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Jennifer Castle and Takamitsu Kurita

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J. L. CASTLE† and T. KURITA‡*

†Magdalen College and Climate Econometrics, University of Oxford, UK
‡Faculty of Economics, Kyoto Sangyo University, Japan

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Abstract

The rapid expansion of the global cryptocurrency market raises the question of whether there are stable relationships between the prices of representative cryptocurrencies and economic indicators capturing expectations of future monetary policy. In this paper multivariate time-series analysis reveals a single but significant cointegrating relationship between cryptocurrencies and the term spread. This evidence reveals direct policy implications for the implementation of monetary policy allowing for the growing influence of digital assets. While the cointegrating linkage plays a critical role in modelling cryptocurrencies in sample, it contributes little to forecasting them out of sample, thus indicating potential efficiency in the digital currency market.

Cryptocurrencies, Economic indicators, Cointegration, Weak exogeneity, Policy simulation, Predictability, Market efficiency.
C22, C50, E43, E44.

1 Introduction

The introduction of Bitcoin by Nakamoto (2009) has brought about the popularity of cryptocurrencies as digital financial assets and also paved the way for a variety of applications of blockchain technology to non-financial sectors. Several representative cryptocurrencies, such as Bitcoin and Ethereum, are considered to have established themselves as reliable digital assets. Given the accepted current status of these selected virtual currencies, with El Salvador classifying Bitcoin as legal tender, it is important from an economic-policy viewpoint to explore the question of whether structural relationships exist between those representative cryptocurrencies and important economic indicator variables. Furthermore, finding evidence indicating the existence of such relationships raises the question of whether there is any predictability of cryptocurrencies by exploiting the revealed structure. As Claeys *et al.* (2018) note, cryptocurrencies are unlikely to replace official currencies in the near future as they do not successfully fulfil the main functions of money, and in particular would need a system of checks and balances to ensure the cryptocurrency issuer is accountable to society.[1] However, Central Bank cryptocurrencies are increasingly being explored, see Bank or England (2020).

This paper undertakes a rigorous econometric analysis of the relationship between a subset of cryptocurrencies and economic indicators reflecting the monetary policy stance. In order to establish if there are stable long-run relationships we use a modelling strategy that embeds economic theory but allows for

*Corresponding author. Email: tkurita@cc.kyoto-su.ac.jp

[1]Also see `https://voxeu.org/article/monetary-policy-world-cryptocurrencies`.

the data to reveal long-run structural relationships, utilizing cointegration analysis and applying control theory to derive policy implications. A vector autoregressive (VAR) analysis of weekly time series data for three representative cryptocurrencies, a measure of forward looking inflation expectations and the term spread is conducted. The analysis shows the existence of a single but significant stable long-run relationship among the variables. This relationship turns out to be subject to several explicit restrictions revealing the underlying economic structure, hence conveying useful implications for future monetary policy. The investigation of weak exogeneity properties indicates the price of Bitcoin has acted as one of the underlying pushing forces in the VAR system. While modelling in-sample cryptocurrency data rests critically on the cointegrating linkage, forecasting out-of-sample data has failed to benefit from the long-run structure, thereby indicating the cryptocurrency market is efficient in the sense that there remains little room for predictability.

The rest of this paper is organized as follows. Section 2 conducts a brief literature review on the relationships between cryptocurrencies and various economic indicators. Section 3 outlines the econometric theory that gives an impetus for our study and also reviews the econometric methodology. A multivariate cointegration analysis is conducted in Section 4 by focusing on long-run relationships between cryptocurrency prices and economic indicators. Given the long-run study, Section 5 performs a pseudo out-of-sample forecasting exercise centering on cryptocurrencies. Section 6 gives concluding remarks. All quantitative analyses of this paper were performed by using *CATS* (Doornik and Juselius, 2018) and *PcGive* (Doornik and Hendry, 2021).

2 Literature Review

The growing interest in cryptocurrencies has led to an increase in the empirical investigation of cryptocurrency prices in the literature of finance and information technology, for example see Corelli (2018), Noam (2019), and Das and Kannadhasan (2018). There are a number of studies that model the second moments of cryptocurrencies, with volatility applications including Chu *et al.* (2017) and Katsiampa (2017). Both Demir *et al.* (2018) and Foglia and Dai (2022) find a clear link between economic policy uncertainty and cryptocurrency uncertainty, suggesting a relationship in the second moments. However, there is less consensus on first moments concerning the presence of stable structural relationships between cryptocurrencies and various economic indicators such as interest rate spreads. This may be attributable to the tendency of existing research to focus on the high-frequency dynamics of cryptocurrency data which are not necessarily associated with the development of monetary and fiscal policies.

There is a lot of speculative discussion as to whether cryptocurrencies are being treated as safe havens during periods of financial turmoil and accelerating inflation. Wang *et al.* (2019) find evidence in support of this hypothesis for Bitcoin, but Conlon *et al.* (2020) find little evidence the hypothesis holds. Choi and Shin (2021) show that Bitcoin prices appreciate under inflation pressures and decline when there is an increase in financial uncertainty, although they do not find any evidence that prices respond to policy uncertainty shocks, suggesting independence from monetary policy. When allowing for asymmetric responses to monetary policy, Nguyen *et al.* (2019) find evidence that cryptocurrencies respond to a tightening of Chinese monetary policy but not to US monetary policy, and Vidal-Tomás and Ibañez (2018) also conclude that there is a lack of evidence that Bitcoin responds to monetary policy events from the Federal Reserve System, European Central Bank, Bank of Japan and Bank of England. Vo *et al.* (2021) use structural break analysis to assess the evolution of Bitcoin over time and they find that over the most recent periods Bitcoin is responsive to underlying macroeconomic factors.

The literature is far from conclusive as to the long-run relationships between cryptocurrency prices and monetary policy. Therefore, by undertaking a rigorous econometric analysis where we proxy monetary policy by the term structure of interest rates based on expectations theory and establish a stable long-run relationship, we can shed light on this unanswered question, delivering both methodological and empirical contributions to the literature.

