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Forecasting Returns of Major Cryptocurrencies: Evidence from Regime-Switching Factor Models

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Abstract

The returns of cryptocurrencies tend to co-move, with their degree of co-movement being contingent on the (bullish- or bearish-) states. Given this, we use standard factor models and regime-switching factor loadings to forecast the returns of a specific cryptocurrency based on its lagged information and informational contents of 14 other cryptocurrencies, with these 15 together constituting 65% of the market capitalization. Considering top five cryptocurrencies namely, Bitcoin, Ethereum, Ripple, Dogecoin, and Litecoin, we find significant forecastability and evidence that factor models, in general, outperform the benchmark random-walk model, with the regime-switching versions standing out in the majority of the cases.

Keywords: Cryptocurrencies; Factor Model; Markov-switching; Forecasting

JEL Codes: C22; C53; G15

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1. Introduction

Cryptocurrencies have emerged as an important asset class appreciated by individual and institutional investors, with a total market capitalization standing at over 3 trillion US dollars as of November, 2021, having increased exponentially from less than 20 billion US dollars in January 2017 (Iyer, 2022). In light of this, and just like in the case of any other asset, accurate real-time forecast of returns on cryptocurrencies is of paramount importance to investors for asset allocation. Hence, it is not surprising that a burgeoning literature has analysed the forecastability of the returns of cryptocurrencies using various (linear and nonlinear) models and (economic, financial, and behavioural) predictors (see for example, Catania et al., (2019), Nasir et al., (2019), Kraaijeveld et al., (2020), Sun et al., (2020), Bouri and Gupta (2021), Plakandaras et al., (2021), Sebastião and Godinho (2021), Koki et al., (2022), among others). Notably, evidence suggests that cryptocurrency returns not only comove, but their degree of co-movement is contingent on the (bullish- or bearish-) states (see for example, Corbet et al., (2018), Bouri et al., (2019, 2020), Ji et al. (2019), Aslanidis et al., (2021), Shahzad et al., (2021), Xu et al., (2021) besides others). In light of this, we aim to contribute to this literature of forecasting of cryptocurrency returns by accounting for these two properties. To this end, we utilize factor models with regime-switching factor loadings to account for regime-specific comovements of 15 major cryptocurrencies.

Technically speaking, it is suitable to use the modelling approach of Guérin et al., (2020), who introduced regime-switching parameters in the three-pass regression filter (3PRF) estimator (that relies on a series of ordinary least squares regressions) developed for factor models by Kelly and Pruitt (2015). The key difference between standard principal component analysis (PCA) and the 3PRF approach is that, while PCA summarizes the cross-sectional information based on the covariance within the predictors, the 3PRF condenses cross-sectional information based on the correlation of the predictors with the target variable of the forecasting exercise, thereby extending partial least squares (Kelly and Pruitt, 2015),. In our case, the target variable happens to be the top five cryptocurrencies, out of the 15 considered, determined by their market share. Guerin et al., (2020) included an additional dimension of regime-switching, and denoted this new framework as Markov-switching three-pass regression filter (MS-3PRF).[1]

[1] A major advantage of this approach is that it can handle large dimensional factor models, as opposed to the existing regime-switching factor models that can only handle models with limited dimensions due to computational complexity. This is possible, since the estimation of the MS-3PRF method is computationally straightforward, with it only requiring estimating a series of univariate Markov-switching regressions. Hence, the approach offers a great deal of flexibility in modelling time variation, as it does not need restricting the regime changes in the cross-sectional dimension to be governed by a single or a limited number of Markov chains.

Understandably, with the comovement of cryptocurrency returns being contingent on market states, the MS-3PRF is ideal for our purpose, although we make comparison with the PCA approach and the benchmark random-walk (RW) model. To the best of our knowledge, this is the first paper to forecast the return of a cryptocurrency based on the returns of other cryptocurrencies and to use the MS-3PRF, besides standard PCA, implemented on a predictive regression framework.

