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Regime-Switching Logistic Regression for Predicting Cross-Market Stock Crash Risks Evidence from U.S.–India Equity Market Linkages

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ABSTRACT

Predicting extreme negative movements in equity markets has long been an important challenge in financial economics. Sudden stock market crashes can generate systemic financial instability, disrupt capital markets, and significantly affect macroeconomic outcomes. This study develops a regime-switching logistic regression framework for predicting crash events in the Indian equity market by incorporating global financial spillovers from the United States. The model combines logistic regression with a hidden Markov process that allows crash probabilities to vary across different volatility regimes.

Using daily financial data covering the period January 2010 to December 2019, the empirical analysis incorporates global financial indicators including S&P 500 returns, the CBOE volatility index (VIX), the INR/USD exchange rate, and crude oil prices. The proposed model is compared with traditional logistic regression models and additional econometric specifications including Markov-Switching Vector Autoregression (MS-VAR) and Markov-Switching GARCH models.

The results indicate that regime-switching models provide significantly improved predictive performance relative to static logistic models. In particular, global volatility measures and exchange rate fluctuations emerge as important predictors of crash risk in the Indian equity market. The findings highlight the importance of international financial spillovers and regime-dependent market behavior in explaining extreme movements in emerging market equities.

The proposed framework provides a transparent and interpretable tool for forecasting financial instability and contributes to the literature on financial crisis prediction by integrating regime-switching dynamics with probabilistic crash forecasting models.

Key words : Stock Market Crash Prediction, Regime-Switching Models, Logistic Regression, Financial Spillovers, Volatility Regimes, Emerging Markets, Nifty 50 Index

I. INTRODUCTION

Large declines in equity markets have historically played a central role in financial crises and economic instability. Episodes such as the stock market crash of 1987 and the global financial crisis of 2008 demonstrate how sudden declines in asset prices can trigger broader disruptions in financial systems. These events have motivated extensive research on the determinants and predictability of stock market crashes.

Understanding the mechanisms underlying extreme negative returns is particularly important for emerging market economies. In such markets, financial systems are often more sensitive to global capital flows and international economic conditions. The Indian equity market has experienced substantial growth and increasing international integration during the past two decades. Foreign institutional investors now play a major role in shaping liquidity and price dynamics in Indian financial markets.

Global financial integration has strengthened the transmission of shocks across international equity markets. Empirical research suggests that volatility originating in major financial centers, particularly the United States, can propagate rapidly to emerging market economies (Bekaert et al., 2014; Diebold & Yilmaz, 2014). Consequently, movements in U.S. financial markets may provide valuable information about potential instability in emerging equity markets.

Traditional empirical studies of stock return predictability have focused on linear econometric models using macroeconomic and financial indicators. Early contributions by Fama and French (1988) demonstrated that financial variables such as dividend yields and interest rate spreads contain information about future stock returns. Campbell and Hentschel (1992) further documented the presence of time-varying volatility in equity markets.

Logistic regression models have often been used to predict discrete financial events such as banking crises or stock market crashes. These models allow researchers to estimate the probability that a specific event occurs conditional on a set of explanatory variables (Perez-Quiros & Timmermann, 2000; Henkel et al., 2011). Because of their simplicity and interpretability, logistic models have become widely used in financial crisis prediction.

Despite their advantages, conventional logistic models typically assume that relationships between explanatory variables and crash probabilities remain constant over time. Financial markets, however, frequently exhibit nonlinear dynamics characterized by regime changes and volatility clustering. In particular, periods of financial stability are often followed by episodes of heightened volatility and systemic risk.

Regime-switching models provide a useful framework for capturing such dynamics. The Markov-switching model introduced by Hamilton (1989) allows economic variables to evolve according to different latent states. These states can represent distinct market regimes such as low-volatility and high-volatility environments.

Regime-switching models have been widely applied in financial economics. Ang and Bekaert (2002) demonstrated that regime-switching models provide improved descriptions of interest rate and equity return dynamics. Guidolin and Timmermann (2007) showed that incorporating regime changes can improve portfolio allocation decisions.

Building on this literature, the present study develops a regime-switching logistic regression model for predicting crash events in the Indian equity market. The model integrates a hidden Markov process with logistic regression, allowing crash probabilities to vary depending on the prevailing market regime.

