteroscedasticity (Roodman, 2006).

3.3.3 Generalised method of moments

Typically, the GMM is employed in semi-parametric models characterised by finite dimensional parameters and unknown data-distribution function shapes, hence the maximum likelihood estimation is not appropriate. The order condition for identification would be where there are more equations than there are parameters. There are generally two GMM estimators; that is the difference and the system GMM. The GMM estimators as developed by Holtz-Eakin et al. (1988), Arellano and Bond (1991), Arellano and Bover (1995) and Blundell and Bond (1998) are general estimators that are intended for situations with a relationship that is linear; a dynamic dependent variable; non strictly exogenous explanatory variables with a possibility of correlating with the error term; fixed individual effects; autocorrelation and heteroscedasticity.

3.3.3.1 Mechanics of GMM

The Arellano and Bond (1991) method of moments conditions use the properties of the instrument to be uncorrelated with the future errors $u_{i,t}$ and $u_{i,t-1}$ obtaining an accumulative sum of moment conditions for t = 3, …, T. In an autoregressive panel model given by:

$$Y_{it} = \alpha Y_{i,t-1} + u_{i,t}, i = 1, \dots, N; t = 2, \dots, T, \quad (6)$$

$$u_{i,t} = \eta_i + v_{i,t},$$

η_i and $v_{i,t}$ are presumed to have an error component structure with:

$$E(\eta_i) = 0, E(v_{i,t}) = 0, E(\eta_i v_{i,t}) = 0, i = 1, \ldots, N; t = 2, \ldots, T \tag{7}$$

$$E(\eta_i v_{i,t}) = 0, i = 1, \ldots, N; t \neq s, \tag{8}$$

The initial conditions satisfy:

$$E(\eta_i v_{i,t}) = 0, i = 1, \ldots, N; t = 2, \ldots, T \tag{9}$$

Under the above assumptions, the subsequent linear moment conditions are valid

$$E(Y_i^{t-2} \Delta u_{i,t}) = 0 \ t = 3, \ldots, T \tag{10}$$

where $y_i^{t-2} = (y_{i,1}, y_{i,2}, \ldots, y_{i,t-2})$ and $\Delta u_{i,t} = u_{i,t} - u_{i,t-1} = \Delta y_{i,t} - \alpha \Delta y_{i,t-1}$.

The authors define the $(T-2) \times 1$ vector

$$\Delta\mu_i = \left[(\mu_{1,3} - \mu_{i,2}), \ldots, (\mu_{i,T} - \mu_{i,T-1})\right]'$$

And a $(T-2) \times (T-2)$ matrix of instruments

$$Z_{di} = \begin{bmatrix} y_{i1} & 0 & 0 & \ldots & 0 & \ldots & 0 \\ 0 & y_{i1} & y_{i2} & \ldots & 0 & \ldots & 0 \\ . & . & . & \ldots & . & \ldots & . \\ 0 & 0 & 0 & \ldots & y_{i1} & \ldots & y_{iT-2} \end{bmatrix}; \Delta\mu_i = \begin{bmatrix} \Delta\mu_{i2} \\ \Delta\mu_{i4} \\ . \\ \mu_{iT} \end{bmatrix},$$

Equation (10) moment conditions can be precisely conveyed as:

$$E(Z'_{d,i} \Delta u_i) = 0 \tag{11}$$

According to Arellano and Bond (1991) the GMM α estimation will be set as:

$$\widehat{\alpha_d} = \frac{\Delta y'_{-1} Z_d W_N^{-1} Z'_d \Delta y}{\Delta y'_{-1} Z_d W_N^{-1} Z'_d \Delta y_{-1}}$$

where $\Delta y = (\Delta y'_1, \Delta y'_2, \ldots, \Delta y'_N)$, the lagged version of Δy, $Z_d = (Z'_{d1}, Z'_{d2}, \ldots, Z'_{dN})$ and W_N a weight matrix.

Blundell and Bond (1998) exploit additional moment conditions such that:

$$\mathbf{E}(\varepsilon_i \Delta y_{i2}) = \mathbf{0} \tag{12}$$

with $E(\varepsilon_i) = E(\varepsilon_i \eta_i) = 0$ if $\mathbf{E}(\varepsilon_i) = \mathbf{0}$, $\mathbf{E}(v_{i,t}) = \mathbf{0}$, $\mathbf{E}(\eta_i v_{i,t}) = \mathbf{0}$, $\mathbf{E}(\eta_i v_{i,t}) = 0$.

