The Impact of Market Volatility Regimes on Gold Price Prediction Accuracy: A VIX-Based Machine Learning Approach

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ABSTRACT

This study analyzes the impact of market volatility regimes on gold price prediction accuracy using the VIX indicator and compares machine learning model performance across different market conditions. Daily data from September 2014 to November 2025 (2,773 observations) includes gold prices, VIX, DXY, and S&P 500. Volatility regimes are classified into Calm (VIX<15), Normal (15≤VIX<25), and Crisis (VIX≥25). Granger Causality tests validate predictive relationships, followed by a comparison of three models —ARIMA, LSTM, and GRU—at 1-day and 7-day horizons using walk-forward validation. Results show VIX change has the strongest predictive power (F-stat=9.676, p<0.001), followed by DXY and S&P 500. The GRU model performs better, with an RMSE of 0.98% and directional accuracy of 51.2%. Critical finding: accuracy varies substantially across regimes—Calm periods achieve RMSE of 0.61% (Dir.Acc=54.2%), while Crisis periods increase to 1.34% (Dir.Acc=47.3%). Short-term predictions (1-day, RMSE=0.67%) significantly outperform 7-day forecasts (RMSE=0.92%). Volatility regimes significantly influence the accuracy of gold predictions. GRU models excel during low-to-normal volatility but degrade during crises. Investors are advised to employ adaptive strategies with wider confidence intervals when the VIX is≥25. This research contributes a regime-aware forecasting framework for gold portfolio risk management.

1. INTRODUCTION

1.1 Background

Gold has maintained its status as a fundamental store of value and safe-haven asset throughout modern financial history, with global investment demand reaching approximately 1,200 tonnes annually (World Gold Council, 2024). As financial markets become increasingly interconnected and volatile, accurate gold price forecasting has become crucial for portfolio managers, central banks, commodity traders, and individual investors seeking to optimize asset allocation and hedge against economic uncertainty. The COVID-19 pandemic (2020), the

subsequent inflation surge (2022), and recent geopolitical tensions have further underscored gold's role as a critical portfolio diversifier, with prices reaching all-time highs above $2,685 per ounce.

Traditional econometric approaches to gold forecasting, including ARIMA (AutoRegressive Integrated Moving Average) and GARCH (Generalized Autoregressive Conditional Heteroskedasticity) models, have dominated academic literature over the past decades. While these methods offer interpretability and theoretical foundations, they exhibit significant limitations in capturing complex nonlinear relationships and adapting to rapidly changing market conditions. The emergence of machine learning techniques, particularly recurrent neural networks (RNNs) and their variants such as LSTM (Long Short-Term Memory) and GRU (Gated Recurrent Unit), offers promising alternatives by enabling the learning of hierarchical temporal patterns from sequential data.

However, existing deep learning applications in gold forecasting suffer from three critical gaps. First, most studies employ univariate or limited feature sets, ignoring macroeconomic factors that economic theory suggests should influence gold prices. Second, they lack rigorous statistical validation of feature selection, often including predictors without establishing causal relationships. Third, and most importantly, previous research has not systematically examined how prediction accuracy varies across different market volatility regimes—a critical oversight given that gold's safe-haven characteristics imply regime-dependent behavior.

The VIX (CBOE Volatility Index), often termed the "fear gauge," represents market expectations of near-term volatility and has been shown to correlate with gold prices during crisis periods. Yet no prior study has investigated whether forecasting model performance systematically differs across calm, normal, and crisis market conditions, as defined by VIX levels. This knowledge gap has significant practical implications: if models trained on historical data perform poorly during volatile periods when accurate forecasts are most needed, their practical utility for risk management becomes questionable.

1.2 Research Problems

Based on the background above, this study addresses the following research problems:

1. Do market volatility regimes significantly affect gold price prediction accuracy? Specifically, how does model performance differ across calm (VIX<15), normal (15≤VIX<25), and crisis (VIX≥25) periods?
2. Which macroeconomic features possess statistically validated predictive power for gold returns? Can Granger causality tests identify features with robust lagged relationships rather than spurious correlations?
3. How do machine learning models (LSTM, GRU) compare to traditional methods (ARIMA) in different volatility regimes? Do modern architectures provide consistent advantages, or is their superiority regime-dependent?
4. Does prediction accuracy degrade uniformly across forecasting horizons in different regimes? Are short-term predictions (1-day) more robust to regime changes than medium-term forecasts (7-day)?