3 Theory-based insight and econometric methods

In this section we introduce the economic theory which motivates the empirical study. The difference between long-term and short-term bond yields is known as the term spread, which is recognised as one of the representative economic indicators containing information on future macroeconomic activities and policies; see Estrella and Mishkin (1997), *inter alia*. Expectations theory is one of the accepted theoretical frameworks for it; see, e.g., Campbell (1995). Let $I_t^{(j)}$ be the j-period zero-coupon bond yield per period in per cent (j-period to maturation). Augmented with the liquidity premium ξ_t covering future uncertainty, arbitrage trading will ensure that the returns on an n-period bond should equal the expected returns on the rollover of 1-period bonds. In other words, the expectations theory of the term structure claims:

$$i_t^{(n)} = \frac{i_t^{(1)}}{n} + \frac{1}{n}\sum_{j=1}^{n-1} \mathrm{E}_t i_{t+j}^{(1)} + \xi_t, \tag{1}$$

where $i_t^{(j)}$ denotes $\ln(1 + I_t^{(j)}/100)$. To be more specific about the term premium, (1) implies the premium term represents uncertainty about future short-term interest rates; that is, future monetary policy stances in response to inflation or deflation. Applying the same manipulation to (1) as that adopted by Giese (2008), we can express the term spread $i_t^{(n)} - i_t^{(1)}$ as

$$\begin{aligned} i_t^{(n)} - i_t^{(1)} &= -\frac{n-1}{n} i_t^{(1)} + \frac{1}{n}\sum_{j=1}^{n-1} \mathrm{E}_t i_{t+j}^{(1)} + \xi_t \\ &= \frac{1}{n}\mathrm{E}_t\left[\left(i_{t+1}^{(1)} - i_t^{(1)}\right) + \left(i_{t+2}^{(1)} - i_{t+1}^{(1)} + i_{t+1}^{(1)} - i_t^{(1)}\right) + \cdots\right] + \xi_t \\ &= \frac{1}{n}\sum_{j=1}^{n-1} (n-j)\,\mathrm{E}_t \Delta i_{t+j}^{(1)} + \xi_t. \end{aligned} \tag{2}$$

Note that neither the first nor the second term on the right hand side is observable. Let $cp_{1,t}, \ldots, cp_{m,t}$ be a class of cryptocurrency prices and $f\left(cp_{1,t}, \ldots, cp_{m,t}\right)$ be their linear function. Let us also introduce the symbol $\mathrm{I}(d)$, which denotes a stochastic process integrated of order d. Suppose the term premium can be modelled as:

$$\xi_t = f\left(cp_{1,t}, \ldots, cp_{m,t}\right) + \eta_t, \tag{3}$$

where η_t is assumed to be mean-zero stationary, or $\mathrm{I}(0)$. The rationale for (3) is given by the hypothesis that the behaviour of current cryptocurrency prices may embody expected future inflation or deflation. Plugging (3) into (2) yields:

$$i_t^{(n)} - i_t - f\left(cp_{1,t}, \ldots, cp_{m,t}\right) = \upsilon_t \sim \mathrm{I}(0) \tag{4}$$

for $\upsilon_t = \frac{1}{n}\sum_{j=1}^{n-1}(n-j)\,\mathrm{E}_t \Delta i_{t+j}^{(1)} + \eta_t$, which is seen as an $\mathrm{I}(0)$ linear combination because all of its components are presumed to be $\mathrm{I}(0)$. Whether or not (4) is revealed as an empirical cointegration relationship is one of the primary objectives of the econometric study in this paper.

Next, we give a brief review of a cointegrated VAR (CVAR) model which is to be used to investigate the validity of (4). See Johansen (1988, 1995), Juselius (2006) and Hunter *et al.* (2017) for further details of the model. Let X_t be a p-dimensional time series subject to the following CVAR representation:

$$\Delta X_t = \alpha\left(\beta', \gamma\right)\left(X_{t-1}', 1\right)' + \sum_{i=1}^{k-1} \Gamma_i \Delta X_{t-i} + \varepsilon_t, \quad \text{for} \quad t = 1, ..., T, \tag{5}$$

where the initial observations $X_{-k+1}, \ldots, X_0$ are given and the error sequence ε_t is distributed as independent and identical normal, $\mathsf{IN}(0, \Omega)$, for a positive definite matrix $\Omega \in \mathbf{R}^{p\times p}$; all the other parameters

are $\alpha, \beta \in \mathbf{R}^{p\times r}$ for $r < p$, $\Gamma_i \in \mathbf{R}^{p\times p}$ and $\gamma \in \mathbf{R}^r$. For future reference, we define $\Gamma = I_p - \sum_{i=1}^{k-1} \Gamma_i$ and introduce the following notational conventions: $\alpha_\perp \in \mathbf{R}^{p\times(p-r)}$ is the orthogonal complement to α, resulting in the non-singularity of $(\alpha, \alpha_\perp)$ and $\alpha'_\perp \alpha = 0$, and the same convention is applied to β. We then assume a set of those regularity conditions, see Johansen (1995, Theorem 4.2), including $\mathrm{rank}(\alpha) = \mathrm{rank}\,(\beta) = r$ and $\mathrm{rank}(\alpha'_\perp \Gamma \beta_\perp) = p - r$, which are both required for $\mathrm{I}(1)$ cointegration analysis. We also define $C = \beta_\perp(\alpha'_\perp \Gamma \beta_\perp)^{-1}\alpha'_\perp$ for further theoretical review.

The index r denotes cointegrating rank, and the r cointegrating combinations in (5),

$$\beta' X_{t-1} + \gamma \sim \mathrm{I}(0), \tag{6}$$

are viewed as mean-zero stationary deviations from the underlying long-run economic relationships (subject to economic interpretations), while α shows how each variable in X_t adjusts to those deviations. The parameters (β', γ) and α are thus called cointegrating and adjustment vectors, respectively. We aim to reveal the evidence that (4) belongs to (6). Furthermore, let us introduce known matrices $a \in \mathbf{R}^{p\times q}$ and $b \in \mathbf{R}^{p\times(p-q)}$ for $p > q \geq r$, which are used as selection matrices by econometricians. Suppose $a'\alpha \neq 0$ and $b'\alpha = 0$, then $b'X_t$ is said to be weakly exogenous for (β', γ). See Engle *et al.* (1993) and Johansen (1995, Ch. 8) for further details. The weakly exogenous variables act as driving or pushing forces in the CVAR system due to the fact that b is contained in the orthogonal complement of α; see Juselius (2006, pp.88-90) for further details. We can, therefore, argue that (β', γ) and α are the parameters of interest in the empirical study.

Lastly, we briefly review CVAR-based control theory developed by Johansen and Juselius (2001). For the sake of simplicity of the exposition, the lag order $k = 1$ is assumed here to simplify (5) as

$$\Delta X_t = \alpha(\beta' X_{t-1} - \gamma) + \varepsilon_t, \quad \text{for} \quad t = 1, ..., T, \tag{7}$$

so that $\Gamma = I_p$. A set of two predetermined matrices $a, b \in \mathbf{R}^{p\times s}$ for $s + r < p$ is then introduced, so that the former leads to the selection of policy instruments $a'X_t$ while the latter leads to that of policy targets $b'X_t$. The objective of economic policy in this context is to have $b'X_t$ stabilised by means of $a'X_t$; that is, to render $b'X_t$ stationary with mean b^*, or a policy target level, by utilising $a'X_t$. A policy intervention is required for this purpose and represented by $\upsilon \in \mathbf{R}^s$. Policy implementation replaces $a'X_t$ with $a'X_t + \upsilon$, with the result that the controlled value of X_t, denoted by X_t^{ctr}, is defined as

$$X_t^{ctr} = X_t + a(a'a)^{-1}\upsilon. \tag{8}$$

Given X_t^{ctr}, the dynamics of (7) will then generate a new series X_t^{new} subject to the requirement that $b'X_t^{new}$ is stationary with mean b^*.

