Comparing the Predictive Performance of LSTM Models with and without Economic Policy Uncertainty: Evidence from Taiwan's Sectoral Stock Indices

Z0207455

Durham University

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Abstract

This study examines whether adding EPU indices from the US, China, and Taiwan, along with the U.S.–China Tension Index, can improve the accuracy of Long Short-Term Memory (LSTM) models in forecasting Taiwan's sectoral stock indices. Using data from 2005 to 2021, the research integrates macroeconomic, technical, and policy uncertainty indicators within a PCA-LSTM framework, employing walk-forward validation to ensure reliable and realistic forecasting. Five key sectors: electronics, finance, transportation, steel, and construction, are studied to assess how uncertainty impacts different industries. Results indicate that EPU indices enhance prediction accuracy, with their effects varying in magnitude. The U.S. EPU yields the most consistent improvements, especially for electronics, steel, and transportation, reflecting Taiwan's reliance on global supply chains and U.S. policies. Taiwan's EPU strongly influences the construction sector, highlighting its domestic focus. The financial industry reacts to both global and local uncertainties, while China's EPU and the U.S.–China Tension Index show less stable effects, leading to episodic signals that decrease accuracy. This research advances the field by shifting the focus from overall stock indices to industry-specific analysis and demonstrating the effectiveness of hybrid PCA-LSTM models for financial forecasting. For investors and policymakers, the findings emphasise sector-specific strategies: closely monitoring U.S. policy uncertainty for export-dependent industries, prioritising domestic signals for construction, and maintaining a balanced approach for finance. The analysis is limited by monthly data and sector-level indices; nevertheless, the findings highlight the importance of integrating policy uncertainty into industry-specific financial forecasting.

1. Introduction

Stocks have emerged as one of the most scrutinised financial instruments in contemporary finance. They not only mirror the performance of individual corporations but are also regarded as indicators of broader economic trends and national prospects. In financial economics, stock markets are often used as early indicators because they quickly respond to changes in economic conditions and investor sentiment. Over time, many researchers have attempted to predict stock prices using various methods, such as technical indicators like Keltner channels, trading volumes, foreign capital flows, or machine learning models trained on historical data. Interest in this area has grown recently, with researchers seeking to use algorithmic learning for more accurate predictions. However, stock prices are influenced by a complex mix of factors, including firm-level fundamentals like financial stability and operational performance, as well as macroeconomic indicators such as interest rates and inflation. In the 21st century, globalisation has added further complexity, affecting a company's performance and financial markets through global supply chains, geopolitical issues, and transnational policy decisions.

As governments increasingly rely on economic policies to manage fiscal, monetary, and external challenges, these decisions greatly influence financial market performance. To effectively capture and quantify this uncertainty, Baker, Bloom, and Davis (2016) developed the Economic Policy Uncertainty (EPU) index, which is now widely recognised in academic research. This index is created by counting the frequency of policy and economic-related words in major newspapers, transforming text into a numerical indicator of policy-related uncertainty. High index values indicate heightened ambiguity about future fiscal, monetary, and regulatory policies, which generally leads to increased market volatility. Conversely, lower index values indicate a more stable policy environment. Empirical studies show that economic policy uncertainty (EPU) in large economies has significant spillover effects on global financial markets, influencing asset prices, investment, and overall global stability. The U.S. and China are the world's two largest economies, and their economic policy uncertainties have a strong impact on the global system. While both countries' EPUs generate spillover effects, the global impact of U.S. policy uncertainty tends to be stronger and more persistent (Zhang et al., 2019). Additionally, recent research indicates that trade tensions between the U.S. and China have had significant impacts on the global economy and finance, disrupting supply chains, reducing trade, and lowering global investment and stock prices (Tam, 2020). This highlights the importance of monitoring both the U.S. and China EPU indices, along with U.S.–China relations, to better predict industry-level stock movements.

In the past several years, machine and deep learning, have become increasingly used for financial forecasting. While the Efficient Market Hypothesis suggests that stock prices reflect all current information and thus cannot be forecasted, many studies demonstrate that stock price movements can be reasonable projected by using the correct variables and models (Liu, 2024). Long Short-Term Memory networks (LSTMs) are also among the many deep learning approaches that have become well-utilised in financial time-series forecasting since they can accurately identify long-term dependencies and complex temporal patterns. Mehtab, Sen, and Dutta (2020), for example, tested variants of LSTM architectures to forecast the NIFTY 50 index and demonstrated that LSTM models can predict trends in the stock market and outperform more than traditional machine-learning methods.

Researchers have increasingly adopted Long Short-Term Memory (LSTM) networks to forecast stock markets based on their proven performance for identifying temporal patterns. Studies have highlighted the ability of LSTMs to learn complex behaviour exhibited in financial markets. Researchers have also advanced LSTM architectures beyond basic prediction where models process external data such as news sentiment and macroeconomic indicators in conjunction with historical price data. For example, Usmani and Shamsi (2023) proposed the WCN-LSTM model, which is an LSTM network incorporating category-specific financial news headlines at the market, sector, and stock level, as well as weighted sentiment factors to achieve enhanced prediction accuracies. The authors provided clear evidence that the improved LSTM model effectively predicted stock market prices by demonstrating improved LSTM learning models creating greater prediction accuracies for short term stock-price forecasting. The literature demonstrates an emerging focus on models that incorporate variables related to economic uncertainty within the broader context of stock prediction using LSTM. Sadorsky (2022) examined the effect of economic policy uncertainty (EPU) on the predictive performance of machine learning algorithms on clean energy stock prices. EPU was not always the most significant predictor variable, but the implied importance provided evidential specificity, which suggested importance ran deeper within a sector specific signal based on industry composition and time window. Altogether, these recent trends in the literature suggested that the inclusion of EPU in LSTM models could improve predictive performance and expand the applicability of deep learning approaches to economic (financial) forecasting.

The Taiwan Stock Exchange (TWSE) is one of the most vibrant and rapidly changing stock exchanges in Asia, where there is plentiful engagement from retail investors and substantial influence from global institutional investors, resulting in a variety of trading behaviours and volatility. The TWSE experienced a series of notable market events happening between 2005 and 2021, including: the 2008 Global Financial Crisis, the European Sovereign Debt Crisis, the U.S.–China Tariff War, and the COVID-19 pandemic; each of which had profound implications for the performance of stock returns and investor decision making processes. Taiwan's export-driven economy and significance within the global semiconductor supply chain leave it open to fluctuations due to geopolitical risks and international policies aimed at financial development; these dimensions make the Taiwanese stock market a primary case study in understanding how uncertainty of monetary policy (EPU) and macroeconomic factors could influence the predictability of stock returns.

This research aims to determine whether incorporating the United States, China, and Taiwan’s Economic Policy Uncertainty (EPU) and the U.S.–China Tension Index into machine learning models improves the prediction of sector-level stock fluctuations in Taiwan, compared to relying solely on traditional macroeconomic variables. Specifically, the study investigates whether policy-related uncertainty influences the predictive accuracy of directional changes in industry-specific stock indices within Taiwan. This research builds on extensive literature emphasising the crucial role of financial development in fostering long-term economic growth. Consequently, analysing the interaction between financial indicators such as the EPU and stock market dynamics can offer valuable insights into market behaviour and enhance forecasting accuracy.

The remainder of this paper is organised as follows: Section 2 reviews relevant literature; Section 3 outlines the methodology; Section 4 details the dataset; Section 5 showcases the empirical results; and Sections 6 and 7 analyse the findings and conclude the study.

2. Literature Review

2.1 The Concept and Measurement of Economic Policy Uncertainty

The concept of Economic Policy Uncertainty (EPU) was formalised by Baker, Bloom, and Davis (2016), who created a new index to measure policy-related uncertainty through measuring the frequency of newspaper articles containing terms such as “economic”, “policy”, and “uncertainty”. The U.S. EPU index, based on ten major newspapers dating back to 1900, is widely used to analyse how uncertainty affects financial markets, investment, and overall macroeconomic stability. It has shown notable shifts during key historical moments such as the September 11 attacks, the 2008 Global Financial Crisis, and debates over the U.S. debt ceiling, illustrating its effectiveness in capturing policy shocks. This method has been adapted for multiple countries, but differences in media freedom and data access pose challenges for cross-country comparison. Although the U.S. EPU index is a standard reference, other countries have developed their own measures, highlighting the importance of examining international differences and their spillover impacts.

2.2 Cross-country Evidence of EPU Spillovers

While the U.S. EPU index has considerable global influence, other countries have also developed their own measures. The China EPU index, primarily derived from two mainland newspapers, the *Renmin Daily* and the *Guangming Daily* (Davis, Liu, & Sheng, 2019), provides some insights into China's policy uncertainty, but it has limitations regarding its representativeness. Empirical data indicate that China's EPU increases during events such as leadership changes, monetary reforms, and the U.S.–China trade war; however, its international spillover effects remain relatively limited (Huang, Yeh, & Chen, 2021). In comparison, Taiwan's EPU index was developed locally using four major Chinese-language newspapers and a topic modelling approach to enhance classification accuracy (Huang et al., 2021). Taiwan's index responds strongly to domestic political and social events, such as presidential impeachments, the 2008 Global Financial Crisis, and the 2014 Sunflower Movement. Empirical findings suggest that the U.S. and Japan's EPU indices exert more significant spillover effects on Taiwan's economy than China's, highlighting Taiwan's closer links to developed markets (Huang et al., 2021). Having established the international scope of EPU, the next step is to investigate how such uncertainty influences financial markets, where volatility and risk transmission are most apparent.

2.3 The Impact of EPU on Financial Markets

An increasing body of scholarly literature emphasises the forecasting significance of Economic Policy Uncertainty (EPU) in financial markets. In the United States, Brogaard and Detzel (2014) show that higher EPU values are associated with lower market returns, but they also significantly predict higher future excess returns, consistent with elevated risk premia under increased uncertainty. Xu et al. (2021) show that China's EPU has significant predictive power for A-share returns, particularly prior to major events such as the Global Financial Crisis and COVID-19 pandemic, although its effectiveness weakens during these crises. Therefore, this literature indicates that EPU is a powerful predictor of stock market volatility, which outperforming traditional macroeconomic indicators. Beyond its predictive power, EPU also significantly impacts financial markets by influencing risk premia, increasing volatility, and changing investment behaviours.

Akber et al. (2023) observed that systematic risk tends to increase with policy uncertainty at the industry level, however, this transmission effect differs by industry in terms of the degree to which uncertainty shapes risk. Other studies support this transmission effect: Sin (2015) showed that the economic policy uncertainty of China has significant effects on Taiwan's economy, including lowering the interest rates, appreciation of the real exchange rate, and decreased output. Similarly, Yung (2025) finds that U.S. Economic Policy Uncertainty (EPU) negatively impacts on the Taiwan Stock Exchange, especially during bearish periods, with short-term effects being more significant than long-term ones. These results suggest that the EPU is not only a valuable indicator for predicting financial market trends but also has varying effects across countries, industries, and time horizons. This has further encouraged researchers to explore the use of the EPU alongside other methods, such as machine learning models, to better understand and predict complex financial dynamics.

2.4 Machine Learning in Stock Market Forecasting

Recent academic research emphasises the ability of machine learning for more precise forecasting in finance beyond the standard measures (particularly econometric approaches to stock forecasts). Prominent models, such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), Random Forests, and Naïve Bayes, have been commonly developed and used for stock index prediction (Huang & Liu, 2019; Patel et al., 2015). For example, numerous projects involving emerging markets, such as studies in Taiwan and India have shown the efficiency of machine modelling techniques, particularly by converting technical indicators into binary predictions for trend forecasting. The studies demonstrated the significance of feature representation and input transformations in improving predictive accuracy. They illustrated that machine learning models present accurate classification alternatives to traditional statistical modelling approaches, at least through varying levels of augmentation and transformation. Although traditional modelling methods reduce the difficulty of prediction, their reliance on feature engineering may limit their potential, whereby deep learning architectures can help address this limitation, such as Long Short-Term Memory (LSTM), meriting further investigation.

2.5 Advances in Deep Learning: The Role of Long Short-Term Memory

Therefore, deep learning models, especially Long Short-Term Memory (LSTM) networks, have demonstrated greater effectiveness in predicting financial time-series data. Unlike traditional machine learning techniques that heavily depend on feature engineering, LSTM models can capture long-term dependencies and complex temporal patterns in sequence data. Research has shown that LSTM-based models outperform traditional methods in forecasting stock price movements, and they remain effective even when adding diverse data such as macroeconomic indicators and news sentiment (Mehtab et al., 2020; Usmani & Shamsi, 2023). Furthermore, Gu et al. (2024) used FinBERT to combine LSTM with sentiment features from financial news, demonstrating that this hybrid approach notably increased predictive accuracy compared to traditional techniques. Despite the significant potential of LSTM for financial forecasting and its ability to incorporate sentiment features, most applications of EPU and LSTM have been limited to national stock indices. Broad market indices encompass a wide range of industries, and different industries react differently to political and economic uncertainty. Therefore, accounting for industry differences is crucial to better understanding how policy uncertainty affects various sectors.