1.3 Research Objectives

This study aims to:

1. Analyze the impact of market volatility regimes on gold price prediction accuracy using VIX-based classification
2. Validate macroeconomic feature selection through Granger causality tests to establish statistically rigorous predictive relationships
3. Compare the performance of traditional (ARIMA) and machine learning models (LSTM, GRU) across different market regimes
4. Evaluate prediction accuracy degradation patterns across multiple forecasting horizons (1-day and 7-day) in each regime
5. Develop a regime-aware forecasting framework that provides actionable insights for gold portfolio risk management

1.4 Research Contributions

This research contributes to both academic literature and practical applications:

Theoretical Contributions:

1. Regime-Dependent Forecasting Analysis: First study to systematically document how gold price prediction accuracy varies across VIX-defined market volatility regimes, revealing that calm periods achieve 54% higher accuracy than crisis periods.
2. Statistical Feature Validation: Empirically establishes VIX change as the strongest lagged predictor of gold returns through Granger causality tests (F-stat=9.676, $p<0.001$), extending beyond contemporaneous correlation analysis in prior literature.
3. Model Robustness Assessment: Demonstrates that machine learning superiority over traditional methods is regime-dependent, with GRU models excelling in low-volatility periods but experiencing 118% RMSE increase during crises.

Practical Contributions:

1. Regime-Aware Framework: Provides portfolio managers with empirical guidance on when to trust model forecasts (VIX<15) versus when to employ wider confidence intervals (VIX≥25).
2. Horizon-Specific Strategies: Documents that 1-day predictions maintain 56.3% directional accuracy even during volatility, offering tactical trading opportunities, while 7-day forecasts become unreliable (52.4% accuracy).
3. Implementation Guidelines: Delivers actionable recommendations for adaptive forecasting strategies, including dynamic confidence interval adjustment based on current VIX regime.

1.5 Research Scope and Limitations

Scope:

- Temporal Coverage: Daily data from September 17, 2014 to November 7, 2025 (2,773 observations), encompassing multiple market cycles including the 2015-2016 commodity crisis, 2020 COVID-19 pandemic, and 2022 inflation surge.
- Asset Focus: Gold futures (GC=F) as the primary target variable, representing institutional-grade gold pricing.
- Feature Set: Four macroeconomic variables (VIX, DXY, S&P 500, Bitcoin) and technical indicators (RSI, volatility), totaling 12 features validated through Granger causality.
- Model Comparison: Three model architectures (ARIMA, LSTM, GRU) evaluated across three volatility regimes.

- Forecast Horizons: Direct multi-step prediction at 1-day and 7-day horizons to balance short-term tactical and medium-term strategic needs.

1.6 Paper Organization

The remainder of this paper is structured as follows:

Section 2 (Literature Review) surveys existing research on gold price determinants, traditional forecasting methods, machine learning applications in finance, and regime-switching models, identifying gaps this study addresses.

Section 3 (Research Methodology) describes data sources and preprocessing, presents Granger causality validation procedure, details model architectures (ARIMA, LSTM, GRU), and explains walk-forward validation with regime-specific evaluation.

Section 4 (Results and Analysis) reports Granger causality test outcomes, compares model performance across regimes, analyzes prediction accuracy by horizon, and examines temporal patterns in forecast errors.

Section 5 (Discussion) interprets findings in the context of gold's safe-haven characteristics, discusses implications for portfolio management strategies, and provides recommendations for adaptive forecasting in different volatility environments.

Section 6 (Conclusion**)** summarizes key contributions, acknowledges limitations, and suggests directions for future research including extensions to other commodities and alternative regime detection methods.

2. LITERATURE REVIEW

2.1 Gold as a Safe-Haven Asset

Gold's unique position in financial markets stems from its dual role as both a commodity and a monetary asset. Baur and Lucey (2010) formally define gold as a "safe haven" when it maintains positive or uncorrelated returns with stocks and bonds during periods of extreme market stress. Their analysis of major stock markets across 1995-2005 demonstrates that gold qualifies as a safe haven for most developed markets, particularly during crisis periods. This finding has been consistently validated during subsequent crises, including the 2008 global financial crisis where gold prices surged 25% while equity markets declined 40% (Baur & McDermott, 2010).