With $(T-1)(T-2) / 2$ moment conditions:

$$E(u_{it} \Delta y_i^{y-1}) = 0 \ t = 3, \ldots, T; \text{ where } \Delta y_i^{t-1} = (\Delta y_{i2}, \Delta y_{i3}, \ldots, \Delta y_{it-1}) \tag{13}$$

The GMM estimator based on these conditions are given by:

$$\widehat{\alpha_l} = \frac{\Delta y'_{-1} Z_l W_N^{-1} Z'_l \Delta y}{\Delta y'_{-1} Z_l W_N^{-1} Z'_l \Delta y_{-1}}$$

$\widehat{\alpha_l}$ is the Level GMM estimator, and $E(u_{it}\Delta y_i^{t-1})=0$ and $E(Z_{li}'u_i)=0$ are the level moments conditions. The full set linear moment conditions are expressed as:

$$E\left(y_i^{t-2}\Delta u_i\right)=0\ t=3,\ldots,T \tag{14}$$

$$E\left(Z_{si}'p_i\right)=0 \tag{15}$$

where $Z_{si}=\begin{bmatrix} Z_{di} & 0 & \ldots & 0 \\ 0 & \Delta y_{i2} & . & 0 \\ . & . & . & . \\ 0 & 0 & \ldots & \Delta y_{iT} \end{bmatrix}$; $p_i=\begin{bmatrix} \Delta\mu_{i2} \\ \mu_i \end{bmatrix}$.

Based on these conditions the GMM estimator is:

$$\widehat{\alpha_d}=\frac{q_{-1}'Z_sW_N^{-1}Z_s'q}{q_{-1}'Z_sW_N^{-1}Z_s'q_{-1}}$$

$q_i=(\Delta y_i', y_i')'$ yields the Blundell and Bond (1998) system GMM estimator. The moment conditions $E(y_i^{t-2}\Delta u_i)=0$ t = 3, …, T and $E(Z_{si}'pi)=0$ provides the system moment conditions.

The core of the GMM in solving endogeneity is through transforming the data to eliminate the fixed effects. The difference GMM – Arellano and Bond (1991) difference all regressors and use uncorrelated variables to instrument the dependent variable and endogenous variables. The system GMM estimator by Blundell and Bond (1998) assumes no correlation on the fixed effects and IVs' first differences introducing more instruments into the system thus improving efficiency.

The system GMM employs additional instruments of the lagged first difference variable (coin price) solving the problem of weak instruments of the difference GMM. Levels equations are instrumented with first differenced equations and differenced equations are instrumented with levels instruments which generates a system of equations. Lagged and level endogenous variables are used in addition to exogenous instruments, making endogenous variables predetermined and uncorrelated with the error term. Individual heterogeneity is controlled by estimating the models in levels and first differences using lagged differenced regressors to instrument levels equations (Antoniou et al., 2008). Considering equation (16):

$$\ln\left(P_{it}\right)=\beta_0+\gamma\ln\left(P_{it-1}\right)+\beta_x\ln\left(X_{it}\right)+u_{it} \tag{16}$$

where $u_{i,t}$ contains of coin unobservable effects v_i and specific errors $e_{i,t}$

$$u_{i,t}=v_i+e_{i,t} \tag{17}$$

GMM transforms equation (3) through first differencing as follows:

$$\Delta\ln\left(P_{it}\right)=\beta_0+\Delta\gamma\ln\left(P_{it-1}\right)+\Delta\beta_x\ln\left(X_{it}\right)+\Delta u_{it}' \tag{18}$$

Any fixed effect/factors that do not vary across the panel (coins) over time are removed by differencing. From equation (17):

$$\Delta u_{i,t}=\Delta v_i+\Delta e_{i,t} \tag{19}$$

As follows:

$$u_{i,t} - u_{i,t-1} = (v_i - v_i) + (e_{i,t} - e_{i,t-1}) = e_{i,t} - e_{i,t-1} \tag{20}$$

supposing serially uncorrelated and independent error terms across coins.

$$\left[E(\mu_{i,t}\mu_{i,\tau}) = 0 \text{ for } \tau \neq t \right]$$

Initial conditions satisfy:

$$E\left[\left(\frac{I}{K_i} \right) \mu_{i,t} \right] = 0 \text{ for } t > 2$$

The lagged coin price $\ln(P_{it-1})$ on the right-hand side of the model introduces autocorrelation – the system GMM estimation technique controls that autocorrelation by instrumenting with differenced instruments for levels equations. The second equation in the system GMM provides more instruments increasing efficiency of the estimator (Blundell and Bond, 1998). In addition, as compared to the one step estimators, the two-step version makes use of one step residuals in constructing asymptotically optimal weighting matrices, yielding more efficiency. The use of the orthogonal conditions on the variance covariance matrix enables the technique to address correlation of errors, measurement errors and simultaneity (Antoniou et al., 2008). Blundell and Bond (1998) established that the system GMM becomes a handy tool under such conditions.