The remainder of the paper is organized as follows: Section 2 presents the data, while Section 3 outlines the methodology; Section 4 discusses the empirical findings of our forecasting experiment, with Section 5 concluding the paper.

2. Data and econometric methodology

2.1. Data

Our dataset comprises the closing prices of 15 major cryptocurrencies, namely Bitcoin, Ethereum, Ripple, Dogecoin, Litecoin, Stellar, Ethereum Classic, Moreno, NEO, Waves, Dash, Decred, Zcash and NEM over the weekly period the 1st week of November, 2016 to the 4th week of September, 2021, according to their availability from: https://coinmarketcap.com. The 15 cryptocurrencies were selected on September 24th, 2021 from wide set containing the largest 100 cryptocurrencies by market capitalization in order to have the largest possible set of cryptocurrencies having the longest price data period and the highest trading volume (i.e., the most liquid cryptocurrencies). Interestingly, the 15 selected cryptocurrencies constitute more than 65% of the market capitalization of all cryptocurrencies. Figure 1 shows the plot of weekly logarithmic returns of the 15 cryptocurrencies over the full sample period. It can be noticed that the returns of most of the cryptocurrencies tend to comove, especially during booms and busts periods, including the COVID-19 pandemic.

Note that we work with weekly logarithmic returns of the 15 cryptocurrencies. The reasons behind using weekly returns to the detriments of daily returns are as follows: Firstly, the extremely volatile cryptocurrency markets involve many individual traders and investors who are very sensitive to news and fears of missing out, which are often manifested at high frequency prices such hourly and daily; therefore, the use of weekly data helps avoiding extreme price fluctuations. Secondly, the heterogeneity of market participants, which includes investors and hedge fund managers, requires the examination of predictability at a low frequency such as weekly, which nicely complements the existing literature that tends to focus on daily frequency only. Finally, a recent article in the Fortune Magazine[2] has pointed to the importance of examining weekly prices given that the cryptocurrency markets tend to crash on weekends due to low trading volume, margin trading, and price manipulation.

Table 1 provides the summary statistics of the weekly returns series for the 15 cryptocurrencies. Dogecoin has the highest mean returns and volatility, while Zcash and Tether have the lowest mean and variance respectively. All returns are, unsurprisingly, non-normal.

As indicated in the introduction section, the aim of this paper is to forecast the price returns of each of Bitcoin, Ethereum, Ripple, Dogecoin, and Litecoin based on the returns of other cryptocurrencies, i.e., the remaining 14 cryptocurrencies under study. The justifications for forecasting the returns of those five cryptocurrencies only are as follows: Bitcoin and Ethereum are the two dominant cryptocurrency, constituting more than 42% and 18% of the market share of all cryptocurrencies, respectively, followed by Ripple (2.3%). Dogecoin is selected given its growing popularity and recent price spike following the comments and tweets of Elon Musk and the acceptance of Dogecoin by Tesla as a payment option. Litecoin is a relatively large and old cryptocurrency, launched in 2013, and importantly a fork of Bitcoin; furthermore, it shares with Bitcoin similar features such as the proof-of-work consensus mechanism but a different cryptographic algorithm and hashing functioning.

2.2. Econometric methodology

The purpose of the 3PRF (Kelly and Pruit, 2015) is to forecast a target scalar variable y_t from a number of factors that drive *N* predictors $\boldsymbol{x}_t = (x_{1,t}, \dots, x_{N,t})'$. Predictors $\boldsymbol{x}_t$ are driven by two sets of common factors, $\boldsymbol{f}_t = (f_{1,t}, \dots, f_{k,t})'$ and $\boldsymbol{g}_t = (g_{1,t}, \dots, g_{p,t})'$. However, not all factors are useful in forecasting the target variable; only factors $\boldsymbol{f}_t$ are associated with y_t. That is, in order to forecast the target variable we want to extract only $\boldsymbol{f}_t$. Kelly and Pruit (2015) assume that data are generated as follows:

$$y_t = \beta_0 + \boldsymbol{\beta}\boldsymbol{f}_{t-1} + u_t, t = 1, \dots, T, \tag{1}$$

$$z_{j,t} = \vartheta_{0,j} + \boldsymbol{\vartheta}_{f,j}\boldsymbol{f}_t + \varepsilon_{j,t}, j = 1, \dots, k_f, \tag{2}$$

$$x_{i,t} = \theta_{0,i} + \boldsymbol{\theta}_{f,i}\boldsymbol{f}_t + \boldsymbol{\theta}_{g,i}\boldsymbol{g}_t + \epsilon_{i,t}, i = 1, \dots, N, \tag{3}$$

[2] https://fortune.com/2021/06/03/why-does-crypto-crash-on-the-weekends-bitcoin-cryptocurrency-markets/.

Where $\boldsymbol{z}_t = (z_{1,t}, \dots, z_{k,t})'$ is a vector of proxy variables whose common components are also driven only by $\boldsymbol{f}_t$. To deliver forecast $\hat{y}_t$, the authors the following (3PRF) filter:

1st pass: For each $i = 1, \dots, N$, run time series regression $x_{i,t}$ on $\boldsymbol{z}_t$ and retain slope estimate $\widehat{\boldsymbol{\theta}}_i$.

2nd pass: For each $t = 1, \dots, T$, run cross section regression $x_{i,t}$ on $\widehat{\boldsymbol{\theta}}_i$ and retain slope estimates $\widehat{\boldsymbol{f}}_t$.

3rd pass: Run time series regression of y_t on predictive $\widehat{\boldsymbol{f}}_{t-1}$ and retain estimated coefficients $\hat{\beta}_0$ and $\widehat{\boldsymbol{\beta}}$.

All regressions use OLS. Kelly and Pruit (2015) show that the (linear) 3PRF estimator converges in probability to the infeasible best forecast in the limit as *N* and *T* become large.

Guerin et al. (2020) extend the (linear) 3PRF approach by introducing regime-switching parameters in the model (1) to (3): $\beta_0(S_{yt}), \boldsymbol{\beta}(S_{yt}), \vartheta_{0,j}\left(S_{z_jt}\right), \boldsymbol{\vartheta}_{f,j}\left(S_{z_jt}\right)$,

$\theta_{0,i}(S_{x_it}), \boldsymbol{\theta}_{f,i}(S_{x_it}), \boldsymbol{\theta}_{g,i}(S_{x_it})$. In this case, all parameters are time varying and driven by independent across variables *y*, $\boldsymbol{x}$ and *z*, *M*-state Markov chains S_{yt}, S_{x_it}, S_{z_jt}, respectively. Each Markov chain is controlled by its own *M*×*M* transition probability matrix.

Guérin et al., (2020) call their approach the Markov-Switching 3PRF (MS-3PRF) which can be applied in the following three steps:

Step 1: Run *N* Markov switching regressions $x_{i,t}$ on $\boldsymbol{z}_t$, estimate the (pseudo) maximum likelihood (ML) regime-specific slope coefficients $\hat{\beta}_0(S_{yt})$ $\widehat{\boldsymbol{\theta}}_i(S_{x_it})$ and calculate the weighted averages $\widehat{\boldsymbol{\theta}}_{A,it}$ or $\widehat{\boldsymbol{\theta}}_{B,it}$ as follows:

$$\widehat{\boldsymbol{\theta}}_{A,it} = \sum_{j=1}^{M} \widehat{\boldsymbol{\theta}}_i(S_{x_it} = j) P(S_{x_it} = j/\Omega_T), \tag{4}$$

$$\widehat{\boldsymbol{\theta}}_{B,it} = \sum_{j=1}^{M} \widehat{\boldsymbol{\theta}}_i(S_{x_it} = j) I\left(P(S_{x_it} = j/\Omega_T)\right), \tag{5}$$

Where Ω_T is the full information set, $P(S_{x_it} = j/\Omega_T)$ is the probability of being in regime *j* and $I(\cdot)$ is an indicator function that selects the regime with the highest probability at time *t*.

