

# Nonstationary Common Factors and the Contrarian Investment Strategies in the Cryptocurrency Market

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January 2023

## Objectives of This Work

- This paper proposes contrarian investment strategies for cryptocurrencies in the presence of nonstationary common factors.
  - Cryptocurrency price as a martingale process (Schilling and Uhlig, 2019) [▶ Crypto Prices](#) [▶ Data Properties](#)
  - CES aggregation to motivate an  $N$ -currency version model
  - Propose contrarian investment strategies with defactored crypto prices (Bai and Ng, 2004, 2010)
  - Proposed strategies outperform conventional momentum/contrarian strategies based on past returns

## Emergence of the Cryptocurrency Market

- Since Nakamoto (2008) introduced the construction and trading system for a cryptocurrency, the original Bitcoin and numerous altcoins have received increasing attention as well as fierce criticism.
  - The cryptocurrency market has experienced rapid growth with extremely high volatility. ▶ [Market Cap](#)
    - The market capitalization of cryptocurrencies reached nearly \$3 trillion in November 2021, which declined to below \$ 1 trillion in November 2022.
  - Skeptics now admit cryptocurrencies have become non-negligible financial assets.
  - Bitcoin futures, cryptocurrency ETFs

## Related Research Work

- Schilling and Uhlig (2019, *JME*) provide a OLG model with a cash-in-advance type constraint to describe the dynamics of the Bitcoin price.
  - See Fernández-Villaverde and Sanches (2019, *JME*) Garratt and Wallance (2018, *EI*) for more skeptical views on the fate of cryptocurrencies.
  - See Liu, Tsyvinski, and Wu (2022, *JF*) for related work to this manuscript.
- This paper applies the investment strategy models of Balvers, Wu, and Gilland (2000, *JF*) and Kim (2009, *JEF*) to the cryptocurrency market utilizing cross-section information via latent common factor models of Bai and Ng (2002, 2004, *Econometrica*).

## Major Takeaways

- The contrarian investment strategy can be useful in the cryptocurrency market when cross-section information is utilized via defactored prices.
- Our factor-contrarian strategies outperform conventional investment strategies, especially momentum strategies, that rely on past return performance.
- How to remove nonstationary common factors is crucial to obtain superb performance via our factor-contrarian strategies.

## The Empirical Baseline model (Bai and Ng, 2004, 2010)

- Let  $p_{i,t}$ ,  $i = 1, \dots, N$ ,  $t = 1, \dots, T$  obeys the following stochastic process.

$$p_{i,t} = c_i + \lambda_i' \mathbf{f}_t + e_{i,t},$$

$$\Delta \mathbf{f}_t = \mathbf{u}_t,$$

$c_i$ : Fixed effect intercept of  $p_{i,t}$ ,

$\mathbf{f}_t$ : Latent common factors,

$\lambda_i$ : Idiosyncratic factor loadings,

$e_{i,t}$ : Idiosyncratic error term.

## The Empirical Baseline model (Bai and Ng, 2004, 2010)

- In the presence of nonstationarity in the data, common factors can be consistently estimated by applying the method of principal components (PC) to the first-differenced data. For this,

$$\Delta p_{i,t} = \lambda_i' \Delta \mathbf{f}_t + \Delta e_{i,t}$$

- After proper normalization, the method of PC yields  $\Delta \hat{\mathbf{f}}_t$ ,  $\hat{\lambda}_i$ , and the residuals  $\Delta \hat{e}_{i,t} = \Delta p_{i,t} - \hat{\lambda}_i' \Delta \hat{\mathbf{f}}_t$ .

## The Empirical Baseline model (Bai and Ng, 2004, 2010)

- By cumulative summing these, we obtain,

$$\hat{e}_{i,t} = \sum_{s=2}^t \Delta \hat{e}_{i,s}, \hat{\mathbf{f}}_t = \sum_{s=2}^t \Delta \hat{\mathbf{f}}_s$$

- We now define  $\tilde{p}_{i,t}$  as follows.

$$\tilde{p}_{i,t} = p_{i,t} - \hat{\lambda}_i' \hat{\mathbf{f}}_t = \hat{c}_i + \hat{e}_{i,t}$$

- $\tilde{p}_{i,t}$ , the *defactored* price of cryptocurrency  $i$ , obeys a stationary mean-reverting process, which provides a justification to employ the contrarian investment strategies.



## Theoretical Motivation: Schilling and Uhlig (2019)

- Using an overlapping generation model with a cash-in-advance constraint, Schilling and Uhlig (2019) derived the following.

$$E_t \left[ u'(c_{t+1}) \frac{P_t}{P_{t+1}} \right] = E_t \left[ u'(c_{t+1}) \frac{(Q_{t+1}/P_{t+1})}{(Q_t/P_t)} \right]$$

where  $Q_t$  is the dollar price of Bitcoin

- If  $u'(c_{t+1})/P_{t+1}$  is uncorrelated with  $Q_{t+1}$ , conditional on time- $t$  information, then the Bitcoin process obeys a martingale,

$$Q_t = E_t Q_{t+1}$$

## Extension to a $N$ -Currency Model

- We may extend Schilling and Uhlig's model to an  $N$ -currency model by using a CES aggregator.

$$Q_t = \left[ \int_0^1 p_{i,t}^{1-\theta} di \right]^{\frac{1}{1-\theta}}$$

- A linear model can be derived by discretizing the following result.

$$d \ln Q_t = \int_0^1 \left( \frac{p_{i,t}^{1-\theta}}{Q_t^{1-\theta}} \right) d \ln p_{i,t} di$$

## Nonstationary Common Factors with Known Factor Loadings

- The baseline model nests the models used in Balvers, Wu, and Gilliland (2000) and Kim (2009).
- Assume that  $p_{i,t}$  is mean-reverting around its time-varying fundamental variable  $f_t$ .

$$p_{i,t} = c_i + f_t + e_{i,t}$$

- $p_{i,t}$  and  $f_t$  are cointegrated with the cointegrating vector  $[1, -1]'$  by assuming that  $e_{i,t}$  obeys a stationary stochastic process.
- This is a special case of our baseline factor model.

## Nonstationary Common Factors with Known Factor Loadings

- $f_t$  is not directly observable. Furthermore, it cannot be estimated via PC because the factor loading is constrained to be one.
- Define the price deviations from a leading cryptocurrency such as the Bitcoin (BTC) price,

$$\tilde{p}_{B,i,t} = p_{B,t} - p_{i,t} = \tilde{c}_i + \tilde{e}_{i,t},$$

where  $\tilde{c}_i = c_B - c_i$  and  $\tilde{e}_{i,t} = e_{B,t} - e_{i,t}$ .

- Similarly,  $\tilde{p}_{E,i,t}$  is defined with Ethereum (ETH).