2.6 Research Gap: From National Indices to Sectoral Perspectives

While existing studies confirm that EPU can predict national stock indices, there is limited research examining its effects at the sector level. Most prior research focuses on the overall market performance of countries like the United States or China, without differentiating between industries. This is a major gap, as different sectors such as electronics, finance, or construction may respond very differently to policy shocks and uncertainty. Additionally, most studies have looked at how U.S. and China EPUs influence their own stock markets, with relatively little attention to Taiwan. This is important because Taiwan plays a critical role between the world's two largest economies. Located amid U.S.–China economic and geopolitical tensions, Taiwan faces direct policy impacts and acts as a pathway for external uncertainties to affect regional and global markets.

In the case of Taiwan, this disparity is particularly pronounced. Taiwan holds a strategic position in the global economy, particularly within the semiconductor supply chain, making its industries highly susceptible to both domestic policies and external shocks from the United States and China. Although empirical evidence indicates that U.S. economic policy uncertainty (EPU) has significant spillover effects on Taiwan’s stock market (Huang, Yeh, & Chen, 2021), research has not thoroughly examined whether such effects remain consistent across industries. Moreover, studies suggest that China’s EPU has limited spillover effects on Taiwan’s market; however, given the close trade and production linkages between Taiwan and China, this may conceal vulnerabilities at the sectoral level. Additionally, the complex U.S.–China relationship, marked by trade conflicts, technological competition, and geopolitical tensions, exerts substantial indirect pressures on Taiwan's industries, increasing their policy uncertainty exposure. To fill this gap, this study examines how EPU indices for the U.S., China, and Taiwan, along with the U.S.–China Tension Index, predict Taiwan's sectoral stock movements, offering a more detailed view than existing research.

2.7 Importance of Selected Industries and Variables

Selecting industries is equally vital when examining Taiwan's equity market, given their distinct roles in economic development and sensitivity to policy changes. To begin with, the electronics sector is the core of Taiwan's economy, contributing the largest portion of GDP and exports, and playing a key role in global supply chains through semiconductors and ICT products (Fu et al., 2021; MOEA, 2024; Reinsch & Whitney, 2025; Nature Electronics, 2021). The financial sector is acknowledged as a main supporter of economic growth by mobilising savings, diversifying risks, and directing investments across industries (Levine, 2004; Adnan, n.d.). Meanwhile, transportation enables Taiwan to enhance international trade and is highly responsive to macroeconomic and policy changes, with Kaohsiung Port serving as a logistics hub for regional flows (Helling, 1997; Lin, 2016; Hsieh, 2001). Similarly, steel, a fundamental industry, has a large multiplier effect due to its extensive global supply chain and remains essential for infrastructure and manufacturing (Oxford Economics, 2019). Lastly, construction is regarded as a "locomotive industry", strongly linked to fiscal policy, infrastructure development, and business cycles. It is particularly influenced by government investment and policy in Taiwan (Finkel, 1997; Lin, 2017).

Beyond industry-specific dynamics, previous research consistently highlights the importance of macroeconomic fundamentals and financial indicators in shaping stock market behaviour. For example, oil prices have acted as financial assets, transmitting global shocks to equity markets through changes in demand, risk appetite, and capital flow patterns (Fratzscher, Schneider, & Van Robays, 2014). Critical variables such as exchange rates, money supply, and inflation are also impactful: Khan and Billah (2022) identify long-term cointegrating relationships among exchange rate fluctuations, money supply (M2), and the consumer price index (CPI) in emerging markets, which influence stock market returns, while Dalal (2013) finds that inflation and exchange rate volatility significantly affect stock returns in Asian economies. Interest rate policies also have immediate effects on asset valuation, as Chen, Mohan, and Steiner (1999) show that unexpected interest rate changes influence returns, volatility, and trading volume. Beyond these economic fundamentals, volatility and technical indicators also provide predictive value. Smales (2022) emphasises the CBOE Volatility Index (VIX) as a forward-looking measure of global risk sentiment, with U.S. volatility shocks impacting international equity markets. Meanwhile, Huang and Liu (2019) demonstrate that including technical indicators like moving averages, RSI, and MACD in machine learning models greatly enhances their predictive accuracy. These insights collectively justify the inclusion of both macroeconomic variables (e.g., oil prices, exchange rates, and interest rates) and market-based or technical indicators (e.g., VIX and moving averages) as explanatory variables in this study.

2.8 Aims and Objectives

This research aims to fill gaps by investigating whether including EPU indices from the U.S., China, and Taiwan, along with the U.S.–China Tension Index, enhances predictions of sector-specific stock indices in Taiwan. While earlier studies mostly focused on macroeconomic fundamentals and global risk sentiment shaping Taiwan's equity market, this study emphasises sector-specific dynamics by analysing five industries: electronics, finance, transportation, steel, and construction. It also factors in various macroeconomic and technical control variables. Using LSTM models with binary directional classification, the study evaluates whether policy-related uncertainty provides additional predictive value at the industry level, thus expanding prior research that mainly considered overall markets and offering new insights into the differential impact of EPU on Taiwan's stock market.

3. Methodology

The research incorporates a quantitative forecasting framework that takes into account machine learning (LSTM) techniques and variables of policy uncertainty, macroeconomic data, and technical indicators. The purpose of the study was to find out whether the Taiwan economic sectoral stock indices could be better predicted by integrating the Economic Policy Uncertainty indices for the U.S., China, or Taiwan, as well as for the U.S.–China Tension Index. A four-step approach is used: (1) collect and pre-process the data, (2) assess the suitability of the data for dimensionality reduction using the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's test, (3) extract features using Principal Component Analysis (PCA) and (4) build the model using Long Short-Term Memory (LSTM) networks and evaluate the model using classification metrics of accuracy, precision, recall and F1-score.

The use of KMO and Bartlett tests is common in econometrics to verify the suitability of variables for factor extraction before conducting principal component analysis. PCA then reduces multicollinearity among variables and will condense high-dimensional macroeconomic and technical data into a smaller set of orthogonal principal components, improving model stability (Chan et al., 2022). In addition, LSTM networks are considered one of the most effective methods for modelling nonlinear relationships and capturing long-term dependencies in financial time series. Studies indicate that LSTMs outperform traditional machine learning methods in capturing complex stock price movements (Zhang, 2022; Tran et al., 2024).

Recent studies indicate that integrating Principal Component Analysis (PCA) with Long Short-Term Memory (LSTM) networks can improve predictive performance by reducing multicollinearity, compressing redundant information, and providing uncorrelated principal components as enriched inputs. Wen et al. (2020) found that using PCA with LSTM for stock price prediction outperforms other models, such as Convolutional Neural Networks (CNN) and Multilayer Perceptrons (MLP), as demonstrated by lower Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) values. Zhang (2022) similarly reported that PCA-LSTM models not only improve prediction accuracy but also shorten training time and increase stability by focusing on the most relevant features. Researching thus far forms the basis for utilising a PCA-LSTM model in this study to ensure the LSTM network can learn from the most relevant and orthogonal features that will comprise the financial data in the models to reduce noise and overfitting. The following sections explain the theoretical basis and practical application of each method, including KMO, Bartlett's test, PCA, and LSTM models, to create a clear framework for the empirical analysis.

3.1 Kaiser-Meyer-Olkin and Principal Component Analysis

Before performing principal component analysis (PCA), it is important to assess whether the dataset is suitable for dimensionality reduction. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was created by Kaiser and Rice (1974), which is commonly used for this purpose (as shown in Eq.(3.1)). The KMO statistic is interpreted dependently on shared variance between variables when comparing simple correlations against partial correlations. When partial correlations are small relative to simple correlations, the KMO value approaches 1.0, indicating that variables share common factors and are appropriate for factor analysis. On the contrary, if KMO values are low, then most correlation extracts would be minimal which indicates the data would be impractical for factor extraction. Typically, KMO values above 0.60 are considered acceptable, while those below 0.50 suggest that the data is not suitable for further factor analysis. These tests are essential prerequisites to ensure factor extractions are valid in this study. Additionally, Bartlett's test of sphericity checks whether the correlation matrix is significantly different from an identity matrix, which would imply uncorrelated variables (as shown in Eq.(3.2)). A significant result ($p < 0.05$) indicates that enough correlations exist among the variables to consider for factor analysis (Bartlett, 1954). These tests confirm that data is applicable for testing valid factor extraction and subsequent further testing.

Equation (3.1). Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy.

$$\mathrm{KMO} = \frac{\sum_{i<j} \gamma_{ij}^2}{\sum_{i<j} \gamma_{ij}^2 + \sum_{i<j} \mathrm{P}_{ij}^2}$$

Equation (3.2). Bartlett's test of sphericity for correlation matrix R.

$$\mathcal{X}^2 \approx -(n - 1 - \frac{2p+5}{6}) \ln|R|, \quad df = \frac{p(p-1)}{2}$$

Notes (Eq.3.2): n = sample size; p = number of variables; R = Pearson correlation matrix; r_{ij} = pairwise correlations; P_{ij} = partial correlations. As a rule of thumb, KMO ≥ 0.60 is acceptable; a significant Bartlett test ($p < 0.05$) rejects the null that R is an identity matrix, indicating the data are suitable for factor analysis.

Principal Component Analysis (PCA) is a statistical technique that reduces the dimensionality of a dataset while retaining most of its variance. It does so by transforming the original correlated variables into fewer, uncorrelated principal components, which makes data representation and analysis more efficient (Mackiewicz & Ratajczak, 1993). The first component captures the maximum variance, and each subsequent component explains decreasing amounts of the remaining variance; all components are orthogonal. PCA is based on eigenvalue decomposition of the covariance or correlation matrix, where eigenvalues indicate the variance explained by each component, and eigenvectors define the linear combinations of the original variables. We standardise all predictors to zero mean and unit variance and perform PCA on the correlation matrix R. This avoids scale effects across variables with different units. Practically, the proportion of total variance explained by the top components determines which are retained, often based on a threshold. In this study, PCA is used to eliminate redundancy among explanatory variables and to identify a smaller set of uncorrelated components for modelling, thereby reducing multicollinearity and highlighting key data patterns for more concise and reliable analysis (Mackiewicz & Ratajczak, 1993).

Equation (3.3). Eigenvalue problem underlying PCA.

$$R\boldsymbol{w}_k = \lambda_k \boldsymbol{w}_k$$

Equation (3.4). Explained variance ratio (EVR) of component k.

$$EVR_k = \frac{\lambda_k}{(\sum_{j=1}^{p} \lambda_j)}$$

Notes (Eq.3.4): Retain the top three PCs such that cumulative EVR ≥80%. We therefore retain the first three PCs across sectors (cf. Section 4.4).

This study uses the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's test of sphericity to assess whether the data are appropriate for factor analysis, followed by Principal Component Analysis (PCA) to reduce dimensions. These techniques are well-established within finance. For example, Yang and Hasuike (2017) applied KMO, Bartlett's test, and PCA to develop an investor sentiment index in China's stock market, demonstrating its strong correlation with stock returns. Similarly, Kumar (2013) applied KMO and PCA to identify macroeconomic factors influencing the Indian stock market, highlighting the significance of macroeconomic and industrial factors. Recent literature also notes that Hu and Wang (2023) used KMO, Bartlett's test, and PCA to condense multiple U.S. stock indicators into three primary factors, demonstrating that this analysis supports stock classification and investment decisions. Many studies have adopted this approach to analyse financial ratios and their effects on stock performance, confirming the effectiveness of these methods in finance. These examples across China, India, and the U.S. collectively confirm that combining KMO, Bartlett's test, and PCA is a standard, reliable method in financial research.

3.2 Long Short-Term Memory

Long Short-Term Memory (LSTM) networks are a specific subset of recurrent neural networks (RNNs) developed by Hochreiter and Schmidhuber in 1997 to address the vanishing and exploding gradient problem traditionally associated with standard RNNs while processing long sequences. Unlike traditional RNNs, LSTMs include a memory cell and three gates: forget, input, and output, which regulate the flow of information. The memory cell preserves relevant information over long durations, while the gates decide what information to keep, update, or discard at each step. This architecture allows LSTMs to learn both short-term patterns and long-term dependencies in sequential data effectively.

LSTMs are extensively used across diverse domains such as natural language processing, speech recognition, and time series prediction. In finance, they are particularly adept at predicting stock and market trends because they can model complex nonlinear patterns and handle noisy data better than traditional econometric models such as ARIMA and GARCH

(Ghosh et al., 2022; Ross, 2023). The key advantages of LSTMs include their capacity to retain long-term dependencies, reduce the vanishing gradient problem, and adapt to different sequential prediction tasks. Consequently, LSTMs have become a preferred approach in financial forecasting, producing more reliable and accurate forecasts than traditional techniques (Hochreiter & Schmidhuber, 1997).

