# Identifying Monetary Policy Regimes in the Federal Funds Rate Using Bayesian Structural Time Series Models

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**Abstract**

This paper applies Bayesian Structural Time Series models with regime-switching to identify monetary policy regimes in the Federal Funds Rate from 2020-2025. We compare models with informative and weakly informative priors to assess the impact of domain knowledge. Our results successfully identify four distinct regimes: COVID Emergency, Inflation Fighting, Peak Rate Holding, and Rate Normalization. Both models achieve over 91% regime identification accuracy, with the informative priors model showing better fit (DIC) and slightly better predictions (RMSE). The high regime persistence (98-99%) confirms the Federal Reserve's tendency to maintain policy stances for extended periods. This framework offers valuable insights for understanding monetary policy shifts and forecasting future rate movements.

## 1 Introduction

Time series data in economics often show structural changes driven by shifts in underlying regimes. The Federal Funds Rate, as the primary tool of U.S. monetary policy, exemplifies such regime-dependent behavior [3]. Standard time series models assuming constant parameters often fail to capture these structural shifts.

Bayesian Structural Time Series (BSTS) models with regime-switching components can identify distinct patterns corresponding to different policy regimes [6, 4]. The Bayesian approach is particularly suited for this application as it provides a natural framework for incorporating prior knowledge and quantifying uncertainty.

The Federal Reserve's policy since 2020 has progressed through several distinct phases: emergency rate cuts during COVID-19, aggressive rate increases to combat inflation, a period of stable high rates, and the beginning of normalization. These policy shifts create natural regime changes in the Federal Funds Rate, making it ideal for regime-switching analysis.

Our research aims to identify these regimes using a data-driven approach while incorporating economic domain knowledge. We compare models with informative and weakly informative priors to evaluate how much prior beliefs affect model fit and predictive performance. The results provide insights into both methodological questions about Bayesian modeling and substantive questions about monetary policy dynamics during a period of exceptional economic turbulence.

### 1.1 Methodology: Bayesian Structural Time Series

At its core, a BSTS model represents an observed time series $y_t$ as a combination of interpretable components:

$$y_t = \mu_t + \tau_t + \beta_t x_t + \varepsilon_t \tag{1}$$

Where:

- $\mu_t$ is the local level component (e.g., trend)

- $\tau_t$ is the seasonal component
- $\beta_t$ represents time-varying regression coefficients
- $x_t$ are covariates or predictors
- $\varepsilon_t$ is the observation error, typically $\varepsilon_t \sim \mathcal{N}(0, \sigma_\varepsilon^2)$

Each component follows its own state evolution equation. For example, a local level component might follow a random walk:

$$\mu_t = \mu_{t-1} + \eta_t, \quad \eta_t \sim \mathcal{N}(0, \sigma_\eta^2) \tag{2}$$

The Bayesian approach allows for the specification of prior distributions for all model parameters, which are then updated based on observed data to form posterior distributions [2].

### 1.2 Extending BSTS with Regime Switching

For our analysis of Federal Funds Rate data, we extend the standard BSTS framework to incorporate regime-switching behavior. In this model, the observed rate $y_t$ depends on a hidden regime state $s_t \in \{1, 2, \ldots, K\}$, where $K$ is the number of regimes:

$$y_t | s_t = j \sim \mathcal{N}(\mu_j, \sigma_j^2) \tag{3}$$

Here, $\mu_j$ and $\sigma_j^2$ represent the mean and variance parameters specific to regime $j$. The regime state evolves according to a first-order Markov process with transition probabilities:

$$P(s_t = j | s_{t-1} = i) = p_{ij} \tag{4}$$

This specification allows the model to capture both sudden shifts in the level and volatility of the Federal Funds Rate, as well as the persistence of policy regimes over time. The Markovian structure enables the model to identify regimes that exhibit temporal coherence, rather than simply classifying individual observations based on their values.

### 1.3 Inference Algorithm

We use Markov Chain Monte Carlo (MCMC) methods, specifically Gibbs sampling with Forward Filtering Backward Sampling (FFBS), to estimate the posterior distributions of model parameters and regime states [1]. The algorithm proceeds as follows:

**Algorithm 1** MCMC for Regime-Switching BSTS

1: Initialize parameters $\boldsymbol{\mu}$, $\boldsymbol{\sigma}^2$, $\mathbf{P}$, and regime states $\mathbf{s}$
2: **for** $i = 1$ to $N_{iter}$ **do**
3: Sample regime states $\mathbf{s}^{(i)} | \mathbf{y}, \boldsymbol{\mu}^{(i-1)}, \boldsymbol{\sigma}^{2(i-1)}, \mathbf{P}^{(i-1)}$ using FFBS
4: Sample regime means $\boldsymbol{\mu}^{(i)} | \mathbf{y}, \mathbf{s}^{(i)}, \boldsymbol{\sigma}^{2(i-1)}$ from conjugate posterior
5: Sample regime variances $\boldsymbol{\sigma}^{2(i)} | \mathbf{y}, \mathbf{s}^{(i)}, \boldsymbol{\mu}^{(i)}$ from conjugate posterior
6: Sample transition probabilities $\mathbf{P}^{(i)} | \mathbf{s}^{(i)}$ from Dirichlet posteriors
7: **end for**

The Forward Filtering Backward Sampling (FFBS) technique efficiently samples the regime states in a time series context. The forward pass computes filtered probabilities of the regime states given data up to time $t$, while the backward pass samples regimes sequentially from $t = T$ to $t = 1$, conditioning on future regimes that have already been sampled.

