Journal of Risk and Financial Management

Article

Forecasting New Zealand Stock Returns Through Intermarket Analysis Using Global Vector Autoregressive Model and Machine Learning Methods

Bisma Dewabrata [1], Nuttanan Wichitaksorn [1,*] and Yoichi Otsubo [2]

[1] Department of Mathematical Sciences, Auckland University of Technology, Auckland 1010, New Zealand; bisma.dewabrata@gmail.com
[2] Graduate School of Economics, Kobe University, Kobe 657-8501, Hyogo, Japan; otsubo@econ.kobe-u.ac.jp
* Correspondence: nuttanan.wichitaksorn@aut.ac.nz

Abstract

This study applies intermarket analysis to forecast the New Zealand NZX 50 stock returns using a hybrid framework that combines econometric models with machine learning (ML) algorithms. Daily return data from 3 January 2001 to 31 December 2024 are employed to examine the interconnectedness between the New Zealand equity market and major global financial markets. This study follows a three-stage methodology: ML-based feature selection using LASSO, ridge, and elastic net regressions; econometric validation through a Global Vector Autoregressive (GVAR) model; and forecasting implementation using Support Vector Regression (SVR), Random Forest (RF), Long Short-Term Memory, and Artificial Neural Networks. Feature selection consistently identifies the Australian ASX 200, Japanese Nikkei 225, U.S. S&P 500, and U.S. 10-year Treasury yield as the most influential predictors, with Australia exerting the strongest impact. GVAR results reveal significant short-term spillover effects, but no long-term co-integrating relationships, indicating independent market trends. The U.S. market emerges as the dominant transmitter of shocks, while New Zealand acts as a net receiver. Forecasting results show RF and SVR outperform alternative models, with optimal performance achieved using a fifth-lag structure. The findings support short-term, spillover-based investment strategies and contribute to a transparent, replicable framework for forecasting equity markets in small open economies.

Keywords: global vector autoregression; intermarket analysis; NZX50; feature selection; machine learning; forecasting

Academic Editor: SeyedSoroosh Azizi

Received: 10 May 2026
Revised: 1 July 2026
Accepted: 4 July 2026
Published: 10 July 2026

1. Introduction

Investment management is a systematic and repeatable process aimed at achieving specific financial objectives through portfolio construction, management, and evaluation (Damodaran, 2012; Maginn et al., 2007). Central to this process are Strategic Asset Allocation (SAA), which determines the portfolio's long-term risk–return profile and is widely recognized as the primary driver of return variability (Brinson et al., 1986; Elkamhi et al., 2021; Ibbotson & Kaplan, 2000; Wein, 2022), and Tactical Asset Allocation (TAA) and market timing, which allow temporary deviations from strategic weights to exploit short- and medium-term opportunities (Bodie et al., 2011; Maginn et al., 2007). Intermarket analysis supports these decisions by examining the relationships among major asset classes—equities, bonds, commodities, and currencies—and identifying lead–lag dynamics through which information is transmitted across markets (Eun & Shim, 1989; Liang &

Yen, 2014; Maier-Paape & Platen, 2016; Murphy, 2004; Schmidt et al., 2024). Such insights can improve forecasting, portfolio monitoring, and timing strategies, although developing robust quantitative frameworks to measure and exploit these relationships remains challenging. Traditionally, expected returns and market dynamics have been modeled using linear factor-based approaches such as the Capital Asset Pricing Model (CAPM) and Arbitrage Pricing Theory (APT), which provide theoretical clarity and interpretability but are often limited in their ability to capture the complex nonlinear interactions that increasingly characterize global financial markets.

Recent advances in machine learning (ML) have significantly transformed investment management, with applications spanning asset allocation, security selection, risk management, and trading execution. By processing large, high-dimensional datasets and capturing complex nonlinear relationships, ML models often outperform traditional econometric approaches in forecasting asset returns and market movements (Fischer & Krauss, 2018; Gu et al., 2020; Heaton et al., 2017). These capabilities make ML particularly well suited to intermarket analysis, where interactions among equities, bonds, commodities, and currencies are often nonlinear and difficult to model using conventional factor-based frameworks.

Despite their predictive strength, many ML models suffer from limited transparency and interpretability, creating challenges for practical adoption in investment management. Investors and practitioners require not only accurate forecasts but also economically meaningful explanations for decisions that influence capital allocation. This has motivated growing interest in hybrid approaches that combine the forecasting power of ML with econometric methods capable of explaining underlying economic relationships (Molnar, 2022; Rudin, 2019). While a substantial body of research has explored ML-based stock market forecasting and economic linkages, important gaps remain in understanding how these methods can be integrated within the broader investment management process, particularly in the context of the New Zealand (NZ) equity market.

The existing literature on global financial market interconnectedness predominantly emphasizes financial shock propagation mechanisms through Vector AutoRegressive (VAR) econometric models as demonstrated in Dees et al. (2007), Galesi and Lombardi (2009), Eickmeier and Ng (2011), Beirne and Gieck (2014), and more recently by Dogah and Premaratne (2021), and Kakran et al. (2023). Studies specifically examining NZ equity market linkages with New Zealand's principal trading partners remain limited. Contemporary analyses have typically either included New Zealand within broader Asia-Pacific market aggregations or concentrated primarily on NZ bilateral relationship with Australia, neglecting trade dynamics with significant economic partners such as China, the United States (U.S.), and European markets. Such analyses were demonstrated in Johnson and Soenen (2002), Narayan and Smyth (2005), Fraser et al. (2008), Qiao et al. (2011), Paramati et al. (2016), Lin and Quill (2016), and Kakran et al. (2023).

Parallel to this strand of literature, research on ML applications in financial forecasting has expanded rapidly, primarily emphasizing algorithmic performance comparisons rather than economic interpretation. Studies consistently demonstrate that ML models outperform traditional econometric approaches in predictive accuracy across various financial contexts; see Athey and Imbens (2019), Garcia-Vega et al. (2020), Pekedis (2020), Ozgur and Akkoc (2021), Zhang and Jia (2021), Coulombe et al. (2022), Belly et al. (2023), and Liu and Wang (2023), among others. While these findings underscore the potential of ML, most research treats ML and econometrics as competing methodologies rather than complementary tools. Consequently, relatively few studies have attempted to integrate ML techniques with established econometric frameworks in a manner that enhances both forecasting performance and interpretability.

The combination of advanced econometric models—particularly the Global Vector AutoRegressive (GVAR) framework—with ML algorithms represents a nascent and under-explored research direction. Existing studies that pursue such integration often focus on policy analysis or regional economic transmission rather than investment decision-making, see, e.g., Varner (2017), and Zhao and Chen (2021). Moreover, applications of these hybrid methodologies to small, open economies such as New Zealand are virtually absent from the literature.

Note that the GVAR framework is originally designed for large cross-country systems with many interconnected country-specific VAR models linked through observable foreign variables, as in the seminal literature (Chudik & Pesaran, 2016). However, in this study, our GVAR refers to the VAR systems augmented with cross-market linkages and common global factors, even when the cross-sectional dimension is relatively small, e.g., a limited set of financial markets. Specifically, our model is closer to a multi-market VAR with weak exogenous global factors and cross-lag interactions rather than a full high-dimensional country-level GVAR of the type used in large international datasets.

The NZ equity market presents a unique research context due to its relatively small size and strong dependence on international trade. Its evolving economic relationship with China, alongside traditional ties with Australia and the United States, may generate distinctive intermarket transmission mechanisms that have not been adequately captured by prior research. Despite this, scholarly attention to NZ stock market forecasting remains minimal, particularly within frameworks that align economic theory with practical investment applications.

We aim to address these gaps by developing an analytical framework that combines econometric modeling with ML techniques to examine intermarket relationships involving the NZ equity market. Specifically, we attempt to quantify co-movements and lead–lag relationships between the NZ equity market and those of the principal trading partners, and to forecast the directional movements in the NZ equity market. The scope of the study is deliberately restricted to examining the unidirectional influence of international equity markets on the NZ market. Given the relatively small capitalization of the NZ equity market, its influence on larger markets is assumed to be negligible—an assumption supported by existing empirical literature.

Our study contributes to both academic literature and investment practice by developing a hybrid framework that integrates econometric rigor with ML-driven predictive capabilities. From a practical perspective, the findings offer valuable insights for TAA and market timing decisions by enhancing understanding of intermarket dynamics involving NZ equities. Improved identification of lead–lag relationships enables investors to exploit short-term market inefficiencies and optimize portfolio allocation decisions.

From a methodological standpoint, this study advances the literature by demonstrating how ML algorithms can be embedded within an econometrically grounded framework to improve forecasting accuracy without sacrificing interpretability. By tailoring this approach to the NZ market context, our study addresses a research gap and provides a foundation for future studies examining small, open economies within a global financial system.

The organization of the remaining sections is as follows. Section 2 describes the investment management framework and its relevance to macroeconomic foundations. Section 3 explains the methodology used in the study. Section 4 presents the results from the empirical analysis. Section 5 concludes.

2. Investment Management Framework and Macroeconomic Foundations

Investment management is a complex and multifaceted discipline grounded in a structured framework that integrates long-term strategic objectives with short-term tactical decision-making (Amenc & Le Sourd, 2003). At its core, this framework balances disciplined portfolio construction with adaptive responses to evolving market conditions. Strategic Asset Allocation (SAA), Tactical Asset Allocation (TAA), and market timing together form the foundational pillars of this process, supported by intermarket analysis, lead–lag dynamics, and price discovery mechanisms. These components collectively enable investors to align portfolios with long-term objectives while exploiting short-term inefficiencies arising from macroeconomic and financial market interdependencies.

2.1. Investment Process and Management Framework

The investment process is a systematic and repeatable framework for constructing, managing, and evaluating portfolios to achieve specific financial objectives (Damodaran, 2012; Maginn et al., 2007). A well-defined process promotes discipline, consistency, and adaptability, enabling investors to respond effectively to changing market conditions, while evidence suggests that the consistent application of a coherent strategy by stable management teams is a stronger predictor of future performance than frequent shifts in investment approach (Sharpe et al., 2007). The process generally includes setting objectives and constraints, SAA, TAA, security selection, portfolio construction, trade execution, and ongoing monitoring. Objectives establish return expectations and risk tolerance, while constraints such as liquidity needs, investment horizon, regulatory requirements, and taxation influence feasible strategies. Within this framework, SAA serves as the long-term foundation of the portfolio by determining capital allocation across major asset classes and defining the portfolio's long-run risk–return characteristics (Rasmussen, 2003). Research has consistently shown that asset allocation is the primary driver of portfolio return variability, highlighting its central role in portfolio resilience and long-term performance (Brinson et al., 1986; Elkamhi et al., 2021; Ibbotson & Kaplan, 2000; Wein, 2022).

While SAA provides the strategic foundation, TAA introduces flexibility by allowing temporary deviations from strategic weights based on short-term market expectations, valuation signals, and macroeconomic conditions (Maginn et al., 2007). Through overweighting asset classes expected to outperform and underweighting those anticipated to underperform, TAA seeks to improve risk-adjusted returns while maintaining diversification benefits (Bodie et al., 2011). Closely related to TAA, market timing focuses on determining optimal entry and exit points based on anticipated price movements. Although timing strategies involve greater implementation risk, particularly when investors become excessively invested or disengaged at unfavorable moments, empirical evidence suggests that skill-based market timing can generate alpha when supported by systematic analysis and robust forecasting methods (Jiang et al., 2009). The effectiveness of both TAA and market timing, therefore, depends on the accurate identification of leading indicators and disciplined execution, emphasizing the value of quantitative frameworks capable of capturing complex market interconnectedness.

2.2. Intermarket Analysis, Lead–Lag Dynamics, and Price Discovery

Intermarket analysis enhances the investment framework by examining the co-movement and transmission of information across asset classes and geographic markets (Murphy, 2004). Financial markets do not operate in isolation; rather, price movements in one market often precede or follow movements in others. Recognizing these relationships enables investors to improve TAA decisions, refine market timing, and enhance portfolio monitoring.

A central concept within intermarket analysis is lead–lag dynamics—the observation that certain markets consistently incorporate information earlier than others. Larger, more liquid markets, particularly the U.S. equity market, often function as global information leaders, with smaller markets responding after observable lags (Eun & Shim, 1989). Empirical studies confirm the existence of statistically significant lead–lag relationships across asset classes and regions, providing exploitable signals for timing strategies (Liang & Yen, 2014; Maier-Paape & Platen, 2016; Schmidt et al., 2024). These dynamics are closely linked to price discovery mechanisms, which describe how markets assimilate information into prices. Markets with higher liquidity and trading volume tend to lead price discovery, reinforcing their role as information hubs (Frijns et al., 2015; Holden et al., 2014).

2.3. Macroeconomy and Equity Markets

Equity markets fundamentally represent claims on future corporate cash flows, rendering them intrinsically sensitive to macroeconomic conditions. Within fundamental analysis, investors commonly employ either top–down or bottom–up approaches. The top–down approach begins with macroeconomic analysis—examining indicators such as GDP growth, inflation, interest rates, and employment—before narrowing focus to industries and firms. This approach allows investors to align portfolios with prevailing and anticipated economic conditions, systematically favoring sectors positioned to benefit from macroeconomic trends (Gastineau et al., 2007).

Macroeconomic variables influence equity valuations through their effects on expected cash flows and discount rates within present value frameworks (Mauboussin & Callahan, 2021). Economic expansions typically enhance corporate earnings potential, while recessions, inflationary pressures, or restrictive monetary policies may depress valuations. Recent empirical evidence continues to demonstrate significant links between stock market performance and macroeconomic indicators, including inflation, interest rates, exchange rates, and economic growth, although the magnitude and direction of these effects vary across countries, market structures, and economic regimes (Alloul & Ferrouhi, 2024; Baek et al., 2024; Časta, 2023; Sari & Riyadi, 2025). Furthermore, growing research highlights that macroeconomic shocks, monetary policy uncertainty, and inflation expectations play an important role in explaining equity return dynamics and cross-market transmission effects, reinforcing the importance of incorporating macroeconomic information into investment decision-making (Chiang, 2023, 2024; Kollias, 2024).

2.4. Economic Interconnectedness and Trade Dependence

Globalization has intensified economic interconnectedness through trade, capital flows, and financial integration. These linkages are particularly consequential for small, open economies such as New Zealand, whose economic performance is heavily influenced by external demand and global conditions. Trade openness has been shown to support long-term economic growth and stability, while simultaneously increasing sensitivity to foreign economic shocks (Weerasinghe, 2009).

New Zealand's economy is highly trade-dependent, with exports and imports comprising a substantial share of GDP. Major trading partners—including China, Australia, the United States, and the European Union—play a decisive role in shaping New Zealand's economic and financial conditions. Export-oriented sectors such as dairy, agriculture, and logistics exert significant influence on the NZ equity market, as fluctuations in global demand directly affect corporate revenues and profitability (Kumar, 2019; Paramati et al., 2016). The NZX 50 index, representing approximately 90% of New Zealand's equity market capitalization, serves as the primary benchmark for assessing domestic market performance. The index's sector composition—dominated by industrials, healthcare, and utilities—reflects the structure of the NZ economy and its exposure to global trade and financial conditions. Empirical studies consistently identify New Zealand as a net recipient of international financial influences, particularly from larger and more liquid markets (Kakran et al., 2023).

