Global Economic Cycles Unveiled: A Hybrid TCN-HMM Approach for Regime Dynamics Across Eight Nations

Bahaa Aly, Tarek

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Tarek Bahaa Aly

Author Note

Tarek Bahaa Aly, PhD, Independent Researcher.

Cairo, Egypt

ORCID ID: 0009-0001-1380-2630

Correspondence email: tarekbahaaaly@gmail.com

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Abstract

This study developed a hybrid Temporal Convolutional Network and Hidden Markov Model (TCN-HMM) framework to identify economic regimes across eight nations: Brazil, China, Egypt, Indonesia, Mexico, South Africa, United Kingdom, and United States, using GDP, inflation, policy rates, equity indices, exchange rates, and yield curve factors. The method integrated MSSA-smoothed data with a TCN autoencoder to extract multi-scale temporal features, optimized through sensitivity analysis, followed by an HMM to classify three regimes: Natural State, Substantial Growth, and Restrictive Policy. The TCN-HMM outperformed standalone HMMs in capturing non-linear dynamics and temporal dependencies. Key findings highlighted several insights. Twelve extracted features were optimal, outperforming eight features (the number of original variables), implying that the TCN enhanced regime differentiation through a richer feature representation. Furthermore, the framework demonstrated generalizability across the panel, as developing markets like Brazil and Egypt exhibited volatile inflation, while developed economies showed stable policy transmission. Finally, China maintained very high growth rates across all regimes, and currencies across the panel showed a high correlation with real interest rates rather than with overall economic conditions, reflecting their sensitivity to capital-flow dynamics.

Keywords*:* TCN, HMM, Economic Regime, *Temporal Dependencies, Non-linear dynamics*

JEL codes: C32, C45, C53, E37

1. Introduction

The objective of this study was to develop a hybrid Temporal Convolutional Network and Hidden Markov Model (TCN-HMM) framework to identify and characterize economic regimes across a panel of eight nations: Brazil (BRA), China (CHI), Egypt (EGP), Indonesia (IND), Mexico (MEX), South Africa (SAF), United Kingdom (UK), and United States (US), capturing non-linear dynamics and temporal dependencies in macroeconomic and financial variables, including GDP growth rate (GDP), inflation rate (INF), central bank's policy rate (POLRATE), equity indices (EQUITY), exchange rates (FX), and yield curve factors (LEVEL, SLOPE, CURVATURE). Traditional Hidden Markov Models (HMMs) have been widely used to model regime transitions by capturing probabilistic state shifts in macroeconomic time series, but their reliance on linear assumptions often limits their ability to handle the complex, non-linear patterns prevalent in diverse, multi-country datasets. In contrast, Temporal Convolutional Networks (TCNs) excel at modeling multi-scale temporal dependencies through dilated convolutions, making them ideal for extracting intricate features from economic data. This study addressed a critical gap in the literature by integrating TCNs' advanced feature extraction capabilities with HMMs' robust state transition modeling, offering a novel approach to global economic regime identification.

By analyzing a diverse panel of developed and developing economies, this study uncovered both generalizable regime patterns and country-specific divergences, providing actionable insights for policymakers, central banks, and investors navigating global economic cycles. The methodology leveraged Multivariate Singular Spectrum Analysis (MSSA) to smooth the input data, followed by a TCN autoencoder to extract multi-scale temporal features, and an HMM to classify regimes into three distinct states: Natural State, Substantial Growth, and Restrictive Policy. This framework not only enhanced the understanding of global economic dynamics but also offered a versatile tool for tailoring monetary policies in volatile developing markets and enhanced investment decisions in stable developed economies, accounting for the distinct economic structures and policy impacts across the eight countries.

2. Literature Review

This literature review examined HMM and TCN methods in academic literature. We first surveyed HMM applications in macroeconomic regime identification. Next, we discussed the advantages of TCN models. Finally, we explored the hybrid HMM model techniques and the benefits of combining a TCN with an HMM. By systematically evaluating these connected methodologies, we identified a significant gap in academic literature that was filled by our study.

Hidden Markov Models (HMMs) have been widely employed in economic research to identify regimes and capture cyclical dynamics in macroeconomic and financial time series, leveraging their ability to model latent state transitions and probabilistic dependencies. Ang and Bekaert (2002) applied an HMM to global equity and bond returns, modeling two regimes: bull and bear markets. They found that bull regimes exhibited positive equity returns and low volatility, while bear regimes showed negative returns and high volatility. Chauvet and Hamilton (2005) employed an HMM to identify U.S. business cycles using GDP, income, and employment data, finding that regimes align with NBER recession dates. Rundle and Medda (2019) proposed a two-step approach combining Independent Component Analysis and HMMs to detect macroeconomic regimes in multivariate time series, finding that variables like GDP and inflation exhibited distinct volatility patterns across states. Wang et al. (2020) employed HMMs to identify regimes in the US stock markets, underscoring HMMs' effectiveness in modeling variable behaviors during economic cycles. Collectively, these studies demonstrated the ability of HMMs to model economic regimes by revealing how variables like the GDP or inflation behaved distinctly across regimes, providing robust insights into cyclical patterns.