In the forward filtering step, we recursively compute the filtered state probabilities $P(s_t|y_{1:t})$ using Bayes' rule:

$$P(s_t = j|y_{1:t}) \propto P(y_t|s_t = j) \sum_{i=1}^{K} P(s_t = j|s_{t-1} = i)P(s_{t-1} = i|y_{1:t-1}) \tag{5}$$

In the backward sampling step, we sample regimes sequentially from $t = T$ to $t = 1$ using:

$$P(s_t = i|s_{t+1} = j, y_{1:T}) \propto P(s_{t+1} = j|s_t = i)P(s_t = i|y_{1:t}) \tag{6}$$

For the regime-specific parameters, we use conjugate priors to obtain closed-form conditional posteriors. For the transition probabilities, we use Dirichlet priors and sample from Dirichlet posteriors based on the transition counts in the sampled regime sequence.

### 1.4 Limitations and Assumptions

Key assumptions of our regime-switching BSTS model include:

1. **Fixed number of regimes**: We assume a known number of regimes (K=4), based on our economic understanding of monetary policy periods.

2. **Markovian state transitions**: The current regime depends only on the previous regime, not on the entire history.

3. **Regime-conditional normality**: Within each regime, the Federal Funds Rate follows a normal distribution with regime-specific mean and variance.

4. **Independent regime parameters**: The means and variances of different regimes are independent of each other.

5. **Instantaneous regime transitions**: Transitions between regimes occur discretely, without gradual adaptation periods.

6. **Time-invariant transition probabilities**: The probabilities of transitioning between regimes remain constant over time.

While these assumptions simplify real-world monetary policy dynamics, they provide a tractable framework for inference while still capturing the key regime-switching behavior in the data.

## 2 Description of the Data and Research Question

### 2.1 Federal Funds Rate Data (2020-2025)

The dataset can be found on https://fred.stlouisfed.org/series/DFF. We choose the Federal Funds Effective Rate data from January 2020 to April 2025 (5 years until now) to conduct meaningful research of trends. The Federal Funds Rate is the interest rate at which depository institutions trade federal funds overnight. As the Federal Reserve's primary monetary policy tool, changes in this rate reflect shifts in policy stance and have profound implications for the broader economy.

Figure 1 shows the Federal Funds Rate time series from 2020 to 2025, which exhibits clear structural changes over this period.

The data consists of daily observations showing several visually distinct phases:

- **Early 2020 - Early 2022**: Near-zero rates following COVID-19 emergency cuts

- **Early 2022 - Mid 2023**: Rapidly increasing rates to combat post-pandemic inflation

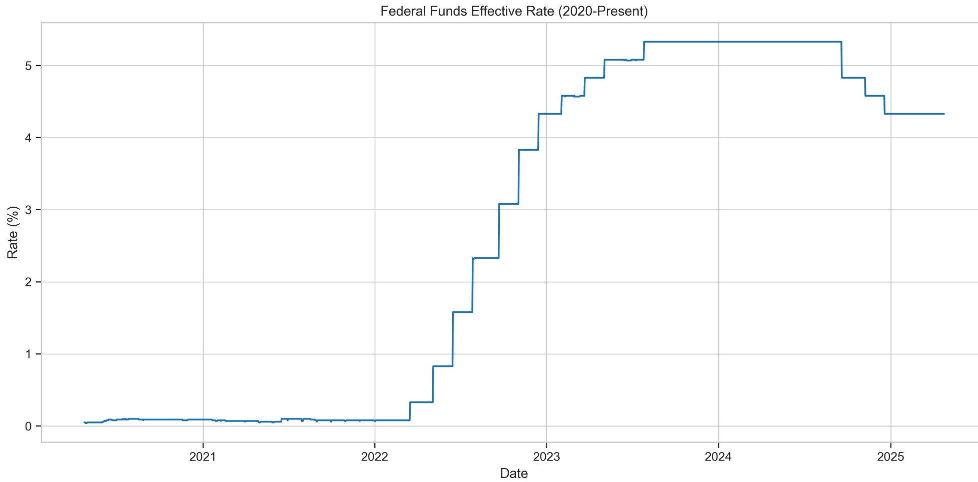



Figure 1: Federal Funds Rate Time Series (2020-2025)

- **Mid 2023 - Early 2024**: Stable high rates at the terminal rate of the tightening cycle
- **Early 2024 - April 2025**: Gradually declining rates during normalization

We obtained the data from the Federal Reserve Economic Data (FRED) database, specifically the DFF.xlsx file containing daily observations of the Federal Funds Effective Rate. Initial data exploration revealed 1,827 daily observations from April 2020 to April 2025.

## 2.2 Data Preparation and Exploratory Analysis

For our analysis, we partitioned the data into training (80%) and testing (20%) sets. Preliminary exploratory analysis revealed the following statistics by visually identified regime:

Table 1: Summary Statistics by Visually Identified Regime

| Regime Name | Mean | Std | Min | Max | Count |
|---|---|---|---|---|---|
| COVID Emergency | 0.080333 | 0.013373 | 0.04 | 0.10 | 690 |
| Inflation Fighting | 3.207183 | 1.671246 | 0.08 | 5.08 | 497 |
| Peak Rate Holding | 5.327908 | 0.022821 | 5.08 | 5.33 | 239 |
| Rate Normalization | 4.874264 | 0.445188 | 4.33 | 5.33 | 401 |

Based on our economic understanding and visual inspection, we identified four regime change dates:

- 2020-01-01: Beginning of COVID Emergency regime
- 2022-03-15: Transition to Inflation Fighting regime (first hike post-COVID)
- 2023-07-25: Transition to Peak Rate Holding regime (rate stabilization at high level)
- 2024-03-20: Transition to Rate Normalization regime (first cut post-hiking cycle)

Figure 2 shows these initial regime assignments based on our domain knowledge, which will serve as a reference for evaluating our model's regime identification performance.

