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Target-Oriented Causal Representation Learning for Robust Cross-Market Return Prediction

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Abstract:

This paper addresses key challenges in cross-market return prediction, including feature redundancy, limited information transfer, and distributional instability. A target-oriented causal representation learning method is proposed to tackle these issues. Centered on the target variable, the method incorporates causal structure modeling to guide the extraction of latent representations that are highly causally relevant to the prediction task from multi-source market data. This enhances both the effectiveness and robustness of the modeling process. Specifically, the model constructs a latent causal space and jointly optimizes three loss functions: minimizing prediction error, maximizing target causal mutual information, and aligning cross-domain representations. This framework balances task relevance, causal interpretability, and cross-market transferability. Extensive experiments are conducted on real-world financial datasets to evaluate the effectiveness of the proposed method. These include comparisons with different models, causal regularization ablation, robustness tests under noise perturbations, stability analysis across time windows, and transfer experiments across different market combinations. The results show that the proposed method consistently outperforms traditional deep models and existing transfer approaches across all performance metrics. It demonstrates clear advantages in handling distribution shifts, non-stationary data, and multi-market heterogeneity, validating the modeling potential and practical applicability of causal-oriented representation learning in cross-market financial prediction tasks.

Keywords:

Cross-market forecasting, causal representation learning, rate of return modeling, structural robustness.

1. Introduction

In the context of increasing integration of global financial markets, asset price volatility is no longer driven solely by domestic factors. It is also increasingly influenced by dynamics from other markets. The interconnection between different markets is strengthening. The speed and intensity of cross-market information flows have significantly increased. As a result, investors must consider the interactions and causal mechanisms across multiple markets when predicting returns and allocating assets [1-2]. However, existing research mainly focuses on modeling within a single market. It lacks a systematic characterization of the potential causal structures across markets. This limitation hinders predictive models from fully utilizing multi-source information for effective inference. Therefore, it is crucial to develop a representation learning method capable of identifying and modeling inter-market causal relationships to improve the accuracy and robustness of return prediction [3].

Traditional financial time series models, such as ARIMA, GARCH, and their variants, have shown success in capturing market-specific volatility. However, they struggle with high-dimensional, multi-market, and nonlinear dependencies in complex data structures. In recent years, deep learning has demonstrated strong fitting and nonlinear modeling capabilities in financial forecasting, especially in representation learning. Nevertheless, most of these methods optimize for correlation with the target, ignoring the structural causal relationships prevalent in financial markets. This often leads to correlation-driven predictions that are sensitive to perturbations and lack generalization. Causality-oriented modeling can explicitly define directional relationships between variables. It offers a more stable foundation when facing distribution shifts or external shocks [4].

In cross-market modeling scenarios, introducing causality not only helps explain the interaction mechanisms between variables but also enhances information filtering during modeling. It enables the identification of key factors that truly drive fluctuations in the target market. Recent advances in causal representation learning attempt to integrate causal inference with representation learning. These methods construct latent spaces with structural constraints, allowing models to automatically capture causal structures and adapt better to target tasks [5-6]. This is especially valuable in finance, where data is often noisy, heterogeneous, and non-stationary. Causal representation learning reduces reliance on irrelevant information and improves the interpretability and stability of predictions. Therefore, combining causal modeling mechanisms with cross-market return forecasting presents a critical breakthrough direction in intelligent financial analytics [7].

This study aims to develop a target-oriented causal representation learning framework. It explores latent causal structures among multiple markets and embeds them into the return prediction model as guiding signals. Unlike traditional unstructured feature extraction methods, this framework explicitly models structural relationships between target variables and latent causal factors [8]. By introducing target-guided causal regularization in the representation space, it drives the model to learn features highly relevant to the prediction objective. This enhances predictive performance under heterogeneous market conditions. The method also mitigates noise interference and improves adaptability to external shocks or sudden market changes. It holds significant practical value for real-world applications [9-10]. In summary, constructing a target-oriented causal representation learning framework provides a structured modeling approach for cross-market return prediction. It also opens new directions for interpretable modeling and causal inference in the financial domain. The study contributes to the integration of causal learning and deep representation methods from a theoretical perspective. Practically, it enhances the scientific rigor and foresight of asset allocation, risk management, and strategy formulation.