Temporal Convolutional Networks (TCNs) have emerged as a powerful tool for modeling temporal dependencies in time-series data, particularly for macroeconomic variables, due to their ability to capture multi-scale patterns through dilated convolutions, making them effective components in hybrid models for economic analysis. Lea et al. (2016) showed that TCNs outperformed traditional recurrent neural networks in forecasting accuracy, capturing complex temporal patterns in GDP growth and inflation, highlighting their suitability for macroeconomic time-series analysis. Atif (2024) compared ARIMA-LSTM and ARIMA-TCN hybrid models for long-term GDP forecasting, concluding that the TCN demonstrated strong capabilities in capturing local and global temporal dependencies through dilated causal convolutions, making them effective for modeling both short-term fluctuations and seasonality. Yang (2025) combined TCNs with a Query-Value attention mechanism to forecast long-sequence gold price time series. The authors found that TCNs excelled at capturing temporal dependencies through dilated causal convolutions, enabling the model to learn long-range patterns efficiently. Their empirical results showed that TCN-QV outperformed LSTM, GRU, and Transformer-based baselines in prediction accuracy and robustness. These studies collectively demonstrated that TCNs excelled in identifying temporal dependencies in macroeconomic variables, due to their flexible architecture.

Hybrid models combining neural networks with HMMs have advanced time-series analysis by integrating the non-linear feature extraction capabilities of neural networks with the probabilistic state transitions of HMMs, significantly improving performance in complex sequence modeling tasks. Liu et al.

(2020) proposed a hybrid model where neural network-based generative models enhanced HMMs by modeling complex emission distributions for each hidden state, concluding that the neural network component improved likelihood estimation by capturing non-linear patterns. Rimella and Whiteley (2025) introduced Hidden Markov Neural Networks (HMNNs), which treated neural network weights as HMM states, concluding that the neural network's ability to model non-linear dynamics boosted forecasting accuracy. Danaa et al. (2024) developed a hybrid HMM-DNN model for speech recognition, where a deep neural network (DNN) extracted acoustic features, concluding that the DNN improved its classification accuracy. These studies highlighted that neural network components enhanced HMMs by extracting non-linear features and modeling complex dependencies, leading to superior performance in tasks requiring regime or sequence identification. Building on these insights, our study leverages the strengths of Temporal Convolutional Networks (TCNs) to create a hybrid TCN-HMM model, capturing non-linearities and multi-scale temporal dependencies to improve economic regime identification. To the best of our knowledge TCN was never combined before with an HMM in academic literature.

3. Research Methodology

3.1. Data Sources

This study was based on macro variables from several countries: Brazil (BRA), China (CHI), Egypt (EGP), Indonesia (IND), Mexico (MEX), South Africa (SAF), the UK (UK), and the US (US). These variables included yield curves first three latent factors: LEVEL (yield curve first latent factor), SLOPE (second latent factor), CURVATURE (third latent factor); in addition to foreign exchange rates (FX), stock market indices (EQUITY), central bank policy rates (POLRATE), GDP growth rates (GDP), and inflation rates as a percentage (INF). The FX was modelled in terms of direct exchange rate, showing how much one unit of home currency was worth in foreign currency ($). We have conducted our analysis based on monthly data from 2006 to 2019. All observations that we have gathered were on a monthly basis, except for the GDP growth rates that were on a quarterly basis. Hence, we transformed the GDP frequency from quarterly to monthly using Cubic Splines, as they performed well in the GDP monthly transformation performed by Kaya (2013).

3.2. TCN-HMM Hybrid Methodology

This study employed a hybrid Temporal Convolutional Network and Hidden Markov Model (TCN-HMM) framework to identify economic regimes across a multi-country panel, building on established methods in time-series analysis and regime-switching models. The data was preprocessed using Multivariate Singular Spectrum Analysis (MSSA) to smooth the time series, following the method described by Bahaa Aly (2025). The preprocessing step standardized GDP, INF, POLRATE, EQUITY, and FX per country to ensure consistent scaling, while preserving LEVEL, SLOPE, and CURVATURE unstandardized (as they were already standardized) as inputs for the TCN, aligning with best practices for handling mixed economic indicators (Hamilton, 1989).

The TCN-HMM model integrated two components. First, the TCN autoencoder extracted latent features from the time-series data, leveraging its ability to capture multi-scale temporal dependencies through dilated convolutions and residual connections, which Bai et al. (2018) showed to be highly effective for sequence modeling tasks like time-series analysis. The TCN architecture employed 64 filters, a kernel size of 8, and dilations of [1, 2, 4, 8], compressing the input into 12 latent features. These optimal hyperparameters were determined through sensitivity analysis, presented in the results, which tested different feature counts, filter sizes, kernel sizes, and dilation combinations to maximize reconstruction accuracy and regime distinctiveness. The autoencoder was trained with a learning rate, tanh activation function, L2 regularization, and early stopping mechanism to prevent overfitting, using mean squared error loss, consistent with neural network optimization strategies (Goodfellow et al., 2016).