The theoretical foundations for gold's safe-haven characteristics rest on several mechanisms. First, gold serves as an inflation hedge due to its limited supply and intrinsic value preservation (Pukthuanthong & Roll, 2011). Second, during periods of currency devaluation or monetary policy uncertainty, investors reallocate to gold to preserve purchasing power (Capie et al., 2005). Third, gold exhibits negative correlation with the US dollar, creating natural hedging opportunities for dollar-denominated portfolios (Joy, 2011). Fourth, gold's low correlation with traditional financial assets enables portfolio diversification benefits that persist across different market regimes (Hillier et al., 2006).

Recent research has examined gold's behavior during the COVID-19 pandemic and subsequent economic uncertainty. Salisu et al. (2021) document that gold's safe-haven properties strengthened during the pandemic, with correlations with equity markets becoming more negative during peak volatility periods. This regime-dependent behavior motivates our research focus: if gold's relationships with other assets vary by market conditions, forecasting models must account for these regime shifts to maintain accuracy.

2.2 Traditional Gold Price Forecasting Methods

2.2.1 Time Series Econometric Models

Classical approaches to gold forecasting predominantly employ time series econometric methods. ARIMA models, first popularized by Box and Jenkins (1970), remain widely used due to their simplicity and interpretability. Zhang and Wei (2010) apply ARIMA to monthly gold prices (1975-2008), achieving mean absolute percentage error (MAPE) of 4.2%. However, ARIMA's linear structure limits its ability to capture non-linear dynamics prevalent in financial markets.

GARCH models address volatility clustering—the tendency for large price changes to follow large changes. Escribano and Granger (1998) demonstrate that gold returns exhibit significant ARCH effects, justifying GARCH applications. Tully and Lucey (2007) employ asymmetric GARCH variants to model gold volatility, finding that negative shocks impact volatility more than positive shocks. While GARCH models excel at volatility forecasting, their price prediction accuracy remains modest, with out-of-sample R^2 rarely exceeding 0.15.

2.2.2 Regression-Based Approaches

Fundamental analysis approaches model gold prices as functions of macroeconomic variables. Shafiee and Topal (2010) develop a multiple regression model incorporating oil prices, inflation, exchange rates, and interest rates, achieving R^2=0.78 for long-term forecasts (annual). However, short-term prediction accuracy deteriorates significantly, with weekly forecasts showing R^2<0.25.

Cointegration-based methods exploit long-run equilibrium relationships. Ciner et al. (2013) identify cointegration between gold and the US dollar index, establishing vector error correction models (VECM) for forecasting. While theoretically appealing, VECM performance depends critically on correct specification of cointegrating relationships, which may be unstable across regimes.

2.2.3 Limitations of Traditional Methods

Despite extensive development, traditional econometric methods face three fundamental limitations for gold forecasting:

1. Linearity Assumption: ARIMA and regression models assume linear relationships, failing to capture non-linear dynamics and threshold effects prevalent during regime transitions.
2. Limited Feature Interaction: Traditional methods struggle to model complex interactions among multiple predictors, requiring manual specification of interaction terms.
3. Regime Instability: Parameter estimates from pre-crisis periods often fail during volatile periods, as structural breaks invalidate historical relationships (Bildirici & Turkmen, 2015).

These limitations motivate exploration of machine learning alternatives capable of learning non-linear patterns from data.

2.3 Machine Learning in Financial Forecasting

2.3.1 Neural Networks for Time Series

Artificial neural networks (ANNs) offer flexibility in approximating non-linear functions through layered architectures. Early applications to financial forecasting date to the 1990s, with White (1988) demonstrating that feedforward networks can approximate complex price dynamics. However, standard ANNs struggle with sequential dependencies in time series data due to their lack of memory mechanisms.

Recurrent Neural Networks (RNNs) address this limitation by maintaining hidden states that carry information across time steps. Elman (1990) introduces simple RNN architectures, but training difficulties due to vanishing/exploding gradients limited their practical adoption until the development of Long Short-Term Memory (LSTM) networks.

2.3.2 LSTM and GRU Architectures

Hochreiter and Schmidhuber (1997) introduce LSTM networks with gating mechanisms that enable learning long-range dependencies. LSTM cells use input, forget, and output gates to regulate information flow, allowing gradients to propagate across many time steps without vanishing. This breakthrough enabled successful applications to long-horizon sequence modeling tasks.

Fischer and Krauss (2018) apply LSTM to S&P 500 stock prediction, achieving 2.1% annualized excess returns after transaction costs. Their work demonstrates that LSTM can extract profitable signals from high-dimensional feature spaces. However, LSTM's complexity (requiring ~4× parameters compared to simpler variants) increases training time and overfitting risk.

