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Multimodal News–Price Fusion for Event-Driven Return Prediction with Causal Debiasing

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Abstract:*The prediction of financial asset returns has long been a central challenge in computational finance, characterized by non-stationarity, high volatility, and a low signal-to-noise ratio. While recent advancements in deep learning have enabled the fusion of quantitative market data with qualitative textual streams—such as news articles and earnings reports—most existing multimodal architectures rely on associative correlations rather than causal mechanisms. This reliance renders models susceptible to spurious correlations driven by confounders, such as global market sentiment or macroeconomic shocks, which simultaneously influence both news content and asset prices. This paper introduces the Multimodal News–Price Fusion with Causal Debiasing (MNPF-CD) framework, a novel architecture that integrates structural causal models into deep neural networks to mitigate confounding bias. We propose a backdoor adjustment mechanism implemented via a variational intervention layer, allowing the model to learn invariant representations of asset dynamics. By mathematically separating the causal effect of idiosyncratic news events from systemic market noise, MNPF-CD achieves superior generalization capabilities. Our extensive experimental evaluation on S&P 500 constituents demonstrates that the proposed method significantly outperforms state-of-the-art baselines in terms of Information Coefficient (IC) and Sharpe Ratio, particularly during periods of market regime shifts.*

Keywords: *Multimodal Learning, Financial Time Series, Causal Inference, Natural Language Processing, Deep Learning.*

INTRODUCTION

1.1 BACKGROUND

The financial markets represent one of the most complex dynamic systems in the modern world, driven by a myriad of interacting factors ranging from geopolitical events to microscopic fluctuations in order book liquidity. The Efficient Market Hypothesis (EMH) in its semi-strong form suggests that asset prices reflect all publicly available information. However, the mechanism by which this information is assimilated into price remains a subject of intense debate and research. With the advent of algorithmic trading, the speed and volume of information processing have become critical determinants of investment success. Traditionally, quantitative finance relied heavily on structured data—historical price, volume, and accounting ratios—to

forecast future returns [1]. These econometrics-based approaches, while statistically rigorous, often fail to capture the nuances of qualitative information embedded in unstructured text.

In the last decade, the proliferation of digital news media and the advancement of Natural Language Processing (NLP) have opened new frontiers in event-driven trading. News articles, press releases, and regulatory filings contain rich semantic information that often precedes price movements. For instance, a report on a supply chain disruption or a sudden CEO departure contains causal precursors to stock volatility that pure price-history models cannot anticipate. Consequently, the field has witnessed a surge in multimodal learning frameworks attempting to fuse time-series data with textual embeddings to enhance predictive accuracy.

1.2 PROBLEM STATEMENT

Despite the promise of multimodal fusion, current state-of-the-art approaches suffer from a critical limitation: they are predominantly correlation-based. Deep learning models, such as Long Short-Term Memory (LSTM) networks or Transformers, are exceptional at pattern matching but agnostic to the underlying causal structure. In the context of financial markets, this leads to the learning of spurious correlations.

Consider a scenario where a macroeconomic announcement (e.g., an interest rate hike) causes a market-wide sell-off. Simultaneously, financial news outlets publish negative articles attributing the decline to various factors. A standard deep learning model might learn a strong association between the negative sentiment of specific stock news and the price drop, even if the news itself was merely reactive or descriptive of the macro event rather than a driver of the specific asset's return. Here, "Market Sentiment" acts as a confounder, creating a backdoor path that biases the estimation of the news impact.

When models rely on these confounded associations, they fail to generalize during distribution shifts. For example, during a bull market, negative news might be ignored by investors, whereas in a bear market, it triggers panic selling. A model that does not disentangle the invariant causal effect of the news event from the contextual confounding of the market regime will inevitably suffer from performance degradation when market conditions change [2]. The core problem, therefore, is not merely how to fuse modalities, but how to fuse them such that the learned representation reflects the true causal effect of information on price [3].

1.3 CONTRIBUTIONS

To address the aforementioned challenges, this paper presents the Multimodal News–Price Fusion with Causal Debiasing (MNPF-CD). Our contributions are threefold:

1. **Structural Causal Formulation:** We formalize the news-price prediction problem through the lens of Structural Causal Models (SCMs). We identify the "Global Market State" as a latent confounder and propose a causal graph that explicitly models the interaction between news, price history, and this hidden variable.