Second, the HMM classified regimes based on TCN-extracted features. The HMM used a Gaussian emission model with full covariance, testing 2 and 3 regimes, with the Bayesian Information Criterion (BIC) selecting the optimal number of states, following standard model selection practices (Hamilton, 1989; Guidolin & Timmermann, 2007). The model was initialized with uniform start probabilities and transition matrices, trained for up to 1000 iterations. For comparative purposes, we ran the HMM alone on the standardized raw data, without TCN preprocessing, to evaluate its performance against the hybrid TCN-HMM model, assessing whether TCN feature extraction improved regime identification, as inspired by Wang et al. (2020) comparative analysis of regime-switching models. This comparison drew on prior work that highlighted the benefits of hybrid models in capturing complex economic dynamics (Bagliano & Morana, 2010).

4. Results

4.1. TCN Hyperparameters Sensitivity Analysis

In this section, we have looped through the TCN hyperparameters: the number of TCN extracted features (latent factors), filters, kernel size, and dilation, and we have analyzed the results.

Table 1 TCN Extracted Features Sensitivity Analysis

Extracted Features	6		8		10		12	
Country	**BIC**	**LogLik**	**BIC**	**LogLik**	**BIC**	**LogLik**	**BIC**	**LogLik**
BRA	-303.9	379.1	-782.4	623.5	-2,601.7	1,819.1	-5,485.4	3,452.4
CHI	-2,026.0	1,158.5	-1,432.1	948.4	-1,919.1	1,299.1	-8,598.3	5,008.9
EGP	985.9	-265.7	47.0	333.9	-12,150.8	6,593.7	-8,038.9	4,729.2
IND	-2,027.1	1,159.1	-6,423.5	3,444.1	-10,276.1	5,477.6	-6,550.8	3,985.1
MEX	-1,051.5	753.0	-3,989.9	2,227.2	-4,933.6	2,985.0	-7,204.2	4,311.8
SAF	-6,076.3	3,265.4	-6,618.3	3,666.6	-6,090.8	3,563.6	-9,588.1	5,503.8
UK	-1,471.9	881.5	-6,306.5	3,510.7	-6,623.1	3,829.8	-9,638.5	5,529.0
US	-1,909.0	1,181.7	-1,040.7	877.8	-6,535.7	3,786.1	-1,036.8	1,228.1
Median	**-1,690.4**	**1,020.0**	**-2,711.0**	**1,587.8**	**-6,313.2**	**3,674.9**	**-7,621.6**	**4,520.5**

In table 1, we have looped through the number of TCN extracted features from 6 to 12 and we have presented the BIC and Log-Likelihood (LogLik) for each country and their medians in the last row. We have capped our loop to 12 features as 14 or 16 features would not be expected to significantly improve the fit, adding to the fact that further expansion could lead to overfitting and potentially fitting noise rather than meaningful economic patterns. Results showed that 12 features were optimal for generalization, as they achieved the lowest median BIC (-7,621.6) and highest median LogLik (4,520.5). However, 10 features were optimum for EGP, IND, and the US, which could imply less complex patterns in the data.

The fact that 12 extracted features in the TCN-HMM model yielded the lowest median BIC and highest median LogLik suggested that the TCN autoencoder captured nonlinear patterns from the original 8 time series per country. This expansion beyond the original 8 variables indicated that the TCN was uncovering valuable latent information, most likely complex interactions or temporal dependencies that enhanced regime detection compared to the plain HMM, which supported the use of TCN for extracting meaningful economic signals.

Table 2 TCN Filters Sensitivity Analysis

Filters	32		64		96		128	
Country	**BIC**	**LogLik**	**BIC**	**LogLik**	**BIC**	**LogLik**	**BIC**	**LogLik**
BRA	-3,702.0	2,560.7	-5,485.4	3,452.4	3,621.3	-1,343.4	4,216.0	-1,640.8
CHI	-4,447.3	2,933.4	-8,598.3	5,008.9	2,472.5	-769.0	2,639.3	-852.5
EGP	-9,104.0	5,261.7	-8,038.9	4,729.2	-931.3	1,175.4	811.5	304.0
IND	-13,054.9	6,994.6	-6,550.8	3,985.1	-4,238.7	2,829.1	1,719.8	-392.7
MEX	-5,857.5	3,638.5	-7,204.2	4,311.8	2,219.1	-399.8	528.2	203.1
SAF	-9,693.4	5,556.4	-9,588.1	5,503.8	2,141.8	-603.7	3,158.0	-1,111.8

Filters	32		64		96		128	
Country	BIC	LogLik	BIC	LogLik	BIC	LogLik	BIC	LogLik
UK	-6,931.9	4,175.7	-9,638.5	5,529.0	-8,383.2	4,901.3	-5,031.9	2,983.2
US	-4,627.4	2,780.9	-1,036.8	1,228.1	694.0	362.7	359.1	530.2
Median	**-6,394.7**	**3,907.1**	**-7,621.6**	**4,520.5**	**1,417.9**	**-18.6**	**1,265.7**	**-94.8**

Based on the previous results, we used the optimum number of extracted features of 12 that generalized, and we have looped through the number of filters applied; results presented in table 2. We have noted that the performance of the model was non-linear, meaning the performance improved from 32 to 64 then dropped for higher filters added [96, 128]. This non-linear drop implied that more filters introduced noise or instability rather than capturing more useful information. As it is illustrated in table 2, 64 filters generalized best as it yielded the lowest median BIC (-7,621.6) and highest median LogLik (4,520.5). This confirms 64 as the best balance for capturing relevant patterns and avoiding overfitting. 64 filters dominated in BRA, CHI, MEX, UK, indicating that in these countries the TCN likely captured complex interactions among the 8 original variables (LEVEL, SLOPE, CURVATURE, EQUITY, FX, POLRATE, GDP, INF) that 32 filters missed. Additionally, 32 filters performed slightly better in these countries: EGP, IND, SAF, US, implying simpler dynamics in their data.