Step 2: Run cross section regressions of the $x_{i,t}$ on $\widehat{\boldsymbol{\theta}}_{A,it}$ or $\widehat{\boldsymbol{\theta}}_{B,it}$ and retain slope estimates $\widehat{\boldsymbol{f}}_t$.

Step 3: Run time series regression of y_t on predictive $\hat{\boldsymbol{f}}_{t-h}$, retain ML estimated coefficients $\hat{\beta}_0(S_{yt})$, $\hat{\boldsymbol{\beta}}(S_{yt})$ and calculate the h step-ahead forecast follows:

$$\hat{y}_{T+h/T} = \sum_{j=1}^{M} \left(P\left(S_{x_i T+h} = j/\Omega_T\right) \hat{\beta}_0\left(S_{yT+h} = j\right) + P\left(S_{x_i T+h} = j/\Omega_T\right) \hat{\boldsymbol{\beta}}\left(S_{yT+h} = j\right) \hat{\boldsymbol{f}}_T \right). \quad (6)$$

3. Empirical evidence

In our forecasting analysis, we use the linear 3PRF introduced by Kelly and Pruit (2015) and four versions of MS-3PRF proposed by Guérin et al., (2020). Specifically, MS-3PRF and MSS-3PRF indicate versions based on $\hat{\boldsymbol{\theta}}_{A,it}$ (Eq.4) and $\hat{\boldsymbol{\theta}}_{B,it}$ (Eq.5), respectively. Furthermore, each of the above-mentioned versions can be calculated with regime switching only in the first step (first pass) or with regime switching in both first and third steps (first and third passes). A single target proxy and regime-switching parameters in the first and third passes. Factors are extracted from a cross-section of 15 cryptocurrencies weekly returns. As indicated earlier, ee forecast five major cryptocurrencies, namely Bitcoin, Ethereum, Ripple, Dogecoin, and Litecoin. Following Guerin et al. (2020), we employ the following forecast equation:

$$\hat{y}_{T+h/T} = \hat{\beta}_0 + \hat{\beta}(L)\hat{\boldsymbol{f}}_T + \hat{\gamma}(L)y_T, \quad (7)$$

where $\beta(L)$ and $\gamma(L)$ are q_β- and q_γ-order lag polynomials, respectively, with q_β and q_γ selected by the Schwarz information criterion (SIC). For the choice of proxy variables, we implement the automated procedure proposed by Kelly and Pruitt (2015). To conduct the forecasting exercise, we consider the first half and the second half of the total sample as an in-sample and out-of-sample periods, respectively. We consider forecast horizons, h, ranging from 1 week to 5 weeks. To compare the out-of-sample forecasting ability, this study focuses on the mean-squared forecast error (MSFE). Specifically, we report the relative MSFEs (RMSFEs), i.e. the rations of MSFEs to the MSFE of the random walk model which is considered as the benchmark. The Diebold and Mariano (1995; DM) test is used to examine the null hypothesis of equal out-of-sample predictive accuracy.[3] As noted, the models are estimated recursively over the out-of-sample period.

[3] As noted in Guérin et al., (2020), the Diebold and Mariano (1995) test of equal out-of-sample forecasting accuracy tends to reject the null of equal MSFEs too often since it is based on the population MSFE and not the actual MSFE. Following the authors, we use the test to gain a sense of statistical significance of the point forecasting results.

Out-of-sample forecasting results are reported in Table 2. Panels A, B, C, D and E refer to the Bitcoin, Ethereum, Ripple, Dogecoin and Litecoin forecasting results, respectively. From the inspection of Table 2, it is evident that almost all figures (RMSFEs) are less than unity indicating that our models beat the RW benchmark. The only exception is the PC-LARS (elastic net soft-thresholding rules, which are special cases of the Least Angle Regressions (LARS) algorithm developed in Efron et al., (2004)) model which fail to improve the out-of-sample forecasting performance over the random walk model for h=1, 4 in the case of Dogecoin.

