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Prediction and Dynamic Correlation of China's Stock Market on Bond Market: Based on the ARIMA Model and the VAR Model

Siyong Lu

School of Statistics and Data Science, Shanghai University of Finance and Economics, Shanghai, China
2023111135@stu.sufe.edu.cn

Abstract. The objective of this study is to examine the predictive relationship between the China stock market and the bond market. With the worsening economic environment entering 2024-2025, the stock-bond linkage mechanism has played an increasingly important role in financial forecasts. But through the current forecasts, it has been noticed that the forecasts often ignore the systematic connection of market information between the markets. The construction of the model was focused on a VAR model with the return of the stock market as an exogenous variable, which was contrasted with the traditional ARIMA model, and the nature of the connection between the two markets was evaluated through Granger causality test, variance decompositions, and impulse responses. The outcome of the test showed the superiority of the VAR model in terms of the key predictive accuracy of the forecast, especially regarding the declining trend of the bond market yields. Overall, the findings suggest that the stock market exhibits significant leading and explanatory power over the bond market, indicating that integrating cross-market information can enhance forecasting accuracy and provide more effective quantitative support for asset allocation and risk early warning by leveraging leading indicators from the stock market.

Keywords: Bond Yield Forecasting, ARIMA Model, VAR Model, Stock-Bond Connectedness, Forecasting Comparison

1. Introduction

1.1. Research background and motivation

In China's financial markets, the stock market and the bond market are the two important pillars. Their dynamic correlations and risk transmission patterns remain the central concern in the eyes of researchers and policymakers. In recent years, affected simultaneously by changes in the shift of the economic cycle and external shocks, the "seesaw" effect and the "synergy" effect between the stock market and the bond market have turned to each other in the complex relationship between them.

In 2024-2025, China's economy is undergoing structural adjustment and transformation. Recent macroeconomic shocks have altered the supply and demand for goods and services, affecting stock

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returns, and it has been demonstrated that the long-run impact of macroeconomic disturbances on stock returns is significant [1]. At the same time, bond return predictability is associated with periods of high/low economic activity, which implies that violations of the expectations hypothesis are state-dependent and linked to features of the business cycle [2]. To be specific, factors such as slowing economic growth, intensified monetary easing, and reduced bank funding costs have been driving bond returns downward since 2024 [3]. It has also been found that the overnight return negatively predicts the first half-hour return of individual stocks, indicating the predictive value of stock market data in economic forecasting [4]. Within this macroeconomic landscape, the stock market has become more sensitive to the prospects of economic recovery, while liquidity conditions and interest rate expectations have a more direct influence on the bond market. The interaction logic and correlation strength between the two markets may undergo new evolution.

Traditional research tends to focus on either unidirectional influences or static correlation analysis, lacking the consideration of dynamic interconnection structures and leading-lag relationships between the two markets over time. This very deficit encourages this study to make use of both the ARIMA and VAR models in capturing both univariate forecasting and multivariate dynamic interactions. Therefore, from a theoretical and practical perspective, deeply exploring predictive power and dynamic correlations between the impact of stock markets and bond markets is of great importance for understanding the operational mechanisms of China’s financial markets and optimizing investment decisions. Based on the research of the ARIMA model, this paper introduces the method of the VAR model to explore the impact and dynamic correlation between the stock market and the bond market. In this respect, the paper tries to describe the characteristic of the forward-looking influence of stock market volatility on the bond market more accurately, so as to provide a more reliable forecast of the bond market based on the volatility of the stock market.

1.2. Literature review

Stock and bond market studies have generated a vast amount of literature with results concentrated in the following three aspects:

(1) Concerning determinants of correlation, literature suggests that macroeconomic conditions, market risk preference, and policy shocks emerge as prominent forces behind stock and bond correlations. Sarwar has identified that stock and bond market uncertainty in the US stock market, stock market tail risk, as well as global credit default risks play a major role in determining stock and bond correlations in times of global financial crises [5]. At the same time, stock and bond correlations decrease, as these market risks play a significantly less prominent role in times of post-GFC, whereas stock and bond correlations increase with rising US and global bond market risks, as illustrated in study [5]. Turning to stock and bond market risk in China, Tang Hanming and Wang Zhenhan state that volatility co-movements show a remarkably high correlation, particularly in terms of tail correlations in stock and bond markets [6].