2. Background

In cross-market return prediction tasks, most existing methods adopt deep neural network-based sequence models, such as LSTM and Transformer. These methods focus on capturing long-term dependencies and nonlinear dynamics in time series [11-13]. They usually use indicators like price, trading volume, and volatility to construct input features. By leveraging complex architectures, they enhance model expressiveness. However, they often rely on large-scale data to learn implicit inter-market relationships and lack explicit modeling of structural causal drivers. Although some studies have tried to integrate information from multiple markets or asset classes, such as jointly modeling index futures and spot markets, the fusion process mainly relies on direct concatenation or attention mechanisms. These approaches overlook the causal dependency structure between variables, resulting in limited robustness to market condition changes [14].

In recent years, causal learning has gained traction in time series modeling and representation learning. It provides theoretical support for structural modeling in complex systems. Methods such as Granger causality detection, structural equation models (SEM), and causal graphs have been used to reveal directional relationships among variables. However, most of these approaches assume static conditions or rely on predefined model structures. They are not well-suited for high-dimensional and dynamically evolving financial data. To incorporate causal modeling into deep learning, researchers have proposed causal representation learning techniques. These aim to capture causal structures during the process of learning latent representations. Techniques include structural constraints, mutual information guidance, and adversarial training. While these methods have shown promise in areas like computer vision and healthcare, they are still in the exploratory stage in noisy and non-stationary financial settings. Moreover, they generally lack mechanisms for selecting causal features that are relevant to specific prediction targets [15-16].

To address target-oriented modeling, some studies introduce target-aware mechanisms to improve generalization on specific tasks. Examples include task-specific attention mechanisms and goal-driven feature selection strategies. These methods focus on enhancing the model's sensitivity to prediction targets during representation learning. However, most still do not incorporate causal reasoning. Therefore, integrating causal inference into target-oriented feature learning can constrain the model to learn structurally valid representations while optimizing target correlation. This represents a significant extension of current work. In cross-market scenarios in particular, guiding the model to capture causal transmission paths between markets can improve return prediction performance. It also enhances model stability and interpretability under distribution shifts.

3. Method

This study proposes a target causal-oriented representation learning framework to improve the accuracy and interpretability of cross-market yield forecasts. The model architecture is shown in Figure 1.

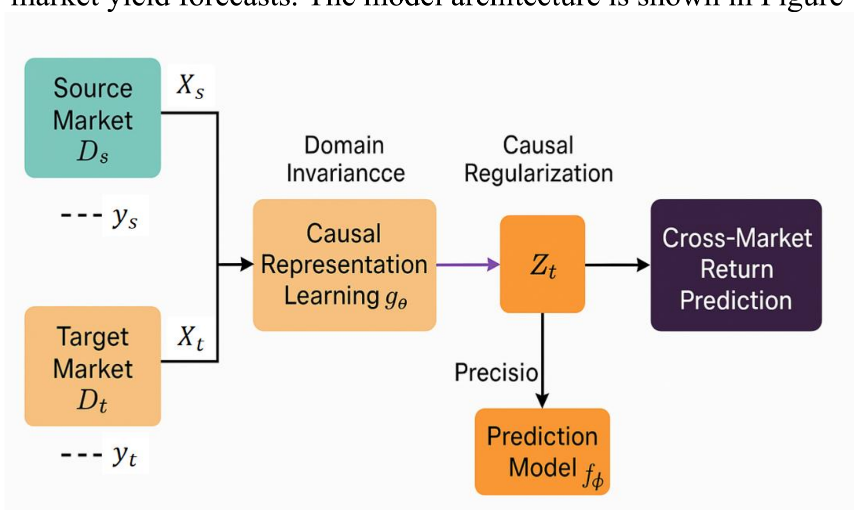

Figure 1. Overall model architecture diagram

The model architecture diagram shows that after extracting features from the source market and the target market, the causal representation learning module is used to extract latent variables that are highly causally related to yield prediction. The Causal Regularization and Domain Alignment modules introduced in the figure correspond to the modeling goals of causal validity and cross-market distribution consistency in the method. Finally, by integrating structural causal representation and prediction goals, the accuracy and generalization ability of cross-market yield prediction are improved.