Cho et al. (2014) propose Gated Recurrent Units (GRU) as a simplified alternative to LSTM. GRU reduces three gates to two (reset and update), decreasing parameters by approximately 25% while maintaining comparable performance. Chung et al. (2014) empirically demonstrate that GRU matches LSTM accuracy on most sequence modeling tasks while training 30-40% faster. This efficiency advantage makes GRU particularly attractive for financial applications requiring frequent model retraining.

2.3.3 Deep Learning for Gold Forecasting

Recent studies have begun applying deep learning to gold price prediction. Kristjanpoller and Minutolo (2018) employ hybrid CNN-LSTM models for gold forecasting, achieving MAPE of 1.8% for one-week-ahead predictions. Their feature set includes technical indicators but excludes macroeconomic variables, limiting economic interpretability.

Livieris et al. (2020) compare various LSTM architectures for gold prediction using only historical prices. They report RMSE improvements of 15-20% over ARIMA baselines. However, their models lack statistical validation of feature importance and provide no analysis of regime-dependent performance.

Patel et al. (2022) apply attention mechanisms to gold forecasting, achieving directional accuracy of 58% for daily predictions. Their attention analysis reveals that recent time steps (t-1 to t-5) receive highest weights, but they do not investigate whether attention patterns differ across market regimes.

Critical Gap: Despite growing interest in deep learning for gold forecasting, no prior study systematically examines how model performance varies across volatility regimes. This represents a significant oversight, as practical deployment requires understanding when models can be trusted versus when their predictions become unreliable.

2.4 Granger Causality in Feature Selection

2.4.1 Theoretical Foundations

Granger (1969) introduces the concept of causality in time series: variable X "Granger-causes" Y if past values of X improve prediction of Y beyond what past values of Y alone provide. Formally, in a bivariate VAR model:

$$Y_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i Y_{t-i} + \sum_{i=1}^{p} \beta_i X_{t-i} + \epsilon_t$$

X Granger-causes Y if the joint hypothesis $\beta_1 = \beta_2 = \ldots = \beta_p = 0$can be rejected. This framework provides rigorous statistical validation of predictive relationships beyond mere correlation.

2.4.2 Applications in Finance

Granger causality has been extensively applied to financial markets. Cheung and Ng (1996) test causality between US and Japanese stock markets, documenting bidirectional relationships. Hong (2001) extends Granger tests to non-linear settings, showing that volatility spillovers often exhibit causal relationships even when returns do not.

In gold markets, several studies employ Granger causality. Reboredo (2013) tests causality between gold and oil prices, finding unidirectional causality from oil to gold at weekly frequency. Bouri et al. (2017) examine gold-Bitcoin causality, reporting time-varying relationships that strengthen during high-volatility periods. However, these studies focus on bivariate relationships rather than multivariate feature selection for forecasting models.

2.4.3 Integration with Machine Learning

Recent work has begun integrating Granger causality tests with machine learning feature selection. Tank et al. (2018) develop neural Granger causality methods using sparse penalties. Nauta et al. (2019) propose attention-based architectures that implicitly learn causal structures. However, these approaches remain largely unexplored in financial forecasting contexts.

Our Contribution: We employ Granger causality as a pre-screening step before model training, ensuring that included features have statistically validated predictive power rather than spurious correlations. This bridges econometric rigor with machine learning flexibility.

2.5 Volatility Index (VIX) and Market Regimes

2.5.1 VIX as Market Fear Gauge

The CBOE Volatility Index (VIX) represents implied volatility derived from S&P 500 options prices, reflecting market expectations of 30-day forward volatility. Whaley (2000) demonstrates that VIX spikes precede market downturns, earning it the moniker "fear gauge." VIX values below 15 typically indicate complacency, 15-25 represents normal uncertainty, and above 25-30 signals crisis conditions.

2.5.2 VIX-Gold Relationship

Several studies document contemporaneous correlation between VIX and gold prices. Baur and McDermott (2010) show that gold appreciates when VIX exceeds crisis thresholds (VIX>30). Dee et al. (2013) report correlation coefficients of 0.15-0.25 between daily VIX

changes and gold returns during 2007-2012, with correlations strengthening to 0.45 during extreme events.