The intervention υ is modelled through the study of (7) and (8) under the condition $det(b'Ca) \neq 0$. Equation (7) is solved out to find

$$X_t = (I_p + \alpha\beta')^t X_0 + \textstyle\sum_{j=1}^{t-1}(I_p + \alpha\beta')^j(\varepsilon_{t-j} - \alpha\gamma).$$

The long-run solution in the context of $t \to \infty$ is thus given as

$$X_\infty = \lim_{t\to\infty} \mathbf{E}(X_t \,|X_0\,) = CX_0 + \alpha(\beta'\alpha)^{-1}\gamma,$$

which allows us to define

$$b^* = b' \lim_{h\to\infty} \mathbf{E}\left(X_{t+h}^{new} \,\middle|X_t^{ctr}\right) = b'\left\{C\left[X_t + a(a'a)^{-1}\upsilon\right] + \alpha(\beta'\alpha)^{-1}\gamma\right\}. \tag{9}$$

Under the assumption of $det(b'Ca) \neq 0$, (9) is solved out to find

$$\upsilon = a'a(b'Ca)^{-1}\left[b'\alpha(\beta'\alpha)^{-1}(\beta'X_t - \gamma) - (b'X_t - b^*)\right],$$

where the identity $I_p = C + \alpha \left(\beta'\alpha\right)^{-1} \beta'$ has been used inside the square brackets. Substituting this into (8) yields

$$X_t^{ctr} = X_t + a(b'Ca)^{-1} \left[b'\alpha(\beta'\alpha)^{-1}(\beta' X_t - \gamma) - (b' X_t - b^*)\right],$$

where $\beta' X_t - \gamma$ is a disequilibrium error at t while $b' X_t - b^*$ is a difference between the actual and desired targets at t. A sequence of interventions implemented at all time points renders the control rule compatible with (7), so that we arrive at a system of equations

$$X_t^{ctr} = X_t^{new} + a(b'Ca)^{-1} \left[b'\alpha(\beta'\alpha)^{-1}(\beta' X_t^{new} - \gamma) - (b' X_t^{new} - b^*)\right] \tag{10}$$

$$X_{t+1}^{new} = (I + \alpha\beta')X_t^{ctr} - \alpha\gamma + \varepsilon_{t+1}. \tag{11}$$

Equations (10) and (11) enable us to simulate a series of X_t^{ctr} and X_t^{new}, given the starting value for $t = 0$. If $det(b'Ca) \neq 0$ is empirically satisfied, the CVAR-based control theory then leads to a data-based policy simulation analysis which is inherently different from that based on conventional impulse response functions. See Boug *et al.* (2021), *inter alia*, for a recent study employing CVAR-based control simulation to gain empirical policy implications.

4 Econometric study of the data

In this section we perform a multivariate econometric analysis of the weekly time series data of cryptocurrencies and economic indicators. Section 4.1 gives an overview of the data. Section 4.2 conducts tests for cointegrating rank and reveals which variables are weakly exogenous for cointegrating parameters. Section 4.3 identifies empirical cointegrating relationships in order to establish the validity of (4). Section 4.4 conducts a policy simulation exercise.

4.1 Data overview

This sub-section gives an overview of weekly time series data for

$$X_t = (eth_t, lit_t, bit_t, for_t, spr_t)',$$

where eth_t, lit_t and bit_t denote the logs of the US dollar prices of Ethereum, Litecoin and Bitcoin respectively; for_t is an indicator of the rate of forward inflation expectation represented by the yield differential between 10-year and 5-year inflation-protected Treasury securities, while spr_t is a business cycle indicator represented by the spread between 10-year and 3-month treasury bond yields. Both for_t and spr_t are treated as candidate approximates for the term-spread component of (4). The data are calculated as the weekly averages of daily observations (ending on Friday) and the sample period for estimation runs from 25th week in 2017 to from 21st week in 2021 denoted as 2017W25 - 2021W21 hereafter. The number of observations for estimation is 205. The time series data over this period is displayed in Figure 1, see the Appendix for the sources of the data. All the series in Figure 1 appear to be anything but stationary, so that the I(1) CVAR model reviewed above is judged to be a suitable device for the empirical investigation.

4.2 Testing for cointegrating rank

The initial unrestricted VAR system needs to be specified with a view to examining the underlying cointegration structure. A preliminary regression analysis of the data shows that the dynamic terms at $k = 2$ are significant but those at $k = 3$ play limited or insignificant roles in the system. The lag order $k = 2$ is thus selected for the system. The analysis reveals several outliers in the data: 2017W50,

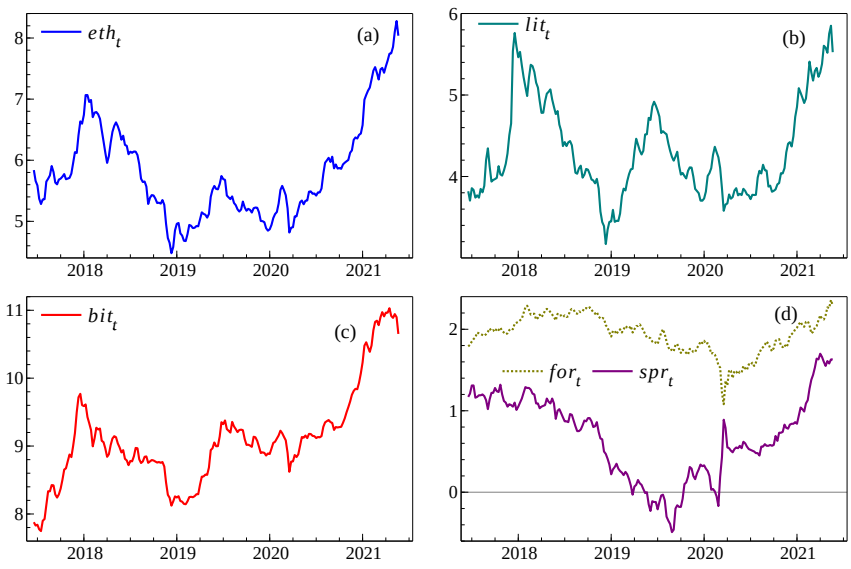


Figure 1: (a) Weekly average log dollar price for Ethereum, (b) Litecoin and (c) Bitcoin; (d) yield differential between 10-year and 5-year inflation-protected Treasury securities and spread between 10-year and 3-month treasury bond yields.