(2) In the aspect of predictive modelling, existing literature employs various time series models to forecast bond markets. In Baghestani’s study, he conducted an ARIMA model to analyze the multiperiod forecasts of the corporate bond yield spread because ARIMA forecasts are considered 'weakly rational’ [7]. In a study by Kiss et al., a VAR model was employed to investigate the relationship between the bond-yield spread and GDP growth, as well as the unemployment rate [8]. In Favero and NuceraWe’s study, they performed a cross-country comparison of stock market risk, modelling stock market returns in a VAR(1) system jointly with bond returns and a set of predictive variables [9,10]. However, most of them focused on bond markets themselves or macroeconomic variables, with limited incorporation of stock market information as core predictors.

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(3) In dynamic relationship studies, Naresh, Robert, and Chris have investigated equity risk and bond risk jointly, as measured by the implied volatility from equity-index options and 10-year T-note futures options, and they suggested a flight-to-quality influence between equity-risk dynamics and longer-term Treasury pricing [11]. Recent analyses of abnormal market volatility, such as Sarwar's, have found that stock–bond correlations rise in times of rising US and global bond market risks, suggesting that such cross-market influences may significantly intensify during specific periods [5].

Collectively, these studies suggest that stock-bond relationships are influenced by multiple factors, including macroeconomic conditions, market risks, and policy shocks, and require dynamic modelling approaches to capture their complex interactions.

1.3. Research gap and objectives

Based on the review of the existing studies, this paper identifies two critical research gaps that require attention:

(1) Insufficient integration in methodology: Most of the studies focus either on VAR models in studying the dynamic correlations between equities and bonds, or on ARIMA models in single-market forecasting.

(2) The perspective of predictive factors remains limited: Although most of the current research into bond market forecasts have focused on historical interest rates and macroeconomic indicators, the systematic modelling of stock market trends, whether across the board or in specific sectors, as a forward-looking and comprehensive predictive variable remains lacking.

Therefore, developing a model which can exploit leading information within the stock market and simultaneously account for the dynamic changes in the correlation among stocks is a significant gap in research and is indeed a direction that this paper would head in.

1.4. Research framework and contributions

Based on the arguments above, the research framework formulated is predictive, consisting of four stages: data processing, model development, prediction assessment, and mechanism explanation. At the data stage, the time-series data of stock and bond yields are combined, followed by separation into the train and test data. The model stage, running in parallel, is about to use stock factors to build the univariate time-series ARIMA model and the multivariate autoregressive VAR model.For prediction evaluation, key metrics such as RMSE and MAE are calculated, with performance differences compared through the Diebold-Mariano test. The mechanism interpretation stage employs Granger causality tests and variance decomposition within the VAR model to quantify the stock market's predictive contribution to bond yields. The framework, thus, will create a bond yield predictive model end result, emphasizing the relationship between predictive accuracy and mechanisms.

The paper adds to the development of the field through three aspects: (i) comparative analysis combined, of ARIMA and VAR model structures, (ii) the systematic development of predictive factors using stock market information, and (iii) through the provision of valuable information pertinent to finance market investment.

DOI: 10.54254/2754-1169/2026.LD31504

2. Method

2.1. Model specifications

This study will employ two mainstream time series analytical frameworks: the Autoregressive Integrated Moving Average (ARIMA) model and the Vector Autoregressive (VAR) model.

