Dynamic Analysis of the Impact of Monetary Policy Changes on Derivatives Market Pricing Behavior from a Behavioral Finance Perspective

Renhao Zhao
School of Business, Macau University of Science and Technology, Macau 999078, China
Corresponding author: Renhao Zhao (e-mail: zhaorenhaomust@163.com)

ABSTRACT This study examines the dynamic effects of monetary policy changes on derivatives pricing behavior, emphasizing applications in financial risk management for industrial commodities. High-frequency policy sentiment is extracted from textual announcements using BERT-based natural language processing, capturing market expectations, confidence, and uncertainty. Multi-source investor sentiment, including trading volume, option volatility, and social media indicators, is fused and incorporated into a time-varying parameter VAR model to analyze nonlinear pricing responses under heterogeneous emotional states. Market participant heterogeneity is further explored using HDBSCAN clustering, while Hawkes processes decompose trading intensity into baseline, sentiment-driven, and feedback-amplified components. The analysis reveals significant overreaction in derivative prices and heterogeneous contributions of different participant clusters following policy shocks. The framework is particularly suitable for integration with real-time high-frequency financial data platforms, wireless monitoring infrastructures, and edge-computing analytics, enabling timely risk assessment and adaptive decision-making for commodity and derivatives markets in an industrial management context.

INDEX TERMS monetary policy, derivatives pricing, investor sentiment, financial data analytics

I. INTRODUCTION

With the acceleration of macroeconomic regulation, volatility induced by policy signals within the financial system has become increasingly interconnected. Price changes in the derivatives market now exhibit marked asymmetry, influencing the hedging strategies of commodity users. During periods of policy adjustment, market traders frequently make emotionally driven decisions; the tendency to pursue rising derivative price sequences and the slow recovery during declining phases create a convoluted trajectory that diverges from rational frameworks [1,2]. Conventional models typically assume investors form judgments based on rational expectations upon the release of policy announcements, making decisions using observable variables [3,4]. However, empirical research demonstrates that a multitude of behavioral biases in the market result in price responses to policy changes manifesting as delays, jumps, and divergences [5]. Policy disturbances influence investor expectations and subsequently affect the leverage structure in the derivatives market, causing unstable expansions in volatility and trading intensity, and resulting in heterogeneous policy effects at different stages [6,7]. The interaction between price structure and emotional fluctuations has become increasingly prominent under macroeconomic regulation, revealing limitations in traditional explanatory frameworks. The irrational behaviors of market participants have long been peripheral in research [8,9]. Systematic exploration of pricing responses triggered by policy changes is essential for understanding energy transmission and impact pathways within the derivatives market. The academic literature contains extensive studies on the correlation between monetary policy and asset prices. Early research, grounded in neoclassical macroeconomics, analyzed the macro transmission paths of interest rates and money supply on asset prices through general equilibrium models. Although these studies laid the theoretical foundation, they did not address micro market structures [10,11]. Subsequent works incorporated rational expectations and arbitrage-free pricing theories, treating policy variables as exogenous shocks in pricing models, yet these models continued to rely on the assumption of perfect markets. The emergence of behavioral finance has propelled advances in this field, with some studies focusing on investor sentiment's moderating role in policy responses within stock and bond markets, confirming that sentiment can provoke asymmetric reactions [12,13]. These limitations have resulted in an inadequate understanding of the financial transmission mechanisms of monetary policy in derivatives markets. This article aims to construct an analytical system capable of depicting behavioral response pathways triggered by policy changes, thereby systematically illustrating the relationship between policy disturbances, emotional structures, trading intensity, and derivative prices. The research design employs high-frequency policy texts for emotion extraction, option volatility structures and market participation behaviors as components of sentiment composition, a multi-subject classification structure as the vehicle for behavioral heterogeneity, and a dynamic parameter framework to capture policy shock changes over time, forming a behavioral finance-oriented policy transmission model. The research encompasses policy emotion recognition, market emotion synthesis, dynamic shock characterization, subject difference structure decomposition, and transaction intensity diffusion modeling, focusing on comprehensive analysis of irrational reactions in derivative pricing. The study seeks to enhance behavioral finance's explanatory depth in policy shock research, offering a detailed structural depiction of shock diffusion, emotional coupling, and pricing behavior deviations and providing methodological innovation and expanded research perspectives for dynamic behavior analysis of derivative prices.

II. METHOD

A. CONSTRUCTION OF HIGH-FREQUENCY POLICY SENTIMENT INDEX

1) Policy Announcement Text Processing and Feature Extraction

Policy announcement texts are initially standardized, removing extraneous symbols, non-policy content, and formatting anomalies, and uniformly encoded in UTF-8 to ensure consistent text input. The cleaned texts are organized into a sequence library in chronological order, each tagged with release time and policy type. Text segmentation employs tools optimized for financial contexts, retaining key nouns, verbs, and modifiers to preserve policy intent and tone. The processed text is then vectorized using a BERT pre-trained model, leveraging contextual semantic capture to extract high-dimensional representations and create embedded vectors for each announcement. These vectors are further input into a fine-tuned emotion classifier, trained through supervised learning on three dimensions: policy confidence, easing expectations, and uncertainty. Training data are derived from emotion labels annotated in historical policy texts, with cross-entropy loss minimized as the optimization objective. Following training, the classifier can rapidly generate probability distributions across the three emotional dimensions for new announcements.