Research examining NZ equity market interconnectedness reveals strong linkages with Australia, the United States, and selected Asian and European markets, though the relative strength and timing of these relationships vary over time (Fraser et al., 2008; Lin & Quill, 2016; Qiao et al., 2011). Information diffusion typically originates in larger markets where price discovery occurs more rapidly, subsequently transmitting to the NZ market with observable lags. Using cross-listed Australian and New Zealand firms, Frijns et al. (2010) show that price discovery is concentrated in the larger and more liquid Australian market, with New Zealand prices adjusting to information revealed abroad. These findings underscore the relevance of intermarket and lead–lag analysis for forecasting NZ equity movements and informing tactical allocation decisions.

2.5. Interest Rates and Equity Market Dynamics

Interest rates represent a critical macroeconomic variable influencing equity markets through borrowing costs, investment incentives, and valuation discount rates. In New Zealand, monetary policy is conducted by the Reserve Bank of New Zealand through adjustments to the Official Cash Rate (OCR). Changes in interest rates can exert both short- and long-term effects on equity valuations, though empirical evidence suggests that the NZ market exhibits stronger short-term sensitivity to interest rate movements than persistent long-term causality (Dassanayake & Jayawardena, 2017; Gan et al., 2006).

Rising interest rates generally increase the cost of capital and reduce equity attractiveness relative to fixed-income assets, while accommodative monetary policy tends to support equity valuations. However, the magnitude and direction of these effects depend on broader economic conditions, sectoral composition, and investor expectations, reinforcing the need for integrated analytical frameworks.

In summary, the investment management framework and macroeconomic foundations establish the conceptual basis for analyzing NZ equity market dynamics within a globally interconnected financial system. Strategic and tactical asset allocation, informed by intermarket analysis and macroeconomic insights, provides a structured yet adaptive approach to portfolio management. For a small, trade-dependent economy such as New Zealand, understanding international economic linkages, lead–lag relationships, and price discovery processes is essential for effective forecasting, market timing, and tactical decision-making. This integrated perspective underpins the methodological framework developed in subsequent sections of this study.

3. Methodology

This study focuses on analyzing how the equity markets of NZ major economic trade partners influence NZ equity market and explores how these insights can be leveraged to identify trends and enhance forecasting of the New Zealand stock index NZX 50. We consider the dynamics and interconnectedness of financial markets as an interdisciplinary endeavour, integrating principles from investment finance, economics, econometrics, and machine learning (ML). Rooted in investment management, the conceptual framework of intermarket analysis provides the foundation for understanding market interconnectedness. Economics offers the theoretical basis for examining market integrations while econometrics using the GVAR model, provides a powerful tool to quantify and validate these complex interactions. ML complements this by generating forecasts for the NZ equity index based on the results of the econometric analysis. Figure 1 summarizes this interdisciplinary approach ensuring that the intermarket analysis is grounded in fundamental analysis, employing a theoretically sound methodology to identify and evaluate directional relationships between markets (Halton, 2024).

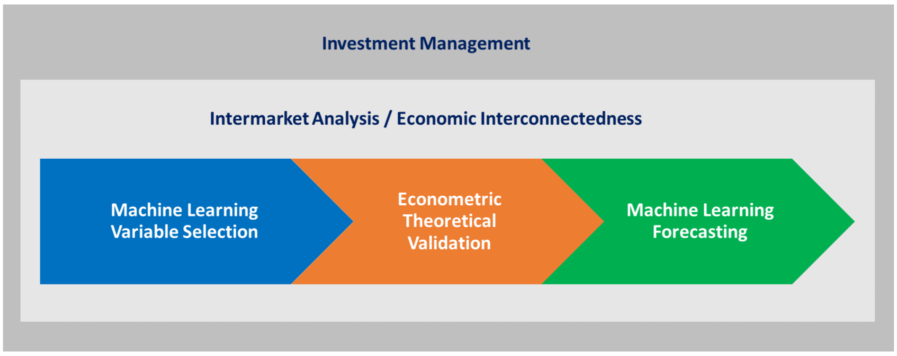

Figure 1. Methodology framework.

3.1. Interconnectedness Measurement

Interconnectedness differs fundamentally from interdependence and cointegration and is more appropriate for describing financial market dynamics. Large markets may transmit information and shocks to smaller markets without being economically dependent on them. Cointegration, by contrast, is a statistical property describing a stable long-run equilibrium relationship between non-stationary time series variables and does not capture the short- and medium-term dynamics, directional interactions, or information transmission mechanisms that characterize financial markets. Consequently, interconnectedness better reflects the dynamic, asymmetric, and time-varying interactions among financial markets, emphasizing lead–lag effects, spillovers, and transmission channels rather than equilibrium dependence.

The quantitative analysis of economic and financial interconnectedness is grounded in econometrics and, more specifically, financial econometrics, which employs models tailored to the stylized facts of financial markets such as volatility clustering, non-stationarity, and structural change. These tools are widely used to test financial theories, measure cross-market linkages, and support investment decision-making in asset allocation, portfolio construction, risk management, and market timing; see, e.g., Costola (2013) and Fabozzi et al. (2014). Model selection is guided by research objectives, data characteristics, and analytical context, with a critical distinction between causal inference and predictive accuracy. Causal analysis requires models grounded in sound economic theory to ensure interpretability, whereas predictive analysis prioritizes forecasting performance, even at the expense of theoretical clarity. This trade-off underscores the importance of selecting econometric frameworks that balance explanatory power with predictive robustness, particularly in the study of international financial market interconnectedness and shock transmission. See Table A1 for the summary of prior studies on interconnectedness measurement.

3.2. Global Vector Autoregression

The Global Vector Autoregressive (GVAR) model, developed by Pesaran et al. (2004) and later extended by Dees et al. (2007), is an econometric framework designed to analyze the interconnectedness of multiple countries or regions within the global economy. Unlike traditional VAR models that focus on a single economy, GVAR integrates individual country-specific VAR models into a unified system by incorporating both domestic variables and foreign variables represented through weighted averages (star variables) of other countries' economic indicators. This approach captures both short-run dynamics and long-run equilibrium relationships while addressing the dimensionality problem through the assumption that foreign variables are weakly exogenous. The methodology involves three main steps: estimating country-specific models, linking them through weighted foreign variables based on trade or financial connections, and combining them into a global system that accounts for international spillovers and feedback effects. Despite challenges related to data requirements, parameter stability, and model complexity, GVAR is mainly used for macroeconomic forecasting, policy analysis, and risk assessment, particularly in evaluating the international transmission of economic shocks and policy changes. Unlike prior works, our study focuses more on using GVAR to examine the interconnectedness between the NZ stock market NZX 50 and the equity markets of its major trading partners, such as Australia ASX 200, Japan Nikkei 225, and U.S. S&P 500. This is a main contribution of our study.

In the first step, the general form of our country-specific model, for a country $i = 0, 1, 2, \ldots, N$, is given by:

$$\begin{aligned} x_{it} = a_{i0} + a_{i1}t + \Phi_{i1}x_{i,t-1} + \ldots + \Phi_{ip_i}x_{i,t-p} \\ + \Lambda_{i0}x^*_{it} + \Lambda_{i1}x^*_{i,t-1} + \ldots + \Lambda_{iq_i}x^*_{i,t-q} \\ + \Psi_{i0}g_t + \Psi_{i1}g_{t-1} + \ldots + \Psi_{iq_i}g_{t-q_i} + u_{it} \end{aligned} \quad (1)$$

where

x_{it} is a $(k_i \times 1)$ vector of domestic variables for a country i in period $t = 0, 1, 2, \ldots, T$;
a_{i0} is a $(k_i \times 1)$ vector of constants;
t is a $(k_i \times 1)$ vector of deterministic time trends;
Φ_{ip}, Λ_{iq}, and Ψ_{iq} are regression coefficients;
x^*_{it} is a $(k_i \times 1)$ vector of foreign variables;
g_t is a $(k_i \times 1)$ vector of global variables (if any);
u_t is a $(k_i \times 1)$ vector of country-specific idiosyncratic shocks;
p and q denote lag lengths for domestic and global variables, respectively.

According to Equation (1), GVAR models the interconnectedness across individual variables within countries by incorporating lags of all variables in the equations. The reduced-form errors are also allowed to be dependent across countries.

Through conditioning domestic variables on weakly exogenous foreign variables, the correlation level of the errors is reduced. In the second step, the foreign variables are constructed from the domestic variables to correspond with the international trade pattern of the country under consideration. Each variable in x^*_{it} is computed as a weighted average of all countries' corresponding domestic variables, with the weights being country-specific, such that:

$$x^*_{it} = \sum_{j=1}^{N} w_{ij}x_{jt}$$

subject to the constraint:

$$\sum_{j=1}^{N} w_{ij} = 1, \quad w_{ii} = 0$$

where w_{ij}, $i, j = 1, 2, \ldots, N$ are bilateral trade weights.

GVAR treats foreign variables x^*_{it} as weakly exogenous, as each economy contributes a relatively small portion to the global economy. The weak exogeneity assumption is the key feature of the GVAR model since it allows country models to be estimated individually and combined at a later stage. GVAR allows for short and long-run dynamics by imposing co-integration relations.

In the third step, abstracting from deterministic variables (i.e., constants and trends) and higher order lags, Equation (1) can be rewritten using a VARX*(1,1) model as:

$$x_{it} = \Phi_{i1} x_{i,t-1} + \Lambda_{i0} x^*_{it} + \Lambda_{i1} x^*_{i,t-1} + u_{it}$$

which can be written in error correction form as:

$$\Delta x_{it} = \alpha_i \mathrm{ECM}_{i,t-1} + \Lambda_{i0} \Delta x^*_{it} + u_{it}$$

where

$$\mathrm{ECM}_{i,t-1} = \beta'_{ix} x_{i,t-1} + \beta'_{ix^*} x^*_{i,t-1}$$

is the vector of long-run cointegrating relations, also known as the VECM. The individual VARX* models are consistently estimated using OLS, conditional on a given estimate of β_i and the vector of the representative foreign countries' corresponding variables.

Note that, in the second step, all the endogenous variables in the global model are solved simultaneously using the estimated country-specific models. Although estimation procedures are implemented on a country-by-country basis, the GVAR model is solved as a whole, as all of the variables are endogenous with respect to the global model. The solution of the GVAR is a mechanical process that does not necessitate any estimation.

3.3. Relevant Tests and Procedures

To prepare the data for the GVAR model, we have to perform several tests/procedures, including the augmented Dickey-Fuller (ADF) test, and lag length selection. The ADF is used to detect unit roots by testing the null hypothesis of non-stationarity against the alternative of stationarity while accounting for autocorrelation through lagged difference terms. When non-stationarity is detected, differencing the series, which is the case for our daily returns, can remove the unit root and produce stationary data suitable for our GVAR modeling. The lag selection is another important step in the VAR/GVAR modeling framework. The lag length is chosen through some information criteria such as Akaike information criterion (AIC), Bayesian information criterion (BIC), and the Hannan–Quinn Information Criterion (HQIC). The lag length that minimizes the chosen criterion is considered optimal and must be determined prior to procedures such as the Johansen cointegration test, which requires a predefined lag structure.

We also use the Johensen cointegration and the Granger causality in the modeling procedures. Generally, the Johansen test is a widely used multivariate approach for detecting and determining the number of cointegrating relationships among multiple non-stationary variables by transforming a VAR model into a vector error correction model (VECM). In our case, the Johansen test plays a key role in validating stock market interconnectedness by identifying long-term cointegrating relationships that underpin equilibrium error correction mechanisms, thereby linking short-term dynamics to long-run trends and enhancing model stability and reliability. Its ability to detect multiple cointegrating vectors allows the GVAR model to capture the complex interdependencies characteristic of global financial markets, improving explanatory and forecasting performance. Importantly, the Johansen test must be applied to variables in their level form rather than differenced data, as differencing removes the long-term information required to identify cointegration.

In GVAR modeling, Granger causality is essential for identifying predictive interdependencies among variables and capturing the directional dynamics of interconnected financial systems, such as how shocks in one market transmit to others. The Granger causality test examines whether lagged values of one variable improve the prediction of another beyond its own past values by comparing models with and without the additional lagged terms. Evidence of Granger causality can reveal leading–lagging relationships, for example, whether major markets like the U.S. influence smaller or regional markets, thereby enhancing the GVAR model's explanatory and forecasting performance. However, such results must be interpreted cautiously, as Granger causality reflects statistical predictability and information flow rather than true structural causation.

3.4. Machine Learning Methods

Machine learning (ML) has become increasingly prominent in financial investment contexts due to its strong performance in predicting security prices, optimizing trading decisions, and modeling complex interdependencies across global markets using techniques such as neural networks, gradient boosting, and Support Vector Machines. ML methods excel in high-dimensional, data-rich environments by capturing nonlinearities and interaction effects without requiring predefined functional forms, enabling superior forecasting of equity returns, market indices, and intermediate drivers such as corporate earnings, often outperforming traditional linear models (Gu et al., 2020; Abe & Nakayama, 2018; Swinkels & Hoogteijling, 2022; Choi et al., 2019). Their ability to autonomously uncover previously unidentified relationships—sometimes referred to as knowledge discovery—enhances alpha generation but also necessitates caution to avoid overfitting and spurious patterns.

Alongside predictive performance, model interpretability has emerged as a critical consideration, as understanding how ML models generate predictions is essential for trust, bias mitigation, ethical accountability, and safe deployment (Konate, 2024; Kotagiri, 2024; Hakkoum et al., 2022). However, highly complex models such as deep neural networks are often treated as black boxes, creating a trade-off between interpretability and performance that requires careful balancing in financial applications (Kotagiri, 2024).

In this study, we use ML models and methods for two purposes. First, three regularization techniques, including least absolute shrinkage and selection operator (LASSO), ridge regression, and elastic net regression, are utilized to identify the most influential international market indices for predicting the New Zealand stock NZX 50 index. Second, we employ support vector regression (SVR), Random Forest (RF), long short-term memory (LSTM), and artificial neural network (ANN) to forecast the NZ stock returns. These were selected because they represent diverse learning paradigms and have demonstrated strong predictive performance in financial forecasting applications. Below are the brief descriptions of the aforementioned ML:

LASSO extends linear regression through the inclusion of a penalty term, which simultaneously performs coefficient shrinkage and variable selection (Tibshirani, 1996). Unlike ridge regression, LASSO can reduce some coefficients exactly to zero, effectively excluding irrelevant variables from the model. This property enhances model interpretability and enables the identification of the most influential predictors, making LASSO particularly attractive in high-dimensional modeling environments.

Ridge regression introduces a penalty term to the ordinary least squares objective function, shrinking regression coefficients toward zero without eliminating them entirely (Hoerl & Kennard, 1970). By reducing coefficient variance, ridge regression improves prediction accuracy and model stability when explanatory variables exhibit strong multicollinearity.