2.1.1. ARIMA model

The ARIMA model is a classic univariate linear approach designed for modelling and forecasting individual time series. It can effectively capture the autocorrelation within a single variable by combining three components: AR (order p), I (order d), and MA (order q).

$$\left(1-\sum_{i=1}^{p}\varphi_i B^i\right)\left(1-B\right)^d Y_t = c+\left(1+\sum_{j=1}^{q}\theta_j B^j\right)\varepsilon_t \tag{1}$$

Where B is the lag operator: $BY_t = Y_{t-1}$; φ_i and θ_j are the AR and MA parameters; c is a constant term; ε_t is a white noise error term satisfying: $\varepsilon_t \sim WN\left(0,\sigma^2\right)$.

2.1.2. VAR model

The VAR model can provide a multivariate framework for analyzing the joint mechanism among multiple time series. The VAR framework is particularly powerful for capturing contemporaneous interactions and lead-lag relationships.

For a system containing n variables with a lag order of k , the VAR(k) model can be expressed as:

$$Y_t = C+\Phi_1 Y_{t-1}+\Phi_2 Y_{t-2}+\ldots+\Phi_k Y_{t-k}+u_t \tag{2}$$

Where Y_t is ann×1vector of endogenous variables; $\Phi_i(i=1,\ldots,k)$ are $n\times n$ coefficient matrices capturing the dynamic interactions across variables and lags; and u_t is an $n\times 1$ vector of uncorrelated white noise innovations, with $E(u_t)=0; E(u_t u_t’)=\sum_u$, where $\sum_u$ is a positive definite covariance matrix.

2.2. Model implementation procedures

2.2.1. ARIMA model implementation

First, this study tested for stationarity in the time series. Following this, the auto.arima function identified the best model automatically by seeking the one that minimized the AIC criterion. The ARIMA model assumed that the time series, after differencing, was stationary and that error terms were uncorrelated white noise. After constructing the model, estimates of parameters were derived from the training set. In this way, the model learned the data-generating process prior to prediction. Then, the fitted model conducted forward forecasting on the test set, generating point estimates as well as 80% and 95% confidence intervals. This yielded benchmark univariate predictions based on past data for bonds. These provide measures of the uncertainty of the predictions and model reliability.

DOI: 10.54254/2754-1169/2026.LD31504

2.2.2. VAR model implementation

For this study to be undertaken, an ecosystem was developed which contained two bivariate variables: stock returns and bond returns. This ensured that these two variables are stationary. Following this, the varselect function was used in identifying the optimal number of lags. Moving forward, there was estimation of parameters, covering diagnostics which include checks on autocorrelation, normality, as well as checks for roots of the characterizing polynomial. After that, there was forecasting for results. There was also variance decomposition and Granger causality test.

2.3. Data collection and processing

This study selected daily data from the Wind Financial database from January 4, 2021, to December 31, 2024 (a period of 4 years). For stock market variables, the CSI 300 index was chosen as an indicator that comprehensively covers the 300 most representative stocks in the Shanghai and Shenzhen stock markets. For bond market variables, the 10-year China government bond yield was selected, serving as a core benchmark for measuring trends in the Chinese bond market. To satisfy the requirements of these 2 models, the data must undergo necessary transformations.

For the CSI 300 index, use a log transformation to stabilize variance and approximate normality:

$$R_t^{stock} = ln(P_t) - ln(P_{t-1}) \tag{3}$$

For the 10-year China government bond yield, the data were divided into a training set and a test set in a 3:1 ratio for evaluating out-of-sample prediction performance.

