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Research article

Regime-Specific interdependencies in cryptocurrency markets: A high-frequency GMM-VAR approach

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Appendix A

Table A1. Regime Classification from 5-Regime GMM model.#

Regimes	Number of Observations
1	2.765e+06
2	3727
3	2497
4	0
5	0

Table A2. Estimated Covariance Matrices for Three-Regime GMM model.

Regime 1			Regime 2			Regime 3		
0.1113	0.0074	0.0031	0.4993	0.2332	0.1433	0.0000	0.0000	0.0000
0.0074	0.1159	0.0039	0.2332	0.6345	0.1564	0.0000	0.0001	0.0000
0.0031	0.0039	0.1151	0.1433	0.1564	0.3781	0.0000	0.0000	0.0001

Note: Covariance values are expressed on 10^{-3} scale. Rows and columns correspond to BTC, ETH, and XMR, respectively

Appendix B. Pseudocode for GMM-VAR Estimation

```
Input: High-frequency returns of BTC, ETH, XMR
1. Preprocessing:
  - Apply log return transformation
  - Conduct ADF test for stationarity
  - Detect structural breaks (Bai-Perron test)

2. Regime Identification (GMM):
  - Fit Gaussian Mixture Model to return series
  - Select optimal number of regimes
  - Estimate Covariance Matrices

3. Regime-Specific VAR Modeling:
  For each regime r:
    - Estimate VAR model
    - Perform diagnostics

4. Analysis:
  - Compute IRFs and FEVD within each regime
  - Perform Granger causality tests

Output: Regime-dependent VAR estimates, IRFs, FEVDs, and causal relationships
```