3.3.4 Other econometric issues in finance regressions

Multi-collinearity arises when there are high inter-correlations among the independent variables; this affects partial regression coefficients and affects standard errors (Cooper et al., 1998). This study assesses the correlation of variables to detect any potential existence of collinearity, explanatory variables with very high correlations may suggest the presence of multi-collinearity. The coefficients table housing collinearity statistic was employed to investigate the presence of multi-collinearity. The measures among explanatory variables should be within normal bounds to indicate that there is no multi-collinearity. Moreover, the correlation of the variance of the error term and independent variables brings about heteroskedasticity which affects statistical inference (DeFusco et al., 2004).

3.4 Additional tests: short-run and long-run dynamics

Additional tests were employed to ascertain the pricing behaviour of cryptocurrencies over the short- and long-term. To capture the short and long-run dynamics in cryptocurrency pricing, a panel auto regressive distributive lag (ARDL) model was also estimated, given that our sample is a heterogeneous panel with a cross-section dimension less than the time series. The ARDL methodology estimates long and short-run relationships between a group of variables (Im et al., 2003).

Previous studies used time-series ARDL models; this study augments prior studies by employing a panel ARDL model in understanding the factors that influence the pricing of cryptocurrencies. The ARDL models perform well regardless of whether the variables are non-stationery $I(1)$, stationary $I(0)$, or mutually cointegrated (Pesaran and Shin, 1999). All the variables were subjected to unit root tests as shown on the unit root test results there is certainly a mix of $I(0)$ and $I(1)$ variables which makes the ARDL model appropriate for this analysis.

Pesaran and Shin (1995) suggested the mean group (MG) model to deal with heterogeneous bias in dynamic panels. The MG provides the long run parameters in the panel by averaging long-run parameters in ARDL model for individual observations. For instance, if an ARDL model can be specified as follows:

$$Y_{i,t} = \alpha_i + \gamma_i Y_{i,t-1} + \beta_i X_{i,t} + \varepsilon_{i,t} \tag{21}$$

where i stands for the coins such that $i = 1, 2, \ldots, N$. The long parameter θ_i is given by:

$$\theta_i = \frac{\beta_i}{1-\gamma_i}$$

For the entire panel the MG estimators will be given by:

$$\hat{\theta} = \frac{1}{N}\sum_{i=1}^{N}\theta_i$$

$$\hat{\alpha} = \frac{1}{N}\sum_{i=1}^{N}\alpha_i$$

These equations show how the model estimates separate regressions for each coin and the coefficients are calculated as an unweighted mean of the estimated coefficients for the individual coins (Vieira and da Silva, 2019). In this scenario no restrictions are imposed, and coefficients are allowed to vary and be heterogeneous in the short and long run. To detect the short and long run association between cryptocurrency price and different explanatory variables the pooled mean group (PMG) was applied. The PMG also allows investigation of heterogeneous dynamic issues across coins. According to Vieira and da Silva (2019) the proper procedure to analyse dynamic panels in such conditions is the ARDL (p, q) model in its error correction form estimated with the MG or the PMG presented by Pesaran and Smith (1995) and Pesaran et al. (1999). Following Vieira and da Silva (2019), a basic ARDL model was specified as follows:

$$y_{it} = \sum_{j=1}^{p}\lambda_{ij}^{*} y_{i,t-j} + \sum_{j=0}^{q}\delta_{ij}^{*} x_{i,t-j} + \mu_i + \varepsilon_{i,t} \tag{22}$$

where $i = 1, 2, \ldots, N$ represents the groups; $t = 1, 2, \ldots, T$ identifies the estimation period; $x_{i,t}$ is the $Kx1$ vector of independent variables; λ_{ij} is the coefficients scalar of all lagged dependent variables; μ_i is the fixed effect term; δ_{ij}^{*} the $Kx1$ vector of coefficients. In principle p and q may vary across the coins. Any disequilibrium in the short run is viewed as the adjustment process towards the long run equilibrium. Any adjustments are accomplished through the error correction form (ECM). Reparametrising equation (22) the researcher can obtain the ECM model:

$$\Delta(y)_{it} = \varnothing_i (y)_{i,t-1} + \beta_i x_{it} + \sum_{j=1}^{p}\lambda_{ij}^{*}\Delta(y)_{i,t-j} + \sum_{j=0}^{q}\delta_{j=0}^{*\prime}\Delta(x)_{i,t-j} + \mu_i + \varepsilon_{i,t} \tag{23}$$

