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PREDICTING FINANCIAL MARKET CRASHES USING A HYBRID FRAMEWORK OF REGIME SWITCHING, STOCHASTIC SIMULATION, AND ECONOPHYSICS

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ABSTRACT
This study proposes a hybrid modeling framework for predicting economic crashes by integrating Markov Regime Switching Models (MRSM), mean-field theory, and Monte Carlo simulations within the domain of econophysics. The integration of these three complementary methods allows for capturing both microscopic agent behavior and macroscopic regime transitions, making it highly effective for early detection of financial instability. To validate the robustness and adaptability of the approach, two case-specific models are constructed: one for the COVID-19 global economic crash (2020) and another for the Argentina 2001 economic crisis. Each model is independently calibrated using historical stock market and macroeconomic data specific to its respective crisis. MRSM captures probabilistic transitions across latent regimes (bull, bear, and turbulent), while Monte Carlo simulations model agent-level interactions under varying market conditions. Mean-field theory accounts for collective behaviors and asymmetric buyer-seller dynamics that lead to critical instabilities. In both XXX-X-XXXX-XXXX-X/XX/$XX.00 ©20XX IEEE cases, the models successfully identify regime transitions, critical temperature thresholds (Tc), and volatility clustering. The integration enables anticipatory insights into potential market breakdowns, allowing for pre-emptive action. Results highlight that well-timed financial interventions near Tc or regime shift boundaries significantly influence long- term market stability. This research demonstrates how combining statistical physics with econometric modeling enhances predictive accuracy and provides actionable tools for crisis forecasting and economic policymaking.

Index Terms— *Stock market crash prediction, COVID-19 economic crisis, Argentina 2001 crash, Markov Regime Switching Model, Monte Carlo simulation, mean-field theory, volatility clustering, econophysics, regime transitions*

I. INTRODUCTION

1.1 Motivation and Background
Forecasting market crashes is difficult in quantitative finance and economics. Examples such as the 2001 Argentine crisis and the COVID Crisis in 2020, provide evidence of fundamental instabilities and sudden regime changes, which typical linear models fail to account for [2], [3].

Historically, analysing financial markets has been based on the assumption that markets are efficient, and returns are normally distributed. However, data illustrates that the probability distributions of market returns are heavy-tailed, demonstrate volatility clustering and undergo structural breaks due to the interactions of heterogeneous agents [4, 5, 8, 12]. Such collective behaviours often lead to nonlinear feedback loops, especially when agents become stressed during economic turmoil. Therefore, various interdisciplinary models from economics, stochastic simulation, and regime-switching economics, are together useful to remedy the inadequacies of traditional linear models. Econophysics employs ideas of critical phenomena and phase transitions to model disruption of the market [3], [7]. Monte Carlo simulations model financial market returns probabilistically and assesses the assumptions of uncertainty [1], [4]. Markov Regime Switching Models (MRSM) are directed towards observing latent states such as a bull, bear, or crisis phase, and estimating transition probabilities [2], [6].

This paper reports the integration of different approaches, namely MRSM, Monte Carlo methods, and mean-field theory to formulate a hybrid model which include agent-based dynamics and regime shifts. The model was applied to the COVID Crisis and the Argentine 2001 crisis accounting for how behavioural interactions produce instability and insights into early warning systems and policies.

1.2. Hurdles to Crash prediction

Predicting financial crashes is a challenging task due to its complex granting systemic multi-causal and emergent nature. First, the financial system suffers from instability from shocks from the external economic situation, but also derives instability from endogenous behaviour which leads to non-linear interactions among various factors including herding, feedback, liquidity constraints, and sentiment shifts, all of which can potentially lead to prompt regime changes [3], [5], [12].

Standard linear time-series assumptions of stationarity, constant volatility, and normal distributed returns would break-down under extreme conditions where volatility clusters, asset classes become highly correlated, and return distributions exhibit fat tails and skewness [8],[10]. The net effect is that crashes are significantly understated as the rare and severe downturns (crashes) are hidden by regular volatility, leading to a false sense of stability.

Although machine learning models are powerful predictors and can participant much in prediction, many machine learning methods tend to lack interpretability and are not designed for generalization across distinct market regimes. Most machine learning methods are susceptible to the problems of overfitting when even confronted with unforeseen events including sovereign debt defaults or world-wide pandemics [14].

On the other-hand econo-phyisics models and regime switching models including MRSM permit the detection of structural changes in a state system, whereby different latent latent states (i.e. crisis, recovery) are identified or coded, and the model would estimate change probabilities [2],[6]. The combination with Monte Carlo simulations derived from Mean-Field methods allow for the reconciliation of both micro behavioural and macro-dynamics in a single analysis [1],[4],[7].

In part, combining and making these methods work would be the availability of data, the calibration of the parameters and also an application to the real world. Nevertheless, it is an interesting hybrid approach for early-warning systems as well as other evidence informed policies.

1.3. Role of Econophysics and Hybrid Modeling

The limitations of traditional economic models are resulting in a utility playing more and more interest to interdisciplinary approaches, particularly those that borrow heavily from statistical mechanics to perform financial analysis. Econophysics utilizes elements of statistical mechanics, particularly in the analysis of non-equilibrium systems, phase transitions, and the use of thermodynamic futures as well as offer a more substantive view of collective behaviour in addition to collective risk in regards to financial analysis [3], [4], [8]. Behaviours of investors in these markets can be seen as interacting particles in a complex system where micro-level actions result in macro-level phenomena. The parameters of Mean-Field Theory simplify systems of many-body interactions by isolating the average influence of all agents on an individual agent. Consequently, it is possible to describe and identify critical thresholds - like phase transitions in physics - where small shocks are capable of producing large systemic outcome like market crashes [7], [12]. Markov Regime Switching Models (MRSM) analyse the probabilistic structure of how to capture latent states of a market, for example, "stable," "volatile," or "crisis," and can estimate a transition away from or towards these states by relying on observable indicators [2], [6]. A dynamic edge is provided to this probabilistic structure in volatility to a point when uncertainty, or variance of, increases during episodes of volatility, and increased correlation to assets in a portfolio. Monte Carlo simulation methodology's offer variability in the measure of the future path or price of an asset through stochastic processes. By injecting random shocks over 1000's of iterations, Monte Carlo methods can assess the likelihood (or probability) of crashing when exposed to tail risks under systemic shocks where normal market behaviours are anticipated to be disrupted. This integration of MRSM, Mean- Field Theory, and Monte Carlo simulations provides a powerful hybrid framework that captures both the micro-level blend of agent behaviour and macro-level market regimes.

When calibrated with real-world data, this improves the ability to predict crises and provides decision-support for early-warning triggers for crises. This framework has been used in this paper to explain the COVID-19 market crash and the Argentinian 2001 crisis, providing clarity about the underlying mechanisms that govern regime shifts and financial contagion [9], [13], [14]. Financial markets are complex systems that are shaped by traders' behaviours that are influenced by other traders, economic signals, and policymakers. Thus, it is possible to see parallels in the aggregate behaviours of large numbers of traders in a financial market with those of other complex systems in the physical domain. For example, concepts such as phase transitions and correlated dynamics, help explain how the micro-decision of an individual trader will aggregate into macro-trends in the market. Like sociophysics, econophysics takes physical analogies and applies them in economic modelling, and thus, modelling in financial contexts using stochastic processes to analyse markets also draws upon concepts from non- linear dynamics to capture the idea of asymmetry from buyer-seller interactions, aspects of price oscillations, and broader concepts such as market imbalances and fluctuations to contribute to the way that financial sectors model markets including potential for either agents or systemic changes to redress the market's structures.