2019W37, 2020W10, 2020W11, 2020W12, 2020W13 and 2020W15. In order to address these outliers, the corresponding seven unrestricted indicator (dummy) variables are introduced in the model.[2]

We also conducted residual-based diagnostic checks on the model augmented with the indicator variables; no evidence was found for the autocorrelation of the residuals, although homoscedasticity failed to be satisfied. The evidence for no autocorrelation allows us to conduct a quasi likelihood-based cointegration analysis by assuming a martingale difference error sequence; see Kurita and Nielsen (2019). In addition, the existing research shows trace tests for cointegrating rank are fairly robust to excess kurtosis and skewness in the error term; see Cheung and Lai (1993). For brevity the test results are not reported here but are available from the authors.

Table 1: Testing cointegrating rank

	$r = 0$	$r \leq 1$	$r \leq 2$	$r \leq 3$	$r \leq 4$
TR	93.525[0.001]**	44.875[0.257]	25.934[0.350]	11.351[0.517]	1.912[0.790]

$Note.$ ** denotes significance at the 1% level.

Table 1 reports a class of log-likelihood ratio (LR) tests for the selection of cointegrating rank, which are referred to as trace tests (TR) here. The test results show strong evidence for the choice of $r = 1$, while all the other hypotheses are not rejected at the 1% level. We are therefore justified in fixing $r = 1$, which gives us the starting point to verify the empirical validity of (4).

In Table 2 we have conducted a set of tests for individual stationarity (ST) and long-run exclusion (LE) given $r = 1$. As regards ST, the hypothesis that each variable can be viewed as a stationary series has been rejected at the 1% level. The use of a CVAR model, instead of a stationary VAR model, has thus been supported by the data. The tests for LE explore the possibility that a variable can be excluded from the cointegrating combination; the hypothesis has been rejected at the 1% level except for for_t.

[2]The retained indicators closely overlap with the seven indicators retained if Impulse Indicator Saturation (IIS: see Hendry, Johansen and Santos (2008), and Johansen and Nielsen (2009)) is applied to the unrestricted VAR at a selection significance level of $\alpha = 0.01\%$.

This evidence indicates (4) may be revealed as the underlying long-run linkage, in which spr_t may play a significant role, instead of for_t.

Table 2: Testing stationarity and long-run exclusion

	eth_t	lit_t	bit_t	for_t	spr_t
ST	$35.418[0.000]^{**}$	$31.098[0.000]^{**}$	$29.836[0.000]^{**}$	$40.666[0.000]^{**}$	$42.023[0.000]^{**}$
LE	$25.248[0.000]^{**}$	$26.686[0.000]^{**}$	$16.582[0.000]^{**}$	$1.3309[0.249]$	$16.097[0.000]^{**}$

Note. Figures in square brackets in the first and second rows are p-values according to $\chi^2(4)$ and $\chi^2(1)$ distributions, respectively.
** denotes significance at the 1% level.

4.3 Identifying the underlying long-run equilibrium

Selecting $r = 1$, we next identify the long-run relationship underlying the data for cryptocurrencies and economic indicators. We express $\hat{\alpha} = (\hat{\alpha}_1, \hat{\alpha}_2, \hat{\alpha}_3, \hat{\alpha}_4, \hat{\alpha}_5)$ and $\hat{\beta} = (\hat{\beta}_1, \hat{\beta}_2, \hat{\beta}_3, \hat{\beta}_4\, \hat{\beta}_5)$ in the rest of this section. Normalising the cointegrating vector for eth_t and excluding for_t from the linear combination (recall the results of Table 2) — that is, $\hat{\beta}_1 = 1$ and $\hat{\beta}_4 = 0$ — leads to

$$\begin{pmatrix} \hat{\alpha}_1 \\ \hat{\alpha}_2 \\ \hat{\alpha}_3 \\ \hat{\alpha}_4 \\ \hat{\alpha}_5 \end{pmatrix} \begin{pmatrix} 1 \\ \hat{\beta}_2 \\ \hat{\beta}_3 \\ 0 \\ \hat{\beta}_5 \\ \hat{\gamma} \end{pmatrix}' \begin{pmatrix} eth_t \\ lit_t \\ bit_t \\ for_t \\ spr_t \\ 1 \end{pmatrix} = \begin{pmatrix} -0.01 \\ (0.038) \\ 0.061 \\ (0.039) \\ 0.02 \\ (0.03) \\ 0.018 \\ (0.015) \\ 0.053 \\ (0.023) \end{pmatrix} \begin{pmatrix} 1 \\ (-) \\ -0.656 \\ (0.074) \\ -0.436 \\ (0.059) \\ 0 \\ (-) \\ -0.557 \\ (0.065) \\ 1.358 \\ (0.401) \end{pmatrix}' \begin{pmatrix} eth_t \\ lit_t \\ bit_t \\ for_t \\ spr_t \\ 1 \end{pmatrix}, \tag{12}$$

where figures in parentheses are standard errors. The LR test statistic against no restrictions is $1.331[0.249]$ with its p-value according to $\chi^2(1)$ in square brackets.

Noting the revealed structure in (12), we impose a set of additional restrictions, $\hat{\beta}_2 + \hat{\beta}_3 = -1$ and $\hat{\alpha}_2 = \hat{\alpha}_3 = \hat{\alpha}_4 = 0$, which yield

$$\begin{pmatrix} \hat{\alpha}_1 \\ 0 \\ 0 \\ 0 \\ \hat{\alpha}_5 \end{pmatrix} \begin{pmatrix} 1 \\ \hat{\beta}_2 \\ -1 - \hat{\beta}_2 \\ 0 \\ \hat{\beta}_5 \\ \hat{\gamma} \end{pmatrix}' \begin{pmatrix} eth_t \\ lit_t \\ bit_t \\ for_t \\ spr_t \\ 1 \end{pmatrix} = \begin{pmatrix} -0.143 \\ (0.024) \\ 0 \\ (-) \\ 0 \\ (-) \\ 0 \\ (-) \\ 0.057 \\ (0.021) \end{pmatrix} \begin{pmatrix} 1 \\ (-) \\ -0.551 \\ (0.057) \\ -0.449 \\ (-) \\ 0 \\ (-) \\ -0.63 \\ (0.058) \\ 1.069 \\ (0.279) \end{pmatrix}' \begin{pmatrix} eth_t \\ lit_t \\ bit_t \\ for_t \\ spr_t \\ 1 \end{pmatrix}, \tag{13}$$

for which the LR test against no restrictions is $6.081[0.298]$ and the p-value is based on $\chi^2(5)$, so that the overall restrictions are acceptable. The revealed structure is interpreted as an empirical representation of (4), strong evidence in support of the presence of a structural relationship between the representative cryptocurrencies and the term structure of interest rates. This structural linkage can be an empirical basis for a future implementation of monetary policy under the growing influence of digital currencies.