Table 3 TCN Kernel Size Sensitivity Analysis

Kernel Size	**4**		**6**		**8**		**10**		**12**	
Country	**BIC**	**LogLik**	**BIC**	**LogLik**	**BIC**	**LogLik**	**BIC**	**LogLik**	**BIC**	**LogLik**
BRA	2,282.0	-431.3	1,211.7	-138.7	-5,485.4	3,452.4	867.2	276.1	-7,102.4	4,260.9
CHI	1,280.7	69.4	-1,635.9	1,285.1	-8,598.3	5,008.9	-1,834.2	1,626.8	-1,873.7	1,646.6
EGP	-591.6	1,005.5	637.7	390.9	-8,038.9	4,729.2	-9,268.8	5,344.1	-9,596.9	5,508.2
IND	-1,820.3	1,619.9	-9,197.9	5,308.7	-6,550.8	3,985.1	-1,300.4	1,117.4	-3,640.7	2,287.6
MEX	-8,727.1	5,073.3	-2,479.0	1,949.2	-7,204.2	4,311.8	1,189.3	115.1	-7,164.0	4,291.7
SAF	873.7	272.9	-9,991.2	5,705.3	-9,588.1	5,503.8	-6,851.8	3,893.1	-11,442.8	6,431.1
UK	-11,979.2	6,699.3	-7,783.7	4,359.0	-9,638.5	5,529.0	-6,442.5	3,688.4	-12,418.9	6,919.2
US	-3,144.5	2,282.0	1,158.8	-112.2	-1,036.8	1,228.1	-4,583.6	3,001.5	-4,069.8	2,744.6
Median	**-1,206.0**	**1,312.7**	**-2,057.5**	**1,617.2**	**-7,621.6**	**4,520.5**	**-3,208.9**	**2,314.2**	**-7,133.2**	**4,276.3**

Based on the previous results, we have used the optimum number of extracted features=12 and filters=64 that generalized, and we have looped through the number of kernels applied; results presented in table 3. We have noted that the performance of the model was non-linear with respect to the kernel size, meaning the model performance improved from 4 to 8, then dropped at 10, and partially recovered at 12. This non-linearity suggested an ideal range where kernels captured optimal receptive fields (temporal spans) without redundancy. This non-linearity is a valuable finding: It showed that TCN uncovered optimal temporal scales (around 8), but exceeding this introduced diminishing returns or instability. This confirmed that 8 was the best kernel size for balancing local and broader temporal patterns, achieving the lowest median BIC (-7,621.6) and highest median LogLik (4,520.5).

Table 4 TCN Dilations Sensitivity Analysis

Dilations	**[1,2]**		**[1,2,4]**		**[1,2,4,8]**		**[1,2,4,8,16]**		**[2,4,8]**	
Country	**BIC**	**LogLik**	**BIC**	**LogLik**	**BIC**	**LogLik**	**BIC**	**LogLik**	**BIC**	**LogLik**
BRA	3,121.8	-1,093.7	965.9	226.8	-5,485.4	3,452.4	-1,978.7	1,699.1	652.6	140.9
CHI	617.0	401.2	474.2	472.6	-8,598.3	5,008.9	-1,624.0	1,521.7	763.5	85.4
EGP	-678.4	1,048.9	2,764.4	-672.5	-8,038.9	4,729.2	-6,349.7	3,884.6	-568.9	994.2
IND	2,166.4	-616.0	-1,679.0	1,549.2	-6,550.8	3,985.1	-11,769.0	6,594.2	-14,500.5	7,960.0
MEX	639.5	390.0	-1,745.4	1,339.9	-7,204.2	4,311.8	-4,339.9	2,879.7	-4,526.3	2,972.9
SAF	3,192.6	-1,129.1	1,787.8	-184.2	-9,588.1	5,503.8	-7,121.8	4,028.1	-9,722.2	5,570.8
UK	-2,338.3	1,878.9	-11,896.8	6,658.1	-9,638.5	5,529.0	-7,045.9	4,232.7	-8,417.6	4,918.5
US	-2,485.8	1,952.6	-4,729.5	3,074.5	-1,036.8	1,228.1	-7,244.7	4,332.1	-3,834.3	2,626.9
Median	**628.2**	**395.6**	**-602.4**	**906.3**	**-7,621.6**	**4,520.5**	**-6,697.8**	**3,956.3**	**-4,180.3**	**2,799.9**