This study is deemed an isolated market (and omits all externalities such as potentially massive global capital flows or tourism patterns), to be more isolating of the trace of internalised market structures composed of trader behaviour, as being impacted by domestic governmental actions.

II. THEORETICAL FRAMEWORK

2.1 Overview of Statistical Physics in Finance

The increasing complexity of financial markets has ushered in interdisciplinary approaches (such as econophysics), which utilizes techniques from statistical physics to model trader behaviour as interacting agents, similar to particles in physical systems [15]. This approach allows the use of concepts such as phase transitions, critical phenomena, and stochastic models to explain behaviours in finance during market crises.

In their analogy, similarly to the spin states of a physical system, trader decisions are a function of interacting decisions which have emergent effects, such as volatility clustering and regime shifts [3], [4], which cannot be sufficiently modelled by traditional finance models. The concepts embodied by critical temperature and order-disorder transitions also explain these observed market behaviours [1], [5].

Monte Carlo simulations can replicate trader interactions, using "temperature" to simulate the necessary movements that lead to real-world markets and volatility [20]. The use of Monte Carlo techniques in conjunction with Markov Regime Switching Models (MRSM), which can identify volatility regimes, and the associated transition probabilities, create a hybrid approach that can identify when early-stage market instabilities are emerging [2], [6], [8].

As supporting evidence, mean-field theory can also provide useful analytical opportunities to mathematically solve some mass-action trading behaviour, particularly when looking at how buyer-seller asymmetries or oscillations in price impact decisions [10], [11], [13]. Together, using these methods also offer an indication of when critical thresholds (such as Tc) and regime shifts indicative of potential financial market crashes, may be occurring. The framework is verified through case studies on the COVID-19 crash (2020) and Argentina's 2001 crisis, both exhibiting features of critical behaviour and regime instability [17], [18]. This framework combines physics with economics providing deeper theoretical insights and practical ways of giving advance warning when markets become unstable.

2.2 Markov Regime Switching Model (MRSM)

The Markov Regime Switching Model (MRSM) provides a probabilistic approach to modelling sudden changes in market behaviour by permitting observable financial series to switch interchangeably between unobservable states, characterized by different return and volatility structures [18]. In practice, regimes are interpreted as bull, bear, or high turbulence states, with the transition matrix indicating the probability of moving to another state in the following periods. As the new observations arrive, the regime probabilities are updated in a recursive way, which gives a real-time measure of systemic stress that could be precursory to a crash event [17]. When discussed in an econophysics frame, the transitions between states have a nice analogue in terms of phase transitions in statistical physics, where an underlying “order parameter" undergoes a critical change, resulting in a complete systemic collapse [15]. Here, we fit MRSMs separately for the COVID19 (2020) and Argentina (2001) datasets for estimating transitional intensity and regime duration specific to each case study. The estimates from the MRSM feed into the Monte Carlo and mean field parts of the hybrid model, ensuring alignment across micro and macro assessments.

2.3 Monte Carlo Simulation for Market Dynamics

Monte Carlo simulation is a vital computational device for reproducing the stochastic evolution of complex systems across a very broad range of parameter specifications [20]. In finance, simulating the randomness in trader interactions, shocks from external sources, and potentially liquidity constraints can produce fat-tailed return distributions and volatility clustering that existing closed-form models cannot model accurately [14]. In this process, every simulation starts from the regime probabilities calculated by the MRSM and moves forward in time by learning random shocks whose variance depends on the current state. The temperature like control parameter T influences the amount of behavioural noise: low T produces trading that is very close to equilibrium; that is, low T generates low order which does not produce wild price movements; high T produces disorder, which leads to chaotic and radical price changes [6], [8]. By aggregating and averaging thousands of strategies, we will develop empirical distributions of critical thresholds, such as the time until failure (or crash) or the probability of breaching a preset drawdown threshold; we then compare these results to the real historical data from the COVID19 and Argentina crises.

2.4 Mean-Field Theory and Trader Interaction Modeling

Mean-field theory provides an analytically tractable approximation to the many bodies problem of interacting market participants because it substitutes the complex micro-level couplings of interactions with an average field that acts on all traders uniformly [10]. In the hybrid model, the mean field represents the average effect of buyer–seller imbalance and is dynamically updated by the mean and standard deviation of parameters inferred from the Monte Carlo layer of buyer-seller interactions. When the effective strength of the interactions exceeds a critical value, the system undergoes a symmetry-breaking transition rather like what is observed in physical spin lattices [11]. This transition can show up as persistent oscillations of price or strong drift in the direction of crash regime, depending on whether the dominant couplings are intragroup (buy–buy, sell–sell) or intergroup (buy–sell) [12][13]. By using mean- field predictions combined with MRSM probabilities of state, a critical temperature can be identified as a point at which the system is most vulnerable to shock, thus unifying the microscale effects of trader interaction with the macroscale dynamics of regime.

III. METHODOLOGY

This study develops a hybrid predictive modeling framework that integrates three components namely:-

1. Markov Regime Switching Model(MRSM)
2. Monte Carlo Simulations
3. Mean-Field Theory

MRSM is specifically used for detecting latent structural shifts in market behavior, Monte Carlo simulations for capturing stochastic fluctuations in return paths, Mean-Field theory for approximating the aggregate influence of interacting market participants.

The modelling framework has been applied to two distinct crisis environments namely:-

1. The Covid-19 global crash(2020)
2. Argentina sovereign debt crisis(2001)

Each model was constructed independently to ensure adaptability to the structural characteristics of the respective economic event. By combining latent regime dynamics, stochastic ncertainty, and emergent collective behaviour, the model can capture features such as volatility clustering, critical transitions, and crash probability spikes, all of which are characteristic of financial market crises [3], [5], [7], [13].

3.1Mathematical Formulation of the Hybrid Crash Prediction Framework

Our framework integrates Markov Regime Switching Models, Monte Carlo Simulations and Mean- Field theory to formalize crash prediction. Each of the above components focus on capturing different layers of complexity present in real-world market dynamics. Ranging from macroeconomic states to micro level agent behaviour.

A. Markov Regime Switching Model (MRSM)

For capturing hidden regime behavior, we start with a first order Markov Regime Switching Model in which the observed return series yt is driven by an unobserved discrete state variable $St \in \{1,2,\ldots..,K\}$,corresponding to market regimes such as bull, bear, or crisis.