Assume that the source market and the target market are D_s and D_t respectively. Each market contains observation variables $X_t \in R^{T \times d}$ in the form of time series, where T represents the number of time steps, d is the feature dimension, and the prediction target is the rate of return $y_t \in R$ in the future. Traditional modeling methods mostly aim to maximize correlation, while this study introduces a causal-oriented mechanism and focuses on modeling the subset variables X_t in y_t that have a causal effect on X_t^c. We assume that there is a potential causal factor space Z_t, so that the prediction target satisfies the following causal relationship:

$$y_t = f(Z_t) + \varepsilon_t, with \quad Z_t = g(X_t)$$

Where $f(\cdot)$ is the yield generation mechanism, $g(\cdot)$ is the characterization mapping function, and ε_t is an independent noise term, satisfying $E[\varepsilon_t \mid Z_t] = 0$.

In order to characterize the goal-oriented causal structure, we introduce mutual information constraints to measure the structural correlation between the latent representation and the target variable. Let the representation space be $Z_t = g_\theta(X_t)$, where θ is a learnable parameter, and the goal is to maximize the conditional mutual information $I(y_t; Z_t \mid X_t \setminus X_t^c)$, that is:

$$\max_\theta I(y_t; Z_t \mid X_t \setminus X_t^c)$$

This optimization term ensures that the learned latent representation can preferentially capture factors that have a causal impact on the prediction task and suppress the interference of non-causal variables. In addition, in order to enhance the generalization ability across markets, we further introduce a domain invariance regularization term so that the source market and the target market are distributed consistently in the latent causal space, which is defined as follows:

$$L_{domain} = MMD(P_s(Z_t), P_t(Z_t))$$

Where $MMD(\cdot)$ represents the maximum mean difference, which is used to measure the distance between two distributions.

The entire training process combines three objective functions to construct a joint loss function: prediction loss, causal regularization term, and domain alignment term. Let the prediction model be $y'_t = f_\phi(Z_t)$, then the final optimization goal is:

$$L_{total} = L_{pred} + \lambda_1 \cdot L_{causal} + \lambda_2 \cdot L_{domain}$$

The prediction loss term is defined as $L_{pred} = E[(y_t - y'_t)^2]$, the causal regularization term is implemented by the mutual information estimator, and the domain alignment term is implemented by the MMD estimator. Hyperparameters B and C control the balance between different objectives. By jointly optimizing the objective function during the training phase, the model can learn a more generalizable latent representation under the guidance of the causal structure and effectively improve the robustness of cross-market yield forecasts.

The core advantage of this method lies in the joint modeling of "structural interpretability" and "goal-oriented optimization”. Unlike traditional feature extraction methods, the proposed framework uses a structural modeling method to enable the model to actively learn the causal path between variables from the data, rather than relying solely on correlation features. This mechanism not only improves the robustness of the model to disturbances and noise but also enhances the interpretability of the results and the credibility of strategy formulation in actual financial systems.

4. Experiment

4.1 Datasets

This study uses the real-world financial time series dataset "MSCI World Index Constituents" as the experimental base. The dataset is published by MSCI and covers stock markets across multiple countries. It exhibits significant cross-market heterogeneity. We select constituent stock data from representative regional markets, including the United States, Europe, Japan, and Hong Kong. The time span ranges from 2010 to 2023. The data has a daily frequency and includes common financial indicators such as closing price, trading volume, price-to-earnings ratio, and price-to-book ratio.