2) Construction and Calibration of High-Frequency Policy Sentiment Index

Once each announcement yields emotion probabilities, the three dimensions are combined into a unified, minute-level policy sentiment index via linear weighting. Weight parameters are adjusted using maximum likelihood estimation to ensure the index is sensitive to policy shocks and smooth in continuity. To mitigate the impact of outliers from individual announcements on index fluctuations, sliding window smoothing is applied, with window length dynamically set based on announcement frequency. The index time series undergoes autocorrelation and unit root testing to confirm stability and statistical validity, and is strictly aligned with announcement timestamps for minute-level mapping of policy information. Upon completion, the index is normalized to unify its dimension, facilitating integration with derivatives price and volatility series. In subsequent modeling, the index serves as a policy shock variable in the dynamic parameter model, characterizing market reaction pathways to policy changes and reflecting the transmission effects of policy sentiment in market irrational pricing under the behavioral finance framework. Figure 1 illustrates the construction and characteristics of the high-frequency policy sentiment index. In Figure 1(a), the horizontal axis represents emotional dimensions—confidence, easing expectations, and uncertainty—while the vertical axis shows corresponding probability values. The box and scatter plots depict the distribution of each dimension. Probability values for the confidence dimension cluster between 0.3 and 0.7, whereas the uncertainty dimension exhibits greater fluctuation and dispersion, indicating market sensitivity to policy uncertainty. Figure 1(b) presents spectral analysis results, identifying primary cyclical components in the policy sentiment index, with frequency peaks around 64 days, 32 days, and 6.9 days. These cycles do not directly correspond to monetary policy announcement frequency, but rather reflect statistical periodicity in policy sentiment time series. This may result from delayed policy transmission, phased market reactions to cumulative policy effects, or synergy with other macroeconomic events (e.g., fiscal meetings, economic data releases). Thus, this periodicity dynamically manifests sentiment signals under high-frequency observation, rather than the institutional rhythm of policy announcements. Although the policy sentiment index is constructed at a minute-level frequency, spectral analysis uses daily aggregate sequences to capture medium- to long-term monetary policy effects. The analysis identifies cyclical features, with significant periods corresponding to frequency peaks at approximately 64 days, 32 days, and 6.9 days, suggesting policy shocks exert seasonal or monthly impacts on the medium-term cycle, while policy sentiment fluctuates weekly in the short term.

To differentiate between policy sentiment conveyed by policy texts and reaction sentiment exhibited by market participants, this paper defines the concepts as follows: The policy sentiment index reflects policy intentions, easing expectations, and uncertainty embedded in official announcements, representing exogenous sentiment signals; the market sentiment factor integrates endogenous market reaction indicators—option volatility structure, retail trading be-

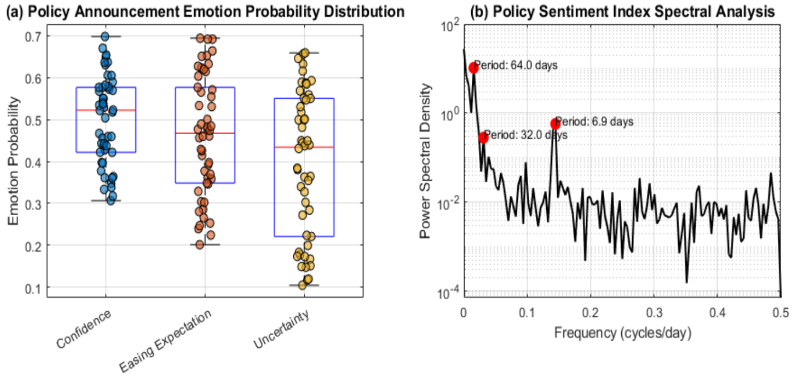

FIGURE 1. Analysis of High-Frequency Policy Sentiment Index Construction. Figure 1 (a). Probability Distribution of Emotional Dimensions in Policy Announcements; Figure 1 (b). Spectral Analysis of Policy Sentiment Index

havior, and social media discussions—reflecting investors' interpretations and emotional feedback. In the TVP-VAR model, these serve as exogenous shock variables and endogenous moderating variables, respectively. The former drives policy disturbances, while the latter modulates the market's nonlinear response, avoiding overlapping variable explanations and ensuring clear model logic.