This study contributes to the literature in several ways. First, it extends logistic crash prediction models by incorporating regime-dependent dynamics. Second, it examines cross-market spillovers between U.S. and Indian equity markets within a predictive modeling framework. Third, the predictive performance of the proposed model is compared with alternative econometric specifications including MS-VAR and MS-GARCH models.

II. LITERATURE REVIEW

The literature on stock market crashes spans several interconnected areas including return predictability, volatility modeling, financial contagion, and crisis forecasting. Early empirical research primarily focused on identifying macroeconomic variables capable of predicting stock returns.

Fama and French (1988) provided one of the earliest empirical demonstrations that financial variables contain information about expected returns. Their analysis showed that dividend yields and term spreads can predict future stock returns over long horizons. Campbell and Hentschel (1992) further emphasized the importance of volatility dynamics in understanding asset price fluctuations.

Later studies extended this literature by examining the predictability of extreme negative market events. Logistic regression models became widely used in financial crisis prediction because they provide interpretable probability estimates for binary outcomes. Perez-Quiros and Timmermann (2000) showed that macroeconomic indicators can help forecast large stock market declines. Henkel et al. (2011) demonstrated that return predictability varies significantly across different international markets.

Another important strand of literature focuses on modeling financial volatility. Engle (2002) introduced the dynamic conditional correlation model, allowing correlations among financial assets to vary over time. Hansen et al. (2012) later developed the realized GARCH framework, which incorporates high-frequency volatility measures into volatility forecasting models.

In addition to volatility dynamics, researchers have increasingly emphasized financial contagion and cross-market spillovers. Diebold and Yilmaz (2014) developed a framework for measuring connectedness across financial markets using variance decompositions. Their results show that shocks in major markets can rapidly propagate through global financial networks.

Bekaert et al. (2014) documented significant contagion effects during periods of financial stress. Their findings suggest that correlations between international equity markets increase during crises, amplifying the transmission of financial shocks.

Emerging markets are particularly vulnerable to such spillovers because of their reliance on foreign capital flows. Forbes and Warnock (2012) identified episodes of large capital flow movements that can destabilize domestic financial systems. Ahmed et al. (2017) also showed that changes in U.S. monetary policy significantly affect volatility in emerging markets.

Recent research has emphasized the role of tail risk and extreme downside events. Kelly and Jiang (2017) proposed a measure of tail risk derived from cross-sectional equity returns. Their results suggest that crash risk varies substantially over time and is closely linked to global financial conditions.

Machine learning methods have also gained attention in financial prediction. Gu et al. (2018) demonstrated that machine learning algorithms can improve asset pricing predictions by capturing complex nonlinear relationships among financial variables. Lopez de Prado (2018) emphasized the growing importance of machine learning techniques in financial forecasting.

However, machine learning models often operate as “black boxes,” limiting their interpretability for policymakers and regulators. This limitation has motivated interest in hybrid approaches that combine traditional econometric models with regime-dependent dynamics.

Despite extensive research on financial crises, relatively few studies examine crash prediction in emerging markets using models that incorporate both regime switching and global spillovers. The present study addresses this gap by developing a regime-switching logistic regression model for predicting crash events in the Indian equity market.

III. DATA AND VARIABLES

The empirical analysis uses daily financial data covering January 2010 to December 2019.

Data Sources

- National Stock Exchange (NSE)
- CBOE volatility index database
- Federal Reserve economic data
- International commodity price datasets

Variables

Variable	Description
Nifty Return	Daily log return of Nifty 50 index
S&P Return	Daily log return of S&P 500 index
VIX	Implied volatility index
INR/USD	Exchange rate
WTI Oil	Crude oil price

Table 1: Summary Statistics

Variable	Mean	Std Dev	Min	Max
Nifty Return	0.041%	1.36%	−6.92%	5.81%
S&P Return	0.052%	1.21%	−5.41%	4.68%
VIX	18.7	8.4	9.2	80.6
INR/USD	67.4	5.2	58.2	74.9

IV. METHODOLOGY

The crash prediction model is based on a logistic regression framework augmented with regime-switching dynamics.