To construct the return prediction task, we compute the logarithmic return of each asset based on the closing price. We generate lagged features and technical indicators as input variables. Considering the need for cross-market information modeling, we annotate data from different national markets with market labels. Each sample is associated with its market category, which is used in the domain alignment and causal representation modeling process. All features are standardized before being input into the model to eliminate scale differences across markets.

This dataset is highly realistic and market-representative. It provides an effective basis to evaluate the adaptability and generalization ability of the proposed method in multi-market return prediction. By modeling potential causal paths and distributional heterogeneity across regional markets, this study further explores the effectiveness of causal-oriented representation learning under real financial conditions. It offers practical data support and an experimental foundation for financial forecasting and quantitative strategy research.

4.2 Experimental Results

a. Performance comparison of different representation learning models in cross-market yield prediction tasks

First, this paper presents the experimental results of a performance comparison among different representation learning models in the context of the cross-market yield prediction task. The objective is to evaluate the effectiveness of various modeling approaches when dealing with heterogeneous financial data from multiple markets. The comparison includes traditional models as well as advanced deep learning-based methods, allowing for a comprehensive assessment of their predictive capabilities under cross-market conditions. The detailed results of this experiment, including multiple evaluation metrics, are provided in Table 1.

Table 1: Experimental results on the performance comparison of different representation learning models in the cross-market yield prediction task

Method	MSE	MAE	R^2
LSTM[17]	0.0192	0.1023	0.672
Transformer[18]	0.0176	0.0985	0.703

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Domain-Adversarial Network[19]	0.0169	0.0954	0.718
Causal Representation Learning[20]	0.0154	0.0910	0.742
Ours	0.0137	0.0856	0.781

b. Comparative analysis of model effects before and after the introduction of causal regularization terms

Next, this paper conducts a detailed comparative analysis of the model's performance before and after the introduction of the causal regularization term. The purpose is to evaluate the impact of incorporating causal constraints on prediction accuracy and model robustness. The corresponding experimental results, which highlight the differences in performance across key evaluation metrics, are presented in Figure 2.

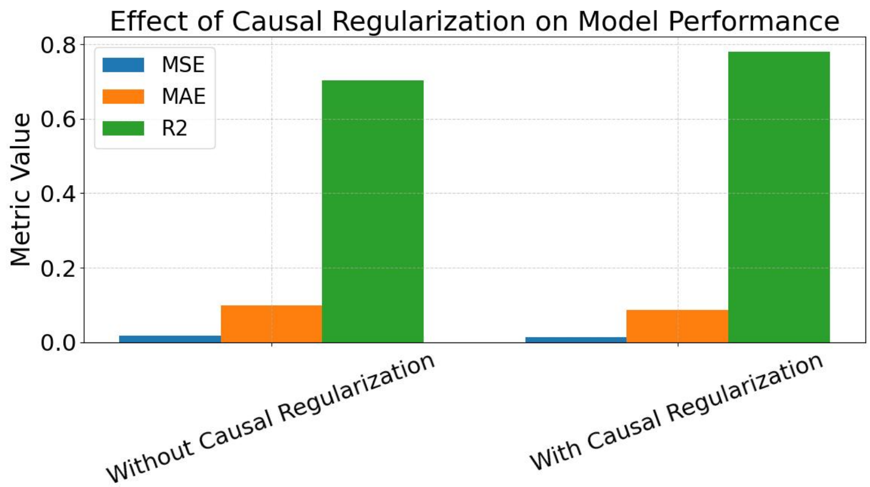

Figure 2. Comparative analysis of model effects before and after the introduction of causal regularization terms

As shown in Figure 2, the introduction of the causal regularization term results in clear and consistent improvements across all evaluated performance metrics. This enhancement demonstrates the effectiveness of integrating causal reasoning into the model's learning process. Notably, when examining the error-related metrics—Mean Squared Error (MSE) and Mean Absolute Error (MAE)—the model equipped with the causal mechanism achieves a significant reduction in prediction errors. This performance gain indicates that the model becomes more capable of filtering out irrelevant or noisy input features. By doing so, it is better able to identify and fit the underlying causal structures embedded within complex financial time series, which often exhibit non-linear and high-dimensional patterns.