Elastic net regression combines the penalties of both ridge regression and LASSO by incorporating a weighted mixture of the regularization terms (Zou & Hastie, 2005). This hybrid approach balances variable selection and coefficient shrinkage, overcoming limitations associated with each individual method. In particular, the elastic net performs well when predictors are highly correlated, as it tends to select groups of related variables rather than arbitrarily choosing a single predictor. Consequently, it offers a flexible and robust framework for financial forecasting and asset allocation applications where complex interdependencies exist among explanatory variables.

These three models are often grouped under a broader subsection such as "regularized regression models", contrasting them with the nonlinear ML models (SVR, RF, LSTM, and ANN) used in forecasting and are described below.

SVR extends the Support Vector Machine framework to regression problems by identifying a function that minimizes prediction error while maximizing model generalization (Drucker et al., 1997; Vapnik, 1998). Through the use of kernel functions, SVR can model complex nonlinear relationships between predictors and target variables. The method is particularly effective when dealing with limited sample sizes and high-dimensional datasets, characteristics commonly encountered in financial applications.

While RF is an ensemble learning method that constructs a large number of decision trees using bootstrap samples and random subsets of predictors, with the final prediction obtained by averaging the outputs of individual trees (Breiman, 2001). By combining multiple trees, RF reduces overfitting and improves predictive accuracy while effectively capturing nonlinear relationships and variable interactions. Its robustness to noise and ability to handle high-dimensional data have made it widely used in financial forecasting and asset allocation studies.

LSTM networks are a specialized form of recurrent neural network designed to capture temporal dependencies in sequential data (Hochreiter & Schmidhuber, 1997). LSTM models incorporate memory cells and gating mechanisms that regulate the flow of information, enabling them to retain relevant long-term patterns while mitigating the vanishing gradient problem. This architecture has proven particularly effective for financial time-series forecasting, where historical information and evolving market dynamics play a critical role in predicting future outcomes.

ANN are computational models inspired by the structure of biological neural systems and consist of interconnected layers of processing units (neurons) (Haykin, 2009). ANNs learn complex functional relationships by adjusting connection weights during the training process. Their ability to approximate highly nonlinear functions makes them suitable for modeling financial markets, where relationships among variables are often dynamic and non-linear.

For more details of the machine learning models and methods used in the analysis, see Appendix B.

4. Empirical Analysis

4.1. Data Description

This study employs daily financial market data spanning from 3 January 2001 (NZX 50 inception date) to 31 December 2024. The start date was selected at the beginning of the millennium, and to avoid the impact of the Asian economic crisis. The end date was set to the point where the data were complete at the time of analysis. The dataset includes stock market indices from New Zealand and its major trading partners—specifically Australia, Japan, and the United States—together with the U.S. 10-year Treasury yield to capture interest rate effects. Data were sourced from multiple authoritative financial databases to ensure comprehensiveness and accuracy. The sources are:

- Yahoo! Finance (https://finance.yahoo.com/markets/world-indices/, accessed on 30 May 2025);
- Investing.com (https://www.investing.com/indices/world-indices, accessed on 1 May 2025);
- Wall Street Journal (https://www.wsj.com/market-data, accessed on 20 April 2025);
- Refinitiv Workspace.

For the GVAR modeling component, a weight matrix was constructed based on the relative market capitalizations of each country's equity market as reported by:

- World Federation of Exchanges (https://www.world-exchanges.org/our-work/statistics/archive/statistics, accessed on 15 May 2025);
- World Bank (https://data.worldbank.org/indicator/CM.MKT.LCAP.CD, accessed on 4 June 2025).

The raw data consist of daily closing prices for each index, subsequently transformed into daily returns to address non-stationarity issues inherent in financial time-series data and to better capture the proportional changes in market movements. Return data in Figure 2 represent the percentage changes or differences of the level data and are typically stationary. Since return series are already stationary, they do not exhibit persistent trends. The dataset was organized into two sets—global trading days and NZ trading days—to evaluate potential differences caused by trading days when the NZ market is open, and when other markets are open, but the NZ market is closed.

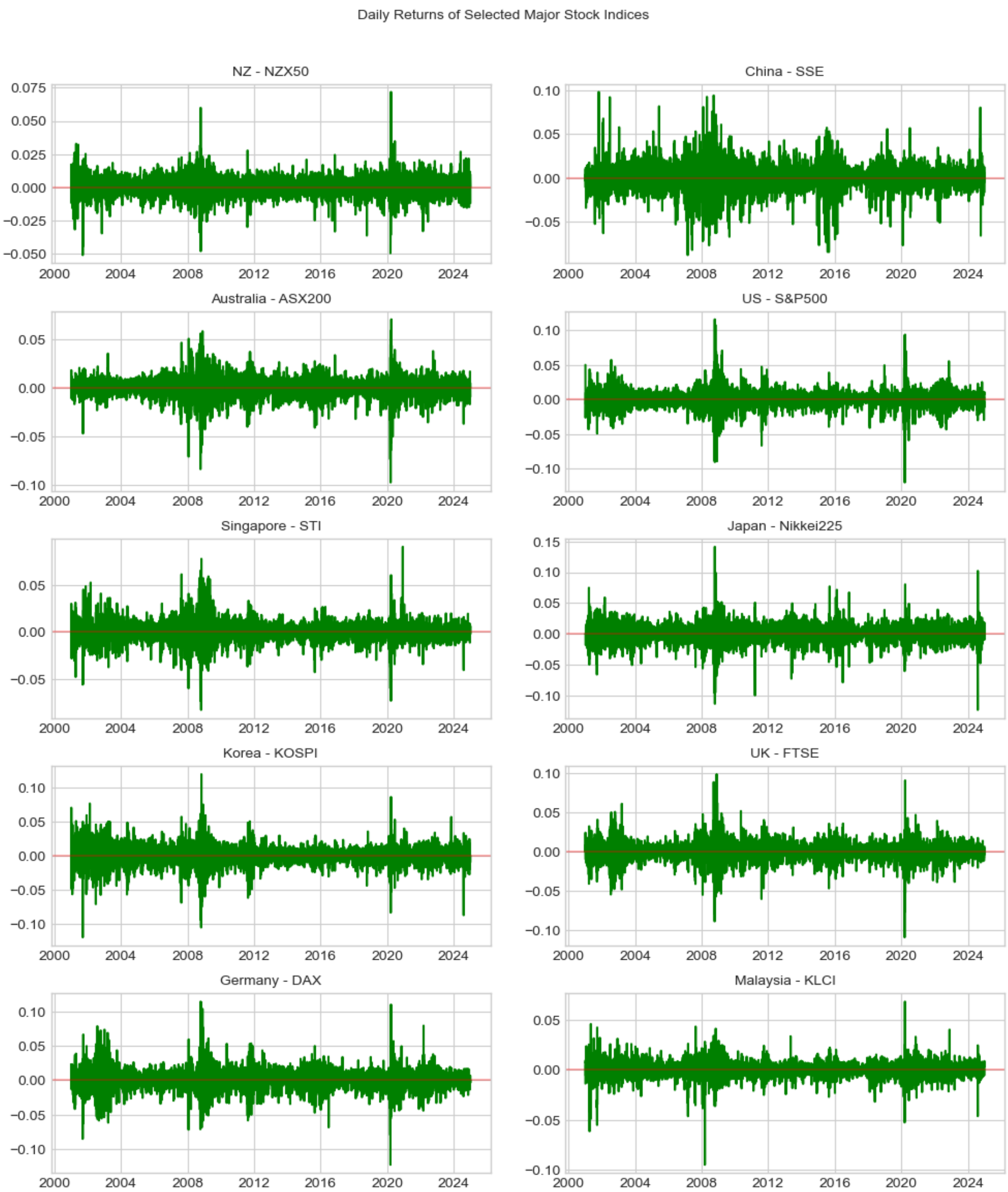

Figure 2. Daily return of selected stock indices (global trading days).

4.2. Exploratory Data Analysis

The two datasets have identical variables: 27 stock indices and bond yields. The global trading days dataset comprises 6203 observations aligned with the global market calendar, while the NZ trading days dataset contains 6071 observations, representing a 2.1% difference (132 days) attributable to NZ market closures that do not coincide with global market holidays. This methodological distinction has implications for the measurement of cross-market relationships and information transmission dynamics.

Both datasets exhibit consistent statistical properties characteristic of financial time series, and the return distributions demonstrate pronounced leptokurtosis; see Table 1. This finding aligns with established financial literature documenting the "fat-tailed" nature of asset returns. The distributions in Figure 3 maintain approximate symmetry around zero, and daily returns typically fluctuate within a ±5% range across markets, with occasional extreme values during periods of market distress (e.g., 2008–2009 financial crisis, 2020 COVID-19 market disruption), where returns exceeded ±10% for several indices.

Table 1. Descriptive statistics of daily return (selected indices and yields).

	NZX 50	ASX 200	Nikkei 225	S&P 500	U.S. Tr. Yield
Global Trading Days					
Count	6203	6203	6203	6203	6203
Mean	0.000397	0.000197	0.000251	0.000317	0.000287
Std Dev.	0.007038	0.009861	0.014142	0.011966	0.024612
Min	−0.051114	−0.096998	−0.123958	−0.119845	−0.293201
25%	−0.003286	−0.004370	−0.006285	−0.004322	−0.011204
50%	0.000488	0.000396	0.000000	0.000379	0.000000
75%	0.004252	0.005223	0.007336	0.005691	0.010835
Max	0.071829	0.070007	0.141503	0.115881	0.498998
NZ Trading Days					
Count	6071	6071	6071	6071	6071
Mean	0.000406	0.000191	0.000252	0.000286	0.000165
Std Dev.	0.007114	0.009905	0.014157	0.011998	0.024661
Min	−0.051114	−0.096998	−0.123958	−0.119845	−0.293201
25%	−0.003402	−0.004439	−0.006368	−0.004393	−0.011353
50%	0.000641	0.000471	0.000000	0.000367	0.000000
75%	0.004351	0.005246	0.007326	0.005682	0.010751
Max	0.071829	0.070007	0.141503	0.115881	0.498998

The descriptive statistics revealed small positive mean returns across all indices, with NZX 50 showing the highest mean return (0.000397 for global trading days and 0.000406 for NZ trading days), suggesting slightly better performance of the NZ market over the sample period. The standard deviations indicate that the Nikkei 225 exhibited the highest volatility (0.014142 for global trading days and 0.014157 for NZ trading days), while the NZX 50 demonstrated the lowest volatility (0.007038 for global trading days and 0.007114 for NZ trading days), highlighting the relative stability of the NZ market. The U.S. 10-year Treasury yield displayed substantially higher standard deviation (0.024612 for global trading days and 0.024661 for NZ trading days) compared to the equity indices, with extreme maximum values (0.498998 for both datasets) indicating significant upward movements in interest rates during certain periods.

The correlation analysis in Table 2 reveals a distinct hierarchy of influence on the NZ equity market. Australia ASX 200 exhibits the strongest correlation with NZX 50 (0.479 in global trading days and 0.482 in NZ trading days), followed by Japan Nikkei 225 (0.352 and 0.356, respectively) and Korea's KOSPI (0.321 and 0.325, respectively). This finding supports the hypothesis that geographical proximity and regional economic integration significantly influence equity market co-movements. Notably, despite considerable trade volume, China's SSE demonstrates only moderate correlation (0.139 in global days and 0.141 in NZ days), while the U.S. S&P 500 exhibits remarkably low correlation (0.063 in global days and 0.064 in NZ days) despite the United States' significant global economic influence. This discrepancy between trade relationships and market correlations suggests that financial market integration operates through mechanisms distinct from direct trade linkages, and that direct trade volumes are not the sole determinants of market correlation.

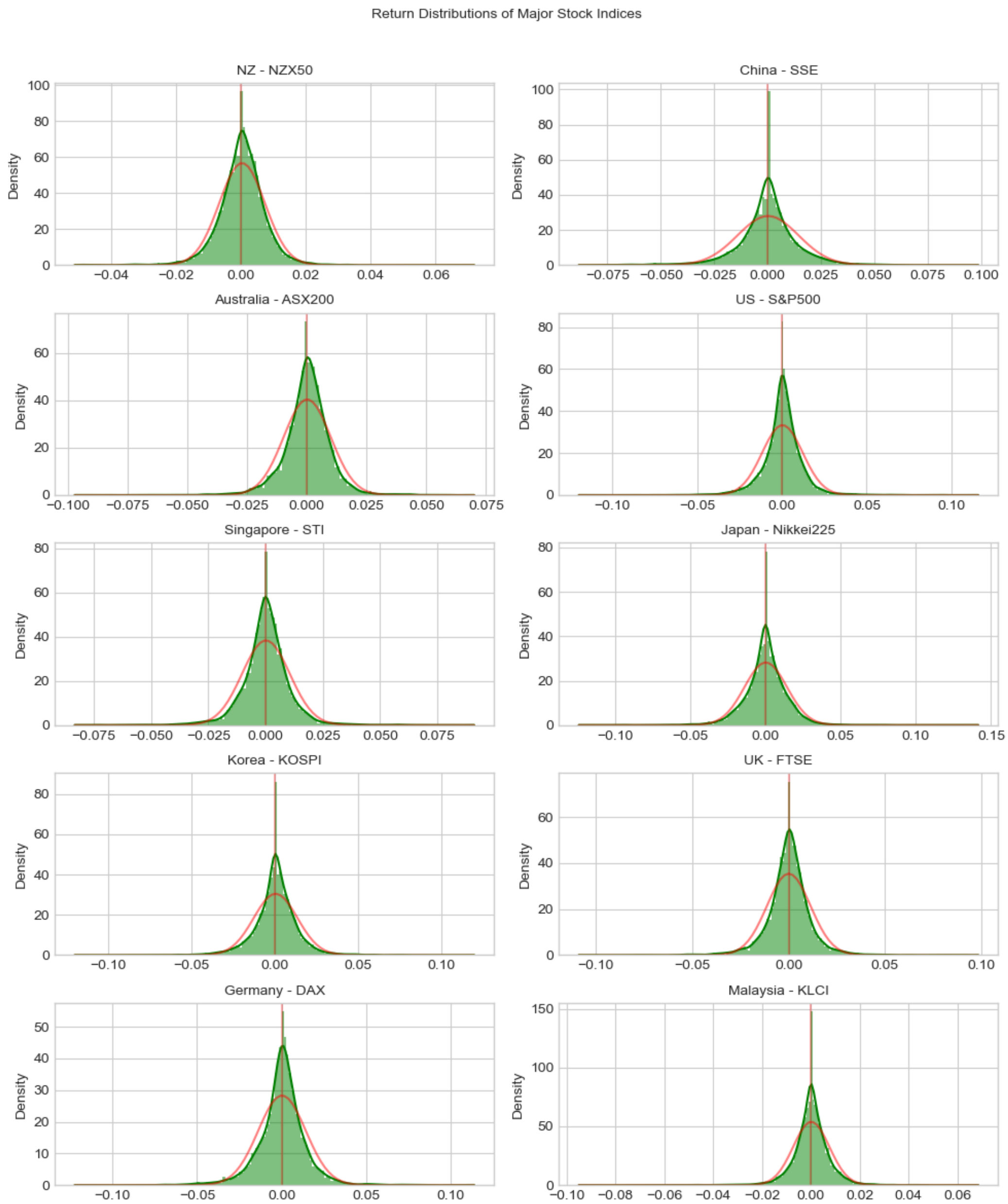

Figure 3. Return distribution of selected stock indices (global trading days).