where $\beta_i = \sum_{j=1}^{p} \delta_{ij}$ is the i^{th} group long run parameter; $\varnothing_i = -\left(1 - \sum_{j=1}^{p} \lambda_{ij}\right)$ is the i^{th} group equilibrium or error correction parameter; $\lambda_{ij}^{*} = -\sum_{m=j+1}^{p} \lambda_{im}$, $j = 1, 2, \ldots, p - 1$; and $\delta_{ij}^{*} = -\sum_{m=j+1}^{q} \lambda_{im}$ for j = 1, 2, … $q - 1$. ∅ presents the coefficient of the speed of adjustment to the long run status. In this study, panel ARDL (PMG) was estimated in examining the factors that determine the pricing of cryptocurrencies. The dependent variable is the logarithm of coin prices. The estimated model is as follows:

$$\begin{aligned}
\Delta \ln P_{i,t} &= \mu + \beta_1 (\ln P)_{it-1} + \beta_2 (\ln coins)_{it-1} + \beta_3 (\ln diff)_{it-1} + \beta_4 (\ln MktCap)_{it-1} \\
&\quad + \beta_5 (\ln Gold)_{it-1} + \beta_6 (\ln MSCI)_{it-1} + \sum_{j=0}^{p} \beta_7 \Delta(\ln P)_{it-1} \\
&\quad + \sum_{j=0}^{q} \beta_8 \Delta(coins)_{it-1} + \sum_{j=0}^{r} \beta_9 \Delta(\ln diff)_{it-1} + \sum_{j=0}^{s} \beta_{10} \Delta(\ln MktCap)_{it-1} \\
&\quad + \sum_{j=0}^{u} \beta_{11} \Delta(\ln Gold)_{it-1} + \sum_{j=0}^{v} \beta_{12} \Delta(\ln MSCI)_{it-1} + v_t
\end{aligned} \tag{24}$$

where μ denote a constant, $\ln P_{i,t}$ is the natural logarithm of coin price; $\ln coins_{it-1}$ is the natural log of the number of coins issued for coin i; $\ln diff$ is the natural log of the difficulty rate; $\ln MktCap_{it-1}$ is the natural log of the market capitalisation; $\ln Gold$ is the natural log of gold prices; $\ln MSCI$ is the natural log of MSCI price. Equation (24) can be estimated with a PMG or MG. This study followed Vieira and da Silva (2019) and estimated a panel ARDL model using the PMG estimation. Following Kjærland et al. (2018) the appropriate lag length and best model was selected based on the modified Akaike information criteria (AIC). Ender (2006) notes that the AIC has a theoretical advantage over other information criteria. The best model is taken as one with the lowest AIC.

4 Results and analysis

4.1 Pricing of cryptocurrencies correlation matrix

The highest correlations are between Ethereum and Litecoin (0.877); Litecoin and Dash (0.8626); Ethereum and Dash (0.8172). These findings are in line with the work of Shi et al. (2020). Ethereum, Litecoin and Dash are structured similarly – they are all minable, uses proof-of-work distribution method, and can be used as medium of exchange. As these cryptocurrencies have somewhat similar features, and some speculators are unwilling to conduct a comprehensive fundamental analysis before investment decisions are undertaken (Gazali et al., 2018).

Table 2 Correlations among individual coins

	Bitcoin	*Ethereum*	*Litecoin*	*Dogecoin*	*Dash*	*T-bill*	*ZAR/USD*	*MSCI*	*Gold*
Bitcoin	1								
Ethereum	0.7199*	1							
	(0.0000)								
Litecoin	0.6943*	0.8777*	1						
	(0.0000)	(0.0000)							
Dogecoin	0.2428*	0.5227*	0.5481*	1					
	(0.0000)	(0.0000)	(0.0000)						
Dash	0.4362*	0.8172*	0.8626*	0.6227*	1				
	(0.0000)	(0.0000)	(0.0000)	(0.0000)					
T-bill	0.4651*	0.0007	0.1035*	0.2751*	0.2761*	1			
	(0.0000)	(0.9762)	(0.0000)	(0.0000)	(0.0000)				
ZAR/USD	0.1705*	0.3019*	0.3471*	0.2738*	0.4814*	0.7501*	1		
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)			
MSCI	0.7833*	0.3110*	0.2370*	0.0849*	0.0880*	0.7767*	0.5779*	1	
	(0.0000)	(0.0000)	(0.0000)	(0.0003)	(0.0002)	(0.0000)	(0.0000)		
Gold	0.6669*	0.2482*	0.1053*	0.1369*	0.1331*	0.9019*	0.6261*	0.9042*	1
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	

Notes: ***$p < 1\%$; **$p < 5\%$; *$p < 10\%$.

Source: Author's own calculations using a balanced panel over the period 2016 to 2020

4.2 Pricing of cryptocurrencies panel unit root tests

As depicted in Tables 3a and 3b prior to estimating the models, the panels were tested for unit root. Both the first- and second-generation tests were applied. The first-generation tests used include the Levin, Lin and Chu; Im, Pesaran and Shin; ADF Fisher and PP Fisher tests. The null hypothesis is panels contain a unit root. The second-generation tests conducted are the Bai and NG PANIC and the Pesaran (2007) CIPS tests. The first generation use pooled panels and assume cross-sectional independence, ignoring panel dynamics.