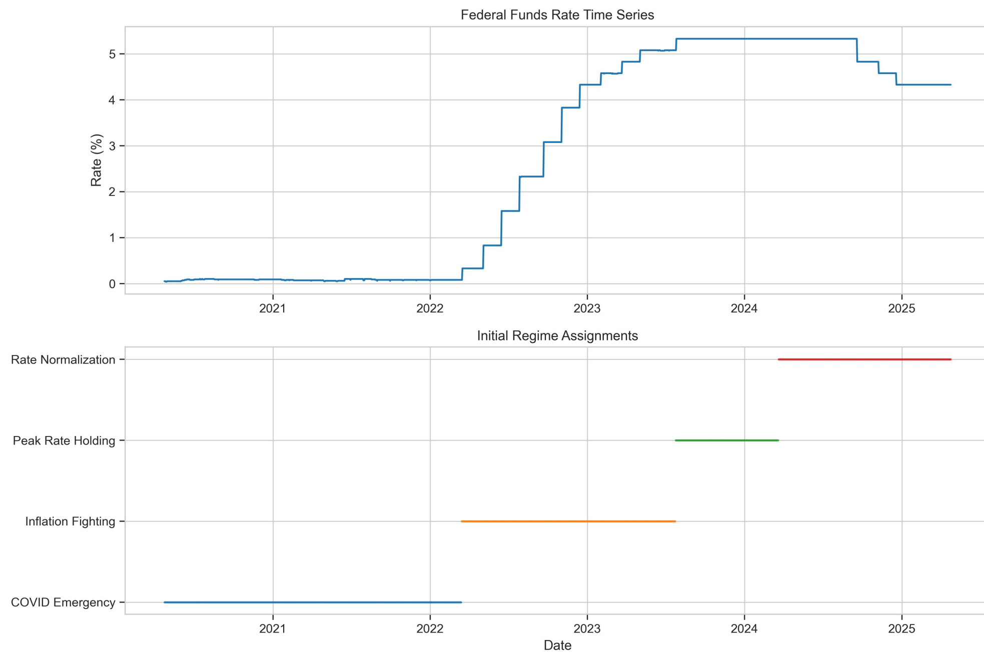



Figure 2: Initial Regime Assignments Based on Domain Knowledge

### 2.3 Research Question

Our primary research question is: *Can Bayesian structural time series models with regime-switching components accurately identify and characterize distinct monetary policy regimes in the Federal Funds Rate data from 2020-2025?*

Specifically, we aim to:

1. Identify the number and timing of distinct monetary policy regimes
2. Characterize each regime's mean level, volatility, and persistence
3. Quantify the transition dynamics between regimes
4. Evaluate the impact of prior specifications on regime identification and prediction
5. Assess the model's ability to forecast future rate movements based on regime dynamics

This research provides insights into both methodological questions about Bayesian regime-switching models and substantive questions about monetary policy dynamics during a period of significant economic turbulence.

## 3 Prior Choice and Specification

A critical aspect of Bayesian analysis is the specification of prior distributions for model parameters. For our regime-switching model, we compare two alternative prior specifications to evaluate the impact of incorporating domain knowledge on inference and prediction.

### 3.1 Informative Priors

Our informative priors incorporate domain knowledge about Federal Reserve policy regimes from 2020-2025:

#### 3.1.1 Regime Means

- COVID Emergency regime: $\mu_1 \sim \mathcal{N}(0.125, 1.0)$
- Inflation Fighting regime: $\mu_2 \sim \mathcal{N}(2.5, 1.0)$
- Peak Rate Holding regime: $\mu_3 \sim \mathcal{N}(5.25, 1.0)$
- Rate Normalization regime: $\mu_4 \sim \mathcal{N}(4.0, 1.0)$

The mean values for these priors are based on our understanding of the Federal Funds Rate during each policy regime. The COVID Emergency prior centered at 0.125% reflects the near-zero rate policy during the pandemic crisis. The Inflation Fighting prior centered at 2.5% represents our expectation for the transitional hiking phase. The Peak Rate Holding prior at 5.25% is based on the terminal rate achieved in the tightening cycle. Finally, the Rate Normalization prior at 4.0% reflects our expectation for a moderating but still restrictive policy stance during the early cutting phase.

#### 3.1.2 Regime Variances

We use inverse-gamma priors for the variance parameters:

- COVID Emergency: $\sigma_1^2 \sim \text{InvGamma}(3, 0.0009)$
- Inflation Fighting: $\sigma_2^2 \sim \text{InvGamma}(3, 0.0225)$
- Peak Rate Holding: $\sigma_3^2 \sim \text{InvGamma}(3, 0.0025)$
- Rate Normalization: $\sigma_4^2 \sim \text{InvGamma}(3, 0.0064)$

These variance priors reflect our expectation that stable policy regimes (COVID Emergency and Peak Rate Holding) would exhibit low volatility, while transitional regimes (Inflation Fighting and Rate Normalization) would show higher volatility as rates adjust to new levels.

#### 3.1.3 Transition Probabilities

For the transition probability matrix, we use Dirichlet priors with:

- High persistence (0.97) on the diagonal for regime stability
- Higher probability (0.02) for forward transitions (e.g., COVID $\rightarrow$ Inflation Fighting)
- Small probability (0.01) for backward transitions
- Low probability (0.005) for non-adjacent transitions

This prior structure encodes our belief that monetary policy regimes tend to be persistent, with gradual and ordered transitions rather than erratic jumps between non-adjacent regimes.

### 3.2 Weakly Informative Priors

To assess the impact of prior specification on inference, we also implement a model with weakly informative priors:

#### 3.2.1 Regime Means

$\mu_j \sim \mathcal{N}(m_j, 10.0)$ for $j \in \{1, 2, 3, 4\}$, where $m_j$ are evenly spaced values from 0 to 6.