2.4. Descriptive statistics and preliminary analysis

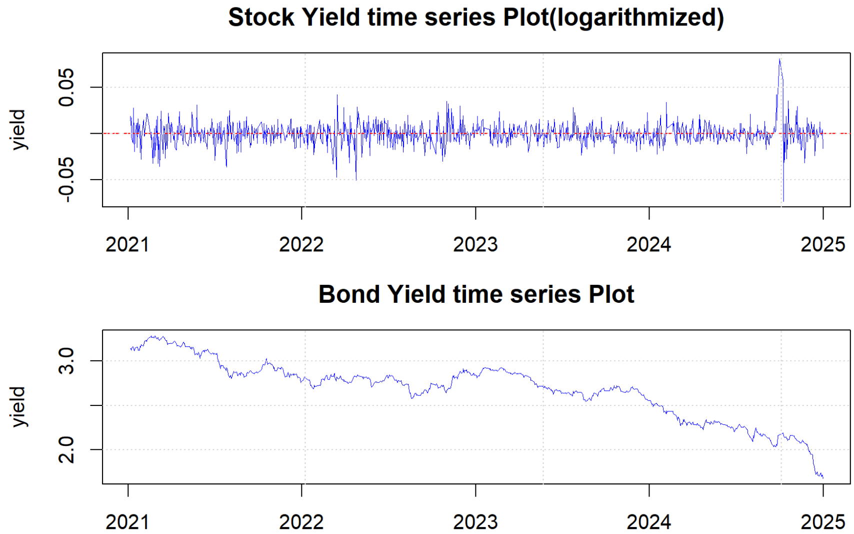

Figure 1. Time series plots for stock yield and bond yield (photo credit: origin)

The Stock Yield time series fluctuated around zero without showing distinct trends, while the Bond Yield showed a clearly non-stationary and downward trend (Figure 1 and Figure 2).

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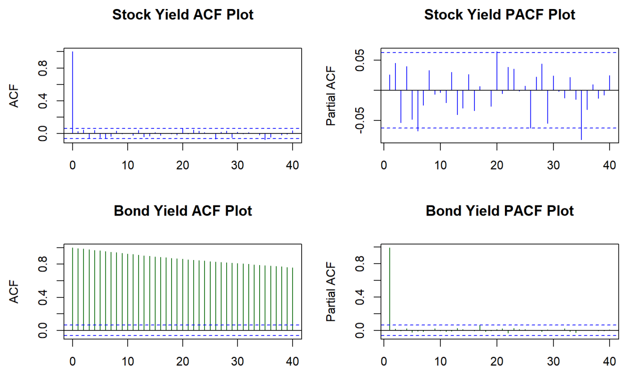

Figure 2. ACF/PACF plots for stock yield and bond yield (photo credit: origin)

For the Stock Yield, the ACF plot showed first-order truncation, while the PACF plot showed multi-period effects. For the Bond Yield, the ACF plot demonstrated a slight downward trend that significantly exceeded the CI, while the PACF plot exhibited a first-order truncation (Table 1).

Table 1. Stability tests for stock yield and bond yield

Method		Stock Yield	Bond Yield
ADF test	Statistical quantity	-10.3746	-0.3799
	p-value	0.01	0.9873
	conclusion	Reject H0,stationary	Accept H0,non-stationary
KPSS test	Statistical quantity	0.1249	9.7077
	p-value	0.1	0.01
	conclusion	Accept H0,stationary	Reject H0,non-stationary

Both the ADF and KPSS tests confirm that the Stock Yield series is stationary, while the Bond Yield series is non-stationary.

3. Empirical results and mechanism analysis

3.1. Model performance and predictive results

3.1.1. ARIMA model performance

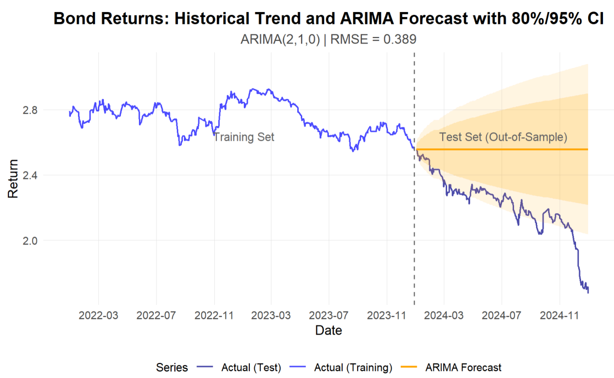

Figure 3. Arima model prediction of bond returns with 80%/95% CI (photo credit: origin)

DOI: 10.54254/2754-1169/2026.LD31504

The ARIMA(2,1,0) model produced flat predictions, failing to capture the downward trend in bond yields (Figure 3).