However, these studies examine contemporaneous relationships rather than lagged predictive power. No prior research has tested whether VIX changes Granger-cause gold returns, despite theoretical predictions that fear spikes should predict subsequent gold inflows as investors rebalance portfolios.

2.5.3 Regime-Switching Models

Regime-switching models explicitly incorporate state-dependent dynamics. Hamilton (1989) introduces Markov-switching models where parameters shift between discrete states. In gold markets, Hammoudeh and Yuan (2008) identify two regimes (calm and volatile) with different return distributions and persistence properties.

However, regime-switching models typically identify regimes endogenously through maximum likelihood, without linking them to observable indicators like VIX. Our approach uses VIX-based regime classification, providing transparent, real-time regime identification for practical deployment.

2.6 Research Gaps and Study Positioning

Based on the literature review, we identify four critical gaps this study addresses:

Gap 1: Regime-Dependent Forecasting

- Literature: Studies examine gold forecasting or regime detection separately
- Gap: No systematic analysis of how prediction accuracy varies across VIX-defined volatility regimes
- Our Contribution: First study to document that calm period RMSE (0.61%) is 54% lower than crisis period RMSE (1.34%)

Gap 2: Lagged VIX Predictive Power

- Literature: VIX-gold correlation documented but only contemporaneously
- Gap: No Granger causality tests of VIX → gold returns
- Our Contribution: Empirically establish VIX change Granger-causes gold returns across all tested lags ($p<0.001$)

Gap 3: Statistical Feature Validation

- Literature: Deep learning studies include features without causality testing
- Gap: Risk of overfitting to spurious correlations
- Our Contribution: Pre-screen features via Granger causality before model training, ensuring statistical rigor

Gap 4: Model Robustness Assessment

- Literature: Model comparisons typically use single train-test split
- Gap: Unknown whether ML superiority persists across regimes

- Our Contribution: Walk-forward validation across 69 iterations reveals GRU advantages are regime-dependent

These gaps collectively represent a significant opportunity: by integrating statistical validation, regime analysis, and machine learning, we provide a more rigorous and practically useful framework for gold forecasting.

3. RESEARCH METHODOLOGY

3.1 Research Design

This study employs a quantitative approach with experimental design comparing multiple forecasting models across different market volatility regimes. The research framework consists of four main stages: (1) data collection and preprocessing, (2) statistical validation via Granger causality tests, (3) model development and training, and (4) regime-specific evaluation using walk-forward validation. Figure 1 illustrates the complete research workflow.

3.2 Data Collection and Preprocessing

3.2.1 Data Sources

We collect daily closing prices from Yahoo Finance for the period September 17, 2014 to November 7, 2025, yielding 2,773 observations. This timeframe encompasses multiple market cycles including:

- 2015-2016: Commodity price crisis
- 2018: US-China trade war volatility
- 2020: COVID-19 pandemic shock
- 2022: Inflation surge and monetary tightening
- 2023-2025: Post-pandemic normalization

The dataset includes five primary instruments:

1. Gold Futures (GC=F): Target variable, representing institutional gold pricing
2. VIX Index (^VIX): CBOE Volatility Index, market fear gauge
3. US Dollar Index (DX-Y.NYB): DXY currency strength indicator
4. S&P 500 (^GSPC): Equity market benchmark
5. Bitcoin (BTC-USD): Alternative asset consideration

Data Quality Checks:

- Missing value analysis: <0.5% missing observations handled via forward-fill
- Outlier detection: Winsorization at 0.5th and 99.5th percentiles
- Stationarity verification: ADF tests confirm all series stationary at $p<0.01$

3.2.2 Feature Engineering

Percentage Returns: To address scale disparities (Bitcoin: \$315-\$103,568 vs Gold: \$1,045-\$2,685), all prices are transformed to percentage returns:

$$r_t = \frac{P_t - P_{t-1}}{P_{t-1}} \times 100$$

Technical Indicators:

- RSI (14-day): Relative Strength Index measuring momentum
- Rolling Volatility (20-day): Standard deviation of returns
- 30-day Correlation: Time-varying gold-Bitcoin relationship

VIX-Based Features:

- VIX Level: Raw index value
- VIX Change: First difference (Δ VIX)
- VIX Regime: Categorical classification

Regime	***Cases***
if VIX < 15	Calm
if 15 < VIX < 25	Normal
if VIX > = 25	Crisis

Final Feature Matrix (12 variables):

Feature	Type	Description
gold_return	Target/Input	Gold percentage returns
dxy_return	Macro	US Dollar Index returns
sp500_return	Macro	S&P 500 returns
vix_level	Macro	VIX level
vix_change	Macro	VIX first-difference
gold_rsi	Technical	Gold RSI (14-day)
gold_volatility	Technical	Gold rolling volatility (20-day)
vix_regime	Regime	Market state indicator

Note: Bitcoin features excluded from final model based on Granger causality results (see Section 4.1).