The modest correlation with China's SSE does not imply that China is economically unimportant for New Zealand. Rather, it suggests that Chinese equity returns may not be the main financial-market channel through which China-related shocks affect the NZX 50. China's influence may instead operate through export demand, dairy and commodity prices, exchange rates, and regional investor sentiment, including indirect transmission through Australia, rather than through direct co-movement with the Shanghai equity market. This interpretation is consistent with Shi (2022), who documents that China–New Zealand stock-market co-movement is relatively modest compared with China's co-movement with other Asia-Pacific markets, despite the importance of bilateral trade.

Similarly, the low same-calendar-day correlation with the S&P 500 should be interpreted cautiously because the NZX 50 trading session occurs before the corresponding U.S. trading session. Thus, same-date correlation does not provide a clean measure of contemporaneous U.S.–New Zealand information transmission. This timing mismatch helps explain why the S&P 500 may exhibit weak same-date correlation with the NZX 50 while still containing substantial lagged predictive information for subsequent NZ trading sessions.

Table 2. Correlations with New Zealand NZX 50.

Rank	Market	Global Trading Days	Rank	Market	NZ Trading Days
1	Australia—ASX 200	0.479	1	Australia—ASX 200	0.482
2	Japan—Nikkei 225	0.352	2	Japan—Nikkei 225	0.356
3	Korea—KOSPI	0.321	3	Korea—KOSPI	0.325
4	Singapore—STI	0.312	4	Singapore—STI	0.310
5	Philippines—PSEi	0.301	5	Philippines—PSEi	0.310
6	Hong Kong—Hang Seng	0.288	6	Hong Kong—Hang Seng	0.292
7	Taiwan—TAIEX	0.288	7	Indonesia—IDX	0.244
8	Malaysia—KLCI	0.256	8	Taiwan—TAIEX	0.237
9	Indonesia—IDX	0.240	9	Malaysia—KLCI	0.233
10	Thailand—SET	0.224	10	Thailand—SET	0.227
11	India—Sensex	0.223	11	India—Sensex	0.226
12	Denmark—OMX	0.217	12	Denmark—OMX	0.219
13	UK—FTSE	0.216	13	UK—FTSE	0.218
14	Ireland—ISEQ	0.214	14	Ireland—ISEQ	0.215
15	Switzerland—SMI	0.207	15	Netherlands—AEX	0.209
16	Netherlands—AEX	0.207	16	Switzerland—SMI	0.208
17	France—CAC 40	0.199	17	France—CAC 40	0.200
18	Italy—FTSE MIB	0.171	18	Italy—FTSE MIB	0.173
19	Germany—DAX	0.166	19	Germany—DAX	0.168
20	Vietnam—VIN	0.142	20	Vietnam—VIN	0.143
21	China—SSE	0.139	21	China—SSE	0.141
22	Canada—TSX	0.135	22	Canada—TSX	0.136
23	Saudi Arabia—TASI	0.092	23	Saudi Arabia—TASI	0.093
24	U.S.—S&P 500	0.063	24	U.S.—S&P 500	0.064
25	NZ 10-year Bond Yield	0.055	25	NZ 10-year Bnd Yld	0.055
26	U.S. 10-year Treasury Yield	0.002	26	U.S. 10-year Treasury Yield	0.002

Using the global trading days dataset, regional aggregation analysis reinforces the pattern of localized influence. The Pacific region (comprising New Zealand and Australia) shows substantial correlation with Asia (0.63), moderate correlation with Europe (0.35), and weaker correlation with the Americas (0.22); see Figure 4. When disaggregated, Australia demonstrates consistently stronger correlations with non-Pacific regions than New Zealand does, suggesting Australia's potential role as a financial intermediary between New Zealand and the global. The correlation structure also reveals established interconnections between developed market blocs, with Europe-Americas correlations ranging from 0.62 to 0.63, substantially exceeding the Pacific-Americas correlation (0.22). The same analysis using the NZ trading days dataset produces similar results. Pacific and Asia correlations stand at 0.63, and Australia has the same consistently stronger correlations with non-Pacific regions than New Zealand does.

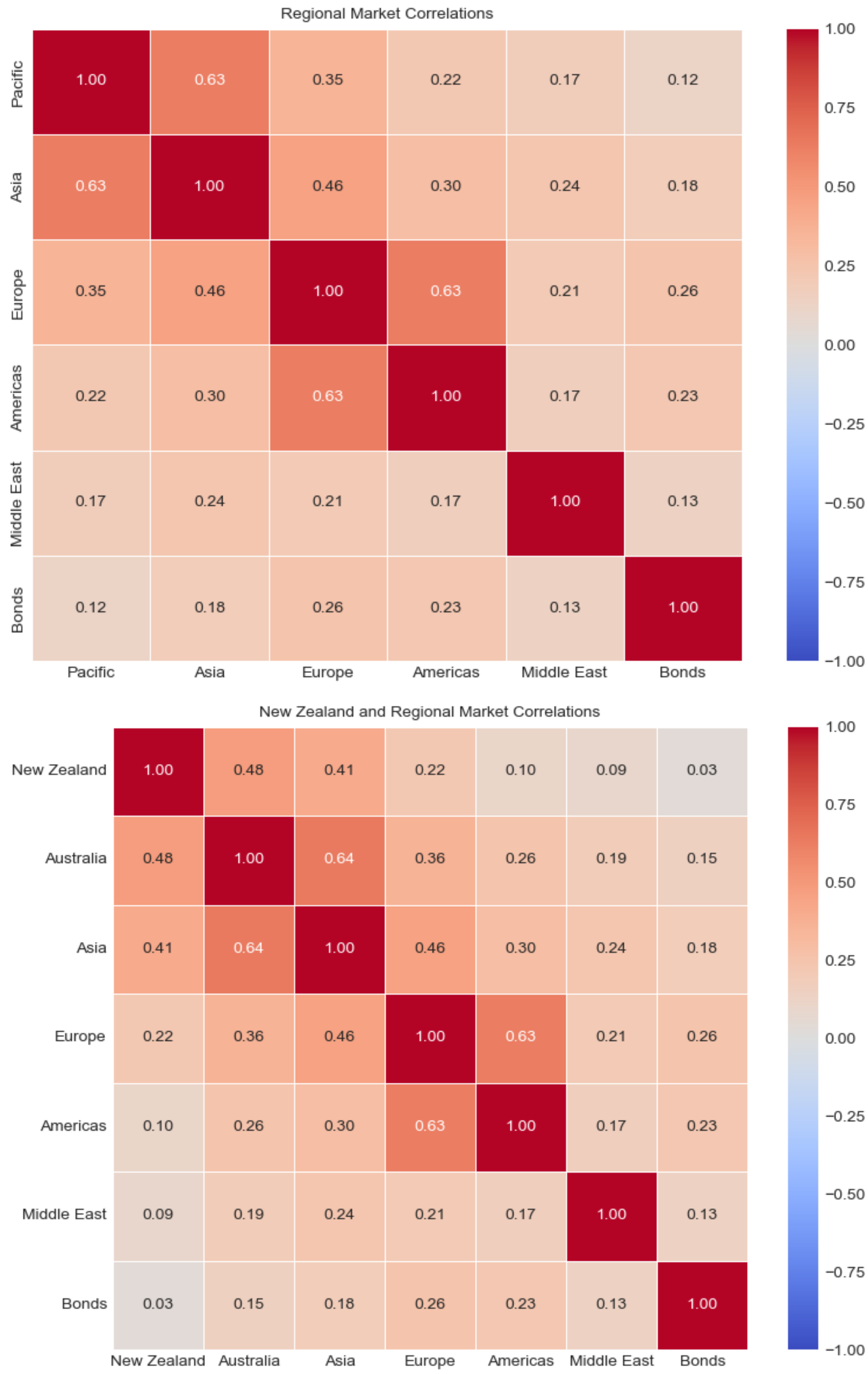

Figure 4. Regional and New Zealand market correlations (global trading days).

The selected rolling correlation analysis of a 252-day (1-year) window in Figure 5 reveals significant time variation in market relationships. The NZX 50 and ASX 200 correlation maintains consistent positivity throughout the observation period, fluctuating between 0.2 and 0.7, with a mean between 0.4 and 0.6. This relationship exhibits remarkable stability, never turning negative during the entire sample period. Conversely, the NZX 50 and S&P 500 correlation demonstrates considerable instability, ranging from −0.2 to 0.25 with multiple sign reversals, suggesting a more complex and potentially lagged relationship. The NZX 50 and China SSE correlation exhibits cyclical patterns, oscillating between −0.10 and 0.30, potentially reflecting the evolving trade relationship between these economies. Rolling correlation analysis using the NZ trading days dataset results in similar characteristics.

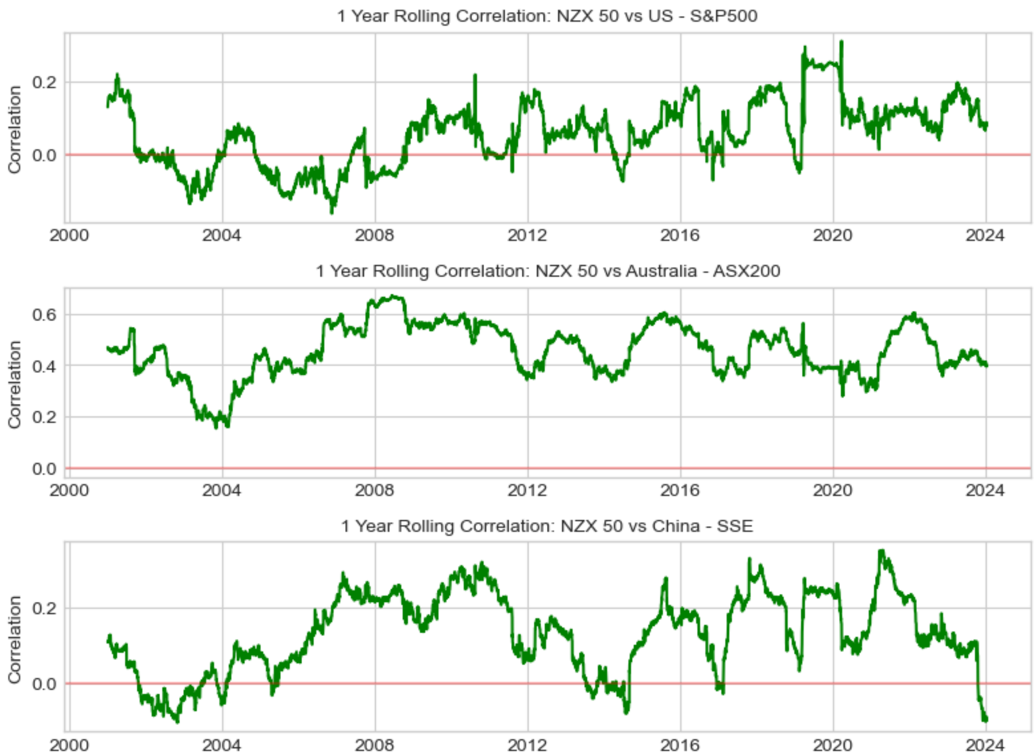

Figure 5. Selected 1-year rolling Correlations (Global Trading Days).

Analysis of rolling standard deviations of a 20-day (1-month) window confirms the presence of volatility clustering across all markets, a fact extensively documented in financial literature; see Figure 6. Pronounced volatility spikes are evident during major financial crises, with the 2008–2009 global financial crisis generating peak rolling standard deviations of approximately 0.030 for NZX 50, 0.04 for ASX 200, and 0.06 for S&P 500. The COVID-19 market disruption produced comparable magnitudes: approximately 0.03 for NZX 50, 0.05 for ASX 200, and 0.06 for S&P 500. The temporal alignment of these volatility episodes across markets corroborates the "correlation breakdown" phenomenon, whereby cross-market correlations approach unity during periods of extreme market stress (Longin & Solnik, 2001). Analysis of rolling standard deviations using NZ trading days produces similar results.

These findings have significant implications for the construction of an intermarket analysis framework for forecasting NZ equity market movements. First, the dominance of regional influences suggests that models prioritizing Asia-Pacific markets, particularly Australia, may yield superior predictive performance compared to models emphasizing more distant markets. Second, the observed discrepancy between trade relationships and market correlations necessitates a nuanced approach that considers financial market integration beyond direct economic linkages. Third, the substantial time variation in correlations underscores the importance of employing methodologies capable of capturing dynamic, non-linear relationships rather than static models. The complex, time-varying nature of these relationships provides strong justification for the application of ML algorithms capable of identifying and exploiting non-linear patterns in the data. Finally, the marginal differences between global and NZ trading day approaches suggest that while the choice of trading calendar affects the precise timing of information incorporation, it does not fundamentally alter the structure of market relationships.

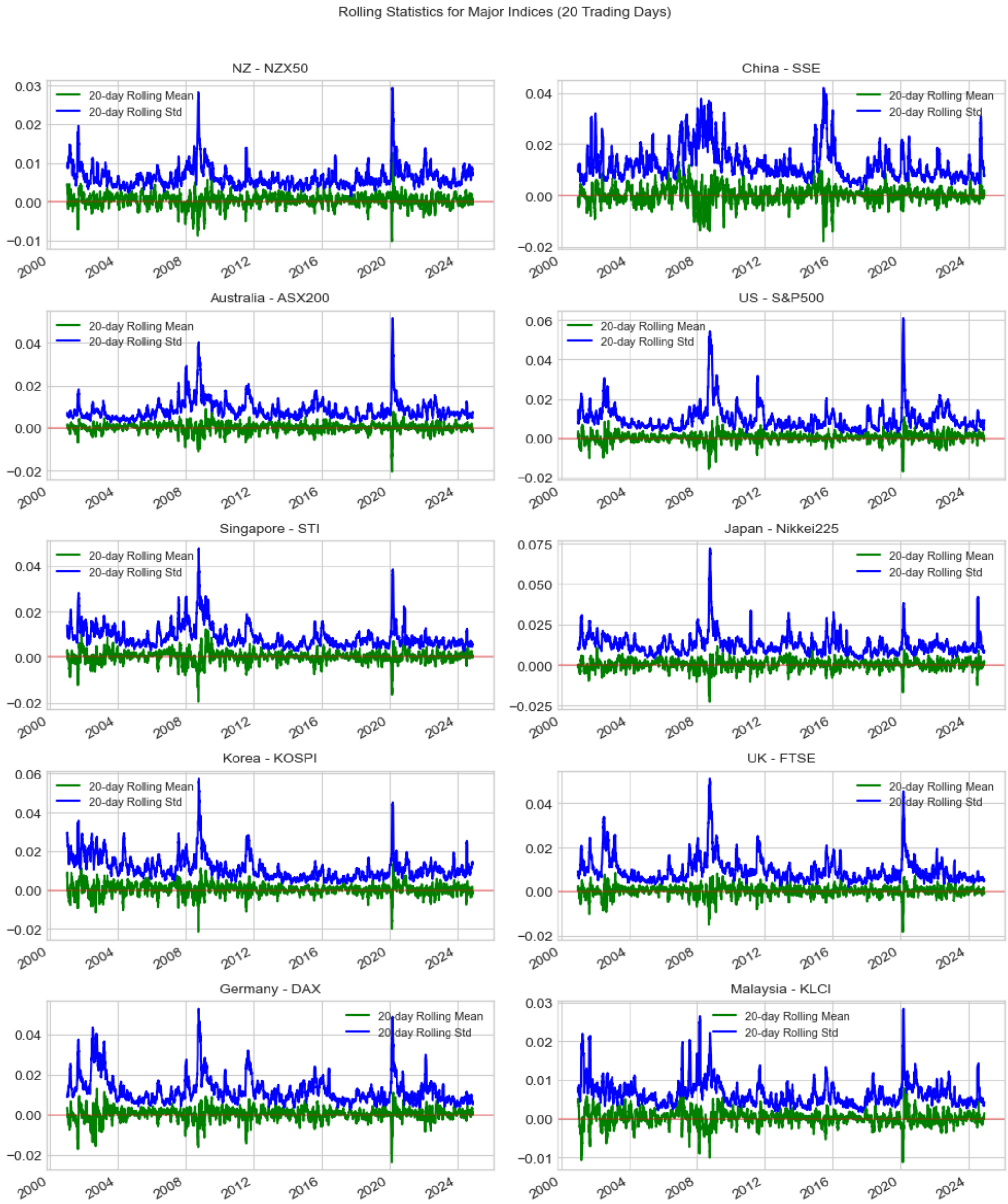

Figure 6. Selected 20-day rolling statistics (global trading days).