3.1.2. VAR model performance

Table 2. Granger causality test for the influence of stock yield on bond yield

Null Hypothesis(H0)	Free Degree	Test Statistics	p-value	conclusion
The Stock Yield is NOT The Granger reason for the Bond Yield	3	3.5831	0.01338 (<0.05)	Reject H0
NO instantaneous causality between the Stock Yield and the Bond Yield	1	4.1384	0.04192 (<0.05)	Reject H0

According to Table 2, the Granger causality test showed that the stock yield has had a significant Granger causality to the bond yield, while the Chi-Square goodness of fit test reflected the instantaneous correlation between the stock yield and the bond yield. These data jointly suggested that the stock yield has a marked influence on the bond yield. This finding could support the hypothesis that stock market information contains valuable leading signals for bond market forecasting.

Table 3. Comparison of key indicators of the ARIMA model and the VAR model

	ARIMA model	VAR model	The Best Model
RMSE	0.3887	0.2838	VAR
MAE	0.3449	0.252	VAR
Theil's U (value<1: obtain better performance than naive prediction)	0.1751	0.1278	VAR
DM statistics	36.5612	19.4882	VAR
Direction Accuracy	39.42%	62.66%	VAR

On comparisons of these key indicators among the models, it was seen that the results obtained in the case of the VAR model were better compared to the ARIMA model in all respects, thus implying that the accuracy of the VAR model is better. This implies that stock yield could be a factor that can influence the forecasting of the bond (Table 3).

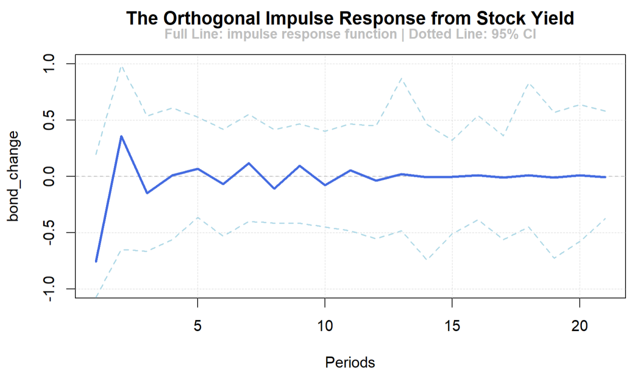

Figure 4. The orthogonal impulse response from stock yield with 95% CI (photo credit: origin)

DOI: 10.54254/2754-1169/2026.LD31504

According to Figure 4, the fluctuation in bond yields demonstrates that the stock market has a substantial real-time influence on the bond market, while the bond market can promptly adjust in the opposite direction and essentially converge to 0 after the tenth order.

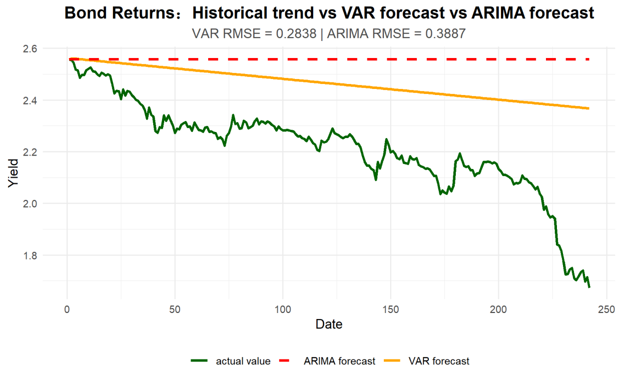

Figure 5. VAR model prediction of bond returns (photo credit: origin)

The results showed that the variance model had a marked advantage over others in the predictions for the bond yields (Figure 5). The model's predictions followed the observed decline in the test data set, while the Arima model maintained a flat line without consideration for the market dynamics.