Based on the previous results, we have used the optimum number of extracted features=12, filters=64, and kernel size=8 that generalized, and we have looped through the number of dilations applied; results presented in table 4. We have applied the following dilations: [1,2] short dilations for local patterns to reduce receptive field and complexity, [1,2,4] mid-range to balance short/medium term dependencies, [1,2,4,8] capturing the short term and extending the medium term, [1,2,4,8,16] extended for broader context to test if longer horizons improved the fit, [2,4,8] skip smallest dilation [1] to focus on medium/long term. We have noted that the performance of the model was non-linear, as the model performance improved from [1,2] to [1,2,4,8], to slightly drop at [1,2,4,8,16], with the dilation [1,2,4,8] performing best overall but with variations by country. This is interesting, as longer dilations (e.g., [1,2,4,8,16]) should have theoretically captured more extended temporal dependencies (e.g., multi-year macro cycles such as GDP cycles), but the data revealed a balance where moderate dilations improved the fit without instability. The best performance of the dilation [1,2,4,8] suggested that the data contained a mix of short, medium, and long-term patterns. Short dilations [1,2] likely captured immediate volatilities (e.g., FX or POLRATE responses to events), medium [4] captured cyclical behaviors (e.g., quarterly INF-EQUITY interactions), and long [8] detected persistent trends (e.g., SLOPE-CURVATURE influencing GDP over years). This balance implied macro variables have hierarchical dependencies, meaning local shocks propagate to longer cycles.

Table 5 HMM vs TCN-HMM Performances

	HMM		TCN-HMM	
Country	**BIC**	**LogLik**	**BIC**	**LogLik**
BRA	2,223.4	-754.3	-5,485.4	3,452.4
CHI	2,548.6	-916.9	-8,598.3	5,008.9
EGP	2,857.6	-1,071.4	-8,038.9	4,729.2
IND	2,476.5	-1,005.9	-6,550.8	3,985.1
MEX	2,896.1	-1,090.6	-7,204.2	4,311.8
SAF	2,378.5	-956.9	-9,588.1	5,503.8
UK	2,773.8	-1,029.5	-9,638.5	5,529.0
US	2,530.6	-1,033.0	-1,036.8	1,228.1
Median	**2,539.6**	**-1,017.7**	**-7,621.6**	**4,520.5**

Based on the optimum Hyperparameters of extracted features=12, filters=64, kernel size=8, and dilation [1,2,4,8], we ran our hybrid TCN-HMM model and compared its performance to the plain HMM; results presented in table 5. The results demonstrated that the TCN-HMM model significantly outperformed the plain vanilla HMM across all countries, as evidenced by substantially lower BIC values and higher log-likelihood scores, indicating a superior balance of model fit and complexity. This outperformance stemmed from the TCN component's ability to extract 12 latent features from the 8 original macroeconomic time series through nonlinear temporal convolutions, capturing complex, multi-scale dependencies (e.g., short-term volatility in FX and EQUITY intertwined with long-term trends in GDP and yield curve factors) that the plain vanilla HMM cannot model as effectively. Furthermore, TCN-HMM excelled in capturing non-linearities inherent in macroeconomic variables, such as asymmetric GDP responses to inflation or regime switching dynamics in equity/FX interactions during crises, which the Gaussian HMM cannot handle because of its linear assumptions. Variables like INF, POLRATE, and EQUITY exhibited non-linear behaviors (e.g., sudden volatility spikes or non-symmetric cycles) that TCN's convolutional architecture and activations (e.g., tanh) modeled effectively, leading to superior BIC/LogLik.

4.2. TCN-HMM Regimes Analysis

To determine the optimal number of regimes for each country, we applied the Bayesian Information Criterion (BIC) to compare the goodness-of-fit of Hidden Markov Models (HMMs) with two versus three regimes, looping through all 8 countries. The BIC consistently favored three regimes for all countries, indicating that three regimes provided the best balance of model fit and complexity, capturing distinct economic states. In academic literature scholars identified between 2-4 regime structures; Guidolin & Timmermann (2007) identified four distinct regimes in their joint distribution of stock and bond returns; Based on a discrete-state Markov process to model regime changes, Hamilton (1989) identified two regimes; Kritzman; Page, & Turkington (2012) identified two regimes only; Wang, Lin, & Mikhelson (2020) identified three regimes; Bagliano & Morana (2010) identified three regimes.

The three regimes identified in our hybrid TCN-HMM model were as follows: Regime 0, the Natural State of the Economy/Stable Growth, with a persistence of 48% (most frequent), represents a state of moderate, sustainable growth, contained inflation, and neutral monetary policy, where financial markets are healthy, reflecting balanced investor sentiment; Regime 1, the Substantial Growth/Boom Regime, with a persistence of 16% (least frequent), characterized by high GDP growth, robust equity markets, and a neutral monetary policy, where Inflation might be rising but is not a concern; and finally, Regime 2, the Restrictive Policy Regime/Tight-Money Equilibrium, with a persistence of 31% (moderate frequency), defined by central banks prioritizing inflation control or currency stability, rather than growth, through aggressive monetary tightening, which led to subdued financial markets and below potential growth, but still not a full-scale recession.

