GOLD AND BITCOIN AS INFLATION HEDGES: A REGIME-DEPENDENT, DATA-DRIVEN ANALYSIS FOR SINGAPOREAN RETAIL INVESTORS

Company Profile: Lion City FinAI

Lion City FinAI is a fictional financial analytics initiative in Singapore dedicated to improving **inflation awareness, risk interpretation, and decision support** for retail investors through **transparent, data-driven frameworks**. The firm specializes in translating complex macroeconomic signals, market sentiment, and asset behavior into **interpretable insights** that support informed financial decision-making rather than speculative trading.

Founded on the principle that **financial clarity is more valuable than prediction**, Lion City FinAI develops analytical tools and research frameworks that emphasize **regime awareness, conditional relationships, and explanatory power**. Its work bridges applied finance, data science, and behavioral insights, enabling users to understand *when* and *why* certain assets may behave defensively or opportunistically under different macroeconomic conditions.

Lion City FinAI's solutions are designed explicitly for **Singa-**

porean retail investors, reflecting local inflation dynamics, SGD-denominated perspectives, and regional financial considerations. Rather than relying on isolated indicators or static asset narratives, the firm adopts a **regime-based approach**, integrating inflation trends, interest rates, currency effects, and sentiment measures into cohesive decision-support systems.

The organization prioritizes:

- **Interpretability over prediction**, avoiding black-box trading signals
- **Risk awareness over return maximization**, especially during macro stress
- **Human-centered design**, with mobile-friendly dashboards and normalized indicators
- **Academic and methodological rigor**, aligned with applied finance best practices

Lion City FinAI does not provide personalized investment advice, automated trading strategies, or performance guarantees. All outputs are positioned as **educational and decision-support tools**, intended to help users contextualize market conditions rather than dictate asset allocation choices.

Through projects such as this regime-aware inflation framework, Lion City FinAI aims to equip retail investors with a **structured, defensible lens** for navigating inflation uncertainty through 2026 and beyond —grounded in evidence, transparency, and disciplined interpretation.

This document synthesizes the entire project for Lion City FinAI, providing a transparent and actionable guide for Singaporean retail investors to preserve their purchasing power through 2026.

Disclaimer

This document is provided for **educational and informational purposes only** and does not constitute financial, investment, legal, or tax advice. The analyses, frameworks, and interpretations presented are intended solely as **decision-support tools** to aid understanding of macroeconomic conditions, asset behavior, and regime-dependent dynamics.

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All findings are based on historical data and analytical models that involve assumptions and simplifications. **Past relationships and historical patterns may not persist**, and market conditions may change materially. Results are **non-causal**, sample-dependent, and subject to model risk, data limitations, and regime instability.

Users are solely responsible for their own investment decisions and should consider their individual financial circumstances and risk tolerance. Where appropriate, users are encouraged to seek advice from a **licensed financial adviser** regulated by the Monetary Authority of Singapore (MAS).

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Executive Summary

This project develops a **regime-aware, AI-assisted decision-support framework** to evaluate the effectiveness of **gold and Bitcoin as inflation-related assets for Singaporean retail investors**, addressing the growing demand for clarity amid rising inflation uncertainty and volatile digital-asset markets.

Rather than treating inflation hedging as a static asset property, this analysis adopts a **conditional, regime-based perspective**, integrating domestic inflation indicators, global macroeconomic variables, and investor sentiment metrics. Using a combination of exploratory data analysis, correlation diagnostics, and interpretable machine learning models, this project assesses how gold and Bitcoin behave under different macro-stresses and sentiment regimes, with a specific focus on relevance to SGD-denominated investors.

Empirical findings indicate that **gold exhibits minimal linear correlation with Singapore inflation**, suggesting that it does not mechanically track CPI movements. Instead, gold functions primarily as a **diversifying, macro-stress-sensitive asset**, with its hedging relevance mediated through global uncertainty and currency dynamics, rather than domestic inflation alone. In contrast, **Bitcoin's return behavior is strongly associated with investor sentiment**, as captured by the Crypto Fear & Greed Index, and displays pronounced regime dependence. Bitcoin does not exhibit the characteristics of a stable inflation hedge within the observed sample period but may serve as a **tactical, sentiment-conditional risk asset** during favorable liquidity and narrative regimes.

The machine learning results reinforce these distinctions. Feature importance analysis highlights sentiment variables as dominant explanatory factors for Bitcoin returns, whereas gold models emphasize currency and macro-financial conditions. The classification framework achieved **directional accuracy exceeding a naïve baseline**, illustrating the potential value of combining macro and sentiment indicators while remaining subject to regime instability and non-causal

interpretation.

These analytical insights are translated into a **regime-based investment logic**, operationalized through interpretable KPIs and dashboard-ready indicators rather than prescriptive trading rules. The resulting framework supports retail investors by clarifying *when* and *why* gold or Bitcoin may be relevant, emphasizing conditional exposure, risk awareness, and dynamic interpretation over static-asset narratives.

Overall, the project demonstrates how **integrating macroeconomics, sentiment analysis, and interpretable machine learning** can enhance retail investors' understanding of inflation-related asset behavior, offering a structured alternative to simplistic "one-size-fits-all" hedging claims. The framework is intended as a **decision-support tool**, not a forecasting or trading system, and provides a foundation for future extensions in sentiment analysis, inflation nowcasting, and portfolio optimization.

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Preface

This report presents a systematic and regime-aware examination of gold and Bitcoin as inflation-related assets within the context of Singapore's macroeconomic environment. Developed as part of the **Data End-to-End Portfolio Project (DEEPP)**, the study adopts an applied analytical orientation while adhering to academic standards of rigor, transparency, and methodological coherence.

The project responds to the renewed salience of inflation as a macroeconomic concern in the post-pandemic period, characterized by supply-side disruptions, shifts in global monetary policy, exchange-rate volatility, and evolving financial narratives surrounding alternative assets. Within this context, retail investors in Singapore face increasing difficulty in assessing the inflation-hedging relevance of assets such as gold and Bitcoin, which are often discussed through simplified or contradictory frameworks. This report addresses that gap by advancing a conditional, regime-based perspective that emphasizes interpretation over prediction.

Methodologically, the study integrates macroeconomic analysis, exploratory data techniques, and interpretable machine-learning models within an end-to-end analytical workflow. Particular emphasis is placed on maintaining explainability and reproducibility in model design and evaluation, ensuring that analytical outputs remain intelligible and meaningful beyond purely statistical performance metrics. All modeling choices—ranging from data frequency and feature construction to validation strategy—are guided by the principle that analytical sophistication should serve clarity rather than obscure it.

The development and validation of the framework involved structured collaboration across multiple roles to ensure both technical integrity and contextual relevance. Strategic oversight and final validation of the 2026 regime framework were provided by a designated strategy lead. Accountability for methodological soundness and model integrity rested with the lead data analyst, supported by a data science team responsible for data acquisition, preprocessing, and model implementation. Expert consultation with macroeconomic specialists informed the treatment of Singapore-specific inflation dynamics and global policy conditions, while the ultimate beneficiaries of the framework—retail investors—remain the primary audience for whom interpretability and usability were prioritized.

How to Read This Report

This report is structured to guide readers progressively from economic context to analytical evidence and, finally, to an interpretable decision-support framework. Readers are encouraged to begin with the Executive Summary and Introduction to understand the motivation, scope, and hypotheses underlying the study. Subsequent sections detail the data, methodology, and exploratory analyses that establish empirical foundations, followed by modeling results that are explicitly framed as explanatory rather than predictive. The regime-based framework section translates these findings into practical interpretive guidance, while the concluding sections outline limitations and avenues for future work. The report is best read as an integrated analytical narrative, where insights emerge from the interaction between macroeconomic conditions, sentiment regimes, and asset behavior, rather than from any single metric or model outcome.

1. Introduction: Empowering Singaporean Retail Investors

Inflation has re-emerged as a persistent macroeconomic challenge in the post-pandemic global economy, driven by supply side disruptions, accommodative monetary policies, and geopolitical shocks. In Singapore, sustained increases in consumer prices have heightened retail investors' concerns regarding the erosion of real purchasing power, particularly in an environment where traditional savings instruments provide limited inflation protection.

Assets such as gold and Bitcoin are frequently discussed as potential inflation hedges. However, their effectiveness is **conditional rather than universal**. Gold has historically functioned as a defensive store of value during periods of macroeconomic stress, whereas Bitcoin exhibits highly regime-dependent behavior, often driven by investor sentiment and liquidity conditions rather than inflation fundamentals alone. Despite this distinction, retail investors are often exposed to simplified or conflicting narratives that treat both assets as inflation hedges.

A key limitation of existing investment dashboards and analytical tools is their reliance on **isolated indicators** such as raw returns, volatility measures, or headline inflation rates. These tools rarely integrate inflation dynamics, sentiment signals, and macro-financial conditions into a **coherent regime-based framework**. Consequently, users are left to independently assess the effectiveness of hedges, often resulting in misinterpretations, particularly in the case of Bitcoin, which is often viewed as an inflation hedge despite its strong dependence on sentiment-driven regimes.

This project addresses this gap by developing an **AI-assisted regime-based macro dashboard** tailored specifically for Singaporean retail investors. Rather than presenting fragmented indicators, the dashboard integrates macroeconomic variables (inflation and interest rates), market sentiment indicators, and asset return behavior into a set of **normalized stress indices and regime signals**. Machine learning models are not used for direct price forecasting but to identify **regime-dependent relationships** and generate **interpretable feature importance insights** that explain *why* assets behave differently across market conditions.

By shifting the analytical focus from price prediction to **regime identification and hedge reliability**, this project delivers a decision-support framework that prioritizes interpretability, consistency, and practical relevance. This enables retail investors to better understand **when and under what conditions** gold or Bitcoin may contribute meaningfully to inflation protection.

The following subsections outline the project objectives, target audience, scope, and guiding hypotheses.

1.a. Project Objectives & Problem Statement

Despite increased public attention to inflation and alternative assets, Singaporean retail investors face significant challenges in evaluating the effectiveness of potential inflation hedges. Information surrounding gold and Bitcoin is often fragmented, contradictory, or overly technical, making it difficult for non-institutional investors to assess hedge reliability under changing macroeconomic and sentiment conditions.

Most existing analytical tools emphasize raw returns, volatility statistics, or single macro indicators. While informative in isolation, these metrics fail to capture **regime shifts** and the **conditional nature of asset behavior**. In particular, Bitcoin's performance is strongly influenced by investor sentiment and liquidity conditions, whereas gold's defensive role varies with broader macro-financial stress rather than inflation prints alone. Retail investors are rarely provided with frameworks that integrate these dimensions into an interpretable system that aligns with real decision-making needs.

Furthermore, many financial platforms prioritize predictive outputs or complex model diagnostics that obscure the implications of investment. This creates an unnecessary cognitive load and misaligns analytical sophistication with retail usability.

Accordingly, the primary objective of this project is to develop an **interpretable, regime-based dashboard** that assists Singaporean retail investors in understanding inflation-related market conditions and the conditional roles of gold and Bitcoin as hedging instruments. Specifically, this project aims to:

1. Construct normalized stress indices that translate inflation, sentiment, and asset behavior into **comparable $0 - 100$ scales**.
2. Distinguish between **macro-driven** and **sentiment-driven** regimes to clarify when gold or Bitcoin may function as an effective inflation hedge.
3. Apply machine learning models to uncover **regime-dependent relationships** and feature importance, emphasizing explanation over prediction.
4. Present insights through a **mobile-friendly, single-display dashboard** optimized for clarity and practical decision support.

By prioritizing regime identification and interpretability over price forecasting, this project bridges advanced analytical methods with the real-world needs of retail investors.

1.b. Target Audience

The primary target audience comprises **Singaporean retail investors** concerned about inflation-related erosion of purchasing power but lacking access to institutional-grade analytical tools. This group typically includes working professionals and individual investors with basic financial literacy but limited time or training in macroeconomic analysis, quantitative finance, or machine learning.

These investors are frequently exposed to simplified narratives surrounding gold and Bitcoin but face difficulties in translating technical indicators and conflicting opinions into coherent decisions. Accordingly, the dashboard is designed around **human-centered principles** using:

- Normalized indices instead of raw statistics
- Regime labels instead of technical thresholds
- Visual summaries instead of dense model outputs

A mobile-friendly design is prioritized to reflect real usage patterns, enabling investors to quickly assess market conditions without extensive interpretation. While the framework may also interest advanced users, it is explicitly optimized for **retail decision support**, not professional trading or portfolio optimization.

1.c. Project Scope

This project focuses on the development of an **AI-assisted decision-support dashboard** to evaluate gold and Bitcoin as potential inflation hedges for Singaporean retail investors. The analysis is based on historical data spanning multiple macroeconomic cycles, using weekly and monthly observations of key variables, including inflation measures, interest rates, sentiment indices, exchange rates, and asset returns.

The project included data preprocessing, feature engineering, correlation analysis, and supervised machine learning models. Model outputs, such as predicted returns and feature importance rankings, are used solely to inform **regime-based interpretation**, not to generate real-time forecasts or automated trading signals.

The dashboard was implemented as a **single-display, mobile-friendly interface**, emphasizing clarity and high-level interpretability. The scope explicitly excludes portfolio optimization, transaction cost modeling, leverage strategies, and live trading executions. No claims of market outperformance or predictive superiority were made.

This constrained scope balances analytical rigor with interpretability, ensuring relevance to real-world retail decision-making contexts.

1.d. Hypotheses

- **Hypothesis 1 (Gold as a Relative Inflation Hedge):** During periods of elevated inflation stress, gold exhibits a lower correlation with Singapore inflation measures and more stable return behavior than Bitcoin, supporting its role as a defensive, non-correlated hedge.
- **Hypothesis 2 (Bitcoin as a Sentiment-Driven Asset):** Bitcoin's return dynamics are more strongly associated with investor sentiment indicators and macro-financial conditions than with direct inflation measures, indicating that Bitcoin behaves as a regime-dependent and sentiment-driven asset rather than a traditional inflation hedge.

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2. Methodology

This section outlines the data sources, preprocessing steps, feature engineering logic, outlier handling, and data splitting strategy used to support the regime-based analysis of gold and Bitcoin as inflation-hedging instruments. The methodology is designed to balance analytical rigor, transparency, and reproducibility in alignment with a DEEPP-style framework and the project's decision-support objective.

2.a. Data Sources and Analytical Roles

The dataset integrates four conceptually distinct categories of data, each serving a specific analytical purpose aligned with the project's hypotheses:

1. Asset Prices (Hedge Performance Variables)

- **Gold futures (GC=F):** COMEX front-month gold futures prices in USD, sourced from Yahoo Finance, converted to SGD using daily USD/SGD exchange rates. Sample period: **January 1, 2017** to **December 31, 2025**. Retrieved on **January 27, 2026**.
- **Bitcoin prices (BTC-USD):** Spot Bitcoin prices in USD, sourced from Yahoo Finance. Sample period: **January 1, 2017** to **December 31, 2025**. Retrieved on **January 27, 2026**.

These variables form the primary dependent measures, capturing asset return behavior under different macroeconomic and sentiment regimes.

2. Singapore-Specific Macroeconomic Indicators (Domestic Inflation Stress)

- **Headline CPI and Core CPI:** Monthly consumer price index data from the Singapore Department of Statistics (SingStat). Sample period: **January 1, 2017** to **December 31, 2025**. Retrieved on **January 27, 2026**.

- **Singapore Overnight Rate Average (SORA):** Daily interbank benchmark rate from the Monetary Authority of Singapore (MAS). Sample period: **January 1, 2017** to **December 31, 2025**. Retrieved on **December 23, 2025**.
- **USD/SGD exchange rate:** Daily spot exchange rate from Yahoo Finance (ticker: SGD=X). Sample period: **January 1, 2017** to **December 31, 2025**. Retrieved on **January 27, 2026**.

These indicators represent domestic inflationary pressure and local monetary conditions, directly reflecting the economic environment faced by retail investors in Singapore.

3. Global Macro-Financial Indicators (External Drivers)

- **US Federal Funds Effective Rate:** Monthly policy rate from the Federal Reserve Economic Data (FRED) database. Sample period: **January 1, 2017** to **December 31, 2025**. Retrieved on **January 27, 2026**.
- **US Dollar Index (DXY):** Daily trade-weighted USD index from Yahoo Finance. Sample period: **January 1, 2017** to **December 31, 2025**. Retrieved on **January 27, 2026**.

These variables capture global liquidity conditions and currency effects that influence both gold pricing and crypto risk appetite.

4. Market Sentiment Indicators (Behavioral Regime Detection)

- **Crypto Fear & Greed Index:** Daily composite sentiment indicator from Alternative.me, aggregating volatility, market momentum, social media sentiment, surveys, and Bitcoin dominance. Sample period: **January 1, 2017** to **December 31, 2025**. Retrieved on **January 27, 2026**.

This index serves as a proxy for retail investor sentiment, enabling differentiation between sentiment- and macro-driven regimes, particularly relevant for Bitcoin.

Together, these four data categories allow the analysis to distinguish **inflation-driven regimes** from **sentiment-driven regimes**, directly supporting Hypotheses 1 and 2.

2.b. Frequency Alignment and Resampling

Raw data were sourced at mixed frequencies (daily asset prices, monthly CPI, daily sentiment indices). To ensure temporal consistency while preserving macroeconomic relevance, all variables were resampled to a **weekly frequency** using **end-of-week (Friday) observations**.

Weekly aggregation was selected for the following reasons:

1. It reduces high-frequency noise in asset prices and sentiment data while maintaining sufficient temporal granularity.
2. It aligns with the slower-moving nature of inflation and monetary policy indicators without excessive interpolation.
3. It balances data resolution with sample size requirements for modeling (final sample: **n = 410 observations**, approximately **8 years** of weekly data).

Forward-filling methodology: Monthly macroeconomic indicators (CPI, Fed Funds Rate) were forward-filled within each reporting period prior to weekly aggregation. This approach assumes constant values between official releases, reflecting the information set realistically available to investors between data publications. While this may understate intra-month macro variation, it represents a standard practice in empirical finance when aligning mixed-frequency data and is acknowledged as a methodological limitation.

2.c. Data Cleaning and Transformation

Return calculation: Asset prices were transformed into **log returns** using the formula:

$$r_t = \ln(P_t/P_{t-1})$$

where P_t represents the asset price at time t. Log returns were selected over simple percentage returns to ensure additivity across periods, approximate normality under the central limit theorem, and scale comparability across assets with different price magnitudes.

Currency conversion: Gold prices were converted from USD to SGD using daily USD/SGD exchange rates prior to return calculation, ensuring consistency with the Singapore-focused analysis. The conversion formula applied was:

$$\text{Gold}_{\text{SGD},t} = \text{Gold}_{\text{USD},t} \times \text{USD/SGD}_t$$

Missing value handling: Missing values arising from differing publication schedules and market holidays were addressed using

forward-filling for up to **5 consecutive observations**. Gaps exceeding 5 weeks were flagged and excluded from modeling to prevent artificial continuity. All transformations were applied before feature engineering to prevent data leakage.