3.2. Mechanism analysis and economic interpretation

3.2.1. Limitations of the ARIMA model

The horizontal pattern noticed in the ARIMA(2,1,0) forecasts for the bond yields was the result of its univariate nature. This result matches the theoretical knowledge that ARIMA models with one variable rarely consider extraordinary shocks or changes in the structure. While it included the second-order autoregressive term, it did not include the drift term in its estimation process. On mathematical grounds, after the first difference, the ARIMA process becomes stationary, implying that the conditional expectation processes tend to move towards the unconditional mean over time. As such, this inherent structure of the time series made it more difficult for the ARIMA process to recognize the adept long-term trends in the data patterns. In financial markets, time series can be impacted by the global macro-economic cycles or changes in policies, making it more difficult for the ARIMA process, which does not consider such aspects, to correctly forecast the data patterns.

3.2.2. Advantages of the VAR model

With stock returns as an endogenous variable included in the equation system, a VAR framework was thus set up that provides several theoretical advantages:.

(1) The result of Granger causality tests shows that while the stock market partly leads the bond market, its statistically significant impact exists in the returns of the latter.

(2) According to the results of the decomposition of variance analysis, stock returns account for the variation of around 2% in bond yields. In highly stochastic financial systems, this level of variation has been found remarkable in order to appreciate the importance of cross-market transmission mechanisms.

(3) Impulse Response Functions of VAR modeled the speed and delay of interactions among stocks and bonds. Utilizing the function revealed that the effect of the shock in the equity market

would cause the corresponding change of 0.5% to 1% in the bonds' yields.

Accordingly, compared to ARIMA, being more in tune with economic markets and interconnections as expressed in the multivariate equation design in the VAR(p) model results in better forecasting results.

3.2.3. Stock-bond transmission mechanism in the 2024-2025 economic context

Compared to the global macroeconomic scenario expected in 2024-2025, distinct conditions characterize a tighter monetary policy that helps bring down bond yields in a more sustained and pronounced manner than is experienced under normal conditions, which reduces the effectiveness of the ARIMA approach. On the other hand, the stock market acts as a leading economic indicator because it might have already factored in the risks of recession and policy changes through equity-debt linkages.

The VAR model directly captures the macroeconomic trends by identifying leading signals from equity markets and provides the crucial bond market forecast. The strength of the linkages between equities and bonds is quantified by the estimated coefficient matrix of the model and hence dynamically models this correlational structure. Once worsening economic expectations begin to drive equities down, the VAR model accommodates that with downward revisions in bond yield forecasts via transmission parameters from the estimated relationships. This is the mechanism whereby flight-to-quality dynamics seem to arise in actual data when capital, in a risk-off mode, flows away from stocks into bonds. Such flight-to-quality dynamics tend to heighten in times of high economic uncertainty.

4. Discussion

4.1. Main findings and theoretical implications

4.1.1. Interpretation and theoretical implications of key findings

The comparison between ARIMA and VAR models, however, showed that incorporating the information from the stock market significantly enhances the predictive ability of the bond yield. Results suggest that the univariate ARIMA (2,1,0) model, mainly because of its structural limitations, could not capture relevant information from other markets or macroeconomic determinants and failed to follow the downtrend. By contrast, the model from the system of VAR turned out distinctly superior in terms of RMSE, MAE, and directional accuracy, as it was able to follow the trend, thanks to its nature as a dynamically multivariate model. This thus indicates that, practically, a consideration of equity market data can be helpful in the prediction of bond market developments. These results suggest, from a forecasting performance perspective, how fundamentally important integrating information across different markets within financial modeling frameworks is.