Regarding the R^2 metric, which reflects the proportion of variance in the target variable that can be explained by the model, the results show a substantial increase. Specifically, the coefficient of determination improves from approximately 0.70 to nearly 0.78 after applying causal regularization. This rise suggests that the model's ability to capture the systematic variation in the target returns is significantly enhanced. It further indicates that the representations learned under causal constraints are more informative and better aligned with the true driving factors of market behavior. This improvement not only underscores the utility of causal regularization in shaping the latent representation space but also validates the hypothesis that causally relevant features contain stronger and more reliable signals for financial return prediction.

In summary, the above findings collectively validate the effectiveness of the proposed target-oriented causal representation learning approach in constructing a robust and generalizable feature space. By explicitly embedding causal structural information into the model during the learning phase, the approach facilitates a more focused and meaningful feature extraction process. As a result, it not only achieves higher prediction accuracy but also demonstrates greater adaptability across diverse market environments. These outcomes provide both a solid theoretical basis and valuable practical insights for future research and applications in financial time series modeling, particularly in scenarios involving data heterogeneity, temporal instability, and multi-market structures.

c. Experiment on model robustness under cross-market noise disturbance

Next, this paper also presents a robustness evaluation of the proposed model under conditions of cross-market noise disturbance. The objective of this experiment is to assess the model's ability to maintain stable predictive performance when exposed to increasing levels of noise, which commonly occur in real-world financial environments characterized by uncertainty and volatility. The experimental setup simulates varying degrees of noise interference across different market domains to test the sensitivity and resilience of the model. The corresponding results, which provide insights into the comparative stability of models with and without the causal regularization term, are illustrated in Figure 3.

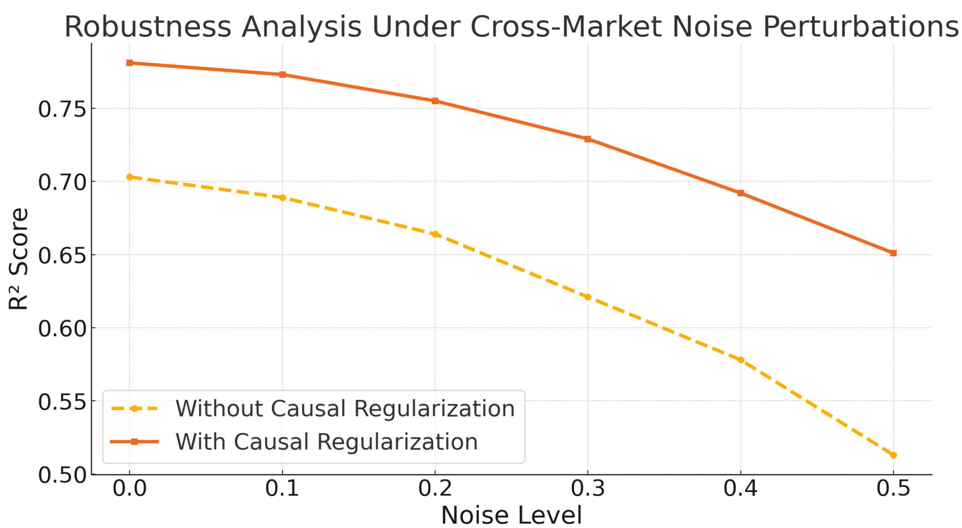

Figure 3. Experiment on model robustness under cross-market noise disturbance

As shown in Figure 3, the overall model performance shows a gradual decline as the noise level increases. This indicates that noise perturbations in a cross-market environment have a significant impact on return prediction tasks. In models without causal regularization, the R^2value drops more rapidly, revealing weaker resistance to interference.