4.3. Feature Selection Analysis

This study employed three regularization techniques (LASSO, ridge regression, and elastic net regression) to identify the most influential international market indices for predicting the New Zealand NZX 50 index. These methods provide complementary approaches to feature selection: LASSO excels at feature selection through its L_1 penalty, ridge handles multicollinearity via L_2 regularization, and elastic net combines both approaches for a balanced methodology.

LASSO regression identified a reduced subset of predictors, selecting 11 features for global trading days and 12 for NZ trading days, with a consistent optimal alpha of 0.000139; see Table 3. The ASX 200 emerged as the most influential variable in both datasets (Table 4 and Figure 7). The PSEi and Nikkei 225 ranked second and third, respectively. Notably, the U.S. 10-year Treasury yield exhibited a negative relationship with the NZX 50, suggesting that rising U.S. interest rates adversely affect the NZ market through global monetary transmission mechanisms.

Table 3. Feature selection model parameters and performance.

Model	Optimal Alpha		Features Selected		Additional Parameters	
	Global	NZ	Global	NZ	Global	NZ
LASSO	0.000139	0.000139	11/26	12/26	–	–
Ridge	10	10	26/26	26/26	–	–
Elastic Net	0.000162	0.000379	11/26	14/26	L_1 Ratio: 0.90	L_1 Ratio: 0.30

Table 4. Top 15 influential indices ranking comparison.

Market	Global Trading Days			NZ Trading Days			Consistency
	LASSO	Ridge	Elastic Net	LASSO	Ridge	Elastic Net	
Australia—ASX 200	1	1	1	1	1	1	✓✓✓
Philippines—PSEi	2	2	2	2	2	2	✓✓✓
Japan—Nikkei 225	3	3	3	3	3	3	✓✓✓
U.S. 10-year Trea. Yield	4	5	4	4	5	4	✓✓✓
Switzerland—SMI	5	6	5	5	6	5	✓✓✓
U.S.—S&P 500	7	4	7	7	4	7	✓✓✓
Vietnam—VIN	6	9	6	6	10	6	✓✓✓
Taiwan—TAIEX	8	13	8	8	11	8	✓✓○
Malaysia—KLCI	9	15	9	11	19	11	✓✓○
Ireland—ISEQ	10	11	10	9	13	9	✓✓○
Denmark—OMX	11	22	11	10	20	10	✓✓○
Hong Kong—Hang Seng	–	7	–	–	9	–	○✓○
Netherlands—AEX	–	8	–	–	7	12	○✓○
Germany—DAX	–	10	–	–	8	–	○✓○
Thailand—SET	–	17	–	12	15	13	○✓○

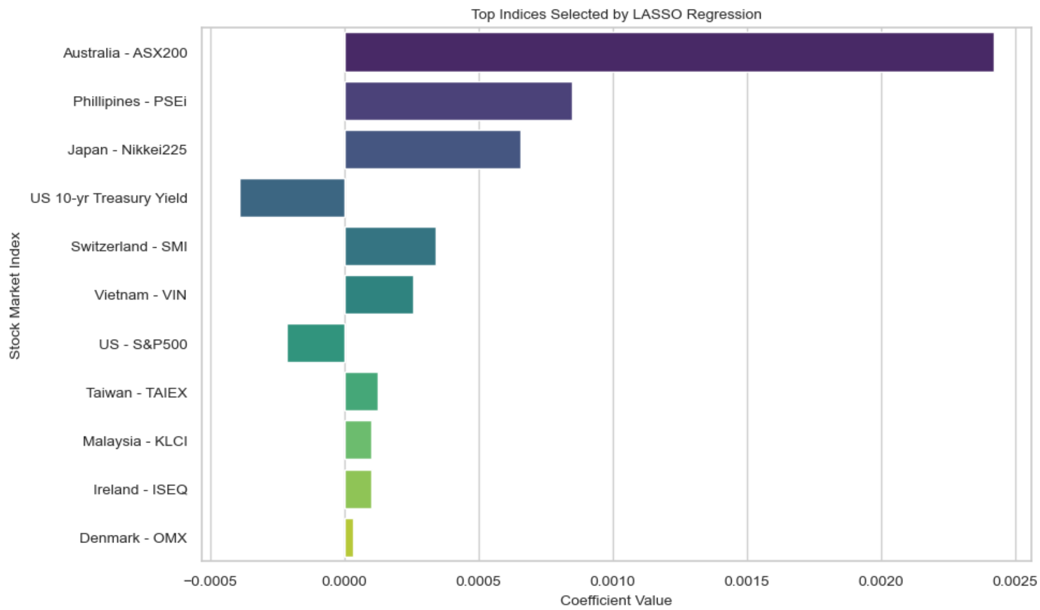

Figure 7. Top indices selected by LASSO.

Ridge regression retained all 26 features, applying stronger regularization (alpha = 10.0) to mitigate multicollinearity. Despite this, the ranking of influential predictors remained consistent with LASSO results. The ASX 200 again dominated, followed by the PSEi and Nikkei 225; see Table 4 and Figure 8. Less influential variables, particularly European indices such as the CAC40, received negligible coefficients, illustrating Ridge's tendency to shrink rather than eliminate predictors.

Elastic net combined LASSO and ridge characteristics, selecting 11 features (global dataset) and 14 features (NZ dataset). The optimal parameters differed slightly between datasets, with a stronger LASSO component in the global dataset and a more balanced approach in the NZ dataset. The ASX 200 remained the most significant predictor, followed by the PSEi and Nikkei 225, reinforcing the robustness of these variables (Table 4 and Figure 9).

A combined analysis across all three methods revealed strong agreement. Seven predictors were consistently identified: ASX 200, PSEi, Nikkei 225, U.S. 10-year Treasury yield, Switzerland's SMI, U.S. S&P 500, and Vietnam's VIN; see Figure 10. This consistency across models and datasets strengthens confidence in the reliability of these predictors.

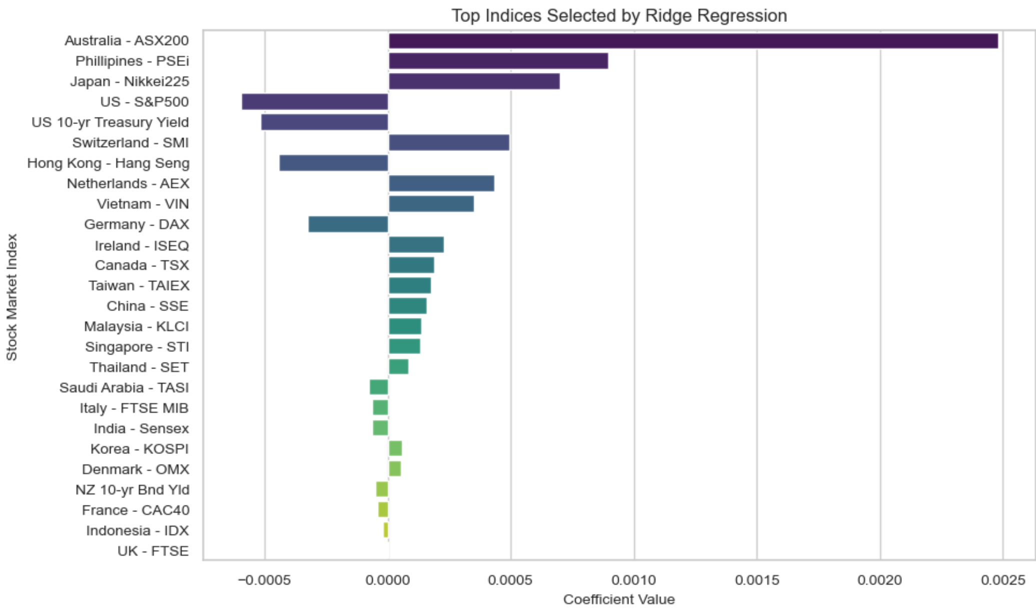

Figure 8. Top indices selected by ridge regression.

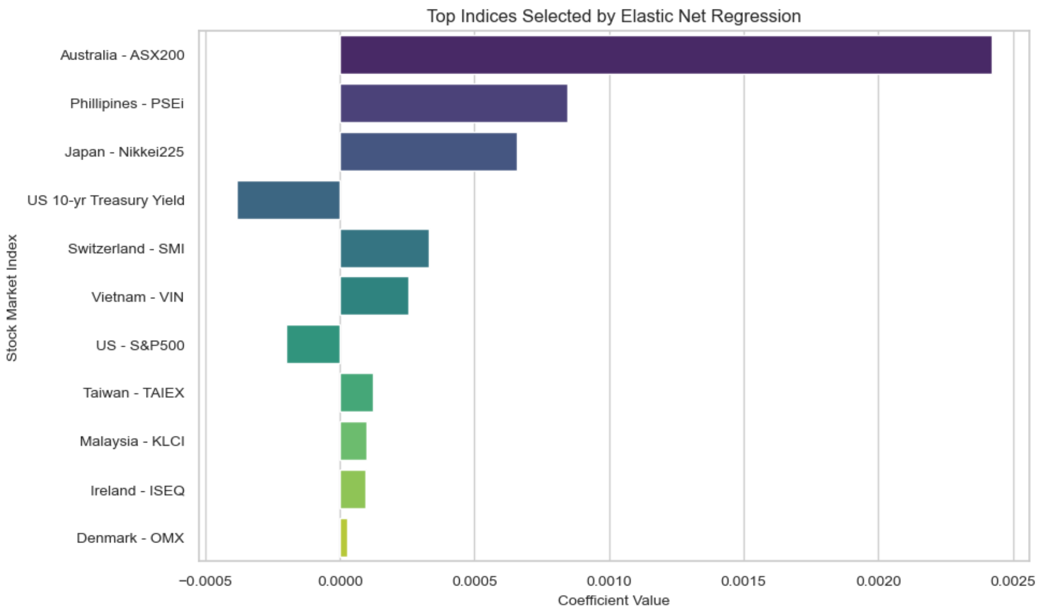

Figure 9. Top indices selected by elastic net regression.

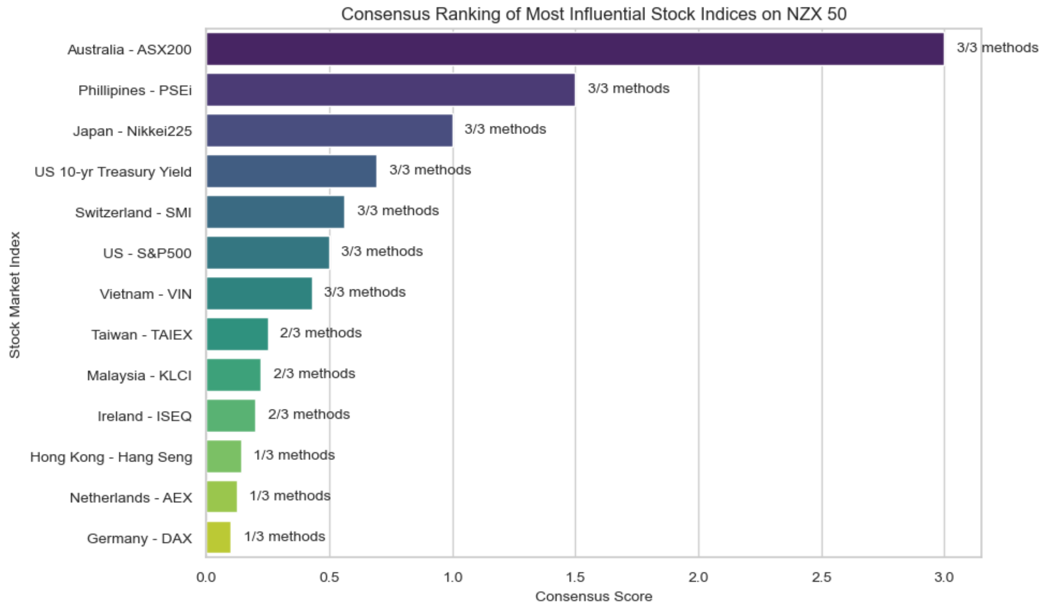

Figure 10. Consensus ranking of most influential indices.

These results align with intermarket analysis theory, which suggests that financial markets are interconnected rather than independent. The findings confirm strong regional dependencies, particularly within the Asia-Pacific region, as well as global influences from U.S. monetary policy and equity markets. The inclusion of both equity indices and bond yields highlights the importance of cross-asset relationships in explaining market dynamics.

Despite the statistical significance of several predictors, the final model prioritizes four key variables: ASX 200, Nikkei 225, S&P 500, and the U.S. 10-year Treasury yield. This selection reflects a balance between empirical results and practical considerations. Although the PSEi and Vietnam's VIN were consistently selected, they represent smaller markets with limited global influence, raising concerns about model robustness. Similarly, Switzerland's SMI, despite statistical relevance, lacks strong economic ties with New Zealand, suggesting potential spurious correlation. China is not retained in the final specification despite its importance as a trading partner because the objective of the model is to identify daily financial market predictors of NZX50 returns, rather than to measure long-run real economic exposure. The Shanghai equity market may be a noisy proxy for China-related demand conditions relevant to New Zealand firms. In particular, China-related effects may be transmitted through commodity demand, dairy prices, exchange rates, or indirectly through Australia, rather than through direct daily return spillovers from the SSE index.