B. MULTI-DIMENSIONAL QUANTIFICATION OF INVESTOR SENTIMENT IN DERIVATIVES

1) Market Data Acquisition and Pre-Processing

Derivatives market data are collected on implied volatility, trading volume, and price from option trading systems, with VIX index and term structure sourced from exchanges and public databases. Retail trading activity is determined by classifying trading accounts and calculating transaction proportions, while social media sentiment data are extracted from financial forums and platforms, filtering non-trading content. All data are synchronized to a unified timestamp, missing values addressed via forward filling and interpolation, and outliers removed using quantile-based censoring to ensure sequence continuity and statistical robustness. To eliminate dimensional discrepancies, all data are standardized using Z-scores, forming a uniform input scale for subsequent multi-source fusion.

2) Construction of Multi-Source Emotion Fusion Network

Standardized market indicators serve as inputs for a multi-source sentiment fusion network, combining multi- channel convolution and attention mechanisms. Each channel independently processes four data types: option implied volatility skew, VIX term structure, retail trading volume proportion, and social media sentiment. The convolution layer captures local time series changes, while the attention mechanism allocates channel weights during sentiment generation, reflecting each data source's contribution to overall market sentiment. The network output is the comprehensive emotional factor E_t, defined by Formula (1):

$$E_t = \sum_{i=1}^{n} w_i \cdot f_i\left(X_t^i\right) \tag{1}$$

Here, X_t^i denotes the time series for the i-th data source, $f_i(\cdot)$ is the channel feature extraction function, and w_i is the channel weight optimized via gradient descent to best match investor behavior fluctuations. Training uses sliding windows to generate samples, enabling the network to learn relationships between short-term emotional fluctuations and long-term trends. Mean square error serves as the loss function, preventing excessive sensitivity to extreme values. Dropout and L2 regularization are incorporated to enhance robustness and reduce overfitting risk, with batch normalization stabilizing network gradients, ensuring continuity and sensitivity in high-frequency environments.

C. DYNAMIC POLICY SHOCK MODEL EMBEDDED IN BEHAVIORAL BIAS

1) Construction of Vector Autoregressive Model with Time-Varying Parameters

Utilizing high-frequency derivatives market data and comprehensive investor sentiment factors, a timevarying parameter vector autoregression (TVP-VAR) model is constructed. Data include derivatives price series, implied volatility, risk premiums, the policy sentiment index, and investor sentiment factors. All explanatory variable coefficients vary over time, capturing the non-static impact of policy shocks and emotional shifts on the market. Time-varying coefficients are estimated using Bayesian filtering, embedding dynamic parameter adjustment via state and observation equations, as in Formula (2):

$$y_t = A_t y_{t-1} + B_t X_t + \varepsilon_t, \quad \varepsilon_t \sim N(0, \Sigma_t) \tag{2}$$

Here, y_t represents derivatives market response variables, X_t includes policy and emotional factors, A_t and B_t are time-varying coefficient matrices, and Σ_t is the time-varying covariance matrix. Bayesian recursive filtering and smoothing algorithms update parameters, capturing the dynamic effects of policy shocks on derivatives prices and volatility across emotional states.

2) Behavioral Bias Embedding and Dynamic Response Calibration

In the TVP-VAR model, comprehensive investor sentiment factors are introduced as regulatory variables for coefficients, describing the irrational responses of market participants driven by sentiment. Emotional factors interact with policy variables, forming emotionally corrected policy shocks to measure price response magnitude and direction at varying emotional levels. Rolling window Bayesian estimation recursively calibrates interaction coefficients over time, enabling adaptive characterization of overreaction and lag effects in price series. Model parameters are updated with each new observation and sentiment index, minimizing prediction error to ensure dynamic responses align with actual market volatility. Posterior distributions are estimated using Markov Chain Monte Carlo (MCMC) sampling, generating parameter time series for impulse response functions and emotional sensitivity coefficients of policy shocks [14,15]. Model output includes dynamic response sequences of policy variables to derivatives prices, volatility, and risk premiums under different emotional states, accurately reflecting investor behavioral bias transmission under high-frequency policy disturbances and providing quantitative input for subsequent heterogeneous actor pricing channel analyses. Figure 2 demonstrates the response characteristics of the dynamic policy shock model with behavioral bias embedding in a simulated financial market. Figure 2(a) compares impulse responses, with the horizontal axis indicating periods (1–20) and the vertical axis representing response amplitude. Blue and red curves depict price and volatility responses under low and high sentiment states, respectively. High sentiment states amplify price responses, while volatility responses remain relatively stable, highlighting increased sensitivity to policy shocks when market sentiment is elevated. Figure 2(b) presents a three-dimensional surface plot, with axes representing policy shock intensity, sentiment level, and price response amplitude. Price response grows nonlinearly with policy shock intensity, and surface height and slope vary significantly across sentiment states, indicating that behavioral biases substantially modulate the transmission effects of policy shocks.