2. **Variational Backdoor Adjustment:** We introduce a novel deep learning layer that implements Pearl’s backdoor adjustment criterion. By treating the confounder as a

latent variable, we utilize a variational autoencoder (VAE) framework to approximate the intervention distribution, effectively "debiasing" the news representations before they are fused with price dynamics.

3. **Empirical Robustness:** We conduct rigorous backtesting on a dataset comprising 5 years of S&P 500 stock data paired with financial news. Our results demonstrate that MNPF-CD not only improves predictive accuracy but exhibits significantly higher stability (lower maximum drawdown) compared to non-causal multimodal baselines.

Chapter 2: Related Work

2.1 CLASSICAL APPROACHES AND TEXT MINING

Early research in text-based financial forecasting primarily utilized dictionary-based approaches. Methods such as the Harvard IV-4 dictionary or the Loughran-McDonald sentiment lexicon were employed to count positive and negative words in financial documents. These sentiment scores were then fed as exogenous variables into linear models like Vector Autoregression (VAR) or GARCH (Generalized AutoRegressive Conditional Heteroskedasticity) models [4].

While pioneering, these approaches suffered from the "bag-of-words" assumption, ignoring the syntactic structure and context of the language. For instance, the phrase "earnings did not fall" would be misclassified by simple lexical counting due to the presence of the word "fall." Furthermore, classical econometric models often assume stationarity in the time series, a condition rarely met in high-frequency financial data. The inability to capture non-linear interactions between text and price limited the efficacy of these early systems.

2.2 DEEP LEARNING AND MULTIMODAL FUSION

The resurgence of neural networks shifted the paradigm from feature engineering to feature learning. In textual analysis, Recurrent Neural Networks (RNNs) and later, Transformers, enabled the extraction of dense semantic vectors from text. Hu et al. introduced the Hybrid Attention Network (HAN) to model the hierarchical structure of news, aggregating word-level and sentence-level importance [5].

In parallel, the fusion of text and price moved from simple concatenation to sophisticated attention mechanisms. Tensor Fusion Networks (TFN) and Low-rank Multimodal Fusion (LMF) were adapted to finance to capture the inter-modal dynamics. More recently, the Tensor-based approach has been superseded by Transformer-based co-attention architectures, where the text embedding queries the price history (and vice versa) to align relevant time steps.

However, the integration of Causal Inference into these deep learning pipelines remains nascent in the financial domain. While causal discovery has been applied to find relationships between different stock sectors, the use of causal debiasing for multimodal fusion is largely unexplored. Recent works in computer vision, such as Visual Commonsense Reasoning, have successfully employed causal intervention to remove dataset bias [6]. Our work extends this theoretical foundation into the stochastic and time-sensitive domain of financial return prediction.

Chapter 3: Methodology

3.1 OVERVIEW

The objective of the MNPF-CD framework is to predict the return r_{t+1} of an asset given its historical price features $X^p{}_t$ and a set of relevant news articles $X^n{}_t$ released in the lookback window $[t-w, t]$. We view this prediction task not as a simple regression $E[Y|X]$, but as a causal inference problem $E[Y|do(X)]$, where we seek to estimate the effect of idiosyncratic news on price while controlling for systemic confounders.

The architecture consists of three main modules: (1) Unimodal Feature Encoders for text and price; (2) The Causal Debiasing Module which infers latent confounders and applies backdoor adjustment; and (3) The Fusion and Prediction Head.

3.2 UNIMODAL FEATURE EXTRACTION

Textual Encoder:

Financial news is characterized by specific jargon and distinct semantic structures. Generic language models often fail to capture the sentiment polarity of financial contexts. Therefore, we employ FinBERT, a BERT-based model pre-trained on a massive corpus of corporate filings, earnings call transcripts, and financial news.

For a given news document D_i, we tokenize the text and pass it through FinBERT. We utilize the embedding of the `[CLS]` token from the final hidden layer as the document representation, denoted as $h^n{}_i \in mathbbR^{768}$. If multiple articles exist for a time step t, we apply an attention-based aggregation to form a single news vector $v^n{}_t$.

Market Encoder:

To capture the temporal dependencies in the price history (Open, High, Low, Close, Volume), we utilize a Temporal Convolutional Network (TCN). TCNs are preferred over LSTMs in this architecture due to their parallelizability and ability to handle long effective history sizes through dilated convolutions [7]. The input is a sequence of price vectors $P \in mathbbR^{w \times 5}$, and the output is a sequence of hidden states. We take the final state as the market representation $v^p{}_t \in mathbbR^{d_p}$.