Our first contribution was to present a unified hidden Markov model (HMM) analysis across a multi-country panel, spanning both developed and developing countries across many regions, rather than focusing on a single country or region-specific sample, thereby enabling a comparative examination of regime dynamics under diverse economic structures and policy frameworks. Our findings demonstrated an alignment with the core principles of regime-switching models in economics and finance. Our identification of three distinct economic states (Stable, Boom, Restrictive) was strongly supported by academic literature. Our results confirmed that economic dynamics were not binary (expansion/recession) but were better described by a three-state model that included a persistent, "normal" condition. Our analysis provided an innovative insight that go beyond the typical classifications by refining the "Bear" or "Recession" state, as labeled by many academics, into a "Restrictive Policy Regime". Our multi-variable approach revealed that this state was not merely a passive recession but was often an active, policy-induced condition. The key differentiators were the combination of the highest policy rates (central bank action), appreciating currency (a consequence of those high rates attracting capital), depressed equities, and an inverted yield curve (the market's reaction to the policy). Our insight also revealed the "Carry Trade" Mechanism and FX dynamics, where the currency was often at its strongest level when domestic growth was slowing and equities were falling, contradicting the view that a weak economy should mean a weak currency. In fact, real interest rates were a strong driver of currencies. Kearns & Manners (2005) confirmed that changes in the policy rate are rapidly transmitted into the foreign exchange rate. According to Ahmed et al. (2017) interest rates caused a slight appreciation in the country's exchange rate. Bahaa Aly (2025) proved that the policy rate Granger caused the FX in the several developed and developing countries.

By integrating policy rates and FX dynamics, we have provided a more sophisticated and economically intuitive framework that better explained the mechanisms behind regime transitions, particularly in today's globalized financial system where capital flows are as influential as domestic demand.

4.2.1. TCN-HMM Regimes Panel Analysis

Table 6 TCN-HMM Regimes Panel Data Statistics

Regime	Median_Spell_Length (Months)	Persistence	GDP_Median	INF_Median	POLRATE_Median	EQUITY_Median	FX_Median	SLOPE_Median
0	18	48.48%	2.31%	3.90%	5.84%	13,233	0.15154	0.10140
1	3.75	16.67%	3.57%	4.24%	5.43%	13,687	0.14401	0.10016
2	42.5	31.52%	2.40%	3.94%	6.71%	9,896	0.16837	-0.03014

The panel level results were presented in table 6, aggregating medians from eight countries. Median spell length measured the typical duration (in months) of a single continuous episode of a regime. It's the median duration of all spells where the economy remained in that regime without switching. A spell is a sequence of consecutive time periods in the same regime, and the median was taken across all such spells. Persistence measured the frequency of a regime, calculated as the proportion of total observations where the economy was in that regime, computed as the number of observations in the regime divided by the total number of observations across all regimes.

As it is presented in table 6, regime 0, the Natural State of the Economy/Stable Growth, was the dominant state of the economy, with the highest persistence of 48.5% and a median spell length of 18 months, more precisely it was the "business-as-usual" state. This state featured moderate GDP growth (2.31%) and inflation (3.90%). The monetary policy was moderate (Policy Rate: 5.84%), and equity markets remained strong (13,233), indicating sustained investor confidence in this stable environment. Additionally, the currency appreciated moderately (FX median: 0.1515), aligning with a higher real interest rate of 1.94% (Real Interest Rate = Policy Rate - Inflation) compared to regime 1, supporting steady capital inflows. In this state the yield curve SLOPE remained steep (0.1014), signaling continued healthy growth expectations. Regime 0 was the baseline "normal" state of the economy, its high persistence underscored a sustainable equilibrium where growth, policy, and financial markets were in balance. Our regime 0 resembled the "expansion" or "normal" regimes in academic literature on HMM regime identification. Kim and Nelson (1998) identified expansionary regimes with high persistence, moderate GDP growth, and stable inflation, where equity markets thrived due to investor confidence.

Chauvet and Piger (2003) described similar expansion states with upward sloping yield curves signaling growth expectations, aligning with our steep SLOPE. Ang and Bekaert (2002) identified bull market regimes characterized by robust equity returns and modest currency gains, aligning well with our FX and equity indicators. Krolzig (2001) identified a normal growth regime with balanced growth and policy rates, mirroring our "business-as-usual" state, regime 0.

Regime 1, the Substantial Growth/Boom Regime, was the least stable, with a low persistence of 16.7% and a short median spell length of 3.75 months, indicating that boom periods are inherently unsustainable. This regime exhibited the highest GDP growth (3.57%) and a slightly elevated inflation rate (4.24%). The central bank policy rate was at its lowest (5.43%). The equity market peaked (13,687), driven by strong growth expectations and low financing costs. Comparatively, Ahmed et al. (2017) found a causality relationship from the exchange rate to the stock market, and Laopodis (2013) suggested that the relationship between the monetary policy and the stock market was dynamic and not consistent. In our regime 1, the currency was at its weakest level (FX median: 0.1440), which was consistent with the low policy rate, which created the lowest real interest rate (1.19%), reducing the currency's attractiveness for carry trades. Additionally, the yield curve slope was steeply positive (0.1002), reflecting market expectations for future growth and inflation. It is worth noting that the yield curve was upward sloping in regime 0 and regime 1, as it is the most common shape, and it's referred to as the normal yield curve shape for 70%-95% of the times for most countries (Bahaa Ali, 2023). Regime 1 represented a classic, transient economic boom. Its low persistence confirmed that the combination of high growth and low rates was not a sustainable equilibrium and typically preceded a shift in regime. Our regime 1 resembled the "high-growth" or "bull" regimes in academic literature on HMM regime identification; Ang and Bekaert (2002) described short-lived bull regimes with high equity returns and growth but low persistence due to unsustainability, similar to our Boom regime 1; Krolzig (2001) identified distinct high-growth regimes characterized by elevated output growth; Guidolin (2011) identified a high-return or bull state that has lower persistence than the normal state.