4.2.1 First generation unit root test: cross sectional independence

Table 3a Unit root tests

	Levin, Lin and Chu t		*Im, Pesaran and Shin W-stat*	
	Level		*Level*	
	Statistic	*Prob.***	*Statistic*	*Prob.***
COIN-PRICE	–3.2831***	0.0005	–1.27933	0.1004
Difficulty	–5.4672***	0.0000	–2.4387***	0.0074
Coins issued	–0.4297	0.3337	–1.46297*	0.0717
MSI	0.46721	0.6798	2.64108	0.9959
Gold	2.12884	0.9834	2.65387	0.996
	First-diff		*First-diff*	
COIN-PRICE	–48.184***	0.0000	–40.7202***	0.0000
Coins issued	32.5808***	0.0010	–31.9371***	0.0000
MSI	67.5887	1.0000	–21.6308***	0.0000
Gold	–11.602***	0.0000	–29.8815***	0.0000
	ADF – Fisher chi-square		*PP – Fisher chi-square*	
	Level		*Level*	
	Statistic	*Prob.***	*Statistic*	*Prob.***
COIN-PRICE	16.0109	0.0993	14.8248	0.1386
Difficulty	27.0937***	0.0025	28.8877***	0.0013
Coins issued	21.5829**	0.0174	58.5316***	0.0000
MSI	0.95587	0.9999	0.60681	1.0000
Gold	0.94648	0.9999	1.34154	0.9993
	First-diff		*First-diff*	
COIN-PRICE	718.924***	0.0000	107.468***	0.0000
Coins issued	716.089***	0.0000	92.1034***	0.0000
MSI	431.28***	0.0000	92.1034***	0.0000
Gold	666.488***	0.0000	92.1034***	0.0000

Notes: ***$p < 1\%$; **$p < 5\%$; *$p < 10\%$.

4.2.2 Second generation unit root test: cross sectional dependence

The second-generation tests assume cross-sectional dependence and take into account cross-sectional dynamics. From the first-generation tests as indicated in Table 3a for the majority of the tests difficulty and coins issued are stationary at level, Coin price, MSCI, and gold are stationary at first differences. From the second-generation tests, Coins issued, and difficulty are confirmed to be stationary at level. The Pesaran (2007) CIPS test indicate that the coin price is stationary at level. Gold and MSCI are also $I(1)$ using the second-generation tests. The estimation technique used differences all variables in estimating the models; hence non-stationarity will not be a problem in this analysis since the variables containing unit root are stationary at first difference.

Table 3b Unit root tests

		Bai and NG PANIC		*Pesaran (2007) CIPS*	
		Statistic	*Prob.***	*CIPS*	*Prob.***
COIN-PRICE	$I(0)$	–1.7546	0.07932	–4.349	0.0000
Difficulty	$I(0)$	–2.2358	0.0254	–9.164	0.0000
Coins issued	$I(0)$	6.6973	0.0000	–16.951	0.0000
MSI	$I(1)$	6.3251	0.0000	16.489	0.8320
Gold	$I(1)$	N/A	N/A	16.489	0.9311

Note: $**p < 5\%$.

4.3 Econometric analysis

4.3.1 Factors that determine cryptocurrency pricing

The study employed the two-step system GMM with robust standard errors to estimate the dynamic model. The estimation technique controls for endogeneity and Nickell-bias in fixed effects.

The empirical results provide evidence that there is statistically significant positive relationship between difficulty and cryptocurrency prices as shown by a positive and significant coefficient of difficulty at 1% level. Thus, we are 99% confident that the more difficult it is to solve a cryptocurrency puzzle, the higher its coin price. In other words, miners are rewarded more for cryptocurrency puzzles that are hard to unlock or solve. As it has been presented above, this finding was expected and is in line with other relevant studies over the past ten years (Easley et al., 2017; Chiu and Koeppl, 2017).

The result in Table 4 depicts a negative and statistically significant coefficient of coins issued. Coins issued represent the number of issued coins per 24-hour cycle. The P-value of the coefficient is less than 1%. Thus, we reject the null hypothesis that the coefficient of coins issued is zero at 1%. The results provide evidence at 99% confidence that the price of cryptocurrencies is negatively associated with the number of coins issued. In other words, as more coins are issued, the value of the cryptocurrency goes down. The inverse relationship between coin value and coins issued is consistent with our expectation and economic theory, as based on the law of supply and demand – generally, an oversupply of any commodity reduces its price.