The cointegrating combination revealed in (13) acts as an equilibrium correction mechanism (ecm) underlying the system:

$$ecm_t = eth_t + \hat{\beta}_2 lit_t - (1 + \hat{\beta}_2) bit_t + \hat{\beta}_5 spr_t + \hat{\gamma} \sim I(0), \tag{14}$$

or, equivalently,

$$eth_t + \hat{\beta}_2 lit_t - (1 + \hat{\beta}_2) bit_t \approx -\hat{\beta}_5 spr_t - \hat{\gamma}, \tag{15}$$

for $\hat{\beta}_2 = -0.551$, $\hat{\beta}_5 = -0.63$ and $\hat{\gamma} = 1.069$. The left-hand side of (15) is interpreted as a cryptocurrency-based spread in which Ethereum plays a pivotal role. Figure 2 displays $eth_t + \hat{\beta}_2 lit_t - (1+\hat{\beta}_2) bit_t$ and $-\hat{\beta}_5 spr_t - \hat{\gamma}$, indicating the validity of (15).

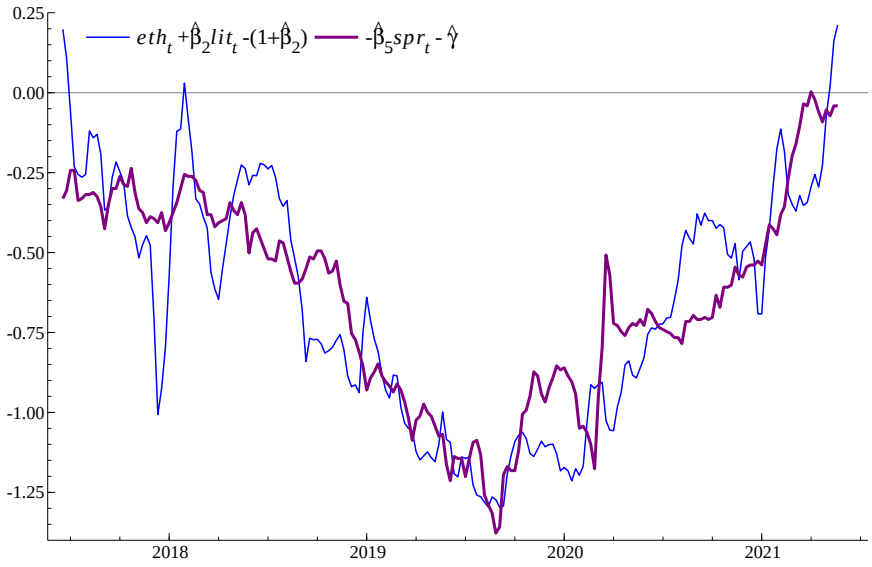


Figure 2: The revealed equilibrium correction mechanism

In addition, the non-rejection of the zero restrictions, $\hat{\alpha}_2 = \hat{\alpha}_3 = \hat{\alpha}_4 = 0$, implies that lit_t, bit_t and for_t can be seen as weakly exogenous with respect to the cointegrating vector. The price of Bitcoin, the most representative cryptocurrency, can thus be viewed as one of the underlying pushing forces in this system, driving the price of Ethereum at least partially. This evidence is consistent with the view that Bitcoin has played a leadership role in the integrated cryptocurrency market, thereby having strong influences on the determination of prices of other cryptocurrencies.

4.4 Policy simulation analysis

Although at the time of writing no policy makers recognise cryptocurrency prices as explicit policy objectives, the significant findings in the previous sub-section nonetheless motivate us to inquire the controllability of the Ethereum price by means of the interest rate term spread. We conduct a counterfactual policy experiment, the impetus for which is given by the preceding empirical findings, and the experiment will give us data-based insights potentially useful for future policy discussion.

In order to conduct a policy simulation exercise reviewed in Section 3, it is necessary to ensure the condition of $det(b'Ca) \neq 0$ is empirically satisfied. Given that eth_t is a policy target while spr_t is a policy instrument, the selection vectors are specified to be

$$a = (0, 0, 0, 0, 1)' \quad \text{and} \quad b = (1, 0, 0, 0, 0)'.$$

The use of spr_t as a policy tool may be justified by referring to the policy of yield curve control; see Amamiya (2017) for further details of this policy. Using the above vectors, we will examine whether or not the controllability condition is met in the empirical context. Under $r = 1$, a set of coefficients for the matrix C has been estimated below, with figures in parentheses representing standard errors.

$$\hat{C} = \begin{bmatrix} \underset{(0.328)}{0.52} & \underset{(0.236)}{0.417} & \underset{(0.37)}{0.865} & \underset{(0.307)}{-0.69} & \underset{(0.27)}{\mathbf{0.471}} \\ \underset{(0.309)}{0.421} & \underset{(0.222)}{0.887} & \underset{(0.348)}{0.249} & \underset{(0.289)}{-0.354} & \underset{(0.255)}{-0.205} \\ \underset{(0.288)}{0.013} & \underset{(0.206)}{-0.257} & \underset{(0.324)}{1.902} & \underset{(0.269)}{-0.367} & \underset{(0.237)}{-0.13} \\ \underset{(0.096)}{0.086} & \underset{(0.069)}{0.018} & \underset{(0.108)}{-0.141} & \underset{(0.09)}{1.099} & \underset{(0.079)}{-0.03} \\ \underset{(0.162)}{0.385} & \underset{(0.116)}{-0.188} & \underset{(0.182)}{-0.187} & \underset{(0.151)}{-0.036} & \underset{(0.133)}{1.1} \end{bmatrix},$$

The coefficient for $b'\hat{C}a$ is found in the upper right corner of the $\hat{C}$ matrix (in bold). It is positive and lies in a borderline case in terms of statistical significance, so we judge there is no strong evidence for the hypothesis of $b'\hat{C}a = 0$. Bearing in mind this marginal significance, along with the limitation that policy simulation involving cryptocurrency prices is a counterfactual exercise potentially useful for future policy developments, we are justified in performing a CVAR-based policy simulation analysis.