This approach ensures that policy shock effects are no longer confined to fixed parameter assumptions but adaptively adjust with market sentiment fluctuations, facilitating dynamic modeling of nonlinear pricing behaviors in the derivatives market. By embedding behavioral bias, the model concurrently reveals overreaction, lag correction, and volatility amplification effects in time series, providing a structured quantitative tool for policy impact analysis within the behavioral finance framework and fully characterizing the sentiment-driven response paths in derivatives pricing mechanisms.

D. HIERARCHICAL PRICING CHANNEL IDENTIFICATION FOR HETEROGENEOUS ACTORS

1) Feature Extraction and Clustering of Market Participants

Derivatives trading data are organized by account type, trading frequency, position leverage ratio, and trading volume sequence, constructing high-dimensional feature vectors for each participant. Trading frequency is standardized by transactions per unit time, position leverage ratio is calculated as the nominal value of option contracts divided by account net value, and trading volume sequence is normalized to ensure comparability across account sizes [16,17]. Feature vectors are classified via unsupervised HDBSCAN clustering, which automatically determines cluster count based on variable density parameters, without preset class numbers. The algorithm establishes cluster boundaries using core distance and cluster stability parameters, categorizing market participants as high-frequency institutions, trend followers, and emotional traders. Internal trading patterns within each category are highly similar, with significant inter-cluster differences. Clustering results are evaluated using silhouette coefficients to confirm stability and distinctiveness, and main cluster labels correspond to time series transactions for analyzing group-specific responses to policy shocks. Figure 3 displays results of hierarchical pricing channel identification for heterogeneous actors. Horizontal and vertical axes represent principal components from principal component analysis, reflecting participants' positions in trading feature space. Scatter points denote market player types: blue for high-frequency institutions, red for trend followers, and yellow for emotional traders. High-frequency institutions cluster in the upper left, trend followers scatter in the lower left, and emotional traders concentrate in the lower right with significant fluctuation, illustrating differences in trading frequency, leverage ratio, position duration, and volume concentration. Black squares mark cluster centers, revealing characteristic aggregation positions for each type and indicating clear hierarchical structure in market participant strategies and behaviors.

2) Cluster Regression and Pricing Bias Identification

Following cluster division, a regression model is constructed for each group, using derivatives prices, implied volatility, and risk premium sequences as dependent variables, and policy shock variables and emotional factors as independent variables [18]. The regression model is defined by Formula (3):

$$Y_{i,t} = \alpha_i + \beta_i P_t + \gamma_i E_t + \varepsilon_{i,t} \tag{3}$$

Here, $Y_{i,t}$ is the price response of the i-th participant at time t, P_t represents policy variable, E_t denotes emotional factor, α_i, β_i, γ_i are the coefficients to be estimated, and $\varepsilon_{i,t}$ is the error term. Weighted least squares estimation is used, with weights generated based on transaction volume distribution among entities, reflecting their market impact. Cluster regression results re-evaluate each group's contribution to derivative pricing deviations under policy impacts and identify sources of overreaction, lag correction, and

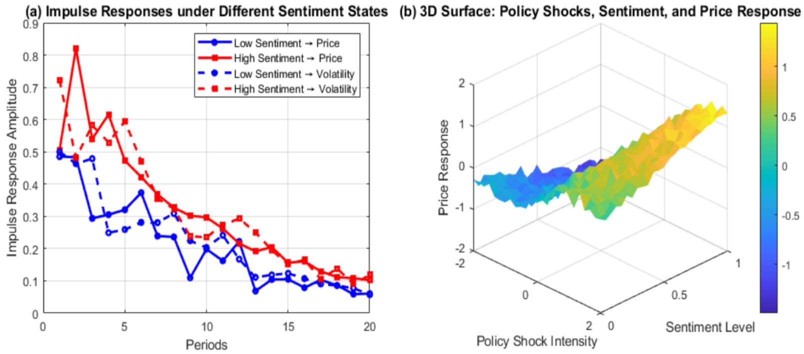

FIGURE 2. Analysis of Dynamic Policy Shock Model with Behavioral Bias Embedding. Figure 2 (a). Comparison of Impulse Responses Across Emotional States; Figure 2 (b). Three-Dimensional Surface Plot of Policy Shock, Emotional State, and Price Response