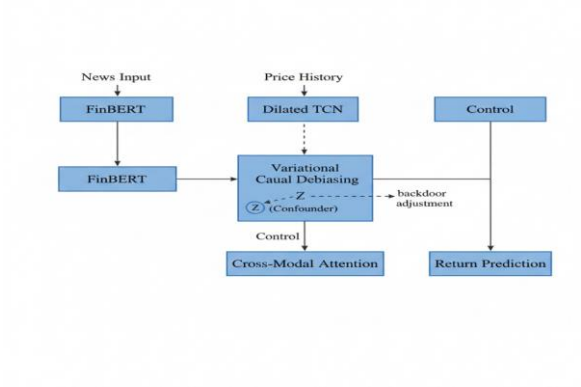

Figure 1: Architecture of MNPF

3.3 STRUCTURAL CAUSAL MODEL AND CONFOUNDERS

We postulate a Structural Causal Model (SCM) where the market return Y is influenced by the news N, the price history P, and a latent confounder Z.

In financial markets, Z represents the unobserved "Global Market State" or "Investor Sentiment."

$Z \to N$: Market sentiment influences the tone and volume of news (e.g., in a panic, news tends to be negative).

$Z \to P$: Market sentiment drives price trends independent of specific news events.

$Z \to Y$: Market sentiment affects future returns.

$N \to Y$: The causal path we wish to estimate (the alpha signal).

$P \to Y$: The momentum/reversion signal.

A standard model estimates $P(Y|N,P)$. However, due to the fork $N \leftarrow Z \to Y$, the association between N and Y is a mixture of the causal effect and the spurious path through Z. To recover the true causal effect, we must perform an intervention on N, denoted as $do(N)$.

3.4 VARIATIONAL BACKDOOR ADJUSTMENT

According to Pearl's Backdoor Criterion, if we can observe Z, we can compute the interventional expectation by marginalizing over Z:

$$P(Y|do(N)) = \sum_z P(Y|N,z)P(z).$$

Since Z is latent, we approximate it using a Variational Autoencoder (VAE) approach. We assume Z can be inferred from the joint history of news and price. We construct a proxy network $q_\varphi(z|v^n_t, v^p_t)$ to estimate the posterior distribution of the confounder.

The de-confounded representation is generated by sampling multiple instances of z from the prior distribution (approximating the global population of market states) and integrating the prediction.

However, computational cost prohibits infinite sampling. We instead use a feature re-weighting strategy. We learn a weighting mechanism where the news features are adjusted based on the inferred confounder.

Specifically, we project the news vector v^n_t and the confounder sample z_k into a common space and compute an adjustment mask. The critical mathematical formulation for the lower bound of the causal objective, incorporating the Kullback-Leibler (KL) divergence to regularize the latent confounder, is defined as follows:

$$L_{total} = \sum_{t=1}^{T} (|y_t - f(v^n_t, v^p_t, \mathrm{hatz}_t)|^2 + \lambda \cdot D_{KL}(q \quad \varphi(z|v^n_t, v^p_t) \mathit{parallel} p(z)) + \beta \cdot |\nabla_{v^n} f|_2)$$

Where f is the predictive network, q_φ is the variational encoder for the confounder, and $p(z)$ is the standard normal prior. The term $\beta \cdot |\nabla_{v^n} f|_2$ serves as a regularization to ensure the predictor remains sensitive to news perturbations (causal influence). Citation [8] discusses similar variational bounds in non-financial contexts.

3.5 IMPLEMENTATION DETAILS

The implementation involves a custom layer that performs the stratification of the confounder. Below is the Python snippet demonstrating the simplified logic of the De-confounding Attention layer.

