CAMEF: Causal-Augmented Multi-Modality Event-Driven Financial Forecasting by Integrating Time Series Patterns and Salient Macroeconomic Announcements

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Abstract

Accurately forecasting the impact of macroeconomic events is critical for investors and policymakers. Salient events like monetary policy decisions and employment reports often trigger market movements by shaping expectations of economic growth and risk, thereby establishing causal relationships between events and market behavior. Existing forecasting methods typically focus either on textual analysis or time-series modeling, but fail to capture the multi-modal nature of financial markets and the causal relationship between events and price movements. To address these gaps, we propose **CAMEF** (Causal-Augmented Multi-Modality Event-Driven Financial Forecasting), a multi-modality framework that effectively integrates textual and time-series data with a causal learning mechanism and an LLM-based counterfactual event augmentation technique for causal-enhanced financial forecasting. Our contributions include: (1) a multi-modal framework that captures causal relationships between policy texts and historical price data; (2) a new financial dataset with six types of macroeconomic releases from 2008 to April 2024, and high-frequency real trading data for five key U.S. financial assets; and (3) an LLM-based counterfactual event augmentation strategy. We compare CAMEF to state-of-the-art transformer-based time-series and multi-modal baselines, and perform ablation studies to validate the effectiveness of the causal learning mechanism and event types.

CCS Concepts

• **Applied computing** → *Economics*; • **Computing methodologies** → **Neural networks**.

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Keywords

Multimodal learning, Causal Learning, Financial dataset, Time-series Forecasting

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1 Introduction

The prices of financial assets reflect all available information, according to Fama's Efficient Market Theory [15, 16]. Major financial releases from government sectors often trigger market movements by shaping investors' expectations and evaluations of economic conditions, asset growth potential, and associated risks. For example, during the FOMC meeting on March 16, 2020, the Fed's emergency rate cut to 0-0.25% sharply altered investors' economic outlook, resulting in a massive sell-off. Major indices, including the S&P 500, NASDAQ, and Dow Jones, dropped by over 10%, marking the steepest single-day decline since 1987 [13]. These salient macroeconomic events cause reactions in financial assets, establishing causal relationships between events and financial assets. Figure 1 illustrates multiple types of events that cause financial market reactions. Therefore, **accurately forecasting the causal consequences of the salient macroeconomic releases on financial market is essential, not only to help investors manage risks and maximize returns, but also to provide policymakers with valuable insights for evaluating and refining future policies.**

Previous studies on event-driven forecasting have primarily adopted three lines of methodologies. The first line of approaches utilizes text feature-based models, where language models, ranging from self-crafted RNN-based architectures [11, 22, 29, 57] to pre-trained transformers [49, 62], embed sentiment information into text vectors, and then stock movements are predicted as a binary classification task (e.g., hawkish vs. dovish). The second line of methodology focuses on historical time-series data, treating