## Nonstationary Common Factors with Known Factor Loadings

- The contrarian investment strategies again apply since  $\tilde{p}_{B,i,t}$  obeys a stationary process.
- If Bitcoin is assumed to be the leading cryptocurrency price  $p_{B,t}$ , one may short cryptocurrencies that are performing better than Bitcoin, but buying the coins that are performing worse than Bitcoin.
- The portfolio is constructed based on their relative performance from the leading coin price dynamics.

## Nonlinear Stationary Models

- In the presence of non-negligible transaction cost, arbitrages occur only when the current state departs substantially away from the equilibrium.
- I employ nonlinear stochastic model approaches following the framework of Park and Shintani (2005, 2016).
- There are two regimes,
  - ①  $\Delta p_{i,t} = e_{i,t}$
  - ②  $\Delta p_{i,t} = \rho_i p_{i,t-1} + e_{i,t}, \rho_i < 0$
- The transition function  $\pi(p_{i,t-d}|\theta)$  is defined as a weight on the stationary regime.

## Nonlinear Stationary Models

- The stochastic process of  $p_{i,t}$  can then be jointly represented by,

$$\Delta p_{i,t} = \rho_i \pi(p_{i,t-d} | \theta) + e_{i,t},$$

where  $p_{i,t-d}$  is the potentially *nonstationary* transition variable with delay lag  $d \geq 1$ .

- I consider a band threshold autoregressive (BTAR) model as follows,

$$\pi(p_{i,t-1} | \theta) = [(p_{i,t-1} - \tau_1)I\{p_{i,t-1} \leq \tau_1\} + (p_{i,t-1} - \tau_2)I\{p_{i,t-1} \geq \tau_2\}]$$

where the stochastic process enters the unit root regime whenever  $p_{i,t-1}$  belongs to  $[\tau_1, \tau_2]$ , while  $p_{i,t}$  follows a stationary process outside the inaction band.

## Nonlinear Stationary Models

- Alternatively, the exponential smooth transition autoregressive (ESTAR) or the band logistic smooth transition autoregressive (BLSTAR) models can be employed.
- The contrarian investment strategies apply only when  $p_{i,t-1}$  is located outside the identified inaction band. No portfolio adjustments would be necessary when  $p_{i,t-1} \in [\tau_1, \tau_2]$ .



## Data Descriptions

- We obtained top 20 cryptocurrency prices from coinmarketcap.com with a minimum \$100 million market capitalization as of April 21, 2021. [▶ Data Properties](#) [▶ Crypto Prices](#)
- Observations are daily frequency and span from August 8, 2015 until April 21, 2021.
- Also used weekly frequency data

## Data Descriptions

- The cumulative returns during the entire sample period range from 246% (BCN) to 901% (XWC).
- The top 2 representative cryptocurrencies, Bitcoin (BTC) and Ethereum (ETH), are ranked 13 and 3, respectively.
- Average returns tend to be greater than the medians with exceptions of the top 2 coins.
- The standard deviations are also substantially higher for these coins in comparison with the top 2 coins.
- The JB test (Jarque and Bera, 1980, 1987; Deb and Sefton, 1996) rejects the null of normality for all crypto price returns, although the p-values of the top 2 turn out to be relatively higher than the others.

## Data Descriptions

- Figure 1 (▸ Crypto Prices) reports dynamics of these top 20 cryptocurrency prices.
- All prices are trending upward, implying the existence of a nonstationarity component in the data generating process.
- All crypto prices seem to be better described as nonstationary processes with stochastic trend.

## Dynamics of Defactored Crypto Prices

- Table 2 (▶ Defactored Prices) presents summary statistics of three types defactored crypto price data:
  - ① PC defactored cryptocurrency prices ( $p_{i,t} - \hat{\lambda}_i' \hat{\mathbf{f}}_t$ )
  - ② Cryptocurrency price percent deviations from the Bitcoin price ( $p_{BCT,t} - p_{i,t}$ )
  - ③ Cryptocurrency price percent deviations from the Ethereum price ( $p_{ETH,t} - p_{i,t}$ )
- In what follows, we present our model estimation results with weekly prices to avoid heavy computational burden especially for nonlinear models.
  - Weekly prices are end of period values on Saturdays.

## Persistence Properties of Defactored Prices

- The contrarian investment strategies require price reversals to occur in a reasonably short investment time horizon.
- One may generate profits by shorting better performing assets but including worse performing assets in the portfolio.
- How to identify over/under performing assets are the key.

## Persistence Properties: $p_{i,t} - \hat{\lambda}'_i \hat{\mathbf{f}}_t$

- Table 3 (► Persistence: PCD) presents supporting evidence in favor of the contrarian strategies in the presence of nonstationarity.
- The ADF test statistic was -1.496 (p-value: 0.536) for the first common factor, thus fails to reject the null of nonstationarity for the PC latent common factor.
  - The ADF test rejects the null for 7 out of 20 cases for defactored prices.

## Persistence Properties: $p_{i,t} - \hat{\lambda}'_i \hat{\mathbf{f}}_t$

- Table 3 (► Persistence: PCD) presents supporting evidence in favor of the contrarian strategies in the presence of nonstationarity.
  - The panel unit root test by Bai and Ng (2004, 2010) rejects the null of nonstationarity at the 1% level.

$$PU_{\hat{p}_{i,t}} = \frac{-2 \sum_{i=1}^N \ln p_{\hat{p}_{i,t}} - 2N}{2N^{1/2}} \rightarrow^d \mathcal{N}(0, 1),$$

where  $p_{\hat{e}_i}$  denotes the p-value of each ADF test of the defactored series.

- Strong evidence to justify the validity of the contrarian investment strategies for utilizing defactored series.

## Persistence Properties (MUE)

- Next, we estimate the persistence of each  $\tilde{p}_{i,t}$  using the median unbiased estimator for  $\alpha_i$  via the grid bootstrap method (Hansen, 1999). ► Persistence: MUE
  - We implement 10,000 nonparametric bootstrap simulations of 30 fine grid points ( $\alpha_{i,j} \in [\alpha_{i,1}, \alpha_{i,2}, \dots, \alpha_{i,30}]$ ,  $i = 1, \dots, N$ ) around the LS estimate to generate the ( $p$  percentile;  $p = 0.5$  for the median unbiased estimator) grid bootstrap quantile function estimates,  $\hat{q}_{T,p}^*(\alpha_{i,j}) = \hat{q}_{T,p}^*(\alpha_{i,j}, \varphi(\alpha_{i,j}))$ , where  $\varphi$  denotes nuisance parameters such as  $\beta$ 's that are functions of  $\alpha_{i,j}$ .
  - We obtain the median unbiased estimate  $\alpha_{MUE}$  by matching the grid- $t$  statistics  $t_N(\alpha_{i,j})$  with the estimated 50% quantile function  $\hat{q}_{T,50\%}^*(\alpha_{i,j})$ .
  - The 95% confidence intervals are constructed similarly.