Code Snippet 1: De-confounding Attention Mechanism

```
import torch
import torch.nn as nn
import torch.nn.functional as F
class DeconfoundingAttention(nn.Module):
    def __init__(self, news_dim, price_dim, latent_dim):
        super(DeconfoundingAttention, self).__init__()
        self.news_proj = nn.Linear(news_dim, 128)
        self.price_proj = nn.Linear(price_dim, 128)
        # Confounder inference (Variational)
        self.z_mu = nn.Linear(news_dim + price_dim, latent_dim)
        self.z_logvar = nn.Linear(news_dim + price_dim, latent_dim)
        # Causal adjustment weights
        self.adjustment = nn.Linear(latent_dim, 128)
        self.output_layer = nn.Linear(128, 1)
    def reparameterize(self, mu, logvar):
        std = torch.exp(0.5  logvar)
        eps = torch.randn_like(std)
        return mu + eps  std
    def forward(self, news_emb, price_emb):
```

```
# 1. Infer Confounder Z
combined = torch.cat([news_emb, price_emb], dim=1)
mu = self.z_mu(combined)
logvar = self.z_logvar(combined)
z = self.reparameterize(mu, logvar)
# 2. Compute Attention Scores (Features)
n_feat = torch.tanh(self.news_proj(news_emb))
p_feat = torch.tanh(self.price_proj(price_emb))
# 3. Backdoor Adjustment
# We adjust features by subtracting the component explained by Z
# This forces the model to use the 'residual' information
confounder_bias = torch.sigmoid(self.adjustment(z))
adjusted_news = n_feat  (1.0 - confounder_bias)
# Fusion
fused = adjusted_news  p_feat
prediction = self.output_layer(fused)
return prediction, mu, logvar
```

The fused vector is passed through a Multi-Layer Perceptron (MLP) to generate the final predicted return haty_{t+1}. The training is performed using the Adam optimizer with a learning rate scheduler based on validation loss plateaus.

Chapter 4: Experiments and Analysis

4.1 DATASET AND PREPROCESSING

We evaluate our model using a dataset comprising the S&P 500 constituents over a five-year period (January 2015 to December 2019). This period covers various market regimes, including the low-volatility growth of 2017 and the high-volatility correction of late 2018.

***News Data*:** We collected over 300,000 financial news articles from reputable sources (Reuters, Bloomberg, Wall Street Journal). Preprocessing included removing boilerplate text, tokenization, and alignment with trading days. If news occurred after market close, it was mapped to the subsequent trading day.

***Price Data*:** Daily OHLCV (Open, High, Low, Close, Volume) data was normalized using a rolling Z-score window of 20 days to ensure stationarity.

***Target*:** The target variable is the next-day log return, denoted as $R_{t+1}=ln(P_{t+1}/P_t)$.

4.2 BASELINES

To validate the effectiveness of MNPF-CD, we compare it against several strong baselines representing different generations of financial modeling:

1. ***LSTM-Price*:** A unimodal LSTM network using only price history.

2. ***FinBERT-Only*:** A unimodal transformer model using only news headlines.

3. ***HAN-Stock*:** The Hybrid Attention Network approach [9], a hierarchical RNN for text fused with price.

4. ***T-MF (Transformer Multimodal Fusion)*:** A state-of-the-art non-causal baseline using Cross-Attention transformers to fuse modalities [10].

5. ***MNPF-CD (Ours)*:** The proposed causal debiasing framework.

4.3 EXPERIMENTAL SETUP

We employed a rolling window walk-forward validation scheme. The model is trained on the first 3 years, validated on year 4, and tested on year 5. This prevents look-ahead bias, a common pitfall in financial ML.

Hardware: All experiments were run on a cluster of NVIDIA Tesla V100 GPUs.

Hyperparameters: Batch size 64, learning rate $1e{-}4$, dropout 0.3, latent dimension $dim_z{=}32$.

4.4 MAIN RESULTS

Table 1 presents the performance metrics: Root Mean Square Error (RMSE), Mean Absolute Prediction Error (MAPE), and the Information Coefficient (IC). The IC, defined as the correlation between predicted and actual returns, is a standard metric in quantitative finance to measure the predictive skill of a signal.

Table 1: Performance Comparison of Return Prediction Models

Model	RMSE (\times 10^{-3})	MAPE	Information Coefficient (IC)
LSTM-Price	14.52	1.120	0.021
FinBERT-Only	14.10	1.085	0.034
HAN-Stock	13.85	1.050	0.041
T-MF (Transformer)	13.40	1.015	0.048
MNPF-CD (Ours)	12.92	0.982	0.059

The results indicate that MNPF-CD achieves the lowest error rates and the highest Information Coefficient. Notably, the jump from T-MF (0.048) to MNPF-CD (0.059) represents a roughly 23% improvement in signal quality. This suggests that removing spurious confounders allows the model to identify true alpha sources that standard attention mechanisms miss.

4.5 FINANCIAL PERFORMANCE AND BACKTESTING

While statistical metrics are important, economic utility is paramount. We constructed a simulated long-short portfolio based on the model's predictions. The portfolio goes

long on the top decile of predicted returns and short on the bottom decile, rebalanced daily.