The use of Long Short-Term Memory (LSTM) models for stock market prediction is widely supported by academic research. For instance, Zhang (2022) compared LSTM's short-term forecasting ability with traditional methods like ARIMA and XGBoost, finding that while LSTM may not always excel in very short-term forecasts, it effectively captures long-term trends and seasonal patterns. Similarly, Tran et al. (2024) applied LSTM with technical indicators (SMA, MACD, RSI) in the Vietnamese stock market, achieving over 93% accuracy, demonstrating the suitability of LSTMs for emerging markets. Nelson, Pereira, and de Oliveira (2017) showed that LSTM outperforms classical machine learning models such as Random Forest and Support Vector Machine (SVM) in predicting stock price movements. This superior performance stems from their ability to model complex nonlinear relationships. More recent research has incorporated LSTM forecasts into portfolio backtesting frameworks, revealing that LSTM signals can improve investment outcomes and risk-adjusted returns, like higher Sharpe ratios, compared to baseline strategies (Ross, 2023). These findings confirm the robustness and practical use of LSTM in stock market forecasting.

While some literature has shown the usefulness of Long Short-Term Memory (LSTM) networks, some studies have further improved their performance by combining them with dimensionality reduction techniques such as principal component analysis (PCA). Therefore, to further enhance model performance, this study explores the combination of principal component analysis (PCA) and long short-term memory (LSTM) networks. Previous research has shown that PCA can reduce redundant data and streamline inputs, and that its combination with LSTM can effectively improve stock forecasting. For example, Zhang (2022) used a PCA-LSTM model with technical indicators like KDJ and MACD, noting that this approach lowered prediction errors, reduced training time, and enhanced model stability. Similarly, Wen, Lin, and Nie (2020) used PCA-LSTM to forecast Ping An Bank’s stock prices, achieving lower RMSE and MAPE than CNN and MLP models. These results demonstrate that PCA-LSTM is an effective hybrid method that combines PCA's dimensionality reduction with LSTM's capacity to model temporal sequences, making it particularly suitable for financial forecasting.

This study also uses a walk-forward validation method to assess the predictive performance of the proposed model. Unlike traditional hold-out validation, which disrupts or ignores the temporal order of the data, causing the model to use future information to predict the past during training, resulting in unrealistic results and potentially ignoring temporal dependencies. Conversely, the walk-forward validation method gradually increases the training set at each new time point and then tests it in the next period, ensuring that the model uses only currently observable data to predict the future. This method closely resembles actual financial forecasting. Recent studies have shown that walk-forward validation generally outperforms other methods in terms of stock market prediction accuracy. For example, Wahyuddin et al. (2025) applied an improved LSTM model with hyperparameter tuning and sentiment indicators on Indonesian stock data. Their 10-fold walk-forward validation demonstrated that this method reduced prediction errors significantly, lowering RMSE by nearly 40% compared to models without walk-forward validation, and yielded more dependable results in real trading conditions.

Based on the aforementioned literature, this study incorporates walk-forward validation into its experimental framework. After confirming data suitability through KMO and Bartlett's tests, performing variable dimensionality reduction through principal component analysis (PCA), and implementing a long short-term memory (LSTM) forecasting model, a walk-forward procedure was employed for evaluation. This approach ensures that the predictive outcomes are both methodologically robust and practically relevant for financial forecasting. Moreover, although the LSTM framework remains consistent across all models, hyperparameters are adjusted for each industry to address variations in data volatility and industry traits, which helps optimise model performance.

3.3 Model Parameter Design across Industries

The performance of models used for stock price forecasting is highly sensitive to hyperparameter settings. Previous studies have demonstrated that parameter optimisation, including adjusting sequence length, batch size, and loss function settings, can notably improve the accuracy of LSTM models for stock prediction (Wang, 2020). Consequently, the LSTM models were tuned according to each industry's characteristics, and optimised hyperparameters were chosen for the final analysis. While the core approach, sequence creation, walk-forward validation, and binary classification stayed the same, the time-step windows and some learning parameters were customised to enhance prediction accuracy per sector. For example, the electronics sector used a sequence length of 20, reflecting higher trading activity and short-term volatility typical of technology stocks. The financial industry employed a longer sequence of 24, aligning with its sensitivity to monetary cycles and policy delays. The transportation and steel sectors employed sequence lengths of 24 and 30, respectively, to capture medium-term trends linked to global trade and commodity cycles. The construction sector also adopted a 24-timestep model to account for gradual responses to domestic policy shifts and fiscal investments. All models across industries used 32 hidden LSTM units, a batch size of 32, and were trained over 100 epochs. The Adam optimiser, with a learning rate of 0.001, helped ensure stable convergence, while dropout regularisation helped prevent overfitting. Hyperparameters were selected by minimising validation loss through five-fold walk-forward validation, ensuring robustness across different temporal dataset segments. This sector-specific tuning allowed the models to better capture industry-specific features while maintaining comparability.

3.4 Experimental Framework

Therefore, this study employs a structured experimental framework to evaluate the predictive power of uncertainty indices and macroeconomic factors on stock trends in specific industries. Initially, data sufficiency is determined using the Kaiser-Meyer-Olkin (KMO) measure and Bartlett’s test of sphericity. The Principal Component Analysis (PCA) technique was used to derive the uncorrelated components from macroeconomic variables and technical indicators, and lower their dimensionality, and eliminate multicollinearity. These uncorrelated components are then input into a long short-term memory (LSTM) neural network since this architecture more effectively models financial time series data by concurrently capturing both short- and long-term dependencies. This is a hybrid PCA-LSTM model developed to combine the PCA's ability to reduce dimensions with the long- and short-term sequential learning objectives of the LSTM, resulting in higher model accuracy. The analysis undertakes 2 phases: 1) a baseline model that only uses macroeconomic and technical indicators, and 2) each of the models adding the EPU index and the U.S.–China Tension Index. We assessed models using an order-preserving sliding-window walk-forward approach. In each iteration, the model trained on a continuous block of past data and was tested on the next segment, which accounted for 20% of the total sample. The window moved forward, and the cycle continued, allowing for model updates with new inputs and generating out-of-sample forecasts that better mimic real-world deployment. All comparisons among models followed this walk-forward method. Performance was summarised through averages of accuracy, precision, recall, and F1-score across folds.

The goal was to generate statistically robust and practically useful evidence for financial forecasting.

4. Data Sources and Preprocessing

4.1 Data Sources and Collection

The data utilised in this study were a complete monthly dataset from May 2005 through June 2021, obtained from various public resources and reputable, commercially available databases. The data contained sectoral stock indices for Taiwan with Economic Policy Uncertainty (EPU) indices for the United States, China, and Taiwan. It also includes the U.S.–China Tension Index, alongside a set of macroeconomic and financial market variables. All series were standardised to a monthly frequency and synchronised to the month-end to ensure temporal consistency across variables. Data validation confirmed the absence of missing values, thus obviating the necessity for imputation procedures.

The monthly closing prices of Taiwan's sector-specific stock indices were obtained from Investing.com and cross-verified with Yahoo Finance. Logarithmic returns were calculated using the formula $ln(\frac{P_t}{P_{t-1}})$ in Microsoft Excel, where P_t denotes the closing price at time t. Based on these returns, binary classification labels were assigned (1 = upward, 0 = downward). Additionally, two moving average indicators (MA5 and MA20) were computed in Excel as the simple averages of the past 5 and 20 monthly prices, capturing short- and medium-term price trends. To capture the impact of policy uncertainty, the Economic Policy Uncertainty (EPU) indices were obtained from the official Policy Uncertainty database (policyuncertainty.com). The U.S. index was originally developed by Baker, Bloom, and Davis (2016), the China index by Davis, Liu, and Sheng (2019), and the U.S.–China Tension Index by Rogers, Sun, and Sun (2024). Furthermore, the Taiwan EPU index was sourced from the academic study "Measuring Economic Policy Uncertainty in Taiwan", published in the Taiwan Economic Review (TER 49-2) by Huang (2021). Macroeconomic variables consist of the USD/TWD exchange rate, Brent crude oil price (POILBREUSDM), and the Volatility Index (VIX), all obtained from Investing.com. Additional data on the discount rate and M2 money supply were sourced from the Central Bank of the Republic of China (Taiwan). The Consumer Price Index (CPI) was retrieved from the Directorate-General of Budget, Accounting and Statistics (DGBAS), Executive Yuan, Taiwan. All macroeconomic series were converted to a monthly frequency and synchronised to the end of each month for consistency.

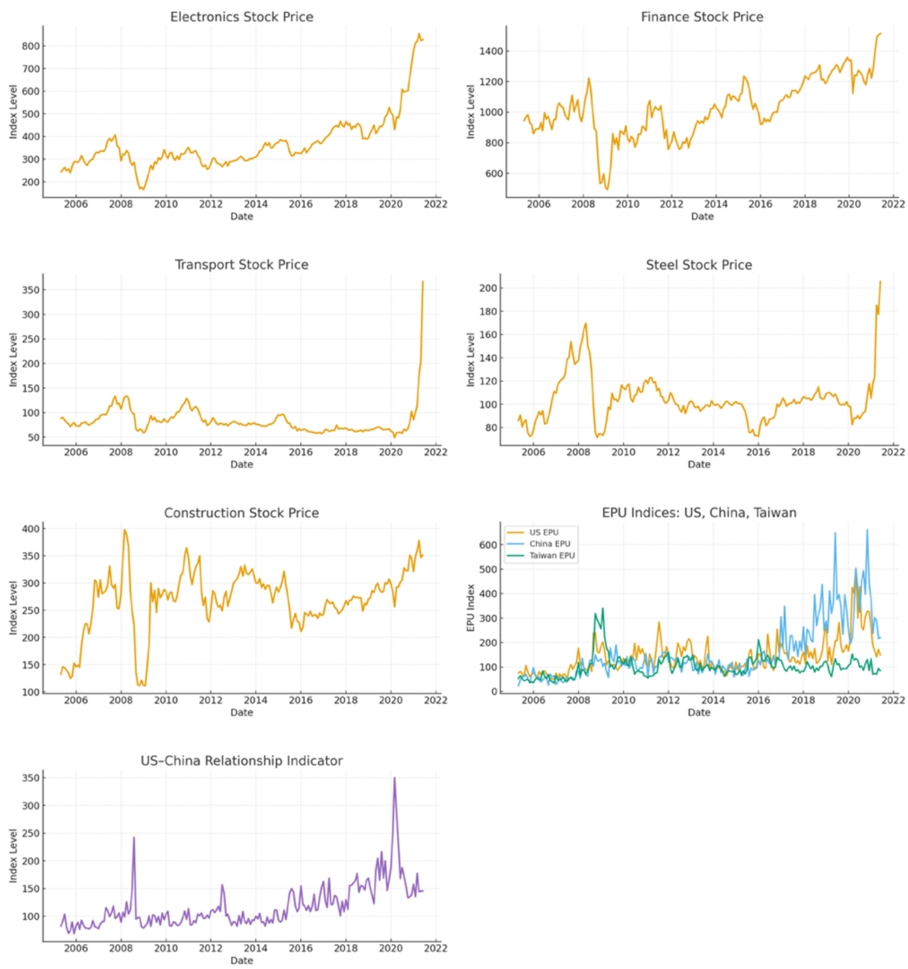
4.2 Descriptive Statistics of Sectoral and Macroeconomic Variables

Table A1.1 (Appendix 1) presents the descriptive statistics for the sectoral stock indices, as well as the uncertainty and macroeconomic variables. Meanwhile, Figure 1 provides a visual summary of the historical price trends for the five sectors: electronics, finance, transportation, steel, and construction, along with the EPU indices for the U.S., China, and Taiwan, as well as the U.S.–China Tension Index. The electronics sector, recognised as Taiwan's largest export-oriented industry, has an average index level of 365.07 and a mean monthly log return of 0.007, with a standard deviation of 0.058. This suggests moderate fluctuations, indicative of its international exposure and sensitivity to global market conditions. The corresponding 5-month moving average and 20-month averages are closely aligned, indicating relatively stable short- and medium-term price dynamics during the sample period. Conversely, the finance sector exhibits a slightly lower average return but similar volatility, while the transportation sector demonstrates the highest variability in returns, aligning with its reliance on oil prices and global trade. The steel and construction sectors also experience notable fluctuations, with their return ranges and standard deviations indicating that they are not significantly more stable than the electronics and transportation sectors. Moreover, Figure 1 further highlights sector-specific dynamics during significant events. In the post-pandemic period, transportation stocks recorded the largest upward surge, with steel stocks showing a comparable rally. By contrast, during the Global Financial Crisis, the construction sector experienced the sharpest decline, followed by the steel industry, reflecting their sensitivity to macroeconomic downturns and market conditions. Therefore, the descriptive statistics highlight the diversity across industries, with transportation and electronics displaying marked volatility, whereas steel and construction remain moderately volatile rather than noticeably stable, underscoring the importance of uncertainty indicators in explaining sector-specific dynamics. Among the uncertainty indicators, the China EPU exhibits the greatest dispersion, with values ranging from 23.7 to 661.8, while the Taiwan EPU demonstrates greater stability with a narrower range. The U.S.–China Tension Index also fluctuates significantly, reflecting the influence of geopolitical events within the sample period. Additionally, the policy uncertainty indices reveal broadly synchronous movements (see Figure 1). The U.S., China, and Taiwan EPU indices, together with the U.S.–China Tension Index, generally rise and fall in tandem, reflecting the transmission of global shocks and bilateral frictions. Nonetheless, Taiwan's EPU is comparatively more stable, exhibiting narrower fluctuations relative to its U.S. and Chinese counterparts.

