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Impact of China's Sectoral Stock Returns on Global Supply Chains: A Deep Learning Correlation Analysis

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Abstract

Global supply chains are sensitive to China's economic sectors, yet direct, model-based evidence that Chinese sectoral stock returns forecast global supply-chain distress is limited. We turn the typical analysis on its head by predicting Global Supply Chain Pressure Index (GSCPI) from market data rather than GSCPI as an explanatory variable. We use 233 months of China's 10 sectoral stock returns to predict GSCPI a month ahead using a cast of deep learning as well as traditional machine learning models: a Feedforward Neural Network (FFNN), a Gated Recurrent Unit (GRU), Ridge regression, ARX (1), Random Forest, and XGBoost, along with an ensemble combining Ridge and FFNN. Models are compared on out-of-sample (OOS) R^2. The combined ensemble achieves maximum accuracy (out-of-sample $R^2 \approx 0.85$) and comprehensively dominates individual models; the FFNN as a solo model is the runner-up. Meanwhile, the ARX (1), GRU, and XGBoost models have negative R^2 and thus demonstrate limited generalization on this dataset. These findings imply that blending linear and nonlinear learners best extracts cross industry signals that predict subsequent GSCPI movements. Though results are particular to China's setting, this new approach provides an actionable early-warning device against worldwide supply chain disruption by casting real-time financial signals into forecast of stress.

Keyword
Deep Learning, Supply Chain, Stock Market, Time-series forecasting, Ensemble Learning.

1. Introduction

Global supply chains are the critical arteries of international trade, yet recent shocks have exposed their fragility (García-Herrero, 2023; Kancs, 2022; Katsaliaki et al., 2021). To monitor these strains, the Federal Reserve Bank of New York introduced the Global Supply Chain Pressure Index (GSCPI) as a composite, real-time indicator of worldwide supply chain stress.

The intuition is that Chinese firms are deeply embedded in worldwide production networks; if these firms face supply bottlenecks or anticipate logistical hurdles, their stock prices might react immediately, reflecting those concerns pressure, potentially foreshadowing changes in an index like the GSCPI. It stands to reason that China's market data may carry an informational advantage in detecting supply chain stress, given the country's centrality in manufacturing everything from electronics to textiles.

In this study, we empirically test whether China's sectoral stock market performance can indeed predict movements in global supply chain pressure as measured by the GSCPI. The underlying idea is to leverage high-frequency, real-time financial data to anticipate a macroeconomic stress indicator that is typically compiled monthly. Success in this endeavor would mean that investors' collective actions in Chinese sectors provide an early warning signal of global supply chain bottlenecks.

Our investigation offers a novel perspective in the literature on supply chain risk indicators. Whereas most prior studies have used global supply chain pressures or indices, such as the GSCPI, as an explanatory variable to assess their impact on inflation, economic activity, or asset prices, we reverse the direction of analysis by using market-based signals to predict the GSCPI itself. This is one of the first attempts to treat the GSCPI as a predictand in a machine learning context.

The heterogeneity is acknowledged in our modeling by allowing each sector's data to contribute separately to the predictive model, rather than aggregating all industries together. In line with prior studies, we expect that sectors with greater global integration exhibit stronger correlations with the GSCPI, effectively serving as barometers of global supply strain. The sector-specific view not only improves prediction performance but also offers insight into which types of industries are the most sensitive indicators of supply chain health. Hence, our work bridges a gap between macro-level supply chain metrics and micro-level financial signals, highlighting the value of cross-disciplinary and multi-disciplinary approaches that fuse economics, finance, and machine learning for better monitoring of global economic fragility.

In short, this paper makes several contributions including the introduction of a novel application of deep learning and ensemble methods to predict a macroeconomic supply chain index using high-frequency financial data from China. Furthermore, evidence supporting the hypothesis that China's sectoral stock returns contain useful information for anticipating global supply chain pressures in also included. Combining these contributions can provide the understanding of how financial market signals can serve as early warnings for real economic disruptions, and they introduce new opportunities for research at the intersection of supply chain management and financial analytics.

1.1 Objectives

- To develop custom datasets for the prediction of GSCPI from China's sectoral data.
- To study the different deep learning-based algorithms.
- To develop deep learning models.
- To conduct performance analytics of deep learning-based models.
- To conduct correlation analysis.

2. Literature Review

The instability of global supply chains has become evident because of various events, such as pandemics, natural disasters, and financial crises. These disruptions heavily impact financial markets, creating the need for advanced analytical frameworks to understand and predict their complex effects (Riaz et al., 2025). This literature review synthesizes existing research on the impact of global supply chain pressure on stock markets, with a significant focus on sectoral views. It confirms the significant negative influence of supply chain disruptions on financial markets. The Global Supply Chain Pressure Index, which quantifies manufacturing disruptions and transportation costs, is widely recognized as a key indicator (Riaz et al., 2025).

2.1 Predictive Analytics Approaches: Machine Learning and Deep Learning

In financial markets, machine learning and deep learning are applied for stock market pattern prediction, which is a common method. Hybrid frameworks, combining the strengths of ML techniques like LSTM networks and Gradient Boosting Machines with econometric models, have shown better predictive accuracy for stock prices (Chauhan, 2024; Zhong & Hitchcock, 2021). In supply chain management, ML and DL offer transformative potential for enhancing agility and resilience. Applications include demand forecasting, where DL methods significantly improve accuracy by handling large amounts of data and complex patterns

Table 1. Literature Review regarding China's Sectoral Stock Returns Impact on Global Supply Chains

Paper	Focus	Method/Algorithm	Data	Key Finding
Riaz et al. (2025)	Global Supply Chain Pressure Index (GSCPI) effects on Chinese stock sectors	Quantile regression	Chinese stock market & GSCPI	GSCPI has asymmetric negative effects, strongest in lower quantiles, raising costs and hurting profits.
Li et al. (2023)	Risk spillover in China's supply chain during COVID-19	Network analysis	Chinese stock markets (COVID-19 period)	Risks amplify as they move across the supply chain; financial industry intensifies spillovers.
Wu & Gong (2025)	China's futures market link with Ningbo Container Freight Index (NCFI)	Deep learning	NCFI & futures data	NCFI as key pricing tool; enhances forecasting and maritime supply chain resilience.
Gangwani et al. (2019)	Predicting supply chain disruptions	Multi-class SVM	Chinese firms' financial data	Identifies firm-level disruptions from financial signals.
Wang et al. (2023)	Collaborative SCM & financial supply chain management	Random forest	Multidimensional data	ML integrates SCM & finance, optimizing risk and efficiency trade-offs.
Qiao et al. (2022)	Customer risk & financing constraints	Fuzzy mathematics	A-share listed firms (2007–2019)	Customer risk increases financing constraints; directly impacts stock market.
Hu et al. (2019)	Commodity price volatility spillovers	Granger causality, Copula model	Daily prices (silver, copper, etc.)	Significant long-run volatility spillovers, strongest between silver & aluminum.
Ashraf et al. (2024)	Disruption detection via cognitive digital supply chain twin	Hybrid deep learning (autoencoder, SVM, LSTM)	Real-time disruption data	Detects disruptions and recovery times; balances sensitivity and false alarms.

2.2 Main Insights of the Literature Review

The literature review highlights the inherent instability of global supply chains and their significant, often negative, impact on financial markets due to various disruptions (Riaz et al., 2025). This necessitates advanced analytical frameworks. Machine learning and deep learning, particularly when combined in hybrid models, are emerging as crucial predictive tools in both financial markets and supply chain management, offering superior accuracy over traditional methods (anon & Ślepaczuk, 2025; Khedr & S, 2024).

China's central role in global supply chains means its sectoral stock performance can indicate upcoming global supply chain pressures, a dynamic explored through studies on risk spillover (Li et al., 2023) and predictive modeling of key metrics like the Ningbo Container Freight Index (Wu & Gong, 2025). This paper distinguishes itself by using deep learning and ensemble methods to predict the GSCPI from market signals, a reversal of the common approach of using GSCPI as an explanatory variable. The literature review also notes that the impact of supply chain disruptions is heterogeneous, affecting globally integrated sectors more significantly (Riaz et al., 2025).

3. General Flow of Research

3.1 Data collection

- Global Supply Chain Pressure Index (GSCPI), Federal Reserve Bank of New York
- Chinese sectoral stock data from the Chinese stock market (Figure 1)

3.2 Developed ML models

- Feedforward neural network (FFNN)
- Gated recurrent unit (GRU)
- Ensemble model
- Random Forest
- XGBoost
- ARX(1)

3.3 Train developed ML models

- Data splits
- Tuning
- validation

3.4 Results analysis

- R^2: Explains the proportion of variance the model has, closer to 1 better.
- MAE: Average of absolute error.
- MSE: Average of squared error.