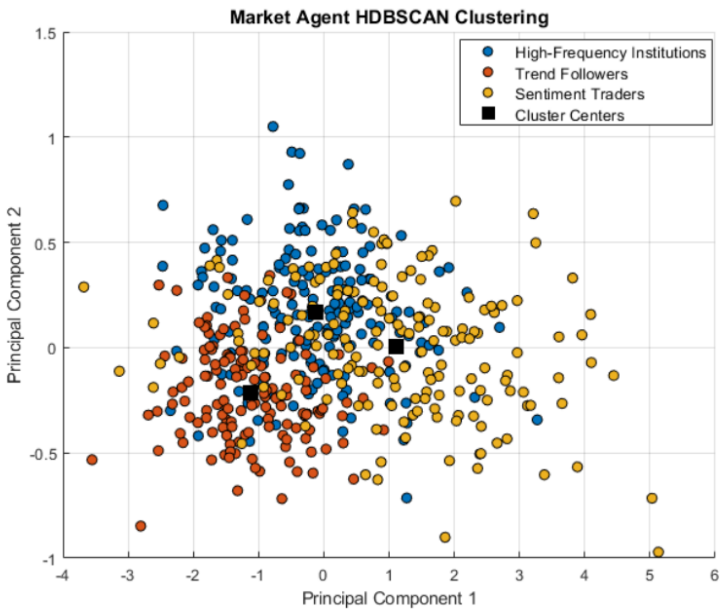

FIGURE 3. Hierarchical Pricing Channel Identification Results for Heterogeneous Actors

volatility amplification mechanisms. Autocorrelation and heteroscedasticity tests are applied to regression residuals to ensure coefficient robustness. Combining subject classification and cluster regression enables decomposition of overall market price changes into contributions from different actors, providing quantitative basis for analyzing policy shock transmission in behavioral heterogeneity contexts and input variables for subsequent leverage amplification and emotional interaction modeling.

E. BEHAVIORAL RESPONSE DECOMPOSITION UNDER LEVERAGE AMPLIFICATION MECHANISM

1) Self-Excited Process Based on Hawkes

Policy announcements in derivatives markets can trigger instantaneous changes in trading intensity. To characterize this self-amplification effect, the Hawkes self-excited process models high-frequency trading event sequences. Each transaction time point is treated as an event, with the conditional intensity function constructed from event to event [19,20], as in Formula (4):

$$\lambda(t) = \mu + \sum_{t_i < t} \alpha e^{-\beta(t-t_i)} \tag{4}$$

Here, $\lambda(t)$ is trading intensity at time t, μ is baseline intensity, α denotes stimulation from a single transaction, β is the attenuation coefficient, and t_i represents historical trading event times. Maximum likelihood estimation optimizes parameters μ, α, and β, ensuring the model accurately reflects self- amplifying features in trading sequences and preserves continuity and quantifiability of high-frequency trading fluctuations.

2) Contribution Decomposition

To empirically analyze the leverage amplification effect, margin data for derivative contracts provided by exchanges are used to calculate actual leverage ratios for each account, defined as the notional value of an option or futures contract divided by the available margin. In the sample, average leverage ratios are 8.3 for high-frequency institutions, 5.7 for sentiment traders, and 4.2 for trend followers. In the Hawkes model, actual leverage ratios weight trading intensity, quantifying the marginal contribution of highly leveraged entities to self-stimulating trading under policy shocks and providing empirical validation for the leverage amplification mechanism. The Hawkes model embeds the policy sentiment index and investor sentiment factors into the conditional intensity function to decompose transaction incentive effects, forming two amplification channels: sentiment and leverage. For sentiment amplification, market emotional intensity interacts with the self-excitation coefficient α to reflect psychologically driven trading enhancement; leverage amplification adjusts the incentive coefficient by account leverage ratio and transaction scale, quantifying the transaction amplification effect of highly leveraged participants under policy shocks. Bayesian estimation and Monte Carlo sampling generate posterior parameter distributions, ensuring contribution quantifiability and robustness. Model output includes trading intensity change sequences for both amplification effects at different time points, aligned with derivative prices and volatility for subsequent dynamic pricing analyses. This methodology systematically distinguishes price fluctuation contributions from psychological and leverage factors under policy shocks, providing refined quantitative tools for nonlinear behavioral analysis in derivatives markets and ensuring model computability and explanatory power in high-frequency environments. Figure 4 illustrates market participants' behavioral responses under leverage amplification. Figure 4(a) decomposes trading intensity into baseline, emotional amplification, and leverage amplification effects, with the x-axis representing trading time (hours) and the y-axis indicating intensity components. When policy shocks occur (dotted line), sentiment and leverage amplification contributions rise substantially, demonstrating rapid market response to policy information and leverage mechanism enhancement. Figure 4(b) displays cumulative trading intensity for each component and their contributions to total intensity. The x-axis is trading time, and the y-axis is cumulative intensity; the leverage amplification curve exhibits a steeper slope, indicating its dominant contribution to long-term cumulative activity. The leverage mechanism significantly influences sustained market activity.

III. EXPERIMENTATION AND EVALUATION

This study utilizes publicly available derivatives trading data, option implied volatility, VIX index, and social media financial discussion data, supplemented with policy announcements from central banks and regulatory authorities. Data are uniformly aligned by high-frequency timestamps to form complete trading event and policy time series, ensuring synchronization between market behavior and policy information in the temporal dimension [21]. All data are standardized before analysis, enabling dimensional comparability across sources. The paper establishes a multi-dimensional quantitative evaluation framework to systematically assess and analyze derivatives market dynamics under policy changes from five perspectives: policy shock response range, pricing deviation, emotional sensitivity, trading intensity self-excitation effect, and behavioral contribution of heterogeneous participants.