Table A1.2 (Appendix 1) also shows that the macroeconomic variables exhibit distinct patterns.

The exchange rate (USD/TWD) remains relatively stable around its long-term mean, though it exhibits cyclical fluctuations. Oil prices, by contrast, show pronounced volatility, ranging from USD 26 to 133, in line with global commodity shocks and crises. The money supply (M2) demonstrates a steady upward trend with comparatively smooth variation, consistent with its role as a slow-moving monetary aggregate. The discount rate fluctuates within a narrow numerical range (1.1~3.6), yet such changes exert disproportionate effects on financial conditions. The CPI index displays the slightest variation, reflecting the gradual evolution of price levels. When used in conjunction with technical indicators such as MA5 and MA20, which are closely tied to stock prices, these variables can lead to significant multicollinearity in the models. These patterns suggest that while macroeconomic and technical indicators capture important cost and monetary dynamics, their high degree of correlation raises concerns about multicollinearity. This necessitates the use of dimensionality reduction techniques, such as PCA, before developing the predictive models.

Figure 1: Historical Trends of Sectoral Stock Indices and Global Uncertainty Indicators (2005-2021)



Notes: The figure illustrates the historical movements of five sectoral stock indices (electronics, finance, transportation, steel, and construction), the Economic Policy Uncertainty (EPU) indices for the U.S., China, and Taiwan, and the U.S.–China Tension Index. Sectoral stock price data are obtained from Investing.com, while the EPU indices are sourced from policyuncertainty.com (Baker, Bloom and Davis, 2016; Davis, Liu and Sheng, 2019; Huang, Yeh and Chen, 2021). The U.S.–China Tension Index is taken from Rogers, Sun and Sun (2024).

4.3 Correlation Analysis of Sectoral Indices and Drivers

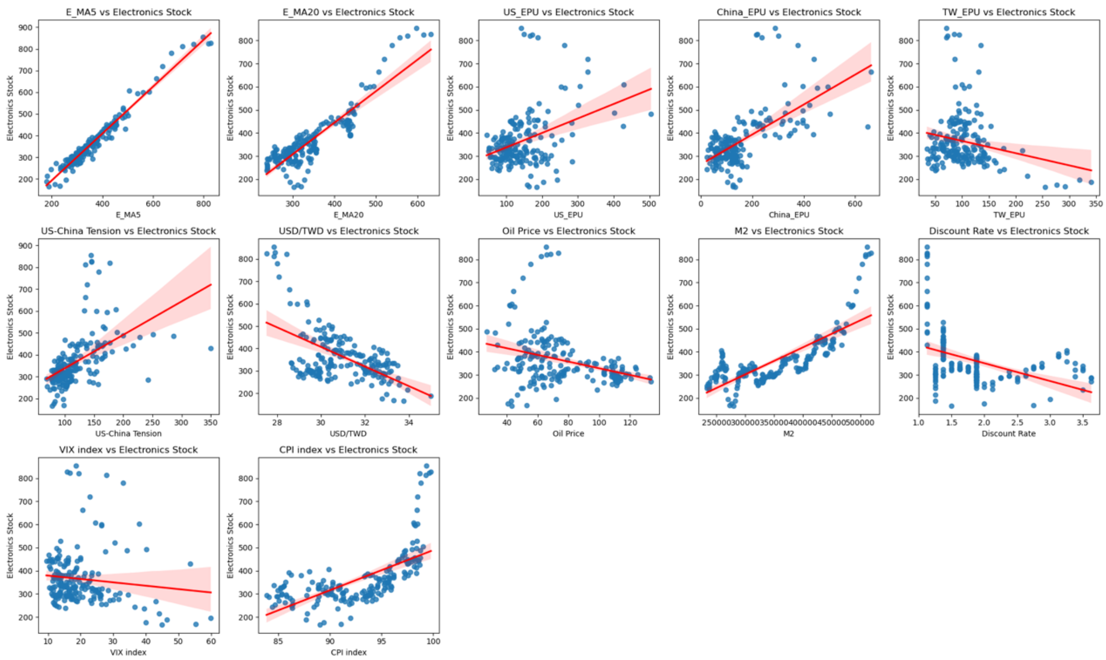
The correlation analysis (Table 1) for the electronics sector indicates strong and significant links between stock prices and their moving averages (MA5 = 0.98; MA20 = 0.89), which aligns with their calculations. Among policy uncertainty indicators, electronics show a notably high correlation with the China EPU (0.63) and a moderate positive link with the U.S.–China Tension Index (0.51), while the Taiwan EPU has a weak, negative correlation (–0.21). Additionally, macroeconomic factors like M2 (0.78) and CPI (0.64) are positively associated with electronics, whereas the exchange rate (–0.55) and discount rate (–0.41) are negatively correlated. These results align with the scatterplots (Figure 2), where upward trends are observed for M2 and CPI, whereas USD/TWD and the discount rate exhibit clear negative slopes.

Table 1: Pearson Correlation of Electronics Sector Index

	E_MA5	*E_MA20*	*US_EPU*	*China_EPU*	*TW_EPU*	*U.S.–China Tension*
Electronics Stock	*0.980*	*0.892*	*0.378*	*0.631*	*-0.206*	*0.513*
P-Value	*<0.0001*	*<0.0001*	*<0.0001*	*<0.0001*	*0.0039*	*<0.0001*
	USD/TWD	*Oil Price*	*M2*	*Discount Rate*	*VIX Index*	*CPI Index*
Electronics Stock	*-0.550*	*-0.307*	*0.776*	*-0.410*	*-0.108*	*0.641*
P-Value	*<0.0001*	*<0.0001*	*<0.0001*	*<0.0001*	*0.1333*	*<0.0001*

Notes: The table presents Pearson correlation coefficients for the electronics sector index and its explanatory variables. P-values are displayed in the second row; correlations are statistically significant at the 1% level unless otherwise noted.

Figure 2: Scatter Plot of Electronics Sector Index



Notes: Scatter plots with fitted regression lines illustrate the relationships between the electronics sector index and explanatory variables. Strong positive correlations are observed with MA5, MA20, M2, and CPI, while negative correlations appear with USD/TWD, discount rate, and Taiwan EPU.

Although this analysis focuses solely on the electronics sector here, the same analyses were carried out for other sectors (see Appendix 2). The finance sector generally shows similar correlations but with some notable differences. While finance stocks also have strong links with the China EPU (0.56) and the U.S.–China Tension Index (0.55), they are more negatively correlated with Taiwan EPU (–0.42) compared to electronics. Moreover, finance stocks are slightly more sensitive to VIX movements (–0.37), indicating a stronger connection to global financial volatility. Conversely, the transportation sector exhibits weaker and less consistent correlations with uncertainty measures. Both the U.S. and China EPU have small negative relationships (–0.17), with only Taiwan EPU demonstrating a moderate negative correlation (–0.27). Instead, transportation stocks are more closely associated with oil prices (0.25) and discount rates (0.22), as indicated by the scatter plots in Figure A2.2 (Appendix 2), which feature slightly positive slopes. These differences imply that the electronics and finance sectors are more closely linked to international uncertainty indices, whereas the transportation sector appears more influenced by macroeconomic factors such as costs. The steel sector displays limited sensitivity to uncertainty indices, with Taiwan's EPU being the only significant negative factor; oil prices, interest rates, and exchange rates are more prominent drivers. The construction sector has moderate exposure to international uncertainty measures but relies heavily on the exchange rate and shows positive correlations with oil prices, M2, and the CPI.

Primarily, the electronics and finance sectors are more affected by international policy uncertainty, particularly China's EPU and U.S.–China tensions. The transportation and steel sectors exhibit weaker connections to uncertainty indices but are more closely linked to cost indicators, such as oil prices and interest rates. Construction has a middle ground, with moderate sensitivity to uncertainty measures and significant responsiveness to exchange rate fluctuations. These heterogeneous relationships imply that linear models may be insufficient to fully capture the interactions among uncertainty indices, macroeconomic variables, and stock prices. Hence, advanced methods such as LSTM are employed to model potential nonlinear dependencies and dynamic effects

4.4 Data Suitability and Dimensionality Reduction

To evaluate whether the dataset is suitable for dimensionality reduction, both the Kaiser-Meyer-Olkin (KMO) test and Bartlett's test of sphericity were conducted across all five industries. The findings show KMO values between 0.65 and 0.78, all above the typical threshold of 0.60, confirming sampling adequacy. Additionally, Bartlett's test results are highly significant (χ^2 above 2,500 with $p < 0.001$ for each sector), rejecting the null hypothesis of an identity matrix. These results suggest that the datasets' correlation structures are appropriate for factor analysis and principal component analysis (PCA).

Principal Component Analysis (PCA) was used to reduce dimensions and address multicollinearity among the explanatory variables across five industries. In the electronics sector, the first three principal components (PC1-PC3) together account for 82.94% of the total variance, confirming that most of the original data's information is preserved (see Table 2). PC1 is heavily influenced by macroeconomic factors such as M2, CPI, and moving averages (MA5 and MA20). PC2 is mainly affected by the exchange rate and oil prices, while PC3 reflects the impact of the VIX index. This pattern indicates that electronics stocks are driven by monetary measures, cost factors, and global financial volatility.

Table 2: The Principal Component Analysis Results of Electronics Stock Variables

	PC1	*PC2*	*PC3*	*PC4*	*PC5*
E_MA5	*0.421*	*-0.013*	*0.037*	*0.448*	*0.408*
E_MA20	*0.440*	*0.045*	*0.156*	*0.382*	*-0.022*

USD/TWD	*-0.308*	*0.556*	*-0.143*	*0.145*	*-0.416*
Oil Price	*-0.137*	*-0.733*	*0.251*	*-0.147*	*-0.182*
M2	*0.469*	*0.048*	*-0.068*	*-0.062*	*-0.296*
Discount Rate	*-0.317*	*-0.213*	*0.155*	*0.748*	*-0.346*
VIX Index	*-0.019*	*0.317*	*0.928*	*-0.148*	*0.015*
CPI Index	*0.441*	*-0.061*	*0.010*	*-0.156*	*-0.648*
Cumulative Variance	*48.76%*	*69.71%*	*82.94%*	*94.82%*	*97.48%*

Notes: The table reports the factor loadings of explanatory variables on the principal components (PC1–PC5) for the electronics sector. Higher absolute values indicate stronger contributions of each variable to the respective component. The cumulative variance row shows the proportion of total variance explained as additional components are included.

For comparison, PCA results for the other sectors (reported in Appendix 3) reveal broadly similar patterns. The finance sector exhibits a very similar structure, with PC1-PC3 accounting for 83.65% of the variance. Its PC1 remains dominated by monetary and price-level indicators, but PC2 shows more substantial loadings from exchange rates and oil prices. PC3 emphasises volatility and interest rate dynamics. Compared to electronics, finance stocks give relatively more importance to risk factors like VIX and discount rates. In the transportation sector, the first three principal components explain 84.18% of the variance. Unlike electronics and finance, the transportation sector's PC1 includes cost-related factors such as oil prices and exchange rates, along with moving averages, reflecting its direct sensitivity to changes in fuel and currency prices. Similarly, steel stocks have 84.02% variance explained by PC1-PC3, with PC1 being more evenly distributed across oil prices, discount rates, and monetary variables, indicating a broader influence of cost and financial factors. Lastly, construction stocks account for 85.57% of the variance through PC1 to PC3. Their PC1 and PC2 emphasise exposure to exchange rates and oil prices, while PC3 strongly relates to the VIX index, highlighting construction's position between macroeconomic fundamentals and international financial conditions.

The PCA results confirm that while the electronics and finance industries are more closely associated with monetary and policy-related indicators, the transportation and steel industries are more cost-sensitive, and construction lies between the two. By retaining only the first three principal components, approximately 83% to 86% of the variance is preserved across industries, while substantially reducing dimensionality and mitigating multicollinearity. These orthogonal components provide a stable and interpretable input structure for the subsequent LSTM framework, allowing the model to more effectively capture the interactions between EPU, U.S.–China tensions, and Taiwan's sectoral stock indices.