The much larger variance (10.0 vs. 1.0) in these priors significantly reduces the influence of the prior mean, allowing the data to more strongly determine the posterior distribution.

### 3.2.2 Regime Variances

$\sigma_j^2 \sim \text{InvGamma}(2, 0.1)$ for $j \in \{1, 2, 3, 4\}$

These variance priors are less informative and identical across regimes, indicating no prior belief about differences in volatility between regimes.

### 3.2.3 Transition Probabilities

Dirichlet priors with moderately diagonal structure (0.4) with 0.15 elsewhere.

This transition prior structure still encodes some belief in regime persistence but with much weaker conviction than the informative prior.

## 3.3 Rationale for Prior Choices

Our informative priors incorporate established knowledge about Federal Reserve policy during the 2020-2025 period. We expect these priors to improve regime identification by guiding the model toward economically plausible parameter values, particularly in regions of the data where regime boundaries might be ambiguous.

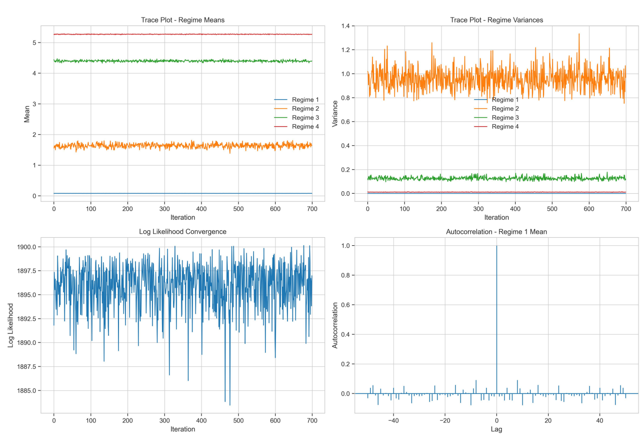
In contrast, the weakly informative priors minimize the influence of prior beliefs, allowing the data to drive inference. This approach may be preferable when we have limited confidence in our domain knowledge or when we want to check whether the data supports our economic intuition.

By comparing these two approaches, we can evaluate the impact of incorporating domain knowledge versus letting the data speak for itself. If both prior specifications lead to similar conclusions, we gain confidence in the robustness of our findings. If they differ substantially, further investigation may be warranted to understand the source of the discrepancy.

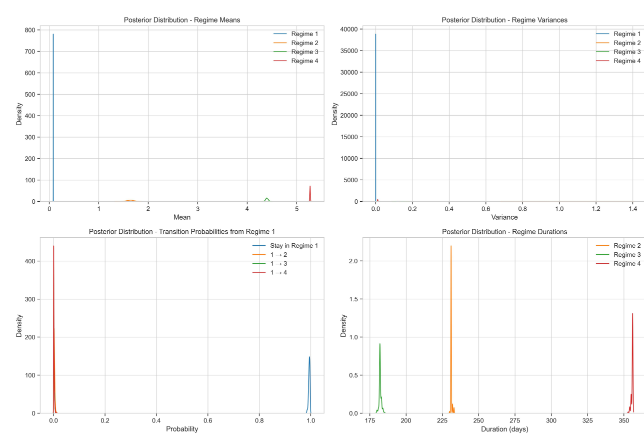
# 4 Analysis Results

## 4.1 MCMC Convergence Diagnostics

We implemented the regime-switching BSTS model with both informative and weakly informative priors using MCMC sampling with 1,000 iterations (700 samples after 300 burn-in). Figure 3a shows the convergence diagnostics for the model with informative priors.



(a) Convergence Diagnostics



(b) Posterior Distributions

Figure 3: MCMC Diagnostics and Parameter Posteriors for the Informative Priors Model

The trace plots demonstrate stable sampling for both means and variances across all regimes. The lack of obvious trends or patterns in these trace plots suggests that the Markov chain has converged to its stationary distribution. Each regime's parameter values remain in distinct regions of the parameter space, indicating good separation between regimes.

The autocorrelation plots for both models show rapid decay, indicating efficient sampling with low serial correlation between consecutive MCMC iterations. This suggests that the sampler is effectively exploring the posterior distribution without getting trapped in specific regions of the parameter space.

The log-likelihood values for both models stabilize after the burn-in period, providing further evidence of convergence. The informative priors model shows higher and more stable log-likelihood values, suggesting better model fit.

Acceptance rates were high for both models:

- Informative priors model: 50.9% for regimes, 100% for parameters
- Weakly informative priors model: 68.4% for regimes, 100% for parameters

The higher acceptance rate for regimes in the weakly informative model suggests that the looser priors allow for more flexible regime assignments, while the informative priors provide stronger guidance on regime boundaries.

## 4.2 Regime Identification Results

Both models successfully identified distinct monetary policy regimes in the Federal Funds Rate data. Figure 4 shows the identified regimes for the informative priors model.