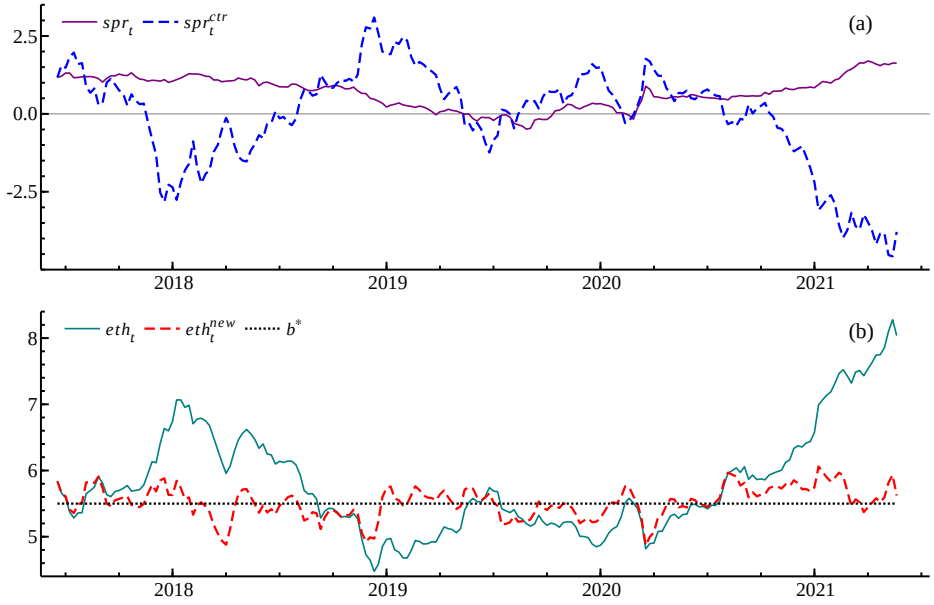


Figure 3: (a) Controlled policy instrument (spr_t^{ctr}), (b) Derived policy target (eth_t^{new}).

Setting the policy target $b^* = 5.5$, which is around the initial value of eth_t given the preset sample period, we have conducted a policy simulation analysis using an empirical version of the system consisting of (10) and (11); see Section 5.3 of Johansen and Juselius (2001) for further details of the conduct of CVAR-based policy simulation. Figure 3 (a) displays a series of a controlled instrument spr_t^{ctr} with the target value b^* fixed, along with those of the actual variable spr_t. The controlled instrument exhibits much larger fluctuations than its actual counterpart, reflecting a series of policy responses implemented to make the policy target (eth_t) move around b^*. As a result of these policy reactions, eth_t^{new}, a new series derived from the system, has become more stabilised around b^* than its actual counterpart eth_t, as shown in Figure 3 (b). In other words, eth_t^{new} appears to be a stationary series with clear mean-reverting features in contrast to eth_t, which shows clear non-stationary trending features.

Under the presumption that the controllability condition is deemed to be satisfied in an empirical context, the simulation exercise has shown that it is feasible to control the Ethereum price by using the interest rate term spread as a policy instrument. This finding will be of use in the future when policy actions related to cryptocurrency prices need to be placed on the agenda in an age of global digital economy.

5 Can cryptocurrencies be forecast?

Given the well specified model, we estimate a parsimonious simultaneous equation model in which we relax the assumption of restricted dummies to allow them to enter equation by equation. We then undertake a sequence of reductions to result in a more parsimonious specification given in equations (16)-(20). The restrictions are accepted with $\chi^2(43) = 35.0$ with a $p-$value of 0.80. The system reveals that out of the cryptocurrencies, only eth depends on long-run information, with lit well approximated by an autoregressive process in differences and bit depending only on dynamics of itself and eth. This suggests that there is not much long term predictability, other than for eth, which we next investigate.

$$\widehat{\Delta eth}_t = \underset{(0.047)}{0.308}\Delta eth_{t-1} - \underset{(0.023)}{0.140} ecm_{t-1} + \underset{(0.071)}{0.189} I_{2017W50} - \underset{(0.074)}{0.196} I_{2020W12} \tag{16}$$

$$\widehat{\Delta lit}_t = \underset{(0.045)}{0.247}\Delta lit_{t-1} + \underset{(0.079)}{0.785} I_{2017W50} \tag{17}$$

$$\widehat{\Delta bit}_t = \underset{(0.048)}{-0.131}\Delta eth_{t-1} \underset{(0.058)}{0.476}\Delta bit_{t-1} - \underset{(0.058)}{0.102} I_{2020W12} + \underset{(0.053)}{0.141} I_{2020W13} \tag{18}$$

$$\begin{aligned}\widehat{\Delta for}_t = {} & \underset{(0.054)}{0.097}\Delta for_{t-1} - \underset{(0.041)}{0.292} I_{2020W11} - \underset{(0.045)}{0.097} I_{2020W12} + \underset{(0.042)}{0.292} I_{2020W13} \\ & + \underset{(0.037)}{0.172} I_{2020W15}\end{aligned} \tag{19}$$

$$\begin{aligned}\widehat{\Delta spr}_t = {} & \underset{(0.058)}{0.200}\Delta spr_{t-1} + \underset{(0.020)}{0.055} ecm_{t-1} + \underset{(0.196)}{0.056} I_{2019W37} + \underset{(0.378)}{0.057} I_{2020W10} \\ & + \underset{(0.181)}{0.066} I_{2020W11} + \underset{(0.425)}{0.066} I_{2020W12} - \underset{(0.171)}{0.069} I_{2020W13}\end{aligned} \tag{20}$$

5.1 Short-term forecasting of cryptocurrencies

Given the dynamics modelled in the system we expect there to be predictability 1 week ahead. To evaluate this, we extend the dataset to 2021W37, giving 16 weeks of out-of-sample data which was not used in the modelling to undertake an ex ante forecasting exercise. We compute 1-week ahead forecasts for the model in (16)-(20) which we denote the VEqCM and compare to a set of benchmark forecasts which include the robust version of the VEqCM (Hendry,2006), an unrestricted VAR(1) and Random Walk (RW), where the dependent variable is the log level in both cases, and finally Cardt (Castle *et al.*, 2021) which is a forecasting device developed for the M4 forecasting competition designed to be adaptive to structural breaks using principles of robustness, trend dampening, averaging, and calibration (see Makridakis *et al.* (2020) for details of the M4 forecasting competition). We evaluate the level forecasts using a median forecast inverse transformation ($\widehat{Y}_{T+h|T} = \exp \widehat{y}_{T+h|T}$, first substituting out differenced transformations) as this is the variable of interest to investors. Although this will not affect the 1-step ahead forecast results it will affect the multi-step forecasts, revealing much greater forecast disparities than if the log differenced forecasts were evaluated.