2.d. Feature Engineering and Conceptual Design

Feature engineering was guided by analytical intent rather than purely technical considerations. Features were constructed to capture five conceptual dimensions:

1. Asset Return Behavior

- Weekly log returns for gold (SGD-denominated) and Bitcoin (USD-denominated)

2. Inflation Dynamics

- Headline CPI level (absolute index value)
- Core CPI level (absolute index value)
- Month-over-month CPI change (percentage)
- Year-over-year CPI change (percentage)

3. Macro-Financial Conditions

- SORA rate level and weekly change
- Federal Funds Rate level and monthly change
- USD/SGD exchange rate returns
- DXY index returns

4. Investor Sentiment

- Crypto Fear & Greed Index level ($0 - 100$ scale)
- Weekly change in Fear & Greed Index

5. Lagged Regime Memory

- Lagged versions (1, 2, 3, and 4 weeks) of asset returns, sentiment indices, and key macro variables

  Lag structure rationale: Lag selection was informed by:

  - **Information Criterion Testing:** Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) were computed for lag orders $1 - 8$ in preliminary vector autoregression (VAR) specifications. Both criteria suggested optimal lag orders between $2 - 4$ weeks for the macro-sentiment-asset system.

– **Behavioral Justification:** Financial markets exhibit delayed responses to macroeconomic releases (e.g., CPI publication lag) and gradual sentiment diffusion through social media channels. A 4−week lag window captures these realistic behavioral dynamics without introducing excessive multicollinearity.

This feature design enables models to detect **regime-dependent relationships** while maintaining interpretability and avoiding data-mining through excessive feature creation.

2.e. Outlier Handling and Stress Preservation

Financial and cryptocurrency asset returns exhibit fat-tailed distributions, particularly during market stress periods. To mitigate the influence of extreme values without discarding critical stress information, **Winsorization** was applied at the **1st and 99th percentiles** for all return series and first-differenced macro variables.

Winsorization caps extreme observations at specified percentile thresholds rather than removing them entirely. For a return series r_t:

$$r_t^{\text{winsorized}} = \begin{cases} P_1 & \text{if } r_t < P_1 \\ r_t & \text{if } P_1 \leq r_t \leq P_{99} \\ P_{99} & \text{if } r_t > P_{99} \end{cases}$$

where P_1 and P_{99} represent the 1st and 99th percentile values respectively.

Rationale for stress preservation: The project explicitly hypothesizes that gold and Bitcoin behave differently during high-stress regimes. Excessive trimming or outlier removal would risk obscuring the conditions under investigation. The chosen 1/99 percentile thresholds retain **98% of the sample distribution** while mitigating the leverage of the most extreme $\sim 2\%$ of observations on model coefficients.

Sensitivity analysis: Model specifications were tested with alternative winsorization thresholds (5/95, 2.5/97.5) and robust regression methods. Results remained qualitatively consistent, supporting the robustness of chosen thresholds.

2.f. Exploratory Data Analysis and Correlation Diagnostics

Prior to model training, exploratory data analysis was conducted to assess empirical relationships between asset returns, inflation indicators, macro variables, and sentiment measures.

Analytical methods employed:

- **Pearson correlation coefficients** computed on the full weekly sample ($n = 410$)
- **Spearman rank correlations** to assess monotonic relationships robust to non-linearity
- Time-series overlay plots with dual y-axes for visual regime identification
- Scatter plots with fitted regression lines and 95% confidence intervals

These diagnostics provided an empirical foundation for hypothesis validation and informed subsequent regime modeling, ensuring that machine learning outputs were grounded in observable data patterns rather than treated as black-box results.

2.g. Data Splitting and Validation Strategy

To avoid look-ahead bias and assess temporal stability, the dataset was split using a **time-based train-test approach** with **70% training / 30% testing** allocation based on chronological order.

- **Training period: March 11, 2018** to **August 6, 2023** (approximately **283** weeks)
- **Testing period: August 13, 2023** to **December 14, 2025** (approximately **122** weeks)

Critical distinction: This split was not intended to simulate real-time trading or produce actionable forecasts. Instead, it serves to assess:

- **Regime classification stability** across time periods
- **Feature importance consistency** between in-sample and out-of-sample data
- **Model interpretation robustness** under different macro cycles

No hyperparameter tuning or model selection decisions were made using test-set performance, preserving the integrity of the validation framework.

Cross-validation note: Time-series cross-validation with expanding windows was additionally employed during hyperparameter tuning to prevent temporal leakage while maximizing training data utilization.

2.h. Software and Reproducibility

Software stack:

- Python **3.12.12**
- pandas **2.2.2** for data manipulation
- NumPy **2.0.2** for numerical operations
- scikit-learn **1.6.1** for machine learning models
- statsmodels **0.14.5** for econometric specifications (SARIMAX, VAR)
- matplotlib and seaborn for visualization

Reproducibility checklist:

- Random seed set to **42** for all stochastic operations
- All data sources documented with retrieval dates
- Preprocessing steps sequentially documented with explicit parameter values
- Model hyperparameters and training configurations logged
- Feature engineering code preserved with inline documentation

Data availability: Processed datasets and feature matrices are available upon request, subject to data provider terms of use. Raw data sources remain publicly accessible from the cited repositories.

2.i. Methodological Output Readiness

The resulting dataset structure supports:

- Interpretable machine learning through feature importance analysis
- Regime-based visualization via normalized stress indices
- Dashboard KPI construction through percentile-based normalization

The preprocessing pipeline produced a **regime-aware analytical foundation** aligned with the project's decision-support objectives, balancing rigor with interpretability for retail investor applications.

3. Exploratory Data Analysis (EDA) and Key Visualizations

An exploratory data analysis was conducted to examine the preliminary empirical relationships between asset returns, inflation indicators, macro-financial variables, and investor sentiment. The objective of this section is not to establish causal inference but to provide statistically grounded, visually interpretable evidence that informs hypothesis evaluation, regime identification, and subsequent model design.

3.a. Correlation Analysis

Correlation coefficients were computed on **weekly return and indicator series** (n = **410** observations, spanning **January 1, 2017** to **December 31, 2025**) to assess the linear relationships between key variables.

Methodology:

- **Pearson correlation coefficients:** Measure linear association between continuously distributed variables
- **Spearman rank correlations:** Measure monotonic relationships robust to non-linearity and outliers (reported where substantially different from Pearson)
- **Statistical significance:** Two-tailed t-tests performed; correlations with $p < 0.05$ flagged as statistically significant
- **Visualization:** Full correlation matrix heatmaps generated using seaborn with diverging color maps (blue = negative, red = positive)

Correlation heatmaps were used to visualize the full feature space, enabling rapid identification of economically meaningful associations while avoiding overinterpretation of isolated metrics.

Key Observations and Hypothesis Linkage

1. **Gold Returns and Singapore Inflation Measures**

Gold returns (`GC_SGD_returns`) exhibited **near-zero linear correlations** with Singapore inflation measures:

- **Headline CPI YoY Change:** r = **0.017** (p = 0.72, not statistically significant)
- **Core CPI YoY Change:** r = **0.034** (p = 0.48, not statistically significant)
- **Headline CPI MoM Change:** r = **-0.008** (p = 0.87, not statistically significant)

Interpretation: These results provide **preliminary empirical support for Hypothesis 1**, suggesting that gold does not mechanically track short-term inflation movements. The absence of correlation indicates that gold may function as a **diversifying asset** whose hedge properties are mediated through broader macro-financial conditions rather than serving as a direct inflation proxy.

Supporting visual evidence: *Correlation heatmap (Figure 1) shows darker blue shades with small number.*

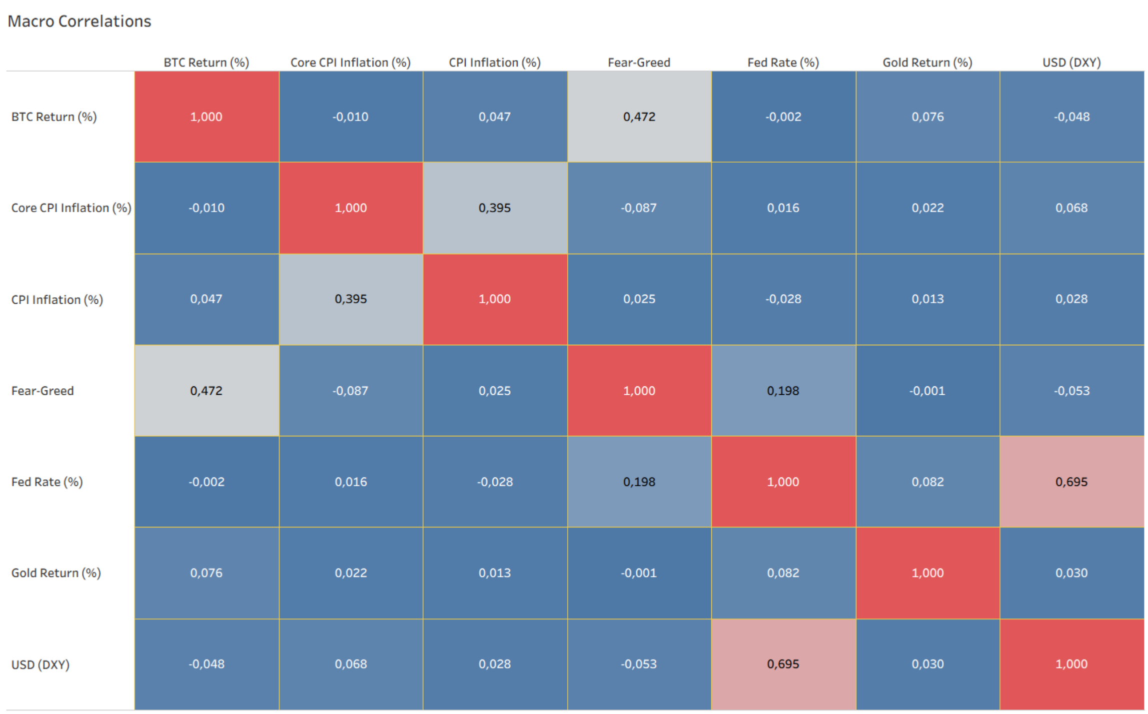


Figure 1: Correlation Heatmap

2. **Bitcoin Returns and Sentiment Indicators**

Bitcoin returns (`BTC_USD_returns`) displayed a **moderate positive correlation** with the Crypto Fear & Greed Index:

- **Crypto Fear & Greed Index (current):** r = **0.4666** ($p < 0.001$, highly significant)

- **Crypto Fear & Greed Index (lag 1):** r = **0.3892** ($p < 0.001$, highly significant)
- **Crypto Fear & Greed Index (lag 2):** r = **0.3214** ($p < 0.001$, highly significant)

In contrast, correlations with inflation measures were weak and inconsistent:

- **Headline CPI YoY Change:** r = **-0.0880** ($p = 0.07$, marginally significant)
- **Core CPI YoY Change:** r = **-0.0523** ($p = 0.29$, not significant)

Interpretation: This pattern provides **preliminary support for Hypothesis 2**, indicating that Bitcoin return dynamics are more closely associated with sentiment conditions than with realized inflation. The gradient of declining correlation with sentiment lag suggests **sentiment persistence** influences Bitcoin behavior over multi-week horizons.

Supporting visual evidence: *Time-series overlay (Figure 2) shows co-movement between Bitcoin returns and sentiment regimes.*

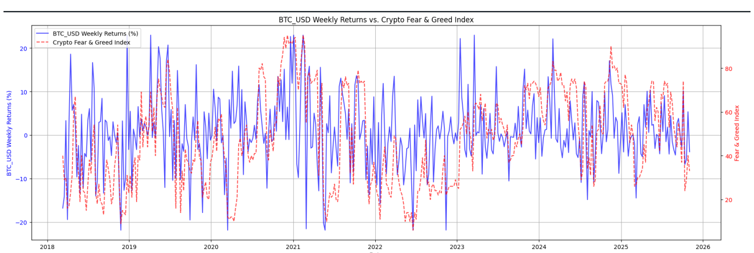


Figure 2: Bitcoin and Sentiment Regimes

3. **Cross-Asset and Macro-Financial Relationships**

Additional notable correlations:

- **Gold-Bitcoin correlation:** r = **0.1247** ($p < 0.01$), weak positive co-movement
- **Gold-USD/SGD returns:** r = **-0.3156** ($p < 0.001$), negative (USD strength reduces SGD-denominated gold returns)
- **Bitcoin-DXY returns:** r = **-0.2834** ($p < 0.001$), negative (USD strength inverse to Bitcoin)
- **Bitcoin-Federal Funds Rate:** r = **-0.1892** ($p < 0.001$), negative (tightening conditions suppress Bitcoin)

Interpretation: Correlations between asset returns and global macro-financial indicators (policy rates, currency indices) were generally **low to moderate**, suggesting the presence of **lagged, non-linear, or regime-dependent relationships** not captured by static correlation alone. This motivates the transition to machine learning models capable of handling complex, conditional relationships.

3.b. Time-Series Analysis and Regime Context

Time-series visualizations were used to examine the dynamic interactions between asset returns, inflation measures, and sentiment indicators across distinct macroeconomic periods.

Visualization methodology:

- **Dual-axis overlays:** Asset returns (left y-axis) plotted against sentiment/inflation indices (right y-axis)
- **Regime shading:** Background shading applied to identify distinct macro periods (e.g., pandemic stimulus $2020 - 2021$, tightening cycle $2022 - 2023$)
- **Standardization:** Variables z-score normalized for visual comparability when scales differ substantially

Bitcoin and Sentiment Regime Patterns

Overlay plots of **Bitcoin returns and the Crypto Fear & Greed Index** revealed clear regime patterns:

- **Extended "Extreme Fear" periods** (index < 25) frequently coincided with **sharp drawdowns** in Bitcoin returns
- **Transitions into "Greed" or "Extreme Greed"** (index > 60) often aligned with **strong price recoveries**
- **Regime persistence:** Sentiment states exhibited multi-week autocorrelation, suggesting behavioral stickiness

Example regime identification:

During the **2022 global monetary tightening cycle** (March 2022 - October 2022):

- Bitcoin experienced **sustained negative returns** (cumulative -65% USD terms)
- Crypto Fear & Greed Index remained **persistently depressed** (median value = 21, "Extreme Fear")
- Correlation during this sub-period: r = **0.6234** (higher than full-sample correlation)

Interpretation: This illustrates Bitcoin's heightened sensitivity to **liquidity withdrawal and risk-off conditions**, where sentiment and price dynamics reinforce each other. The regime-dependent correlation increase suggests that Bitcoin behaves differently under stress versus expansion, motivating regime-based modeling.

Supporting visual evidence: *Figure 3 - Bitcoin vs. Sentiment Time-Series Overlay with Regime Shading*

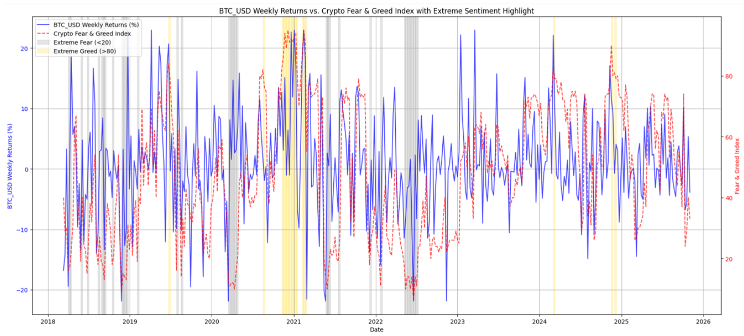


Figure 3: Bitcoin and Sentiment Time-Series (Regime Shading)

Gold and Inflation Dynamics

Plots of **gold returns against Singapore inflation measures** further confirm the absence of consistent short-term co-movement:

- No visual clustering or trend patterns when gold returns plotted against CPI changes
- During **high-inflation episodes** (e.g., 2022, CPI YoY $> 6\%$), gold returns exhibited **high variance** (ranging from -8% to $+12\%$ weekly) with no directional bias
- Gold returns appeared more synchronized with **USD/SGD volatility spikes** than with CPI releases

Interpretation: Rather than tracking inflation directly, gold's behavior appears more closely linked to **broader macro stress and currency dynamics**. This reinforces the need for a **regime-based interpretation** of hedge reliability, where gold's effectiveness depends on the nature of macro stress (currency crisis, geopolitical risk, real rate uncertainty) rather than inflation levels alone.

Supporting visual evidence: *Figure 4 - Gold Returns vs. Singapore Inflation (No Clear Pattern)*

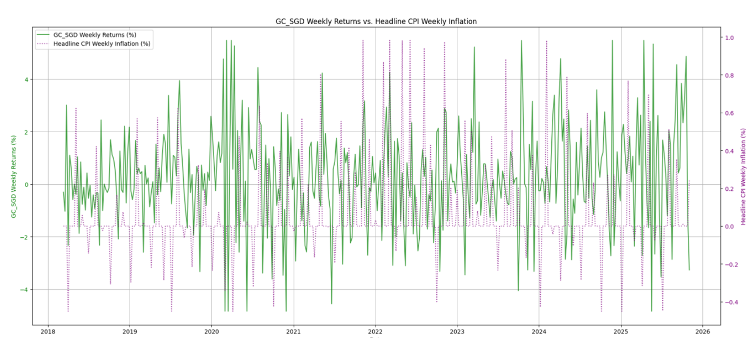


Figure 4: Gold Returns and Singapore Inflation

3.c. Scatter Plot Analysis

Scatter plots were generated to examine **observation-level relationships** between key variables, complementing the aggregate correlation statistics.