5. Results

5.1 Electronics Sector Model Performance

In Table 3, the baseline LSTM model for Taiwan's electronics sector achieved an accuracy of 0.4882, with precision, recall, and F1-score values of 0.5122, 0.4141, and 0.4092, respectively, indicating limited predictive power when relying solely on technical and macroeconomic variables. Incorporating external uncertainty measures improved model performance to varying degrees. The inclusion of the U.S. EPU index yielded the most substantial improvement, raising accuracy to 0.5582 and F1-score to 0.6765, driven by notable gains in both precision (0.6469) and recall (0.7203). Taiwan's domestic EPU also enhanced performance, particularly in recall (0.6107) and F1-score (0.5819), though the improvement was less pronounced compared with the U.S. EPU. By contrast, the addition of China's EPU and the U.S.–China Tension Index produced only marginal or inconsistent improvements, with overall F1-scores remaining below 0.47. These results suggest that while external uncertainty measures, particularly the U.S. and Taiwan EPU indices, can enhance predictive accuracy for the electronics sector, the predictive value of China-related indices and geopolitical tension is relatively weaker. While the correlation analysis indicated that China's EPU and the U.S.–China Tension Index exhibit relatively strong positive linear associations with Taiwan's electronics sector, the LSTM results demonstrated that the U.S. and Taiwan EPU indices exert a greater influence on predictive accuracy. This underscores the distinction between static linear relationships and the dynamic predictive capabilities of time-series models.

Including China's EPU index slightly increased accuracy and recall but decreased precision and F1-score. This suggests that China's policy uncertainty sends signals relevant to Taiwan's electronics sector, although these signals tend to be noisy and inconsistent. As Mark and Graham (2023) explain, Beijing generally employs selective, short-term economic pressure, such as sudden regulatory shifts, rather than sustained, wide-ranging measures. Therefore, fluctuations in China's EPU may represent episodic disruptions, which enhance the model's sensitivity to potential events and improve recall, but also lead to false positives that lower precision and overall stability. In contrast, the U.S. and Taiwan EPU indices tend to have more enduring, structural impacts on market expectations, which the LSTM model captures more effectively. These findings imply that models yield better results when using uncertainty measures that directly affect investor sentiment and capital flows, rather than broader geopolitical indicators with indirect, delayed, or highly variable effects.

Table 3: Long Short-Term Memory Performance of Electronics Index

	Accuracy	*Precision*	*Recall*	*F1-Score*
Baseline Model	*0.4882*	*0.5122*	*0.4141*	*0.4092*
+ US EPU	*0.5582*	*0.6469*	*0.7203*	*0.6765*
+ China EPU	*0.5000*	*0.4543*	*0.5252*	*0.4650*
+ Taiwan EPU	*0.5176*	*0.6174*	*0.6107*	*0.5819*
+ US-China Tension	*0.5000*	*0.4945*	*0.5157*	*0.4506*

Notes: The table reports LSTM model performance across different input settings. Metrics (Accuracy, Precision, Recall, F1-Score) are computed on the test set, with the baseline excluding and other models including EPU or tension indices. Positive class = upward (label = 1).

5.2 Model Prediction Results Across Sectors

In the finance sector (see Table 4), the initial model showed limited predictive accuracy (accuracy: 0.4588; F1-score: 0.3931). Incorporating EPU-related variables significantly enhanced all performance metrics. Of these, the Taiwan EPU had the most substantial impact, increasing the F1-score to 0.5864, with the U.S.–China Tension Index close behind at 0.5541, followed by the U.S. EPU (0.5385) and China EPU (0.5043). These findings indicate that regional economic policy uncertainty, particularly in Taiwan, plays a crucial role in predicting stock market movements. Furthermore, geopolitical influences, as reflected in the U.S.–China Tension Index, also have a notable effect, highlighting the sector's responsiveness to both domestic and international economic factors.

The baseline model for the transportation sector had limited predictive accuracy (0.4588). Incorporating the U.S. EPU index significantly enhanced all metrics, with accuracy increasing to 0.5588, precision to 0.6176, recall to 0.6393, and F1-score to 0.5585, illustrating the industry's sensitivity to U.S. economic uncertainty. The China EPU index yielded moderate improvements, particularly in precision (0.5613), whereas the Taiwan EPU index showed weaker results, with lower accuracy (0.4765) and recall (0.3481). The U.S.–China Tension Index achieved the highest recall (0.5794), indicating a strong ability to detect upward trends, though its lower precision (0.4206) suggests a tendency to overpredict positive returns.

In the steel industry, the baseline model performed relatively well compared to other sectors, with an accuracy of 0.5687 and an F1-score of 0.5981. This indicates that technical and macroeconomic indicators alone were already effective at detecting patterns there. When policy uncertainty indices were added, the U.S. and Taiwan EPU variables showed the most significant gains, increasing accuracy to 0.5938 and raising F1-scores to 0.6317 and 0.5944, respectively, along with improved recall values (U.S.: 0.7548; Taiwan: 0.6442). These findings suggest enhanced capability to predict upward stock movements when accounting for uncertainty in these economies. Conversely, adding China's EPU and the U.S.–China Tension Index resulted in only modest, less consistent improvements, indicating that China-related uncertainty measures yield irregular signals, and the bilateral tension index influences Taiwan's steel sector episodically rather than steadily.

In the construction industry, the baseline model performed moderately, with an accuracy of 0.5235 and an F1-score of 0.5121. The Taiwan EPU index was the most impactful among the EPU-related variables, reaching the highest F1-score of 0.5276 and demonstrating improvements in accuracy (0.5353), precision (0.6045), and recall (0.5580). It can be concluded that domestic economic policy uncertainty plays an important determining effect on the construction sector. However, the effect of incorporating the U.S. and China's EPU indices demonstrated little discrepancy with results generally observing marginal declines in performance metrics, such as accuracy and F1-score, which were generally found to be marginally lower than that of the baseline results. Notably, the U.S.–China Tension Index performed the worst overall, generally declining in all metrics, attaining F1-score of 0.3965, indicating its poor ability to indicate significant changes to the construction sector. The findings suggest that the construction industry of Taiwan is mainly a function of domestic policy determinate factors, as compared to the marginally inconsistent effects from outside uncertainties.

The evidence presented indicates that the introduction of economic policy uncertainty indices significantly enhances the LSTM model's forecasting ability. The variations in performance across sectors also suggest that each sector reacts distinctly to policy and geopolitical uncertainty, which provides valuable information on the influence of macroeconomic signals on stock performance in each sector.

Table 4: Long Short-Term Memory Performance of Sector Index

	Accuracy	*Precision*	*Recall*	*F1-Score*
Finance Baseline Model	*0.4588*	*0.4180*	*0.4362*	*0.3931*
+ US EPU	*0.5176*	*0.5773*	*0.5902*	*0.5385*
+ China EPU	*0.5235*	*0.5868*	*0.5697*	*0.5043*
+ Taiwan EPU	*0.5118*	*0.5582*	*0.6621*	*0.5864*
+ US-China Tension	*0.5588*	*0.5859*	*0.5632*	*0.5541*
Transportation Baseline Model	*0.4588*	*0.3721*	*0.4106*	*0.3651*
+ US EPU	*0.5588*	*0.6176*	*0.6393*	*0.5585*
+ China EPU	*0.5176*	*0.5613*	*0.4989*	*0.4810*
+ Taiwan EPU	*0.4765*	*0.3779*	*0.3481*	*0.3555*
+ US-China Tension	*0.5294*	*0.4206*	*0.5794*	*0.4599*
Steel Baseline Model	*0.5687*	*0.5272*	*0.7134*	*0.5981*
+ US EPU	*0.5938*	*0.5533*	*0.7548*	*0.6317*
+ China EPU	*0.5875*	*0.5321*	*0.6473*	*0.5693*
+ Taiwan EPU	*0.5938*	*0.5810*	*0.6442*	*0.5944*
+ US-China Tension	*0.5875*	*0.5543*	*0.6509*	*0.5802*
Construction Baseline Model	*0.5235*	*0.5573*	*0.5220*	*0.5121*
+ US EPU	*0.5176*	*0.5629*	*0.4568*	*0.4455*
+ China EPU	*0.5176*	*0.5307*	*0.5168*	*0.4784*
+ Taiwan EPU	*0.5353*	*0.6045*	*0.5580*	*0.5276*

+ US-China Tension	*0.5118*	*0.4348*	*0.3979*	*0.3965*

Notes: This table reports the performance of LSTM models across the finance, transportation, steel, and construction sectors. Metrics are based on the test set. Baseline excludes policy uncertainty; other models include EPU or tension indices.

5.3 Cross-Sector Summary

The findings indicate that incorporating Economic Policy Uncertainty (EPU) indices and the U.S.–China Tension Index significantly enhances the forecasting accuracy of Long Short-Term Memory models across various sectors. These improvements differ in magnitude and character. The U.S. EPU consistently enhances model performance, particularly in the electronics, steel and transportation sectors, where the most substantial gains are seen in accuracy and recall. The finance sector, in particular, benefits from all types of uncertainty indices, which lead to notable improvements in prediction accuracy. This suggests that financial stocks are widely influenced by both domestic and international policy uncertainties, along with geopolitical tensions. Taiwan's EPU has the most pronounced impact on the construction industry, highlighting the importance of domestic policy uncertainty for sectors with higher local exposure. By contrast, the effects of China's EPU and the U.S.–China Tension Index are inconsistent: they occasionally enhance recall but often reduce precision and F1-scores, making them less reliable predictors. This is consistent with the descriptive and correlation analyses in Chapter 4, where China's EPU and the U.S.–China Tension Index exhibited less stable associations with Taiwan's sectoral indices.

In summary, the evidence clearly suggests that the introduction of economic policy uncertainty indices have substantially increased the predictive power of the LSTM model. The differences in performance among sectors also indicate that each sector responds differently to policy and political uncertainty, which provides meaningful insights into the channel through which macroeconomic signals act to drive stock behaviour across sectors.

6. Discussion

6.1 Summary of Key Findings

Chapter 5's findings show that incorporating Economic Policy Uncertainty (EPU) indices and the U.S.–China Tension Index notably enhance the accuracy of LSTM models across Taiwan's various sectoral stock indices. Nonetheless, the extent and consistency of these improvements differ among industries. This chapter extends the previous analysis to delve deeper into the reasons for these sectoral differences, linking the findings with existing research and broader economic factors. The discussion is organised by industry, explaining why specific sectors are more affected by particular policy uncertainty sources.

6.2 Discussion of Findings

6.2.1 Electronics Sector

Building on the results in Chapter 5, the findings reveal that the predictive accuracy of Taiwan's electronics sector is particularly sensitive to policy uncertainty originating from the U.S. and Taiwan. These findings underscore the electronics industry's pronounced vulnerability to policy and geopolitical uncertainties, reflecting its structural reliance on global supply chains and downstream markets, notably within the United States. Prior studies confirm that disruptions in Taiwan's semiconductor manufacturing can rapidly transmit to international markets, causing price volatility and supply chain shocks (Jones et al., 2023). Similarly, Liu, Tang, Kao and Chou (2025) highlight that persistent U.S. policies, including export controls, the CHIPS Act, and security alliances, reinforce the centrality of U.S. policy in shaping Taiwan's semiconductor industry, thereby augmenting the predictive significance of U.S. EPU.

In contrast, adding China's EPU led to weaker and less consistent outcomes. While recall saw a slight increase, both precision and F1-score declined, indicating that China's policy uncertainty generates scattered and noisy signals that undermine predictive reliability. This supports the notion that Beijing often employs selective, short-term coercive actions, like abrupt regulatory measures or grey-zone activities, rather than long-term, industry-wide policies (Liu et al., 2025). Similarly, the U.S.–China Tension Index mainly reflects indirect or delayed impacts, such as reputation shocks and supply chain issues, which are not consistently factored into the Taiwanese electronics sector. Consequently, these indices have less predictive value than those based on the U.S. and Taiwan EPU.

These findings not only forecast outcomes but also emphasise Taiwan's significant geopolitical role within the electronics sector. Mainly focused on semiconductors, this industry is crucial in the strategic contest between the U.S. and China. The United States' actions against Huawei, support for TSMC's expansion, and China's ongoing tech theft and cyber activities position Taiwan's electronics sector at the heart of international tensions (Shattuck, 2020). Moreover, Sehgal (2023) describes Taiwan's semiconductor leadership as its "Silicon Shield", where semiconductors function both as an economic engine and a strategic resource. This context explains why global powers are eager to influence Taiwan's semiconductor industry, with policy uncertainty playing a key role in shaping market expectations.