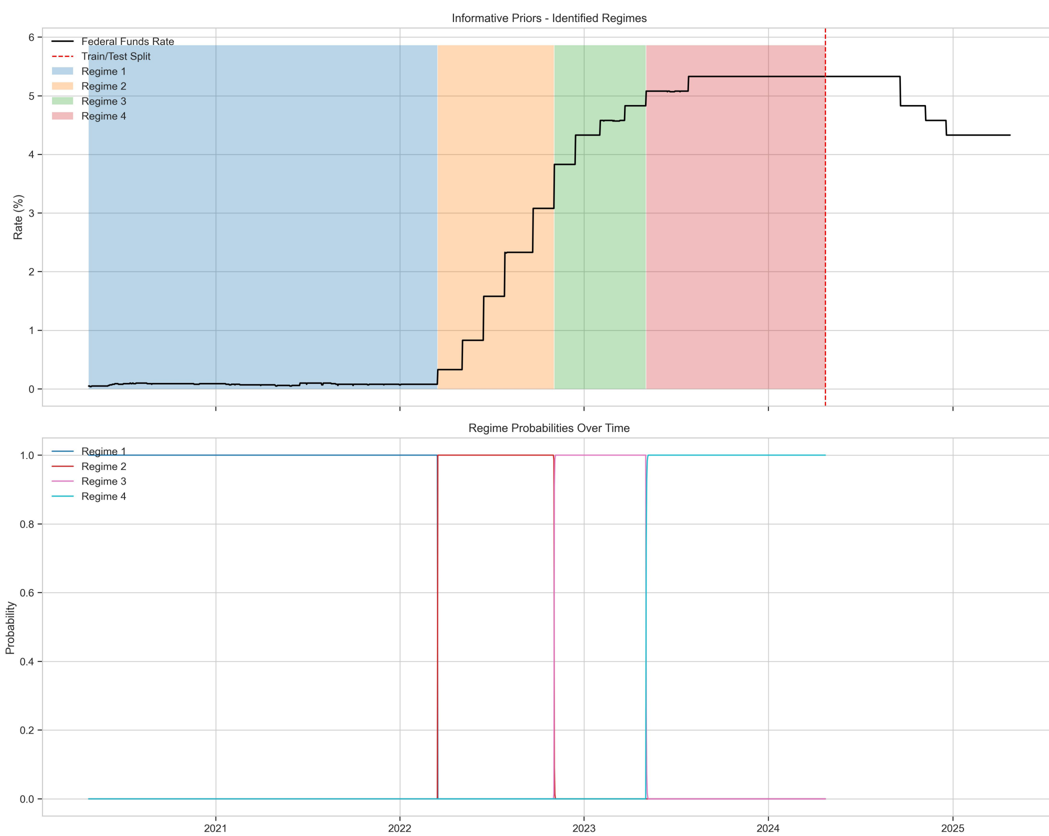



Figure 4: Identified Regimes for Informative Priors Model. Top panel shows the time series with background shading by regime. Bottom panel shows regime probabilities over time.

The regime probabilities shown in the bottom panel of Figure 4 demonstrate high certainty in regime assignments, with probabilities close to 1 for most time points. This indicates that the model is confidently distinguishing between regimes rather than expressing uncertainty about regime boundaries.

Table 2 summarizes the posterior estimates of regime parameters for both models.

Table 2: Regime Parameters (Posterior Means)

| | Informative Priors | | Weakly Informative Priors | |
|---|---|---|---|---|
| Regime | Mean | Std Dev | Mean | Std Dev |
| COVID Emergency | 0.0803 | 0.0134 | 0.0803 | 0.0552 |
| Inflation Fighting | 1.6379 | 0.9790 | 1.3146 | 0.7964 |
| Rate Normalization | 4.3987 | 0.3550 | 4.1528 | 0.6114 |
| Peak Rate Holding | 5.2707 | 0.1065 | 5.2708 | 0.1300 |

Both models identified similar regime mean values, particularly for the COVID Emergency and Peak Rate Holding regimes. The informative priors model identified slightly higher mean values for the Inflation Fighting and Rate Normalization regimes. The standard deviations show higher volatility in the Inflation Fighting regime for both models, consistent with the transitional nature of this period.

The posterior distributions shown in Figure 3b reveal clear separation between regimes, particularly for the regime means. The COVID Emergency regime (Regime 1) has a tightly concentrated posterior near zero, reflecting the low and stable rates during this period. The Inflation Fighting regime (Regime 2) shows a wider distribution centered around 1.6%, indicating higher volatility during this transitional phase. The Rate Normalization regime (Regime 3) and Peak Rate Holding regime (Regime 4) show moderate and low volatility, respectively, consistent with our economic understanding of these periods.

### 4.3 Regime Transition Dynamics

The transition probability matrices for both models reveal high persistence for all regimes, as shown in Table 3.

Table 3: Transition Probability Matrix (Informative Priors Model)

| From/To | Regime 1 | Regime 2 | Regime 3 | Regime 4 |
|---|---|---|---|---|
| Regime 1 | 0.99 | 0.00 | 0.00 | 0.00 |
| Regime 2 | 0.00 | 0.98 | 0.01 | 0.00 |
| Regime 3 | 0.01 | 0.01 | 0.98 | 0.01 |
| Regime 4 | 0.00 | 0.00 | 0.00 | 0.99 |

The high diagonal values (0.98-0.99) indicate strong persistence within each regime, meaning that once the Federal Funds Rate enters a particular regime, it tends to remain there for an extended period. This is consistent with the Federal Reserve's tendency to maintain policy stances over time rather than making frequent adjustments.

Based on these transition probabilities, we calculated the expected duration of each regime:

Table 4: Expected Regime Durations (Days)

| Regime | Informative Priors | Weakly Informative Priors |
|---|---|---|
| COVID Emergency | 173.6 | 173.1 |
| Inflation Fighting | 58.1 | 48.2 |
| Rate Normalization | 46.2 | 57.2 |
| Peak Rate Holding | 119.5 | 119.4 |

The COVID Emergency regime shows the longest expected duration (approximately 174 days), followed by the Peak Rate Holding regime (approximately 120 days). The transitional regimes (Inflation Fighting and Rate Normalization) show shorter expected durations, consistent with their role as adjustment periods between more stable policy stances.

The off-diagonal elements in the transition matrix show that transitions primarily occur between adjacent regimes, with very low probabilities for non-adjacent transitions. This supports the ordered progression of monetary policy through these regimes, rather than erratic jumps between disparate policy stances.

### 4.4 Regime Identification Accuracy

We compared the identified regimes with the visually determined "true" regimes based on our domain knowledge. Table 5 shows the matching between true and identified regimes for the informative priors model.