In the case of the Bicoin (Panel A), 3PRF models are the best forecasting models for all horizons with the Markov-switching variants of the 3PRF showing best forecasting ability for horizons h = 1, 2, and 5 (though the DM test suggest statistical significance only for h =1, 2). For Ripple, MS-3PRF models forecast best for horizons h = 1, 3, 4, 5, with PCA being the best model for h = 2. Similar patterns are observed for Ethereum and Litecoin, with the Markov-switching models performing the best for h = 1, 2, 5, and h=2, 3, 4, respectively. Lastly, in the case Dogecoin, the results from MSS-3PRF(1st pass), PC-LARS and PCA, show the best forecasting ability for h=3, 4, h=1, 4 and h=2, respectively.

Overall, the results show that the principal component approach leads to significant gains in forecasting cryptocurrencies relative to the RW model. Furthermore, the results suggest that Markov-switching variants of the 3PRF can, under majority of the cases, produce superior results relative other principal components forecasting approaches.

4. Conclusions

Cryptocurrencies have evolve into an important asset class for traders and investors, and have been shown to commove in a market-state-specific manner. Given this, we forecast the returns of top five major cryptocurrencies (Bitcoin, Ethereum, Ripple, Dogecoin, and Litecoin), considered in turn, using the information content of 14 other cryptocurrencies. The forecasting methods involve standard factor models and with regime-switching factor loadings. The 15 cryptocurrencies all together constitute 65% of the total market capitalization. Our results show that factor models, in general, outperform the benchmark random walk model in a statistically significant manner, with the regime-switching versions being the standout performer in majority of the cases.

Our main results imply that investors can design their optimal investment portfolios containing cryptocurrencies by relying on regime-switching versions of factor models, which not only account for comovements in this market, but also the fact that connectedness is contingent on whether the market is in a bearish- or bullish-phase. Also note, from an academic perspective, our results imply that the cryptocurrency market cannot be considered efficient, at least in the semi-strong sense, i.e., based on the information content of other cryptocurrencies. This should serve as relevant information for academician aiming to build realistic asset pricing models for the cryptocurrency market.

As part of future research, it would also be interesting to perform a similar analysis on the volatility of cryptocurrencies, which have also been depicted to commove in the literature.

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Figure 1: Data Plot of the 15 Major Cryptocurrencies