Therefore, the findings indicate that U.S. and Taiwan EPU indices offer stronger and more reliable predictive signals because they directly incorporate structural risks inherent in the electronic supply chain. In contrast, China's EPU and the U.S.–China Tension Index tend to generate sudden short-term shocks, but their spillover effects on Taiwan's electronics sector appear limited over the longer term, thereby reducing their predictive reliability. This suggests that U.S. and Taiwan policy uncertainty indices provide more dependable predictive signals for Taiwan' s electronics sector, while China-related indicators seem less trustworthy.

These results carry important implications for investors and policymakers. For investors, the results emphasise the importance of monitoring U.S. and Taiwan EPU indices as reliable indicators of market trends in the electronics sector. Since these indices directly reflect structural risks related to the global semiconductor supply chain, they can be integrated into risk management, portfolio strategies, and hedging approaches. Professional investors and fund managers might find value in including U.S. and Taiwan policy uncertainty metrics in their trading models to anticipate episodes of increased volatility. Conversely, China's EPU and the U.S.–China Tension Index should mainly serve as supplementary, short-term risk indicators rather than stable forecasting tools. From a policy standpoint, the study underscores the importance of strengthening Taiwan's industrial resilience against external shocks. Policymakers should prioritise supply chain diversification, regional cooperation, and reducing over-dependence on single markets. Additionally, transparency and stability in domestic policies are essential for minimising the transmission of local uncertainty to capital markets. Considering Taiwan's strategic position in the semiconductor industry, enhanced collaboration with allied economies in technological R&D, export security, and investment protections can help mitigate risks stemming from the U.S.–China rivalry. Combining vigilant market monitoring with supportive public policies will enable investors and policymakers to better manage the uncertainties affecting Taiwan's electronics industry.

6.2.2 Finance Sector

Taiwan's financial sector shows notable improvements in predictive accuracy when including the U.S., China, and Taiwan EPU indices, along with the U.S.–China Tension Index. This underscores its increased responsiveness to both local and global policy uncertainties. Among these indicators, the U.S. EPU delivers the greatest enhancement, reinforcing Chiang's (2023) conclusion that Taiwan's monetary policy and capital markets are deeply reliant on and profoundly shaped by U.S. economic and financial policies. This illustrates Taiwan's dependence on U.S. dollar liquidity and international financial cycles, which directly influence investor sentiment and domestic monetary policy decisions.

China’s EPU is also relevant as it has implications for Taiwan’s economy, showing the financial and economic links between these two economies. Previous research by Liao and Chou (2013) shows how stock markets often co-move in reactions to major institutional or policy events, such as the ECFA agreement. This interdependence indicates that changes in China’s policy uncertainty can rapidly influence Taiwan’s financial markets, increasing volatility and changing investment patterns.

The Taiwan EPU index improves explanatory power by assessing local policy uncertainty, which directly impacts credit conditions and investor confidence. Meanwhile, the U.S.–China Tension Index reflects broader geopolitical risks like trade conflicts and strategic disputes, which prior studies show can threaten Taiwan’s financial stability (Hsieh & Yeh, 2020; Neely, 2025). Although its effects are less consistent than those of local or U.S. EPU, it still provides valuable signals during times of heightened geopolitical tension.

The enhancement in predictive accuracy can also be understood by considering the financial sector’s intermediary role in worldwide markets. According to Raddant and Kenett (2020), financial institutions act as hubs, transmitting shocks and capital movements internationally. In times of increased uncertainty, these connections become more robust, causing stronger co-movement in global financial markets and intensifying the impact of worldwide risk factors. This systemic role clarifies why Taiwan’s financial sector is especially affected by U.S. and Taiwan EPU indices, which reflect risks that quickly influence global capital flows. These findings highlight that Taiwan’s financial industry is very vulnerable to policy uncertainties in various countries, worldwide financial changes, and geopolitical issues. This emphasises the need to use a variety of EPU indicators in financial performance models, since each index reflects different yet related pathways for how uncertainty propagates.

To summarise, the results of this study suggest that investors can employ the U.S. and Taiwan EPU indices in managing risk in Taiwan’s financial markets, using the China EPU and the U.S.–China Tension Index as additional risk signals. Policymakers can support Taiwan’s financial resilience by increasing the transparency of their monetary policies, maintaining moderate reserve levels, and engaging in full cooperation with its international partners. Overall, these actors will assist Taiwan, its policymakers, and their international partners in undercutting shocks from outside forces while instilling stability in Taiwan's financial system.

6.2.3 Transportation Sector

The results for Taiwan’s transportation sector show that including different EPU and geopolitical indices in the LSTM model leads to varied outcomes. The U.S.–China relations index improves accuracy but slightly improves precision, recall, and F1-score, highlighting the impact of trade conflicts on shipping demand. Rapid tariff changes, rerouted supply chains, and short-term freight fluctuations disrupt typical demand patterns, making it difficult for the model to detect consistent relationships (Lin, 2020). In contrast, the U.S. EPU index has a more systematic and stable influence on Taiwan's transportation. As Taiwan's leading export partner is the U.S., and key West Coast ports like Los Angeles and Long Beach are highly responsive to U.S. trade policies, U.S. policy uncertainty directly affects freight flows and port activities, enhancing model stability. These findings support broader discussions on the vulnerability of global supply chains, where ports, as critical nodes, are highly susceptible to systemic shocks such as trade disputes and geopolitical tensions (Notteboom and Haralambides, 2020).

The heightened predictive ability of the U.S. EPU is partly due to the importance of ports in global supply chains. Verschuur, Koks, and Hall (2022) demonstrate that a few key ports account for the majority of international trade, with each U.S. dollar of port activity generating approximately 4.30 dollars in global output. Taiwanese ports like Kaohsiung are deeply integrated into these networks, making them particularly sensitive to U.S. policy uncertainty. In contrast, the impacts of China's EPU and the U.S.–China Tension Index are more variable. While they improve prediction accuracy, they do not consistently boost recall and F1-score because disruptions from China tend to be episodic or rerouted, especially as manufacturing shifts to Southeast Asia. Yang and Hayakawa (2023) demonstrate that Taiwan's exports increased through trade diversion during the U.S.–China trade war; however, disturbances from Chinese intermediate inputs created instability in Taiwan's exports. This implies that China's EPU had limited predictive ability for Taiwan's transportation sector, as much of the export change was based on trade substitution rather than China's policy uncertainty.

These findings emphasise a structural asymmetry: the U.S. EPU provides stronger and more consistent predictive signals because Taiwan is integrated into U.S.-focused shipping networks. In contrast, China's EPU and bilateral tensions tend to exhibit more localised and sporadic shocks. This explains why U.S. policy uncertainty improves the overall accuracy of the model, even though its precision and recall may vary. It highlights both the potential and challenges of including highly volatile geopolitical indicators in transportation industry predictive models. Therefore, for investors, this stresses the importance of monitoring U.S. policy uncertainty when managing freight-related risks, while policymakers should focus on strengthening port resilience, diversifying trade routes, and enhancing international cooperation to mitigate external shocks.

6.2.4 Steel Sector

Based on the results in the previous chapter, the steel sector demonstrates relatively strong predictive performance even under the baseline model, reflecting its sensitivity to fundamental demand drivers and global market cycles. Nevertheless, the inclusion of EPU indices provides additional explanatory power, particularly with respect to directional forecasts. The outcomes of the Long Short-Term Memory (LSTM) analysis for Taiwan's steel industry demonstrate that integrating the U.S. EPU index results in the most significant enhancements across all performance indicators, notably in recall and F1-score. These findings emphasise Taiwan's reliance on export markets and the sensitivity of its steel sector to U.S. trade policies. As noted in "The Value Chain and Competitiveness of the Steel Industry" (CTCI Foundation, 2014), Taiwan's steel value chain indicates that Taiwanese steel exports are frequently subjected to anti-dumping duties and safeguard measures implemented by the United States and the European Union, which directly influence demand dynamics and market access. Therefore, variations in U.S. policy uncertainty provide the most accurate and reliable predictive signals for Taiwan's steel industry.

Conversely, the predictive advantages derived from incorporating China's EPU and the U.S.–China Tension Index exhibit reduced stability. Although these variables enhance the accuracy of the model, they lead to weaker precision and recall, indicating more volatile and episodic effects. This observation is consistent with the structural dynamics outlined in the literature: Taiwan's steel industry maintains close ties to Chinese supply chains and pricing mechanisms, yet such linkages are susceptible to short-term disruptions from Chinese industrial policies and trade frictions (CTCI Foundation, 2014). While trade diversion or temporary demand shifts may elevate Taiwanese exports, the lack of these shocks diminishes the stability of predictive outcomes.

Taiwan's EPU has a relatively limited impact. Due to the small size of domestic demand and the industry's focus on exports, local policy uncertainty mainly influences the sector indirectly, through factors like energy prices, environmental rules, and production expenses. These findings highlight a structural imbalance: U.S. policy uncertainty has the most significant and consistent effect on Taiwan's steel industry, while uncertainties related to China and local issues affect the sector through less stable, more indirect pathways. Investors should therefore closely monitor U.S. trade policy developments as primary risk signals, while treating China- and Taiwan-related uncertainties as secondary, short-term factors. For policymakers, diversifying export markets, enhancing competitiveness, and engaging in international trade governance are essential to reducing vulnerability to external shocks.

6.2.5 Construction Sector

The baseline model for the construction industry, which uses only traditional macroeconomic data and technical indicators, already demonstrates strong predictive performance. This supports Hung's (2021) findings that Taiwan's real estate prices are closely linked to long-term macroeconomic factors and industry-specific metrics such as the money supply, consumer prices, the building cost index, and the house price-to-income ratio. Our results further show that including Taiwan's EPU index improves the model's accuracy and F1-score. This highlights the construction sector's high sensitivity to domestic policy uncertainty, indicating that Taiwan's real estate and construction markets are mainly shaped by local macroeconomic conditions, financial stability, and regulatory changes rather than international influences.

Including the U.S. EPU, China's EPU, or the U.S.–China Tension Index adds minimal value to the model's predictive ability. This highlights the localised nature of Taiwan's construction sector: external policy shocks are vital for export-dependent industries, but construction is mainly driven by domestic policies like housing credit, interest rates, and government infrastructure projects. Song and Zhou (2025) show that U.S. EPU impacts analyst forecast accuracy in foreign markets mainly through economic dependence on the U.S. This indicates that industries with limited trade or financial connections to the U.S., such as Taiwan's domestic construction sector, are less influenced by U.S. EPU spillovers. Similarly, the impact of China's EPU on foreign sectors varies depending on economic ties, with sectors focused domestically experiencing less spillover. Previous correlation analyses and scatter plots also clarify why the U.S. and China EPU indices do not enhance stock prediction models. Correlation analyses indicate the coefficients between construction stocks and U.S. EPU (0.147) or China EPU (0.260) are comparatively low, and scatter plots confirm this with dispersed points and flat slopes, implying limited explanatory power. These results suggest that the U.S. and China EPU indices may add noise to predictions, and their weak correlation with construction stocks accounts for why they do not improve model performance. This means that investors should pay close attention to Taiwan's credit environment, interest rate trends, and regulatory changes, which is more valuable than tracking foreign EPU indices.

6.2.6 Cross-Sector Comparison

The cross-sector analysis highlights structural differences in how Taiwan's industries react to policy and geopolitical uncertainties. Electronics, steel, and transportation are very responsive to global policy changes and trade shocks. In contrast, the construction industry is primarily influenced by domestic economic and regulatory factors, while the financial industry is intrinsically impacted by both domestic and global factors. This means that the efficacy of uncertainty indicators will vary from sector to sector, depending on their characteristics. This argues for an investor's strategy concerning risk management across the industries. For example, industries that are more global in nature, such as electronics and steel, will need to pay more attention to policy uncertainty originating in the U.S, more so than the construction sector. The construction industry will need to account more for domestic monetary and regulatory uncertainty, while the finance sector, which sits wedged between the global and local factors, requires investors to consider their uncertainty indicators across all types simultaneously. On the policy front, the findings suggest a pathway for strengthening Taiwan's resilience, across both exposure to shocks stemming from tensions in the U.S.–China relationship and simultaneously enhancing transparency and stability in domestic policies. Overall, these findings suggest we need to tailor responses to align investments and policies with different vulnerabilities across industries. Such a strategy will enhance the resiliency and adaptive capacity of Taiwanese institutions against economic uncertainties.

7. Conclusion and Future Research Suggestions

This study set out to investigate whether adding EPU indices from the U.S., China, and Taiwan, along with the U.S.–China Tension Index, improves the prediction ability of Long Short-Term Memory (LSTM) models for Taiwan's sectoral stock indices. It used traditional macroeconomic and technical indicators, employed Principal Component Analysis (PCA) for dimension reduction, and applied walk-forward validation to create a solid and practical approach for financial forecasting.