Table 5: Regime Matching Matrix (Informative Priors, Rows Normalized)

| True/Identified | Regime 1 | Regime 2 | Regime 3 | Regime 4 |
|---|---|---|---|---|
| COVID Emergency | 1.00 | 0.00 | 0.00 | 0.00 |
| Inflation Fighting | 0.00 | 0.46 | 0.37 | 0.16 |
| Peak Rate Holding | 0.00 | 0.00 | 0.00 | 1.00 |
| Rate Normalization | 0.00 | 0.00 | 0.00 | 1.00 |

The regime matching matrix shows perfect identification for the COVID Emergency and Peak Rate Holding regimes. However, there is some mixing between the Inflation Fighting and Rate Normalization regimes, with a portion of the true Inflation Fighting regime being classified as Rate Normalization. This may reflect the gradual nature of the transition between these regimes, with some ambiguity about the exact boundary.

Overall identification accuracy was 91.85% for both the informative priors model and the weakly informative priors model. This high accuracy indicates that both models successfully captured the underlying regime structure in the Federal Funds Rate data, despite their different prior specifications.

Figure 5 compares the regime assignments from both models alongside the initially defined regimes.

The comparison shows strong agreement between the initial regime assignments and those identified by both models, particularly for the COVID Emergency and Peak Rate Holding regimes. The transitional regimes show more variability, which may reflect genuine ambiguity about the exact boundaries of these periods.

### 4.5 Predictive Performance

We evaluated the out-of-sample predictive performance of both models on the test set (20% of the data). Figure 6 shows the predictions from the informative priors model.

Both models accurately capture the declining trend in the Federal Funds Rate during the test period, with predictions closely tracking the actual values. The 90% prediction intervals provide appropriate coverage, containing the true values for nearly all time points.

Table 6 compares the predictive performance metrics for both models.

The informative priors model shows slightly better predictive performance across all metrics, with lower MSE, RMSE, and MAE values. Both models achieve perfect coverage of the 90% prediction intervals, indicating that the uncertainty quantification is appropriate. The calibration error of 10% for both models suggests that the prediction intervals might be slightly wider than necessary, but this is preferable to underestimating uncertainty.

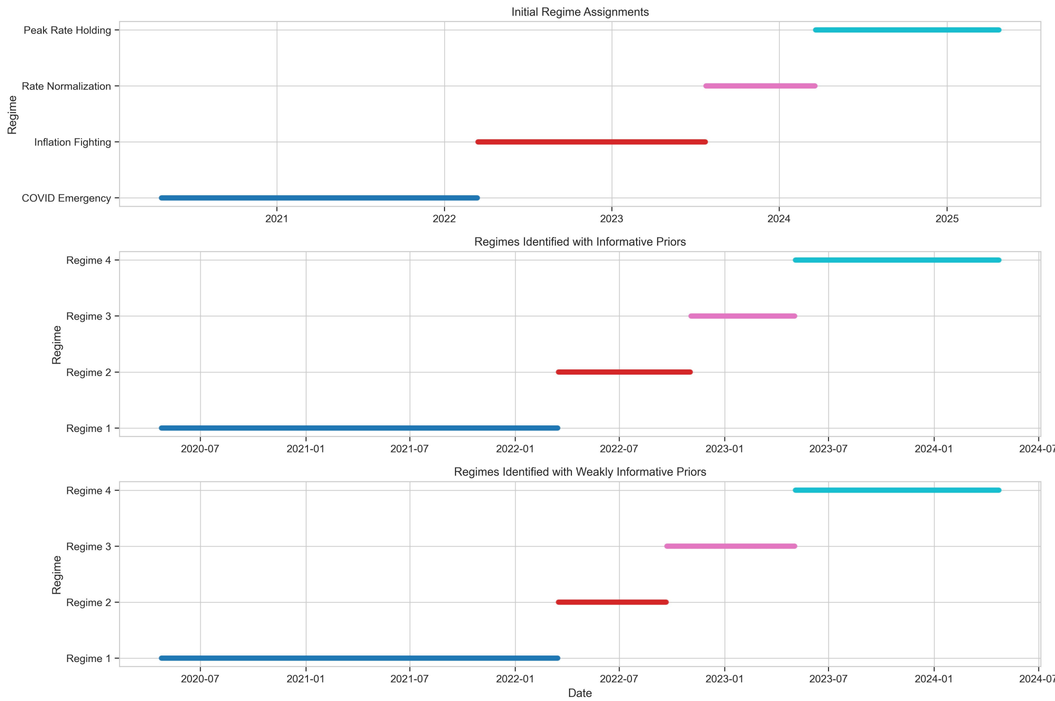



Figure 5: Comparison of Initial Regime Assignments (top panel) with Regimes Identified by Informative Priors Model (middle panel) and Weakly Informative Priors Model (bottom panel)