In contrast, the model equipped with the causal regularization term exhibits a more stable and gradual downward trend across the entire spectrum of noise disturbances. At each noise level tested, it consistently outperforms the counterpart model that lacks the causal mechanism. This consistent superiority indicates that the inclusion of causal constraints not only improves predictive performance in relatively clean, low-noise environments but also significantly enhances the model's robustness when confronted with deteriorating data quality. Such robustness is crucial in financial settings, where noisy and volatile data is a common occurrence.

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This experimental finding further reinforces the importance of incorporating causal structure modeling into cross-market return prediction. By actively filtering out noise-driven and irrelevant features, while simultaneously strengthening the representation of causally valid information, the model becomes more resilient to irrational market perturbations and unpredictable distributional shifts. These are frequently encountered challenges in real-world financial applications. As a result, the proposed method demonstrates stronger practical adaptability, improved performance stability, and higher value for real-world deployment in dynamic and heterogeneous market environments.

d. Experiment on predictive stability across time windows

To further verify the generalization ability of the proposed target causal-oriented representation learning method along the temporal dimension, this paper designs a prediction stability experiment across multiple time windows. The objective is to assess how well the model adapts to evolving market conditions over an extended period. Specifically, the entire dataset is segmented into a series of continuous, non-overlapping time windows covering the period from 2010 to 2022. For each time window, the model is independently trained and evaluated, with the R^2 score recorded as the primary metric of performance. This experimental setup enables a detailed analysis of the model's adaptability to changes in market structure, as well as its ability to maintain predictive stability and accuracy over long-term temporal shifts. By observing the performance across different time stages, the experiment provides valuable insight into the model's robustness and effectiveness under real-world, time-varying financial scenarios.

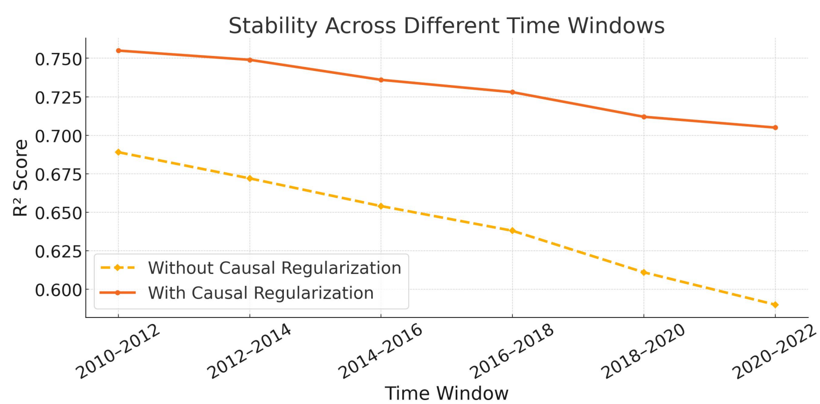

Figure 4. Experimental results on predictive stability across time windows

As shown in Figure 4, the model with the causal regularization term consistently outperforms the baseline model without it across all time windows. This indicates that the causal representation learning mechanism effectively improves the model's adaptability to temporal distribution shifts. The performance advantage is especially pronounced during periods of high market volatility, such as 2020–2022, demonstrating stronger temporal robustness.

In contrast, the model without the causal mechanism shows a continuous decline in R^2 over time. This suggests that its learned features rely more on short-term correlations and fail to adapt to long-term structural changes. This further confirms the limitation of correlation-based modeling in supporting stable prediction in financial tasks.

These experimental results clearly demonstrate that incorporating causal structures into the training process not only improves prediction accuracy but also significantly enhances the model's generalization across different time periods. This provides stronger practical applicability and long-term deployment value.

Journal of computer science and software applications
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Vol. 5, No. 5, 2025

e. Verification of the cross-domain generalization ability of the model under different market combinations

In order to verify the generalization ability of the proposed model when applied to different market environments, this paper designs a migration prediction experiment across multiple market combinations. The goal is to evaluate how well the model adapts when trained on one market and tested on another, reflecting its capacity to handle distributional shifts and structural differences between markets. Specifically, we select several representative and practically relevant market combinations, such as US→EU, EU→CN, and CN→US. In each experimental setting, the model is first trained using data from the designated source market and then evaluated on data from the corresponding target market. The R^2 score is adopted as the evaluation metric to quantify the model's prediction performance and its cross-domain adaptability. This setup provides a comprehensive assessment of the model's effectiveness in capturing transferable patterns under real-world cross-market scenarios.