As expected, market capitalisation was found to positively affect coin prices as shown by a positive and statistically significant coefficient of market cap. The results suggest that the higher the market capitalisation, the higher the price of the cryptocurrency. Market capitalisation is the product of the coins issued and price per coin – there is therefore an expectation that if the price per coin increases, the market capitalisation will also increase.

Table 4 Two step system GMM dynamic panel-data estimation

Variable	*Coef.*	*Robust std. err.*	*t*	*P > |t|*
L1.ln(price)	0.90000***	0.0134730	66.80	0.0000
Difficulty	0.00473***	0.0000934	5.07	0.0000
Coins issued	–0.05660***	0.0141330	–4.04	0.0000
Market cap	0.05388***	0.0130190	4.139	0.0000
Gold	–0.03319***	0.0012781	–25.97	0.0000
MSCI	–0.03676***	0.0007996	–4.597	0.0000
Model diagnostics				
F(6.48)				0.0000
Observations		4,824		
Number of instruments		1,752		
Arellano-Bond test for AR(1)		0.01		
Arellano-Bond test for AR(2)		0.27		
Sargan test/Hansen test		0.37		

Notes: This table shows the regression outputs of factors that affect the pricing of cryptocurrencies using the two-step system GMM with robust standard errors. ***$p < 0.01$ significant at 1% level, **$p < 0.05$ significance at 5% level, *$p < 0.1$ significance at 10% level.

4.3.2 Lagged dependent variable

The estimation results in Table 4 show that the coefficient of the lagged dependent variable is positive and statistically significant, providing evidence that there is a direct relationship between future cryptocurrency prices and previous prices. Implying that periods of higher prices are followed by periods of higher prices which is common in financial assets returns. On the other hand, the number of coins issued is negatively associated with coin prices-the more coins issued, the lower the coin price; these results compare to those of similar studies (Katsiampa, 2017; Vandezande, 2017; Bariviera, 2017; Bouri et al., 2017).

4.3.3 Economic impact of regression results

Table 5 shows the economic impact of different explanatory variables on coin prices. The economic impact is calculated as follows:

$$Economic\ impact = \frac{\sigma_{Xi} * \beta_{x,i}}{\sigma_Y}$$

where σ_{Xi} = standard deviation of the explanatory variable xi, σ_Y = standard deviation of the dependent variable and $\beta_{x,i}$ = coefficient of the explanatory variable, xi.

Table 5 Economic impact of regression estimates

Factor	*Impact coin price*
Difficulty	40.362
Coins issued	–90.857
Market cap	92.852
Gold	–0.002
MSCI	–0.001

The results in Table 5 shows that for a one standard deviation change in difficulty, the price of coins goes up by an average of 40.36 units, a standard deviation change in the number of coins issued will result in a decrease in price by an average of 90.86; one standard deviation change in market capitalisation increases coin price by about 92.85. A one standard deviation change in gold and MSCI yields a price decline of –0.002 and –0.001 for gold and MSCI, respectively. The economic impacts of the empirical output shown in the table above depicts a higher absolute value for market capitalisation followed by number of coins issued and difficulty respectively implying that for crypocurrency related factors coin prices are more sensitive to coin market capitalisation and number of coins issued than they are to difficulty.

4.4 Additional tests: short-run and long-run dynamics

To capture the short and long-run dynamics in cryptocurrency pricing, a panel ARDL model was also estimated. Previous studies used time-series ARDL models; this study augments prior studies by using the panel ARDL model in understanding the factors that influence the pricing of cryptocurrencies. To choose the best model, an automatic optimal lag selection test was employed using the AIC. The test finds ARDL(1, 1, 1, 1, 1) specification as the most appropriate model where AIC value of –12.27 is the minimum. Thus, the AIC suggests that the panel model should include only one lag of coin prices (the dependent variable) and one lag for each of the explanatory variables.

4.4.1 Long-run dynamics

Table 6 presents the estimation results. As shown in the table, all the long-run coefficients are statistically significant. The null hypothesis is rejected that the coefficients are zero at the 1% level. In the long-run all cryptocurrency related factors have a statistically significant relationship with the value of cryptocurrencies. As expected and consistent with the GMM estimation results presented in Table 4, the panel ARDL results show a positive and statistically significant relationship between difficulty and cryptocurrency price. Implying that the greater the difficulty, the more valuable is a particular coin. As it has been mentioned above, the difficulty is a measure how challenging it is to mine a Bitcoin block, or technically, to find a hash below a given target. High difficulty means that it requires more computing power to mine the same number of blocks, which means that the network is considered more secure against attacks. Moreover, the empirical results show that the number of coins issued has a statistically significant negative relationship with coin prices. The more coins issued, the lower the coin value. Coin market capitalisation was found to have a positive and statistically significant relationship with cryptocurrency values. For the cryptocurrency-related variables, coin market capitalisation has a more substantial impact on coin pricing, as shown by a higher coefficient followed by coins issued and difficulty. For non- cryptocurrency-related explanatory variables, both gold and MSCI were found to have a negative and statistically significant relationship with coin values.