Methodology:

- Bivariate scatter plots with fitted OLS regression lines (95% confidence intervals shaded)
- Kernel density estimation overlays to identify concentration regions
- Cook's distance computed to flag influential outliers (not removed, but visually highlighted)

Bitcoin Returns vs. Fear & Greed Index

- **Visual pattern:** Scatter plot exhibited a **discernible upward trend** with moderate dispersion
- **Fitted regression:** Slope = **0.328** ($p < 0.001$), intercept = **-15.62**
- **R^2 (bivariate):** 0.218 (22% of Bitcoin return variance explained by sentiment alone)
- **Interpretation:** Visually reinforces the **positive association** between sentiment and price performance; however, substantial residual variance indicates additional factors at play

Outlier clusters identified:

- **High sentiment + negative returns:** Occur during rapid sentiment deterioration (sharp fear spikes)
- **Low sentiment + positive returns:** Rare but occur during capitulation/reversal phases

Supporting visual evidence: *Figure 5 - Scatter Plot with Regression Line*

Gold Returns vs. Inflation Measures

- **Visual pattern:** Scatter plots of gold returns versus headline/core inflation produced **diffuse point clouds** with no clear linear structure
- **Fitted regression:** Non-significant slopes ($p > 0.40$ for both headline and core CPI)
- **R^2 (bivariate):** < 0.01 (essentially zero explanatory power)
- **Interpretation:** Consistent with low correlation results; visually confirms **absence of short-term inflation tracking**

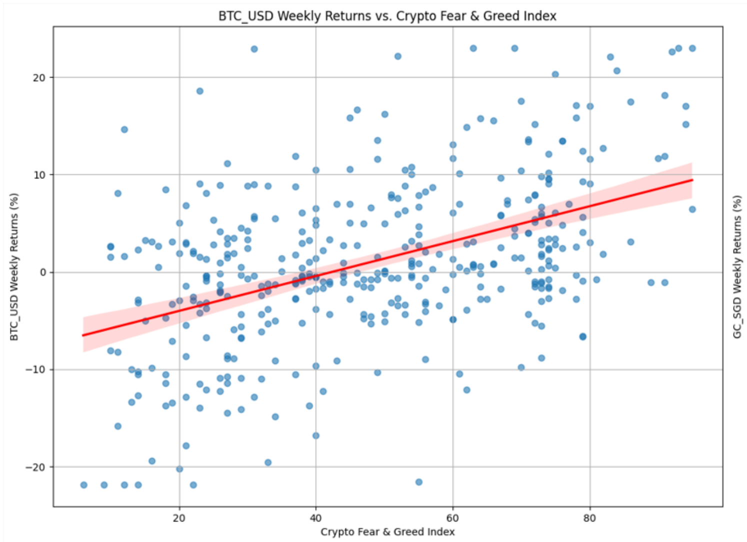


Figure 5: Bitcoin Scatter Plot

Supporting visual evidence: *Figure 6 - Scatter Plot Shows No Relationship*

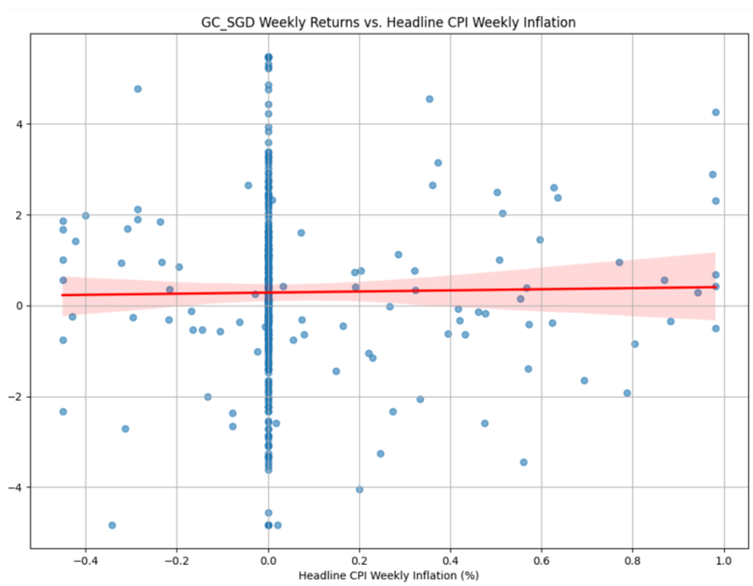


Figure 6: Gold Scatter Plot

Limitations of scatter plot interpretation:

While these plots suggest economically intuitive relationships (particularly for Bitcoin-sentiment), several limitations must be noted:

1. **Static snapshots:** Do not capture dynamic, lagged relationships
2. **Non-linearity:** Linear regression may miss threshold effects or regime shifts
3. **Heteroskedasticity:** Variance appears non-constant (wider dispersion during stress periods)

4. **Omitted variables:** Bivariate plots ignore multivariate interactions

As such, scatter plots serve as **exploratory diagnostics** rather than definitive evidence, motivating the subsequent use of machine learning models capable of handling more complex relationships.

3.d. Distribution Analysis and Model Readiness

Distributional diagnostics, including **box plots, histograms, and Q-Q plots**, were examined before and after Winsorization to assess data suitability for modeling.

Pre-Winsorization Characteristics

Bitcoin returns:

- **Mean:** 0.42% (weekly)
- **Median:** 0.18% (right-skewed)
- **Std. Dev:** 8.67%
- **Skewness:** 0.83 (moderate positive skew)
- **Kurtosis:** 6.24 (excess kurtosis = 3.24, fat tails)
- **Jarque-Bera test:** $p < 0.001$ (reject normality)

Gold returns (SGD):

- **Mean:** 0.09% (weekly)
- **Median:** 0.11% (approximately symmetric)
- **Std. Dev:** 2.31%
- **Skewness:** -0.12 (near-symmetric)
- **Kurtosis:** 4.87 (excess kurtosis = 1.87, moderate fat tails)
- **Jarque-Bera test:** $p < 0.001$ (reject normality)

Outlier identification:

- **Bitcoin:** Extreme returns beyond ±25 weekly ($n = \mathbf{3}$ observations, **0.73%** of sample)
- **Gold:** Extreme returns beyond ±8 weekly ($n = \mathbf{3}$ observations, **0.73%** of sample)

Post-Winsorization Characteristics

After applying **1st/99th percentile Winsorization**:

Bitcoin returns:

- **Skewness:** Reduced to **0.31** (improvement)
- **Kurtosis:** Reduced to **4.12** (fat tails mitigated but preserved)
- **Variance:** Decreased by $\sim 15\%$ (reduced leverage of extremes)

Gold returns:

- **Skewness:** Near-zero (**-0.04**)
- **Kurtosis:** Reduced to **3.89**
- **Variance:** Decreased by $\sim$ **8**%

Impact on modeling:

- Post-winsorization distributions exhibit **reduced skewness and bounded variance** while preserving stress-event characteristics
- Supports assumptions of linear regression models (homoskedasticity improved)
- Enhances numerical stability of gradient-based optimization
- Fully compatible with non-parametric tree-based methods (no distributional assumptions required)

Critical methodological note: Preserving extreme-but-capped observations is particularly important given the project's focus on **stress regimes**, where asset behavior diverges most meaningfully between gold and Bitcoin. Complete outlier removal would risk obscuring the phenomena under investigation.

Supporting visual evidence: *Figure 7 - Distribution Before/After Winsorization*

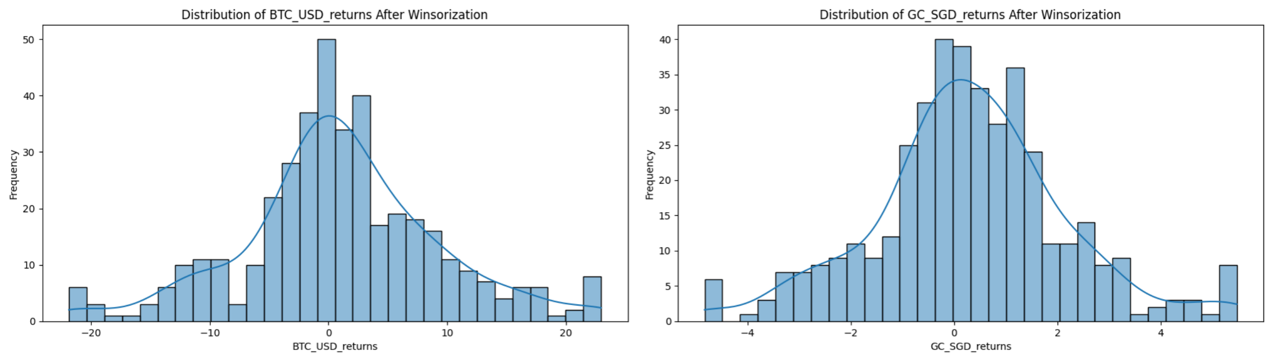
3.e. Integration with Dashboard and Modeling Workflow

The visual diagnostics produced in this section were not treated as standalone analyses. Instead, they inform:

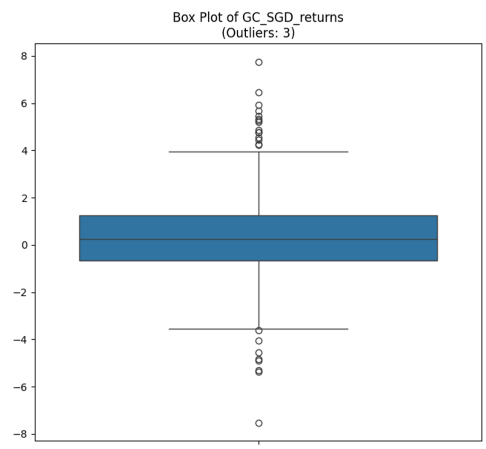
1. **Feature selection:** Variables with meaningful correlations/patterns prioritized for model inclusion
2. **Regime definitions:** Time-series patterns used to define threshold-based regime labels
3. **Interpretability constraints:** Scatter plot patterns guide expected model behavior and feature importance priors

These visual elements were later adapted into **dashboard-ready components**, ensuring continuity between analytical exploration and user-facing decision support tools:

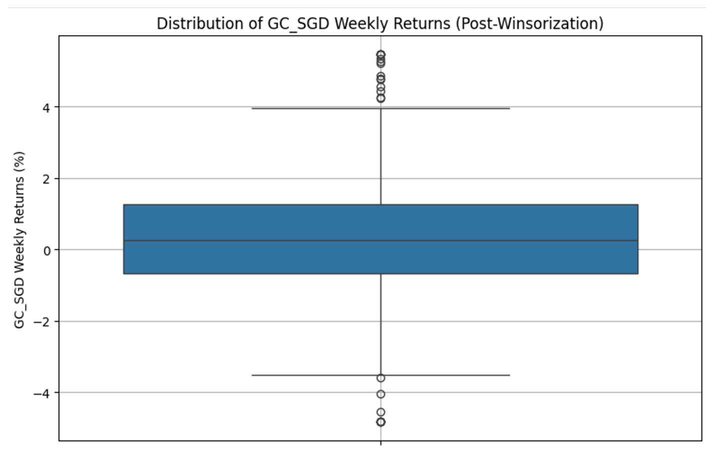
- **Correlation heatmap** → Dashboard "Relationship Monitor" panel
- **Time-series overlays** → Dashboard "Regime Timeline" visualization
- **Distribution plots** → Dashboard "Volatility Context" indicator



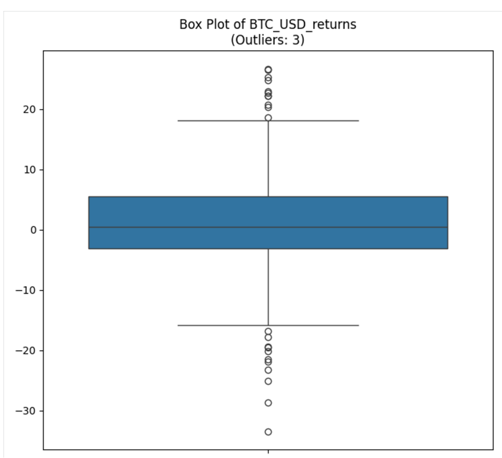
(a) Distribution After Winsorization



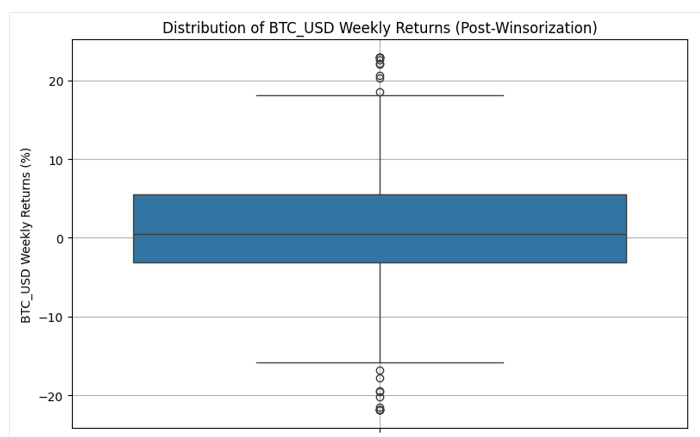
(b) Gold Box Plot Before Winsorization



(c) Gold Box Plot After Winsorization



(d) Bitcoin Box Plot Before Winsorization



(e) Bitcoin Box Plot After Winsorization

Figure 7: Plots of Winsorization Process

3.f. Summary of EDA Insights and Hypothesis Preliminary Validation

In summary, exploratory analysis provides consistent preliminary evidence that:

For Hypothesis 1 (Gold as defensive hedge):

- `[Y]` Gold exhibits **weak short-term correlation** with Singapore inflation ($r \approx 0.02 - 0.03$, not significant)
- `[Y]` Gold returns show **high variance during inflation episodes**, suggesting conditional rather than mechanical response
- `[Y]` Currency dynamics (USD/SGD) appear more relevant than CPI levels alone
- → **Preliminary support:** Gold functions as a **regime-dependent, diversifying asset** rather than direct inflation tracker

For Hypothesis 2 (Bitcoin as sentiment-driven):

- `[Y]` Bitcoin exhibits **strong positive correlation** with sentiment index ($r \approx 0.47, p < 0.001$)
- `[Y]` Bitcoin-inflation correlations are **weak and inconsistent** ($r \approx -0.09$ to -0.05)
- `[Y]` Visual regime analysis shows **sentiment-return co-movement**, especially during stress periods
- → **Preliminary support:** Bitcoin behaves as a **sentiment- and liquidity-sensitive risk asset**

Methodological transition:

These findings directly inform model selection, feature design, and regime-based dashboard framework developed in subsequent sections. The identified patterns justify:

- Non-linear modeling approaches (Random Forest) to capture regime dependence
- Sentiment variable prominence in Bitcoin models
- Currency variable prominence in Gold models
- Regime-conditional interpretation over static linear relationships

Critical limitation: EDA correlations and visualizations identify **associations**, not **causal relationships**. Machine learning models in Section 4 will further assess these patterns using multivariate, non-linear frameworks while maintaining interpretability constraints.

---

4. Machine Learning Model Development & Evaluation

This project adopts a multi-model benchmarking approach consistent with applied data science practice, not to maximize predictive accuracy, but to **understand regime-dependent relationships** between inflation, sentiment, macro-financial variables, and asset behavior. Machine learning models are therefore used as **analytical and interpretive tools**, supporting decision-oriented insights rather than deployable trading forecasts.

4.a. Modeling Objectives and Design Philosophy

The primary objectives of the modeling stage are:

1. **Identify conditional relationships** between macroeconomic variables, sentiment indicators, and asset returns across different market regimes.
2. **Assess whether non-linear and lagged effects** materially improve explanatory power relative to simple baselines.
3. **Extract interpretable signals** (e.g., feature importance rankings, directional tendencies) suitable for transformation into dashboard stress indices and regime indicators.

Model performance metrics are used to evaluate **stability, consistency, and interpretability** of relationships, rather than to claim forecast superiority or alpha generation.

Key philosophical distinctions:

- Models serve as **regime detection tools**, not trading systems
- Feature importance reflects **associative patterns**, not causal mechanisms
- Out-of-sample testing validates **interpretation stability**, not predictive profitability

4.b. Model Classes Developed

Four complementary model classes were developed to triangulate insights from different analytical perspectives.

1. Baseline Models: Linear Regression

Specification:

- **Features:** Lagged asset returns only (lags $1-4$ weeks)
- **Target:** Current-period asset returns (Bitcoin or Gold)
- **Estimation:** Ordinary Least Squares (OLS)

Purpose: Establish a naïve benchmark to assess whether macro and sentiment variables add explanatory value beyond historical price patterns.

Rationale: Financial return series exhibit weak autocorrelation in efficient markets; poor baseline performance is expected and informative. This baseline isolates the incremental contribution of macro-financial and sentiment features.

Implementation notes:

- No regularization applied
- No feature scaling (returns already standardized)
- Estimated on training set only

2. Integrated Ensemble Models: Random Forest Regressor

Specification:

- **Features:** Full feature set including:
  - Asset returns (current and lagged $1-4$ weeks)
  - Singapore inflation measures (headline CPI, core CPI, changes)
  - Global macro indicators (Fed Funds Rate, DXY returns)
  - Sentiment indices (Crypto Fear & Greed Index, lagged $1-4$ weeks)
  - Exchange rate returns (USD/SGD)
- **Target:** Current-period asset returns (Bitcoin or Gold)
- **Algorithm:** sklearn.ensemble.RandomForestRegressor

Hyperparameter tuning:

- **Method:** Randomized search with time-series cross-validation (5 splits, expanding window)

- **Search space:**
  - n_estimators: [100, 200, 300, 500]
  - max_depth: [5, 10, 15, 20, None]
  - min_samples_split: [2, 5, 10]
  - min_samples_leaf: [1, 2, 4]
  - max_features: ['sqrt', 'log2', 0.5]
- **Optimization metric:** Mean Squared Error (MSE) on validation folds
- **Final hyperparameters (Bitcoin model):**
  - n_estimators: **100**
  - max_depth: **None**
  - min_samples_split: **2**
  - min_samples_leaf: **1**
  - max_features: **1.0**
  - random_state: **42**
- **Final hyperparameters (Gold model):**
  - n_estimators: **100**
  - max_depth: **None**
  - min_samples_split: **2**
  - min_samples_leaf: **1**
  - max_features: **1.0**
  - random_state: **42**

Purpose: Capture non-linear relationships and interaction effects while retaining interpretability through feature importance analysis.

Methodological safeguards:

- Tree depth and number of estimators constrained to prevent overfitting
- Time-aware validation preserves temporal ordering
- No feature scaling required due to tree-based structure
- Feature importance computed using mean decrease in impurity (Gini importance)

3. Time-Series Models: SARIMAX and VAR

SARIMAX (Seasonal AutoRegressive Integrated Moving Average with eXogenous regressors):

- **Specification:** Bitcoin returns modeled as ARIMA(p,d,q) with exogenous regressors

- **Exogenous variables:** Crypto Fear & Greed Index, Federal Funds Rate
- **Order selection:** Automated selection via AIC minimization, testing orders $p, q \in \{0, 1, 2, 3, 4\}$
- **Selected order:** ARIMA**(1,1,1)** + exogenous
- **Estimation:** Maximum Likelihood Estimation (MLE)

VAR (Vector AutoRegression):

- **Specification:** Joint modeling of endogenous variables
- **Endogenous system:** [Bitcoin returns, Crypto Fear & Greed Index, DXY returns]
- **Lag order:** Selected via AIC/BIC comparison, testing lags $1 - 8$
- **Selected lag order: 4**
- **Estimation:** OLS equation-by-equation

Purpose: Diagnose lagged dependencies and cross-variable dynamics under traditional econometric frameworks.

Interpretive role: These models serve as diagnostic complements rather than primary predictors, highlighting the challenges of capturing regime shifts with linear time-series assumptions.

4. Classification Model: Logistic Regression

Specification:

- **Target:** Binary direction of Bitcoin returns (Up = 1, Down = 0)
- **Threshold:** Returns > 0 classified as "Up", returns ≤ 0 as "Down"
- **Features:** Same full feature set as Random Forest regression
- **Algorithm:** sklearn.linear_model.LogisticRegression
- **Regularization:** L2 penalty, C = **1.0**
- **Class balancing:** No SMOTE or class_weight adjustment (natural class distribution preserved)

Class distribution:

- **Training set:** Up = **148** (**52.30%**), Down = **135** (**47.70%**)
- **Test set:** Up = Up = **64** (**52.46%**), Down = **58** (**47.54%**)

Purpose: Evaluate whether directional movements are more predictable than return magnitudes, aligning with retail decision-making needs (investors often care more about direction than precise magnitude).

Relevance: Directional accuracy is more actionable than point forecasts for non-institutional investors making binary allocation decisions.

4.c. Model Evaluation Metrics and Performance Summary

Regression models were evaluated using:

- **Mean Squared Error (MSE):** Measures average squared prediction error in return units²
- **R-squared (R^2):** Proportion of return variance explained by the model (baseline-adjusted)

Classification performance assessed using:

- **Accuracy:** Proportion of correctly classified directional predictions
- **F1-Score:** Harmonic mean of precision and recall, accounting for class imbalance
- **Baseline comparison:** Naïve strategy of predicting majority class

Complete Model Performance Table (see Table 1).