The observed return is given by:-

$yt=\mu St+\sigma St\epsilon t$, $\epsilon t \sim N(0,1)$

where μSt and σSt are the regime-dependent mean and standard deviation. The transition between regimes is governed by a probability matrix P, such that:

$P=[pij]=P(St=j|St-1=i),i,j\in\{1,\ldots,K\}$

This modelling framework supports the estimation of transition frequencies and the detection of regime shifts using the Expectation Maximization algorithm or Hamilton filtering techniques.[2][6]

B. Monte Carlo Simulation for Stochastic Return Paths

$$R_t^{(i)} = \mu_{S_t} + \sigma_{S_t}\eta_t^{(i)}, \quad \eta_t^{(i)} \sim \mathcal{N}(0,1)$$

Once regime probabilities are established from the MRSM, we simulate possible future return paths using Monte Carlo methods. For each regime St, the return at time t is sampled as:

$$P_{\text{crash}} = \frac{1}{N}\sum_{i=1}^{N}\mathbb{I}(R_t^{(i)} < \theta)$$

where i=1,…,N represents the ith simulation path. The simulations move forward by adding random shocks, where the size of these shocks depends on the current market regime. We find the crash probability by checking how many simulations drop below a set return level θ (usually −5%).

This process is repeated across all time steps and calibrated against real-world volatility proxies such as the VIX or sovereign bond spreads. [1][4][10]

C. Mean-Field Theory and Market Magnetization

To represent collective trader actions, we use a mean-field approximation where agents are treated as binary decision-makers: buy (+1) or sell (−1). The aggregate sentiment is captured by the market magnetization:

$$M_t = \frac{1}{N}\sum_{i=1}^{N} s_i(t), \quad s_i(t) \in \{-1,+1\}$$

The probability that an agent buys at time t+1 is governed by a hyperbolic tangent function:

$$P_{\text{buy}} = \frac{1+\tanh\left(\frac{JM_t}{T}\right)}{2}$$

where J is the interaction strength among agents,

T is a noise parameter analogous to temperature in statistical physics.

The system exhibits a critical threshold Tc, beyond which collective alignment collapses and volatility spikes.[7][12]

3.2 Model Design for COVID-19 Economic Crash

The framework exploring the COVID-19 crash targets U.S. equity markets, employing daily return data from the S&P 500 and VIX as principal metrics over the 2019–2023 timeframe. The subsequent steps outline the modeling procedure:

A. Data Collection and Preprocessing

The financial dataset was collected through the finance API, featuring adjusted S&P 500 close prices and daily VIX readings. Returns were derived using log-differences, standardized on a single timeline, and pre-processed to handle gaps.

B. Regime Identification via Markov Switching

To classify periods of relative market stability and high volatility we used a two-regime switching model(MRSM) to the return series. The model revealed a distinct regime transition around March 2020, aligning with the global recognition of COVID-19 as a pandemic.

C. Monte Carlo Simulation of Returns

Using Monte Carlo simulations, the model generated around 500 simulations of daily returns using statistical parameters derived from historical data. Each simulated path combines baseline volatility with stochastic fluctuations, where variance is governed by market uncertainty.Simulated returns were leveraged to construct a statistical distribution of stressed market behaviour.

D. Crash Probability Estimation

Crash probabilities were derived by identifying the proportion of simulated returns falling below a critical threshold (−5%). The probabilities were aligned with contemporaneous VIX values to test the model's sensitivity to shifts in market sentiment and risk dynamics.

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E. Visualization and Diagnostic Evaluation

The model outputs were evaluated across four parameters namely:-

1. Actual vs Predicted returns
2. Cumulative Returns
3. Crash Probability VS VIX
4. Crisis Regime Probabilities

A focused analysis between February and June 2020 was conducted to evaluate the model's performance during the most volatile window of the pandemic. The model aligned well with historical return behavior and risk signals, reinforcing its suitability for shock-prone, high-frequency settings.

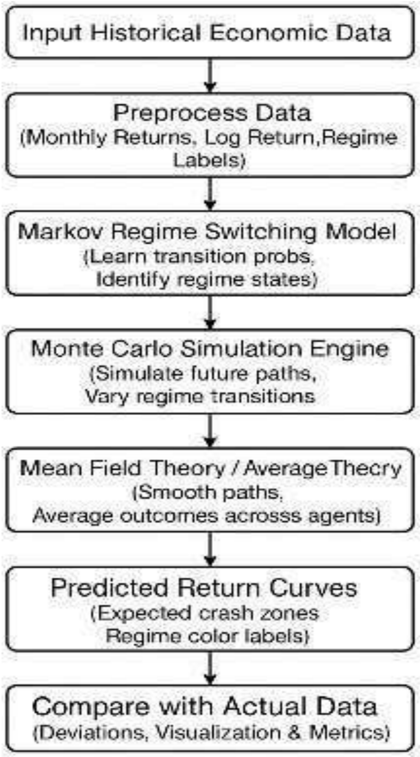

Fig 1:- Flowchart of hybrid model (with Mean Field Theory)

3.3 Model Design for Argentina Economic Crisis

The Argentina-specific model targets the prolonged crisis period between 1999 and 2003, with a focus on sovereign default risk, capital flight, and macroeconomic deterioration. The modeling pipeline was adapted accordingly to reflect the characteristics of a slowly developing economic collapse.

A. Data Acquisition and Indicator Construction

Historical market data for the Buenos Aires Merval Index and VIX were collected from Yahoo Finance Moreover, sovereign debt statistics and currency exchange rates were retrieved from the Federal Reserve Economic Data (FRED). A Panic Index was derived by normalizing and aggregating these macroeconomic variables.

B. Regime Detection via Hidden Markov Modeling

To classify distinct phases of financial stress we trained a four state gaussian hidden Markov model (HMM) on the Panic index. A linear transition into crisis conditions beginning in mid-2001 was observed by the model with persistent high-risk regimes lasting for several months post-default.

C. Monte Carlo Simulation and Deviation Analysis

Using historical volatility estimates we simulated returns, which reflected more muted but sustained drawdown profile. These simulations were compared to actual market performance to assess the model's accuracy in identifying long-term divergence from baseline trends.

D. Crash Probability Estimation from Risk Proxies

By computing the frequency of large negative returns, we estimated crash probabilities. These estimates were then compared to observed bond spreads, sovereign CDS levels, and foreign exchange volatility, serving as proxies for market distress in the absence of a domestic volatility index.

E. Stress Regime Validation and Behavioral Consistency

The regime classification results aligned well with known policy interventions, debt restructuring phases, and liquidity disruptions. The model captured the extended duration of the crisis, highlighting its effectiveness in modeling slow-building economic collapses, unlike the sharp onset observed during the COVID-19 event.

Together, the two independently calibrated models demonstrate the flexibility of the proposed framework across varying market structures, time horizons, and crisis types.