A. ASSESSMENT OF POLICY SHOCK RESPONSE

The immediate derivatives market response to monetary policy shocks is evaluated using high-frequency prices, implied volatility, and risk premium sequences. By calculating changes in market variables within fixed windows preceding and following impacts, response values at each time point post-policy announcement are obtained. Response margins compare market response intensity across different policy types and measure behavioral deviations under shocks. Indicators are strictly timestamp-aligned during processing, excluding non-policy event interference to ensure result relevance and comparability. The relationship between policy shock intensity and market response is visualized through scatter plots and fitted curves. Figure 5 depicts policy shock impacts on market variables. Figure 5(a) presents responses to five policy types—interest rate adjustment, reserve requirements, macroprudential regulation, exchange rate intervention, and window guidance—on prices, volatility, and risk premiums. The vertical axis is response range; the horizontal axis is policy type. Reserve adjustment and macroprudential interventions yield larger price responses, while interest rate adjustments are relatively mild. Volatility and risk premiums also increase more with reserve adjustments and exchange rate interventions than with other policies. Figure 5(b) shows positive correlations between policy intensity and responses in price, volatility, and risk premium; fitted lines indicate average R2 values of 0.440 for price, 0.331 for volatility, and 0.277 for risk premium. Greater policy intensity produces more substantial market responses, especially in price and volatility.

B. EVALUATION OF PRICING DEVIATION

Pricing deviation is measured by comparing actual derivatives market prices with model-predicted prices. The predicted price series from the dynamic model are aligned with observed values, and deviation levels at each trading time point are calculated using absolute or squared error, with statistics including mean deviation, standard deviation, skewness, and kurtosis. This quantifies price overreaction or lag correction under policy shocks and reveals the influence of investor groups and market sentiment on deviation. Abnormal trading points are excluded or weighted in processing to ensure robustness. Figure 6 depicts absolute pricing deviation characteristics across four pricing models—Black-Scholes-Merton (BSM), Heston, local volatility, and neural network—over a year of trading days and the impact of market conditions. Figure 6(a) shows mean deviation, standard deviation, skewness, and kurtosis. BSM model's

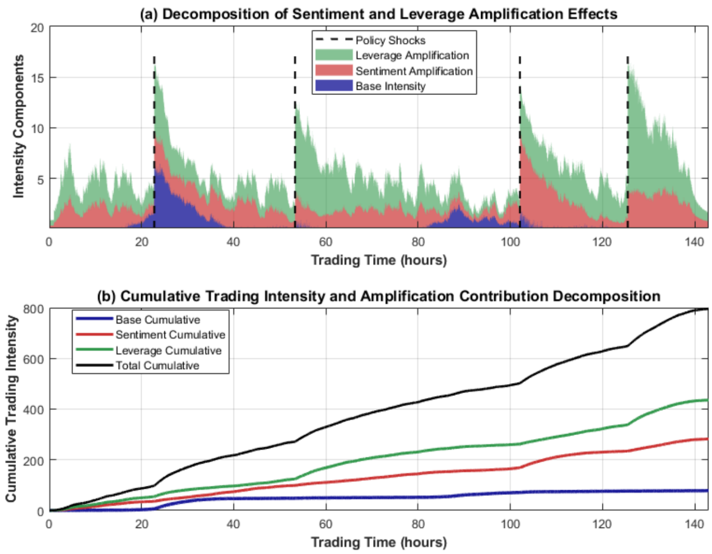

FIGURE 4. Behavioral Response Decomposition Under Leverage Amplification Mechanism. Figure 4 (a). Emotional and Leverage Amplification Effect Decomposition; Figure 4 (b). Cumulative Trading Intensity and Amplification Effect Contribution Decomposition

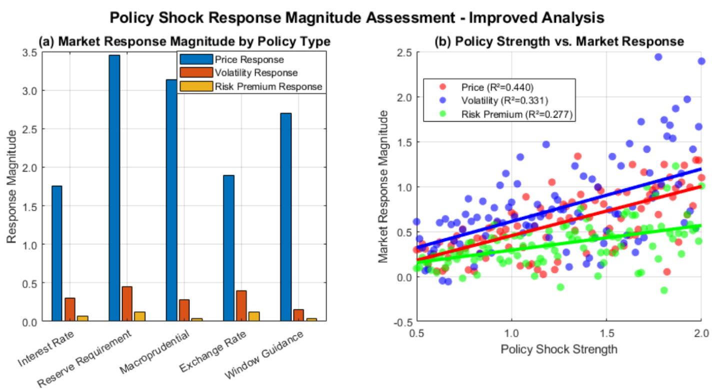

FIGURE 5. Policy Shock Response Assessment. Figure 5 (a). Comparison of Market Response Ranges for Different Policy Types; Figure 5 (b). Relationship Between Policy Intensity and Market Response

average absolute deviation is about 0.5, standard deviation 0.17, with low skewness and kurtosis, indicating concentrated deviation. Heston's standard deviation and kurtosis are higher, reflecting volatility adjustment effects. Neural network model yields lower average deviation, demonstrating superior price fit. Figure 6(b) displays average pricing deviation under normal, high, and low volatility market states; deviations are larger in high volatility and smaller in low volatility, highlighting volatility's effect on model performance. Neural network model consistently has the lowest deviation, confirming its stability in complex market conditions.