## Persistence Properties (MUE)

- $\alpha_{MUE}$  estimates imply highly persistent dynamics of  $\tilde{p}_{i,t}$ .
  - ▶ Persistence: MUE
    - Estimated finite half-lives range from 0.126 (RDD) to over 4 years (XLM).
    - For DOGE, its persistence parameter estimate is over 1, meaning that very weak evidence of mean reversion (price reversal) in a reasonably short investment time horizon.
    - The 95% confidence intervals extend to infinity with two exceptions, RDD and EMC2.
- We also report a panel version median unbiased estimate via the fixed effect panel regression model.
  - The 95% confidence interval of  $\alpha_{PMUE}$  is compact, roughly 6-month to 11-month. The point HL estimate is roughly 7-month.

## Persistence Properties: $p_{BCT,t} - p_{i,t}$ and $p_{ETH,t} - p_{i,t}$

- We report evidence that price reversals are less likely to occur for  $p_{BCT,t} - p_{i,t}$  and  $p_{ETH,t} - p_{i,t}$  possibly due to remaining nonstationary common factors.
  - ▶ Persistence: BTC
  - ▶ Persistence: ETH
- The ADF test rejects the null of nonstationarity for 2 out of 19  $\tilde{p}_{BTC,i,t}$ .
- The test rejects the null for 8 out of 19  $\tilde{p}_{ETH,i,t}$ .
- Ethereum seems to play a stronger role in leading the price dynamics in the cryptocurrency market.

## Persistence Properties: $p_{BCT,t} - p_{i,t}$ and $p_{ETH,t} - p_{i,t}$

- Persistence parameter estimates deliver similar information.
  - $\alpha_{MUE}$  estimates of the deviations with BTC tend to be close to unity.
  - The panel half-life estimate from  $\alpha_{PMUE}$  was 5.66 years. The upper bound half-life estimate was over 13 years.
  - The half-life estimates of ETH deviations tend to be shorter than BTC deviations.
- Cryptocurrency prices seem to fluctuate around the ETH price more closely than the BTC price, although deviations require quite long time to trigger price reversals.

## Nonlinear Speed Adjustment

- We allow such reversion occurs only when the size of deviations is large enough, employing the band threshold autoregressive (BTAR) model specifications.
- Table 6 (▶ BTAR: PC) reports estimation results for  $\tilde{p}_{i,t}$ .
  - We first report  $\inf_T$  statistics by Park and Shintani (2005, 2016), which rejects the null of nonstationarity against the stationary BTAR model for 19 (15) out of 20 cryptocurrencies at the 10% (5%) significance level.
  - The median half-life estimate was 1.2 months (0.102 year), which is substantially shorter than those from linear models.

## Nonlinear Speed Adjustment

- We allow such reversion occurs only when the size of deviations is large enough, employing the band threshold autoregressive (BTAR) model specifications.
- Table 6 (▶ BTAR: PC) reports estimation results for  $\tilde{p}_{i,t}$ .
  - We also report the realized probability of the cryptocurrency price to stay in the inaction band,  $[\tau_1, \tau_2]$ , which ranges from 0.3% (GTS) to 69.4% (BTS and BCN).
  - We report strong evidence of nonlinear mean reversion that demonstrates substantially high speed of price reversal in the cryptocurrency market when the PC factor is used.

## Inaction Bands

- Figure 2 (▶ Inaction Band) provides intuitive illustration of the empirical findings from this nonlinear model estimations for the top 2 cryptocurrencies, BTC and ETH.
  - Unlike  $p_{BTC,t}$  (right axis), defactored price  $\tilde{p}_{B,i,t}$  (left axis) does not exhibit particular trending dynamics, reflecting that its nonstationary common factor component  $\lambda_B' \mathbf{f}_t$  has been removed.
  - Furthermore, large deviations from the inaction band, area between the two dotted lines, often revert back to the inaction band, providing strong evidence in favor of nonlinear stationary behavior of  $\tilde{p}_{B,i,t}$ .
  - Report a longer duration in its inaction band of  $\tilde{p}_{E,i,t}$ .

## Nonlinear Adjustments: $\tilde{p}_{B,i,t}$ and $\tilde{p}_{E,i,t}$

- Table 7 (► BTAR: BTC), the  $\text{inf}_T$  test rejects the null of nonstationarity against nonlinear stationarity for only 4 (3) cryptocurrencies out of 19 cases at the 10% (5%) significance level.
- The convergence back to its inaction band turns out to be slow in comparison with  $\tilde{p}_{i,t}$ .
- The median half-life estimate was 0.173-year, which is longer than the median half-life (1.2-month) for  $\tilde{p}_{i,t}$ .
- The median probability to be in the inaction band was 55.9%.

## Nonlinear Adjustments: $\tilde{p}_{B,i,t}$ and $\tilde{p}_{E,i,t}$

- Table 8 (► BTAR: ETH), the  $\text{inf}_T$  test rejects the null of nonstationarity against nonlinear stationarity for only 12 (8) cryptocurrencies out of 19 cases at the 10% (5%) significance level.
- The median half-life estimate was 0.143-year, which is longer than the median half-life (1.2-month) for  $\tilde{p}_{i,t}$ .
- The median probability to be in the inaction band was 45.5%.



## Detecting Remaining Nonstationarity

- We investigate the presence of common factors in the defactored prices, using Pesaran's (2021) cross-section dependence (CD) test statistic.

$$CD = \left( \frac{2T}{N(N-1)} \right)^{1/2} \left( \sum_{i=1}^{N-1} \sum_{j=i+1}^N \hat{\rho}_{i,j} \right) \rightarrow^d \mathcal{N}(0, 1),$$

where  $\hat{\rho}_{i,j}$ ,  $i, j = 1, \dots, N$  is the pair-wise correlation coefficients from the residuals ( $\hat{\varepsilon}_{i,t}$ ) of the ADF regressions.

## Detecting Remaining Nonstationarity

- Table 9 (▶ CDS) reports the average values of  $\hat{\rho}_i = N^{-1} \sum_{i \neq j}^N \hat{\rho}_{i,j}$  for the weekly crypto returns ( $\Delta p_{i,t}$ ) as well as the three defactored series.
- We observe strong degree of remaining correlations in all specifications except the PC defactored series  $\tilde{p}_{i,t}$ , which implies the existence of remaining nonstationary common factors in these series.
- The formal cross-section dependence test via the CD statistics also confirmed these findings.

## Detecting Remaining Nonstationarity

- In the presence of remaining (near) nonstationarity, the momentum strategies are likely to perform better because price reversals may take a long time even if it occurs.
- See also heatmaps. [▶ Heatmaps](#)

## Detecting Remaining Nonstationarity

- We further investigate this issue by estimating common factors in  $\tilde{p}_{BCT,i,t}$ , and  $\tilde{p}_{ETH,i,t}$  via the PANIC approach.
  - We chose 1 common factor in both cases by the IC (Bai and Ng, 2002).
  - However, we estimate and report up to 2 common factors to better understand the crypto price dependence on the underlying data generating process.