The empirical results show that incorporating EPU indices significantly enhances the predictive accuracy of LSTM models, with the level of influence differing among industries. The U.S. EPU index consistently delivers the most robust predictive power, especially for the electronics, transportation, and steel sectors, highlighting Taiwan's reliance on U.S. economic and trade policies. Conversely, Taiwan's domestic EPU index has the strongest impact on the construction sector, emphasising its dependence on local financial and regulatory conditions. The financial industry is affected by both international and domestic uncertainties, benefiting from multiple indices. On the other hand, China's EPU and the U.S.–China Tension Index provide less consistent signals, sometimes improving recall but often decreasing precision, which limits their reliability for forecasting. As Huang, Yeh, and Chen (2021) suggest, Taiwan's financial markets are highly exposed to U.S. policy uncertainty, with spillover effects from the U.S. being considerably more potent than those from China.

These results have important theoretical and practical implications. Academically, the study advances previous research by shifting focus from overall stock indices to sector-specific movements, emphasising how economic policy uncertainty impacts industries differently. It also illustrates the effectiveness of hybrid PCA-LSTM models in managing multicollinearity and enhancing prediction accuracy in financial time series. On a practical level, the findings indicate that investors and policymakers should consider sector-specific strategies when monitoring uncertainty indicators. For instance, global policy uncertainty significantly affects export-driven sectors like electronics and steel, while domestic uncertainty is more pertinent to construction. The financial sector needs to monitor both international and domestic uncertainty due to its role in global capital exchanges. At the policy level, the study highlights the importance of boosting Taiwan's economic resilience. For sectors vulnerable to external shocks, diversifying export markets and enhancing international cooperation can decrease dependence on global uncertainties. Domestic-oriented industries should focus on transparent and stable policies to limit fluctuations. Additionally, the findings stress that policymakers need to acknowledge the strategic role of Taiwan's electronics industry in global supply chains, emphasising the importance of collaborating with allied economies to address risks from geopolitical tensions.

Nevertheless, this study has certain limitations. First, using monthly data helps reduce noise but limits the ability to detect short-term shocks and quick market adjustments. Future research could use daily data for a more accurate analysis of immediate market responses to policy uncertainty. Creating a daily EPU index for Taiwan would also be a helpful resource for future scholars and practitioners. Second, this study uses sector-level stock indices as the analysis unit. While these indices show overall industry trends, they combine multiple firms that may react differently to political and economic instability. Consequently, the improved predictive accuracy at the sector level might underestimate differences among individual firms. This research provides an industry-wide view of how uncertainty indices affect Taiwan' s financial markets, but future work could include firm-level analyses to better understand the varied responses of individual companies. Additionally, examining cross-border links and spillover effects with multi-country sector data could yield valuable insights into how policy uncertainty propagates through global financial networks.

In conclusion, this research shows that incorporating economic policy uncertainty measures into sophisticated machine learning models significantly improves the prediction accuracy of

Taiwan’s sectoral stock indices. The findings highlight how uncertainty transmission is asymmetric and varies across sectors, offering valuable insights for financial forecasting theories as well as practical advice for investors and policymakers dealing with the growing global uncertainty.

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Appendix

Appendix 1: Descriptive Statistics

Table A1.1: Descriptive Statistics of Industries' Sector Index

	Mean	Std	Min	25%	50%	75%	Max
Electronics Stock	365.07	118.48	165.72	294.82	333.11	398.48	854.52
Log Return	0.007	0.058	-0.197	-0.029	0.012	0.041	0.156
E_MA5	358.88	107.32	178.84	295.00	331.55	399.38	827.97
E_MA20	341.53	77.63	236.48	289.16	321.58	366.26	632.46
Finance Stock	1022.66	189.26	493.47	894.39	1015.17	1145.53	1514.14
Log Return	0.003	0.063	-0.249	-0.022	0.006	0.033	0.262
F_MA5	1017.16	175.54	533.58	915.34	1007.29	1135.56	1438.88
F_MA20	1005.45	146.26	730.51	909.39	981.48	1089.15	1303.68
Transportation Stock	82.97	29.35	49.25	66.24	77.27	89.72	366.57
Log Return	0.007	0.091	-0.385	-0.037	0.005	0.045	0.584
T_MA5	81.32	19.11	57.22	66.67	77.33	87.28	192.43
T_MA20	81.12	13.29	62.37	66.63	79.70	89.64	111.16
Steel Stock	103.97	20.29	71.34	93.73	101.15	109.50	205.41
Log Return	0.004	0.066	-0.265	-0.024	0.006	0.034	0.406
S_MA5	103.10	16.86	73.94	93.93	100.88	108.46	161.83
S_MA20	102.58	11.21	85.05	95.68	99.99	107.56	138.04
Construction Stock	268.78	56.69	111.40	247.96	277.59	300.07	397.97
Log Return	0.005	0.091	-0.495	-0.037	0.007	0.042	0.479
C_MA5	266.66	53.05	113.80	250.58	276.10	297.69	357.02

C_MA20	*260.09*	*43.77*	*147.88*	*241.79*	*270.95*	*294.43*	*320.57*

Notes: The table reports descriptive statistics (mean, standard deviation, minimum, maximum, and quartiles) of Taiwan's sectoral stock indices and their technical indicators. Log return refers to the logarithmic return of each sector index, while MA5 and MA20 represent 5-month and 20-month moving averages, respectively.

Table A1.2: Descriptive Statistics of Variables

	Mean	*Std*	*Min*	*25%*	*50%*	*75%*	*Max*
US_EPU	*143.16*	*71.58*	*44.78*	*96.98*	*125.36*	*171.57*	*503.96*
China_EPU	*156.43*	*115.35*	*23.72*	*82.60*	*121.01*	*178.99*	*661.83*
TW_EPU	*101.07*	*46.26*	*34.07*	*73.26*	*93.92*	*120.65*	*340.92*
US-China Tension	*117.51*	*39.78*	*68.46*	*90.13*	*105.98*	*136.92*	*349.95*
USD/TWD	*30.96*	*1.49*	*27.52*	*29.88*	*30.68*	*32.28*	*35.00*
Oil Price	*74.96*	*25.15*	*26.85*	*56.20*	*68.48*	*98.53*	*133.59*
M2	*353704.93*	*78513.35*	*233068.00*	*286718.50*	*344071.00*	*421222.00*	*518576.00*
Discount Rate	*1.82*	*0.63*	*1.13*	*1.38*	*1.75*	*1.88*	*3.63*
VIX Index	*19.43*	*8.76*	*9.51*	*13.43*	*16.68*	*23.27*	*59.89*
CPI Index	*92.86*	*4.37*	*83.86*	*89.60*	*93.66*	*96.63*	*99.77*

Notes: The table reports descriptive statistics of explanatory variables, including U.S., China, and Taiwan EPU indices, the US–China Tension Index, and macroeconomic indicators. These statistics provide an overview of the distributional characteristics of the input variables used in the empirical analysis.

Appendix 2: Pearson Correlation and Scatter Plot of Industries' Sector Indices

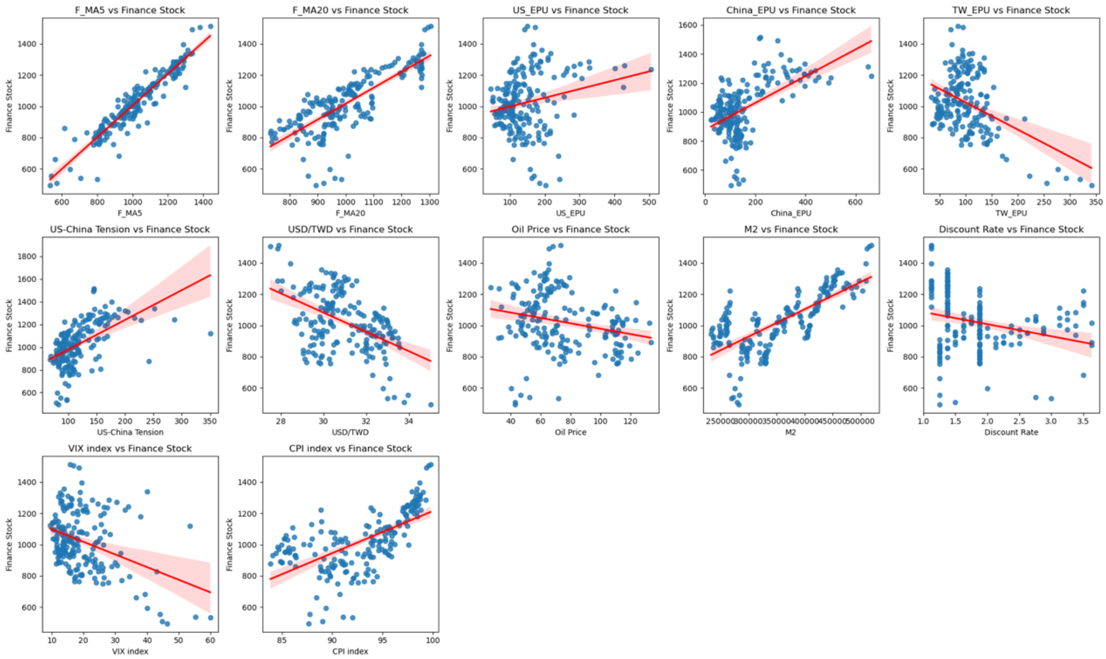
Table A2.1: Correlation Analysis of Finance Sector Index

	F_MA5	*F_MA20*	*US_EPU*	*China_EPU*	*TW_EPU*	*US-China Tension*
Finance Stock	*0.942*	*0.786*	*0.213*	*0.562*	*-0.425*	*0.551*

P-Value	*<0.0001*	*<0.0001*	*0.0029*	*<0.0001*	*<0.0001*	*<0.0001*
	USD/TWD	*Oil Price*	*M2*	*Discount Rate*	*VIX Index*	*CPI Index*
Finance Stock	*-0.487*	*-0.229*	*0.725*	*-0.258*	*-0.375*	*0.623*
P-Value	*<0.0001*	*0.0013*	*<0.0001*	*0.0003*	*<0.0001*	*<0.0001*

Notes: The table presents Pearson correlation coefficients for the finance sector index and its explanatory variables. P-values are displayed in the second row; correlations are statistically significant at the 1% level unless otherwise noted.

Figure A2.1: Scatter Plot of Finance Sector Index



Notes: Scatter plots with fitted regression lines illustrate the relationships between the finance sector index and explanatory variables.

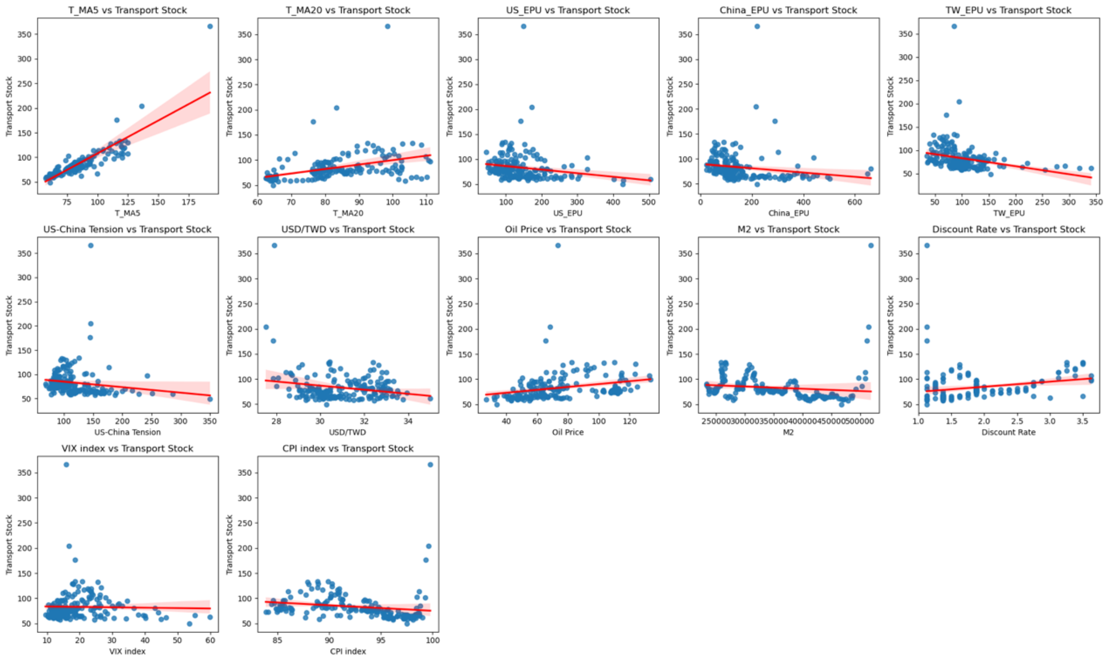
Table A2.2: Correlation Analysis of Transportation Sector Index

	T_MA5	*T_MA20*	*US_EPU*	*China_EPU*	*TW_EPU*	*US-China Tension*
Transportation Stock	*0.869*	*0.400*	*-0.175*	*-0.169*	*-0.271*	*-0.154*
P-Value	*<0.0001*	*<0.0001*	*0.0149*	*0.0186*	*0.0001*	*0.0318*
	USD/TWD	*Oil Price*	*M2*	*Discount Rate*	*VIX Index*	*CPI Index*

Transportation Stock	*-0.208*	*0.246*	*-0.122*	*0.218*	*-0.024*	*-0.164*
P-Value	*0.0037*	*0.0005*	*0.0912*	*0.0023*	*0.7402*	*0.0224*

Notes: The table presents Pearson correlation coefficients for the transportation sector index and its explanatory variables. P-values are displayed in the second row; correlations are statistically significant at the 1% level unless otherwise noted.