C. EMOTIONAL SENSITIVITY ASSESSMENT

Market price and volatility sensitivity to investor sentiment fluctuations are evaluated by aligning sentiment factors with market variables, calculating response relationships, and analyzing immediate impacts via dynamic window methods. Sensitivity indicators quantify market reaction intensity under high or low sentiment, revealing sentiment's role in price formation and volatility diffusion. Standardization and temporal synchronization of sentiment factors across sources ensure comparability and continuity of results, supporting dynamic model calibration. Figure 7 illustrates the impact of various sentiment factors on key market variables and their dynamic evolution. In Figure 7(a), the horizontal axis is market variables—yield, volatility, trading volume, leverage ratio; the vertical axis is sentiment factors—social media, news, option skew, VIX term, retail, institutional sentiment. Color blocks represent correlation coefficients, with social media sentiment showing a strong positive correlation with yield (0.63), and VIX term correlating with volatility (0.52). Figure 7(b) charts the nine months of 2024 on the x-axis and rolling correlation coefficients on the y-axis, showing high sensitivity of trading volume and yield to social media sentiment, indicating emotional information's substantial impact on high-frequency trading activity and price volatility.

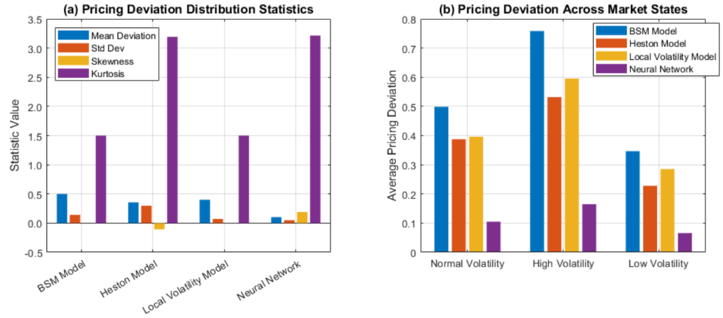

FIGURE 6. Derivative Pricing Deviation Evaluation. Figure 6 (a). Distribution Statistics of Pricing Deviation; Figure 6 (b). Pricing Deviations Under Different Market Conditions

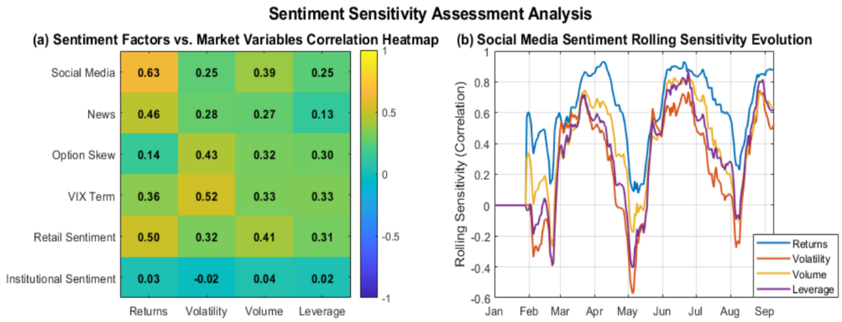

FIGURE 7. Emotional Sensitivity Analysis. Figure 7 (a). Heat Map of Correlation Between Sentiment Factors and Market Variables; Figure 7 (b). Temporal Evolution of Social Media Sentiment Rolling Sensitivity

D. EVALUATION OF TRADING INTENSITY AND SELF-EXCITATION EFFECT

Policy shock impacts on trading frequency and self-excitation in derivatives markets are evaluated by counting transaction changes per unit time before and after shocks and analyzing continuous trading aggregation. Quantitative assessment of trading intensity and self-excitation under policy shocks measures trading activity increases and declines, revealing self-excitation mechanisms in high-frequency markets. Abnormal transactions and non-policy events are excluded in data processing, and results are aligned with price and volatility series, providing quantitative foundations for leverage amplification and emotional diffusion analysis. Table 1 presents quantitative evaluation of derivatives market trading intensity and self-excitation under policy impacts, showing activity changes among trading entities and the market's internal self-excitation mechanism. Post-policy impact, overall trading intensity rises from 125.6 to 348.2 trades per minute (177.2% increase), indicating strong policy-induced stimulation of trading behavior. Decay half-life is 45.3 minutes, with self-excitation coefficient $\alpha = 0.82$, confirming significant aggregation effects. High-frequency institutional trading increases from 68.3 to 215.7 trades per minute (215.8% increase), decay half-life 28.6 minutes, self-excitation coefficient 0.91, reflecting rapid institutional response and pronounced self-excitation. Emotional traders' intensity rises by 123.7%, with a decay half-life of 85.7 minutes and self-excitation coefficient 0.68, indicating limited response but prolonged trading behavior and delayed effects. Option trading intensity grows by 214.2%, highlighting high activity and self-excitation among complex derivatives under policy impacts.