At the theoretical mechanism level, this study provided robust empirical support for the lead-lag relationship between the stock market and bond market, as well as corroborating the “stock-bond seesaw” effect. The Granger causality test demonstrated that stock yields significantly influence bond yields, and this effect is synchronous, indicating that stock price movements contain useful information for predicting bond trends, thereby supporting the theoretical hypothesis that stock markets serve as “barometers”. Variance decomposition results showed that stock markets can explain approximately 2% of bond market volatility variance, a proportion of significant economic

DOI: 10.54254/2754-1169/2026.LD31504

importance in high-frequency and complex financial data. While this percentage may seem modest, it is economically meaningful, given that the majority of bond yield variation is driven by its own lags and idiosyncratic shocks. This degree of exogenous explanatory power is supporting evidence for comparable other high-frequency financial models for research endeavors. The Impulse Response Functions actually clarified the flow: the stock market stirs up extreme counter-cyclical adjustments to the bond yields within the short run and dissipates with time. This is in line with the theoretical stipulations by the researchers Tang Hanming and Wang Zhenhan that extreme conditions within one market can precede extreme events within the other [6].

Moreover, it reveals the process of "risk-averse capital flows" between the equity and bond markets with the presence of market risks and uncertainties in line with the research work of Sarwar on the influence of the correlation between stocks and bonds [5]. These implications not only emphasize the importance of risk sentiment of investors as the transmission channel in the phase of economic transition such as the period of 2024-2025 considered in this study, but the equity market's reaction in relation to its own growth becomes the paramount leading indicator of the changes in the bond market based on the flight-to-quality capital flows.

4.1.2. Analytical framework innovations

This study has made significant contributions to existing literature. Firstly, it expands upon Sarwar's research on inter-market risk transmission by demonstrating how stock markets influence bond markets through expectation channels under specific macroeconomic conditions (2024-2025) [5]. Second, by systematically incorporating stock returns as core predictors within a VAR framework, this study extends the work of Baghestani et al., moving beyond single-market modelling to provide a cross-market empirical perspective on bond yield prediction [7]. Furthermore, the findings support Naresh, Robert, and Chris's "flight to quality" phenomenon, where investors withdraw from equities and shift to bonds during risk escalation. By bridging the methodological comparison gap and expanding the set of predictive factors to include equity market signals, this research offers a more integrated view of cross-market dynamics. In summary, this study not only validated the superiority of VAR models in bond forecasting but also deepened the understanding of stock-bond linkage mechanisms and cross-market risk transmission theories from a dynamic perspective.

4.2. Methodological contributions

4.2.1. Model comparison

This paper systematically compared the advantages of the ARIMA model and the VAR model, and it has important methodological references for its follow-up research. The empirical result shows that, compared with the ARIMA model, the VAR model has stronger adaptation and explanatory power and can significantly improve the precision of predicting outcome. With the use of the co-movement mechanism of multiple variables, the VAR model can well extract the short-term and long-term relationship of dynamic reaction and equilibrium relationship of variables, and thus accurately describe the complicated relationship in the financial market.

4.2.2. Technological innovation

First, by using stock returns as the core predictor, it overcame the limitation of traditional bond prediction that relies on its own sequence, thereby enhancing the model's information content. Second, it establishes a comprehensive analytical framework that integrates Granger causality tests,

DOI: 10.54254/2754-1169/2026.LD31504

variance decomposition, and impulse response functions, enabling a thorough investigation that moves beyond mere correlation to establish temporal precedence (Granger causality), quantify the relative importance of shock transmission (variance decomposition), and trace out the time profile of cross-market effects (impulse response).

4.2.3. Scalability and feasibility

This framework is highly scalable, extending to other financial markets such as foreign exchange and commodities. Its open model structure can facilitate expansion into multivariate systems, incorporating macroeconomic variables such as inflation and interest rates, thereby providing a flexible methodological foundation for subsequent research.