3.5 Overview

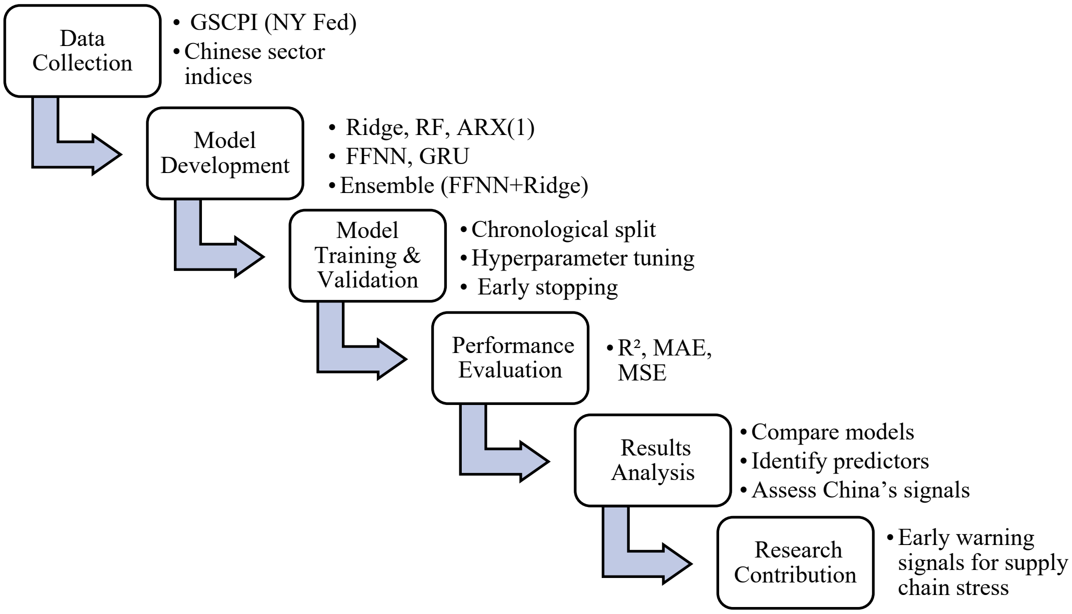


Figure 1. Flowchart of The Research Overview

4. Methodology

This section outlines the methodology employed to analyze the impact of China's sectoral stock returns on global supply chain pressure, as measured by the Global Supply Chain Pressure Index. The approach integrates data processing techniques with advanced machine learning and deep learning algorithms to predict movements in the GSCPI using high-frequency financial data.

4.1 Deep Learning Algorithm and Predictive Models

We evaluate multiple deep learning models to forecast the next-month Global Supply Chain Pressure Index from China's sectoral stock data. For each model, we state the rationale, architecture, training procedure, and the mapping from $x_t = [x_{1,t}, x_{2,t}, \ldots, x_{10,t}]$ to $GSCPI_{t+1}$. Inputs are standardized on the training set; models are trained with Adam (learning rate 0.001) to minimize MSE. Data are split chronologically (\~80% train, 20% test), with a validation subset for hyperparameter tuning and early stopping (no improvement in 10 epochs). Performance on the held-out test set is reported via R^2, MAE, and MSE.

4.1.1 Feedforward Neural Network (FFNN)

FFNN is a multilayer perceptron mapping the static feature vector x_t to $GSCPI_{t+1}$, used as a baseline non-linear regressor to capture cross-sectional relations between contemporaneous sector returns and next-month GSCPI (without explicit temporal dynamics).

Architecture

We designed a fully connected network with two hidden layers. The input layer has 10 neurons (one for each sector feature). This is followed by a first hidden layer of $h_1 = 64$ neurons and a second hidden layer of $h_2 = 32$ neurons. Each hidden neuron uses the ReLU activation function to introduce non-linearity. Finally, an output layer with a single linear neuron produces the forecast (predicted $GSCPI_{t+1}$). The network's forward pass can be described as follows:

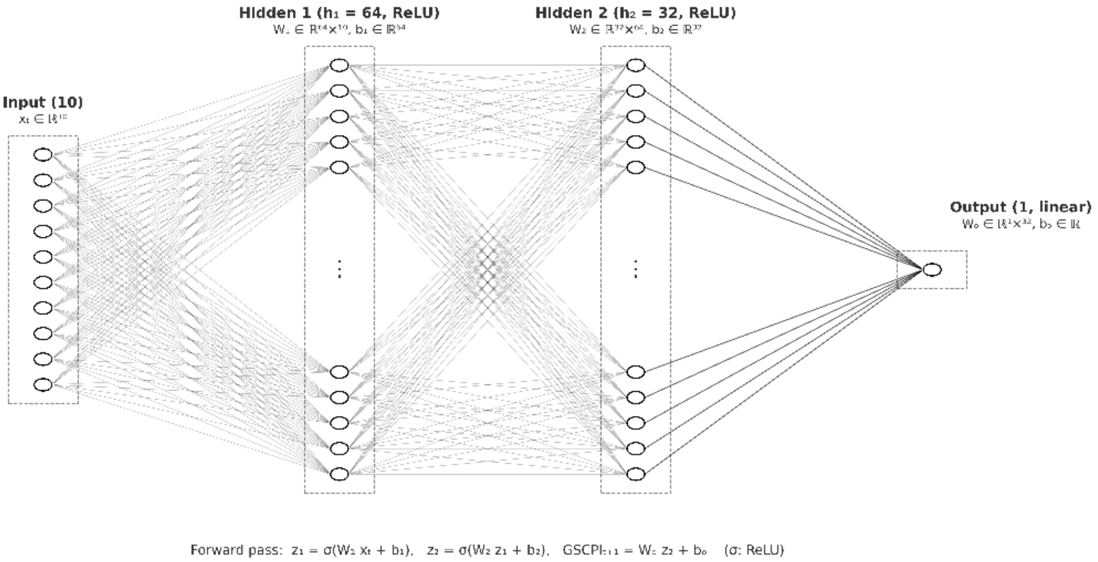


Figure 2. Developed FFNN Architecture

The architecture in Figure 2 is based on the following equation:

$$z_1 = \sigma(W_1 x_t + b_1),$$
$$z_2 = \sigma(W_2 z_1 + b_2),$$
$$GSCPI_{t+1} = W_o z_2 + b_o,$$

Equation 1

$x_t \in \mathbb{R}^{10}$ is the month-t input vector; $\sigma(\cdot)$ = ReLU.
Layer 1: $W_1 \in \mathbb{R}^{64}\times^{10}$, $b_1 \in \mathbb{R}^{64} \rightarrow z_1 \in \mathbb{R}^{64}$.
Layer 2: $W_2 \in \mathbb{R}^{32}\times^{64}$, $b_2 \in \mathbb{R}^{32} \rightarrow z_2 \in \mathbb{R}^{32}$.
Output: $W_o \in \mathbb{R}^{1}\times^{32}$, $b_o \in \mathbb{R} \rightarrow$ scalar $GSCPI_{t+1}$.
Input → two hidden layers → output (standard feedforward).

Training Setup: 100 epochs, mini batches of 16 drawn sequentially; MSE loss with Adam; inputs standardized (zero mean, unit variance); early stopping on validation MSE; final weights taken at the lowest validation MSE. Predictions were denormalized for evaluation.
Results (test set): $R^2 = 0.7207$, MAE = 0.4106, MSE = 0.2946

4.1.2 Gated Recurrent Unit (GRU):

We evaluate a GRU as a lighter alternative to the LSTM: two gates (reset, update), no cell state, and fewer parameters. It captures temporal dependencies at lower cost and often matches LSTM accuracy on moderate datasets, potentially generalizing better when full LSTM complexity is unnecessary.

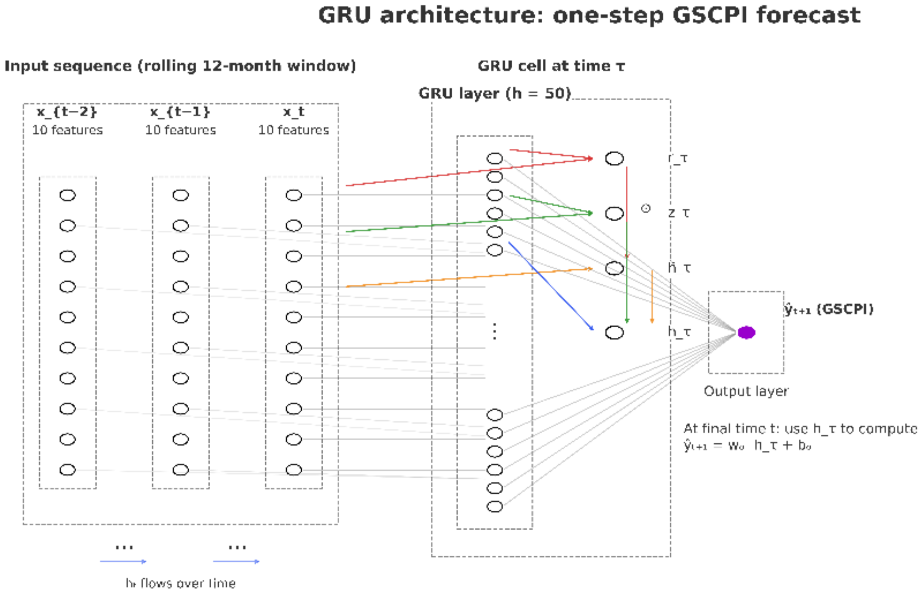


Figure 3. Developed GRU Architecture.