TABLE 1. Quantitative Evaluation of Trading Intensity and Self-Excitation Effect Under Policy Impact

Evaluation Dimension	Pre-Shock Mean	Post-Shock Peak	Increase (%)	Decay Half-Life	Self-Excitation Coefficient (α)
Overall Trading Intensity	125.6 trades/min	348.2 trades/min	177.2%	45.3	0.82
High-Frequency Institutional Trading	68.3 trades/min	215.7 trades/min	215.8%	28.6	0.91
Trend-Follower Trading	42.1 trades/min	98.5 trades/min	134.0%	62.4	0.75
Sentiment-Driven Trading	15.2 trades/min	34.0 trades/min	123.7%	85.7	0.68
Options Trading Intensity	35.8 trades/min	112.5 trades/min	214.2%	38.9	0.87
Futures Trading Intensity	89.8 trades/min	235.7 trades/min	162.5%	51.2	0.79

E. ASSESSMENT OF BEHAVIORAL CONTRIBUTION OF HETEROGENEOUS SUBJECTS

This evaluation examines differences in contributions of various market participants to derivatives prices and volatility under policy shocks. Using subject classification and cluster regression, the method quantifies price responses from high-frequency institutions, trend followers, and emotional traders, comparing their relative influence under emotional and leverage conditions, and revealing market heterogeneity's effect on dynamic pricing behavior. Transaction records are strictly matched to primary labels, with invalid or abnormal transactions excluded to ensure accuracy and interpretability. Table 2 details contribution differences among market participants to derivatives prices and volatility under policy shocks, highlighting market heterogeneity's role in dynamic pricing. High-frequency institutions have the highest average price response contribution (45.2%), rising to 48.0% in high sentiment, signifying their leadership in rapid market response and emotional amplification. Trend followers contribute 28.6% to price response and 25.4% to volatility, demonstrating moderate influence dependent on trend continuation. Emotional traders' contributions increase in high sentiment (18.5%) and leverage conditions (21.3%), reflecting sensitivity to short-term volatility. Retail participants exert limited impact, with price response at 10.4% and only 3.3% in high sentiment. Table 2 quantifies heterogeneous response characteristics in policy shock contexts: high-frequency institutions and trend followers dominate price and volatility transmission, while emotional traders amplify volatility under specific emotional and leverage environments.

TABLE 2. Behavioral Contribution Assessment for Heterogeneous Subjects

Participant Type	Average Price Response Contribution (%)	Volatility Contribution (%)	Contribution in High Sentiment (%)	Contribution under Leverage Conditions (%)
High-Frequency Institutions	45.2	38.7	48.0	42.5
Trend Followers	28.6	25.4	30.2	27.1
Sentiment Traders	15.8	20.1	18.5	21.3
Others/Retail	10.4	15.8	3.3	9.1

IV. CONCLUSION

This paper provides a dynamic analysis of monetary policy changes on derivatives market pricing behavior from a behavioral finance perspective, emphasizing implications for raw material price risk management. It introduces methodologies including high-frequency policy sentiment indexing, multisource investor sentiment factor generation, TVP-VAR dynamic policy shock modeling, hierarchical pricing channel identification for heterogeneous subjects, and Hawkes self-stimulated trading intensity decomposition. By systematically embedding these methods, the study achieves dynamic correlation modeling of policy variables, market sentiment, and trading behavior in high-frequency series, quantifying nonlinear impacts of policy shocks on prices, volatility, and risk premiums. Results demonstrate that investor sentiment is pivotal in market reactions, with significant differences in participant contributions to price deviations. Leverage structure and trading self-stimulation further magnify dynamic fluctuations from policy shocks. This approach elucidates emotional bias transmission pathways and offers practical quantitative tools for policy-making, risk early warning, and market microstructure research. However, the model's generalizability under extreme market crashes or black swan events remains to be validated. Future research should focus on integrating reinforcement learning to optimize dynamic emotional weight adjustment, exploring cross-market emotional contagion modeling—essential for assessing financial risks affecting and developing real-time emotional policy early warning systems to enhance the explanatory power and practical utility of behavioral finance frameworks in complex macroeconomic environments.

AUTHOR CONTRIBUTIONS

Renhao Zhao designed, collected and analyzed the data, and drafted the manuscript. Renhao Zhao conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Renhao Zhao participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

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