## Detecting Remaining Nonstationarity


- we report the shares of variation in  $\tilde{p}_{BCT,i,t}$  defined as follows.

$$SV_{BTC,i,j} = \frac{\sigma \left( \lambda_i^j f_t^j \right)}{\sigma \left( \tilde{p}_{BCT,i,t} - \lambda_i' f_t^j \right)}, \quad i = 1, \dots, N, \quad j = 1, 2,$$

where  $\sigma$  denotes the standard deviation,  $f_t^j$  is the  $j^{th}$  common factor at time  $t$ , and  $\lambda_i^j$  is crypto  $i$ 's factor loading for  $f_t^j$ .

- $SV_{BTC,i,j}$  measures the relative importance of the  $j^{th}$  common factor to its idiosyncratic component.

## Detecting Remaining Nonstationarity

- Figure 4 () , we observe consistently high ratios for  $SV_{BTC,i,1}$  that often exceeds unity, whereas  $SV_{BTC,i,2}$  values are mostly below one.
- Factor loadings on the first common factor are of equal signs, while those on the second common factor do not show any patterns.
- Strong evidence in favor of one remaining common factor in  $\tilde{p}_{BCT,i,t}$ .

## Detecting Remaining Nonstationarity

- Figure 5 ( $\triangleright SV_{ETH}$ ) shows much weaker, but non-negligible evidence of remaining nonstationary common factors in  $\tilde{p}_{ETH,i,t}$ .
- $SV_{BTC,i,1}$  tends to be a little greater than  $SV_{BTC,i,2}$ , although the shares are smaller than those of BTC
- Stronger evidence of remaining nonstationary common factors when BTC is used as the leading cryptocurrency.
- Overall, Weaker evidence regarding the usefulness of the contrarian investment strategies when the top 2 dominant players in the crypto market are used to remove the nonstationarity.

## Simulations

- We report empirical assessment of the validity of our investment strategies that utilize the indiosyncratic components of cryptocurrency prices after removing nonstationary common factors.
- We implement an array of simulation exercises employing different portfolio switch strategies for the top 20 cryptocurrencies.



## Simulation Schemes

- We focus on the following state variables:  $\Delta p_{i,t}$ ,  $\tilde{p}_{i,t}$ ,  $\tilde{p}_{BTC,i,t}$ , and  $\tilde{p}_{ETH,i,t}$ .
- Under the contrarian investment scheme, cryptocurrencies that underperformed in the past are selected in the portfolio.
- Cryptocurrencies that are currently outperforming others are selected in the portfolio under the momentum investment scheme.

## Simulation Schemes

- Consider simulation exercises that one adjust/reformulate the portfolio every  $j$  weeks based on the immediate past performance of each cryptocurrency.
  - Obtain the initial  $j$ -week price information for all cryptocurrencies at time  $t = T_0$ .
  - Under the contrarian (momentum) strategy principle, 5 worst (best) performing cryptocurrencies, i.e., first (fifth) quintile group, of the initial  $j$ -week returns are included with equal weights in the portfolio.
  - At time  $t = T_0 + 1$ , realize and keep the return from the first stage portfolio, then reformulate the portfolio based on the same principle for the the next period.

## Simulation Schemes

- Consider simulation exercises that one adjust/reformulate the portfolio every  $j$  weeks based on the immediate past performance of each cryptocurrency.
  - At time  $t = T_0 + 2$ , the  $j$ -week return from this portfolio is realized, and we add it to the previous portfolio return to obtain the compound gross returns from  $t = T_0$  to  $T_0 + 2$ .
  - We continue this procedure until we reach the end of the sample period  $t = T$ . That is, the last portfolio that was reformulate at time  $t = T - 1$  is realized at time  $t = T$ , then we evaluate the cumulative return of the portfolio during the entire sample period.

## Simulation Schemes

- The investment strategies with defactored idiosyncratic prices,  $\tilde{p}_{i,t}$ ,  $\tilde{p}_{BTC,i,t}$ , and  $\tilde{p}_{ETH,i,t}$ , utilize the recent past  $j$ -week average values.
  - Calculate the average  $\tilde{p}_{i,T_0}$  during the first  $j$  weeks, then include the cryptocurrencies in the first quintile group in the portfolio under the contrarian scheme that are kept until  $t = T_0 + 1$ .
  - After calculating the realized capital gain/loss during the initial investment period, the portfolio is reformulated using the first quintile of  $\tilde{p}_{i,T_0+1}$ .
  - We continue this process until  $t = T - 1$ .
  - At time  $t = T$ , we calculate the compound gross returns by adding all period realized returns.

## Simulation Schemes

- The momentum strategy employs the same process except it utilizes the fifth quintile group cryptocurrencies.
- The portfolio switching schemes with deviations from either Bitcoin or Ethereum are implemented similarly using  $\tilde{p}_{BTC,i,t}$  or  $\tilde{p}_{ETH,i,t}$ , respectively.

## Simulation Results

- Figure 6 (▶ 8-week Sim) reports our findings from our exercises with an 8-week investment horizon.
  - The first panel shows the cumulative returns from the contrarian and the momentum strategies using the past return state variables ( $\Delta p_{i,t}$ ).
  - The compound gross return of the former was 880% that surpasses 280% return from the latter.
  - The contrarian strategy outperforms the momentum investment scheme with a great margin.

## Simulation Results

- Figure 6 (▶ 8-week Sim) reports our findings from our exercises with an 8-week investment horizon.
  - The contrarian scheme with  $\tilde{p}_{i,t}$  performs particularly well dominating all other investment strategies.
  - The gross compound return was over 1,000%, whereas the momentum strategy with  $\tilde{p}_{i,t}$  yields much weaker 250% returns.
  - When  $\tilde{p}_{BTC,i,t}$  or  $\tilde{p}_{ETH,i,t}$  are used as the state variable, the momentum and the contrarian strategies perform overall similarly, yielding 550% to 730%.
  - Maybe due to remaining nonstationary component

## Simulation Results

- Figure 7 (▶ 4-week Sim) reports our findings from our exercises with an 4-week investment horizon. Results are similar.
  - When one uses the past return ( $\Delta p_{i,t}$ ) or  $\tilde{p}_{i,t}$  for the state variable, the contrarian strategy outperforms the momentum strategy with a big margin.
  - the PC defactored price model with the contrarian investment strategy generates 1,180% gross returns, while the momentum strategy yields 150% returns.
  - The models that employ either BTC or ETH as a leading cryptocurrency perform overall better under the momentum strategy, yielding over 800% returns each, implying the existence of remaining nonstationary common factors.