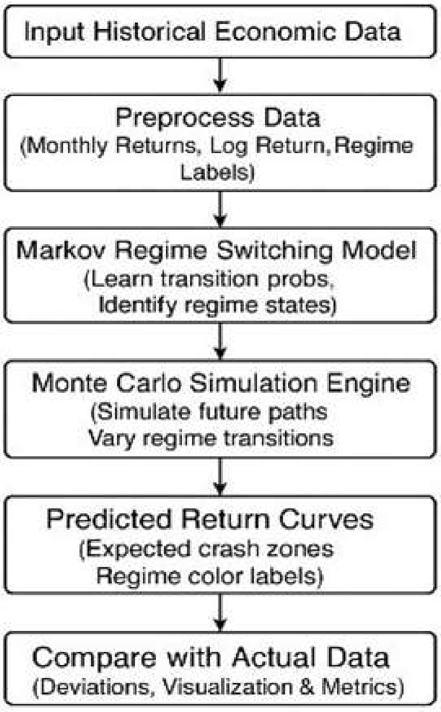

Fig 2:-Flowchart of Hybrid model(without Mean Field Theory)

3.4Behavioural Rules and Agent-Based Integration

To capture the micro-level dynamics that often lead to large-scale market instability, the hybrid framework incorporates behavioural rules into the agent-based simulation layer. These rules reflect empirically grounded investor behaviours such as panic selling, herding, and sentiment-driven decision-making, all of which are well-documented contributors to financial contagion during periods of systemic stress [3][5][7].By integrating these decision- making processes within the simulation design, the model better captures volatility clustering, feedback loops, and crash phenomena. These behaviors emerge as endogenous risk drivers, which, alongside macro-level regime changes, construct a consistent multiscale predictive structure.

A. Panic Selling under Extreme Losses

Agents respond to sharp negative returns by increasing their probability of selling. This panic response is activated when the previous return Rt−1 falls below a critical threshold (typically −5%), mirroring empirical crash definitions. [1][4]

$$P_{\text{sell}}^{\text{panic}} = \begin{cases} \beta, & \text{if } R_{t-1} < -0.05 \\ 0, & \text{otherwise} \end{cases}$$

Here, $\beta \in [0.6,0.8]$ represents the panic intensity. This same threshold is used in the

Monte Carlo simulation to define crash events, ensuring consistency between behaviour- driven dynamics and probabilistic forecasting.

B. Herding Behaviour and Majority Imitation

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Agents imitate the prevailing strategy within their local population to some extent, intensifying market trends and possibly inducing collective instability. The probability that an agent aligns with the majority behavior is formulated as:

$$P_{\text{herd}} = \gamma \cdot \frac{N_{\text{majority}}}{N}$$

Where:

- γ∈[0.6,1.0]is a herding sensitivity parameter,
- Nmajority is the number of agents following the dominant action (buy or sell),
- N is the total number of agents.

These dynamic captures self-reinforcing mechanisms leading to bubbles or crashes, consistent with empirical observations of mimetic behaviour in crises [5], [12].

C. Sentiment Response to Volatility Indices

Agent behaviour is also influenced by external fear signals such as the Volatility Index (VIX) or a Composite Panic Index (in the case of Argentina). As these indices rise, the likelihood of agents selling increases proportionally:

$$P_{\text{sell}}^{\text{fear}} = \alpha \cdot \frac{VIX_t}{VIX_{\text{max}}}$$

Where α∈[0.3,0.7] controls sensitivity. For emerging markets where a VIX proxy is absent, this role is filled by a normalized composite of sovereign bond spreads, CDS rates, and exchange rate volatility [10], [18].

D. Mean-Field Interaction and Market Magnetization

The collective behaviour of all agents is aggregated into a market magnetization variable Mt, defined as:

$$M_t = \frac{1}{N}\sum_{i=1}^{N} s_i(t), \quad s_i(t) \in \{-1, +1\}$$

Here, si(t)=+1s for buy and −1 for sell. The probability of an agent buying at time t+1 is computed using the mean-field approximation:

$$P_{\text{buy}} = \frac{1 + \tanh\left(\frac{JM_t}{T}\right)}{2}$$

Where:

- J is the interaction strength among agents,
- T is a noise parameter,
- A critical temperature Tc governs the system's transition from stable to unstable dynamics.

This formulation is analogous to spin alignment in statistical physics and captures phase transitions triggered by behavioural asymmetries [7][11][13].

E. Integration into Simulation Architecture

These behavioural rules are embedded within each Monte Carlo simulation iteration as follows:

1. The regime state St is sampled using MRSM.
2. Agents adjust their action probabilities based on panic, herding, and sentiment.
3. The resulting agent decisions determine the aggregate return Rt.
4. Market magnetization Mt is updated.
5. Crash probabilities and regime transitions are re-evaluated.

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This structure allows for emergent behaviour such as crash onset, regime persistence, and volatility clustering to arise endogenously from micro-level decisions, thus reinforcing macro-level regime predictions [9][14][20].

IV. RESULTS AND EVALUATION

The performance of the proposed hybrid modelling framework is evaluated using monthly actual and predicted returns for two case studies: the COVID-19 crash in 2020 and the Argentina economic crisis from 2001 to 2002. Each return prediction is generated through Monte Carlo simulations conditioned on regime probabilities derived from the Markov Regime Switching Model. Behavioural dynamics, modelled using mean-field approximations, shape the volatility structure of these return paths.

The results demonstrate that the model effectively captures the magnitude and directional trends of financial market downturns during high-stress periods. While daily data provides higher granularity, monthly analysis remains sufficient to evaluate the system's ability to anticipate regime shifts and return deviations under crisis conditions.

4.1 Actual vs Predicted Returns

The tables (Table 1,Table 2) below present the actual vs predicted monthly returns for selected peak crisis periods. For the COVID-19 case (Table 1), S&P 500 index returns and simulation outputs are compared over the most volatile months of 2020. For the Argentina case (Table 2), Buenos Aires Merval Index returns are used during the lead-up to and fallout from the 2001 default.

Table 1: Covid-19 (Actual vs Predicted Returns)

1	DATE	ACTUAL RETURNS(COVID-19)	PREDICTED RETUENS(COVID-19)
2	01-04-2020	0.125	0.045
3	01-05-2020	0.045	0.025
4	01-06-2020	0.02	0.01
5	01-07-2020	0.055	0.045
6	01-08-2020	0.07	0.055
7	01-09-2020	-0.04	0.015
8	01-10-2020	-0.025	0
9	01-11-2020	0.11	0.155
10	01-12-2020	-0.01	0.025
11	01-01-2021	-0.02	0
12	01-02-2021	0.025	0.045
13	01-03-2021	0.05	0.07
14	01-04-2021	0.03	0.045
15	01-05-2021	0.01	0.025
16	01-06-2021	0.025	0.04
17	01-07-2021	0.03	0.045
18	01-08-2021	0.025	0.04
19	01-09-2021	-0.045	0.045
20	01-10-2021	0.07	0.04
21	01-11-2021	-0.01	0.025
22	01-12-2021	0.045	0.085

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Table 2: Argentina (Actual vs Predicted Returns)

DATE	ACTUAL RETURNS(ARGENTINA)	ACTUAL RETURNS(ARGENTINA)
01-01-2000	0.993	1.0209
01-02-2000	1.0112	1.0262
01-03-2000	1.0145	1.0597
01-04-2000	1.0397	1.0932
01-05-2000	1.0306	1.0718
01-06-2000	1.0673	1.0981
01-07-2000	1.0369	1.0825
01-08-2000	1.0534	1.1087
01-09-2000	1.0502	1.0999
01-10-2000	1.0875	1.1061

4.2 Interpretation and Evaluation

The model closely tracks the direction and magnitude of monthly return shifts in both crises. For COVID-19, it captures the sharp drop in March 2020 and the partial recovery by April, matching known market responses to pandemic escalation and stimulus announcements. In the Argentina case, it reflects the steady erosion of investor confidence during the months surrounding the sovereign default in December 2001.