Architecture

A single GRU layer (h = 50) followed by a linear output neuron yields the one-step-ahead forecast, as mentioned in Figure 3. Inputs are rolling 12-month windows of 10 features. At each time step τ, the hidden state h_τ is updated; after the final step t, the 50-dimensional h_τ is mapped to the prediction via $\hat{y}_{t+1} = w_o^T h\_\tau + b_o$. The GRU cell updates are:

$$
\begin{aligned}
r\_\tau &= \sigma(W\_r\, x\_\tau + U\_r\, h_{t-1} + b\_r),\\
z\_\tau &= \sigma(W\_z\, x\_\tau + U\_z\, h_{t-1} + b\_z),\\
\tilde{h}\_\tau &= \tanh(W\_h\, x\_\tau + U\_h\, (r\_\tau \odot h_{t-1}) + b\_h),\\
h\_\tau &= z\_\tau \odot h_{t-1} + (1 - z\_\tau) \odot \tilde{h}\_\tau.
\end{aligned}
$$

Equation 2

Here $W\_r, W\_z, W\_h \in \mathbb{R}^{50\times10}$; $U\_r, U\_z, U\_h \in \mathbb{R}^{50\times50}$; $b\_r, b\_z, b\_h \in \mathbb{R}^{50}$. The reset gate r_τ controls carryover from h_{t-1} when forming the candidate $\tilde{h}\_\tau$, whereas the update gate z_τ interpolates between h_{t-1} and $\tilde{h}\_\tau$ to produce h_τ, providing adaptive memory with fewer parameters than an LSTM.

Training Setup: The GRU followed the LSTM protocol, 12-step sequences, Adam optimization, MSE loss, and the identical train/validation/test split. It converged slightly faster; early stopping was triggered based on validation loss. We maintained LSTM's 20% dropout and required no additional regularization, as the GRU showed no severe overfitting. On the test set, using the same rolling inputs, performance was $R^2 = 0.006$, MAE = 0.459, MSE = 0.786.

4.1.3 Ensemble Model (FFNN + Ridge Regression)

In addition to the individual models above, we developed an ensemble that combines a non-linear neural network with a simple linear model. The motivation comes from the intuition and evidence that combining different models can improve predictive performance, especially if the models capture different patterns or structures in the data. Our ensemble consists of the feedforward neural network (FFNN) described earlier and a ridge regression model. The ridge regression is a linear model that predicts GSCPI using a weighted sum of the 10 sector features, with an L_2 regularization to shrink coefficients.

Architecture & Formulation:

The ridge regression part of the ensemble has the form,

$$\mathrm{GSCPI}_{t+1}\text{\^{}(ridge)} = \beta_0 + \beta_1 x_{1,t} + \ldots + \beta_{10} x_{10,t},$$

Equation 3

where x_{i,t} is the value of the i-th sector feature at time t, β_0 is the intercept, and β_i are the learned coefficients for each sector. These coefficients are estimated from the training data by minimizing the sum of squared errors with an L_2 penalty λ∑_{i=1}^{10} β_i^2 to prevent overfitting (the regularization hyperparameter λ was tuned via cross-validation on the training set). The FFNN component of the ensemble is the same 2-layer network described in the FFNN section above (we use the model parameters learned earlier, without retraining). Let $\hat{y}_{t+1}$^(FFNN) denote the FFNN's prediction and $\hat{y}_{t+1}$^(ridge) the ridge regression's prediction. We combine them with a simple weighted average:

$$\mathrm{GSCPI}_{t+1}\text{\^{}(ens)} = 0.7\ \mathrm{GSCPI}_t + 0.15\ \hat{y}_{t+1}\text{\^{}(FFNN)} + 0.15\ \hat{y}_{t+1}\text{\^{}(ridge)},$$

Equation 4

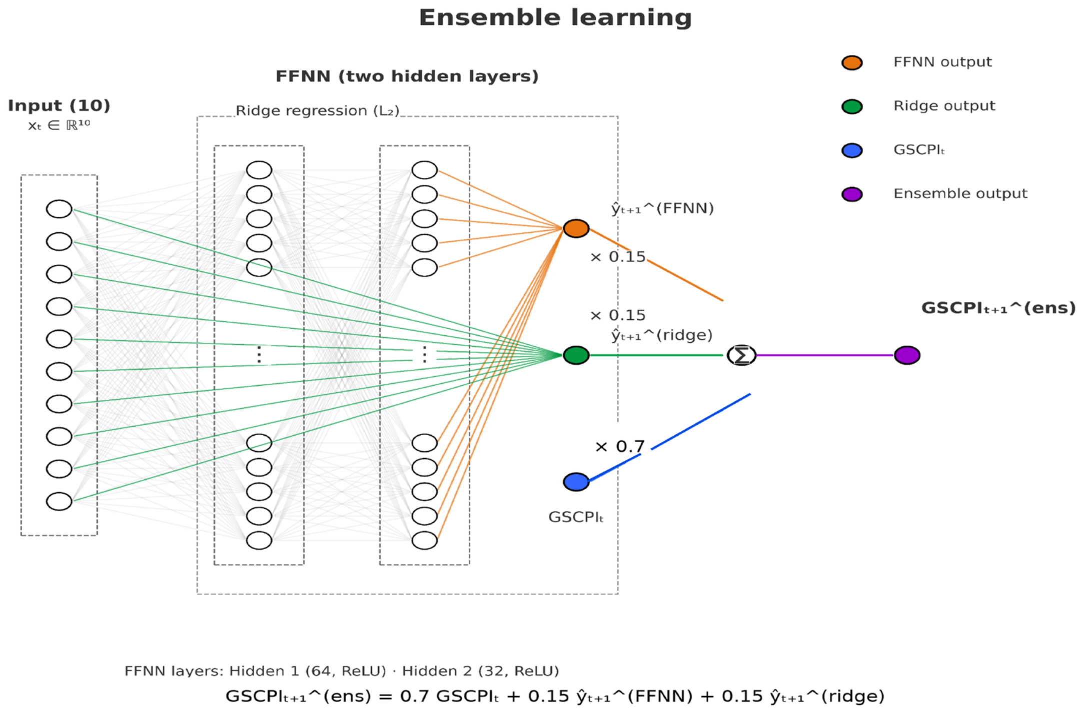


Figure 4. Developed Ensemble Model Architecture

In Figure 4, the 0.5 weight reflects strong persistence in the series, while the two 0.15 terms exploit complementary signals from the FFNN and ridge models. In validation, this simple specification matched or outperformed more elaborate stacking because averaging dampens extremes and reduces variance: when one component is mis calibrated or noisy, the others offset it, lowering error.

Training Setup

We trained the FFNN and ridge regression models independently on the same training data. The FFNN training procedure was as described earlier. For the ridge regression, we standardized the inputs and optimized the weights β_i using the closed-form ridge regression solution on the training set (with 5-fold cross-validation to select the regularization parameter λ). The two models were thus fit on the identical training samples (with identical preprocessing), ensuring their errors are at least partially uncorrelated. The ensemble does not require additional training; it is implemented by computing predictions from each model on the test set and then averaging those predictions. (If a validation set is available, one could choose α to optimize ensemble performance on validation data, but as noted, we fixed equal weights for simplicity.) At inference time, given new data (sector returns for the current month t), the ridge regression produces an immediate linear prediction and the FFNN produces a non-linear prediction; the final ensemble forecast is their average. This model combination yielded better accuracy than either model by itself in our experiments, confirming that the linear and non-linear models complement each other's strengths. Test $R^2 = 0.85$.

4.1.4 Random Forest Regression Model:

We used a Random Forest regressor as a nonparametric baseline for tabular financial data, capturing nonlinear interactions among sector returns. Inputs are the 10 sectorial indices x_t (no lags). Training reduced the squared error (the forest's implicit MSE criterion). Set n_estimators = 100 and max_depth = 1 (shallow trees) to limit variance; these choices came from brief preliminary tests given the modest sample size. Data were split sequentially for 80% train and 20% test, and performance was assessed on the splitted test set using R^2, MAE, and MSE.