## Simulation with Nonlinear Models

- Figure 8 (▶ Nonlinear Sim) reports nonlinear model simulation results, showing overall similar results as those from linear models.
  - The contrarian investment scheme significantly outperforms whenever PC defactored idiosyncratic prices are employed, yielding over 1,200% and 1,390% gross returns with 8-week and 4-week investment horizons, respectively.
  - The momentum strategy generates much lower returns, 98% and -27% with 8- and 4-week horizons.

## Simulation with Nonlinear Models

- Figure 8 ( ▶ Nonlinear Sim ) reports nonlinear model simulation results, showing overall similar results as those from linear models.
  - The momentum strategy performs better than the contrarian strategy when deviation prices from either BTC or ETH are used.
  - Cumulative returns range from around 780% to 970%, whereas the contrarian scheme yields from around 310% to 620%.
  - These results again highlight the possibility of the existence of remaining nonstationary common factors in the defactored series using a leading cryptocurrency.

## Simulation with Nonlinear Models

- In a nutshell, the contrarian investment strategy outperforms other alternative investment schemes both under the linear and nonlinear frameworks when nonstationary common factors are thoroughly removed.

## Concluding Remarks

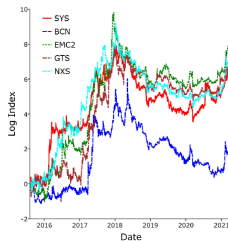
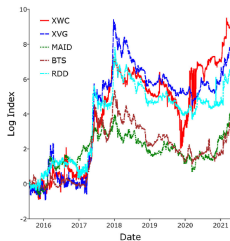
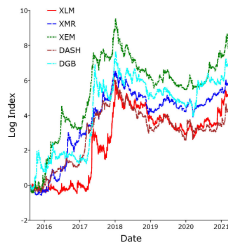
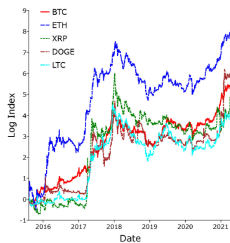
- I propose a factor-contrarian investment strategy for the cryptocurrency market.
- Show nonstationary common factors can be identified and removed via the principal component approach.
- Over- and underpriced cryptos can be identified more effectively when nonstationary common factors are thoroughly removed.
- The contrarian approach with PC defactored prices outperform other conventional investment approach with a great margin.

Thank You!  
😊

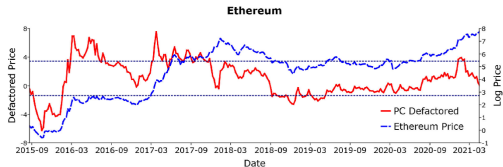
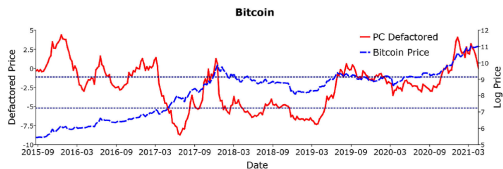
# MARKET CAPITALIZATION OF CRYPTOCURRENCIES



# NORMALIZED CRYPTOCURRENCY PRICE DYNAMICS

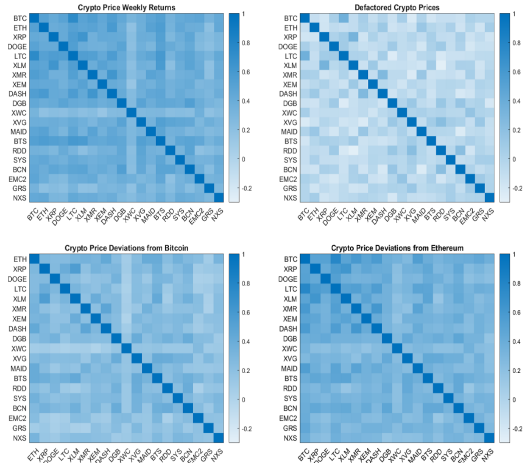


# BAND THRESHOLD AR MODEL ESTIMATIONS

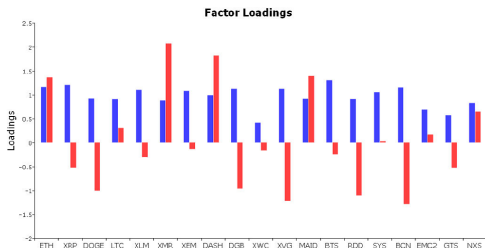
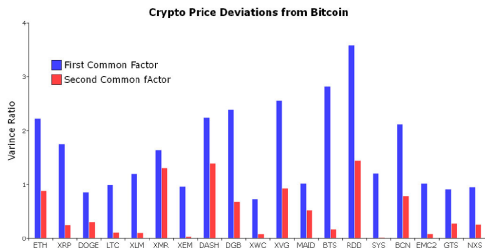




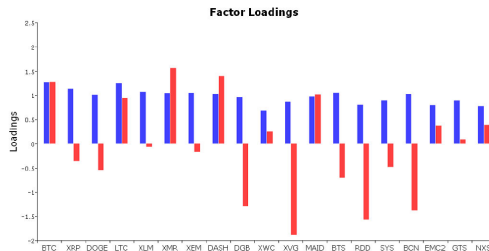
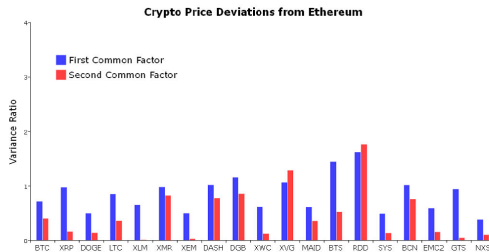
# CROSS-SECTION CORRELATIONS



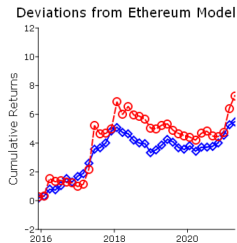
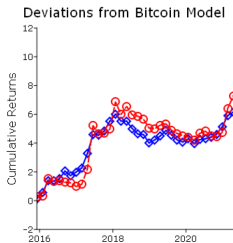
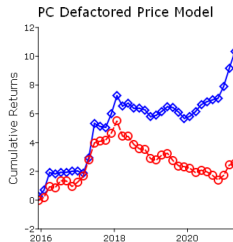
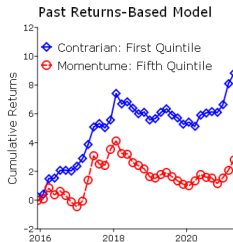
# RELATIVE VARIATION ANALYSIS OF FACTORS: $\tilde{p}_{B,i,t}$