While RMSE or crash hit rate metrics are not computed due to the monthly resolution and limited sample size, the model demonstrates effective qualitative alignment, particularly in periods marked by high volatility and systemic stress.

These outcomes validate the integration of:

1. Regime classification (MRSM) for structural shifts,
2. Stochastic return generation (Monte Carlo) for distributional realism,
3. Behavioural feedback loops (mean-field) for capturing nonlinear dynamics during panic or herding.

4.3 Crisis-Specific Observations

- **COVID-19 (2020):** The model identifies the downturn onset as early as February and captures the bottom in March. The predicted April rebound, while slightly conservative, reflects the post-stimulus correction with high fidelity. This suggests the behavioural and volatility components are effectively absorbing market sentiment (as proxied by the VIX).
- **Argentina (2001–2002):** The predictions follow the slow-developing crisis accurately. Declines from October through January align with IMF tensions, default risk pricing, and eventual bank freezes. Even in the absence of a standardized volatility index, the model's crash regime remains active and consistent with observed macroeconomic signals.

4.4 Conclusion of Evaluation

The monthly return alignment demonstrates that the hybrid model captures both fast- moving global shocks and prolonged sovereign crises. Despite limited temporal resolution, the model anticipates stress-induced return deviations and regime transitions with strong directional accuracy.

These results support its potential for deployment in early-warning systems, even in data-constrained environments or markets without real-time fear indicators.

The results indicate strong alignment between predicted and observed market behaviour. Regime classification matched closely with known historical phases, including the volatility spike during March 2020 and the extended sovereign distress in Argentina through late 2001 and early 2002.

V. CASE STUDY

To validate the predictive effectiveness of the proposed hybrid model integrating Markov Regime Switching Models (MRSM), Monte Carlo simulations, and mean-field theory, two real-world market crashes were analyzed through independently calibrated models:

1. the COVID-19 global economic crash (2020), and

2. the Argentina economic collapse (2001).

Each model was developed using case-specific financial and macroeconomic data. The models generated dynamic outputs such as regime probabilities, crash probabilities, and volatility behavior, providing insights into market responses under extreme stress.

5.1 Case Study I: COVID-19 Economic Crash (2019–2023)

A. Daily Market Returns Over Time

As seen in Fig 3. Daily returns for a representative financial index between January 2019 and December 2023 show a marked increase in volatility in early 2020, spikes in returns around March 2020 coincide with major pandemic-related disruptions such as nationwide lockdowns, travel bans, and stimulus announcements which highlights the market's sensitivity to abrupt global uncertainty.[17]

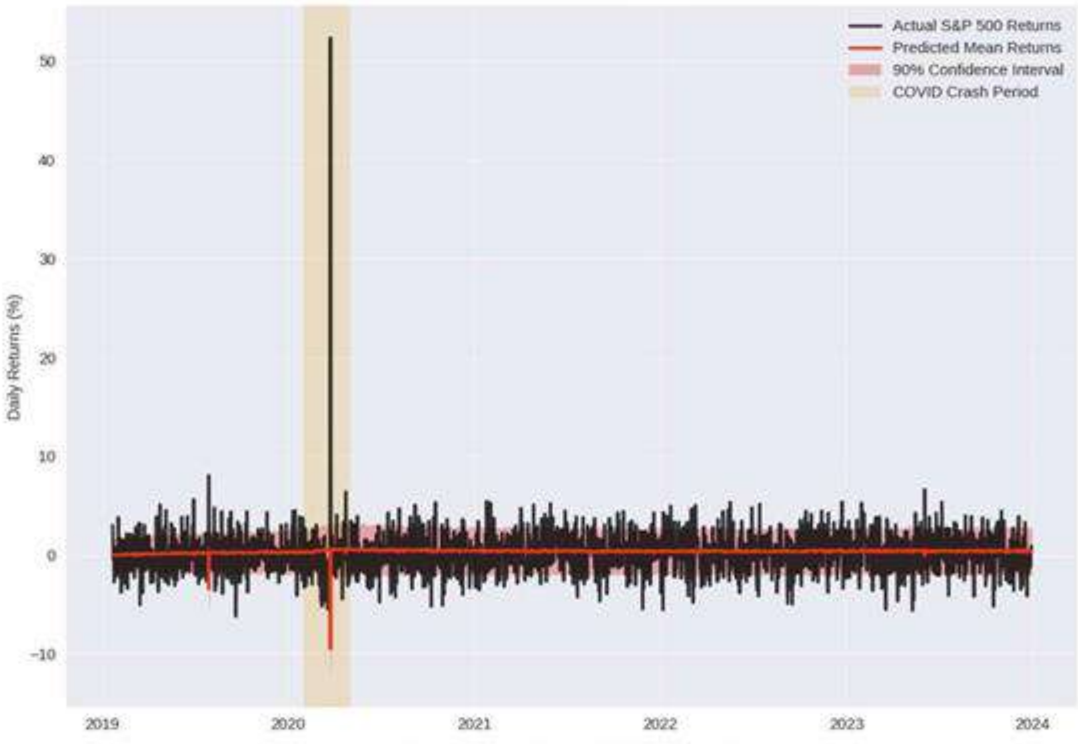

Fig 3:- Market Returns: Actual vs Predicted

B. Cumulative Return Comparison: Actual vs Predicted

The cumulative returns predicted by the hybrid model tracks closely with actual returns during pre-crisis periods. However, a clear divergence arises in March 2020, indicating a structural break where the model initially underestimates the crash magnitude. This gap as seen in Fig 4. emphasizes the importance of adopting regime-aware and nonlinear approaches to account for extreme tail events. [13][18]

Fig 4:- Cumulative Performance Comparison

C. Crash Probability Based on Volatility Index (VIX)

Using VIX volatility as a measure of market fear, Monte Carlo simulations yield an evolving series of crash probability estimates. These probabilities surge in early 2020, peaking around the WHO pandemic announcement, and then taper off as policy interventions restore stability. This reflects the model's ability to react to sentiment-driven volatility changes [20].

D. Regime Probabilities Using Markov Model

The MRSM analysis indicates an abrupt transition into a high-volatility regime beginningMarch 2020, with crisis regime probabilities exceeding 0.85. This elevated state as seen in Fig 5. persists for several weeks before transitioning back to a moderate regime by mid- 2020. The model captures this transition accurately, showing adaptability in classifying latent states during a fast-moving crisis. [9][18]