The final selection emphasizes economically meaningful and widely recognized markets. The ASX 200 captures regional integration effects, the Nikkei 225 represents developed Asia-Pacific dynamics, the S&P 500 reflects global market sentiment, and the U.S. Treasury yield captures international monetary conditions. This parsimonious specification enhances interpretability while maintaining predictive power. The selection of the ASX 200 is consistent with evidence that the Australian market plays a leading role in regional price discovery and information transmission to New Zealand equities (Frijns et al., 2010). The S&P500 is retained not because it has high contemporaneous correlation with the NZX50, but because it contains lagged predictive information. U.S. market movements incorporate global risk sentiment, macro-financial news, and monetary policy expectations after the NZ market has closed, and this information can be reflected in the NZX50 during subsequent trading sessions. In addition, changes in global risk appetite originating in U.S.

markets may trigger international portfolio rebalancing and capital flows that subsequently affect New Zealand equity prices.

The predictive relevance of the Nikkei 225 may reflect Japan's position as one of the largest and most liquid equity markets in the Asia-Pacific region and a key regional information hub. As one of the first major markets in the Asia-Pacific trading session to incorporate overnight global developments into asset prices, the Nikkei 225 may embed information regarding regional risk sentiment, macroeconomic conditions, and global financial developments that subsequently influence investor expectations in smaller markets such as New Zealand. Unlike Australia, whose influence is supported by close economic integration and substantial overlap in trading hours, the forecasting relevance of the Nikkei 225 is more likely to arise from its central position within the Asia-Pacific information transmission network. This suggests that a market's predictive importance depends not only on bilateral economic linkages but also on its role in the regional and global dissemination of financial information.

The consistency of results across global and NZ trading day datasets indicates that the identified relationships are stable regardless of temporal alignment. Though most of the coefficient values are close to zero (indicating low influence from the regularization terms), the NZ trading days dataset produced slightly stronger coefficients and selected marginally more features in LASSO and elastic net models (Table 5). This suggests that aligning data to local trading conditions may provide incremental predictive benefits.

Table 5. Coefficient value comparison for top predictors.

Market	Global Trading Days			NZ Trading Days		
	LASSO	Ridge	Elastic Net	LASSO	Ridge	Elastic Net
Australia—ASX 200	0.002422	0.002479	0.00242	0.002441	0.002484	0.002444
Philippines—PSEi	0.000847	0.000894	0.000845	0.000915	0.00094	0.000919
Japan—Nikkei 225	0.000657	0.0007	0.000657	0.00069	0.000731	0.000691
U.S. 10-year Trea. Yield	−0.000392	−0.000518	−0.000384	−0.000411	−0.000535	−0.000438
Switzerland—SMI	0.00034	0.000496	0.000332	0.000354	0.000525	0.000375
US—S&P 500	−0.000214	−0.000594	−0.0002	−0.000213	−0.000634	−0.000266
Vietnam—VIN	0.000258	0.000352	0.000254	0.000279	0.000367	0.000294

4.4. Relevant Test Results

Following feature selection, the stationarity properties of the New Zealand NZX 50 stock returns and its key predictors—Australia ASX 200, Japan Nikkei 225, U.S. S&P 500, and the U.S. 10-year Treasury yield—were evaluated using the Augmented Dickey–Fuller (ADF) test. Results from both global trading days and NZ trading days datasets provide overwhelming evidence of stationarity across all return series. The ADF statistics were large in magnitude (e.g., NZX 50: approximately −74 in both datasets), with p-values effectively zero, leading to a strong rejection of the null hypothesis of non-stationarity. See Table A2 in Appendix C for the detailed results. This confirms that all variables are suitable for time series modeling in their return form and avoids the risk of spurious regression.

Autocorrelation function (ACF) and partial autocorrelation function (PACF) analysis showed significant spikes at Lag 1, followed by minimal persistence at higher lags, consistent with the stylized facts of financial returns. However, volatility dynamics differ. The Ljung-Box test applied to squared returns revealed strong ARCH effects across all markets (see Table A3 in Appendix C), confirming volatility clustering and time-varying variance.

Importantly, both datasets yield nearly identical results, indicating that restricting the sample to NZ trading days does not materially alter statistical properties. Minor variations are attributable to differences in sample size and trading day alignment. Overall, the confirmed stationarity and presence of heteroskedasticity support the use of return-based modeling in subsequent forecasting stages.

Lag selection was conducted to identify lead–lag dynamics using Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Hannan–Quinn Information Criterion (HQIC) (see Table A4 in Appendix C). The results highlight a trade-off between model complexity and parsimony. AIC selected higher lag orders (9–10), potentially capturing richer dynamics but increasing the risk of overfitting. In contrast, BIC consistently selected two lags, while HQIC suggested five lags across both datasets. Given the large sample size, BIC's conservative choice is preferred, consistent with established econometric practice (Kass & Raftery, 1995; Schwarz, 1978).

The consistency across datasets suggests stable temporal relationships. A second-lag structure implies that international market information is incorporated into the NZ market within approximately two trading days. Meanwhile, the fifth-lag specification aligns with the practical "trading week" framework commonly used by market participants. To balance statistical rigor and practical relevance, this study adopts both second-lag and fifth-lag specifications for subsequent modeling, allowing comparison of forecasting performance under different lag structures.

Long-run relationships between equity markets were examined using the Johansen cointegration test. Since cointegration requires non-stationary inputs, the analysis was conducted on price level data rather than returns. Across all specifications (lag orders and deterministic terms), both the Trace and Maximum Eigenvalue tests consistently failed to reject the null hypothesis of no cointegration (see Table A5 in Appendix C). This result holds for both global and NZ trading day datasets.

The absence of cointegration implies that these markets do not share a common long-term equilibrium and instead follow independent stochastic trends. This has several implications. First, a Vector Autoregressive (VAR) model in differences is more appropriate than a VECM. Second, despite economic linkages, long-term integration appears limited. Third, the lack of cointegration suggests potential diversification benefits, as deviations across markets are not systematically corrected over time.

The consistency of findings across datasets further reinforces robustness, indicating that trading day alignment does not materially affect long-run relationships.

Short-term predictive relationships were assessed using Granger causality tests (see Table A6 in Appendix C). The results reveal asymmetric and regionally concentrated influences on the NZ market. The ASX 200 demonstrates the strongest and most consistent predictive power for the NZX 50, with statistical significance improving under NZ trading day alignment. This confirms Australia's dominant influence, reflecting strong economic integration and geographic proximity.

The Nikkei 225 also exhibits significant influence, with stronger effects observed when accounting for trading day sequencing. This supports the role of Asia-Pacific market timing in information transmission. The U.S. 10-year Treasury yield shows a weaker but statistically significant impact, indicating that global monetary conditions influence NZ equities through interest rate and risk sentiment channels.

In contrast, the S&P 500 does not exhibit statistically significant direct causality at the 5% level, although it approaches significance in the NZ dataset. This suggests that U.S. equity market influence may be transmitted indirectly through regional channels rather than direct transmission.

While Granger causality provides insights into predictive relationships, it does not establish true economic causation. The results may reflect indirect linkages, shared global shocks, or time-zone effects rather than direct influence. Additionally, the linear framework may overlook nonlinear dynamics and contemporaneous interactions.

Overall, the findings highlight strong short-term regional linkages, particularly with Australia and Japan, limited long-term integration across global equity markets, and the importance of global interest rates in shaping NZ market dynamics. These results support the use of short-term dynamic models, such as VAR and machine learning approaches, focusing on spillover effects rather than long-run equilibrium relationships.

4.5. GVAR Results

We employ a GVAR-type model to examine the interconnectedness between the NZ stock market NZX 50 and the equity markets of its major trading partners—Australia ASX 200, Japan Nikkei 225, and U.S. S&P 500. The purpose of this study is not to estimate a full-scale global macroeconomic GVAR. Rather, the objective is to construct a New Zealand-centered daily financial-market spillover model for forecasting NZX 50 returns. Because our focus is on daily return forecasting, i.e., we use daily data, the inclusion of conventional macroeconomic variables such as GDP, inflation, trade flows, or industrial production is not feasible without introducing mixed-frequency complications. Accordingly, the final system is intentionally parsimonious. Each market-specific equation is based on daily equity index returns, while foreign financial conditions are summarized through market-capitalization-weighted external equity returns, and the U.S. 10-year Treasury yield is included as a global financial factor. This specification allows the model to capture short-term international financial spillovers and lead-lag dynamics relevant for daily return forecasting while avoiding the over-parameterization that would arise in an unrestricted VAR framework. The analysis was conducted using two methodological approaches: one considering global trading days, and another focusing exclusively on NZ trading days from 3 January 2001 to 31 December 2024. For each dataset, models with different lag structures (second-lag and fifth-lag specifications) were estimated to determine the optimal specification for capturing market dynamics. See the estimated equations in Appendix D.

The estimation results demonstrate consistency across both datasets (global and NZ trading days), suggesting that the underlying relationships between these markets are robust regardless of the trading calendar used. This consistency validates the reliability of the estimated relationships and indicates that market interdependencies are not artifacts of specific trading day alignments. The similar results across both datasets suggest that time zone differences and non-synchronous trading do not fundamentally alter the estimated relationships. This implies that the GVAR model effectively captures the essential interdependencies despite the temporal complexities of global markets. The consistency between global trading days and NZ trading days datasets indicates that the exclusion of days when specific markets are closed (but others remain open) does not materially affect the estimated relationships, supporting the robustness of the GVAR framework.

The NZX 50 consistently shows the strongest positive response to S&P 500 movements (coefficients ranging from 0.2615 to 0.2683 at the first lag; see Appendix D), indicating NZ equity market is heavily influenced by U.S. market sentiment. Interestingly, the NZX 50 exhibits negative responses to Nikkei 225 movements at the first lag (−0.0118 to −0.0150), suggesting potential competitive or substitution effects between these Asia-Pacific markets. The US market shows the least responsiveness to other markets, with generally smaller coefficient magnitudes, confirming its role as a leader rather than follower in global equity markets.

Table 6 shows the summary of the GVAR model results, which indicate from F-statistics that all are statistically significant. The second-lag models capture the most economically significant relationships, with first-lag coefficients generally being larger than second-lag coefficients. This suggests that most information transmission between these markets occurs within one trading day, consistent with the speed of modern financial markets. The fifth-lag specifications reveal that market relationships extend beyond immediate responses. Notable patterns include coefficients that often alternate in sign across lags, suggesting oscillatory adjustment processes where markets tend to overshoot and then correct in subsequent periods. The sum of coefficients across all lags provides insight into long-term multiplier effects, indicating the cumulative impact of shocks as they work through the system over time. The modest improvements in adjusted R-squared when moving from second-lag to 5-lag models suggest diminishing returns to additional complexity. This pattern is consistent across all markets and both datasets, indicating that the most important predictive relationships are captured in the first two lags.

Table 6. Summary of GVAR model statistics.

	Adj. R^2		**RMSE**		**F-Statistics**	
	2-Lag	**5-Lag**	**2-Lag**	**5-Lag**	**2-Lag**	**5-Lag**
Global Trading Days						
NZX 50	0.1957	0.2014	0.00631	0.006287	168.7	75.43
ASX 200	0.2914	0.3014	0.0083	0.008242	284.3	128.3
Nikkei 225	0.2496	0.2544	0.01225	0.01221	230.1	101.7
S&P 500	0.1062	0.1071	0.0113	0.01129	82.87	36.41
NZ Trading Days						
NZX 50	0.1979	0.2044	0.00637	0.006343	167.3	75.19
ASX 200	0.2824	0.2912	0.00839	0.008339	266.3	119.7
Nikkei 225	0.2443	0.2480	0.01231	0.01228	218.9	96.27
S&P 500	0.1057	0.1060	0.01133	0.01133	80.65	35.24

In constructing the weight matrix for the GVAR model, this study incorporated market capitalization data for the NZX 50, ASX 200, Nikkei 225, and the S&P 500 indices. The weighting methodology involved calculating the relative market capitalization proportions among these indices to establish their respective influence magnitudes.

The examination of the market capitalization data reveals substantial disparities in market size among the selected indices. The S&P 500 demonstrates overwhelming dominance with an average market capitalization of approximately USD 34.8 trillion, representing 85.32% of the combined market value of the selected indices. The Nikkei 225 constitutes the second largest market at USD 3.7 trillion (9.06%), followed by ASX 200 at USD 1.98 trillion (4.85%), while NZX 50 represents the smallest market at USD 0.31 trillion (0.76% of the total).

Following GVAR methodological principles, these market capitalizations were transformed into a standardized weight matrix where each row sums to unity (excluding self-weights, which are set to zero); see Table 7. For the NZX 50, the normalized weights assigned to foreign markets were calculated as the proportion of each foreign market's capitalization relative to the sum of all foreign market capitalizations. This resulted in weights of 0.0527 for the ASX 200, 0.0913 for the Nikkei 225, and 0.8560 for the S&P 500, reflecting their proportional influence on the NZ market after excluding self-referential effects. New Zealand's weight in the market capitalization matrix is standardized to 1% across all foreign equations to avoid under-representing its influence and to ensure meaningful detection of spillover effects while remaining consistent with GVAR principles. Additionally, using average market capitalizations over the full sample period—rather than point-in-time values—reduces distortions from temporary fluctuations and provides a more stable representation of cross-market relationships.

Table 7. GVAR weight matrix.

$$w_{ij} = \begin{array}{cl} \begin{pmatrix} 0.00 & 0.05 & 0.09 & 0.86 \\ 0.01 & 0.00 & 0.15 & 0.84 \\ 0.01 & 0.05 & 0.00 & 0.94 \\ 0.01 & 0.21 & 0.78 & 0.00 \end{pmatrix} & \begin{array}{l} \leftarrow \text{NZ Weights} \\ \leftarrow \text{Aus Weights} \\ \leftarrow \text{Jpn Weights} \\ \leftarrow \text{U.S. Weights} \end{array} \\ \begin{array}{cccc} \text{NZ} & \text{Aus} & \text{Jpn} & \text{U.S.} \end{array} & \end{array}$$

Note: Based on 2001–2024 average market capitalization.

The Impulse Response Functions in Figures 11 and 12 show that the NZX 50 responds to its own shocks with a standard unit impact followed by a smooth and rapid decay, indicating efficient absorption and strong mean reversion. Responses to external markets vary: shocks from the ASX 200 generate a modest, short-lived positive effect, reflecting close regional ties, while shocks from the Nikkei 225 produce small negative responses, suggesting potential counterbalancing or portfolio reallocation effects. In contrast, shocks from the S&P 500 have the strongest and most persistent positive influence, highlighting the dominant role of the U.S. market in driving NZ equity dynamics. The fifth-lag models reveal more complex and sometimes oscillatory behavior, capturing delayed adjustments and feedback effects, while comparisons between global and NZ trading day datasets show broadly similar patterns but slightly stronger and more persistent U.S. spillovers in the global dataset, underscoring the importance of overnight and non-synchronous market information flows.