The 1-step ahead Root Mean Squared Forecast Errors (RMSFE) are reported in Table 3, with bold highlighting the smallest RMSFE, and the forecasts are recorded in Figure 5. The VEqCM model produces the best forecasts for Lit and Bit, neither of which include the long-run cointegrating relation in the model, whereas Eth does depend on the cointegrating relation but a simple random walk outperforms

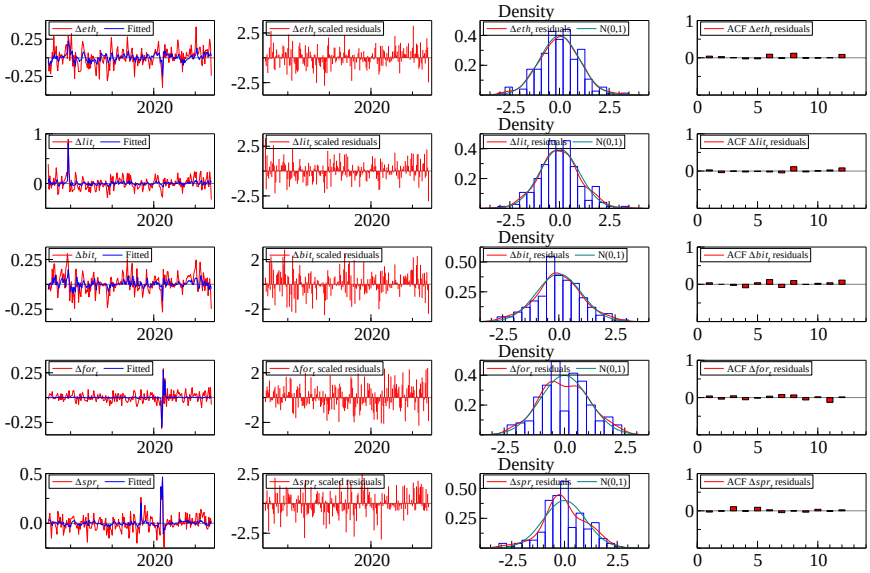


Figure 4: Model fit, scaled residuals, residual density and residual correlogram for simultaneous equation model (16)-(20).

Table 3: RMSFEs for 1-week ahead forecasts ofcryptocurrencies over 2021W22-2021W37.

	Eth	Lit	Bit
VEqCM	346	**19.3**	**2876**
Robust	330	24.4	5257
VAR(1)	305	23.5	2991
RW	**276**	22.6	2896
Cardt	361	23.2	3159

Note. Bold denotes smallest RMSFE.

in the 1-week ahead forecasting context. To assess forecast encompassing, we regress the cryptocurrency on all five sets of forecasts and apply selection at $\alpha = 0.01$ using Autometrics (Doornik, 2009) such that we retain only the significant forecasts at a significance level of 1%:

$$Eth = \underset{(0.143)}{0.447}\text{Robust} + \underset{(0.147)}{0.570}\text{VAR}; \;\; \hat{\sigma} = 245; \;\; R^2 = 0.95$$

$$Lit = \underset{(24.25)}{60.1} + \underset{(0.150)}{0.615}\text{VEqCM}; \;\; \hat{\sigma} = 16.9; \;\; R^2 = 0.55$$

$$Bit = \underset{(9677)}{30858} - \underset{(5.7)}{18.6}\text{VAR} + \underset{(5.4)}{18.8}\text{RW}; \;\; \hat{\sigma} = 2341; \;\; R^2 = 0.87$$

For Ethereum, the Robust VEqCM and the VAR enter with roughly equal weights, with no other forecasting models yielding additional information and both the forecasts explain most of the variation in Ethereum. Litecoin, on the other hand, is best forecast only by the VEqCM, with no additional information coming from the benchmark forecasts. Litecoin is just an AR(1) in differences in the VEqCM model, and only just over half of the variation is explained by this forecasting device. For Bitcoin, the VAR and RW deliver offsetting forecast information, meaning the forecasts enter as differences in the encompassing equation. Despite the VEqCM delivering the lowest RMSFE for Bit, the model in (18) is similar to a VAR(1) delivering highly collinear forecasts. Although the selection algorithm retains the

VAR forecasts in the encompassing equation similar results are obtained when replacing the VAR with the VEqCM forecasts. In summary, we conclude that there is some predictability in the cryptocurrencies 1-week ahead. Although the random walk delivers the smallest RMSFE for Eth over the forecast period, encompassing tests reveal additional information in the Robust and VAR forecasts, and for Lit and Bit the RW is not sufficient to encompass other forecasting models.

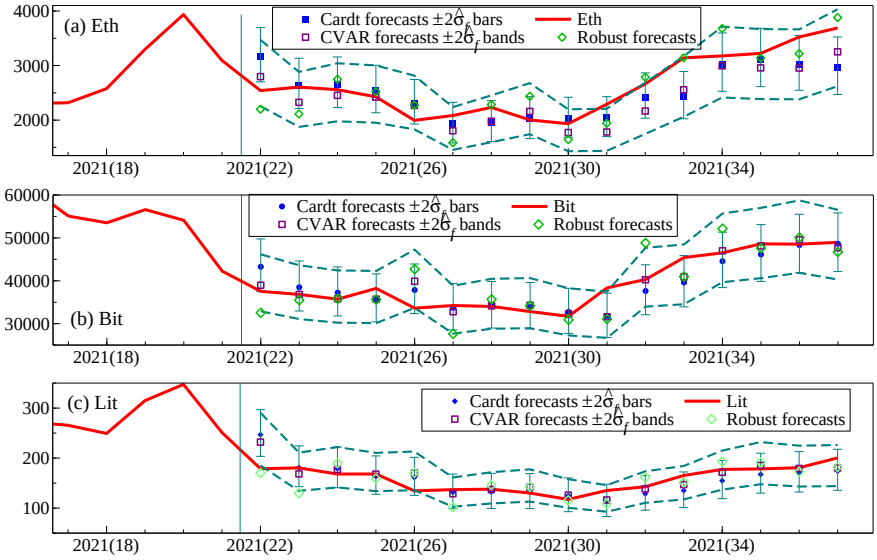


Figure 5: 1-step ahead forecasts for the levels of Eth, Lit and Bit for the VEqCM, Robust and Cardt.

5.2 Longer-term predictability of cryptocurrencies

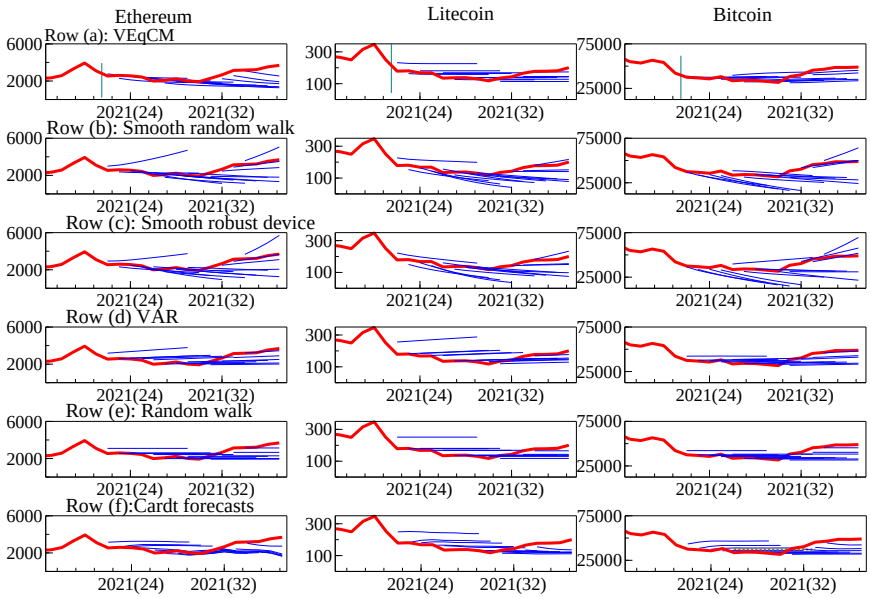


Figure 6: Forecasts for the levels of Eth, Lit and Bit.