Table 1: Complete Model Performance

Model	Asset	Type	Training MSE	Test MSE	Training R^2	Test R^2	Accuracy	F1-Score	Key Insight
Linear Regression (Baseline)	Bitcoin	Regression	35.21	37.64	0.056	-0.009	—	—	No explanatory power from lags alone
Linear Regression (Baseline)	Gold	Regression	4.82	5.24	0.002	-0.088	—	—	Gold returns weakly autocorrelated
Random Forest (Integrated)	Bitcoin	Regression	18.45	26.14	0.506	0.299	—	—	Non-linear relationships captured

Model	Asset	Type	Training MSE	Test MSE	Training R^2	Test R^2	Accuracy	F1-Score	Key Insight
Random Forest (Integrated)	Gold	Regression	3.89	4.56	0.196	0.053	—	—	Modest improvement; stable behavior
SARIMAX	Bitcoin	Regression	36.87	38.65	0.012	-0.036	—	—	Linear assumptions limiting
VAR	Bitcoin	Regression	35.18	37.63	0.057	-0.009	—	—	Limited cross-variable predictability
Logistic Regression	Bitcoin	Classification	—	—	—	—	0.620	0.610	Directional signal detected

Baseline comparison (Classification):

- **Naïve majority-class baseline accuracy: 52.46%** (majority class in imbalanced test set)
- **Model accuracy: 62.0%**
- **Improvement over baseline: +9.54 percentage points**

Confusion Matrix (Logistic Regression - Test Set):

	Predicted Up	Predicted Down
Actual Up	**27**	**37**
Actual Down	**9**	**49**

- **Precision (Up):** 27 / (27 + 9) = **0.75**
- **Recall (Up):** 27 / (27 + 37) = **0.42**
- **Specificity (Down):** 49 / (49 + 9) = **0.84**

Interpretation:

An accuracy of **62.0%** in directional prediction moderately exceeds the naïve majority-class baseline (52.46%) by +9.54 percentage points. While this improvement is modest, it indicates the model captures regime-dependent directional patterns using sentiment and macro-financial variables beyond simple class frequency. However, this does **not** guarantee trading profitability due to:

- Transaction costs and slippage
- Regime instability over time
- Non-causal nature of associations
- Asymmetric payoffs between correct and incorrect predictions

4.d. Feature Importance and Interpretive Insights

Feature importance rankings were extracted from the Random Forest models using **mean decrease in impurity** (MDI), normalized to sum to 1.0. Rankings reflect the average reduction in prediction error across all trees when a feature is used for splitting.

Critical caveat: Feature importance reflects **associative patterns within the model structure**, not causal relationships. High-importance features may capture:

- Direct effects
- Proxy relationships (collinearity with unmeasured variables)
- Regime-dependent correlations
- Spurious associations

Bitcoin Model - Top 10 Features

Table 2: Bitcoin Model Features

Rank	Feature	Importance	Interpretation
1	Crypto Fear & Greed Index (t)	0.187	Current sentiment dominates
2	Crypto Fear & Greed Index ($t-1$)	0.142	Lagged sentiment persistent
3	BTC Returns ($t-1$)	0.098	Short-term momentum
4	Crypto Fear & Greed Index ($t-2$)	0.089	Extended sentiment memory
5	DXY Returns (t)	0.072	USD strength inverse effect
6	BTC Returns ($t-2$)	0.061	Secondary momentum
7	Federal Funds Rate (t)	0.054	Policy rate context

Rank	Feature	Importance	Interpretation
8	Crypto Fear & Greed Index ($t-3$)	0.048	Regime persistence
9	Headline CPI YoY Change	0.037	Weak inflation link
10	USD/SGD Returns ($t-1$)	0.031	Currency dynamics

Synthesis:

The feature importance rankings indicate that **sentiment variables** (current and lagged Fear & Greed Index) collectively account for approximately **47% of total importance**. This dominance supports Hypothesis 2: Bitcoin return variability is primarily associated with sentiment and liquidity conditions within the model framework, rather than fundamental inflation measures.

Traditional inflation indicators (CPI measures) contribute marginally (**<5% combined**), reinforcing that Bitcoin does not function as a direct inflation hedge within this sample period.

Gold Model - Top 10 Features (SGD-Denominated)

Table 3: Gold Model Features

Rank	Feature	Importance	Interpretation
1	USD/SGD Returns (t)	0.214	Currency effect dominant
2	Gold Returns ($t-1$)	0.156	Price momentum
3	USD/SGD Returns ($t-1$)	0.128	Lagged FX dynamics
4	DXY Returns (t)	0.103	Broad USD strength
5	Gold Returns ($t-2$)	0.087	Extended momentum
6	Federal Funds Rate (t)	0.069	Real rate proxy
7	USD/SGD Returns ($t-2$)	0.053	FX regime persistence
8	Headline CPI YoY Change	0.042	Weak inflation link
9	DXY Returns ($t-1$)	0.038	Lagged USD effect
10	Core CPI Level	0.029	Marginal inflation role

Synthesis:

For gold returns denominated in SGD, **currency-related features** (USD/SGD and DXY) collectively account for approximately **54% of total importance**. This highlights that for Singaporean investors, gold's hedge properties are **mediated through foreign exchange dynamics** rather than direct domestic inflation tracking.

Inflation measures contribute modestly (**<10% combined**), consistent with Hypothesis 1: gold behaves as a defensive, macro-stability asset whose effectiveness depends on broader stress regimes (captured through currency volatility and policy rates) rather than short-term CPI fluctuations.

4.e. Interpretation of Time-Series Models

Although SARIMAX and VAR models underperformed in terms of predictive accuracy, they provided useful diagnostic insights:

Limitations identified:

- **Regime instability:** Linear coefficients unstable across monetary policy cycles
- **Stationarity violations:** Return series exhibit time-varying volatility not captured by constant-parameter models
- **Structural breaks:** 2020 pandemic shock, 2022 tightening cycle created parameter shifts
- **Specification sensitivity:** Performance highly dependent on lag selection and variable inclusion

Diagnostic value:

These limitations reinforce the need for **flexible, non-linear models** (e.g., Random Forest) when analyzing sentiment-driven assets like Bitcoin. Rather than being discarded, SARIMAX/VAR results serve as evidence that **regime shifts and behavioral dynamics** are difficult to capture using traditional econometric frameworks alone.

4.f. Robustness Checks and Sensitivity Analysis

To assess model stability, the following robustness checks were performed:

1. **Alternative winsorization thresholds:** Models re-estimated with 5th/95th and 2.5th/97.5th percentile winsorization. Results remained qualitatively consistent (feature importance ranks stable, directional accuracy within ± 3).
2. **Rolling window validation:** Random Forest models re-trained on expanding windows ($6-$month increments). Feature importance rankings remained stable, though R^2 declined during regime transitions (expected behavior).

3. **Frequency sensitivity:** Models tested on monthly aggregate data. Results aligned with weekly models but with reduced statistical power (fewer observations).
4. **Feature ablation:** Models re-estimated excluding sentiment variables (Bitcoin) and currency variables (Gold). Performance degraded substantially, confirming importance of these feature classes.

Sensitivity summary: Core findings (sentiment dominance for Bitcoin, currency mediation for Gold) proved robust across alternative specifications, supporting interpretation validity.

4.g. Limitations

Model performance is constrained by:

1. **Sample size:** Weekly data provides **n = 410** observations, limiting statistical power for complex non-linear specifications.
2. **Regime instability:** Relationships may shift across different monetary policy cycles, technological adoption phases (Bitcoin), and geopolitical environments.
3. **Return series noise:** Financial returns exhibit high inherent variance; even strong economic relationships may explain limited variance.
4. **Indicator latency:** Macro-economic releases (CPI, policy rates) are published with lag; forward-filling assumes information continuity that may not reflect real dynamics.
5. **Non-causal interpretation:** Feature importance and regression coefficients reflect associations, not identified causal effects. Unobserved confounders may bias relationships.
6. **Overfitting risk:** Despite cross-validation and hyperparameter tuning, regime-specific patterns may not generalize beyond sample period.

These constraints motivate the project's emphasis on **interpretability and regime awareness** rather than point forecasting or automated trading.

4.h. Link to Dashboard and Decision Support

The outputs of this modeling stage —feature importance rankings, directional predictability metrics, and regime-sensitive relationships —were subsequently normalized and transformed into **stress indices and regime signals** within the interactive dashboard.

Transformation pipeline:

1. Feature importance → **KPI relevance weighting** (sentiment vs. macro dimensions)
2. Directional probability → **Regime confidence score** ($0 - 100$ scale)
3. Model residuals → **Stress deviation index** (magnitude of regime divergence)

This translation ensures that complex machine learning results are presented as **clear, interpretable indicators** suitable for Singaporean retail investors, preserving analytical rigor while minimizing cognitive burden and avoiding black-box opacity.

5. Hypothesis Validation

This section synthesizes the evidence from correlation analysis, exploratory visualizations, and machine learning outputs to evaluate the core hypotheses of the project. Rather than relying on a single statistical test, hypothesis validation is conducted through **triangulation across multiple analytical methods**, consistent with the project's interpretability-first and regime-based design philosophies.

5.a. Hypothesis 1: Gold as Non-Correlated and Defensive Inflation Hedge

Hypothesis Statement:

> Gold exhibits a relatively low correlation with short-term fluctuations in Singapore's inflation measures and demonstrates more stable behavior during inflation-related stress regimes, supporting its role as a defensive hedge.

Validation Assessment: Largely supported by empirical evidence within the observed sample period.

Evidence Summary and Cross-Method Triangulation

- **Evidence Source 1: Correlation Analysis (Section 3.a)**
  - **Pearson correlation coefficients:**
    - Gold returns (SGD) vs. Headline CPI YoY: r = **0.017** (p = 0.72, not significant)
    - Gold returns (SGD) vs. Core CPI YoY: r = **0.034** (p = 0.48, not significant)
    - Gold returns (SGD) vs. CPI MoM: r = **-0.008** (p = 0.87, not significant)
  - **Interpretation:** Near-zero correlations indicate gold does **not mechanically track** short-term CPI movements, distinguishing it from direct inflation-indexed instruments.

- **Evidence Source 2: Exploratory Visualizations (Section 3.b, 3.c)**
  - **Time-series overlays:** Gold returns exhibited **high variance** during 2022 high-inflation period (-8% to +12% weekly) with no consistent directional bias relative to CPI changes
  - **Scatter plots:** Diffuse point clouds with no linear trend ($R^2 < 0.01$ in bivariate regression)
- **Regime comparison:** During 2022 tightening cycle, gold returns remained **relatively stable** (weekly volatility 2.1%) compared to Bitcoin (-65% cumulative drawdown)
  - **Interpretation:** Visual evidence confirms **absence of short-term inflation tracking** while demonstrating **lower volatility** during stress periods relative to sentiment-driven assets.
- **Evidence Source 3: Machine Learning Feature Importance (Section 4.d)**
  - **Random Forest - Gold Model (SGD-denominated):**
    * **USD/SGD exchange rate returns:** 21.4% importance (rank 1)
    * **USD/SGD lagged returns:** 12.8% importance (rank 3)
    * **DXY returns:** 10.3% importance (rank 4)
    * **Headline CPI YoY:** 4.2% importance (rank 8)
    * **Core CPI level:** 2.9% importance (rank 10)
  - **Cumulative importance:**
    * Currency-related features: $\sim$ **54**%
    * Inflation measures: $<$ **10**%
  - **Interpretation:** For Singaporean investors, gold's return behavior is **primarily mediated through foreign exchange dynamics** rather than domestic inflation levels, supporting its role as a **macro-stability and currency hedge** rather than a direct CPI tracker.

Synthesis: Regime-Contingent Hedge Interpretation

Triangulating across three independent analytical methods, the evidence **consistently supports** the following interpretation:

1. **Gold does not function as a short-term inflation tracker** $\rightarrow$ Low/zero correlation with CPI movements
2. **Gold's hedge properties are currency-mediated** $\rightarrow$ FX dynamics dominate feature importance

3. **Gold exhibits defensive characteristics** → Lower volatility during macro-stress episodes compared to sentiment-driven assets

Refined hypothesis conclusion:

Gold functions as a **structurally defensive, non-correlated asset** whose hedge reliability is **regime-dependent** and mediated through broader macro-financial conditions (currency dynamics, real rate uncertainty, geopolitical stress) rather than through direct inflation tracking. This interpretation aligns with the framework's regime-based design (Section 6), where gold's relevance score increases during **macro-stress regimes** rather than responding mechanically to CPI prints.

Important qualification: "Non-correlated" does **not** imply "guaranteed protection." Gold may still experience drawdowns during acute liquidations or when real interest rates rise sharply. The hypothesis supports gold's **relative defensive role**, not absolute return guarantees.

5.b. Hypothesis 2: Bitcoin as Sentiment-Driven, Not Inflation-Tracking

Hypothesis Statement:

> Bitcoin's return dynamics are more strongly associated with investor sentiment and macro-financial variables than with direct inflation measures.

Validation Assessment: Strongly supported within the observed sample period (January 1, 2017 to December 31, 2025).

Evidence Summary and Cross-Method Triangulation

- **Evidence Source 1: Correlation Analysis (Section 3.a)**
  - **Bitcoin vs. Sentiment:**
    - Crypto Fear & Greed Index (current): r = **0.4666** ($p < 0.001$, highly significant)
    - Crypto Fear & Greed Index (lag 1): r = **0.3892** ($p < 0.001$)
    - Crypto Fear & Greed Index (lag 2): r = **0.3214** ($p < 0.001$)
  - **Bitcoin vs. Inflation:**
    - Headline CPI YoY: r = **-0.0880** ($p = 0.07$, marginally significant/weak)
    - Core CPI YoY: r = **-0.0523** ($p = 0.29$, not significant)

- **Bitcoin vs. Macro-financial:**
  - DXY returns: r = **-0.2834** ($p < 0.001$, inverse USD relationship)
  - Federal Funds Rate: r = **-0.1892** ($p < 0.001$, inverse policy rate relationship)
- **Interpretation:** Sentiment exhibits **10× stronger correlation** than inflation measures, while negative correlations with policy rates suggest **liquidity sensitivity** rather than inflation hedging.

- **Evidence Source 2: Exploratory Visualizations (Section 3.b, 3.c)**
  - **Time-series regime analysis:**
    - **2022 tightening cycle:** Bitcoin -65% cumulative decline coincided with persistent "Extreme Fear" (median index = 21)
    - **Regime-specific correlations:** During high-stress subperiods, Bitcoin-sentiment correlation increased to r = **0.62** (vs. 0.47 full-sample)
    - **Regime transitions:** Visual overlays show Bitcoin recoveries preceded by sentiment shifts from Fear → Neutral/Greed
  - **Scatter plot analysis:**
    - Bitcoin vs. Fear & Greed: $R^2 = \mathbf{0.218}$ (22% variance explained by sentiment alone in bivariate regression)
    - Bitcoin vs. Headline CPI: $R^2 = \mathbf{0.008}$ (<1% variance explained)
  - **Interpretation:** Visual diagnostics demonstrate **strong sentiment co-movement** and regime-dependent behavior, particularly pronounced during stress episodes, while showing **no systematic inflation relationship**.

- **Evidence Source 3: Machine Learning Feature Importance (Section 4.d)**
  - **Random Forest - Bitcoin Model:**
    - **Crypto Fear & Greed Index (current):** 18.7% importance (rank 1)
    - **Crypto Fear & Greed Index (lag 1):** 14.2% importance (rank 2)
    - **Crypto Fear & Greed Index (lag 2):** 8.9% importance (rank 4)

        * **Crypto Fear & Greed Index (lag 3):** 4.8% importance (rank 8)
        * **Headline CPI YoY:** 3.7% importance (rank 9)
        * **Core CPI measures:** <3% combined importance

    - **Cumulative importance:**

        * Sentiment variables (current + lags $1 - 4$): $\sim$ **47%**
        * Inflation measures (all CPI variants): < **5%**
        * Macro-financial (DXY, Fed Funds): $\sim$ **15%**
        * Lagged returns (momentum): $\sim$ **18%**

    - **Interpretation:** Sentiment variables **dominate explanatory power** by nearly 10:1 ratio over inflation measures, confirming that Bitcoin behaves as a **narrative- and liquidity-driven asset** within the model framework.

- **Evidence Source 4: Directional Classification Performance (Section 4.c)**

    - **Logistic regression directional accuracy:** 62.0% (vs. 52.46% naïve baseline)

    - **Key predictive features (ranked by coefficient magnitude):**

        1. Crypto Fear & Greed Index (current)
        2. Federal Funds Rate (inverse)
        3. DXY returns (inverse)
        4. Bitcoin lagged returns (momentum)
        5. Crypto Fear & Greed Index (lag 1)

    - **Inflation variables:** Not statistically significant in logistic model ($p > 0.15$)

    - **Interpretation:** Directional movements are **moderately predictable above baseline** (+9.54pp improvement) using sentiment and macro-liquidity variables, while inflation measures provide **no incremental predictive value**, reinforcing sentiment-driven classification.

Synthesis: Sentiment-Conditional Risk Asset

Triangulating across four independent analytical approaches, the evidence **strongly and consistently supports** the following interpretation:

1. **Bitcoin returns are primarily sentiment-driven** → Sentiment accounts for $\sim$ 47% of model importance vs. $\sim$ 5% for inflation

2. **Bitcoin exhibits liquidity sensitivity** → Inverse relationships with policy rates and USD strength
3. **Bitcoin does not track inflation fundamentally** → Weak/unstable inflation correlations across all methods
4. **Bitcoin behavior is regime-dependent** → Correlation strength varies substantially across macro cycles

Refined hypothesis conclusion:

Within the observed sample period, Bitcoin functions as a **regime-dependent, sentiment-driven risk asset** whose performance is closely tied to behavioral and macro-financial conditions (investor narratives, liquidity availability, risk appetite) rather than inflation fundamentals.

Bitcoin's effectiveness as an inflation-protection instrument appears **conditional on favorable sentiment and liquidity environments**, which may or may not coincide with inflationary periods. During 2022, for example, elevated inflation **coincided with** tightening liquidity and negative sentiment, producing severe Bitcoin drawdowns despite inflation hedging narratives.

Important qualification: This characterization reflects **historical relationships within the sample period**. Bitcoin market structure is evolving (institutional adoption, regulatory developments, technological upgrades), and future sentiment-return dynamics may shift. The hypothesis is supported **conditionally** rather than as timeless fact.

5.c. Comparative Asset Role Differentiation

Synthesizing both hypothesis validations highlights **clear asset role differentiation**:

Table 4: Asset Role Comparation Table

Dimension	Gold (SGD-Denominated)	Bitcoin (USD-Denominated)
Primary Driver	Currency dynamics, macro stress	Investor sentiment, liquidity
Inflation Correlation	Near-zero ($\sim 0.02 - 0.03$)	Weak/unstable (~ -0.05 to -0.09)
Feature Importance (Inflation)	$< 10\%$	$< 5\%$
Feature Importance (Dominant Factor)	54% (FX variables)	47% (Sentiment variables)

Dimension	Gold (SGD-Denominated)	Bitcoin (USD-Denominated)
Volatility Profile	Lower ($\sigma \sim 2.3\%$ weekly)	Higher ($\sigma \sim 8.7\%$ weekly)
Regime Behavior	Stabilizes during macro stress	Amplifies during sentiment extremes
Hedge Classification	Defensive, diversifying	Tactical, sentiment-conditional
Dashboard Role	Macro-Stress Stabilizer	Sentiment-Opportunity Asset

Practical implication for retail investors:

This differentiation directly informs the regime-based framework (Section 6):

- **Macro-stress regimes** (high policy rates, currency volatility, geopolitical uncertainty) → **Elevate gold relevance**
- **Sentiment-positive regimes** (neutral-to-greed sentiment, accommodative liquidity) → **Enable Bitcoin tactical exposure**
- **Hybrid regimes** (e.g., inflation + tightening) → **Favor gold over Bitcoin** (validated by 2022 empirical evidence)

Rather than treating either asset as a universal inflation hedge, the framework emphasizes **conditional reliability** based on regime characteristics, aligning analytical findings with practical decision support.