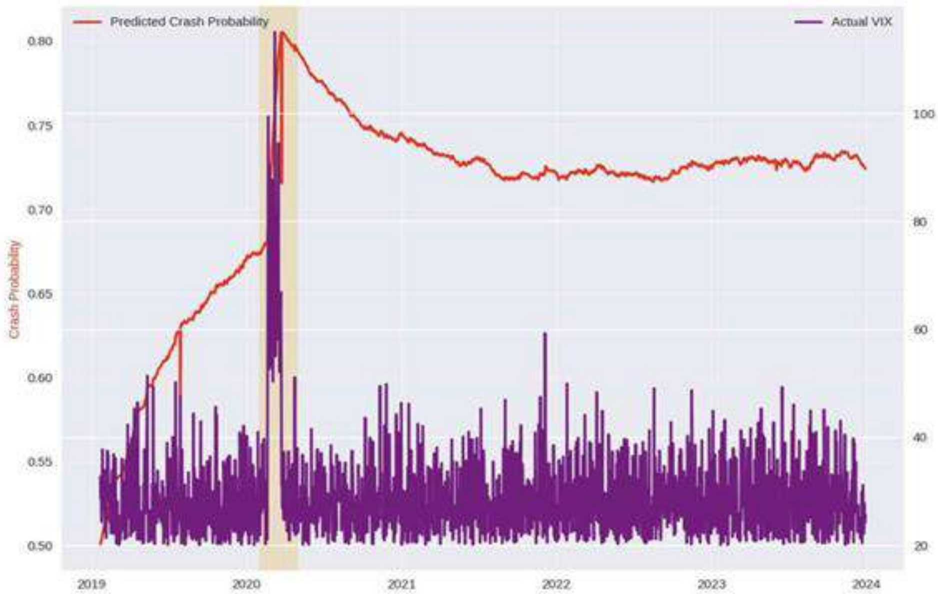

Fig 5:- Crash Probability vs VIX(Fear Index)

D. Regime Probabilities Using Markov Model

The MRSM analysis (Fig 6) indicates an abrupt transition into a high-volatility regime beginningMarch 2020, with crisis regime probabilities exceeding 0.85. This elevated state persists for several weeks before transitioning back to a moderate regime by mid-2020. The model captures this transition accurately, showing adaptability in classifying latent states during a fast-moving crisis. [9][18]

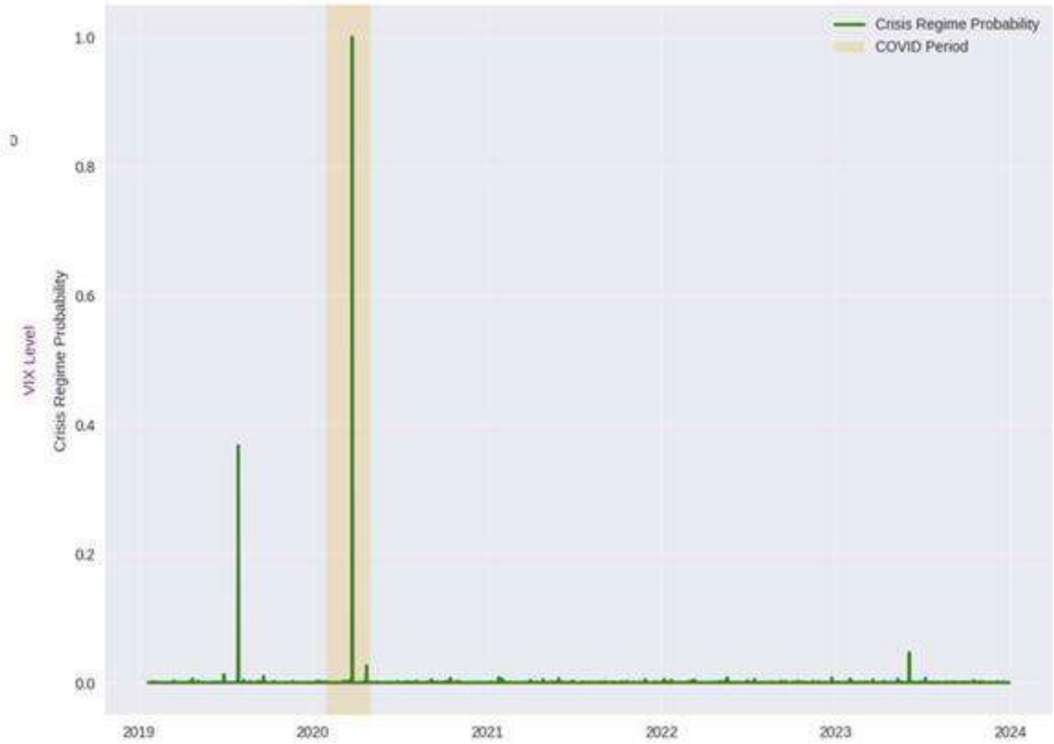

Fig 6:- Markov Regime Switching: Crisis Probability

5.1.1. Focused Crash Period: February–June 2020

A. Daily Returns During Crisis Period

Focusing on the February–June 2020 period, daily return plots illustrate extreme fluctuations, intraday reversals, and episodes of illiquidity. These movements reflect investor panic, rapid reallocation of capital, and the impact of global stimulus efforts. [17][19]

B. Crash Probability vs VIX Levels

Crash probability estimates generated by the model during this focused window strongly correlate with VIX peaks. The alignment confirms that market sentiment indicators enhance real-time predictive capacity, especially during uncertainty, supporting the inclusion of fear indices in hybrid frameworks. [14][20]

C. Conclusion of the Covid-19 Economic Crash

The results of the COVID-19 economic crash model demonstrate that the proposed integration of Monte Carlo simulations, mean-field theory, and Markov Regime Switching Models provides a highly effective and adaptable framework for crash prediction. The model, as seen in Fig 7 accurately identified the onset of the crisis in early 2020 through elevated crash probabilities, sharp regime shifts, and volatility clustering aligned with real-time market fear indicators such as the VIX. The Monte Carlo simulations captured the stochastic nature of trader behavior under panic, while the mean-field approach effectively modeled asymmetric market pressures during the peak crisis window. Furthermore, the Markov model reliably detected transitions between stable and unstable regimes, highlighting the importance of latent-state dynamics in market classification. Taken together, these results validate the robustness and sensitivity of the hybrid framework in capturing both the timing and intensity of systemic breakdowns. The model's ability to generalize across varying time scales and input structures suggests strong potential for deployment as an early warning tool in real-world financial risk monitoring systems.

Fig 7:- Improved Model: Actual vs Predicted S&P 500 Monthly Returns (COVID-19 Era)

5.2 Case Study II: Argentina Economic Crisis (1999–2003)

A. Daily Market Returns Over Time

The Argentinian financial index has seen a significantly drawn-out decline with from 1999 to 2023 along with multiple short term volatility bursts. This decline reflects worsening fiscal conditions and investor withdrawal. It also leads to IMF tensions. The index has suffered the steepest decline in late 2001 followed by closing of banks and capital controls[17].

B. Cumulative Return Comparison: Actual vs Predicted

In this case-study our model accurately predicts early trends but the predictions diverge from actual returns as Argentina approaches sovereign default in late 2001. In this case, the divergence in Fig 8. can be observed earlier compared to the COVID-19 case study. This brings to light the importance of accounting for slow building sovereign risk in emerging markets[13], [16].