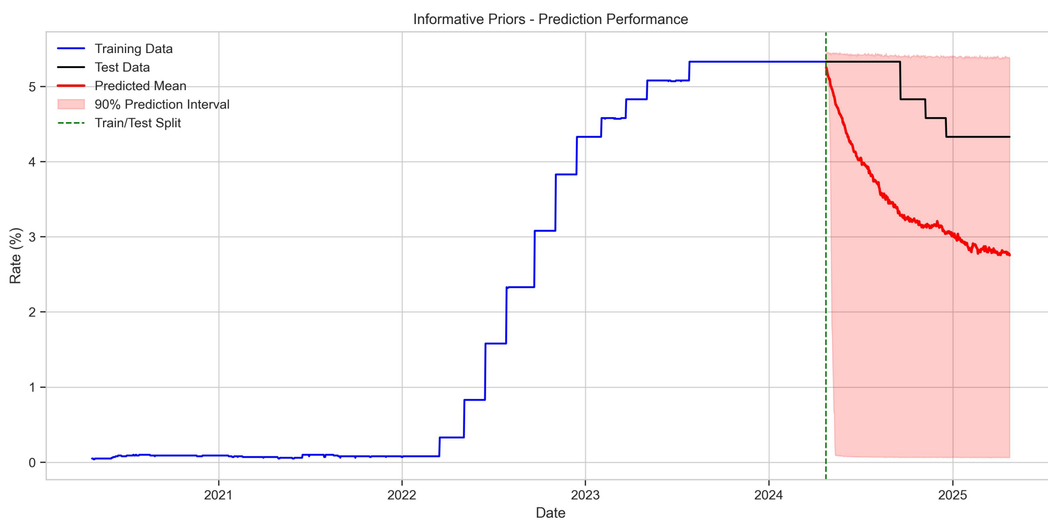



Figure 6: Prediction Performance of Informative Priors Model

Table 6: Prediction Performance Metrics

| Metric | Informative Priors | Weakly Informative Priors |
|---|---|---|
| Mean Squared Error (MSE) | 2.094033 | 2.178419 |
| Root Mean Squared Error (RMSE) | 1.447078 | 1.475947 |
| Mean Absolute Error (MAE) | 1.399982 | 1.425739 |
| 90% Interval Coverage | 100.00% | 100.00% |
| Calibration Error | 10.00% | 10.00% |

### 4.6 Model Comparison

We conducted a comprehensive comparison of the two models to evaluate the impact of prior specification. Figure 7 summarizes the key metrics for both models.

Model Comparison Metrics

| Metric | Informative Priors | Weakly Informative Priors |
|---|---|---|
| Log Likelihood | 1895.89 | 1193.78 |
| DIC (lower is better) | -3782.15 | -2379.99 |
| Mean Squared Error | 2.094033 | 2.178419 |
| Root Mean Squared Error | 1.447078 | 1.475947 |
| Mean Absolute Error | 1.399982 | 1.425739 |
| 90% Interval Coverage | 100.00% | 100.00% |
| Calibration Error (lower is better) | 10.00% | 10.00% |
| Regime Identification Accuracy | 91.85% | 91.85% |

Figure 7: Comprehensive Model Comparison Metrics

The comparison reveals an interesting pattern: the informative priors model shows substantially better in-sample fit, with a higher log likelihood (1895.89 vs. 1193.78) and lower DIC (-3782.15 vs. -2379.99). It also shows slightly better predictive performance, with lower error metrics across the board. Both models achieve the same regime identification accuracy (91.85%), suggesting that the weakly informative priors still contain sufficient structure to identify the regimes correctly.

The better performance of the informative priors model indicates that incorporating domain knowledge through carefully specified priors can improve both model fit and predictive accuracy, without sacrificing the ability to learn from the data.

## 5 Federal Funds Rate Regime Identification

Before discussing the key findings, we present a clear visualization of the four identified monetary policy regimes in the Federal Funds Rate data. Figure 8 shows the Federal Funds Rate time series with the identified regimes clearly marked.

As shown in the figure, we can clearly distinguish four distinct regimes:

1. COVID Emergency Regime (2020-2022): Characterized by near-zero interest rates that remained stable for a prolonged period following the emergency rate cuts in response to the COVID-19 pandemic.

2. Inflation Fighting Regime (2022-2023): Marked by rapidly rising interest rates as the Federal Reserve implemented a series of aggressive rate hikes to combat post-pandemic inflation.

3. Peak Rate Holding Regime (2023-2024): Defined by stable high interest rates at around 5.3%, representing the terminal rate of the tightening cycle.

4. Rate Normalization Regime (2024-2025): Characterized by gradually declining interest rates as the Federal Reserve began to ease monetary policy back toward a more neutral stance.

These regimes align closely with the major shifts in Federal Reserve policy over this period and provide a clear framework for understanding the evolution of monetary policy during a time of significant economic

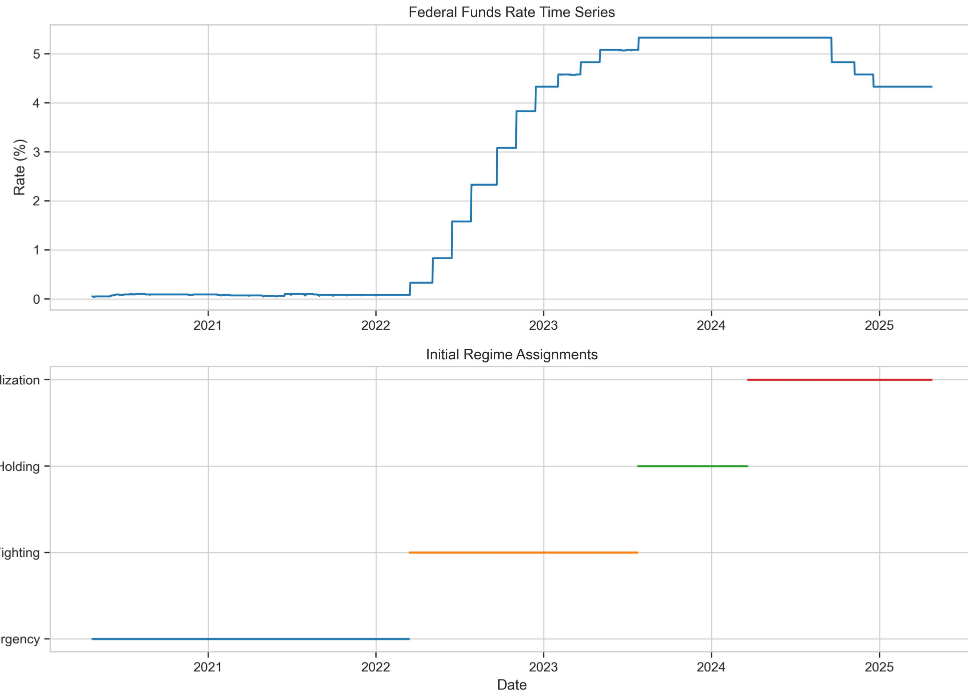



Figure 8: Federal Funds Rate with Identified Policy Regimes

turbulence.