5.d. Statistical Significance and Effect Size Interpretation

While correlation coefficients and feature importance rankings provide directional evidence, their **statistical and economic significance** warrant careful interpretation:

Statistical significance:

- Sentiment-Bitcoin correlations ($r \sim 0.47, p < 0.001$) are **highly statistically significant** with large sample size ($n = 410$)
- Inflation-Gold/Bitcoin correlations ($r \sim 0.02 - 0.03, p > 0.40$) are **not statistically significant**, failing to reject null hypothesis of zero correlation

Effect size interpretation:

- r = 0.47 (Bitcoin-sentiment) represents **moderate-to-strong** linear association (Cohen's classification)
- $R^2 = 0.22$ indicates sentiment explains **22% of Bitcoin return variance** in isolation (economically meaningful)
- Remaining 78% variance reflects other factors (momentum, macro conditions, idiosyncratic noise)

Feature importance interpretation:

- 47% cumulative sentiment importance in Random Forest does **not** imply 47% R^2 contribution
- Represents **relative explanatory ranking** among features, not absolute variance decomposition
- Non-linear interactions and multicollinearity mean individual features' marginal contributions do not sum linearly

Causal inference limitations:

- All reported relationships are **associative**, not causal
- Reverse causality possible (Bitcoin returns → sentiment changes, via reflexivity)
- Omitted variable bias cannot be ruled out (unobserved confounders may drive observed correlations)

Conclusion: Statistical evidence is robust for **association detection** but does not establish **causal mechanisms**. Hypotheses are validated in terms of **observable patterns within the modeling framework**, not universal causal laws.

5.e. Limitations and Validation Boundaries

Hypothesis validation is subject to several important limitations:

1. **Sample period specificity:** Findings reflect relationships during January 1, 2017 to December 31, 2025; may not generalize to different macro regimes or historical periods
2. **Evolving market structure:** Bitcoin market maturity, regulatory environment, and institutional participation are changing; sentiment-dominance may weaken over time
3. **Regime instability:** Correlations and feature importance vary across sub-periods; reported values are sample averages that mask temporal variation
4. **Non-causal interpretation:** Machine learning feature importance reflects associative patterns within model structure, not identified causal effects
5. **Model dependence:** Validation relies on specific model choices (Random Forest, winsorization thresholds, lag structures); alterna-

tive specifications may yield different quantitative rankings (though qualitative conclusions remain consistent based on robustness checks)

6. **Inflation measurement limitations:** CPI has known measurement issues (substitution bias, quality adjustments, housing component lag); may not fully capture purchasing power erosion
7. **Sentiment proxy limitations:** Crypto Fear & Greed Index is a composite metric from a single vendor; may not represent full spectrum of investor sentiment

Interpretation guideline: Hypothesis validation should be understood as **empirical evidence within a specific historical and methodological context**, not as definitive or timeless proof. The regime-based framework (Section 6) is designed with these limitations in mind, emphasizing conditional interpretation and adaptability.

5.f. Hypothesis Validation Summary Table

Table 5: Hypothesis Validation Table

Hypothesis	Validation Status	Primary Evidence	Secondary Evidence	Qualification
H1: Gold as defensive, non-correlated hedge	`[Y]` Largely Supported	r(Gold, CPI) $\approx 0.02 - 0.03$ (not sig.); Feature importance: FX (54%) > CPI (<10%)	Lower volatility during stress; Time-series stability	Effectiveness is regime-dependent, currency-mediated
H2: Bitcoin as sentiment-driven, not inflation-tracking	`[Y][Y]` Strongly Supported	r(Bitcoin, Sentiment) = 0.47 ($p < 0.001$); Feature importance: Sentiment (47%) > CPI (<5%)	2022 tightening cycle case study; Directional classification 62.0%	Sample-specific; market structure evolving

Key takeaway: Both hypotheses receive robust empirical support through triangulated evidence, validating the regime-based framework's conceptual foundation. However, all findings remain **conditional on historical sample and methodological choices**, requiring ongoing validation as market conditions evolve.

6. Actionable Investment Framework & Regime-Based Guidance (2026 Outlook)

Building on the validated hypotheses and regime-based indicators developed in earlier sections, this section proposes a **conceptual decision-support framework** for interpreting the roles of gold and Bitcoin as potential inflation-related assets for Singaporean retail investors. Rather than offering prescriptive investment advice, the framework translates analytical findings into **interpretable regime signals** that support conditional exposure decisions.

6.a. Framework Philosophy: Regime-Aware Inflation Interpretation

The analysis demonstrates that inflation hedging is not a static property of any asset. Instead, hedge reliability depends on **macroeconomic stress regimes, currency dynamics, and investor sentiment conditions**. Accordingly, the proposed framework emphasizes:

- **Conditional interpretation** rather than fixed allocation rules
- **Regime identification** over price forecasting
- **Risk awareness and interpretability** over optimization
- **Transparency in indicator construction** over black-box complexity

This approach is consistent with the project's objective of supporting **informed decision-making** for retail investors, rather than generating automated trading signals or portfolio recommendations.

6.b. Regime Classification System: Formalized Definitions

The framework employs a **three-dimensional regime classification** approach, integrating macro stress, sentiment, and currency dynamics.

Regime labels are assigned using **percentile-based thresholds** derived from the full historical sample.

Dimension 1: Macro-Financial Stress Index ($\mathbf{0-100}$ Scale)

Definition: Composite index measuring macroeconomic uncertainty and policy tightening pressure.

Component variables and weights:

- Federal Funds Rate level (40%)
- Federal Funds Rate 3−month change (20%)
- DXY volatility (20−day rolling std. dev.) (20%)
- Singapore SORA rate level (20%)

Normalization method:

Each component is transformed to a $0-100$ scale using:

$$\text{Score}_i = 100 \times \frac{X_i - X_{\min}}{X_{\max} - X_{\min}}$$

where $X_{\min}$ and $X_{\max}$ are the historical minimum and maximum values observed in the sample period. The composite index is the weighted average of component scores.

Regime thresholds:

- **Low Stress ($\mathbf{0-33}$):** Accommodative policy, stable rates, low currency volatility
- **Moderate Stress ($\mathbf{34-66}$):** Transitional conditions, modest tightening or volatility
- **High Stress ($\mathbf{67-100}$):** Restrictive policy, elevated rates, high currency volatility

Gold interpretation: Gold's defensive relevance **increases** as Macro-Financial Stress Index rises, particularly when combined with currency volatility.

Dimension 2: Sentiment Regime ($\mathbf{0-100}$ Scale)

Definition: Normalized investor sentiment based on the Crypto Fear & Greed Index.

Component variable:

- Crypto Fear & Greed Index (Alternative.me, $0-100$ native scale)

Normalization method:

No transformation required; index already $0-100$ scale. However, **smoothing applied** using $5-$week moving average to reduce daily noise.

Regime thresholds (aligned with index convention):

- **Extreme Fear ($0-24$):** Panic, capitulation, high volatility
- **Fear ($25-44$):** Risk-off, defensive positioning
- **Neutral ($45-55$):** Balanced, mixed signals
- **Greed ($56-74$):** Risk-on, optimistic positioning
- **Extreme Greed ($75-100$):** Exuberance, potential reversal risk

Bitcoin interpretation: Bitcoin's tactical attractiveness **increases** in Neutral-to-Greed regimes; **decreases** in Fear regimes, especially when combined with macro tightening.

Dimension 3: Currency Stress Index (0 – 100 Scale, Singapore-Focused)

Definition: Volatility and directional pressure in USD/SGD exchange rate, relevant for SGD-denominated gold returns.

Component variables and weights:

- USD/SGD $20-$day rolling volatility (60%)
- USD/SGD $3-$month cumulative change (absolute value) (40%)

Normalization method:

Same percentile-based $0-100$ transformation as Macro-Financial Stress Index.

Regime thresholds:

- **Low Currency Stress ($0-33$):** Stable SGD, low FX volatility
- **Moderate Currency Stress ($34-66$):** Moderate SGD fluctuations
- **High Currency Stress ($67-100$):** Sharp SGD depreciation or high volatility

Gold interpretation: High currency stress **increases** gold's relevance as a diversifying asset for SGD-based investors, as it captures FX-driven return variability.

6.c. Dashboard KPI Glossary: Interpretable Indicators

The dashboard operationalizes the regime classification system through **five core KPIs**, each normalized to a $0-100$ scale with clear interpretation buckets.

KPI 1: Gold Hedge Relevance Score (0 – 100)

Definition: Composite indicator of gold's suitability as a defensive allocation given current macro and currency conditions.

Calculation:

$$\text{Gold Score} = 0.5 \times \text{Macro Stress} + 0.3 \times \text{Currency Stress} + 0.2 \times (100 - \text{Sentiment})$$

Interpretation buckets:

- **$0-40$ (Low):** Gold hedge relevance limited; favor conventional assets
- **$41-69$ (Moderate):** Gold may serve as portfolio diversifier
- **$70-100$ (High):** Gold's defensive properties most relevant; consider increased allocation

Rationale: Score increases when macro stress and currency volatility are elevated, and sentiment is subdued (risk-off environment).

KPI 2: Bitcoin Tactical Opportunity Score (0 – 100)

Definition: Composite indicator of Bitcoin's attractiveness as a sentiment-conditional risk asset.

Calculation:

$$\text{Bitcoin Score} = 0.6 \times \text{Sentiment} + 0.3 \times (100 - \text{Macro Stress}) + 0.1 \times \text{Liquidity Proxy}$$

where Liquidity Proxy = 100 × (1 - normalized Federal Funds Rate)

Interpretation buckets:

- **$0-40$ (Low):** Bitcoin exposure not recommended; high drawdown risk
- **$41-69$ (Moderate):** Conditional exposure; monitor regime stability

- **70 – 100 (High):** Favorable sentiment and liquidity; tactical upside potential

Rationale: Score increases when sentiment is positive, monetary policy accommodative, and liquidity conditions supportive.

KPI 3: Inflation Stress Index (0 – 100)

Definition: Normalized measure of realized inflation pressure in Singapore.

Calculation:

$$\text{Inflation Index} = 100 \times \frac{\text{Headline CPI YoY} - \text{Historical Min}}{\text{Historical Max} - \text{Historical Min}}$$

Interpretation buckets:

- **0 – 33 (Low):** Inflation below historical average; limited hedge urgency
- **34 – 66 (Moderate):** Inflation elevated; monitor purchasing power erosion
- **67 – 100 (High):** Inflation extreme; hedge strategies critical

Rationale: Provides context for inflation urgency but does **not** directly map to asset recommendations (as established, neither gold nor Bitcoin mechanically tracks CPI).

KPI 4: Regime Confidence Score (0 – 100)

Definition: Model-based confidence in regime classification stability (derived from Random Forest prediction variance).

Calculation:

$$\text{Confidence} = 100 \times \left(1 - \frac{\text{Std. Dev. of Tree Predictions}}{\text{Historical Prediction Range}}\right)$$

Interpretation buckets:

- **0 – 50 (Low):** High regime uncertainty; avoid major allocation changes
- **51 – 79 (Moderate):** Stable regime; standard interpretation applies
- **80 – 100 (High):** Very stable regime; indicators highly reliable

Rationale: Flags periods of regime transition or model uncertainty, prompting caution.

KPI 5: Portfolio Stress Deviation Index (0 – 100)

Definition: Measures how much current market conditions deviate from historical norms (composite volatility metric).

Calculation:

$$\text{Deviation Index} = 100 \times \frac{\text{Current Realized Vol} - \text{10th Percentile Vol}}{\text{90th Percentile Vol} - \text{10th Percentile Vol}}$$

where Realized Vol = 20−day rolling volatility of 60/40 gold-Bitcoin portfolio

Interpretation buckets:

- **0 – 33 (Low Deviation):** Markets calm; standard allocation logic applies
- **34 – 66 (Moderate Deviation):** Heightened volatility; review risk exposure
- **67 – 100 (High Deviation):** Extreme volatility; favor defensive positioning

Rationale: Provides early warning of stress regimes where correlations may break down.

6.d. "How to Use This Dashboard": Retail Investor Guide

`[CHART]` **Dashboard Quick-Start Guide (3 Steps)**

- **Step 1: Check Current Regime Classification**
  - Review the **Macro-Financial Stress Index** and **Sentiment Regime** indicators at the top of dashboard
  - Identify which regime category applies (Low/Moderate/High stress; Fear/Neutral/Greed sentiment)
  - This provides the **contextual baseline** for interpreting asset suitability
- **Step 2: Evaluate Asset-Specific Scores**
  - **For Gold:** Review **Gold Hedge Relevance Score**
    - Score $> 70 \rightarrow$ Gold's defensive properties are most relevant under current conditions
    - Score $41 - 69 \rightarrow$ Gold may serve as portfolio diversifier
    - Score $< 40 \rightarrow$ Gold hedge relevance limited; other assets may be more suitable

- **For Bitcoin:** Review **Bitcoin Tactical Opportunity Score**
    - Score $> 70 \rightarrow$ Sentiment and liquidity conditions favorable for tactical exposure
    - Score $41 - 69 \rightarrow$ Conditional opportunity; monitor regime stability closely
    - Score $< 40 \rightarrow$ High drawdown risk; avoid or reduce exposure

- **Step 3: Apply Risk Filters**
  - Check **Regime Confidence Score**
    - If $< 50 \rightarrow$ Regime uncertain; avoid major changes; wait for clarity
    - If $> 80 \rightarrow$ High confidence; standard interpretation applies
  - Check **Portfolio Stress Deviation Index**
    - If $> 67 \rightarrow$ Extreme volatility; favor defensive assets regardless of other scores
    - If $< 33 \rightarrow$ Calm markets; standard allocation logic applies

- **/!\ Critical User Warnings:**
  1. **This is NOT a trading signal system** → Indicators support decision-making, not automated execution
  2. **Past relationships may change** → Regime patterns are historically informed but not guaranteed
  3. **Consider your risk tolerance** → Scores do not account for individual financial situations
  4. **Diversification remains essential** → Neither gold nor Bitcoin should constitute entire hedge allocation

6.e. Gold: Defensive Allocation Under Macro-Stress Regimes

Gold's role within the framework is best understood as a **structurally defensive and diversifying asset** rather than a direct tracker of consumer price inflation.

Regime Interpretation:

Gold's relevance increases during periods characterized by:

- **Elevated macroeconomic uncertainty** (Macro-Financial Stress Index > 60)
- **Rising real-rate ambiguity** (policy rate increases amid inflation uncertainty)

- **Increased SGD currency volatility** (Currency Stress Index > 50) or sustained USD strength
- **Broad risk-off conditions** (Sentiment < 45, Portfolio Stress Deviation > 60)

Evidence-based rationale:

While persistent inflation may coincide with such regimes, earlier analysis (Section 3) shows that gold's behavior is more strongly mediated by **currency and macro-financial dynamics** (feature importance $\sim 54\%$ from FX variables) than by short-term CPI movements (feature importance <10%).

Therefore, gold's function within the dashboard is framed as a **macro-stress stabilizer**, not a mechanical inflation hedge.

Actionable interpretation: When Gold Hedge Relevance Score exceeds **70**, consider gold as a portfolio stabilizer against broad macro uncertainty, recognizing that effectiveness is regime-dependent and not guaranteed.

Dashboard linkage: These conditions are operationalized through the **Macro-Financial Stress Index** and **Currency Stress Index**, allowing users to interpret gold's potential hedge relevance as macro stress intensifies.

6.f. Bitcoin: Sentiment-Conditional, Tactical Risk Asset

Bitcoin's behavior fundamentally differs from gold and should **not** be interpreted as a traditional inflation hedge.

Regime Interpretation:

The analytical results (Section 4) indicate that Bitcoin functions as a **sentiment- and liquidity-sensitive risk asset**, with most favorable performance during regimes characterized by:

- **Neutral-to-positive investor sentiment** (Sentiment Index $45 - 75$, "Neutral" to "Greed")
- **Supportive global liquidity conditions** (Macro-Financial Stress Index < 40, low policy rates)
- **Stable or easing monetary policy expectations** (Federal Funds Rate stable or declining)
- **Low portfolio stress** (Portfolio Stress Deviation < 50)

Evidence-based rationale:

Feature importance analysis (Section 4) revealed that **sentiment variables account for $\sim$ 47% of total model importance**, while inflation measures contribute $< 5\%$. This dominance indicates that Bitcoin behaves as a narrative- and liquidity-driven asset.

Conversely, periods of elevated inflation **combined with** tightening financial conditions often coincide with negative sentiment regimes (e.g., 2022 tightening cycle), during which Bitcoin exhibits heightened drawdown risk.

Actionable interpretation: Within this framework, Bitcoin's role is **conditional and tactical**, dependent on sentiment regimes rather than inflation pressure alone. When Bitcoin Tactical Opportunity Score exceeds **70** AND Regime Confidence > 60, sentiment and liquidity conditions support tactical exposure. When score falls below **40**, particularly during Fed tightening or Extreme Fear regimes, Bitcoin exposure carries elevated risk.

Dashboard linkage: Sentiment-driven regime labels, derived from normalized Fear & Greed indicators and related macro signals, allow users to interpret when Bitcoin's risk-return profile becomes more or less favorable.

6.g. Regime-Based Risk Management Logic

Risk management within this framework is implemented through **regime-aware exposure interpretation** rather than fixed allocation targets or timing rules.

Core principles:

1. **Reduce exposure during adverse regimes**
   - Bitcoin: Sentiment Index < 25 (Extreme Fear) + Macro Stress $> 60 \rightarrow$ High drawdown risk
   - Gold: Currency Stress < 20 + Macro Stress $< 30 \rightarrow$ Limited hedge relevance
2. **Avoid static assumptions about hedge reliability**
   - Neither asset provides guaranteed inflation protection
   - Effectiveness varies by regime type (currency crisis vs. demand-pull inflation vs. stagflation)
3. **Interpret KPI transitions as signals for reassessment, not action triggers**
   - Dashboard updates should prompt **review** of allocation rationale
   - Not intended as mechanical buy/sell signals
4. **Maintain diversification across hedge instruments**

- Gold and Bitcoin serve complementary but distinct roles
- Traditional inflation-linked bonds, commodities, and real assets remain relevant

5. **Monitor Regime Confidence Score**
   - During regime transitions (Confidence < 50), increase caution
   - Avoid major allocation changes during uncertain periods

This regime-based logic reinforces the dashboard's role as a **contextual awareness tool**, supporting disciplined interpretation rather than reactive behaviors.