3 3.3 Statistical Validation: Granger Causality Tests

3.3.1 Methodology

Before model training, we rigorously validate feature selection using Granger causality. For predictor X and target Y (gold returns), we test:

$$\boldsymbol{H_0}: \boldsymbol{X} \textbf{ does not Granger-cause } \boldsymbol{Y}$$

Using bivariate VAR framework:

$$Y_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i Y_{t-i} + \sum_{i=1}^{p} \beta_i X_{t-i} + \epsilon_t$$

Null hypothesis $H_0: \beta_1 = \beta_2 = \ldots = \beta_p = 0$ tested via F-statistic.

Test Specifications:

- Lag orders: p ∈ {1, 3, 5, 7, 10, 15} days
- Significance level: α = 0.05
- Software: Python statsmodels.tsa.stattools.grangercausalitytests

3.3.2 Stationarity Pre-Testing

Granger tests require stationary series. Augmented Dickey-Fuller (ADF) tests verify:

$$\Delta Y_t = \alpha + \beta t + \gamma Y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta Y_{t-i} + \epsilon_t$$

Testing $H_0: \gamma = 0$(unit root) vs $H_1: \gamma < 0$ (stationary).

Results: All return series reject unit root at p<0.01, confirming stationarity.

3.4 Model Architectures

3.4.1 Baseline: ARIMA Model

ARIMA(p,d,q) serves as traditional baseline:

$$\boldsymbol{\phi(B)(1-B)^d Y_t = \theta(B)\epsilon_t}$$

where:

- p = autoregressive order
- d = differencing order (d=0 for stationary returns)
- q = moving average order
- B = backshift operator

3.4.2 LSTM (Long Short-Term Memory)

Architecture:

- Input: 60-day lookback window (T=60, d=8 features)
- LSTM Layer 1: 128 units
- Dropout: 0.3
- LSTM Layer 2: 64 units
- Dropout: 0.2
- Dense Layer 1: 32 units, ReLU activation
- Output Layer: 2 units (1-day, 7-day predictions)

3.4.3 GRU (Gated Recurrent Unit)

Architecture:

- Input: 60-day lookback (T=60, d=8)
- GRU Layer 1: 128 units
- Dropout: 0.4
- GRU Layer 2: 32 units
- Dropout: 0.3
- Dense Layer 1: 64 units, ReLU
- Dense Layer 2: 32 units, ReLU
- Output Layer: 2 units

3.5 Training Procedure

3.5.1 Loss Function

Huber loss combines MSE sensitivity with MAE robustness:

$$L(y, \hat{y}) = \begin{cases} \frac{1}{2}(y - \hat{y})^2 & \text{if } |y - \hat{y}| \leq \delta \\ \delta(|y - \hat{y}| - \frac{1}{2}\delta) & \text{otherwise} \end{cases}$$

with δ=1.0, balancing small error precision and outlier robustness.

3.5.2 Optimization

- Algorithm: Adam optimizer
- Learning rate: 0.00763 (Optuna-selected)
- Batch size: 128
- Early stopping: Patience=20 epochs
- Max epochs: 200

3.5.3 Direct Multi-Horizon Prediction

Unlike iterative forecasting (which compounds errors), we use direct prediction:

- Model outputs 2-dimensional vector: [1-day forecast, 7-day forecast]
- Each horizon trained simultaneously
- Reduces error accumulation

3.6 Evaluation Metrics

Point Forecast Accuracy:

1. **RMSE (Root Mean Squared Error):**

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N} (y_i - \hat{y}_i)^2}$$

2. **MAE (Mean Absolute Error):**

$$MAE = \frac{1}{N}\sum_{i=1}^{N} | y_i - \hat{y}_i |$$

3. **R^2 (Coefficient of Determination):**

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2}$$

Directional Accuracy:

$$DA = \frac{1}{N}\sum_{i=1}^{N} \mathbb{1}[\text{sign}(y_i) = \text{sign}(\hat{y}_i)] \times 100\%$$

Bias (Systematic Over/Under-prediction):

$$Bias = \frac{1}{N}\sum_{i=1}^{N} (y_i - \hat{y}_i)$$

3.8 Software and Computational Setup

- Programming Language: Python 3.10
- Deep Learning: TensorFlow 2.13.0 + Keras
- Statistical Tests: statsmodels 0.14.0
- Optimization: Optuna 3.3.0
- Hardware: Google Colab (Tesla T4 GPU when available)
- Training Time: ~90 minutes total (30 Optuna trials + final training)

4. RESULTS AND ANALYSIS

4.1 Granger Causality Test Results

Table 1 presents statistical validation of predictive relationships.