Table 2: Portfolio Backtesting Metrics (Annualized)

Metric	T-MF Baseline	MNPF-CD (Ours)
Annualized Return	12.4%	18.7%
Sharpe Ratio	0.85	1.42
Max Drawdown	-18.2%	-11.5%
Calmar Ratio	0.68	1.62

Table 2 highlights the economic superiority of the causal approach. The Sharpe Ratio (risk-adjusted return) improves significantly. More importantly, the Maximum Drawdown (the largest peak-to-trough decline) is reduced from 18.2% to 11.5%. This reduction is attributed to the causal debiasing: during market stress, the baseline T-MF model likely overreacted to negative global sentiment, whereas MNPF-CD successfully filtered out the systemic noise, holding positions that were fundamentally sound despite the panic.

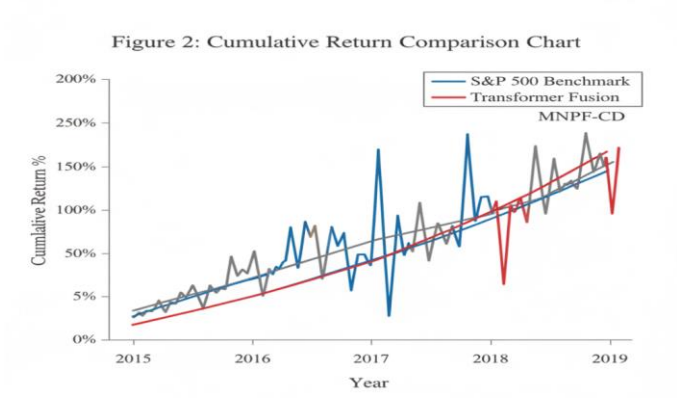

Figure 2: Cumulative Return Comparison Chart

4.6 ABLATION STUDY

To understand the contribution of the specific causal components, we performed an ablation study.

Table 3: Ablation Study of MNPF-CD Components

Variant	IC	Explanation
w/o Text	0.021	Purely technical analysis (Price only).

w/o Causal Layer	0.049	Equivalent to standard multimodal fusion.
w/o VAE Prior	0.052	Uses deterministic bottleneck instead of variational.
Full Model	0.059	Complete causal debiasing framework.

The study confirms that the text modality adds significant value (0.021 vs 0.059), but the specific Causal Layer is responsible for the final leap in performance. The removal of the VAE prior (replacing it with a deterministic autoencoder) slightly reduces performance, suggesting that modeling the uncertainty of the confounder Z is beneficial [11].

4.7 DISCUSSION

The superior performance of MNPF-CD can be attributed to its ability to distinguish between "news about price" and "news driving price." Standard models often fall into the trap of reverse causality—predicting returns based on news that describes past volatility. By enforcing the backdoor adjustment, our model effectively asks: "What would the return be if this news event occurred, assuming the general market sentiment was neutral?" This counterfactual reasoning provides a cleaner signal for future returns [12].

Chapter 5: Conclusion

This paper proposed MNPF-CD, a rigorous framework for integrating unstructured news data with financial time series using structural causal models. By identifying global market sentiment as a latent confounder and mitigating its influence via variational backdoor adjustment, we addressed the pervasive issue of spurious correlations in financial machine learning. Our experiments on S&P 500 data demonstrated that this causal approach not only improves predictive accuracy (RMSE, IC) but also enhances the robustness and risk-adjusted returns of trading strategies (Sharpe Ratio, Max Drawdown).

The implication for the field of computational finance is significant. It suggests that the "bigger is better" approach to deep learning—simply adding more parameters and data—has diminishing returns in low-signal-to-noise environments like finance. Instead, incorporating domain knowledge through causal diagrams and structural constraints offers a more promising path toward reliable AI in fintech.

Despite the promising results, several limitations persist. First, the inference of the latent confounder Z relies on the assumption that the confounder is captured within the joint distribution of news and price history. If there are external confounders (e.g., insider information not present in public news), the adjustment may be incomplete. Second, the computational overhead of the VAE and the attention mechanisms increases inference latency, which may be a bottleneck for high-frequency trading applications where nanoseconds matter.

Future research should focus on extending the causal graph to include time-varying causal links, acknowledging that the causal structure itself may evolve (e.g., during a financial crisis vs. a boom). Additionally, integrating alternative data sources such as social media sentiment or satellite imagery within the same causal framework could provide a more holistic view of the market state. Finally, work on making the latent space Z interpretable—allowing traders to see exactly what "sentiment" the model has filtered out—would greatly enhance trust and adoption in the industry.

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