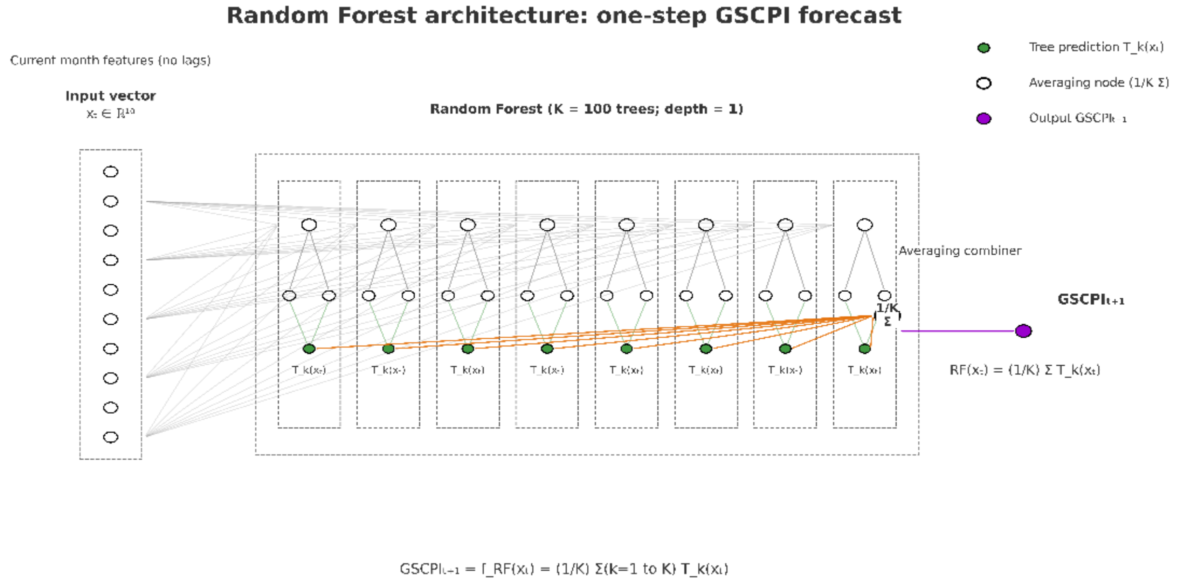


Figure 5. Developed Random Forest Architecture

Mathematical formulation: Let in Figure 5, $x_t = (x_{1,t}, \ldots, x_{10,t})$ be the feature vector at time t. The Random Forest implements a nonlinear mapping

$$GSCPI_{t+1} = f\_RF(x_t) = (1/K)\ \Sigma(k=1 \text{ to } K)\ T\_k(x_t),$$

Equation 5

where each $T\_k(\cdot)$ is a regression tree and $K = 100$ is the number of trees. The target is $GSCPI_{t+1}$, the predicted GSCPI one month ahead. In this model the input features $x\_\{i,t\}$ are not lagged (aside from the implicit one-month shift in the target); that is, each tree uses the current sector values to predict next-month GSCPI. No single linear form is assumed for f_RF beyond the ensemble structure. All symbols in the formula above are as defined: T_k are tree predictors and K = 100 is the number of trees. Test set results: $R^2 = 0.434$, MAE = 0.727, MSE = 1.056.

4.1.5 ARX (Autoregressive with eXogenous) Model

An ARX(1) linear model was also implemented, which combines an autoregressive term for GSCPI with contemporaneous exogenous regressors (the sector returns). This is a simple time-series regression capturing linear dynamics. The model was included as a baseline econometric specification: it regresses next-month GSCPI on its own lag and on the sectoral inputs.

Features: The model uses one lag of the GSCPI index (i.e., $GSCPI_t$) as an additional predictor, along with the 10 sector returns at time t (raw values, no additional lags). We create a new feature "GSCPI_prev" = $GSCPI_t$ and include it in the regression. We fit the ARX model via ordinary least squares (minimizing squared error) on the training data (chronologically up to end-2022) and evaluated it on the subsequent test period (2023–2024). All inputs (including the lagged GSCPI and sector returns) were mean-standardized based on the training set, and the OLS fit was done on the scaled data. No hyperparameters were tuned, since OLS has a closed-form solution. Model performance on the test set was measured by test R^2, MAE, and MSE.

Mathematical formulation: Let y_t denote the actual GSCPI at month t, and let x_{i,t} be as before the return of sector i at month t. The ARX(1) model has the form,

$$\hat{y}_{t+1} = \alpha + \beta\, y_t + \gamma_1\, x_{1,t} + \ldots + \gamma_{10}\, x_{10,t}.$$

Equation 6

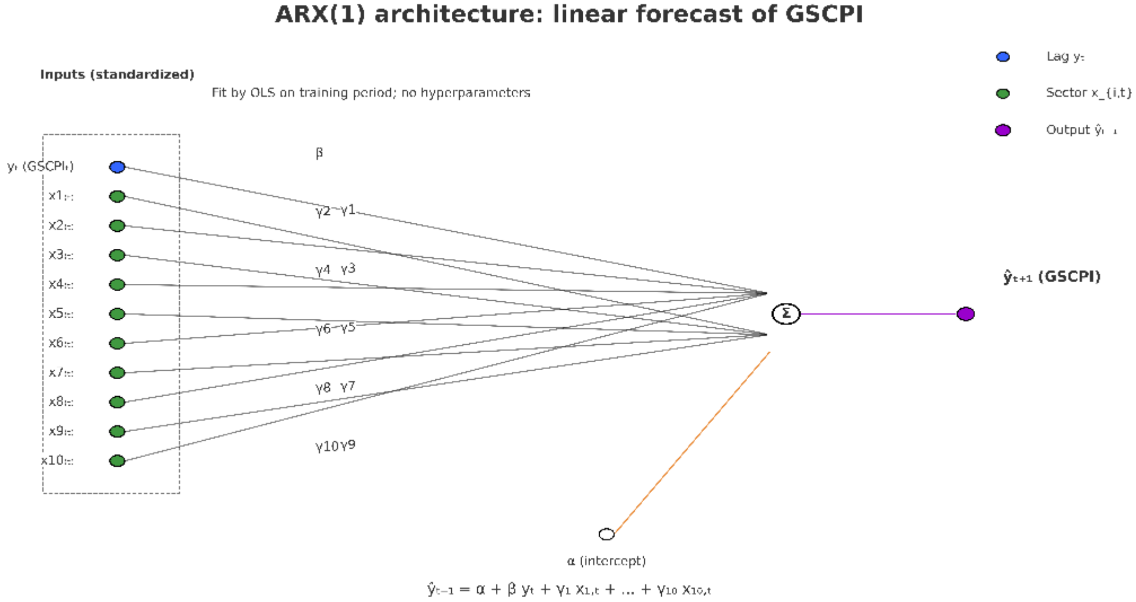
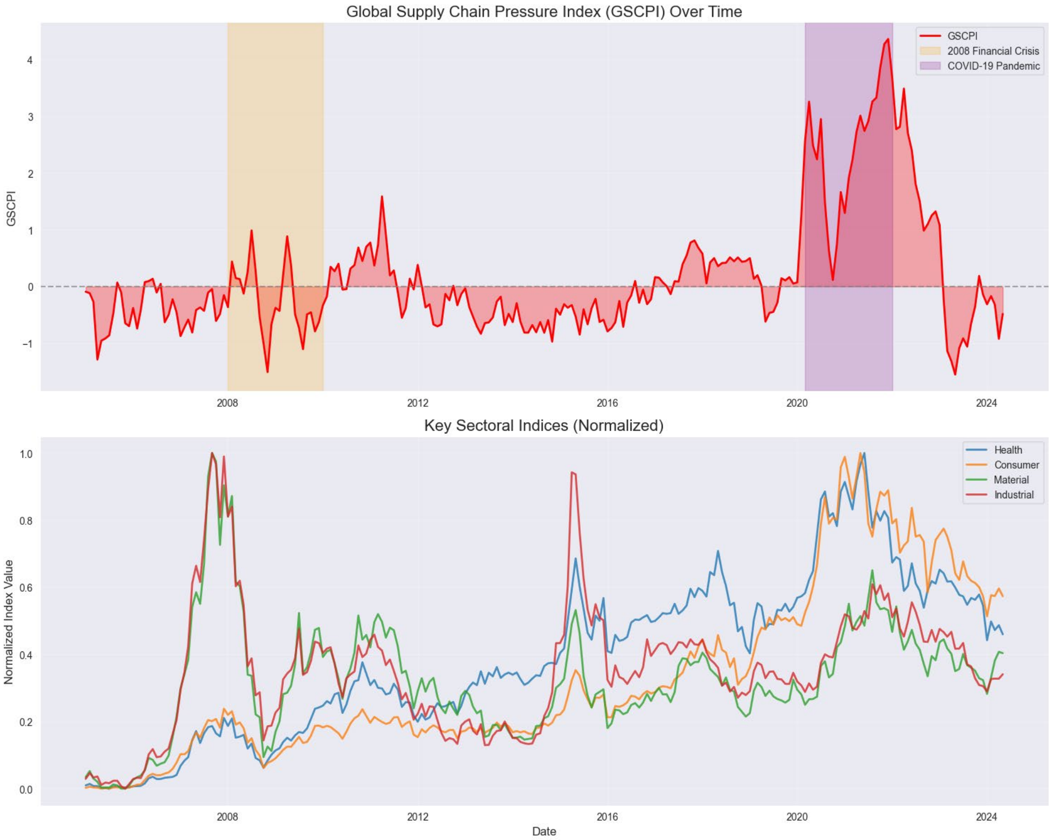


Figure 6. Developed ARX(1) Algorithm

Here in Figure 6, $\hat{y}_{t+1}$ is the forecasted GSCPI for month t+1, y_t = GSCPI_t is the one-period lag of the index, and x_{i,t} (i=1,…,10) are the ten sector returns at time t. The parameters α, β, and γ_i are estimated by least squares. Thus, in ARX we linearly combine the previous GSCPI value and the current sectoral values to predict the next GSCPI. Test Set Results: $R^2 = -0.277$, MAE = 0.541, MSE = 0.491.

5. Data Collection

The study assembled an extensive dataset comprising Chinese stock market indices across ten major economic sectors. These sectoral stock return series served as the primary predictors in the supervised learning framework. The target variable for prediction was the monthly GSCPI time series. The underlying idea was to leverage high-frequency, real-time financial data to anticipate a macroeconomic stress indicator that is typically compiled monthly.