Figure A2.2: Scatter Plot of Transportation Sector Index



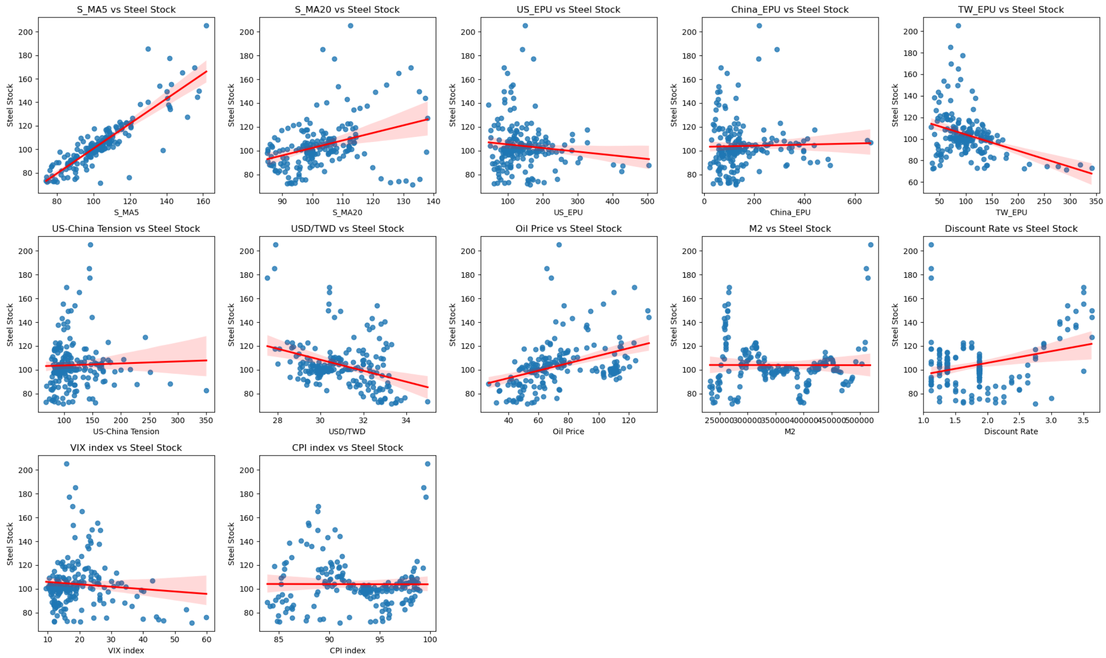
Notes: Scatter plots with fitted regression lines illustrate the relationships between the transportation sector index and explanatory variables.

Table A2.3: Correlation Analysis of Steel Sector Index

	S_MA5	*S_MA20*	*US_EPU*	*China_EPU*	*TW_EPU*	*US-China Tension*
Steel Stock	*0.879*	*0.349*	*-0.108*	*0.027*	*-0.343*	*0.033*
P-Value	*<0.0001*	*<0.0001*	*0.1336*	*0.7120*	*<0.0001*	*0.6502*
	USD/TWD	*Oil Price*	*M2*	*Discount Rate*	*VIX Index*	*CPI Index*
Steel Stock	*-0.339*	*0.389*	*-0.002*	*0.306*	*-0.087*	*-0.004*
P-Value	*<0.0001*	*<0.0001*	*0.9757*	*<0.0001*	*0.2277*	*0.9592*

Notes: The table presents Pearson correlation coefficients for the steel sector index and its explanatory variables. P-values are *displayed in the second row; correlations are statistically significant at the 1% level unless otherwise noted.*

Figure A2.3: Scatter Plot of Steel Sector Index



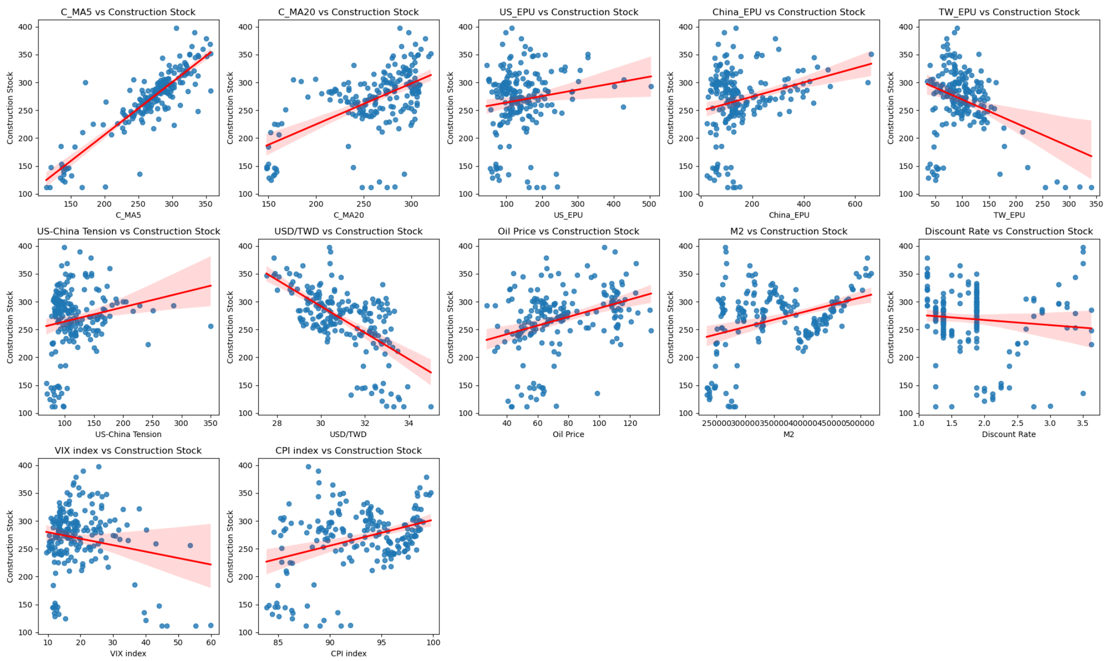
Notes: Scatter plots with fitted regression lines illustrate the relationships between the steel sector index and explanatory variables.

Table A2.4: Correlation Analysis of Construction Sector Index

	C_MA5	*C_MA20*	*US_EPU*	*China_EPU*	*TW_EPU*	*US-China Tension*
Construction Stock	*0.882*	*0.567*	*0.147*	*0.260*	*-0.345*	*0.181*
P-Value	*<0.0001*	*<0.0001*	*0.0414*	*0.0002*	*<0.0001*	*0.0117*
	USD/TWD	*Oil Price*	*M2*	*Discount Rate*	*VIX Index*	*CPI Index*
Construction Stock	*-0.624*	*0.346*	*0.367*	*-0.102*	*-0.180*	*0.359*
P-Value	*<0.0001*	*<0.0001*	*<0.0001*	*0.1554*	*0.0123*	*<0.0001*

Notes: The table presents Pearson correlation coefficients for the construction sector index and its explanatory variables. P-values are displayed in the second row; correlations are statistically significant at the 1% level unless otherwise noted.

Figure A2.4: Scatter Plot of Construction Sector Index



Notes: Scatter plots with fitted regression lines illustrate the relationships between the construction sector index and explanatory variables.

Appendix 3: The Principal Component Analysis Results of Industries' Sector Index

Table A3.1: The Principal Component Analysis Results of Finance Stock Variables

	PC1	*PC2*	*PC3*	*PC4*	*PC5*
F_MA5	*0.412*	*-0.036*	*-0.431*	*0.201*	*0.210*
F_MA20	*0.416*	*0.192*	*-0.314*	*0.320*	*0.073*
USD/TWD	*-0.288*	*0.577*	*-0.194*	*-0.100*	*-0.588*
Oil Price	*-0.168*	*-0.717*	*0.093*	*0.208*	*-0.308*
M2	*0.488*	*0.010*	*0.112*	*-0.039*	*-0.228*
Discount Rate	*-0.307*	*-0.127*	*-0.541*	*0.509*	*-0.223*
VIX Index	*-0.060*	*0.297*	*0.577*	*0.737*	*0.078*
CPI Index	*0.458*	*-0.100*	*0.177*	*0.021*	*-0.634*
Cumulative Variance	*50.37%*	*69.57%*	*83.65%*	*94.50%*	*97.46%*

Notes: The table reports the factor loadings of explanatory variables on the principal components (PC1–PC5) for the finance *sector. Higher absolute values indicate stronger contributions of each variable to the respective component. The cumulative variance row shows the proportion of total variance explained as additional components are included.*

Table A3.2: The Principal Component Analysis Results of Transportation Stock Variables

	PC1	*PC2*	*PC3*	*PC4*	*PC5*
T_MA5	*0.330*	*0.374*	*0.100*	*0.738*	*-0.247*
T_MA20	*0.444*	*0.146*	*0.294*	*-0.066*	*-0.173*
USD/TWD	*0.220*	*-0.636*	*-0.046*	*0.049*	*0.105*
Oil Price	*0.226*	*0.580*	*-0.096*	*-0.556*	*0.113*
M2	*-0.475*	*0.159*	*0.123*	*0.272*	*0.190*
Discount Rate	*0.405*	*0.034*	*-0.201*	*0.204*	*0.830*
VIX Index	*0.082*	*-0.114*	*0.903*	*-0.124*	*0.203*
CPI Index	*-0.445*	*0.243*	*0.149*	*0.095*	*0.344*
Cumulative Variance	*48.17%*	*70.23%*	*84.18%*	*90.65%*	*95.88%*

Notes: The table reports the factor loadings of explanatory variables on the principal components (PC1–PC5) for the transportation sector. Higher absolute values indicate stronger contributions of each variable to the respective component. The cumulative variance row shows the proportion of total variance explained as additional components are included.

Table A3.3: The Principal Component Analysis Results of Steel Stock Variables

	PC1	*PC2*	*PC3*	*PC4*	*PC5*
S_MA5	*0.252*	*0.478*	*-0.081*	*0.565*	*0.468*
S_MA20	*0.286*	*0.422*	*0.415*	*-0.061*	*-0.367*
USD/TWD	*0.248*	*-0.507*	*0.240*	*0.276*	*-0.404*
Oil Price	*0.262*	*0.428*	*-0.342*	*-0.509*	*-0.287*
M2	*-0.514*	*0.213*	*0.078*	*0.286*	*-0.143*
Discount Rate	*0.477*	*0.021*	*-0.175*	*0.432*	*-0.329*

VIX Index	*0.116*	*0.124*	*0.778*	*-0.169*	*0.228*
CPI Index	*-0.469*	*0.303*	*0.074*	*0.212*	*-0.469*
Cumulative Variance	*39.00%*	*66.75%*	*84.02%*	*91.72%*	*95.08%*

Notes: The table reports the factor loadings of explanatory variables on the principal components (PC1–PC5) for the steel sector. Higher absolute values indicate stronger contributions of each variable to the respective component. The cumulative variance row shows the proportion of total variance explained as additional components are included.

Table A3.4: The Principal Component Analysis Results of Construction Stock Variables

	PC1	*PC2*	*PC3*	*PC4*	*PC5*
C_MA5	*-0.372*	*0.364*	*-0.009*	*0.338*	*0.708*
C_MA20	*-0.418*	*0.256*	*0.315*	*0.180*	*-0.367*
USD/TWD	*0.423*	*-0.204*	*0.170*	*0.429*	*-0.181*
Oil Price	*-0.068*	*0.636*	*-0.080*	*-0.416*	*-0.336*
M2	*-0.450*	*-0.317*	*-0.054*	*0.210*	*-0.070*
Discount Rate	*0.282*	*0.457*	*0.036*	*0.621*	*-0.197*
VIX Index	*0.013*	*-0.029*	*0.928*	*-0.183*	*0.136*
CPI Index	*-0.471*	*-0.214*	*-0.008*	*0.186*	*-0.395*
Cumulative Variance	*46.24%*	*71.60%*	*85.57%*	*92.18%*	*95.63%*

Notes: The table reports the factor loadings of explanatory variables on the principal components (PC1–PC5) for the construction sector. Higher absolute values indicate stronger contributions of each variable to the respective component. The cumulative variance row shows the proportion of total variance explained as additional components are included.