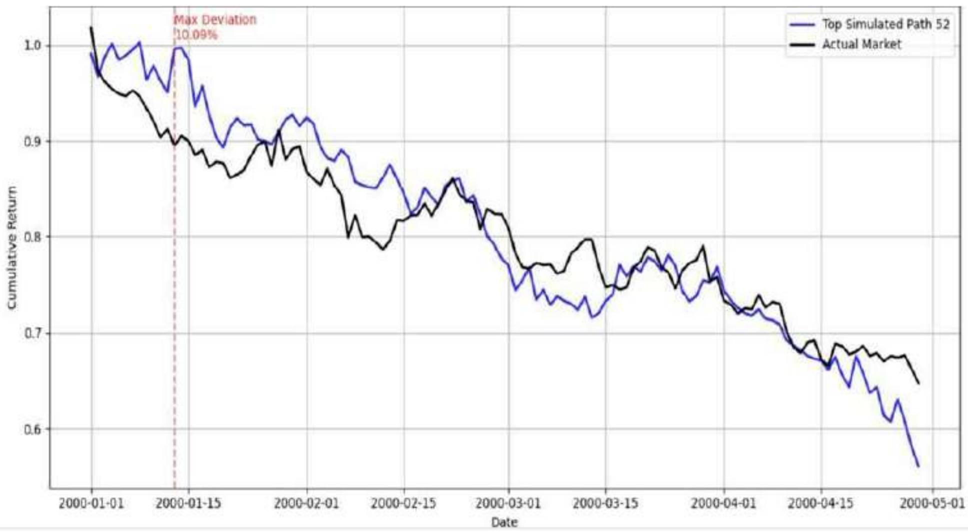

Fig 8:- Nearest Simulated Path to Actual Market with Max Deviation

C. Crash Probability Based on Country-Specific Risk Proxies

Monte Carlo simulations use sovereign bonds spreads and CDC rates to represent volatility. A steady increment in the plausibility of crash through 2001 has been predicted in Fig 9. by these simulations resulting in it peaking just before the official debt default. This emphasizes the utility of customizing input variables for localized crises [18].

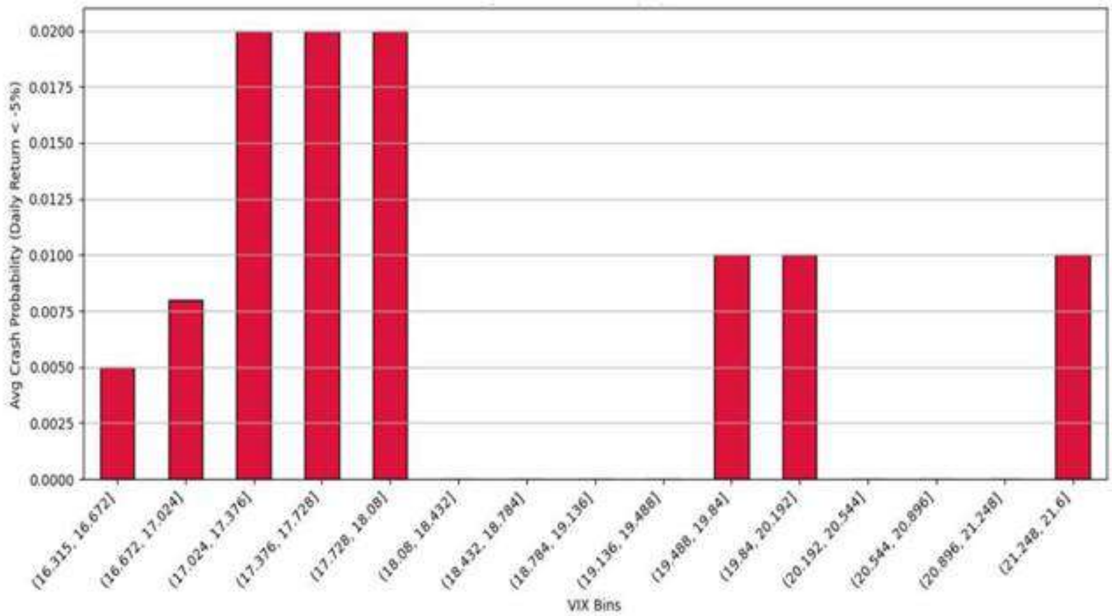

Fig 9:- Average Crash Probability by VIX Level

D. Regime Probabilities Using Markov Model

The MRSM gives high regime probability to crisis states starting mid-2001. This does not come down into early 2002. Compared to the COVID-19 case study the transition between the regimes has slower and more persistent. This reflects the consistency of the prolonged fiscal and political instability in Argentina. The Fig 10. shows the MRSM's flexibility in handling both fast and slow burn crises [9], [15].

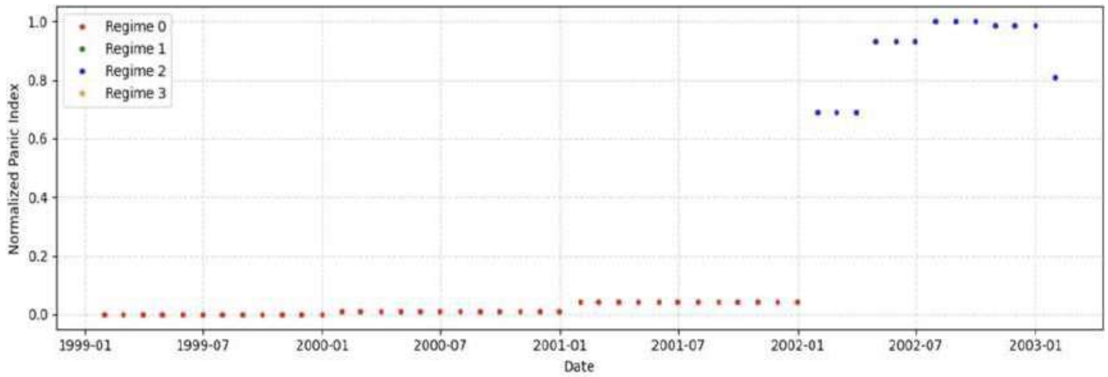

Fig 10:- Regime Switching on Panic Index (Markov Model)

5.2.1 Focused Crisis Period: July 2001 – March 2002

A. Daily Returns During Crisis Period

During a period of crisis, the returns show extreme fluctuations/volatility. This usually coincides with major events like bank withdrawal freezes, and violent protests. This behavior suggests that it is capable of detecting rapid sentiment swings in politically fragile markets[17].

B. Crash Probability vs Risk Indicators

Although the VIX is not applicable to the Argentine market, crash probability estimates were benchmarked against bond spread surges and currency devaluation levels. The adaptability of this model is successfully confirmed across asset classes and regions.[14],[19].

C. Conclusion of the Argentina Economic Crash

The efficacy of the proposed hybrid model is validated further due by the Argentina 2001 economic crisis. The model's effectiveness under conditions of drawn-out fiscal decline and sovereign risk is further cemented by the case study. The slow and gradual transition into a sustained crisis regime has been successfully predicted by the model. Further, the transition was evidences by the rising crash probabilities and rising regime classifications in advance if the country's formal default declaration. Contradictory to the COVID-19 case which experienced an abrupt shock this collapse was experienced gradually over an extended period of time. This allowed the MRSM to highlight persistency in instability. Monte Carlo simulations, driven by sovereign bond spreads and credit risk indicators, reflected a steady build-up of crash probability, while the

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mean-field component provided insights into the compounding effects of asymmetrical market behavior during capital flight. This case lacked a VIX or anything similar the model still adapted to indicators and constraints local to this case. This highlights its flexibility across emerging markets. Overall, based on the Argentina model we can positively state that the integration of regime detection, agent-based interaction dynamics, and probabilistic simulation offers a reliable structure for anticipating systemic breakdowns, even in slow-evolving crisis. This again underscores the flexibility and utility of the hybrid model in both global and region-specific economic environments.