Regime 2, the Restrictive Policy Regime/Tight-Money Equilibrium, characterized by a moderate persistence of 31.5% but a very long median spell length of 42.5 months, indicating that while it was less stable than the baseline state, once entered, it persisted for an extended period, creating prolonged financial strain. This regime was defined by the highest central bank policy rate (6.71%), which subdued GDP growth to 2.40%, while inflation (3.94%) was contained. Equity markets were deeply depressed (9,896) because high interest rates increase the cost of capital and depressed valuations. The currency recorded the largest appreciation (FX median: 0.1684) as a direct consequence of the highest positive real interest rate (2.77%), which attracted foreign capital via carry trades. The yield curve was inverted (-0.03014), signaling market expectation that the tight policy would curb future growth. Regime 2 was a period of sustained monetary restraint. The combination of a long spell length and moderate persistence suggested that exiting this "tight-money equilibrium" was difficult, often requiring a significant shift in the economic outlook or policy mandate. The central bank's tight policy kept inflation low and the currency strong, and imposed a financial strain. Our regime 2 resembled the "contractionary" or "tight policy" regimes in academic literature on HMM regime identification; Kim and Nelson (1998) described contractionary regimes with high policy rates suppressing growth and equities, with extended durations; Ang and Bekaert (2002) identified bear market regimes with depressed equities and strong currency appreciation due to high real interest rates.

4.2.2. TCN-HMM Regimes Country Analysis

We have presented in table 7 in the appendix similar metrics to the ones presented in table 6 but this time per country, rather than panel. We have analyzed, in this section, the cross-country similarities and discrepancies. Based on the country specific data presented in table 7, we have noted first consistent patterns across countries, conform to panel data, as follows: Regime 0 (Natural State) had the highest persistence in 5 of 8 countries (IND 63.6%, MEX 63.0%, UK 59.4%, SAF 53.9%, US 43.0%), with moderate growth rates between 1.48%-7.81% (excluding BRA's anomalous -0.01%), and positive or near-flat yield curves in 7 of 8 countries (BRA, IND, MEX, SAF, UK, US positive; EGP near-flat; CHI inverted); Regime 1 (Substantial Growth/Boom) had a low persistence (5.5%-41.8% across all countries), with a short duration (1-26.5 months median spell length), and mixed equity performance with 4 countries showing peak equities during booms; Regime 2 (Restrictive Policy) had the longest spell lengths in 6 of 8 countries (34-84 months), with higher policy rates than regime 0 in 6 of 8 countries, and inverted yield curves in 6 countries. On the other hand, we have noted notable deviations from expected patterns in terms of GDP growth rates, inflation, equity markets and policy rates. In terms of GDP growth rates: BRA showed a contraction (-0.01%) in its "Natural State"; CHI maintained very high growth (6.79%-8.07%) across all regimes; SAF showed near stagnation (0.87%) levels during the restrictive policy regime. In terms of inflation: EGP exhibited crisis-level inflation (10.1%-13.2%) across all regimes; IND showed highest inflation (8.5%) during the restrictive policy regime; US maintained very low inflation (1.6%-3.0%) across all regimes. In terms of equity markets: BRA and SAF showed highest equities markets during restrictive policy regimes; IND showed lowest equities during restrictive policy despite highest growth; US equities peaked during natural state, not boom periods. And finally in terms of policy rates: EGP maintained high rates (9.6%-15.7%) across all regimes; US showed lowest rates (0.3%) during restrictive policy.

Additionally, we have observed structural economic divergences from developed to developing countries in the Natural State regime, such as the inflation in BRA, IND, and EGP ranging higher (3.9%-10.1%) compared to developed countries (1.6%-2.6%), growth rates varying from -0.01% (BRA) to 7.8% (CHI). Furthermore, developed markets (US, UK) showed clear policy transmission to inflation, compared to limited inflation control despite high rates in developing countries (EGP, IND). The impact of policy rate changes on currencies varied significantly, ranging from strong in the UK to the lowest in IND. Our analysis also revealed pronounced effects of financial market development, wherein developed economies exhibited a consistent, theoretically sound relationship between equity markets and the yield curve slope. In contrast, several developing markets displayed notable equity anomalies, such as peak stock market performance in BRA and SAF occurring during the Restrictive Policy Regime. Furthermore, the predictive power of the yield curve over the economy varied from one country to another.