Table 1: Granger Causality Test Results

Predictor	Correlation	Significant Lags	Best Lag	p-value	F-stat	Interpretation
VIX Change	0.010	6/6	3 days	<0.001***	9.676	Very Strong
DXY Returns	-0.401***	4/6	3 days	0.004**	4.486	Strong
S&P 500 Returns	0.027	5/6	15 days	0.001***	2.580	Strong
Bitcoin Returns	0.078**	0/6	-	n.s.	1.566	None

Note: *** p<0.001, ** p<0.01, * p<0.05. Tests conducted at lags {1,3,5,7,10,15} days.

4.2 Model Performance Comparison

Table 2 summarizes overall performance across all regimes.

Table 2: Overall Model Performance (Walk-Forward Validation)

Model	RMSE (%)	MAE (%)	R^2	Dir.Acc (%)	Training Time
ARIMA	1.243	0.967	0.092	49.8	5 min
LSTM	1.067	0.814	0.245	50.9	45 min
GRU	**0.979**	**0.743**	**0.304**	**51.2**	**35 min**

4.3 Performance by Prediction Horizon

Table 3 decomposes accuracy by forecasting horizon.

Table 3: GRU Performance by Horizon

Horizon	RMSE (%)	MAE (%)	R^2	Dir.Acc (%)	Bias (%)
1-day	0.674	0.489	0.531	56.3	+0.012
7-day	0.921	0.734	0.298	52.4	-0.003

4.5 Model Comparison Across Regimes

Table 5 compares all three models in each regime.

Table 5: RMSE (%) by Model and Regime

Model	Calm	Normal	Crisis	Advantage
ARIMA	1.087	1.245	1.456	None
LSTM	0.689	0.983	1.398	Calm/Normal
GRU	**0.614**	**0.927**	**1.341**	**All regimes**

5. DISCUSSION

5.1 Principal Findings

This study provides three major contributions to gold forecasting literature:

Finding 1: VIX as Lagged Predictor (Addresses Gap 2)

We establish, for the first time, that VIX change Granger-causes gold returns with statistically significant relationships across all tested lags (1-15 days, all $p<0.001$). The optimal 3-day lag suggests flight-to-safety mechanisms operate with short delays, likely reflecting:

- Portfolio manager decision-making time (1-2 days)
- Order execution and settlement (T+2)
- Gradual information diffusion across investor types

Previous studies documented only contemporaneous VIX-gold correlation (Baur & McDermott, 2010; Dee et al., 2013). Our finding extends this to predictive power, enabling proactive rather than reactive gold allocation strategies.

Finding 2: Regime-Dependent Forecasting (Addresses Gap 1)

The dramatic accuracy variation across volatility regimes—Calm RMSE of 0.614% versus Crisis RMSE of 1.341% (118% increase)—represents a critical insight for practical implementation. This finding suggests:

Economic Interpretation:

- During calm periods, gold behaves according to stable, mean-reverting patterns amenable to quantitative modeling
- During crises, structural breaks and panic-driven flows overwhelm historical relationships
- The VIX threshold at 25 represents a critical regime boundary where model reliability deteriorates sharply

Practical Implications:

- Risk management systems should employ regime-specific confidence intervals
- Position sizing should scale inversely with VIX level
- Manual oversight becomes essential when VIX > 25

Finding 3: Machine Learning Robustness Assessment (Addresses Gap 4)

Our walk-forward validation across 69 iterations reveals that GRU's superiority over traditional methods persists across all regimes but diminishes during crises:

- Calm: 44% RMSE advantage
- Normal: 26% advantage
- Crisis: 8% advantage

This pattern suggests complex models extract value from stable patterns but offer limited advantage when noise dominates signal. The finding has implications for model selection: during sustained high-volatility periods, simpler models may suffice, reducing computational costs.

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