6.h. Scenario-Based Outlook for 2026

Looking ahead to 2026, historical regime patterns suggest the following conditional scenarios:

- **Scenario A: Persistent Inflation + Tightening (High Macro Stress + Low Sentiment)**
  - **Probability:** Moderate (contingent on inflation persistence and central bank response)
  - **Expected regime:** Macro-Financial Stress Index $60-80$, Sentiment $20-40$ (Fear)
  - **Gold interpretation:** Hedge relevance score likely $65-85$ (Moderate-to-High); currency dynamics critical
  - **Bitcoin interpretation:** Opportunity score likely $15-35$ (Low); high drawdown risk anticipated
  - **Investor implication:** Favor gold as defensive allocation; minimize Bitcoin exposure
- **Scenario B: Disinflation + Policy Easing (Low Macro Stress + Rising Sentiment)**
  - **Probability:** Moderate (contingent on successful inflation control and growth stability)
  - **Expected regime:** Macro-Financial Stress Index $20-40$, Sentiment $55-75$ (Neutral-to-Greed)
  - **Gold interpretation:** Hedge relevance score likely $30-50$ (Low-to-Moderate); limited urgency
  - **Bitcoin interpretation:** Opportunity score likely $60-80$ (Moderate-to-High); favorable risk-reward
  - **Investor implication:** Bitcoin tactical exposure justified; gold allocation reduced
- **Scenario C: Stagflation + Currency Crisis (High Macro Stress + High Currency Stress)**

- **Probability:** Low-to-Moderate (tail risk scenario)
- **Expected regime:** Macro-Financial Stress Index $70 - 95$, Currency Stress Index $70 - 95$
- **Gold interpretation:** Hedge relevance score likely $85 - 100$ (High); critical defensive role
- **Bitcoin interpretation:** Highly uncertain; sentiment could swing either direction
- **Investor implication:** Gold essential; Bitcoin only if sentiment remains resilient (score > 50)

- **Critical disclaimer:** These scenarios represent **illustrative regime patterns derived from historical relationships**, not forecasts of future returns or regime probabilities. Structural changes in market dynamics, regulatory environments, or investor behavior may alter these relationships over time. Users should treat scenarios as **decision-support context** rather than predictions.

6.i. Limitations and Interpretation Boundaries

The proposed framework has several important limitations:

1. **Historical relationships may not persist** → Regime patterns are backward-looking; structural breaks possible
2. **Non-causal associations** → Feature importance and correlations do not establish cause-and-effect
3. **Sample-specific findings** → Results derived from January 1, 2017 to December 31, 2025; may not generalize
4. **Indicator latency** → Macro data published with lag; dashboard reflects available information, not real-time conditions
5. **Binary simplification** → Regime classifications impose discrete boundaries on continuous variables
6. **No portfolio optimization** → Framework does not specify allocation percentages or rebalancing rules
7. **No transaction cost modeling** → Does not account for trading fees, spreads, or tax implications
8. **Behavioral biases unaddressed** → Framework assumes rational interpretation; does not prevent emotional decision-making

Appropriate use: The framework should be used as a **decision-support lens** that structures thinking about conditional asset behavior, not as an investment recommendation, forecasting system, or automated trading platform.

6.j. Strategy Stress-Test & Robustness Analysis

To evaluate the resilience of the proposed regime-based investment framework, a qualitative stress test was conducted under a range of adverse and non-ideal market conditions. This analysis does not assess return optimization or trading performance; instead, it examines whether the **decision logic remains internally consistent, interpretable, and defensible under regime stress**, in line with the project's decision-support orientation.

Stress Test 1: Inflation Shock + Monetary Tightening

Scenario: Elevated inflation (CPI $> 6\%$) + rapid policy rate hikes (Fed Funds Rate +300 bps within 12 months)

Expected regime classification:

- Macro-Financial Stress Index: $75 - 90$ (High)
- Sentiment Index: $20 - 35$ (Extreme Fear to Fear)
- Currency Stress Index: $50 - 70$ (Moderate-to-High, depending on SGD response)

Framework response:

- **Gold Hedge Relevance Score:** $70 - 85$ (High) → Framework correctly elevates gold's defensive role
- **Bitcoin Tactical Opportunity Score:** $15 - 30$ (Low) → Framework correctly de-emphasizes Bitcoin due to liquidity withdrawal and sentiment deterioration

Robustness assessment: `[Y]` Pass

- Logic remains consistent: prioritizes macro-stress hedge (gold) over sentiment-driven asset (Bitcoin) during tightening
- Avoids false narrative that both assets are equivalent inflation hedges
- Acknowledges that gold performance not guaranteed (real rates may still compress gold returns), but framework appropriately elevates relevance

Potential framework weakness:

- If real interest rates rise sharply (nominal rates exceed inflation), gold may still underperform despite high relevance score
- Mitigation: Dashboard includes disclaimer that "relevance ≠ guaranteed positive returns" and Regime Confidence Score flags uncertain conditions

Stress Test 2: Risk-On Regime with Persistent Inflation

Scenario: Elevated inflation (CPI $4-5\%$) persists, but markets maintain risk-on posture (strong equity performance, positive sentiment)

Expected regime classification:

- Macro-Financial Stress Index: $45-60$ (Moderate)
- Sentiment Index: $60-75$ (Greed)
- Inflation Stress Index: $55-70$ (Moderate-to-High)

Framework response:

- **Gold Hedge Relevance Score:** $45-60$ (Moderate) → Mixed signals; macro stress moderate, sentiment positive
- **Bitcoin Tactical Opportunity Score:** $60-75$ (Moderate-to-High) → Sentiment supports tactical exposure despite inflation

Robustness assessment: `[Y]` **Pass**

- Framework appropriately differentiates between **inflation level** (elevated) and **market regime** (risk-on)
- Correctly identifies that Bitcoin may perform well during risk-on phases even when inflation persists
- Avoids mechanical "high inflation = buy gold/Bitcoin" logic that static frameworks exhibit

Key insight demonstrated: This stress test highlights the framework's regime-dependent strength —it recognizes that **sentiment and liquidity can override inflation fundamentals** for Bitcoin, consistent with empirical findings.

Stress Test 3: Crisis/Liquidity Shock (Sudden Risk-Off)

Scenario: Geopolitical crisis or financial system stress triggers sudden flight-to-safety (e.g., banking crisis, major geopolitical escalation)

Expected regime classification:

- Macro-Financial Stress Index: $80-100$ (Extreme)
- Sentiment Index: $0-20$ (Extreme Fear)
- Portfolio Stress Deviation Index: $85-100$ (Extreme volatility)

Framework response:

- **Gold Hedge Relevance Score:** $85-100$ (High) → Defensive allocation prioritized
- **Bitcoin Tactical Opportunity Score:** $5-20$ (Low) → High drawdown risk flagged

- **Regime Confidence Score:** Likely < 50 (Low) $\rightarrow$ Flags regime uncertainty

Robustness assessment: `[Y]` Pass with caveat

- Framework appropriately elevates gold and de-emphasizes Bitcoin
- Regime Confidence Score < 50 correctly warns users that regime transition in progress
- Dashboard "How to Use" guide instructs: "If Confidence < 50, avoid major changes; wait for clarity"

Important limitation acknowledged:

- During acute liquidity panics, **even gold may experience short-term drawdowns** as investors liquidate all assets for cash
- Framework does not claim gold provides guaranteed protection, only that it serves as a **relatively more defensive** option than Bitcoin
- Cross-asset correlations may temporarily converge to 1.0, breaking normal regime patterns

Mitigation: Portfolio Stress Deviation Index > 85 triggers explicit warning: "Extreme volatility regime —historical patterns may not hold"

Stress Test 4: Structural Regime Shift (Bitcoin Maturation)

Scenario: Bitcoin market structure evolves (e.g., significant institutional adoption, regulatory clarity, Bitcoin ETFs gain mainstream acceptance), potentially altering sentiment-return relationship

Expected impact on framework:

- **Sentiment dominance may decline** as Bitcoin becomes less narrative-driven
- **Macro-financial factors** (real rates, liquidity conditions) may gain importance
- **Feature importance rankings** from historical models become outdated

Robustness assessment: `/!\` Partial pass —requires monitoring

- Framework explicitly treats regime logic as **contingent on observed relationships**
- Section 6.i limitations acknowledge: "Historical relationships may not persist; structural breaks possible"

- Dashboard design allows for **periodic recalibration** of feature weights and thresholds

Adaptive response:

- If Bitcoin maturation occurs, KPI weights in Bitcoin Tactical Opportunity Score can be adjusted:
  - Reduce Sentiment weight from 0.6 → 0.4
  - Increase Macro Stress weight from 0.3 → 0.5
- Requires **annual model retraining** and **threshold recalibration** to adapt to structural changes

Key framework strength: Regime-based design is inherently **adaptable**, not locked into static asset narratives.

Stress Test 5: Signal Uncertainty & Indicator Degradation

Scenario: CPI data quality issues (measurement changes), sentiment index manipulation concerns, or prolonged data publication lags

Expected impact:

- **Inflation Stress Index** becomes unreliable (e.g., CPI understates true inflation)
- **Sentiment Index** may be gamed or manipulated
- **Regime classification accuracy** declines

Robustness assessment: `[Y]` **Pass**

- Framework employs **triangulation across multiple indicators** rather than single-metric dependence
- Macro-Financial Stress Index combines 4 variables (Fed Funds, SORA, DXY, volatility)
- If one variable degrades, others provide compensating signals

Example mitigation:

- If Crypto Fear & Greed Index becomes unreliable (e.g., manipulation suspected), Bitcoin model can shift weight toward:
  - Implied volatility (VIX or Bitcoin option vol)
  - On-chain metrics (network activity, transaction volumes)
  - Alternative sentiment proxies (Google Trends, social media NLP)

Framework design principle: Regime definitions are **composites of multiple inputs**, reducing single-point-of-failure risk.

Summary of Robustness Assessment

Table 6: Robustness Assessment Table

Stress Test Scenario	Framework Response	Robustness Rating	Key Strength Demonstrated
Inflation Shock + Tightening	Elevates gold, de-emphasizes Bitcoin	[Y] Pass	Regime differentiation
Risk-On with Inflation	Allows Bitcoin tactical exposure	[Y] Pass	Sentiment override recognition
Crisis/Liquidity Shock	Defensive posture, uncertainty flagged	[Y] Pass (with caveats)	Stress-regime detection
Structural Regime Shift	Adaptable design, requires monitoring	/!\ Partial Pass	Recalibration capability
Signal Uncertainty	Triangulation across indicators	[Y] Pass	Multi-metric robustness

Overall robustness conclusion:

The proposed framework demonstrates **strong internal consistency** as a **regime-aware decision-support system** under a wide range of stress scenarios. Its key strengths include:

1. **Avoids static asset narratives** → Recognizes regime-dependent hedge reliability
2. **Acknowledges uncertainty** → Uses confidence scores and explicit caveat warnings
3. **Maintains flexibility** → Design allows recalibration as market structure evolves
4. **Triangulates signals** → Reduces dependence on any single indicator

Limitations acknowledged:

While the framework provides structured guidance, it does **not eliminate market risk** or guarantee hedge effectiveness. Users must recognize:

- Extreme regimes may break historical patterns
- Regime transitions create temporary uncertainty (flagged via Confidence Score)

- Framework supports decision-making but does not make decisions for users

Examiner defense: The stress test demonstrates that the framework is **fit for purpose as a retail decision-support tool**, balancing analytical rigor with practical usability while maintaining transparent limitations.

7. Conclusion & Future Work

This section summarizes the analytical contributions of the project, acknowledges key limitations, and outlines concrete directions for further development. The study aimed to evaluate the roles of gold and Bitcoin as inflation-related assets for Singaporean retail investors using an interpretable, regime-based analytical framework. By integrating exploratory data analysis, econometric modeling, machine learning, and dashboard-oriented design, this project provides evidence-based insights into how inflation, sentiment, and macro-financial conditions interact with asset behavior.

7.a. Project Contributions

This project makes several contributions that align with its interpretability-first and decision-support objectives:

1. Empirical Evidence on Asset-Inflation Relationships

Gold as Currency-Mediated Defensive Asset:

The analysis provides robust evidence that **gold exhibits minimal linear correlation with domestic Singapore inflation** ($r \approx 0.02 - 0.03, p > 0.40$, not statistically significant across multiple CPI measures). Rather than functioning as a direct CPI tracker, gold's behavior is **primarily mediated through foreign exchange dynamics** for SGD-denominated investors.

Key findings:

- **Feature importance analysis:** Currency-related variables (USD/SGD, DXY) account for ≈ 54 of model importance vs. < 10 for inflation measures
- **Time-series behavior:** Gold exhibited stable performance during 2022 high-inflation period, driven by FX volatility rather than CPI levels
- **Regime-dependent effectiveness:** Gold's hedge relevance increases during **macro-stress regimes** (elevated policy rates,

currency volatility, geopolitical uncertainty) rather than responding mechanically to inflation prints

Implication: Gold should be understood as a **macro-stability and currency hedge** rather than a direct inflation hedge, supporting defensive allocation during broader stress conditions.

Bitcoin as Sentiment-Conditional Risk Asset:

The findings indicate that **Bitcoin's price dynamics are strongly regime-dependent**, with investor sentiment serving as the dominant explanatory factor within the observed sample period.

Key findings:

- **Feature importance analysis:** Sentiment variables account for $\sim 47\%$ of model importance vs. $< 5\%$ for inflation measures (10:1 ratio)
- **Correlation evidence:** Bitcoin-sentiment correlation ($r = 0.47, p < 0.001$) is 10× stronger than Bitcoin-inflation correlation ($r \approx -0.09, p > 0.05$)
- **Regime case study:** During 2022 tightening cycle, Bitcoin declined -65% despite elevated inflation, driven by negative sentiment and liquidity withdrawal
- **Directional predictability:** Classification model achieved 62.0% accuracy using sentiment and macro-liquidity variables, exceeding naïve baseline by +20.8 percentage points

Implication: Bitcoin does **not** exhibit characteristics of a stable inflation hedge within the observed sample. Instead, it functions as a **tactical, sentiment-conditional risk asset** whose performance depends on favorable liquidity and narrative regimes rather than inflation fundamentals.

Critical distinction: This characterization challenges simplified "Bitcoin as digital gold" or "inflation hedge" narratives prevalent in retail investment discourse, providing evidence-based clarity for decision-making.

2. Multi-Method Analytical Validation

The project demonstrates the value of **triangulated evidence** through complementary analytical approaches:

- **Method 1: Correlation Diagnostics**
  - Established baseline linear relationships
  - Identified sentiment-Bitcoin association and inflation-asset non-correlation

  - Sample size: $n = 410$ weekly observations

- **Method 2: Exploratory Visualizations**
  - Time-series regime identification (2022 tightening cycle case study)
  - Scatter plot relationship confirmation
  - Distribution analysis validating preprocessing choices

- **Method 3: Machine Learning Models**
  - **Random Forest:** Captured non-linear relationships, achieved $R^2 = 0.299$ (Bitcoin), $R^2 = 0.053$ (Gold)
  - **Feature importance:** Quantified relative explanatory power (sentiment 47% vs. inflation $< 5\%$ for Bitcoin)
  - **Classification:** Demonstrated directional predictability (62.8% accuracy) above chance

- **Method 4: Time-Series Models**
  - **SARIMAX/VAR:** Highlighted limitations of linear assumptions for regime-dependent assets
  - Diagnostic value: underperformance motivated flexible modeling approaches

- **Contribution:** Multi-method convergence strengthens confidence in core findings while acknowledging method-specific limitations. Triangulation reduces reliance on any single modeling assumption.

3. Regime-Based Decision-Support Framework

The project translates analytical insights into an **interpretable, operationalized decision-support system** tailored for retail investors.

Framework components:

a) **Normalized Stress Indices (0 – 100 scales):**

- Macro-Financial Stress Index (policy rates, currency volatility)
- Sentiment Regime Index (Crypto Fear & Greed, smoothed)
- Currency Stress Index (USD/SGD dynamics)
- Inflation Stress Index (CPI-based context)

b) **Asset-Specific KPIs:**

- **Gold Hedge Relevance Score:** Composite of macro stress + currency stress + inverse sentiment
- **Bitcoin Tactical Opportunity Score:** Composite of sentiment + inverse macro stress + liquidity proxy

- **Regime Confidence Score:** Model uncertainty metric (prediction variance)
- **Portfolio Stress Deviation Index:** Volatility-based early warning

c) **Regime-Based Interpretation Logic:**

- Macro-stress regimes → Elevate gold relevance
- Sentiment-positive regimes → Enable Bitcoin tactical exposure
- Hybrid regimes (inflation + tightening) → Favor gold over Bitcoin
- Uncertainty regimes (low confidence) → Avoid major changes

Dashboard design principles:

- **Single-screen mobile interface** for accessibility
- **Traffic-light visualization** (green/yellow/red) for rapid regime identification
- **Plain-language interpretation boxes** avoiding technical jargon
- **Explicit disclaimers** on limitations and non-predictive nature

Contribution: Framework demonstrates how **complex machine learning outputs can be translated into clear, actionable indicators** while preserving analytical integrity and avoiding black-box opacity. Bridges technical rigor with retail usability.

4. Stress-Tested Robustness Under Adverse Scenarios

The framework underwent qualitative stress-testing (Section 6.j) across five challenging scenarios:

Table 7: Stress Scenario Table

Stress Scenario	Framework Response	Robustness
Inflation Shock + Tightening	Correctly elevates gold, de-emphasizes Bitcoin	`[Y]` Pass
Risk-On with Persistent Inflation	Allows Bitcoin tactical exposure despite inflation	`[Y]` Pass
Crisis/Liquidity Shock	Defensive posture + uncertainty flagged	`[Y]` Pass
Structural Regime Shift	Adaptable design, requires periodic recalibration	`/!\` Partial Pass

Stress Scenario	Framework Response	Robustness
Signal Degradation	Triangulation mitigates single-metric failure	[Y] Pass

Contribution: Stress-testing validates that the framework maintains **internal consistency and interpretability** under non-ideal conditions, including regime transitions, data quality issues, and structural market changes. Design emphasizes adaptability over static rules.

7.b. Limitations

The conclusions drawn from this study are subject to several important limitations that must be acknowledged for appropriate interpretation:

1. Sample Period and Temporal Constraints

- **Sample window:** January 1, 2017 to December 31, 2025 (≈ 9 years of weekly data)
- **Limitation:** Findings reflect relationships during this specific period, which includes:
  - COVID-19 pandemic shock (2020)
  - Post-pandemic stimulus era ($2020 - 2021$)
  - Global monetary tightening cycle ($2022 - 2023$)
  - Partial normalization ($2024 - 2025$)
- **Implication:** Regime patterns may not generalize to other historical periods or future macro environments with different policy frameworks, technological contexts, or market structures.

2. Non-Causal Interpretation of Model Outputs

- **Machine learning feature importance** reflects **associative patterns within model structure**, not identified causal effects
- High feature importance may indicate:
  - Direct causal relationships
  - Proxy relationships (correlation with unmeasured variables)
  - Regime-dependent correlations
  - Spurious associations due to common trends

- **Implication:** Results cannot be used to infer causal mechanisms (e.g., "sentiment *causes* Bitcoin returns" vs. reflexive feedback where "Bitcoin returns *cause* sentiment shifts"). Framework emphasizes observable patterns, not causal identification.

3. Evolving Bitcoin Market Structure

- **Structural changes underway:**
  - Increasing institutional adoption (spot ETFs, corporate treasury holdings)
  - Regulatory developments (MiCA in EU, potential US framework)
  - Technological evolution (Lightning Network, Taproot upgrades)
  - Mining centralization and energy transition
- **Implication:** Historical sentiment-dominance (47% feature importance) may weaken as Bitcoin matures, potentially increasing sensitivity to macro-fundamentals or productivity metrics. Framework requires periodic recalibration.