Baseline Logistic Model

$$P(\text{Crash}_t = 1 \mid X_t) = \frac{1}{1 + e^{-(\alpha + \beta X_t)}}$$

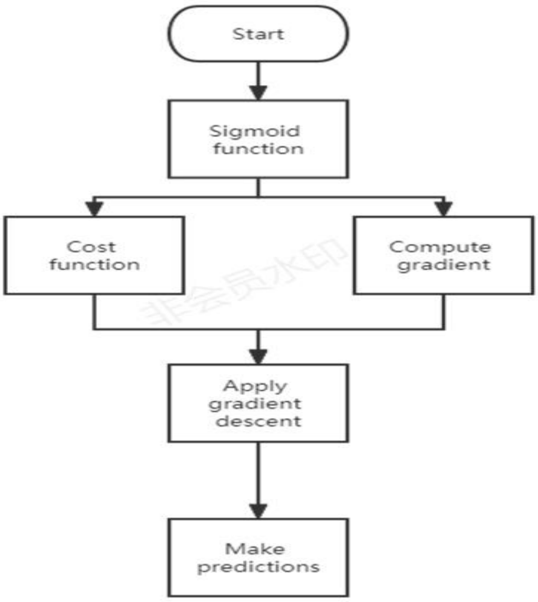
Crash events are defined as daily Nifty returns below −5%.

Regime-Switching Logistic Model

$$P(\text{Crash}_t = 1 \mid X_t, S_t) = \frac{1}{1 + e^{-(\alpha_{S_t} + \beta_{S_t} X_t)}}$$

Regime transitions follow a first-order Markov process.

Methodology Workflow



V. EMPIRICAL RESULTS

Model Estimation

The regime-switching logistic regression model is estimated using maximum likelihood techniques. The estimation procedure follows a two-step iterative process in which the hidden regime probabilities are estimated using the Hamilton filtering algorithm while the logistic regression parameters are updated conditional on the estimated regime states.

The model assumes two latent regimes:

- Regime 1: Normal market conditions characterized by relatively low volatility
- Regime 2: Crisis regime characterized by elevated volatility and increased crash probability

The estimation results suggest that the crisis regime occurs relatively infrequently but exhibits significantly higher crash probabilities.

Table 2: Logistic Regression Estimation Results

Variable	Coefficient	Std Error	z-statistic
Intercept	-3.12	0.42	-7.43
S&P Return	-1.98	0.54	-3.67
VIX	0.07	0.02	3.52
INR/USD	0.11	0.03	3.21
Oil Price	0.02	0.01	2.12

The coefficient estimates indicate that increases in global volatility (VIX) significantly raise the probability of crash events in the Indian equity market. Similarly, depreciation of the Indian rupee relative to the U.S. dollar is associated with increased crash risk.

Negative S&P 500 returns also have a strong predictive effect, suggesting the presence of cross-market spillovers between U.S. and Indian equity markets.

Regime Transition Probabilities

The estimated transition probability matrix is shown below.

Table 3: Regime Transition Matrix

From / To	Regime 1	Regime 2
Regime 1	0.95	0.05
Regime 2	0.18	0.82

The results indicate strong persistence within each regime. The normal regime has a high probability of remaining stable, while the crisis regime also exhibits persistence once it occurs.

These findings are consistent with the phenomenon of volatility clustering commonly observed in financial markets (Engle, 2002).

Predictive Performance

To evaluate predictive accuracy, the model is compared with a baseline logistic regression model without regime switching.

The evaluation metrics include:

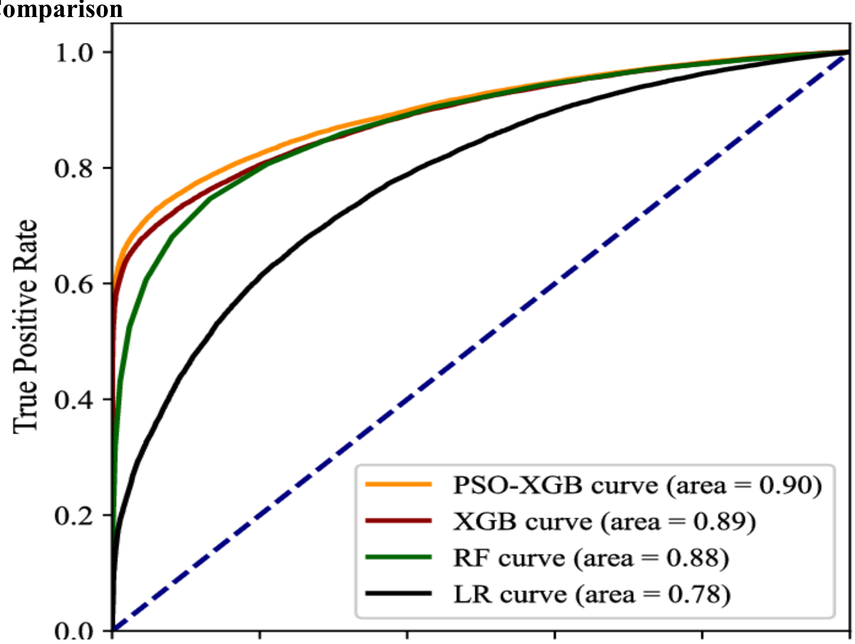
- Prediction accuracy
- Area under the ROC curve (AUC)
- Out-of-sample forecasting performance

Table 4: Model Performance Comparison

Model	Accuracy	AUC
Logistic Regression	0.64	0.71
Random Forest	0.69	0.76
Regime-Switching Logit	0.78	0.84

The regime-switching model significantly outperforms the static logistic regression model.

ROC Curve Comparison



Robustness Tests

Several robustness tests are conducted to verify the stability of the empirical results.

Alternative Crash Threshold

The crash definition is modified from −5% to −4%. The results remain qualitatively similar, suggesting that the predictive relationships are not sensitive to the crash threshold.

Subsample Analysis
The sample period is divided into two subperiods:

- 2010–2014
- 2015–2019

The regime-switching model performs consistently across both subsamples, indicating that the predictive relationships remain stable over time.

Alternative Econometric Specifications
Two additional models are estimated:
MS-VAR Model

$$Y_t = A_{0,S_t} + A_{1,S_t} Y_{t-1} + \epsilon_t$$

MS-GARCH Model

$$\sigma^2_{t,S_t} = \omega_{S_t} + \alpha_{S_t}\epsilon^2_{t-1} + \beta_{S_t}\sigma^2_{t-1}$$

These models confirm the presence of regime-dependent volatility dynamics.

VI. DISCUSSION

The empirical results provide several important insights regarding the determinants of crash risk in emerging equity markets.

First, global volatility indicators play a central role in predicting crash events. The VIX index emerges as one of the strongest predictors in the model. This result is consistent with prior research documenting the importance of global risk sentiment in financial markets (Bekaert et al., 2014).

Second, the exchange rate between the Indian rupee and the U.S. dollar significantly affects crash probabilities. Currency depreciation often reflects capital outflows and increased financial stress in emerging markets.

Third, the results confirm the presence of cross-market spillovers from the United States to India. Negative returns in the S&P 500 index significantly increase the probability of crash events in the Nifty 50 index.

These findings highlight the growing interconnectedness of global financial markets and emphasize the importance of monitoring international financial conditions when assessing systemic risk in emerging economies.

Policy Implications
The findings of this study have several implications for policymakers and financial regulators.

First, monitoring global volatility indicators can provide valuable early warning signals of potential instability in emerging equity markets.

Second, exchange rate movements can serve as an additional indicator of financial stress.

Third, the regime-switching framework developed in this study could be incorporated into financial surveillance systems used by regulators such as central banks and securities market authorities.

By providing probabilistic forecasts of crash events, the model can assist policymakers in identifying periods of elevated financial risk.

VII. CONCLUSION

This study develops a regime-switching logistic regression framework for predicting stock market crash events in the Indian equity market. By integrating logistic regression with a hidden Markov process, the model captures regime-dependent dynamics in financial markets.

Using daily financial data from 2010 to 2019, the empirical analysis demonstrates that global financial indicators such as the VIX index and exchange rate movements significantly influence crash probabilities.

The regime-switching model significantly improves predictive performance relative to conventional logistic regression models. These results highlight the importance of nonlinear dynamics and international financial spillovers in explaining extreme movements in emerging market equities.

Future research may extend this framework by incorporating additional global financial variables or exploring alternative nonlinear modeling approaches.

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