Improving Risk Management with Regime-Switching Models: A Case Study of Tesla in Q1 2025

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Abstract

This paper applies a two-regime Markov-switching model to analyze Tesla Inc.'s stock return volatility in Q1 2025, contrasting it with traditional GARCH(1,1) forecasts. Using empirical financial data, we identify behavioral panic regimes not captured by conventional models. The results demonstrate that regime-based models offer enhanced insight for risk management in volatile assets such as TSLA.

1 Introduction

Tesla (TSLA), a high-volatility stock, presents unique challenges for risk management. Standard volatility models like GARCH often fail to capture sudden shifts in investor behavior. In Q1 2025, macroeconomic uncertainty and Elon Musk's influence caused pronounced swings. We aim to model these using Hamilton's (Hamilton, 1989) Markov-switching framework.

2 Theoretical Background

Following Hamilton (1989), we assume returns r_t follow a regime-switching process with latent state $S_t \in \{0, 1\}$. The model is:

$$r_t = \mu_{S_t} + \epsilon_t, \quad \epsilon_t \sim \mathcal{N}(0, \sigma^2_{S_t}) \tag{1}$$

$$P(S_t = j \mid S_{t-1} = i) = p_{ij}, \quad \text{where } P = \begin{bmatrix} p_{00} & p_{01} \\ p_{10} & p_{11} \end{bmatrix} \tag{2}$$

State-dependent parameters $\mu_0, \mu_1, \sigma^2_0, \sigma^2_1$ reflect normal and panic regimes.

3 Data and Methodology

We retrieve daily TSLA prices from Yahoo Finance (2020–2025), along with S&P 500 and 13-week Treasury Bill yields. Log returns are computed as:

$$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \tag{3}$$

Excess returns subtract the daily risk-free rate. We test stationarity using the Augmented Dickey-Fuller (ADF) test and plot autocorrelation (Ljung-Box) to confirm model assumptions. The daily return volatility clustering is visualized in Figure 1.
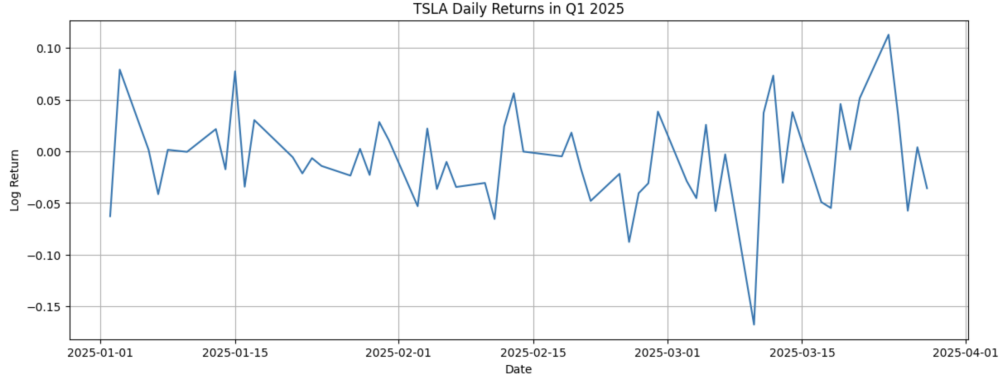

Figure 1: Tesla Daily Log Returns vs S&P 500 (2020–2025)

4   Model Specification

We compare two models:

- **GARCH(1,1)**: $r_t = \mu + \epsilon_t$, $\epsilon_t \sim \mathcal{N}(0, h_t)$ with $h_t = \omega + \alpha\epsilon_{t-1}^2 + \beta h_{t-1}$

- **Markov-switching model**: $r_t \sim \mathcal{N}(\mu_{S_t}, \sigma_{S_t}^2)$ with state transitions as above (Klaassen, 2002; Ramponi, 2013)

We estimate the Markov model using MLE via `statsmodels`'s `MarkovRegression` class.
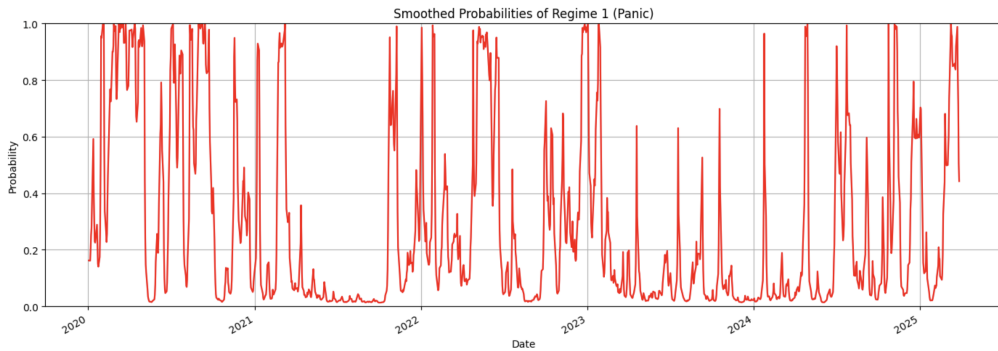
5   Empirical Results