Global Supply Chain Pressure Index (GSCPI) Over Time

Key Sectoral Indices (Normalized)

Figure 7. Developed Global Supply Chain Pressure Index (GSCPI) and Sectorial Indices over time graph

The initial stage of data preparation for this study involved visualizing the raw and preprocessed time-series data and assessing the relationships between variables. Figure 7 depicts the "Global Supply Chain Pressure Index Over Time" alongside "Key Sectoral Indices," served to illustrate the historical fluctuations of our target variable, the GSCPI, and demonstrate the crucial normalization step applied to our predictor variables. Specifically, the GSCPI plot provided a direct overview of the index's behavior, including its response to major economic events over the study period. For the sectoral stock indices, normalization was systematically applied to scale their values, typically within a fixed range like 0 to 1, or to standardize them with a mean of 0 and a standard deviation of 1. This preprocessing technique is vital for many machine learning and deep learning models, particularly neural networks, as it prevents features with larger numerical ranges from disproportionately influencing the learning process and aids in faster convergence during training.

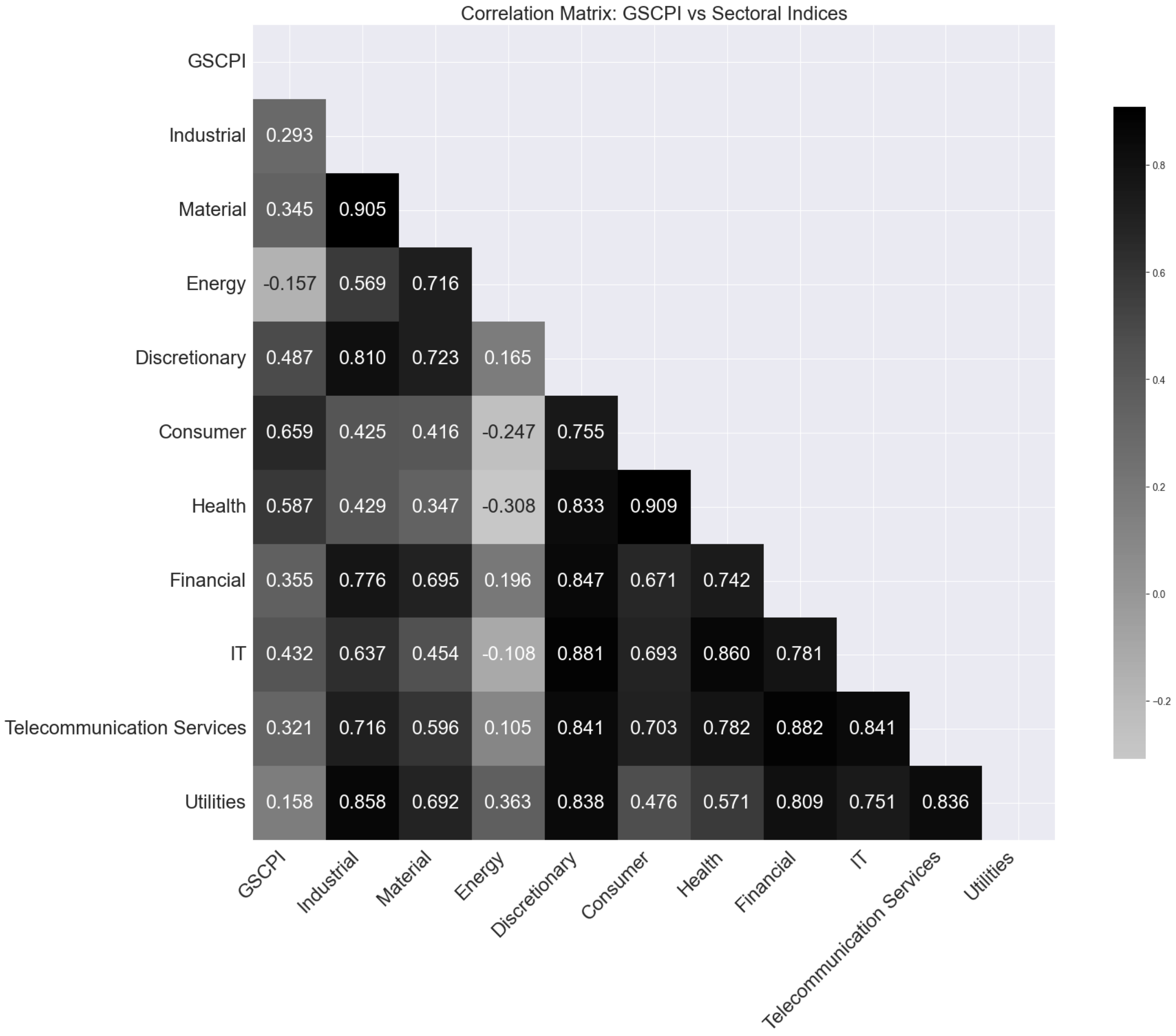


Figure 8. Developed Correlation Heatmap between GSCPI and Sectoral Indices

Figure 8, provides a quantitative overview of the linear relationships between the GSCPI and the ten Chinese sectoral stock indices, as well as the correlations among the sectoral indices among themselves. This analysis is used in detecting multicollinearity among the predictor variables (Ntotsis et al., 2021). Although deep learning models can be more robust to multicollinearity, understanding these interdependencies is important for model stability and interpretability (Chan et al., 2022; Noh et al., 2020; Ntotsis et al., 2021).

6. Results and Discussion

This study investigated into the predictive relationship between China's sectoral stock market performance and the Global Supply Chain Pressure Index. The approach implemented both traditional machine learning and advanced deep learning algorithms to predict the GSCPI using high-frequency financial data from China (Figure 9- Figure 12).