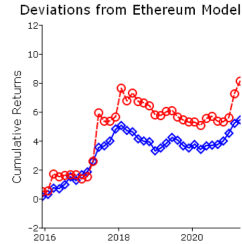
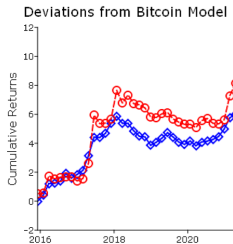
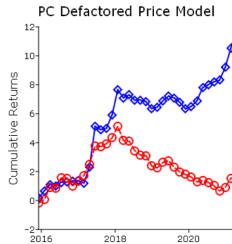
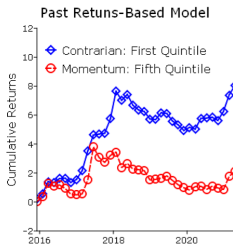
# RELATIVE VARIATION ANALYSIS OF FACTORS: $\tilde{p}_{E,i,t}$



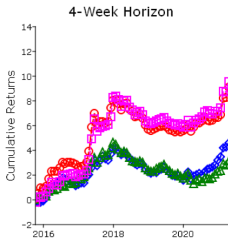
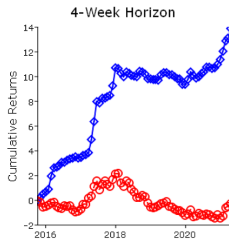
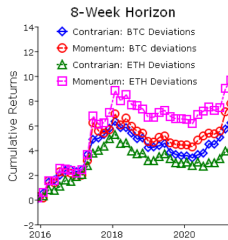
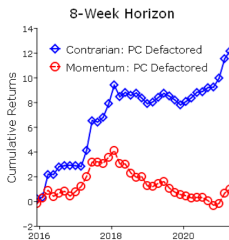
## 8-WEEK HORIZON SIMULATION EXERCISE



## 4-WEEK HORIZON SIMULATION EXERCISE



# NONLINEAR (BTAR) MODEL SIMULATION EXERCISE



## TOP 20 CRYPTOCURRENCY PRICES

Cryptocurrency	Symbol	M. Cap (\$Bil)	Cum Rtn (%)	Mean/Med Rtn	SD	JB
Bitcoin	BTC	\$1,007.389	533.05	0.018/0.015	0.111	80
Ethereum	ETH	\$273.282	805.17	0.024/0.021	0.165	74
XRP	XRP	\$58.866	503.29	0.018/ - 0.002	0.195	779
Dogecoin	DOGE	\$39.679	756.98	0.025/ - 0.004	0.206	3009
Litecoin	LTC	\$17.275	420.80	0.015/0.006	0.149	120
Stellar	XLM	\$11.278	531.53	0.019/ - 0.008	0.200	1506
Monero	XMR	\$6.795	633.12	0.022/0.008	0.166	313
NEM	XEM	\$3.215	787.49	0.028/0.003	0.189	91
Dash	DASH	\$2.985	456.50	0.016/ - 0.002	0.157	136
DigiByte	DGB	\$2.159	783.33	0.026/ - 0.004	0.260	1997
WhiteCoin	XWC	\$1.170	901.48	0.031/ - 0.003	0.352	624
Verge	XVG	\$0.961	793.83	0.028/0.001	0.298	659
MaidSafeCoin	MAID	\$0.485	387.04	0.013/0.004	0.160	42
BitShares	BTS	\$0.334	328.64	0.012/ - 0.011	0.213	542
ReddCoin	RDD	\$0.298	678.59	0.022/0.002	0.278	1559
Syscoin	SYS	\$0.223	690.56	0.023/0.013	0.215	70
Bytecoin	BCN	\$0.156	246.01	0.009/ - 0.001	0.239	2994
Einsteinium	EMC2	\$0.108	816.03	0.028/ - 0.003	0.256	185
Groestlcoin	GRS	\$0.106	726.65	0.027/ - 0.008	0.263	1052
Nexus	NXS	\$0.104	704.83	0.024/0.000	0.226	512

# SUMMARY STATISTICS OF DEFACTORED PRICES

Symbol	$P_{i,t} - \hat{\lambda}_i \hat{\tilde{e}}_t$			$PBTC,t - P_{i,t}$			$PETC,t - P_{i,t}$		
	Mean/Med	SD	JB	Mean/Med	SD	JB	Mean/Med	SD	JB
BTC	-2.315/-2.071	2.933	257	-	-	-	-3.649/-3.537	0.853	273
ETH	1.031/1.008	2.499	260	3.649/3.537	0.853	273	-	-	-
XRP	-1.795/-1.741	0.195	779	10.49/10.52	0.828	745	6.799/6.873	0.770	336
DOGE	-8.683/-10.05	4.095	9200	14.73/14.76	0.492	7526	11.08/11.16	0.884	2179
LTC	-2.607/-2.731	2.878	239	4.815/4.830	0.473	571	1.165/1.267	0.835	128
XTM	-2.135/-0.679	3.683	2578	11.65/11.81	0.879	1651	7.997/8.018	0.896	488
XMR	2.949/2.758	2.946	2035	4.784/4.678	0.846	1529	1.134/1.084	0.560	381
XEM	6.286/5.271	4.493	1441	11.66/11.67	1.286	732	8.005/7.992	0.595	257
DASH	2.540/1.995	2.643	299	4.094/4.227	0.870	343	0.445/0.420	0.788	402
DGB	0.431/0.300	2.285	2560	13.55/13.65	0.949	3233	9.896/9.979	0.650	2035
XWC	-1.933/-1.421	2.377	605	12.66/12.29	1.519	635	9.013/8.752	1.230	361
XVG	-0.012/0.862	2.662	737	14.73/14.60	1.691	2288	11.08/10.92	1.232	750
MAID	-1.765/-3.053	3.820	54	10.14/10.18	1.019	172	6.489/6.929	1.322	6
BTS	-1.327/-0.959	2.265	2141	11.80/11.71	1.061	876	8.152/8.002	1.152	184
RDD	0.893/1.266	1.630	4149	15.81/16.03	1.023	3758	12.16/12.20	0.711	1674
SYS	2.134/1.136	3.365	301	11.63/11.47	1.138	89	7.979/7.847	0.746	486
BCN	-0.766/-0.386	2.650	1972	16.21/16.23	1.262	4116	12.56/12.30	1.249	2462
EMC2	1.928/2.258	1.957	799	12.24/12.11	1.414	403	8.592/8.448	0.837	583
GRS	2.207/1.947	2.580	2525	10.93/10.74	1.292	2086	7.280/7.111	0.921	850
NXS	4.581/4.016	3.874	278	10.01/10.25	1.360	336	6.360/6.188	0.883	215