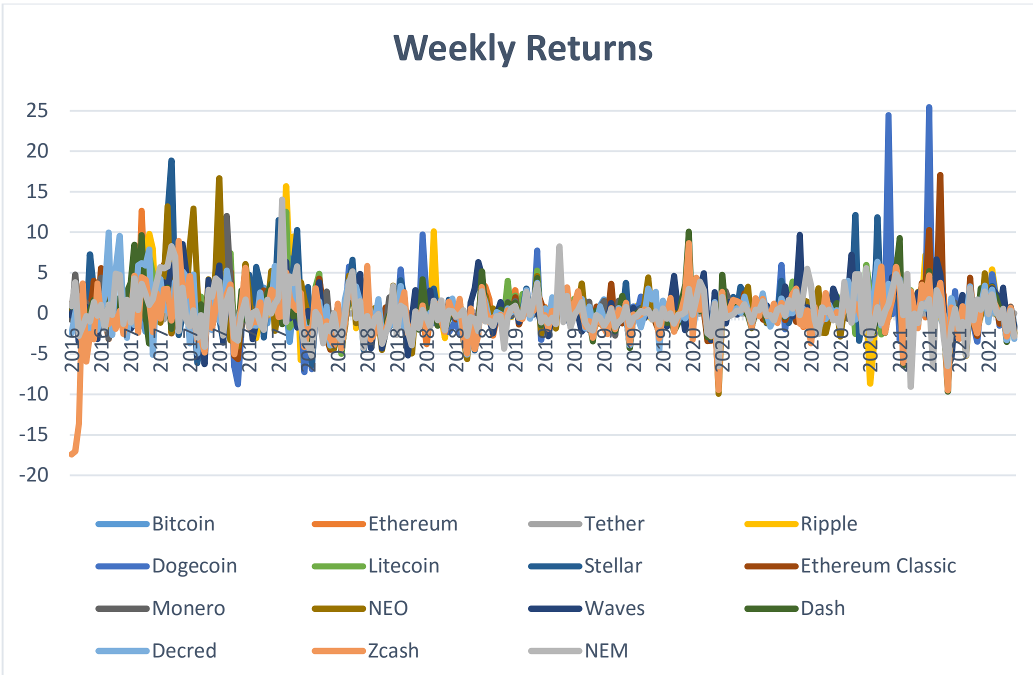

Table 1: Summary Statistics

	Mean	Median	Max	Min	Std. Dev.	Skewness	Kurtosis	Jarque-Bera
Bitcoin	0.2284	0.2384	5.8840	-7.0641	1.5776	-0.3320	5.0149	48.0063***
Ethereum	0.3146	0.2047	12.6409	-8.6198	2.2516	0.5009	7.2358	202.0896***
Tether	0.0000	0.0000	0.5603	-0.7403	0.0999	-0.6246	19.0494	2764.2070***
Ripple	0.2682	-0.2124	15.6926	-8.6864	2.8437	1.6161	8.6571	452.7964***
Dogecoin	0.3820	-0.0058	25.4343	-8.7438	3.3592	3.2160	24.3852	5319.4200***
Litecoin	0.2018	0.1026	12.5134	-8.4791	2.2888	0.7085	7.6247	249.5574***
Stellar	0.2773	-0.0916	18.8507	-6.6495	3.0192	1.8635	10.9357	819.8999***
Ethereum Classic	0.2222	0.0116	17.0690	-7.5022	2.5532	1.4448	11.2335	812.1630***
Monero	0.2130	0.2787	12.0144	-8.9480	2.1104	0.3158	8.0442	275.6529***
NEO	0.3045	0.1245	16.6694	-9.9137	2.8342	1.2929	9.9445	585.7299***
Waves	0.2400	0.0567	9.6593	-6.7944	2.5388	0.4055	4.2632	24.0359***
Dash	0.1650	0.0611	10.0528	-9.6590	2.4273	0.3793	6.5976	144.1916***
Decred	0.2800	0.0286	9.9515	-8.2929	2.5070	0.4797	4.6142	37.6099***
Zcash	-0.1627	-0.0598	8.9067	-17.4193	3.0459	-1.6119	11.4269	868.3167***
NEM	0.2095	-0.1256	14.0223	-9.0727	2.6668	0.6869	6.1543	126.2589***

Note: This table presents the summary statistics of weekly returns of the 15 cryptocurrencies under study over the period 1st week of November, 2016 - 4th week of September, 2021. Std. Dev.: stands for standard deviation; *** indicates rejection of the null of normality for the Jarque-Bera test; the total number of observations is 256.