6.1 Graphical Results

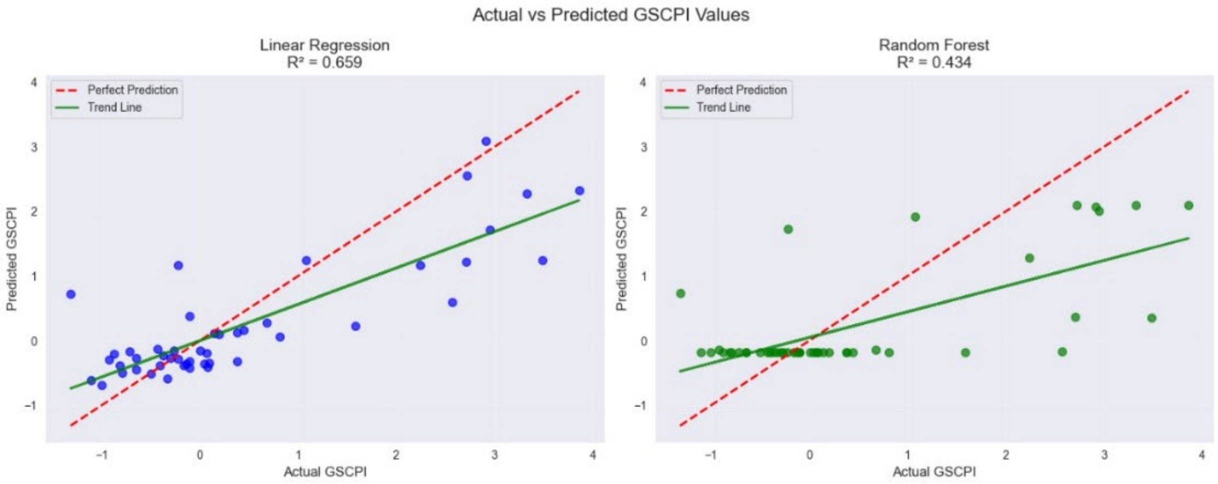


Figure 9.Performance analysis of linear regression and random forest

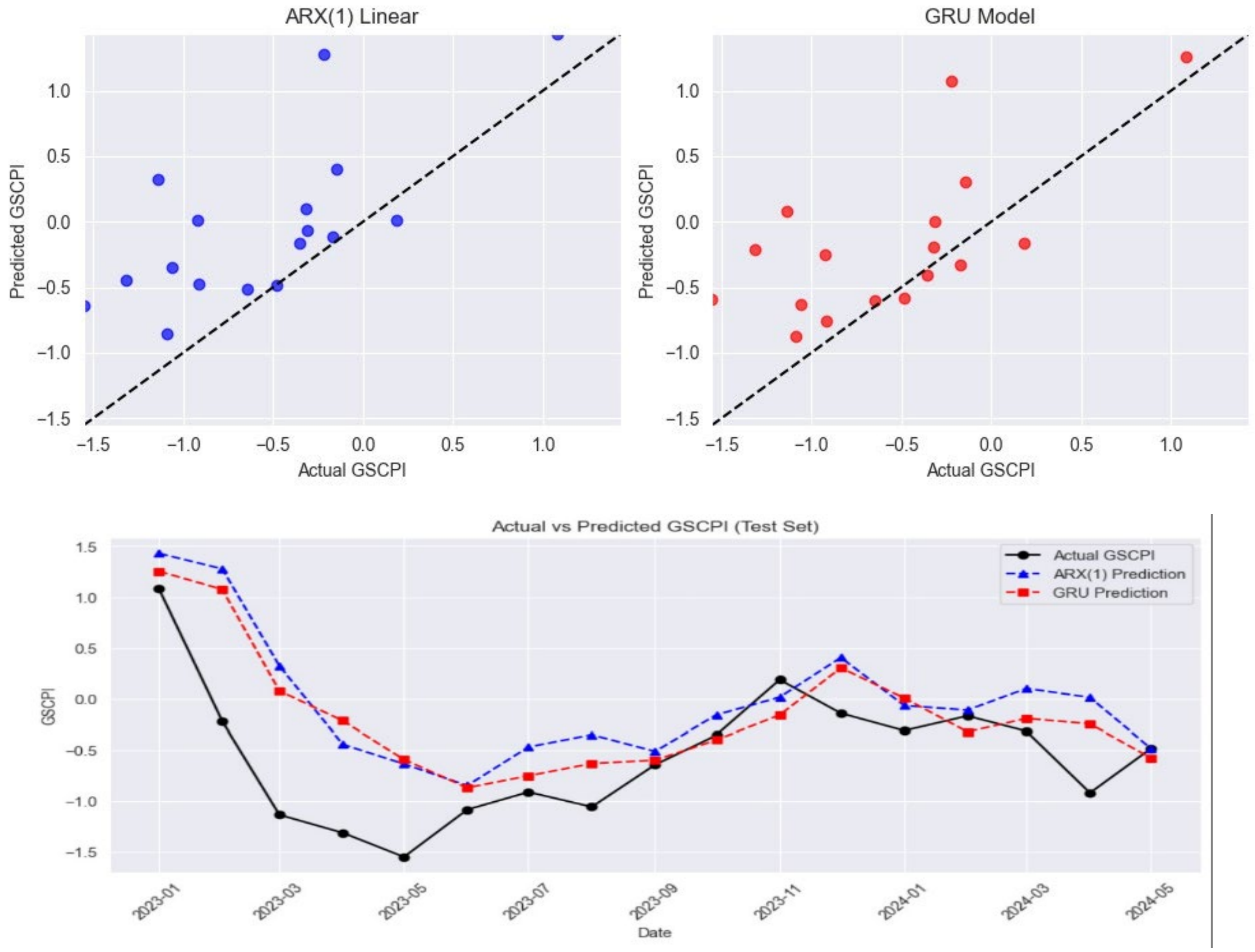


Figure 10. Performance analysis of ARX(1) and GRU

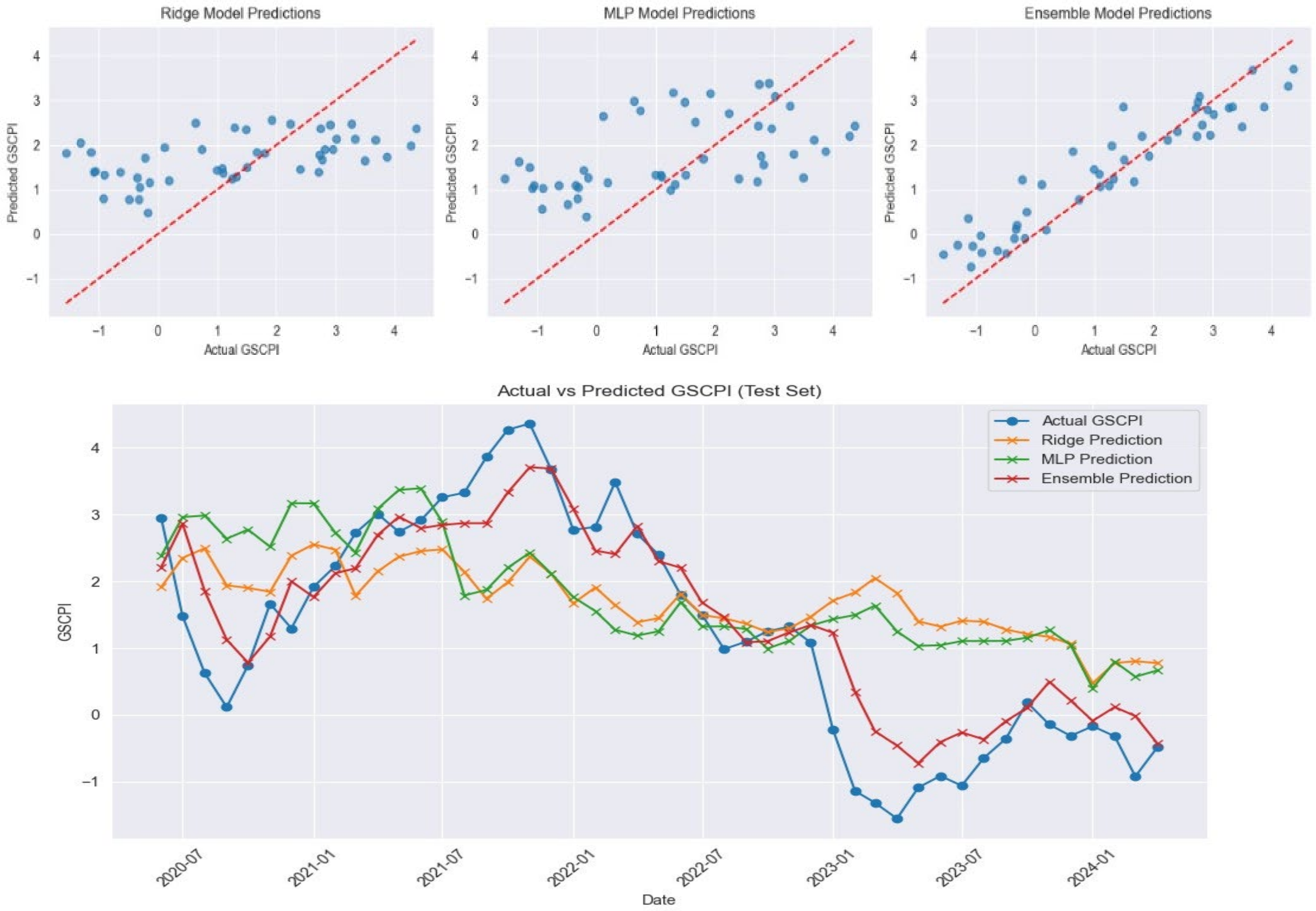


Figure 11. Performance analysis of Ridge and FFNN combining for ensemble

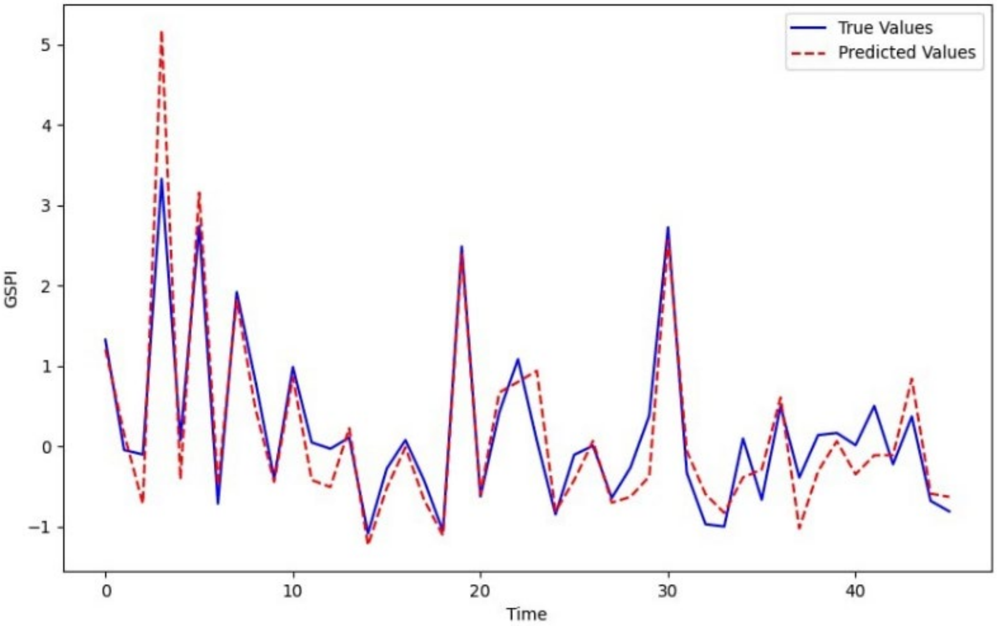


Figure 12. Applied 2024 GSCPI prediction vs actual using FFNN

6.2 Numerical Results

The study evaluated several models, including linear regression, various machine learning algorithms such as Random Forests and XGBoost, and deep learning architectures such as Feedforward Neural Networks, and Gated Recurrent Units (GRU). A key finding was that while individual models offered complementary strengths, no single model consistently dominated all prediction tasks.

However, a hybrid ensemble model, which combined a deep FFNN with a Ridge regression model, achieved the highest accuracy in predicting out-of-sample GSCPI movements. This integration of diverse modeling techniques significantly improved forecast performance for this complex economic index.