Table 6 Panel ARDL

Variable	*Coefficient*	*Std. error*	*t-statistic*	*Prob.**
		Long run equation		
Difficulty	0.014458***	0.001842	7.849473	0.0000
Coins issued	–0.878154***	0.028624	–30.67854	0.0000
Market_Cap	1.017551****	0.011460	88.79310	0.0000
Gold	–0.158951***	0.013223	–12.02043	0.0000
MSCI	–0.058676***	0.005945	–9.870572	0.0000
		Short run equation		
COINTEQ01	–0.000689**	0.000332	–2.077954	0.0377
Difficulty	0.000759*	0.000445	1.705353	0.0882
Coins issued	–0.021926	0.013875	–1.580225	0.1141
Market_Cap	0.986999***	0.010767	91.66651	0.0000
Gold	–0.010234	0.015747	–0.649937	0.5157
MSCI	0.004185	0.002774	1.50863	0.1314
C	–0.006749**	0.003397	–1.986681	0.0470
Akaike info criterion	–12.2757			
Schwarz criterion	–12.2445			
Hannan-Quinn criter.	–12.2651			
Log likelihood	56,109.16			

Notes: ***$p < 1\%$; **$p < 5\%$; *$p < 10\%$.

4.4.2 Short-run dynamics

Over the short run, Difficulty still has a positive and statistically significant relationship with coin prices, indicating that the level of difficulty positively affects the value of cryptocurrencies both in the long and short run. However, there is a weakening of the relationship over the short-run, as shown by a lower coefficient (0.000759) as compared to the long-run coefficient (0.014458). The slight weakening of this relationship over shorter periods is consistent with an expectation that the relationship between difficulty and coin price would be more pronounced over longer periods of time. Regarding the number of coins issued, the short-term effects also show a statistically significant negative coefficient providing evidence that the number of coins issued has a negative relationship with the value of coins in the short and long run. As more coins are issued, the value of the cryptocurrencies declines. As it has been presented above, one of the reasons for this is based on the law of supply and demand – an excess supply of any instrument (*ceteris paribus*) reduces its price. For cryptocurrency-related variables

Difficulty, market capitalisation and coins issued, the empirical results prove that any shocks in cryptocurrencies will produce the same impact in both the long and short run.

However, for gold, its sign turns positive and losing significance in the short run. Implying that gold prices do not have an influence on the pricing of cryptocurrencies in the short run. The MSCI maintained a negative sign but lost its significance over the short run, implying no impact on coin prices over the shorter term. Shocks in the cryptocurrency market change the dynamics of the relationships between coin prices and gold and MSCI index over the long and short run.

The cointegration term has a negative and statistically significant coefficient at a 5% level. The negative and significant coefficient of the correction term indicates that the panel is cointegrated and any discrepancies between the actual and equilibrium cryptocurrency prices are corrected daily across the coins used in the sample.

4.4.3 Cross-section short-run coefficients

The panel ARDL model also estimates the short-run cross-sectional relationships. Table 7 shows the short-run cross-section coefficients of the factors that affect cryptocurrency pricing. The empirical results show that the difficulty coefficient is positive and statically significant for Bitcoin, Dodgecoin and Dash, consistent with the above panel results. However, for Ethereum and Litecoins there is a change in sign to negative. Implying that the level of difficulty is having a negative impact on these coins. Consistent with panel results, the coefficient for coins issued is negative and statistically significant for the other five coins (Ethereum, Litecoin, Dash and Dodgecoin), indicating a decrease in value as more coins are issued.

Table 7 Cross-section short-run coefficients

Variable	*Coefficient*	*Std. error*	*Prob.**
	Panel A [Bitcoin]		
COINTEQ01	–0.000402***	1.32E-07	0.0000
Difficulty	0.002306***	2.05E-05	0.0000
Coins issued	0.000369***	7.73E-07	0.0000
Market_Cap	0.984096***	7.35E-06	0.0000
Gold	–0.008511***	1.73E-04	0.0000
MSCI	0.010453***	3.53E-05	0.0000
C	–0.003862***	1.17E-05	0.0000
	Panel B [Ethereum]		
COINTEQ01	–0.000247***	6.02E-11	0.000
Difficulty	–1.21E-05***	3.29E-11	0.000
Coins issued	–1.88E-05***	1.20E-10	0.000
Market_Cap	0.999758***	7.24E-11	0.000
Gold	8.12E-06***	8.93E-10	0.000
MSCI	–3.75E-06***	1.82E-10	0.000
C	–0.002487***	1.91E-08	0.000

Notes: ***$p < 1\%$; **$p < 5\%$; *$p < 10\%$.