Table 2: Out-of-sample forecasting results

	Horizon				
	1	2	3	4	5
Panel A: Bitcoin					
Linear 3PRF	0.6230***	0.5515***	**0.5112*****	**0.6034*****	0.6152
MS-3PRF(1st pass)	0.6063***	0.5495***	0.5181***	0.6179***	0.6196
MS-3PRF(1st & 3rd pass)	**0.6040*****	0.5493***	0.5208***	0.6335***	0.6139
MSS-3PRF (1st pass)	0.6156***	0.5505***	0.5185***	0.6076***	0.6188
MSS-3PRF (1st & 3rd pass)	0.6093***	**0.5437*****	0.5180***	0.6229**	**0.6115**
PC-LARS	0.6813***	0.5878***	0.5366***	0.6126***	0.6602***
PCA	0.6217***	0.5597***	0.5149***	0.6158**	0.6209***
Panel B: Ethereum					
Linear 3PRF	0.5929***	0.5414***	0.4846***	0.6131***	0.5451**
MS-3PRF(1st pass)	0.5846***	0.5484***	0.4842***	0.5943***	0.5334**
MS-3PRF(1st & 3rd pass)	**0.5837*****	**0.5361*****	0.4930***	0.6150***	**0.5350****
MSS-3PRF (1st pass)	0.5842***	0.5526***	0.4849***	0.6131***	0.5451
MSS-3PRF (1st & 3rd pass)	0.6034***	0.5466***	0.5223***	0.6193***	0.5494
PC-LARS	0.6176***	0.5700***	0.4954***	0.5926***	0.5754***
PCA	0.5955***	0.5743***	**0.4804*****	**0.5454*****	0.5595***
Panel C: Ripple					
Linear 3PRF	0.7902**	0.7047	0.6925**	0.9097**	0.7718*
MS-3PRF(1st pass)	**0.7736****	0.7108	**0.6908***	0.8917**	**0.7636***
MS-3PRF(1st & 3rd pass)	0.7858**	0.7335	0.7075**	**0.8865**	0.7765
MSS-3PRF (1st pass)	0.7875**	0.7130*	0.6938*	0.8909**	0.7841*
MSS-3PRF (1st & 3rd pass)	0.8034**	0.7480	0.7520*	0.9276	0.8496
PC-LARS	1.0375***	0.8280***	0.8437***	1.0596***	0.9319***
PCA	0.7931***	**0.7061*****	0.6946***	0.9116***	0.7757***
Panel D: Dogecoin					
Linear 3PRF	0.5887***	0.4961***	0.5562***	0.6122**	0.5719**
MS-3PRF(1st pass)	0.5858***	0.5192***	0.5419***	0.6152**	0.5426**
MS-3PRF(1st & 3rd pass)	0.5779***	0.8113	0.6402	0.8038	0.6455
MSS-3PRF (1st pass)	0.5809***	0.5162***	**0.5381*****	0.6162**	**0.5303****

MSS-3PRF (1st & 3rd pass)	0.5731***	0.6710***	0.5704***	0.6896***	0.5553*
PC-LARS	**0.5610****	0.5453***	0.5435***	**0.5431****	0.5446***
PCA	0.5858***	**0.5034****	0.5436***	0.6122***	0.5719***
Panel E: Litecoin					
Linear 3PRF	0.6109***	0.5565**	0.5681**	0.6290**	0.6000**
MS-3PRF(1st pass)	0.5995***	0.5683**	0.5609**	0.6191***	0.5932***
MS-3PRF(1st & 3rd pass)	0.6222***	**0.5546***	**0.5328****	0.6570**	0.5943***
MSS-3PRF (1st pass)	0.6030**	0.5603**	0.5726**	**0.6166****	0.6034***
MSS-3PRF (1st & 3rd pass)	0.6382***	0.5740**	0.5570***	0.6399**	0.5782***
PC-LARS	0.7513***	0.5793***	0.5875***	0.6556***	0.6273***
PCA	**0.5921****	0.5548***	0.5680***	0.6201***	**0.5712****

Note: This table reports the MSFE of a given approach relative to the MSFE of random walk for forecast horizons ranging from one-week- to five-week-ahead. A relative MSFE below unity indicates that the forecasting model outperforms the benchmark forecasting model according to the MSFE metric. Linear 3PRF uses a single target proxy. MS-3PRF (1st pass) and MSS-3PRF (1st pass) are regime-switching 3PRFs based on a single target proxy and regime-switching parameters in the first pass only; MS-3PRF (1st and 3rd passes) and MSS-3PRF (1st and 3rd passes) are regime-switching 3PRFs based on a single target proxy and regime-switching parameters in the first and third passes. For these approaches, the target proxy is the variable to forecast. Statistical reductions in MSFE relative to PCA according to the Diebold and Mariano (1995) test are indicated by asterisks, with *, **, and *** denoting significance at the 10%, 5% and 1% levels, respectively. Bold entries show the best performing model.