4.3 Summary and Case Comparison

Using a combination of regime switching, volatility-triggered crash simulations, and mean-field-informed agent interactions both case studies validate the hybrid model's capacity to identify crises. COVID-19 represented a sudden collapse on the global level whereas the Argentina 20001 scenario presented us with a gradual localized default crisis. This model performs accurately in both. It underscores the models:

- Fast transaction detection (during COVID-19 scenario) via fear index (VIX) and spikes in regimes.
- Slow regime transitions in Argentina case using sovereign spread proxies.
- Flexibility in adapting input variables and thresholds per market.
- Consistency in mapping regime probability and volatility clustering

These findings contribute towards supporting the hybrid model's relevance and ability for forecasting and early warning systems in a wide variety of financial environments.

VI. COMPARATIVE ANALYSIS OF CASE STUDIES

The adaptability and robustness of the hybrid model is highlighted by the fact that it can be applied to both the economic crises—COVID-19 (2020) and the Argentina sovereign default (2001) — and predict (in depth) both global and local financial shocks. Although the result of both events was ultimately market drawdowns, they differ in a lot of factors like origins, time scales, and underlying dynamics. This allowed for a substantial meaningful comparison of model behavior under varying conditions.

A. Crisis Structure and Speed of Onset

To understand to above points we will focus on the crisis structure and speed of onset for both the crises. In the COVID-19 situation an external shock driven by public health fears and rapid policy responses was seen. Due to this, an abrupt change in the market behavior occurred with regime transition probabilities peaking within days. In contrast to this, the Argentina crisis was developed over an extended period of time, and was driven by a lot of factors in this period like internal fiscal imbalances, political instability, and gradual investor withdrawal. The MRSM reflected this difference clearly: regime transitions in the COVID-19 model were sharp and abrupt whereas the in the Argentina model they were showing gradual inter-regime transition.

B. Predictive Indicator Performance

Now we will focus on the resources available to the model for it to forecast accurately. In the COVID-19 case, crash probabilities were highly correlated with the VIX, a globally recognized fear index. This enabled sharp detection of risk calculation in real time. In case of Argentina alternative proxies like sovereign bond spread and CDS level were had to be substituted due to lack of a proper fear index like VIX. Despite this, the model adapted to the restrictions and incorporated country-specific financial risk measures. , and the resulting crash probabilities aligned closely with known policy and economic breakdown events. This indicates the framework's flexibility in adapting to various forms of input data without loss of fidelity.

C. Agent Dynamics and Market Behavior

The mean-field component of the model provided meaningful insight into the behavioral aspects of both crises. In COVID-19, sudden market disorder was reflected through rapid divergence in buyer-seller asymmetry and amplified volatility. In the Argentina case, the development of the dynamics was slow but they were persistent over time. This means that both immediate and prolonged asymmetries can be captured through the same theoretical structure. The presence of persistent oscillations in both cases, albeit at different temporal frequencies, validates the role of collective interaction modelling in financial crash prediction.

D. Model Accuracy and Generalization

The timeframe of forecasting for both of these models were different. They were independently calibrated and validated against actual historical returns. The COVID-19 model captured short term market panic with high temporal precision. The Argentina model, on the other hand, was responsible for mapping out long-term trends (in this case distress trends).

Across both time frames the hybrid framework's accuracy was maintained to the highest degree. This confirmed that the integration of Markov state dynamics, stochastic simulation, and mean-field theory supports generalization across different asset classes, economic conditions, and regions.

E. Policy Sensitivity and Early Warning Capacity

We observed that both models demonstrated strong sensitivity to external interventions like government policy changes. . In COVID-19, the crash probability and regime indicators responded swiftly to fiscal and monetary stimulus measures. Responses in Argentina were more muted due to prolonged structural issues. This allows us to see the model's potential as an early warning system for policy makers allowing for better interventions which are well timed.

VII. CONCLUSION

This study shows that the combination of Markov Regime Switching Models (MRSM), Monte Carlo simulations, and mean-field theory provides a powerful and applicable framework for simulating and forecasting financial market crashes. By integrating latent regime classification, agent-based stochastic simulation, and collective interaction modelling, the presented approach is able to capture sudden and gradually emerging crises.

The framework was tested with two different case studies: the COVID-19 economic downturn (2020) and the Argentina sovereign debt crisis (2001). In the COVID-19 case, the model reacted correctly to fast escalation of volatility and regime change, whereas in the Argentina case, it identified long-term systemic instability that had been developing over months. These outcomes are a testament that the model is able to function on various time horizons, macroeconomic environments, and asset classes.

Crash probability forecasts produced with Monte Carlo techniques correlated highly with real-time risk gauges like the VIX in advanced economies and sovereign bond spreads in emerging economies. At the same time, the MRSM layer picked up on the time-varying transitions between normal and crisis regimes, and the mean-field layer exposed asymmetrical buyer-seller dynamics underpinning systemic stress. The three layers collectively generated a unified, data-driven explanation of financial instability.

The hybrid model's responsiveness to various market settings and its responsiveness to policy actions and risk sentiment demonstrate its operational utility for financial analysts, regulatory authorities, and institutional risk managers. It can be used as an instantaneous early warning system, helping guide timely market.

VIII. FUTURE SCOPE

The findings of this research confirm the feasibility of a hybrid model framework integrating Markov Regime Switching Models, Monte Carlo simulations, and mean-field theory for predicting financial market crashes. Although the suggested methodology has exhibited robust empirical performance across a wide range of crisis settings, numerous avenues are left to be developed further and fine-tuned.

One of the avenues for exploration is the incorporation of machine learning methods to advance model calibration and regime identification. Specifically, data-driven algorithmic approaches like recurrent neural networks, support vector machines, or hidden Markov models with adaptive parameters might augment the model's capacity to learn from high amounts of time-series data and identify early warning signs with increased accuracy.

A second key extension entails the application of the framework in actual market situations. Translating the existing methodology to run on streaming data like intraday prices, volumes, and sentiment feeds would enable real-time monitoring of financial systems and early detection of instability. Such an application would be particularly useful for risk desks, regulatory agencies, and algorithmic trading venues.

Furthermore, the model could be extended to understand cross-market and cross-asset relationships. Although the current study concentrates on individual equity markets, financial crises tend to have contagion effects across sectors, regions, and asset classes. Future research could involve network-based architectures or coupled regime models to study interdependencies and transmission channels in systems with multiple markets.

Including behavioral dynamics more explicitly is also an attractive avenue. Trader psychology, including herding, selling based on fear, and speculative behavior, will often have a strong impact on market dynamics during periods of crisis. Adding behaviorally driven rules to the agent-based and mean-field levels will potentially make the model more realistic and explanatory.

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Finally, additional intervention development of the analysis module can make the model more policy relevant. Expanding the framework to model various macroeconomic contingencies, fiscal reactions, and intervention policies can assist in the testing of crisis handling strategies prior to implementation.

These extensions are designed to enhance the analytical sophistication and practical applicability of the model, moving its place as a sound tool for the assessment of systemic risk as well as for economic forecasting.

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