4.3. Practical applications

The empirical results of this research, the leading position of the stock market, the measurable dynamic connection between the markets, can be applied in the following ways for different participants in financial markets:

The study was of great practical relevance to financial market participants, as it provided scientific backing for informed decision-making. Concerning investment strategies, the scientific findings of the study can be of great use to institutional investors as quantitative benchmarks regarding stock and bond asset allocation. By employing forecasts of bond yield trends with the aid of VAR models and adjusting their portfolio structures accordingly to the movements of the stock market, institutional investors can maximize the risk-return ratio of the portfolio. Moreover, the leading-lag structures among markets of the model can be of great use in finding pricing disparities, which can serve as actionable investment recommendations regarding the exploitation of arbitrage opportunities among markets in the bond as well as the stock market.

In the risk management field, the technical approach provided by this research can be used to design a dynamic risk warning system. On the basis of the framework provided in the VAR model, it can be done to set up a real-time monitoring system to monitor abnormal fluctuation of stock-bond correlation and send early warnings for risky situations. In the meantime, the variance decomposition and impulse response analysis obtained from the VAR model can provide institutions with quantitative information on the specific asset contributing to the overall portfolio risk.

At the policy-making level, this study can provide regulators with effective indicators to monitor the transmission of cross-market risk. By tracking the strength and direction of stock-bond linkages, regulators can more sensitively perceive the accumulation of systemic risks and assess market stability. This data support enhances the foresight and precision of financial regulation, facilitating the formulation and evaluation of macroprudential policies.

5. Conclusion

This study empirically examined the joint effect of stock market information on bond yield forecasting through systematic comparisons of ARIMA and VAR models. Results indicated that the univariate ARIMA(2,1,0) model, which lacked exogenous variable drivers, exhibited a “horizontal line” characteristic in predictions, failing to capture downward trends in bond yields and thus proving ineffective. In contrast, the VAR model demonstrates significantly better performance than ARIMA in metrics such as RMSE, MAE, and directional accuracy by incorporating stock returns as the core variable, effectively tracking market dynamics and exhibiting stronger predictive power.

DOI: 10.54254/2754-1169/2026.LD31504

The Granger causality test confirmed a significant causal relationship between stock returns and bond yields, with contemporaneity, which validated the stock market's inherent leading role in providing information for bond trends. Variance decomposition revealed that the stock market accounts for approximately 2% of bond market volatility, holding substantial economic significance in high-frequency and high-noise financial markets. The impulse response function further demonstrated that stock market shocks trigger short-term adjustments in bond yields of approximately 0.5% to 1%, with effects decaying over time, corroborating the existence of a "risk aversion transfer" mechanism. This dynamic relationship became particularly pronounced against the backdrop of monetary policy tightening and weakening economic expectations in 2024-2025, supporting the theoretical logic of the "stock-bond seesaw" effect and risk appetite transmission mechanism.

These empirical findings—specifically, the leading indicator property of the stock market and the quantifiable dynamic linkage—carry important implications for financial practice. This study offers significant practical value for financial market participants. In investment management, it provided institutional investors with quantitative tools for stock and bond allocation, enhancing asset allocation efficiency and risk-adjusted returns. Regarding risk management, the developed VAR framework could evolve into a dynamic risk early-warning system, assisting financial institutions in identifying cross-market risk transmission. For regulators, the interconnected indicators generated by the model served as references for monitoring systemic risks, which can support the formulation and evaluation of macro prudential policies. On a broader level, this research underscores a critical paradigm shift. Amid intensifying global financial market linkages, there is an urgent need to transcend single-market prediction models. The results of this study advocate for the adoption of cross-market, integrated analytical frameworks, such as the VAR model employed here, to enhance the practical applicability and robustness of financial forecasting.

This study primarily relies on publicly available secondary market data. Hence, it does not involve factors that might have had an effect on the outcome, like market sentiment and text data that is unstructured and is drawn from the announcement of policies, mostly related to stocks. There is room for enhancing this model in two major ways: the addition of other asset classes to analyze the interaction among markets for various investments like currency and commodities; the addition of other data types that are unstructured, for example, news data that is related to the overall economic surprises that might affect stocks.

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