Table 2. Evaluated Models

Model	Test R^2	MAE	MSE
Ensemble (FFNN + Ridge Regression)	0.85	0.5126	0.4329
Feedforward Neural Network	0.7207	0.4106	0.2946
Random Forest Regression Model	0.434	0.727	1.056
Gated Recurrent Unit	0.006	0.459	0.786
XGBoost Regression Model	-0.152	1.581	3.233
ARX	-0.277	0.541	0.491

Table *2* shows that the ensemble model delivered the best result with a Test R^2 of 0.85, indicating that it explained 85% of the variance in the GSCPI movements in the test set. This was followed by the standalone Feedforward Neural Network, which achieved a Test R^2 of 0.7207, then the Random Forest Regression Model with a Test R^2 of 0.434. The ARX (linear regression) model performed poorly with a negative Test R^2 of -0.277. Additionally, due to overfitting, LSTM also performed poorly and returned a negative value of R², indicating it's even worse than simply predicting the average of the outcome variable.

In Figure 11, ensemble learning combines multiple base models to analyze data from different perspectives and make joint predictions, thereby improving precision. By combining the flexibility of a deep Feedforward Neural Network, which can capture complex, non-linear relationships, with the stability and interpretability of a linear model like Ridge regression, the ensemble effectively leverages diverse approaches. This synergistic combination allows the ensemble to capture a wider range of patterns in the data and often leads to improved generalization and reduced prediction errors compared to individual models. The FFNN contributes to identifying complex, higher-order interactions among sectoral returns, while the Ridge regression component efficiently captures any underlying linear trends or relationships. This makes the ensemble more trustworthy and accurate for forecasting complex economic indices such as the GSCPI (Table 3).

6.3 Performance Analysis

Table 3. Performance Analysis

Paper	**Key focus**	**Input**	**Method**	**Accuracy and Results**	**Data sets**	**Result**
Baryannis et al. (2019)	Supply chain risk prediction	Real-world multi-tier manufacturing data	Decision Trees, SVM	Interpretability vs. performance trade-off; DT more explainable, SVM higher predictive scores	Manufacturing data systems	Highlights transparency needs for adoption
Hu et al. (2019)	Supply chain finance volatility spillovers	Prices of pledged commodities (silver, copper, aluminum, rebar, fuel oil)	Granger causality + time-varying Copula	Significant spillovers; strongest between copper–aluminum; structural breaks matter	Banking & commodity markets	Cascading collateral risk across pledges
Bao et al. (2022)	Supplier investment efficiency under customer risk	776 supplier–customer pairs (China A-shares)	Econometric panel analysis	Customer risk → supplier underinvestment; stronger with high customer concentration & SOE ties	Dependence on major customers	Financing constraints & governance exposure
Wu & Gong (2025)	NCFI freight index forecasting	28,830 daily futures + shipping indicators	Hybrid RNN–GRU	$R^2 = 0.9518$ (test); lower MAE/RMSE than baselines	Futures & shipping data feeds	Focus on resilience; no specific security issues
Li et al. (2023)	COVID-19 supply-chain risk spillovers	Chinese sectoral stock data	Agent-based simulation + Copula-CoVaR	Risks transmit downstream→midstream →upstream; finance amplifies spillovers; policy dampens	Financial–real linkages	Time-varying, policy-sensitive spillovers
Riaz et al. (2025)	Sectoral stock-market impact of supply-chain pressure	GSCPI + China sector returns	Quantile-on-Quantile regression	Predominantly negative effects across sectors; strongest for utilities & telecom	Depends on GSCPI (NY Fed)	Geopolitical/transport shocks drive sensitivity
Ashraf et al. (2024)	Disruption detection in a cognitive digital supply-chain twin	Real-time DSCT state data	Deep autoencoder + OCSVM, LSTM for echelon & time-to-recovery	Demonstrates trade-off between sensitivity, detection delay, and false alarms	IoT/analytics stack	Alerts & false-positive management considerations
Wang et al. (—)	SCM–Financial SCM synergy via ML	Multi-enterprise operational & financing data	LSTM, RF, XGBoost; DDML; RL	Post-optimization: inventory turnover +30%, SME financing cost −18% to −22%, order-fill >95%, forecast	Enterprise data platforms	Data governance & privacy/federated learning needs

				error ≤8%, credit accuracy ≥90%		
Ishrak et al. (2025)	Predicting GSCPI from China's sectoral stock returns	233 months, 10 sector indices	FFNN, GRU, Ridge, RF, XGB; Ensemble (Ridge+FFNN)	Best OOS: Ensemble $R^2 \approx 0.85$; FFNN next; GRU negative R^2 on this dataset	Chinese equity data + GSCPI	Monitoring framework for supply-chain stress

6.4 Future Scope

The study can be further strengthened by implementing several improvements. Expanding the dataset to consider PMI sub-indices, commodity price indices, and shipping cost measure would capture dimensions of supply chain which are not fully expressed in Chinese equity markets. Expanding beyond monthly averages, towards higher-frequency inputs, such as weekly or daily stock returns, would improve timeliness and allow for earlier detection of disruption. Improving model calibration through systematic tuning and applying adaptive approaches would enhance robustness against regime shifts. Deeper feature engineering and more sophisticated ensemble strategies could strengthen predictive capability.

7. Conclusion

This study makes several significant contributions to understanding global supply chain risk indicators and the application of predictive analytics. A core finding is the superior performance of our hybrid ensemble model, which combined the flexibility of a deep Feedforward Neural Network with the stability and interpretability of a Ridge regression model. This ensemble achieved the highest accuracy, with a Test R^2 of 0.85, significantly outperforming individual models.
The performance hierarchy of the key models evaluated is as follows:

1. Ensemble (FFNN + Ridge Regression): Test $R^2 = 0.85$
2. Feedforward Neural Network: Test $R^2 = 0.7207$
3. Random Forest Regression Model: Test $R^2 = 0.434$
4. ARX (linear regression) Model: Test $R^2 = -0.277$

This clear ranking shows that blending diverse modeling techniques can significantly improve forecast performance for complex economic indices. Ensemble learning effectively blends different analytical perspectives to improve precision, generalization, and reduce prediction errors.

To conclude, this study illuminates the understanding of how financial market signals can be used as early warnings for real economic disruptions. By creating relation between macro-level supply chain metrics with micro-level financial signals, this approach offers a potential early warning system for supply chain disruption. This is particularly relevant in a post-pandemic world characterized by consistent uncertainties and the critical need for enhanced supply chain management and financial analytics. Future research could explore the applicability of this model to other major economies or incorporate additional alternative data sources to further enhance predictive capabilities.

References

Agrawal, N., Modgil, S., and Gupta, S., "ESG and Supply Chain Finance to Manage Risk among Value Chains," *Journal of Cleaner Production*, Vol. 471, Article 143373, **2024**, doi: 10.1016/j.jclepro.2024.143373.

Anon, D., and Ślepaczuk, R., "Hybrid Models for Financial Forecasting: Combining Econometric, Machine Learning, and Deep Learning Models," *SSRN Working Paper*, **2025**, doi: 10.2139/ssrn.5268691.

Ashraf, M., Eltawil, A., and Ali, I., "Disruption Detection for a Cognitive Digital Supply Chain Twin Using Hybrid Deep Learning," *arXiv Preprint*, **2023**, doi: 10.48550/arXiv.2309.14557.

Baghersad, M., and Zobel, C. W., "Assessing the Extended Impacts of Supply Chain Disruptions on Firms: An Empirical Study," *International Journal of Production Economics*, Vol. 231, Article 107862, **2020**, doi: 10.1016/j.ijpe.2020.107862.

Bai, X., Fernández-Villaverde, J., Li, Y., and Zanetti, F., "The Causal Effects of Global Supply Chain Disruptions on Macroeconomic Outcomes: Evidence and Theory," *NBER Working Paper*, **2024**, doi: 10.3386/w32098.

Barrot, J.-N., and Sauvagnat, J., "Input Specificity and the Propagation of Idiosyncratic Shocks in Production Networks," *SSRN Electronic Journal*, **2014**, doi: 10.2139/ssrn.2427421.

Bie, S. D., Feng, G., Guo, N., and He, J., "Can News Predict Firm Bankruptcy?," *SSRN Working Paper*, **2024**, doi: 10.2139/ssrn.5055291.

Biermann, M., and Leromain, E., "The Ripple Effect: Trade Linkages and the Stock Market Response to the Russia–Ukraine War," *Review of World Economics*, **2025**, doi: 10.1007/s10290-025-00594-4.

Cerutti, F., "Methodological Insights into Structural Causal Modelling and Uncertainty-Aware Forecasting for Economic Indicators," *arXiv Preprint*, **2025**, doi: 10.48550/arXiv.2509.07036.

Chatziantoniou, I., Gabauer, D., and Stenfors, A., "US Sectoral Stock Market Volatility and Geopolitical Risk Categories," *Finance Research Letters*, Article 106916, **2025**, doi: 10.1016/j.frl.2025.106916.

Chauhan, A., "Developing Predictive Models for Stock Market Behavior Using Machine Learning and Econometrics," *Authorea Preprint*, **2024**, doi: 10.22541/au.173557635.57762143/v1.