# PERSISTENCE OF PC DEFACTORED CRYPTO PRICES

ID	ADF	$\alpha_{MUE}$	95% CI	HL (years)	95% CI
BTC	-2.442	0.977	[0.948, 1.007]	0.571	[0.249, $\infty$ )
ETH	-2.701*	0.967	[0.934, 1.007]	0.396	[0.195, $\infty$ )
XRP	-2.444	0.975	[0.943, 1.009]	0.525	[0.227, $\infty$ )
DOGE	-1.501	1.001	[0.971, 1.015]	$\infty$	[0.452, $\infty$ )
LTC	-1.917	0.989	[0.958, 1.013]	1.202	[0.310, $\infty$ )
XLM	-1.671	0.997	[0.968, 1.014]	4.425	[0.409, $\infty$ )
XMR	-2.461	0.974	[0.943, 1.009]	0.505	[0.227, $\infty$ )
XEM	-1.668	0.997	[0.972, 1.011]	4.425	[0.468, $\infty$ )
DASH	-2.751*	0.967	[0.934, 1.005]	0.396	[0.195, $\infty$ )
DGB	-2.755*	0.961	[0.923, 1.006]	0.334	[0.166, $\infty$ )
XWC	-2.890†	0.948	[0.901, 1.006]	0.249	[0.128, $\infty$ )
XVG	-2.293	0.974	[0.937, 1.011]	0.505	[0.204, $\infty$ )
MAID	-1.727	0.995	[0.965, 1.014]	2.652	[0.373, $\infty$ )
BTS	-1.938	0.986	[0.949, 1.015]	0.943	[0.254, $\infty$ )
RDD	-3.800‡	0.900	[0.842, 0.963]	0.126	[0.077, 0.353]
SYS	-1.986	0.987	[0.957, 1.012]	1.016	[0.302, $\infty$ )
BCN	-1.713	0.993	[0.954, 1.017]	1.892	[0.282, $\infty$ )
EMC2	-4.036‡	0.913	[0.866, 0.964]	0.146	[0.092, 0.363]
GTS	-2.998†	0.951	[0.910, 1.003]	0.265	[0.141, $\infty$ )
NXS	-1.780	0.993	[0.963, 1.013]	1.892	[0.353, $\infty$ )
$\alpha_{PMUE} : 0.977, [0.969, 0.986]$ HL (years) : 0.571, [0.422, 0.943]					

# PERSISTENCE OF $\tilde{p}_{B,i,t}$

Symbol	ADF	$\alpha_{MUE}$	95% CI	HL (years)	95% CI
ETH	-2.082	0.990	[0.967, 1.009]	1.323	[0.396, $\infty$ )
XRP	-2.473	0.978	[0.952, 1.007]	0.598	[0.270, $\infty$ )
DOGE	-1.811	0.975	[0.927, 1.015]	0.525	[0.175, $\infty$ )
LTC	-1.939	0.989	[0.960, 1.012]	1.202	[0.326, $\infty$ )
XLM	-1.877	0.991	[0.964, 1.011]	1.470	[0.363, $\infty$ )
XMR	-1.805	0.995	[0.971, 1.011]	2.652	[0.452, $\infty$ )
XEM	-2.528*	0.988	[0.972, 1.005]	1.101	[0.468, $\infty$ )
DASH	-1.447	1.001	[0.976, 1.012]	$\infty$	[0.547, $\infty$ )
DGB	-3.067 <sup>†</sup>	0.966	[0.937, 1.001]	0.384	[0.204, $\infty$ )
XWC	-1.480	1.001	[0.966, 1.016]	$\infty$	[0.384, $\infty$ )
XVG	-1.781	0.995	[0.972, 1.011]	2.652	[0.468, $\infty$ )
MAID	-1.213	1.003	[0.982, 1.014]	$\infty$	[0.732, $\infty$ )
BTS	-1.645	0.997	[0.970, 1.012]	4.425	[0.436, $\infty$ )
RDD	-2.494	0.974	[0.943, 1.008]	0.505	[0.227, $\infty$ )
SYS	-1.756	0.996	[0.971, 1.012]	3.317	[0.452, $\infty$ )
BCN	-1.306	1.003	[0.977, 1.015]	$\infty$	[0.571, $\infty$ )
EMC2	-1.964	0.992	[0.970, 1.009]	1.655	[0.436, $\infty$ )
GTS	-2.046	0.989	[0.963, 1.011]	1.202	[0.353, $\infty$ )
NXS	-1.778	0.996	[0.975, 1.011]	3.317	[0.525, $\infty$ )
$\alpha_{PMUE} : 0.998, [0.996, 0.999]$					
HL (years) : 5.662, [3.458, 13.719]					

# PERSISTENCE OF $\tilde{p}_{E,i,t}$

Symbol	ADF	$\alpha_{MUE}$	95% CI	HL (years)	95% CI
BTC	-2.082	0.990	[0.967, 1.009]	1.323	[0.396, $\infty$ )
XRP	-2.987 <sup>†</sup>	0.965	[0.934, 1.003]	0.373	[0.195, $\infty$ )
DOGE	-1.983	0.986	[0.955, 1.012]	0.943	[0.289, $\infty$ )
LTC	-2.572*	0.981	[0.958, 1.006]	0.693	[0.310, $\infty$ )
XLM	-2.363	0.981	[0.954, 1.009]	0.693	[0.282, $\infty$ )
XMR	-2.654*	0.965	[0.929, 1.007]	0.373	[0.181, $\infty$ )
XEM	-3.599 <sup>‡</sup>	0.944	[0.908, 0.984]	0.231	[0.138, 0.824]
DASH	-1.632	0.998	[0.968, 1.013]	6.640	[0.409, $\infty$ )
DGB	-3.781 <sup>‡</sup>	0.927	[0.884, 0.973]	0.175	[0.108, 0.486]
XWC	-1.906	0.984	[0.945, 1.015]	0.824	[0.235, $\infty$ )
XVG	-1.940	0.988	[0.958, 1.013]	1.101	[0.310, $\infty$ )
MAID	-1.469	1.001	[0.984, 1.011]	$\infty$	[0.824, $\infty$ )
BTS	-1.730	0.997	[0.974, 1.011]	4.425	[0.505, $\infty$ )
RDD	-3.236 <sup>†</sup>	0.939	[0.894, 0.992]	0.211	[0.119, 1.655]
SYS	-1.830	0.988	[0.951, 1.015]	1.101	[0.265, $\infty$ )
BCN	-1.805	0.994	[0.969, 1.012]	2.209	[0.422, $\infty$ )
EMC2	-2.606*	0.968	[0.932, 1.008]	0.409	[0.189, $\infty$ )
GTS	-2.682*	0.964	[0.928, 1.008]	0.363	[0.178, $\infty$ )
NXS	-2.121	0.982	[0.951, 1.011]	0.732	[0.265, $\infty$ )
$\alpha_{PMUE} : 0.995, [0.993, 0.997]$					
HL (years) : 2.599, [1.869, 3.958]					