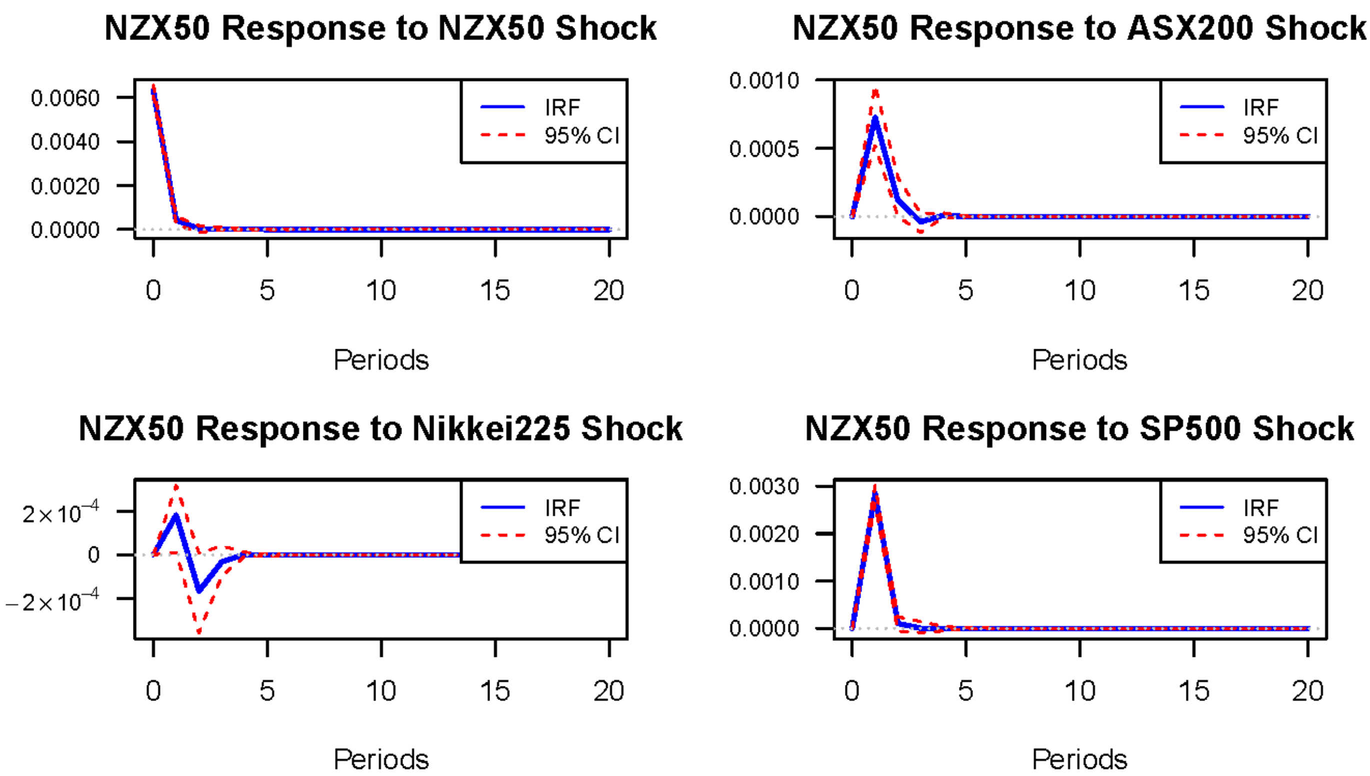

Figure 11. Impulse response (2-lag, global trading days).

The U.S. 10-year Treasury yield, included as an exogenous global factor, has a consistently positive and significant effect on all four equity markets, indicating that increases in yields are associated with higher equity returns despite appearing counterintuitive. This relationship can be explained by the tendency for both yields and equities to rise during periods of strong economic growth and improving expectations, as well as the likelihood that yield increases in the sample period reflected growth rather than inflation concerns. Additionally, because the model uses first differences of yields, the results capture the relationship between changes in yields and equity returns, which can differ from the relationship observed in levels.

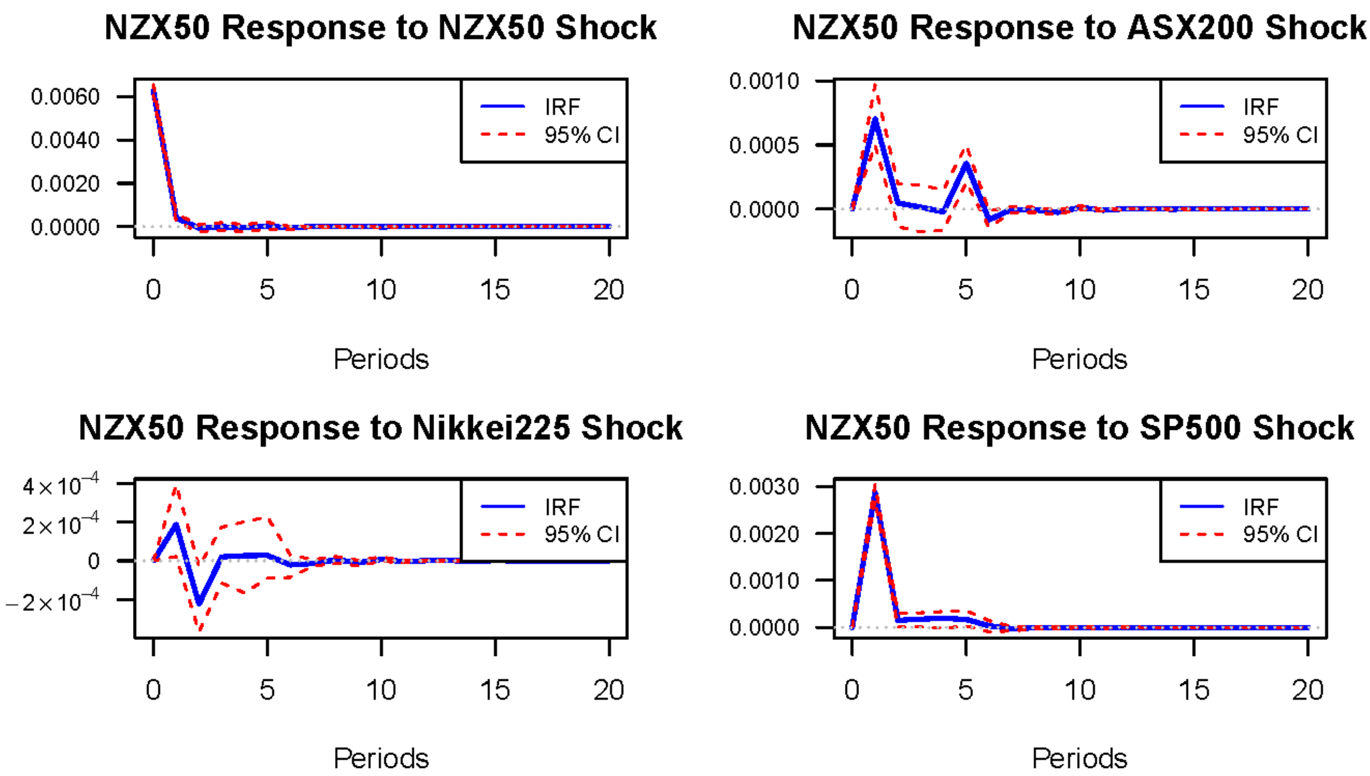

Figure 12. Impulse response (5-lag, global trading days).

The magnitude of the U.S. 10-year Treasury yield's impact varies across markets; see Table 8. In the second-lag model for global trading days, the coefficient is largest for the S&P 500 (0.150), followed by the Nikkei 225 (0.071), ASX 200 (0.059), and NZX 50 (0.007). This pattern is consistent across model specifications and datasets, suggesting that the U.S. market is most sensitive to changes in US Treasury yields, followed by the Asian markets, with the NZ market showing the least direct sensitivity.

Table 8. U.S. 10-year Treasury yield significance.

	Coefficient		p-Value		Significant	
	2-Lag	**5-Lag**	**2-Lag**	**5-Lag**	**2-Lag**	**5-Lag**
Global Trading Days						
NZX 50	0.0066	0.0059	4.31×10^{-2}	6.88×10^{-2}	Yes	No
ASX 200	0.0591	0.0587	1.79×10^{-42}	3.09×10^{-42}	Yes	Yes
Nikkei 225	0.0700	0.0696	3.60×10^{-28}	9.61×10^{-28}	Yes	Yes
S&P 500	0.1496	0.1496	1.47×10^{-137}	1.02×10^{-136}	Yes	Yes
NZ Trading Days						
NZX 50	0.0075	0.0069	2.36×10^{-2}	3.72×10^{-2}	Yes	Yes
ASX 200	0.0604	0.0603	1.15×10^{-42}	1.46×10^{-42}	Yes	Yes
Nikkei 225	0.0713	0.0705	2.26×10^{-28}	1.22×10^{-27}	Yes	Yes
S&P 500	0.1481	0.1479	8.46×10^{-132}	2.30×10^{-130}	Yes	Yes

Note: $p < 2 \times 10^{-16}$ is highly significant.

4.6. Machine Learning Forecasting Comparison

After learning the interconnectedness using the GVAR models, this section investigates the effectiveness of machine learning models in capturing intermarket relationships influencing the NZX 50 index, with a focus on explanatory power (adjusted R^2), prediction accuracy (root mean squared error/mean absolute error), and model robustness. The dataset was split into 80% training and 20% test sets. For example, in NZ trading days with the twp-lag structure, the training covers 5 January 2001 to 9 April 2020, while the test set is from 13 April 2020 to 31 December 2024. However, for the fifth-lag structure, the training set starts from 10 January 2001, while other dates remain the same. The results demonstrate that global financial linkages play a meaningful role in explaining New Zealand's equity market movements while also highlighting the importance of model selection, lag structure, and dataset construction.

Among all models tested, the Random Forest (RF) model with a fifth-lag structure applied to the NZ trading days dataset achieved the highest explanatory power, with an adj. R^2 of 0.157; see Table 9. This indicates that approximately 15.7% of NZX 50 price movements can be explained by lagged international market indices. While modest in absolute terms, this is significant given the inherent complexity and stochastic nature of financial markets.

Table 9. Performance metrics comparison.

Model	**Dataset**	**Lag**	**RMSE (Test)**	**MAE (Test)**	**Adj. R^2 (Test)**	**Train/Test RMSE Ratio**	**Next Day Forecast**
SVR	Global Trading Days	2-lag	**0.0064**	0.0047	0.1268	0.8271	−0.0108
SVR	Global Trading Days	5-lag	**0.0064**	**0.0046**	0.1534	0.6860	−0.0115
SVR	NZ Trading Days	2-lag	0.0066	0.0049	0.1195	0.8164	−0.0109
SVR	NZ Trading Days	5-lag	0.0067	0.0049	0.0785	0.6793	−0.0115
RF	Global Trading Days	2-lag	**0.0064**	0.0047	0.1430	0.5929	−0.0015
RF	Global Trading Days	5-lag	**0.0064**	**0.0046**	0.1534	0.7679	−0.0025
RF	NZ Trading Days	2-lag	0.0065	0.0048	0.1437	0.5449	−0.0022
RF	NZ Trading Days	5-lag	**0.0064**	0.0047	**0.1571**	0.7643	−0.0022
LSTM	Global Trading Days	2-lag	**0.0064**	0.0047	0.1322	0.9325	−0.0035
LSTM	Global Trading Days	5-lag	0.0065	0.0047	0.1266	0.9074	−0.0015
LSTM	NZ Trading Days	2-lag	0.0065	0.0048	0.1475	0.9307	−0.0031
LSTM	NZ Trading Days	5-lag	0.0066	0.0048	0.1234	0.9086	−0.0009
ANN	Global Trading Days	2-lag	0.0069	0.0049	0.0172	1.0089	0.0003
ANN	Global Trading Days	5-lag	0.0069	0.0050	0.0019	1.0214	0.0005
ANN	NZ Trading Days	2-lag	0.0070	0.0051	−0.0011	1.0123	0.0007
ANN	NZ Trading Days	5-lag	0.0072	0.0052	−0.0401	1.0001	0.0016

Note: Bold fonts indicate the best results.

The superior performance of RF models reflects their strength in capturing non-linear relationships and complex interactions between variables. This is particularly relevant in intermarket analysis, where relationships between global indices are rarely linear or stable over time. The findings support the use of RF within a top–down investment framework, where macroeconomic and global market signals are used to inform local market positioning. In contrast, Artificial Neural Networks (ANNs) performed poorly in terms of explanatory power, with some models producing negative adj. R^2 values. This suggests that ANNs struggled to identify meaningful intermarket relationships in this context, underscoring the importance of algorithm selection when modeling financial data.

In terms of forecasting accuracy, Support Vector Regression (SVR) and RF models using the global trading days dataset produced the lowest error metrics, with root mean squared error (RMSE) of 0.0064 and mean absolute error (MAE) of 0.0046, respectively.

These results highlight the value of incorporating global market information—even on days when the NZ market is closed—into predictive models.

This finding reinforces the notion that New Zealand, as a small open economy, is highly influenced by international market dynamics. The inclusion of global trading days allows models to capture information flows and developments that occur outside NZ trading hours, improving forecast accuracy.

Interestingly, while global datasets improved error metrics for SVR and LSTM models, RF models achieved slightly better adj. R^2 values using the NZ trading days dataset. This suggests that RF may better capture direct causal relationships when focusing on aligned trading periods, whereas other models benefit more from broader information inclusion.

The analysis of lag structures reveals that longer memory improves model performance for certain algorithms. Both RF and SVR models consistently performed better with a fifth-lag structure compared to a second-lag structure, indicating that international market movements may take several days to fully transmit to the NZ market. This supports the concept of lead-lag relationships in global finance, where information is gradually incorporated into prices across markets due to differences in trading hours, liquidity, and investor behavior.

For LSTM models, results were mixed. While their architecture is designed to capture long-term dependencies, second-lag models sometimes performed better, particularly with NZ trading days data. ANN models, on the other hand, showed better performance with shorter (second-lag) structures, suggesting a greater sensitivity to short-term relationships but limited ability to model deeper temporal dependencies.

A notable finding is the consistency in directional forecasts across most models. SVR, RF, and LSTM models all predicted negative returns for the NZX 50 during the forecast period, while ANN models predicted positive returns. The actual market outcome—a decline of approximately -0.33% between 31 December 2024 and 3 January 2025—validated the negative forecasts. This directional accuracy is particularly important in investment contexts, where correctly predicting market direction is often more valuable than estimating precise return magnitudes. The agreement among multiple models strengthens confidence in the forecast and supports the use of ensemble thinking in tactical asset allocation.

However, the magnitude of predicted returns varied across models. SVR predicted larger declines (-1.0% to -1.1%), while RF and LSTM forecasts were more conservative (-0.1% to -0.3%). This variation highlights the uncertainty inherent in financial forecasting and suggests that combining models may provide more balanced insights. The positive forecasts from ANN models may reflect either model limitations or a potential contrarian signal, warranting further investigation in a broader investment framework.

The study also evaluates model robustness through Train/Test RMSE ratios. ANN models exhibited the least overfitting, with ratios close to 1, indicating stable performance across training and testing datasets. LSTM models also showed strong robustness, with ratios between 0.91 and 0.93.