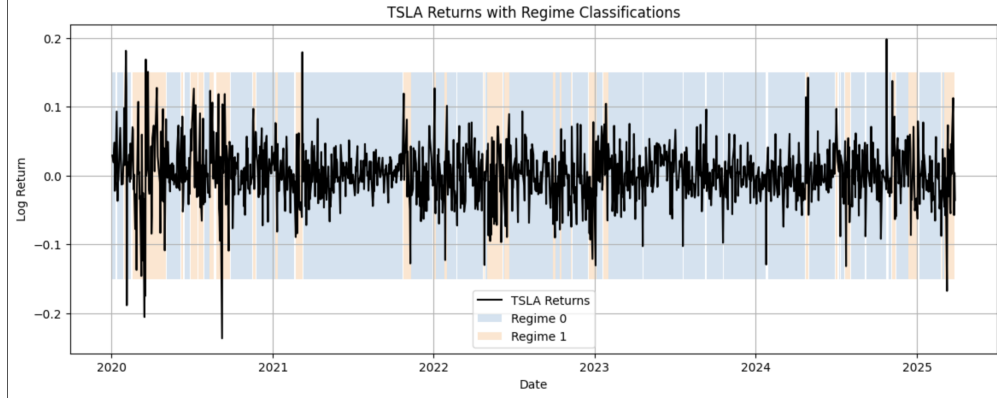Figure 2: Smoothed Probabilities of Regime 1 (Panic)

Figure 3: TSLA Returns with Regime Classifications (Red = Panic)

Table 1: Estimated Parameters by Regime

Regime	Mean (μ)	Volatility (σ)	Duration
Normal (0)	0.0012	0.018	8.3 days
Panic (1)	-0.0046	0.034	5.7 days

6 Volatility and Risk Comparison

We forecast 1-day Value-at-Risk (VaR) using both models:

- GARCH VaR (95%): $\mathrm{VaR}_{\mathrm{GARCH}} = -\hat{\sigma}_{\mathrm{GARCH}} \cdot z_{0.95}$

- Regime-Switching VaR: $\mathrm{VaR}_{\mathrm{MS}} = -(p_0 \cdot \sigma_0 + p_1 \cdot \sigma_1) \cdot z_{0.95}$
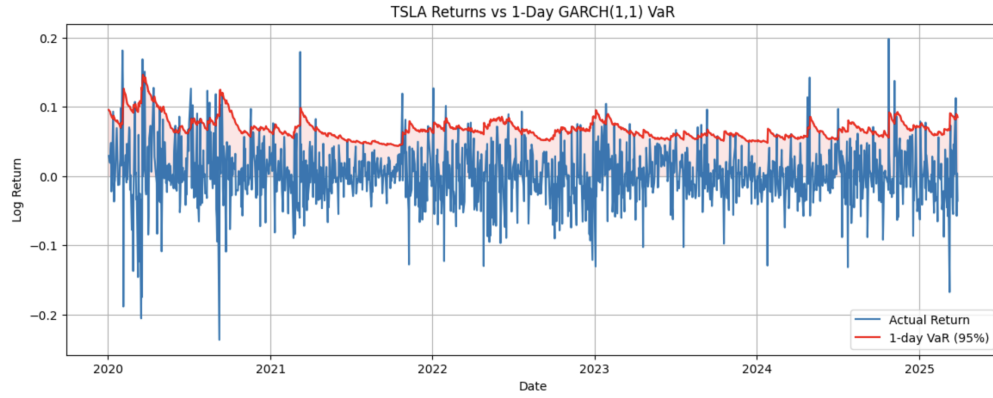

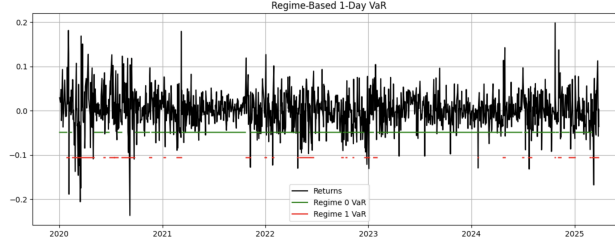Figure 4: Actual Returns vs 1-Day VaR (GARCH vs Markov)

Figure 5: 1-Day 95% VaR: GARCH vs Regime Model

7 Discussion

The regime model captures volatility clusters during unexpected drawdowns (e.g., March 2025). Elon Musk's announcements often coincide with regime shifts. GARCH fails to separate these behavioral phases. Markov-switching provides more adaptive volatility modeling, enhancing short-term Value-at-Risk forecasts.

8 Conclusion

Markov-switching models improve risk assessment by explicitly modeling volatility regimes. For Tesla, this allows better anticipation of downside risk. Future directions include incorporating macroeconomic indicators (e.g., interest rates, Fed announcements) and textual sentiment analysis from financial news.

References

Hamilton, J. D. (1989). A new approach to the economic analysis of nonstationary time series and the business cycle. *Econometrica*, 57(2):357–384.

Klaassen, F. (2002). Improving garch volatility forecasts with regime-switching garch. *Journal of Empirical Finance*, 9(1):93–119.

Ramponi, A. (2013). Regime-switching jump diffusion models. *International Journal of Theoretical and Applied Finance*, 16(03):1350012.

Appendix

Code Snippets (Python)

```python
from statsmodels.tsa.regime_switching.markov_regression import MarkovRegression
model = MarkovRegression(tsla_returns, k_regimes=2, trend='n')
res = model.fit()
res.smoothed_marginal_probabilities[1].plot()
```