# NONLINEAR PERSISTENCE OF $p_{i,t} - \hat{\lambda}'_i \hat{\mathbf{f}}_t$

Symbol	$\inf_T$	$1 + \rho_i$	HL (years)	$\tau_1$	$\tau_2$	Pr(Inaction)
BTC	-2.515*	0.939	0.211	-5.200	-1.129	0.408
ETH	-3.674 <sup>‡</sup>	0.851	0.082	-1.373	3.435	0.646
XRP	-2.663*	0.865	0.092	-5.373	0.552	0.592
DOGE	-1.859	0.964	0.363	-10.130	-5.231	0.320
LTC	-3.480 <sup>‡</sup>	0.848	0.081	-5.233	0.167	0.541
XLM	-3.360 <sup>‡</sup>	0.892	0.116	-6.534	0.324	0.537
XMR	-3.113 <sup>‡</sup>	0.884	0.108	-0.299	5.709	0.673
XEM	-2.544*	0.892	0.116	2.046	11.978	0.643
DASH	-4.357 <sup>‡</sup>	0.870	0.095	0.996	5.286	0.578
DGB	-3.187 <sup>‡</sup>	0.841	0.077	-1.971	3.201	0.697
XWC	-2.911 <sup>‡</sup>	0.927	0.175	-2.178	-1.465	0.119
XVG	-3.912 <sup>‡</sup>	0.822	0.068	-3.693	1.477	0.537
MAID	-2.978 <sup>‡</sup>	0.892	0.116	-4.056	3.289	0.476
BTS	-3.121 <sup>‡</sup>	0.828	0.070	-3.951	0.876	0.694
RDD	-5.561 <sup>‡</sup>	0.704	0.038	-0.754	1.763	0.503
SYS	-2.804 <sup>‡</sup>	0.884	0.108	-0.789	5.228	0.480
BCN	-3.716 <sup>‡</sup>	0.717	0.040	-3.835	2.120	0.694
EMC2	-4.961 <sup>‡</sup>	0.789	0.056	-0.089	2.998	0.592
GTS	-2.773 <sup>‡</sup>	0.944	0.231	1.960	1.964	0.003
NXS	-2.515*	0.934	0.195	1.668	7.268	0.435

# NONLINEAR PERSISTENCE OF $\tilde{p}_{B,i,t}$

Symbol	$\inf_T$	$1 + \rho_i$	HL (years)	$\tau_1$	$\tau_2$	Pr(Inaction)
ETH	-2.175	0.978	0.598	3.348	3.538	0.203
XRP	-3.600 <sup>†</sup>	0.804	0.061	9.440	11.391	0.664
DOGE	-1.988	0.938	0.208	14.255	14.764	0.353
LTC	-3.600 <sup>†</sup>	0.808	0.062	4.264	5.351	0.678
XLM	-2.384	0.926	0.173	10.396	12.129	0.539
XMR	-2.062	0.954	0.282	4.378	5.824	0.458
XEM	-2.505	0.976	0.547	10.553	11.668	0.308
DASH	-3.592 <sup>†</sup>	0.869	0.095	2.959	4.946	0.695
DGB	-2.499	0.909	0.139	12.578	14.239	0.559
XWC	-2.695	0.764	0.049	11.055	14.507	0.698
XVG	-2.334	0.921	0.162	13.080	16.716	0.644
MAID	-2.861 <sup>*</sup>	0.822	0.068	8.872	11.399	0.692
BTS	-2.226	0.937	0.204	10.785	12.936	0.678
RDD	-2.190	0.964	0.363	15.778	16.032	0.115
SYS	-2.396	0.933	0.192	10.475	12.548	0.508
BCN	-1.765	0.958	0.310	15.172	17.494	0.624
EMC2	-2.273	0.959	0.318	11.427	13.418	0.461
GTS	-2.400	0.912	0.144	9.648	12.160	0.546
NXS	-2.588	0.923	0.166	8.494	11.390	0.654

# NONLINEAR PERSISTENCE OF $\tilde{p}_{E,i,t}$

Symbol	$\inf_T$	$1 + \rho_i$	HL (years)	$\tau_1$	$\tau_2$	Pr(Inaction)
BTC	-2.173	0.978	0.598	-3.546	-3.346	0.210
XRP	-3.234 <sup>†</sup>	0.929	0.181	6.423	7.214	0.454
DOGE	-2.047	0.965	0.373	10.501	11.160	0.353
LTC	-2.701*	0.969	0.422	1.262	1.568	0.180
XLM	-2.402	0.970	0.436	8.012	8.079	0.041
XMR	-3.040 <sup>†</sup>	0.897	0.122	0.761	1.715	0.644
XEM	-4.266 <sup>‡</sup>	0.842	0.077	7.422	8.391	0.580
DASH	-2.010	0.971	0.452	0.412	1.121	0.359
DGB	-3.661 <sup>‡</sup>	0.852	0.083	9.279	10.310	0.580
XWC	-2.873*	0.833	0.073	7.877	10.363	0.631
XVG	-3.409 <sup>†</sup>	0.816	0.065	9.813	12.859	0.698
MAID	-2.214	0.949	0.254	4.975	7.510	0.539
BTS	-2.116	0.973	0.486	7.997	9.233	0.349
RDD	-3.297 <sup>†</sup>	0.866	0.092	11.640	12.573	0.427
SYS	-2.705*	0.898	0.124	7.596	8.815	0.397
BCN	-2.364	0.961	0.334	12.298	13.840	0.349
EMC2	-3.309 <sup>†</sup>	0.911	0.143	8.121	9.119	0.495
GTS	-3.187 <sup>†</sup>	0.849	0.081	6.485	8.121	0.556
NXS	-2.875*	0.885	0.109	5.522	7.301	0.698

# CROSS-SECTION DEPENDENCE IN THE DEFACTORED PRICES

Symbol	Average Cross-Correlations ( $\hat{\rho}_i$ )			
	$\Delta p_{i,t}$	$p_{i,t} - \hat{\lambda}_i \hat{f}_t$	$p_{BTC,t} - p_{i,t}$	$p_{ETC,t} - p_{i,t}$
BTC	0.489	0.003	—	0.479
ETH	0.450	−0.008	0.315	—
XRP	0.426	0.002	0.297	0.419
DOGE	0.409	0.001	0.238	0.375
LTC	0.494	−0.001	0.254	0.466
XTM	0.440	−0.006	0.292	0.396
XMR	0.430	−0.005	0.254	0.396
XEM	0.408	−0.009	0.275	0.395
DASH	0.453	0.002	0.280	0.396
DGB	0.438	0.000	0.295	0.381
XWC	0.278	0.017	0.151	0.280
XVG	0.415	0.007	0.299	0.346
MAID	0.405	−0.003	0.258	0.372
BTS	0.490	0.004	0.341	0.401
RDD	0.359	0.014	0.249	0.320
SYS	0.415	0.002	0.290	0.350
BCN	0.433	0.002	0.307	0.393
EMC2	0.379	0.004	0.208	0.321
GRS	0.307	0.014	0.185	0.350
NXS	0.383	−0.001	0.234	0.306
Average $\hat{\rho}_i$	0.384	−0.050	0.224	0.341
CD	90.667 <sup>†</sup>	−11.908	50.115 <sup>†</sup>	76.541 <sup>†</sup>