Having identified long-run information that drives Ethereum, a natural question is whether this can be used to predict future prices of the cryptocurrency. To assess this we look at dynamic forecasts over the 16 week out-of-sample period, computing 1- to 8-week ahead forecasts. We compare the VEqCM model to forecasts from a VAR(1), random walk and Cardt as above, but also include two robust forecasting variants, denoted smoothed robust device and smoothed random walk, based on Martinez *et al.* (2022), where we estimate an AR(1) in log differences to obtain iterative multistep forecasts. Denote Δy_t as the log difference of Eth, Lit or Bit:

$$\widehat{\Delta y}_{T+h|T} = \widehat{\mu} + \widehat{\rho}^h \left(\Delta y_T - \widehat{\mu}\right) \tag{21}$$

where $\widehat{\mu}$ is calculated by:

$$\widehat{\widetilde{\mu}} = \frac{1}{N} \sum_{j=0}^{N-1} \Delta y_{T-j} \tag{22}$$

for the smoothed random walk device (SRW) and

$$\widehat{\widetilde{\mu}} = \frac{1}{N} \sum_{j=0}^{N-1} \left(\Delta y_{T-j} + \frac{\widehat{\rho}}{1-\widehat{\rho}} \Delta^2 y_{T-j} \right) \tag{23}$$

for the smoothed robust device (SRD), and $\widehat{\rho}$ is obtained from $\Delta y_t = \beta + \rho \Delta y_{t-1} + \eta_t$, estimated in-sample.

The forecasts are recorded in Figure 6, with RMSFEs reported in Table 4. For Ethereum, the VEqCM forecasts which include long-run cointegrating information produce some of the worst forecasts over all horizons, systematically underforecasting when there is an upturn in the price. A simple average (denoted AVE) dominates over shorter horizons, with the random walk producing the smallest forecast errors over longer horizons, reinforcing the view that cryptocurrency prices are unforecastable, (see, e.g., Manuelli and Peck, 1990). For Litecoin the VEqCM is similar to the VAR and random walk, although averaging does help as the robust devices are differentially biased. For Bitcoin, the VEqCM model dominates at most horizons, but there is no long-run information tied to monetary conditions driving the VEqCM forecasts.

6 Concluding remarks

In this paper we have explored the presence of stable relationships between the prices of three representative cryptocurrencies and two economic indicators including a measure of forward inflation expectations and the term spread. The contribution of our research is three-fold. First, a cointegrated vector autoregressive analysis has revealed strong evidence for a stable and systematic relationship involving the term structure of interest rates and Bitcoin, Litecoin and Ethereum. This evidence is crucial for the implementation of monetary policy taking account of the cryptocurrency market, which will be more influential in the global economy with advances in information technology. Furthermore, we find evidence that Bitcoin plays a leadership role in the integrated cryptocurrency market, thereby having strong influences on the determination of the prices of other cryptocurrencies.

Our second contribution to the literature concerns the policy implications that can be drawn from the existence of a stable long-run relationship. The counterfactual policy simulation exercise demonstrates that the Ethereum price can be stabilized by the interest rate spread. While we don't anticipate monetary policy including cryotocurrencies in their set of targets in the mainstream, the exercise provides insights into future policy discussions of Central Bank cryoptocurrencies. In particular, it demonstrates the need for much more active policy given the increase in volatility that the term spread required to control the Ethereum price if such targets did become relevant.

Finally, our paper also provides empirical evidence on efficiency in the integrated cryptocurrency market. Although monetary conditions do play a role in determining the price of cryptocurrencies as

Table 4: RMSFEs for 1 to 8 week head forecasts of cryptocurrencies over 2021W22-2021W37.

	VEqCM	SRW	SRD	VAR	RW	Cardt	AVE
Eth							
1-step	297	271	278	302	291	312	**266**
2-step	540	448	469	451	435	467	**406**
3-step	767	609	634	577	561	630	**532**
4-step	982	820	871	710	695	790	**681**
5-step	1181	999	908	895	**864**	983	897
6-step	1306	1254	1138	1007	**968**	1066	1054
7-step	1397	1531	1404	1076	**1024**	1136	1197
8-step	1406	1790	1648	1076	**1021**	1175	1287
Lit							
1-step	20.8	20.5	**20.4**	25.8	24.5	24.8	21.5
2-step	24.0	23.8	23.9	31.3	28.8	32.7	**23.7**
3-step	31.7	32.8	32.5	40.0	36.3	41.8	**30.2**
4-step	36.0	39.8	39.4	46.1	41.8	48.8	**34.5**
5-step	47.0	54.9	52.6	58.4	52.7	57.0	**46.3**
6-step	49.8	65.0	61.9	62.7	55.5	59.0	**49.5**
7-step	**54.1**	78.7	75.6	67.8	58.8	60.6	55.0
8-step	**52.6**	89.3	86.2	70.7	59.1	61.5	57.0
Bit							
1-step	3122	3387	3598	3075	3158	3448	**2981**
2-step	4022	5035	5568	4238	4519	5565	**3998**
3-step	**5535**	7515	8357	5682	6128	7358	5582
4-step	**6534**	9813	11121	6683	7306	8465	6829
5-step	**8084**	11284	12169	8298	9060	10045	8487
6-step	**8530**	13590	14248	8996	9906	10776	9521
7-step	**9585**	16729	17012	9885	10841	11470	11247
8-step	**9057**	18888	19175	9652	10764	11513	11687

$Note.$ Bold denotes smallest RMSFE.

identified by the cointegrating relation, there is little predictability in the price evolution of the three cryptocurrencies. This lack of predictability implies that there is no significant information in out-of-sample forecasting. Such a result highlights the dichotomy between modelling economic and financial relationships, and exploiting such relationships for forecasting. Future research could investigate a broader range of cryptocurrencies to establish whether there are subsets of currencies or periods that do reveal predictability in longer-horizon forecasting.

Appendix

Data sources (accessed on 23rd May and 10th September in 2021):
Cryptocurrencies (eth_t, lit_t, bit_t) — https://fred.stlouisfed.org/categories/33913
for_t — https://fred.stlouisfed.org/series/T5YIFR
spr_t — https://fred.stlouisfed.org/series/T10Y3M

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