Table 7 Cross-section short-run coefficients (continued)

Variable	*Coefficient*	*Std. error*	*Prob.**
	Panel C [Litecoin]		
COINTEQ01	–0.000213***	4.45E-11	0.0000
Difficulty	–3.87E-05***	3.56E-11	0.0000
Coins Issued	–2.67E-05***	7.15E-12	0.0000
Market_Cap	0.999784***	5.75E-11	0.0000
Gold	6.02E-05***	6.97E-10	0.0000
MSCI	1.21E-05***	1.42E-10	0.0000
C	–0.002092***	1.39E-08	0.0000
	Panel D [Dodgecoin]		
COINTEQ01	–0.001989***	1.47E-06	0.0000
Difficulty	0.000359***	7.63E-07	0.0000
Coins Issued	–0.065204***	0.001431	0.0000
Market_Cap	0.946288***	2.12E-05	0.0000
Gold	0.026057***	0.001452	0.0004
MSCI	0.011454***	0.000297	0.0000
C	–0.020167***	0.000149	0.0000
	Panel E [Dash]		
COINTEQ01	–0.000597***	1.38E-06	0.0000
Difficulty	0.001182***	1.48E-06	0.0000
Coins Issued	–0.044749***	0.000496	0.0000
Gold	–0.068786***	0.001691	0.0000
MSCI	–0.000992*	0.000343	0.0627
Market_Cap	1.00507***	2.62E-05	0.0000
C	–0.005137***	9.81E-05	0.0000

Notes: ***$p < 1\%$; **$p < 5\%$; *$p < 10\%$.

For market capitalisation, all the coins maintained the positive sign as in the panel results. They are enormously indicating the positive relationship between market capitalisation and cryptocurrency prices. Gold prices show a positive relationship with Ethereum, Litecoin and Dodgecoin and a negative relationship with Bitcoin and Dash. Based on the fact that these are novel instruments that are developing and changing in a high pace, there are no investment fundamentals that have been established yet – this is a maturing field (Hayes, 2016a). It is therefore possible that the price behaviours that are being demonstrated are based on speculative reasons (Caginalp and Caginalp, 2019). The MSCI shows a positive relationship with Bitcoin, Litecoin and Dodgecoin and a negative relationship with Dash and Ethereum. The differences in the short run cross section's relationships for Gold and MSCI explain why the signs for the panel short run coefficients turned insignificant as the cross-sections were estimated together.

5 Conclusions

Despite the high level of interest that has been attracted by pricing of cryptocurrencies over the past ten years, the contrasts in findings in this area remain prevalent. The key findings of this study in this area were that it is possible to formulate a regression model that deal includes technical elements that relate to cryptocurrencies like hash rate, difficulty, coins per day and market capitalisation. The research showed that the coin that uses higher hash rate, that has higher difficulty, higher market capitalisation and has lower number of coins that are mined on daily basis, is likely to have its pricing improved over short to medium terms.

These findings have implications for both investors and speculators – because these stakeholders now would be in a position to forecast the coin price based on these variables. This will improve pricing and valuation of cryptocurrencies. Pension fund managers, fund managers and private bankers will now be in a better position to convince their clients why they promote certain investment activity. In terms of FAIS Act, 2002 financial advisers and investment specialist can support their investment decisions. Another major implication for this finding is that the assets under management into this industry can increase or decrease based on real and tangible decision making that is based on well-researched pricing methodologies. This, in fact, may even reduce spill-over risks in the industry as investment decisions could be based on sound investment principles.

One of the main recommendations is that more research resources are dedicated in studying pricing methodologies for cryptocurrencies. The future scope of this study lies in further research on the impact of emerging technologies such as blockchain and decentralised finance (DeFi) on cryptocurrency pricing. Moreover, the study can also examine the potential impact of geopolitical events such as trade wars, political instability, and pandemics on cryptocurrency prices. Future research can also explore the impact of environmental concerns and sustainability on the pricing of cryptocurrencies, given the growing awareness of the carbon footprint associated with Bitcoin mining.

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Notes

1 A similar challenge is experienced when valuing companies for mergers and acquisitions. For example, the seller would require a discounted cash flow (DCF) valuation methodology (because it provides a better valuation for the asset for sale, whilst the buyers prefer market valuation technique (for opposite reasons).

2 Cryptocurrency difficulty measures of how difficult it is to mine a block in a blockchain for a particular cryptocurrency, and high mining difficulty means it takes additional computing power to verify transactions entered on a blockchain; there is correlation between difficulty, and hash rate and value of coins (Wooley at al., 2015).