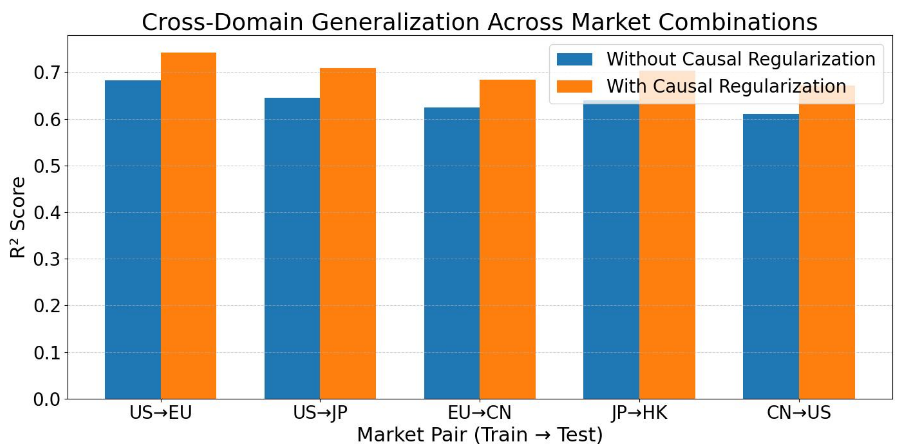

Figure 5. Cross-domain generalization across market combinations

As shown in Figure 5, the model with the causal regularization term outperforms the baseline model across all market combinations. The improvement is especially notable in combinations such as US→EU and EU→CN. This indicates that the proposed method effectively enhances the model's adaptability to transfers between structurally different markets. In contrast, traditional methods often suffer from performance instability due to distribution shifts during market transfer.

Specifically, the model also demonstrates robust generalization in regional combinations like JP→HK. This suggests that even when market feature distributions are not fully aligned, the causal structure extraction mechanism can still reliably capture the driving variables. This highlights the universality and robustness of causal-oriented representations in cross-market information modeling.

Overall, the experimental results show that the proposed target-oriented causal learning framework not only improves prediction accuracy within a single market but also achieves strong cross-domain generalization. It is well-suited for diverse financial market transfer tasks and supports the development of more practical cross-market intelligent analysis systems.

5. Conclusion

This paper proposes a target-oriented causal representation learning method for cross-market return prediction. The goal is to effectively model structural causal relationships between markets, thereby improving prediction accuracy and generalization in multi-source financial data environments. By integrating causal representation learning with the target prediction task, the model not only captures nonlinear dependencies but also actively identifies and emphasizes features with true causal impact on the prediction target. Under various experimental settings — including model comparison, causal regularization ablation, temporal stability testing, and cross-market generalization evaluation — the proposed method consistently outperforms baseline models. In particular, when facing distribution shifts, noise disturbances, or structural changes across markets, the model with causal structure demonstrates greater robustness and stability. This confirms the critical role of causal mechanisms in enhancing the generalization ability of financial models.

This study integrates the strengths of causal inference and deep representation learning. It also validates the method's applicability in complex financial scenarios from a practical perspective. This fusion strategy offers an effective approach to address the problem of structural instability driven by high-dimensional heterogeneous data in real-world financial systems. It also provides methodological insights for future research. Future work may further explore adaptive mechanisms for causal discovery. This would enable automatic learning and dynamic adjustment of causal structures without requiring strong prior knowledge. Additionally, the method can be extended to more complex tasks such as multi-task prediction and multi-asset allocation, further enhancing its value in intelligent financial decision-making and real-world deployment.

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