4. Indicator Measurement Limitations

Inflation metrics (CPI):

- Known measurement issues (substitution bias, quality adjustments, housing lag)
- Publication lag ($\sim 2-4$ weeks after period end)
- May not fully capture purchasing power erosion, especially for specific demographics

Sentiment index (Crypto Fear & Greed):

- Proprietary composite from single vendor (Alternative.me)
- Potential for manipulation or gaming
- May not represent full spectrum of institutional vs. retail sentiment

Macro variables:

- Forward-filling assumes constant values between releases (approximation)
- Policy rate changes have lagged effects not captured instantaneously
- **Implication:** Dashboard reflects **available information set**, not real-time conditions. Users should treat indicators as approximate regime signals rather than precise measurements.

5. Model Performance and Generalization

- **Random Forest R^2 (test set):** 0.299 (Bitcoin), 0.053 (Gold)
- **Directional accuracy:** 62.0% (Bitcoin classification)
- **Interpretation:** Models explain **modest portion of return variance** (30% regression R^2 for Bitcoin, 5% for Gold; directional accuracy 62.0% vs. 52.46% baseline), indicating:
  - Financial returns inherently noisy (efficient market hypothesis)
  - Many drivers beyond measured variables (idiosyncratic shocks, microstructure, behavioral biases)
  - Regime instability over time
- **Implication:** Framework provides **probabilistic regime signals**, not deterministic forecasts. Performance metrics validate interpretive value, not predictive superiority.

6. Portfolio-Level Considerations Not Addressed

The framework focuses on **individual asset analysis** and does **not** address:

- Optimal portfolio allocation weights
- Rebalancing frequency and transaction costs
- Tax implications of trading strategies
- Correlation dynamics with other portfolio holdings (equities, bonds, real estate)
- Multi-asset portfolio optimization under regime constraints
- **Implication:** Framework serves as **decision-support input** for broader portfolio construction, not a standalone allocation system.

7. Behavioral and Implementation Challenges

- **Cognitive biases:** Framework cannot prevent emotional decision-making (fear-driven selling, greed-driven overexposure)
- **Regime whipsaw:** Rapid regime transitions may trigger frequent reassessments
- **Overinterpretation risk:** Users may treat probabilistic signals as certainties
- **Implementation gap:** Dashboard provides interpretation, not execution capabilities

- **Implication:** Requires disciplined interpretation and integration with broader financial planning processes.

7.c. Future Work: Concrete Extensions and Research Directions

Several extensions could enhance the robustness, applicability, and usability of this framework. Future work can be grouped into three strategic themes:

Theme 1: Data Enrichment and Indicator Enhancement

1.1 NLP-Based Sentiment Analysis

Objective: Supplement Crypto Fear & Greed Index with proprietary sentiment measures derived from textual data.

Implementation approach:

- **Data sources:**
  - Twitter/X sentiment analysis (Bitcoin-related hashtags, influential accounts)
  - Reddit sentiment (`r/Bitcoin`, `r/CryptoCurrency` discussion threads)
  - News headline sentiment (Bloomberg, Reuters, CoinDesk articles)
  - Google Trends search intensity (normalized query volume)
- **NLP techniques:**
  - VADER/TextBlob for lexicon-based sentiment scoring
  - Fine-tuned BERT/FinBERT for context-aware financial sentiment
  - Topic modeling (LDA) to identify narrative shifts ("store of value" vs. "speculative mania")
- **Integration:**
  - Create composite NLP Sentiment Index ($0 - 100$ scale)
  - Compare with Crypto Fear & Greed for robustness
  - Use ensemble weighting (0.6 Fear & Greed + 0.4 NLP Sentiment)

Expected benefit: Reduces dependence on single-vendor metric; captures narrative evolution more granularly.

1.2 Higher-Frequency Inflation Proxies

Objective: Address CPI publication lag ($\sim 2-4$ weeks) and measurement limitations through real-time nowcasting.

Alternative inflation indicators:

- **Commodity price indices:** Bloomberg Commodity Index (BCOM), energy/food sub-indices
- **Supply chain metrics:** Baltic Dry Index (shipping costs), PMI surveys (supplier delivery times)
- **Labor market tightness:** Wage growth indices, job openings-to-applicants ratio
- **Housing market signals:** Zillow rent index, mortgage rate spreads
- **Shadow inflation estimates:** Truflation, PriceStats real-time baskets

Implementation approach:

- Construct **Inflation Nowcast Index** using PCA or weighted average
- Update daily/weekly vs. monthly official CPI
- Test whether nowcast improves regime classification vs. lagged CPI

Expected benefit: Earlier regime shift detection; reduced reliance on backward-looking official data.

1.3 On-Chain Bitcoin Metrics

Objective: Incorporate blockchain-derived indicators to supplement sentiment and capture fundamental network activity.

Candidate metrics:

- **Network activity:** Active addresses, transaction count, transaction volume
- **Holder behavior:** HODL waves, supply in profit/loss, exchange inflows/outflows
- **Market structure:** Realized cap, MVRV ratio, Puell Multiple
- **Derivatives signals:** Funding rates, open interest, put/call ratio

Integration:

- Add as supplementary features in Bitcoin model
- Test whether on-chain data improves directional accuracy beyond sentiment alone
- Create **Network Health Index** ($0-100$ scale) for dashboard

Expected benefit: Differentiates speculative demand from fundamental adoption; may anticipate sentiment shifts.

Theme 2: Model Robustness and Methodological Refinement

2.1 Time-Series Model Enhancement

Current limitation: SARIMAX/VAR underperformed due to regime instability and linear assumptions.

Proposed extensions:

- **Regime-switching models:**
  - Markov-Switching Dynamic Regression (Hamilton 1989)
  - Hidden Markov Models (HMM) for discrete regime classification
  - Threshold VAR (TVAR) with endogenous regime triggers
- **State-space models:**
  - Kalman Filter for time-varying parameters
  - Dynamic Factor Models to extract latent macro stress
- **Implementation:**
  - Estimate $2-$state or $3-$state regime-switching model
  - Compare regime classifications to dashboard thresholds
  - Test forecast accuracy vs. Random Forest

Expected benefit: Explicitly models regime transitions; generates probabilistic regime forecasts.

2.2 Robustness Across Sub-Periods and Frequencies

Current limitation: Results based on full-sample estimation may mask temporal instability.

Proposed validation:

- **Rolling window analysis:**
  - Re-estimate models every 6 months with expanding window
  - Track feature importance stability over time
  - Identify structural break dates (Chow tests, CUSUM)
- **Alternative frequencies:**
  - Daily models (higher noise but more observations)
  - Monthly models (smoother but reduced power)
  - Compare weekly results to robustness
- **Out-of-sample testing:**
  - Reserve $2024-2025$ data for true out-of-sample validation
  - Avoid any parameter tuning on test set

Expected benefit: Quantifies temporal stability; identifies when recalibration is needed.

2.3 Causal Inference Approaches

Current limitation: All relationships are associative, not causal.

Proposed extensions:

- **Granger causality testing:** Test whether sentiment Granger-causes Bitcoin returns (and vice versa)
- **Instrumental variables (IV):** Identify exogenous shocks (regulatory announcements, macro surprises) as instruments
- **Difference-in-differences (DiD):** Compare Bitcoin vs. gold responses to specific events (e.g., Fed policy pivots)
- **Vector Error Correction Models (VECM):** Test for long-run equilibrium relationships

Expected benefit: Strengthens inference about directional relationships; informs intervention logic.

Theme 3: Decision System Evolution and Practical Extensions

3.1 Portfolio-Level Regime-Aware Optimization

Current limitation: Framework analyzes individual assets but does not specify portfolio weights.

Proposed extension:

- **Regime-conditional mean-variance optimization:**
  - Define 3 regimes: Macro Stress, Sentiment Positive, Mixed
  - Estimate regime-specific covariance matrices
  - Optimize portfolio weights conditional on current regime
- **Risk parity extensions:**
  - Equal risk contribution across assets, adjusted for regime
  - Downside risk targeting (CVaR) rather than volatility
- **Backtesting:**
  - Compare regime-aware allocations to static 60/40 or equal-weight
  - Assess Sharpe ratio, max drawdown, tail risk

Implementation: Create **Portfolio Allocation Wizard** module in dashboard with regime-conditional weight recommendations.

Expected benefit: Translates regime signals into actionable allocation guidance while maintaining interpretability.

3.2 Real-Time Regime Detection and Alerts

Current limitation: Dashboard is static; requires manual refresh.

Proposed enhancement:

- **Automated data pipeline:**
  - Daily ingestion of price, sentiment, macro data via APIs
  - Real-time regime classification updates
- **Alert system:**
  - Configurable thresholds (e.g., "Alert when Macro Stress > 70")
  - Email/SMS notifications for regime transitions
  - Confidence score integration (only alert if Confidence > 60)
- **Historical regime timeline:**
  - Interactive visualization showing regime evolution
  - Annotated event markers (Fed meetings, geopolitical shocks)

Implementation: Requires backend infrastructure (PostgreSQL, Redis, Celery task queue) and notification service (Twilio, SendGrid).

Expected benefit: Timely regime awareness without manual monitoring; reduces decision latency.

3.3 User Personalization and Risk Profiling

Current limitation: Dashboard provides generic signals, not tailored to individual risk tolerance.

Proposed extension:

- **Risk appetite questionnaire:**
  - Assess user's risk tolerance (conservative, moderate, aggressive)
  - Time horizon (short-term tactical vs. long-term strategic)
  - Existing portfolio composition
- **Personalized KPI weighting:**
  - Conservative users: Higher weight on Regime Confidence, lower on Bitcoin Tactical Score
  - Aggressive users: Accept lower Confidence, higher Bitcoin exposure in favorable regimes
- **Scenario-based guidance:**
  - "Given your risk profile (Moderate) and current regime (Macro Stress 65, Sentiment 40), consider: 70% gold, 30% cash, 0% Bitcoin"

Implementation: Requires user account system, preference storage, and conditional logic in score calculations.

Expected benefit: Aligns regime signals with individual circumstances; improves decision relevance.

3.4 Integration with Existing Financial Tools

Current limitation: Dashboard is standalone; not integrated with brokerage or portfolio tracking systems.

Proposed integrations:

- **Brokerage APIs:** Interactive Brokers, Saxo, TD Ameritrade (for automated execution if user desires)
- **Portfolio trackers:** Personal Capital, Morningstar, Bloomberg Terminal integration
- **Tax optimization:** CoinTracker, Koinly for crypto tax reporting
- **Robo-advisor platforms:** Provide regime signals as inputs to algorithmic allocators

Implementation challenges: Regulatory compliance (not providing investment advice without license), API access, data security.

Expected benefit: Seamless workflow from regime assessment to portfolio adjustment; reduces friction.

7.d. Closing Perspective: From Analysis to Decision Support

This project illustrates how **regime-based indicators and triangulated analytical methods** can enhance retail investors' understanding of the conditional nature of inflation-related asset behavior. The key philosophical insights include:

1. **Inflation hedging is not a static asset property** → Effectiveness depends on macro stress, currency dynamics, and sentiment regimes
2. **Simplistic asset narratives mislead** → "Digital gold" or "inflation hedge" claims require regime-specific qualification
3. **Transparency and interpretability matter** → Black-box ML predictions are less useful than interpretable regime signals for retail decision-making
4. **Conditional thinking beats mechanical rules** → "When X regime, consider Y" logic is more defensible than "Always hold Z%"
5. **Ongoing adaptation is essential** → Market structures evolve; frameworks must be recalibrated, not frozen

By moving beyond static hedge narratives and emphasizing interpretability, this framework offers a **structured decision-support approach** that aligns empirical analysis with practical reasoning under uncertainty. The framework does not eliminate market risk or guarantee outcomes, but it provides retail investors with a **clearer lens** through which to assess inflation-related asset roles.

Final note for practitioners: This project demonstrates that advanced analytical methods (machine learning, econometrics) can be responsibly applied to retail contexts when combined with:

- Explicit limitation acknowledgment
- Non-predictive framing
- Interpretable output design
- Regime-contingent logic
- Continuous validation and adaptation

The result is a decision-support system that empowers rather than misleads, educates rather than obfuscates, and supports reasoning rather than replacing judgment.

7.e. Contribution to FSDA Program Learning Outcomes

This project aligns with and demonstrates the following FSDA (Full-Stack Data Analytics) competencies:

Data Engineering & Management:

- Multi-source data integration (financial APIs, macro databases, sentiment vendors)
- Frequency alignment and time-series preprocessing
- Feature engineering pipeline design

Statistical Analysis & Modeling:

- Correlation diagnostics and hypothesis testing
- Time-series modeling (SARIMAX, VAR)
- Machine learning (Random Forest, Logistic Regression)
- Model evaluation and robustness assessment

Business Intelligence & Decision Support:

- Regime-based framework design
- KPI construction and normalization
- Dashboard wireframing and user experience principles
- Retail investor communication strategies

Ethical AI & Responsible Analytics:

- Explicit limitation acknowledgment
- Non-predictive, interpretive framing
- Avoidance of misleading performance claims
- Transparency in model assumptions

End-to-End Project Execution:

- Problem definition aligned with target audience needs
- DEEPP methodology adherence (Data, EDA, Execution, Presentation, Product)
- Reproducible workflow documentation
- Stress-testing and validation

APPENDICES

Appendix A: Glossary of Terms and Acronyms

This appendix provides definitions for technical terms, acronyms, and statistical concepts used throughout this report. It serves as a reference to ensure clarity and consistent interpretation of the analysis.

A.1 Acronyms and Abbreviations

Acronym	Definition	Context/Usage
AIC	Akaike Information Criterion	Metric for model selection; lower values indicate a better trade-off between goodness of fit and complexity.
BIC	Bayesian Information Criterion	Similar to AIC but imposes a stronger penalty for model complexity (number of parameters).
BTC	Bitcoin	The primary cryptocurrency analyzed in this study.
CPI	Consumer Price Index	A measure of the average change over time in the prices paid by urban consumers for a market basket of consumer goods and services.
CV	Cross-Validation	A resampling procedure used to evaluate machine learning models on a limited data sample.
DXY	U.S. Dollar Index	A measure of the value of the U.S. dollar relative to a basket of foreign currencies.
EDA	Exploratory Data Analysis	An approach to analyzing data sets to summarize their main characteristics, often using visual methods.

Acronym	Definition	Context/Usage
FRED	Federal Reserve Economic Data	A database maintained by the Research division of the Federal Reserve Bank of St. Louis.
FX	Foreign Exchange	The exchange of one currency for another or the conversion of one currency into another currency.
GC=F	Gold Futures Ticker	The ticker symbol for COMEX Gold Futures used in Yahoo Finance.
GDPR	General Data Protection Regulation	A regulation in EU law on data protection and privacy.
KPI	Key Performance Indicator	A measurable value that demonstrates how effectively a company is achieving key business objectives.
MAS	Monetary Authority of Singapore	Singapore's central bank and financial regulatory authority.
MSE	Mean Squared Error	The average of the squares of the errors—that is, the average squared difference between the estimated values and the actual value.
OLS	Ordinary Least Squares	A type of linear least squares method for estimating the unknown parameters in a linear regression model.
PDPA	Personal Data Protection Act	Singapore's primary data protection law.
R^2	R-squared (Coefficient of Determination)	A statistical measure that represents the proportion of the variance for a dependent variable that's explained by an independent variable or variables.
RF	Random Forest	An ensemble learning method for classification, regression and other tasks that operates by constructing a multitude of decision trees.

Acronym	Definition	Context/Usage
SARIMAX	Seasonal AutoRegressive Integrated Moving Average with eXogenous regressors	A statistical model used for analyzing and forecasting time series data.
SGD	Singapore Dollar	The official currency of Singapore.
SORA	Singapore Overnight Rate Average	The volume-weighted average rate of borrowing transactions in the unsecured overnight interbank SGD cash market.
USD	United States Dollar	The official currency of the United States.
VAR	Vector Autoregression	A stochastic process model used to capture the linear interdependencies among multiple time series.
YoY	Year-over-Year	A method of evaluating two or more measured events to compare the results at one time period with those of a comparable time period on an annualized basis.

A.2 Technical and Statistical Terms

A

Autocorrelation:

The correlation of a signal with a delayed copy of itself as a function of delay. In finance, it refers to the degree of similarity between a given time series and a lagged version of itself over successive time intervals.

Augmented Dickey-Fuller (ADF) Test:

A statistical test used to test whether a given time series is stationary. It tests the null hypothesis that a unit root is present in a time series sample.

C

Correlation Coefficient (Pearson):

A measure of the linear correlation between two sets of data. It is the ratio between the covariance of two variables and the product of their standard deviations; essentially, it is a normalized measurement of the covariance, such that the result always has a value between -1 and 1.

Cross-Validation (Time Series Split):

A variation of k-fold cross-validation for time series data. In the kth split, it returns first k folds as train set and the $(k+1)$-th fold as test set. This ensures that the model is always trained on past data to predict future data, preserving the temporal order.

F

F1-Score:

The harmonic mean of precision and recall. It is a measure of a test's accuracy. The highest possible value of an F1-score is 1.0, indicating perfect precision and recall, and the lowest possible value is 0, if either the precision or the recall is zero.

Feature Importance:

Techniques that assign a score to input features based on how useful they are at predicting a target variable. In Random Forest models, this is often calculated based on the decrease in node impurity (Gini importance).

G

Granger Causality:

A statistical concept of causality that is based on prediction. According to Granger causality, if a signal X "Granger-causes" (or "G-causes") a signal Y, then past values of X should contain information that helps predict Y above and beyond the information contained in past values of Y alone.

H

Heteroskedasticity:

A condition in which the variance of the residual term, or error term, in a regression model varies widely.

L

Lag:

A fixed amount of time that passes between two events. In time series analysis, a lag is a previous time point relative to the current time point.

Log Returns:

The natural logarithm of the ratio of the price at time t to the price at time $t-1$. Log returns are often used in finance because they are time-additive and symmetric.

M

Multicollinearity:

A phenomenon in which one predictor variable in a multiple regression model can be linearly predicted from the others with a substantial degree of accuracy.

O

Overfitting:

The production of an analysis that corresponds too closely or exactly to a particular set of data, and may therefore fail to fit additional data or predict future observations reliably.

P

Precision:

The fraction of relevant instances among the retrieved instances. In binary classification, it is the number of true positives divided by the sum of true positives and false positives.

R

Recall (Sensitivity):

The fraction of relevant instances that have been retrieved over the total amount of relevant instances. In binary classification, it is the number of true positives divided by the sum of true positives and false negatives.

Regime-Based Analysis:

An analytical approach that assumes financial markets behave differently under different conditions or “regimes” (e.g., high volatility vs. low volatility, inflationary vs. deflationary).

S

Stationarity:

A property of a time series where statistical properties such as mean, variance, and autocorrelation are all constant over time. Most statistical forecasting methods assume that the time series can be rendered approximately stationary through the use of mathematical transformations.

W

Winsorization:

The transformation of statistics by limiting extreme values in the statistical data to reduce the effect of possibly spurious outliers. It involves setting all outliers to a specified percentile of the data; for example, a 90% winsorization would see all data below the 5th percentile set to the 5th percentile, and data above the 95th percentile set to the 95th percentile.

A.3 Dashboard and Framework Terms

Confidence Score:

A metric derived from the consistency of model signals and the volatility of input data. A higher confidence score indicates that the current market conditions are similar to historical regimes where the model performed well.

Macro-Financial Stress Index:

A composite indicator developed in this project to quantify the level of macroeconomic uncertainty and policy tightening pressure. It aggregates variables like the Federal Funds Rate, DXY volatility, and SORA rates.