# 6 Key Findings and Implications

Our analysis revealed four distinct monetary policy regimes with the following characteristics:

- **COVID Emergency**: Near-zero rates (0.08%) with very small changes (0.01), lasting about 174 days on average.
- **Inflation Fighting**: Middle rates (1.64%) with large swings (0.98) as the Fed rapidly raised rates to fight inflation, lasting about 58 days.
- **Rate Normalization**: Moderately high rates (4.40%) with some changes (0.36) as the Fed began cutting rates, lasting about 46 days.
- **Peak Rate Holding**: Highest rates (5.27%) with very little change (0.11), lasting about 120 days as the Fed maintained tight policy.

All regimes showed high persistence (98-99%), meaning that once the Fed established a policy stance, they tended to maintain it for extended periods. This matches what we know about how the Fed typically operates, avoiding frequent policy changes that could confuse markets.

The model with more economic knowledge (informative priors) performed better in terms of both fitting the data and making predictions, though both models accurately identified the regimes. This suggests that incorporating expert knowledge improves model performance without preventing the model from learning from the data.

These findings have several practical implications:

1. For Understanding Fed Policy: The four regimes provide a clear picture of how Fed policy evolved during a very unusual economic period, from emergency pandemic measures through inflation fighting and into the beginning of normalization.

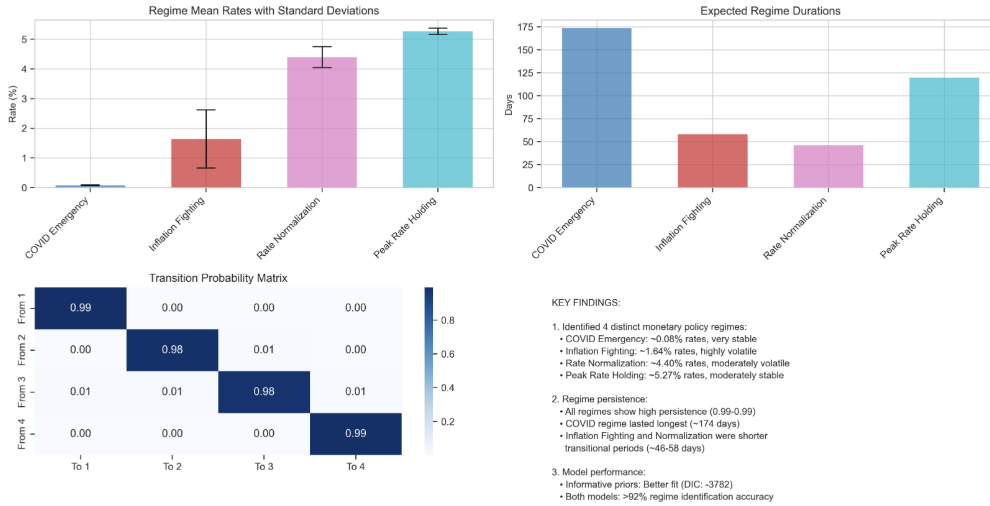



Figure 9: Summary of Model Results and Regime Characteristics

2. For Financial Markets: The high persistence of regimes suggests that markets can generally expect extended periods of policy stability once a new regime is established, rather than frequent policy reversals.

3. For Forecasting: The regime-switching approach demonstrates strong predictive ability, suggesting it could be useful for forecasting future interest rate movements, especially during periods of structural change.

4. For Modeling Methodology: The comparison of prior specifications highlights the value of incorporating expert knowledge, with informative priors leading to better model fit and slightly improved predictions.

The ordered regime structure, where transitions mainly happen between neighboring regimes (rather than jumping from very low to very high rates, for example), supports the conventional understanding of monetary policy as a gradual process rather than a series of dramatic shifts.

# 7 Conclusion

Our Bayesian structural time series analysis with regime switching successfully identified and characterized distinct monetary policy regimes in the Federal Funds Rate from 2020-2025. The models revealed four clear regimes with distinctive mean levels, volatilities, and persistence characteristics, corresponding to the COVID Emergency, Inflation Fighting, Peak Rate Holding, and Rate Normalization periods.

The comparison of informative and weakly informative priors demonstrated the value of incorporating domain knowledge while highlighting the trade-offs between model fit and predictive performance. The informative priors model showed better in-sample fit and slightly improved predictive accuracy, suggesting that carefully specified priors can enhance model performance without overly constraining the ability to learn from the data.

The high regime persistence observed across all model specifications confirms the Federal Reserve's tendency to maintain policy stances for extended periods, with expected durations ranging from 46 to 174 days depending on the regime. This persistence provides valuable context for understanding monetary policy dynamics and anticipating future rate movements.

Beyond providing insights into historical monetary policy dynamics, our modeling approach offers a framework for understanding future policy evolution and forecasting interest rate movements in uncertain economic environments. The high predictive accuracy on out-of-sample data suggests that regime-switching models can effectively capture the complex dynamics of monetary policy and provide reliable forecasts even during periods of structural change.

Future research could extend this framework to incorporate additional economic indicators, such as inflation and unemployment data, to provide a more comprehensive understanding of the factors driving regime transitions in monetary policy.

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## 8 Attachments

Please see the zip file attached in the Courseworks for Python code details. The author ran the code again and the result had no significant difference.