From that stand point, although the three-regime framework was generalizable across the panel of countries, each country's economic structure, policy effectiveness, and market development level created distinctive regime characteristics that required country-specific interpretation.

5. Conclusion

The objective of this study was to develop a hybrid Temporal Convolutional Network and Hidden Markov Model (TCN-HMM) framework to identify economic regimes across a panel of eight nations (Brazil, China, Egypt, Indonesia, Mexico, South Africa, United Kingdom, United States), capturing non-linear dynamics and temporal dependencies in macroeconomic and financial variables. The method integrated MSSA-smoothed data with a TCN autoencoder to extract multi-scale temporal features, followed by an HMM to classify regimes, using variables such as GDP, inflation, policy rates, equity indices, exchange rates, and yield curve factors. Three regimes were identified: Natural State, Substantial Growth/Boom, and Restrictive Policy.

This study’s primary contribution lies in its novel TCN-HMM framework, which advances regime identification by leveraging TCNs’ ability to capture non-linear, multi-scale temporal patterns, surpassing the linear assumptions of traditional HMMs. The sensitivity analysis performed revealed that 12 extracted features were optimal, outperforming 8 features (the number of original variables), implying that the TCN captured latent patterns beyond the 8 input variables, enhancing regime differentiation through a richer feature representation. Unlike country- or region-specific HMM studies, our TCN-HMM framework demonstrated generalizability across a diverse panel, revealing structural divergences: developing countries showed volatile inflation and equity anomalies, while developed markets exhibited stable policy transmission, offering a unified model for global economic analysis. The TCN's dilation structure with factors [1, 2, 4, 8] optimally captured short-term fluctuations and long-term trends, enhancing regime transition detection; narrower dilations, such as [1, 2, 4], missed long-term macroeconomic cycles, while broader dilations, such as [1, 2, 4, 8, 16], introduced noise. This balance implied macro variables have hierarchical dependencies, meaning local shocks propagate to longer cycles.

We believe that this paper would benefit policymakers, central banks, and investors by providing a versatile tool for global regime detection, enabling tailored monetary policy adjustments in volatile financial markets. Although the analysis was performed on a panel and later compared to country-specific behaviors, the findings cannot be fully generalized due to country-specific economic structures influencing variable behaviors, necessitating tailored interpretations, which was a limitation of the study. Future research could explore TCNs with residual connections (ResTCN-HMM) to enhance feature robustness, and attention-based TCN-HMM models to prioritize key temporal patterns.

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Appendix

Table 7 TCN-HMM Regimes Country Data Statistics

Country	Regime	Median_Spell_Length	Persistence	GDP_Median	INF_Median	POLRATE_Median	EQUITY_Median	FX_Median	SLOPE_Median
BRA	0	8	36.36%	-0.01%	6.21%	11.75%	52,173	0.43719	0.17254
BRA	1	11	41.82%	3.73%	5.46%	11.33%	59,867	0.53397	0.22816
BRA	2	36	21.82%	1.06%	3.56%	6.77%	81,363	0.27651	-0.42036
CHI	0	12	38.79%	7.81%	2.61%	5.68%	3,377	0.15221	-0.05212
CHI	1	5	26.67%	6.79%	1.86%	4.38%	3,406	0.14752	0.03038
CHI	2	20	34.55%	8.07%	2.26%	6.02%	2,461	0.15731	-0.00454
EGP	0	27.5	33.33%	1.99%	10.06%	9.59%	5,605	0.15087	-0.00756
EGP	1	26.5	32.12%	4.50%	13.19%	15.65%	14,277	0.06487	0.09803
EGP	2	57	34.55%	6.19%	11.12%	9.67%	6,654	0.17942	-0.07155
IND	0	2.5	63.64%	5.10%	3.95%	6.25%	4,913	0.00008	0.10915
IND	1	1	13.33%	5.71%	4.49%	6.33%	4,335	0.00010	-0.04064
IND	2	38	23.03%	6.41%	8.48%	8.69%	2,024	0.00011	0.01282
MEX	0	25	63.03%	2.70%	3.86%	4.44%	42,970	0.06628	0.14976
MEX	1	2.5	8.48%	3.25%	3.99%	4.53%	40,798	0.07607	0.33009
MEX	2	47	28.48%	1.96%	4.31%	6.98%	26,831	0.08952	-0.00174
SAF	0	24	53.94%	2.62%	5.88%	5.99%	25,529	0.12866	0.02795
SAF	1	1	5.45%	3.40%	5.10%	6.98%	23,627	0.14051	-0.01453
SAF	2	67	40.61%	0.87%	5.02%	6.64%	47,164	0.07406	-0.01502
UK	0	30	59.39%	1.48%	2.58%	0.51%	6,652	1.50912	0.22164
UK	1	11	20.00%	2.07%	1.15%	0.52%	6,328	1.55190	0.00180
UK	2	34	20.61%	2.74%	2.70%	4.98%	5,914	1.96553	-0.14840
US	0	3	43.03%	1.98%	2.16%	2.07%	19,814	1.15061	0.25036
US	1	1	6.06%	1.86%	2.95%	3.81%	13,098	0.92470	0.05501
US	2	84	50.91%	2.06%	1.61%	0.26%	13,138	1.01022	0.06334