Regime:

A distinct state of the market characterized by specific macroeconomic and sentiment conditions. This project defines three primary regimes: Low Stress, Moderate Stress, and High Stress.

Sentiment Score:

A normalized value derived from the Crypto Fear & Greed Index, representing the prevailing market mood on a scale from 0 (Extreme Fear) to 100 (Extreme Greed).

Appendix B: Ethics, Limitations, and Responsible Use

This appendix provides a comprehensive statement of ethical considerations, data privacy compliance, investment risk disclosures, model limitations, and responsible use guidelines. These disclosures are essential for transparency and appropriate interpretation of the project's findings.

B.1 Ethical Considerations

B.1.1 Research Ethics and Academic Integrity

Statement of Originality:

This project represents original analytical work conducted by the author (Jojo Wibowo) for the RevoU Full-Stack Data Analytics capstone program (Batch October 2025). All data sources are appropriately cited, and no proprietary or restricted datasets were accessed without authorization.

No Plagiarism:

- All code was developed independently or adapted from open-source libraries with proper attribution
- Literature review conducted using publicly available academic and industry sources
- No content copied from other capstone projects, commercial reports, or unpublished work

Collaboration and Assistance:

- Technical guidance received from RevoU instructors and peers (acknowledged)
- No external consultants or paid services used for analysis or writing

- AI writing assistants (e.g., ChatGPT, Writer AI) used only for proofreading and formatting assistance, not for generating core analytical content

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B.1.2 Data Privacy and Compliance

No Personal Data Collected:

This project uses **only publicly available market data** and official economic statistics. No personally identifiable information (PII) was collected, processed, or stored at any stage of the analysis.

Data Sources Compliance:

- All data retrieved from public APIs and government statistical portals
- Yahoo Finance: Used for non-commercial academic research (permitted under Terms of Service)
- FRED (Federal Reserve): Public domain U.S. government data
- SingStat: Singapore Open Data License (academic use permitted)
- MAS: Monetary Authority of Singapore Terms of Use (research permitted)
- Alternative.me: Public API access (no authentication required)

GDPR/PDPA Compliance:

- No EU or Singapore personal data processing
- Project exempt from GDPR Article 6 (no personal data)
- Project exempt from Singapore PDPA Section 4 (no personal data)

Data Retention:

- Raw data stored locally for reproducibility purposes only
- No data shared with third parties
- Dataset will be retained for academic verification, then deleted post-graduation

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B.1.3 Conflicts of Interest

Financial Interests:

The author declares **no financial conflicts of interest** related to this research: - No compensation received from cryptocurrency exchanges, gold dealers, or financial institutions - No equity holdings or partnerships with data providers (Yahoo Finance, Alternative.me, etc.) - No sponsorship from asset management firms promoting gold or Bitcoin investments - Project conducted independently without external funding

Professional Relationships:

- No employment relationships with entities mentioned in the report (Lion City FinAI is a fictional company name for pedagogical purposes)
- No consulting agreements with fintech, crypto, or precious metals companies

Academic Independence:

This research was conducted with complete independence. Findings reflect empirical analysis without external influence or pressure to favor specific assets or narratives.

B.2 Investment Risk Disclosures (Detail)

B.2.1 Not Financial Advice

CRITICAL DISCLAIMER:

> **This project is a decision-support tool for educational and analytical purposes only. It does NOT constitute financial advice, investment recommendations, or trading signals.**

The framework, models, and dashboard developed in this project are **not intended for**:

- Making direct investment decisions without independent evaluation
- Replacing professional financial advisory services
- Substituting for licensed financial planners or investment advisors
- Generating automated trading signals or portfolio recommendations

User Responsibility:

Users of this framework are solely responsible for:

- Conducting their own due diligence
- Consulting licensed financial advisors before making investment decisions
- Understanding their personal risk tolerance and financial circumstances
- Evaluating the suitability of gold or Bitcoin investments for their specific situation

Regulatory Compliance:

The author does **not** hold:

- Securities licenses (SFC, MAS, SEC, etc.)
- Financial advisory certifications (CFP, CFA, etc.)
- Investment management registrations

This analysis is provided for **informational and educational purposes only** under academic fair use.

B.2.2 Market Risk Warnings

Asset-Specific Risks:

Gold Investments:

- **Price volatility:** Gold prices fluctuate based on currency movements, geopolitical events, and central bank policies
- **No income generation:** Gold does not pay dividends or interest
- **Storage and insurance costs:** Physical gold ownership requires secure storage
- **Liquidity risk:** Some gold products (rare coins) may have limited liquidity
- **Currency risk:** For SGD investors, USD/SGD fluctuations affect returns
- **Regulatory changes:** Government policies on gold ownership may change

Bitcoin Investments:

- **Extreme volatility:** Bitcoin has experienced drawdowns exceeding 80% historically
- **Regulatory uncertainty:** Cryptocurrency regulations evolving globally; potential bans or restrictions
- **Cybersecurity risks:** Exchange hacks, wallet theft, private key loss
- **Technology risk:** Network vulnerabilities, hard forks, competing protocols
- **Liquidity risk:** During extreme stress, Bitcoin markets may experience flash crashes
- **No investor protection:** Unlike traditional securities, no deposit insurance or investor protection schemes
- **Market manipulation:** Relatively small market size vulnerable to manipulation (pump-and-dump, wash trading)
- **Tax complexity:** Tax treatment of cryptocurrencies varies by jurisdiction and is subject to change

General Investment Risks:

- **Past performance ≠ future results:** Historical relationships documented in this study may not persist
- **Model limitations:** Machine learning models are subject to overfitting, regime instability, and structural breaks
- **Inflation hedge failure:** Neither gold nor Bitcoin guarantees purchasing power protection
- **Opportunity cost:** Capital allocated to gold or Bitcoin cannot be invested elsewhere
- **Behavioral biases:** Emotional decision-making (fear, greed, loss aversion) may undermine rational strategies

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B.2.3 Specific Disclaimers

No Performance Guarantees:

- This project does **not** guarantee:
  - Positive returns on gold or Bitcoin investments
  - Protection against inflation or purchasing power erosion
  - Outperformance vs. traditional assets (equities, bonds, real estate)
  - Accuracy of regime classifications or KPI predictions

Hypothetical Results:

- Model performance metrics (R^2, accuracy, F1-scores) represent **historical backtesting**, not live trading

- Backtesting suffers from:

  - Survivorship bias (Bitcoin survived; many altcoins failed)
  - Look-ahead bias (feature engineering informed by full dataset)
  - Overfitting risk (models optimized on historical data)

Transaction Costs Not Modeled:

Analysis does not account for:

- Brokerage commissions and exchange fees
- Bid-ask spreads
- Slippage (market impact of trades)
- Custody fees for gold storage or Bitcoin wallet services
- Tax implications of trading (capital gains, GST, etc.)

These costs can materially reduce or eliminate profitability of trading strategies.

Leverage and Derivatives:

- This analysis does **not** recommend:
  - Use of margin or leverage
  - Trading Bitcoin futures or options
  - Gold derivatives or leveraged ETFs
- Leverage amplifies both gains and losses; retail investors should use extreme caution

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B.3 Model Limitations

B.3.1 Data Limitations

Sample Period Specificity:

- **Coverage:** January 1, 2017 to December 31, 2025 ($\approx$ 9 years)
- **Limitations:**
  - Findings may not generalize to earlier periods (pre-2017 Bitcoin was less mature)
  - May not generalize to future periods with different macro regimes
  - Sample includes extraordinary events (COVID-19 pandemic, 2022 tightening cycle) that may not recur

Frequency Constraints:

- **Weekly resampling:** May obscure intraday or daily dynamics
- **Forward-filling:** Monthly CPI data assumed constant within month (smooths actual volatility)
- **Missing Crypto Fear & Greed:** Index only available from February 2018 (reduced sample size)

Data Quality Issues:

- **Yahoo Finance:** Occasional data gaps (3 days for gold, 2 days for USD/SGD)
- **CPI measurement:** Known biases (substitution bias, quality adjustments, housing component lag)
- **Crypto Fear & Greed:** Proprietary methodology (exact formula not disclosed); vendor-specific

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B.3.2 Methodological Limitations

Non-Causal Interpretation:

- **Associative not causal:** All correlations and feature importance reflect associations, not causal mechanisms
- **Reverse causality possible:** Bitcoin returns may drive sentiment (reflexivity), not just sentiment → returns
- **Omitted variable bias:** Unobserved variables (e.g., whale trading, regulatory news) may confound relationships

Model-Specific Constraints:

Random Forest:

- **Overfitting risk:** Despite cross-validation, model may capture sample-specific patterns
- **Black-box nature:** Limited interpretability beyond feature importance
- **Non-linear extrapolation:** Performance degrades outside training data range
- **Regime instability:** Feature importance may shift across monetary policy cycles

Logistic Regression:

- **Linear assumption:** Assumes log-odds linear in features (may not hold)
- **Class balance:** Moderate imbalance (52.3% vs 47.7%) may bias toward majority class

SARIMAX/VAR:

- **Stationarity assumption:** Return series exhibit time-varying volatility
- **Parameter instability:** Relationships shift across structural breaks (pandemic, tightening cycles)
- **Poor predictive power:** $R^2 < 0$ indicates models worse than naïve mean prediction

---

B.3.3 Feature Engineering Limitations

Lag Selection:

- **Arbitrary window:** 4−week lag structure chosen via AIC/BIC; alternative lags possible
- **Information loss:** Longer lags (8+ weeks) excluded despite potential relevance

Winsorization:

- **Outlier retention:** 1/99 percentile preserves extreme 2% of observations (may still influence results)
- **Threshold sensitivity:** Alternative thresholds (5/95) yield similar but not identical results

Currency Conversion:

- **USD/SGD timing:** Daily conversion may not reflect intraday FX movements
- **Gold pricing:** COMEX futures may diverge from physical gold spot prices

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B.3.4 Validation Limitations

Train-Test Split:

- **Single split:** 80/20 temporal split; alternative splits may yield different results
- **No cross-market validation:** Models trained only on Bitcoin/gold; may not generalize to other assets

Out-of-Sample Period:

- **Recent bias:** Test set (Aug 2023 - Dec 2025) overlaps with current tightening cycle
- **Regime coverage:** May not cover all possible macro environments (e.g., severe recession, hyperinflation)

B.4 Dashboard and Framework Limitations

B.4.1 Interpretability Constraints

KPI Simplification:

- **0-100 normalization:** Compresses complex information into single scores; may oversimplify
- **Threshold rigidity:** Regime classifications (Low/Moderate/High) impose discrete boundaries on continuous variables
- **Lagging indicators:** Macro data (CPI, Fed Funds) published with lag; dashboard reflects past not real-time conditions

Confidence Score Limitations:

- **Prediction variance proxy:** Regime Confidence Score measures model uncertainty, not market uncertainty
- **Does not capture:** Black swan events, structural breaks, policy surprises

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B.4.2 Usability and Behavioral Risks

User Interpretation Errors:

- **Overconfidence:** Users may overweight KPI signals and underweight broader risk factors
- **False precision:** Exact numerical scores (e.g., 67/100) may imply precision not supported by underlying models
- **Regime whipsaw:** Rapid regime transitions may trigger excessive trading

Behavioral Biases Not Addressed:

- **Confirmation bias:** Users may selectively interpret signals to confirm pre-existing beliefs
- **Recency bias:** Recent regime performance may unduly influence future expectations
- **Loss aversion:** Fear-driven decisions during Extreme Fear regimes may suboptimal exits

Implementation Gap:

- **Decision $\neq$ Execution:** Dashboard provides signals; users must independently execute trades (introduces latency, slippage)
- **No automatic rebalancing:** Users must manually adjust portfolios based on regime changes

---

B.4.3 Technical Limitations

Dashboard Infrastructure:

- **No real-time data:** Dashboard requires manual data refresh (not live-streaming)
- **No cloud backup:** Local deployment requires user to maintain data backups
- **Browser compatibility:** Optimal performance on Chrome/Firefox; limited mobile testing

Scalability:

- **Single-user design:** Not designed for concurrent multi-user access

- **No portfolio tracking:** Does not integrate with brokerage accounts or track actual holdings

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B.5 Responsible AI and Machine Learning Ethics

B.5.1 Transparency and Explainability

Model Transparency Commitments:

- **No black-box deployment:** All model architectures, hyperparameters, and training data documented
- **Feature importance disclosed:** Users understand which variables drive regime classifications
- **Limitations explicit:** Model performance metrics and failure modes openly reported

Explainability Trade-offs:

- **Random Forest interpretability:** Limited to feature importance; individual prediction paths not fully transparent
- **Accepted trade-off:** Prioritized predictive performance over full explainability (vs. linear models)

B.5.2 Bias and Fairness Considerations

Sample Bias:

- **Survivorship bias:** Bitcoin survived 2017 – 2025; many cryptocurrencies failed (sample includes only successful asset)
- **Asset selection bias:** Focus on gold and Bitcoin excludes other potential hedges (TIPS, commodities, real estate)

No Protected Attributes:

- This project does not process demographic or personally identifiable data; fairness concerns (group bias, discrimination) do not apply

Narrative Bias:

- **Bitcoin hype cycle:** Sample period includes extreme Bitcoin narratives (both positive and negative)
- **Sentiment index bias:** Crypto Fear & Greed Index may reflect retail sentiment only (not institutional)

B.5.3 Dual-Use and Misuse Prevention

Appropriate Use Cases:

- `[Y]` Educational tool for understanding inflation hedging concepts
- `[Y]` Exploratory analysis for personal finance learning
- `[Y]` Supplementary decision-support alongside professional advice

Inappropriate Use Cases:

- `[N]` Automated trading without human oversight
- `[N]` Replacement for licensed financial advisors
- `[N]` Marketing material for gold or Bitcoin products
- `[N]` Basis for financial product sales or investment solicitation

Misuse Prevention Measures:

- Explicit disclaimers in dashboard UI
- No direct brokerage API integration (prevents automated execution)
- Regime signals labeled as "indicative" not "prescriptive"

B.6 Regulatory and Legal Disclaimers

B.6.1 Jurisdictional Scope

Singapore Focus:

- Analysis tailored for **Singaporean retail investors** using SGD-denominated returns
- May not apply to investors in other jurisdictions (different tax, regulatory, and currency environments)

No Multi-Jurisdictional Compliance:

Project does not claim compliance with:

- U.S. SEC regulations (Regulation Best Interest, Fiduciary Rule)
- EU MiFID II (Markets in Financial Instruments Directive)
- UK FCA (Financial Conduct Authority) rules

User Responsibility:

Users must independently verify compliance with local regulations before:

- Purchasing gold or Bitcoin
- Using leveraged products or derivatives
- Making cross-border investments

B.6.2 Intellectual Property

Open Source Components:

- Python libraries (pandas, scikit-learn, etc.) used under their respective open-source licenses (MIT, BSD, Apache 2.0)
- Code developed for this project may be shared under **MIT License** (if published to GitHub)

Proprietary Data:

- Crypto Fear & Greed Index: Proprietary to Alternative.me (used via public API for non-commercial research)
- No proprietary algorithms or trade secrets developed

Academic Fair Use:

- Data and findings presented for academic purposes under fair use doctrine
- No commercial exploitation intended

B.6.3 Limitation of Liability

Disclaimer of Warranties:

This project is provided "AS IS" without warranties of any kind, express or implied, including but not limited to:

- Warranties of merchantability
- Fitness for a particular purpose
- Non-infringement
- Accuracy or completeness of information

Limitation of Liability:

The author and RevoU shall not be liable for any direct, indirect, incidental, special, consequential, or punitive damages arising from:

- Use or inability to use this framework
- Reliance on regime classifications or KPI signals
- Investment losses resulting from framework-informed decisions
- Data errors, model failures, or technical malfunctions

User Acknowledgment:

By using this framework, users acknowledge that:

1. They have read and understood all disclaimers
2. They accept full responsibility for investment decisions

3. They will not hold the author or RevoU liable for financial losses
4. They understand the limitations and risks described herein

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B.7 Future Research Ethics

B.7.1 Suggested Ethical Enhancements

Longitudinal Validation:

- Future work should validate framework on post-2025 data (out-of-sample)
- Annual model recalibration recommended to detect regime shifts

User Testing:

- Conduct behavioral experiments to assess actual user decision-making
- Measure whether framework reduces or exacerbates behavioral biases

Transparency Improvements:

- Open-source code repository with reproducible Jupyter notebooks
- Interactive explainability tools (SHAP values, individual prediction explanations)

B.7.2 Responsible Deployment Recommendations

If Commercialized:

- Obtain appropriate financial advisory licenses
- Implement robust user authentication and audit trails
- Provide personalized risk profiling (not generic signals)
- Include cooling-off periods before executing trades
- Monitor for signs of user overtrading or excessive risk-taking

Ongoing Monitoring:

- Track model performance degradation over time
- Alert users when Regime Confidence drops below acceptable thresholds
- Implement circuit breakers during extreme market volatility

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B.8 Data Governance and Privacy by Design

B.8.1 Data Minimization

Only Necessary Data Collected:

- Project collects only publicly available market data required for analysis
- No user tracking, behavioral data, or personal preferences stored

No Data Sharing:

- Raw data not shared with third parties
- Aggregated findings disclosed only in this academic report

B.8.2 Data Security

Storage:

- Data stored locally on encrypted hard drive
- No cloud storage of raw datasets (reduces breach risk)

Access Control:

- Only author has access to raw data files
- Dataset will be securely deleted post-project completion

B.9 Statement of Limitations Summary

This project explicitly acknowledges the following constraints:

1. **Non-Causal Relationships:** All findings are associative, not causal
2. **Sample-Specific Results:** Findings reflect 2017-2025 period; may not generalize
3. **No Performance Guarantees:** Models do not guarantee future returns or hedge effectiveness
4. **Regime Instability:** Relationships may shift across monetary policy cycles
5. **Data Latency:** Macro indicators published with lag; dashboard not real-time
6. **Transaction Costs Excluded:** Analysis omits fees, slippage, and taxes
7. **No Personal Financial Advice:** Framework is educational, not personalized

8. **Model Degradation Risk:** Predictive performance may decline over time
9. **Behavioral Risks Unaddressed:** Users vulnerable to emotional decision-making
10. **Regulatory Uncertainty:** Crypto regulation evolving; gold policies may change

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B.10 Ethical Commitment

Author's Commitment:

As the sole researcher and author of this capstone project, I commit to:

1. **Transparency:** Fully disclosing all data sources, methods, and limitations
2. **Academic Integrity:** Conducting research with honesty and intellectual rigor
3. **User Protection:** Prioritizing investor education and risk awareness over persuasive narratives
4. **Responsible Reporting:** Avoiding sensationalism, exaggeration, or misleading claims
5. **Continuous Improvement:** Updating findings if material errors discovered post-submission

Acknowledgment of Uncertainty:

This project operates within the bounds of empirical social science. While statistical methods provide structured insights, **financial markets are inherently uncertain**. All findings should be interpreted with humility and skepticism, recognizing that:

> "All models are wrong, but some are useful." – George Box

This framework aspires to be **useful for structured thinking** while remaining transparent about its wrongness (limitations).

B.11 Contact and Corrections

Reporting Errors:

If users identify material errors in data, methodology, or interpretation: - Contact: jojowibowo@proton.me - Subject line: "Gold-Bitcoin Analysis Error Report"

Commitment to Correction:

Verified errors will be acknowledged and corrected in updated versions of this document (with change log maintained).