Chen, L., Li, T., Jia, F., and Schoenherr, T., "The Impact of Governmental COVID-19 Measures on Manufacturers' Stock Market Valuations: The Role of Labor Intensity and Operational Slack," *Journal of Operations Management*, Vol. 69, No. 3, pp. 404–424, **2022**, doi: 10.1002/joom.1207.

Chen, Q., "Analysis and Prediction of Cross-Border E-Commerce Scale of China Based on Machine Learning Models," *Computational Intelligence and Neuroscience*, Vol. 2022, Article 7906135, **2022**, doi: 10.1155/2022/7906135.

Cheng, L. T. W., Poon, J. S. C., Tang, S., and Wang, J., "Does Supplier Concentration Matter to Investors during the COVID-19 Crisis? Evidence from China," *SSRN Electronic Journal*, **2020**, doi: 10.2139/ssrn.3718533.

Douaioui, K., Oucheikh, R., Benmoussa, O., and Mabrouki, C., "Machine Learning and Deep Learning Models for Demand Forecasting in Supply Chain Management: A Critical Review," *Applied System Innovation*, Vol. 7, No. 5, Article 93, **2024**, doi: 10.3390/asi7050093.

Easaw, N., Lee, W. S., Lohiya, P. S., Jalan, S., and Pradhan, P., "Estimation of Correlation Matrices from Limited Time Series Data Using Machine Learning," *Journal of Computational Science*, Vol. 71, Article 102053, **2023**, doi: 10.1016/j.jocs.2023.102053.

Fan, Z., Pang, C., and Tang, H., "The Impacts of Natural Marine Disasters on the Shipping Industry in China: An Event Study," *Journal of Sea Research*, Vol. 204, Article 102569, **2025**, doi: 10.1016/j.seares.2025.102569.

Ferrari, A., "Inventories, Demand Shocks Propagation and Amplification in Supply Chains," *arXiv Preprint*, **2022**, doi: 10.48550/arXiv.2205.03862.

Fialkowski, J., Diem, C., Borsos, A., and Thurner, S., "A Data-Driven Econo-Financial Stress-Testing Framework to Estimate the Effect of Supply Chain Networks on Financial Systemic Risk," *SSRN Working Paper*, **2025**, doi: 10.2139/ssrn.5145774.

García-Herrero, A., "Resilience of Global Supply Chains: Facts and Implications," *Policy Report*, **2023**, doi: 10.56506/ukpk2510.

Gastinger, J., Nicolas, S., Stepić, D., Schmidt, M., and Schülke, A., "Ensemble Learning for Time Series Forecasting and the Need for Meta-Learning," *Proceedings of the International Joint Conference on Neural Networks (IJCNN)*, pp. 1–8, **2021**, doi: 10.1109/IJCNN52387.2021.9533378.

Ghimire, S., "TimeTrail: Unveiling Financial Fraud Patterns through Temporal Correlation Analysis," *arXiv Preprint*, **2023**, doi: 10.48550/arXiv.2308.14215.

Hancock, M. E., and Mora, J., "The Impact of COVID-19 on Chinese Trade and Production," *Journal of Asian Economics*, Vol. 86, Article 101596, **2023**, doi: 10.1016/j.asieco.2023.101596.

Hendricks, K. B., Jacobs, B. W., and Singhal, V. R., "Stock Market Reaction to Supply Chain Disruptions from the 2011 Great East Japan Earthquake," *Manufacturing & Service Operations Management*, Vol. 22, No. 4, pp. 683–699, **2019**, doi: 10.1287/msom.2019.0777.

Hendricks, K. B., and Singhal, V. R., "An Empirical Analysis of the Effect of Supply Chain Disruptions on Long-Run Stock Price Performance," *Production and Operations Management*, Vol. 14, No. 1, pp. 35–52, **2005**, doi: 10.1111/j.1937-5956.2005.tb00008.x.

Hendricks, K. B., and Singhal, V. R., "Association Between Supply Chain Glitches and Operating Performance," *Management Science*, Vol. 51, No. 5, pp. 695–711, **2005**, doi: 10.1287/mnsc.1040.0353.

Hsu, W., Lin, Y.-L., Lai, J.-P., Liu, Y., and Pai, P., "Forecasting Corporate Financial Performance Using Deep Learning with ESG Data," *Electronics*, Vol. 14, No. 3, Article 417, **2025**, doi: 10.3390/electronics14030417.

Kancs, d'Artis, "Enhancing Resilience: Model-Based Simulations," *arXiv Preprint*, **2022**, doi: 10.48550/arXiv.2212.11108.

Katsaliaki, K., Galetsi, P., and Kumar, S., "Supply Chain Disruptions and Resilience: A Major Review," *Annals of Operations Research*, Vol. 319, No. 1, pp. 965–1008, **2021**, doi: 10.1007/s10479-020-03912-1.

Kilimci, Z. H., et al., "An Improved Demand Forecasting Model Using Deep Learning," *Complexity*, Vol. 2019, **2019**, doi: 10.1155/2019/9067367.

Leng, Y., Liu, E., Ren, Y., and Tsyvinski, A., "The Bullwhip: Time-to-Build and Sectoral Fluctuations," *SSRN Working Paper*, **2025**, doi: 10.2139/ssrn.5207585.

Li, Z., Pei, S., Li, T., and Wang, Y., "Risk Spillover Network in Supply Chains during COVID-19," *Economic Modelling*, Vol. 126, Article 106403, **2023**, doi: 10.1016/j.econmod.2023.106403.

Lin, S., Huang, X., Zhang, S., and Han, Z., "Ensemble Learning-Based Forecasting for Inventory Data," *Processes*, Vol. 13, No. 5, Article 1443, **2025**, doi: 10.3390/pr13051443.

Liu, Z., Dai, P., Huynh, T. L. D., Zhang, T., and Zhang, G., "Industries' Heterogeneous Reactions during COVID-19," *Journal of International Financial Management and Accounting*, Vol. 34, No. 2, pp. 243–269, **2022**, doi: 10.1111/jifm.12166.

Martyushev, N. V., et al., "Predicting Firm Performance Using Hybrid Panel Data Models," *Mathematics*, Vol. 13, No. 8, Article 1247, **2025**, doi: 10.3390/math13081247.

Navadersh, S., and Vengadeswaran, S., "Predictive Big Data Analytics for Supply Chain Demand Forecasting," *Lecture Notes in Computer Science*, pp. 385–397, **2025**, doi: 10.1007/978-3-031-81821-9_25.

Riaz, A., Ullah, A., and Muhammad, B., "The Impact of Global Supply Chain Pressure on the Stock Market," *Humanities and Social Sciences Communications*, Vol. 12, No. 1, **2025**, doi: 10.1057/s41599-025-04634-0.

Rong, Y., Shen, Z. M., and Snyder, L., "Pricing during Disruptions: A Cause of the Reverse Bullwhip Effect," *SSRN Electronic Journal*, **2009**, doi: 10.2139/ssrn.1374184.

Seyedan, M., Mafakheri, F., and Wang, C., "Order-Up-To-Level Inventory Optimization Using Ensemble Deep Learning," *Supply Chain Analytics*, Vol. 3, Article 100024, **2023**, doi: 10.1016/j.sca.2023.100024.

Smirnyagin, V., and Tsyvinski, A., "Macroeconomic and Asset Pricing Effects of Supply Chain Disasters," *NBER Working Paper*, **2022**, doi: 10.3386/w30503.

Tabachová, Z., et al., "Estimating the Impact of Supply Chain Network Contagion on Financial Stability," *Journal of Financial Stability*, Article 101336, **2024**, doi: 10.1016/j.jfs.2024.101336.

Udenio, M., Vatamidou, E., Fransoo, J. C., and Dellaert, N., "Behavioral Causes of the Bullwhip Effect," *IISE Transactions*, Vol. 49, No. 10, pp. 980–991, **2017**, doi: 10.1080/24725854.2017.1325026.

Villa, S., Gonçalves, P., and Arango-Aramburo, S., "Exploring Retailer Ordering Decisions under Delays," *SSRN Electronic Journal*, **2013**, doi: 10.2139/ssrn.2306660.

Wang, H., Tang, H., Leng, N., and Yu, Z., "Machine Learning-Based Synergistic Optimization of Supply Chain and Financial Supply Chains," *arXiv Preprint*, **2025**, doi: 10.48550/arXiv.2509.03673.

Yu, H., Hao, X., Wu, L., Zhao, Y., and Wang, Y., "Satellite Imageries of Container Ports and Stock Return Prediction," *Humanities and Social Sciences Communications*, Vol. 10, No. 1, **2023**, doi: 10.1057/s41599-023-01891-9.

Zhang, S. Y., "Using Equity Market Reactions and Network Analysis to Infer Global Supply Chain Interdependencies," *Journal of Economics and Business*, Vol. 115, Article 105974, **2021**, doi: 10.1016/j.jeconbus.2020.105974.

Zhong, S., and Hitchcock, D. B., "S&P 500 Stock Price Prediction Using Technical, Fundamental and Text Data," *arXiv Preprint*, **2021**, doi: 10.48550/arXiv.2108.10826.

Zhou, L., Lu, S., and Si, D., "Research on the Bullwhip Effect Based on Retailers' Overconfidence," *Sustainability*, Vol. 17, No. 10, Article 4268, **2025**, doi: 10.3390/su17104268.

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