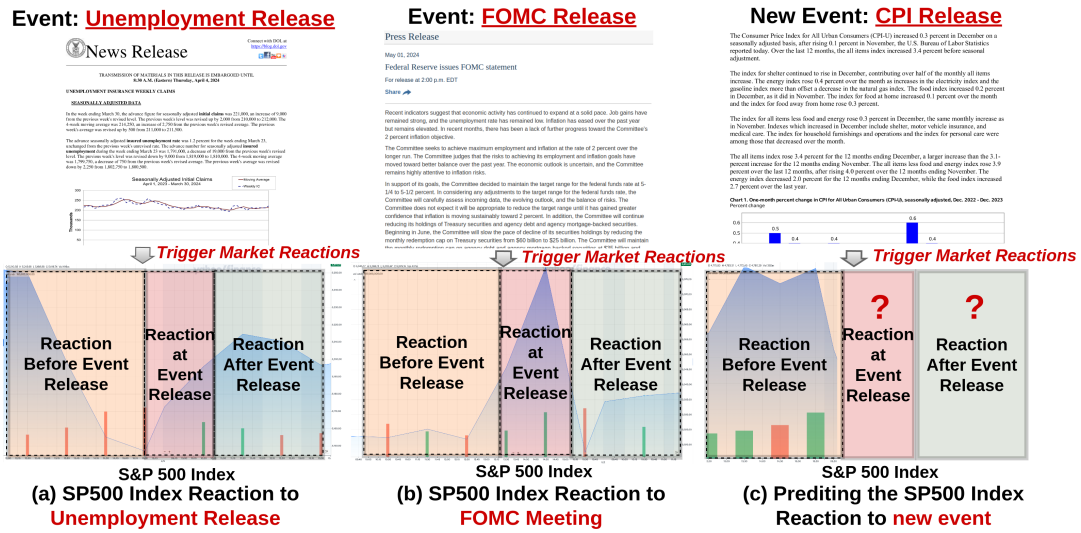

Figure 1: Event-Driven Forecasting Examples: (a) Market reaction to employment insurance release; (b) Market reaction during FOMC meeting; (c) Forecasting market reactions to future events.

stock price movements as a regression problem [7, 54]. Recently, transformer-based architectures have been applied for time-series prediction, including Informer [60], FedFormer [61], and AutoFormer [8], etc. However, both of these directions typically focus on a single modality, neglecting multi-dimensional information. The third line of research adopts a multi-modality approach, leveraging multiple types of data sources to enhance forecasting performance. For instance, studies like [35, 37] incorporate textual, video, and audio data from FOMC meetings alongside corresponding market movements. While these approaches show promise for event-driven financial forecasts, they face three major limitations:

- **Data Limitation:** Existing approaches predominantly focus on a single type of event, such as FOMC meetings [35, 37, 49], while neglecting other crucial macroeconomic events like unemployment insurance releases, CPI, PPI, and GDP advance reports. Additionally, many studies rely on daily-based time-series data for financial assets [7, 8, 35, 37, 49, 54, 60, 61], which limits their applicability and precision in real-time trading scenarios where high-frequency data is mostly adopted.
- **Modality Limitation:** Most prior studies rely on single-modality analysis, using either textual models [11, 22, 29, 49, 57, 62] or time-series models [7, 8, 54, 60, 61], which fail to integrate the complementary strengths of both modalities. While some multi-modality approaches have been proposed [35, 37], they often lack advanced mechanisms for feature fusion, effective decoding strategies, and causal learning, which are critical for understanding the complex interplay between event texts and market dynamics.
- **Causality Limitation:** Existing methods [35, 37] fail to incorporate causal reasoning frameworks, overlooking the causal relationships between events and market reactions. Without explicitly modeling these relationships, such approaches cannot fully capture the drivers of financial market behavior, limiting their predictive robustness.

To address the limitations of previous studies, we propose a novel multi-modality framework, **CAMEF**[1] (**c**ausal-**A**ugmented **M**ulti-Modality **E**vent-Driven Financial **F**orecasting). CAMEF integrates time-series and textual features through specially designed multi-feature fusion techniques, time-series decoding mechanisms, and causal learning strategies. By conducting a thorough review of financial literature, we identify six types of salient macroeconomic events for the forecasting analysis. Furthermore, the framework employs causal data augmentation powered by Large Language Models (LLMs) and a causal contrastive learning approach to enhance the causal understanding and forecast accuracy of CAMEF. This paper offers three key contributions:

- **Novel Dataset:** We introduce a novel open-source synthetic dataset comprising 6 types of macroeconomic event scripts (ref to Tab. 1 for details) from 2008 to April 2024 through reviewing from financial literature [3, 10, 17–20, 26, 33, 34, 38, 42–44, 52], alongside intra-day _high-frequency financial data at 5-minute intervals from key U.S. stock indexes and Treasury bonds. To support causal learning, the dataset also includes counterfactual event scripts generated using our LLM-based causal argumentation prompting, making it the first to integrate policy texts, high-frequency trading data, and causally augmented content.
- **Novel Multi-Modality Model:** We propose a novel multi-modality approach, CAMEF, that integrates time-series and textual features, incorporating specifically designed multi-feature fusion and time-series decoding networks, which

[1] *The dataset and code for CAMEF are open-sourced at: https://github.com/lakebodhi/CAMEF*