In contrast, RF models demonstrated higher levels of overfitting, particularly with shorter lag structures. Despite strong in-sample performance, their out-of-sample reliability may be weaker. This trade-off between explanatory power and robustness is a key consideration in practical applications. Interestingly, models with longer lag structures (fifth-lag) generally showed reduced overfitting compared to second-lag models, suggesting that incorporating more historical data can improve generalization.

The final model evaluation prioritizes explanatory power (adj. R^2) and prediction accuracy (RMSE/MAE), as these are most relevant for investment decision-making. While robustness is important, it is secondary in this context due to the inability of ANN models to capture meaningful relationships. Overall, RF models rank highest in terms of explanatory power, making them valuable for understanding intermarket dynamics; see Table 10. SVR models offer strong predictive accuracy, while LSTM models provide a balance between accuracy and robustness, making them suitable for longer-term forecasting.

Table 10. Model rankings.

Model	RMSE Rank	MAE Rank	Adj. R^2 Rank	Overall Rank
SVR	1	1	2	2
RF	1	1	1	1
LSTM	2	2	3	3
ANN	3	3	4	4

Notes: 1 = Best and 4 = Worst.

5. Conclusions

This study investigates the effectiveness of intermarket analysis in forecasting the NZX 50 index using a hybrid framework that combines econometric techniques and machine learning models. The research examines how global financial markets influence New Zealand's equity market and evaluates the practical value of incorporating international market signals into investment decision-making.

A systematic feature selection process using LASSO, ridge, and elastic net regression consistently identified four major predictors of NZX 50 returns: Australia's ASX 200, Japan's Nikkei 225, the U.S. S&P 500, and the U.S. 10-year Treasury yield. Among these, the ASX 200 emerged as the strongest predictor, reflecting the close economic integration between New Zealand and Australia. The Nikkei 225 also showed strong influence, emphasizing the importance of Asia-Pacific regional market dynamics and overlapping trading hours. Although the S&P 500 had weak direct correlation with the NZX 50, it still influenced the market indirectly through global investor sentiment and regional transmission channels. The U.S. 10-year Treasury yield displayed a stable negative relationship with NZX 50 returns, highlighting the importance of global monetary policy and interest rates in shaping equity valuations.

Econometric analysis using the Global Vector Autoregression (GVAR) model supported these findings. Stationarity tests confirmed the suitability of using return data, while lag selection criteria indicated that second-lag and fifth-lag structures best captured short-term market dynamics. Importantly, the study found no evidence of long-term cointegration between the NZX 50 and major international markets. This suggests that while markets are strongly linked in the short term, they maintain independent long-term trends, supporting the continued benefits of international diversification for long-term investors.

Granger causality tests confirmed that the ASX 200 and Nikkei 225 possess significant predictive power for NZX 50 movements, while the U.S. Treasury yield also contributed meaningful forecasting information. Spillover analysis showed that approximately 24% of NZX 50 forecast variance is driven by cross-market effects, validating the relevance of intermarket analysis. The S&P 500 acted as the primary global shock transmitter, whereas the NZX 50 mainly functioned as a net receiver of external shocks. Impulse response analysis further revealed that international market shocks influence the NZX 50 for approximately 2–3 trading days, confirming the presence of actionable lead-lag relationships.

Among the machine learning models tested, Random Forest achieved the highest explanatory power, particularly with a fifth-lag structure using NZ trading day data. Support Vector Regression and Random Forest also generated the lowest prediction errors, making them highly effective forecasting tools. LSTM models demonstrated good robustness with minimal overfitting but did not outperform simpler machine learning methods. Artificial

Neural Networks performed poorly overall, indicating limited effectiveness in capturing intermarket relationships within this dataset.

The consistent superiority of fifth-lag structures suggests that information transmission from global markets to the NZX 50 occurs gradually over several days rather than immediately. This supports the practical usefulness of weekly forecasting horizons. Out-of-sample forecasting results further demonstrated model effectiveness. During the forecast period from 31 December 2024 to 3 January 2025, the NZX 50 declined by 0.33%, which was accurately predicted by the SVR, Random Forest, and LSTM models, while ANN predictions failed.

The findings provide important implications for investment management. The absence of long-term cointegration supports Strategic Asset Allocation through continued international diversification benefits. Meanwhile, the strong short-term spillovers and lead-lag relationships support Tactical Asset Allocation strategies based on momentum and signal-driven trading. In particular, signals from the Australian and Japanese markets, as well as changes in U.S. Treasury yields, offer valuable indicators for improving market timing and portfolio performance.

While this study provides substantial insights, several limitations suggest avenues for future investigation. The focus on daily return data may miss longer-term relationship patterns that could emerge at weekly or monthly frequencies. The analysis period, while comprehensive, encompasses specific market regimes that may not persist indefinitely. By using a different data frequency (i.e., monthly), the application of the GVAR model that typically emphasizes short-term spillovers, the model can be aligned well with the typical time horizons of TAA strategies, which generally range from one to twelve months.

Future research could extend this framework to include additional asset classes (commodities, currencies, real estate) and financial variables, both technical and fundamental, to develop more comprehensive intermarket models. The integration of alternative data sources (sentiment indicators, economic surprise indices, geopolitical risk measures) with the established framework could enhance predictive accuracy and provide additional tactical signals for investment management applications. The methodology could also be applied to sector-level analysis within markets to identify more granular relationship patterns. In addition, the proposed GVAR model can be extended to incorporate the time-varying parameters, mixed-frequency modeling, and GARCH components to analyze their dynamism.

Author Contributions: Conceptualization, B.D. and N.W.; methodology, B.D.; software, B.D.; validation, B.D., N.W. and Y.O.; formal analysis, B.D.; data curation, B.D.; writing—original draft preparation, B.D.; writing—review and editing, N.W. and Y.O.; visualization, B.D.; supervision, N.W. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data supporting the conclusions of this article will be made available by the authors on request.

Acknowledgments: We thank the reviewers for their useful comments and feedback that help improve the manuscript. Grammarly has been used for grammar checking.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A. Studies of Measuring Interconnectedness

Table A1. Studies of measuring interconnectedness.

Authors	Title	Model Employed
Soydemir (2000)	International Transmission Mechanism of Stock Market Movements: Evidence from Emerging Equity Markets	Vector AutoRegressive (VAR)
Dees et al. (2007)	Exploring the International Linkages of the Euro Area: a Global VAR Analysis	Global Vector AutoRegressive (GVAR)
Cuadro-Saez et al. (2009)	Transmission of Emerging Market Shocks to Global Equity Markets	Panel-Corrected Standard Errors (PCSE)
Wong and Fong (2011)	Analysing Interconnectivity among Economies	Conditional Value at Risk (CoVaR)
Billio et al. (2012)	Econometric Measures of Connectedness and Systemic Risk in the Finance and Insurance Sectors	Principal Components Analysis (PCA) & Granger-Causality
Diebold and Yilmaz (2013)	Measuring the Dynamics of Global Business Cycle Connectedness	Variance Decomposition
Raddant and Kenett (2016)	Interconnectedness in the Global Financial Market	Generalized AutoRegressive Conditional Heteroskedasticity (GARCH)
Geraci and Gnabo (2018)	Measuring Interconnectedness between Financial Institutions with Bayesian Time-Varying Vector AutoRegressions	Bayesian Vector AutoRegressive (BVAR)
Greenwood-Nimmo et al. (2021)	Measuring the Connectedness of the Global Economy	Vector AutoRegressive (VAR)
Buchwalter et al. (2026)	Clustered Network Connectedness: A New Measurement Framework with Application to Global Equity Markets	Vector AutoRegressive (VAR) and Forecast Error Variance Decompositions (FEVDs)

Appendix B. Summary of Machine Learning Methods

Appendix B.1. LASSO Regression

The Least Absolute Shrinkage and Selection Operator (LASSO) is a linear regression technique that improves prediction accuracy and interpretability by combining variable selection with regularization, making it particularly useful in high-dimensional settings where overfitting is a concern. See more details on LASSO in Tibshirani (1996), Efron et al. (2004), Hastie et al. (2015), among others. It extends ordinary least squares by adding an L_1 penalty term to the objective function, constraining the sum of the absolute values of coefficients and shrinking some to zero. Mathematically, LASSO minimizes the objective function of:

$$\min J(\beta) = \sum_{i=1}^{n}\left(y_i - \beta_0 - \sum_{j=1}^{p} \beta_j x_{ij}\right)^2 + \lambda \sum_{j=1}^{p} |\beta_j|$$

where

$\lambda \sum_{j=1}^{p} |\beta_j|$ is the L_1 penalty term;

$J(\beta)$ is the cost function;

y_i are the observed actual values of the target/dependent variable;

x_{ij} are the values of predictor/independent variable;

β_j are the coefficients for the predictor variables x_{ij};
β_0 is the intercept;
λ is the regularization/tuning parameter to control the strength of the penalty term.

The penalty term forces some coefficients to shrink exactly to zero, effectively performing variable selection while reducing overfitting. Its primary strength lies in producing sparse and interpretable models, making it highly suitable for financial datasets with many potentially irrelevant or redundant predictors. In the presence of multicollinearity, LASSO tends to select one representative variable from a correlated group, simplifying the model structure.

However, LASSO introduces bias by shrinking all coefficients equally, which can underestimate the influence of strong predictors. Its variable selection can also be unstable, as small changes in the dataset may lead to different selected features. Despite these limitations, LASSO remains a powerful tool for identifying key drivers in high-dimensional financial environments.

Appendix B.2. Ridge Regression

Ridge regression is a linear regression technique that mitigates multicollinearity and overfitting by applying an L_2 regularization penalty, which adds the sum of squared coefficients to the OLS objective function. Unlike LASSO, it does not eliminate predictors but instead shrinks all coefficients continuously, improving generalization performance, especially in high-dimensional or highly correlated datasets. See more details on the ridge regression in Hoerl and Kennard (1970), Hastie et al. (2009), James et al. (2013), among others. Mathematically, ridge regression minimizes the objective function of:

$$\min J(\beta) = \sum_{i=1}^{n} \left(y_i - \beta_0 - \sum_{j=1}^{p} \beta_j x_{ij} \right)^2 + \lambda \sum_{j=1}^{p} \beta_j^2$$

where
$\lambda \sum_{j=1}^{p} \beta_j^2$ is the L_2 penalty term.

This approach stabilizes coefficient estimates and improves predictive performance, especially when predictors are highly correlated or when the number of variables is large relative to observations. Ridge is particularly useful in financial markets, where multiple factors collectively influence asset prices and excluding variables may result in loss of valuable information.

The main drawback is its lack of feature selection, which can reduce interpretability. Additionally, like LASSO, Ridge introduces bias and requires careful tuning of the regularization parameter to balance bias and variance.

Appendix B.3. Elastic Net Regression

Elastic net regression is a regularized regression technique that combines LASSO and Ridge by incorporating both L_1 and L_2 penalty terms, enabling simultaneous variable selection and handling of multicollinearity (Zou & Hastie, 2005; Hastie et al., 2023). The balance between these penalties is controlled by hyperparameters λ (overall regularization strength) and α (mix between L_1 and L_2), allowing it to overcome the limitations of using either method alone. Mathematically, elastic net minimizes the objective function:

$$\min J(\beta) = \frac{1}{2n} \sum_{i=1}^{n} \left(y_i - \beta_0 - \sum_{j=1}^{p} \beta_j x_{ij} \right)^2 + \lambda \left(\alpha \sum_{j=1}^{p} |\beta_j| + \frac{1-\alpha}{2} \sum_{j=1}^{p} \beta_j^2 \right)$$

where

$\lambda\alpha \sum_{j=1}^{p} |\beta_j|$ is the L_1 penalty term;
$\lambda \frac{1-\alpha}{2} \sum_{j=1}^{p} \beta_j^2$ is the L_2 penalty term;
$\alpha \in [0, 1]$ is the balance between L_1 (LASSO $\rightarrow \alpha = 1$) and L_2 (Ridge regression $\rightarrow \alpha = 0$).
n is the sample size.

A key advantage is its ability to select groups of correlated variables rather than arbitrarily choosing one, addressing a major limitation of LASSO. This makes it particularly suitable for financial datasets where predictors often exhibit strong correlations and complementary effects.

Elastic net balances sparsity and inclusion, allowing weaker but informative variables to remain in the model with reduced influence. However, it increases computational complexity due to the need to tune multiple hyperparameters and still introduces bias in coefficient estimation.

Appendix B.4. Support Vector Regression

Support Vector Regression (SVR) is an extension of Support Vector Machines (SVMs) that adapts the algorithm from classification to regression tasks by estimating a function that captures the relationship between input features and continuous target variables. It aims to keep prediction errors within a specified margin while minimizing deviations beyond it, automatically determining complex relationships unlike traditional linear regression. See more details on the ridge regression in Drucker et al. (1997), Smola and Schölkopf (2004), Uemoto and Naito (2022), among others. The mathematical formulation of SVR can be expressed as minimizing the objective function:

$$\min y = \frac{1}{2} w^T w + C \sum_{i=1}^{N} (\xi_i + \xi_i^*)$$

Subject to:

$$y_i - w \cdot x_i - b \leq \varepsilon + \xi_i$$
$$w \cdot x_i + b - y_i \leq \varepsilon + \xi_i^*$$
$$\xi_i, \xi_i^* \geq 0$$

where

w is the weight vector;
b is the bias term;
ε is the maximum margin (margin of tolerance);
C is the regularization parameter to control between model complexity and training error;
ξ_i, ξ_i^* are slack variables for values that fall outside of ε (positive and negative deviations from the margin ε).

Through kernel functions (e.g., linear, polynomial, radial basis), SVR can capture complex non-linear relationships between predictors and target variables. The model balances complexity and accuracy using the regularization parameter C.

SVR is well suited for financial forecasting due to its strong generalization ability and robustness. However, it requires careful tuning of hyperparameters and kernel selection, and can be computationally intensive for large datasets. Its interpretability is also limited compared to linear models.

Appendix B.5. Random Forest

Random Forest (RF) is an ensemble learning method that constructs multiple decision trees using bootstrapped samples and random subsets of features. Final predictions are obtained by averaging outputs across trees, see Figure A1 The process of RF algorithm is as follows.

1. Bootstrapping. RF uses bootstrapping technique to generate several different samples from the dataset. Bootstrapping randomly selects data points are replaces them. The same data point may appear several times in different samples.
2. Building Individual Trees. For each sample, the algorithm builds a separate decision tree and each tree is grown using a random sample of features, not the entire feature set. By randomizing data sampling and feature selection, the decision-making process is diversified and each tree has different prediction paths. The randomness reduces the variance of the ensemble predictor while maintaining low bias.
3. Growing Trees. Each tree grows by finding the best splits using its random feature subset. The optimal split at each node is determined by minimizing the mean squared error. A tree might stop growing when it reaches its maximum allowed depth, when no further improvements can be made in prediction accuracy, or when the minimum number of samples in a leaf node is reached.
4. Making Predictions. For regression problems, the predictions from all trees are averaged to produce the final predicted value while mode is calculated for classification problems.

This approach reduces variance and improves predictive accuracy while maintaining low bias. RF excels at capturing non-linear relationships, feature interactions, and complex patterns without requiring extensive preprocessing.

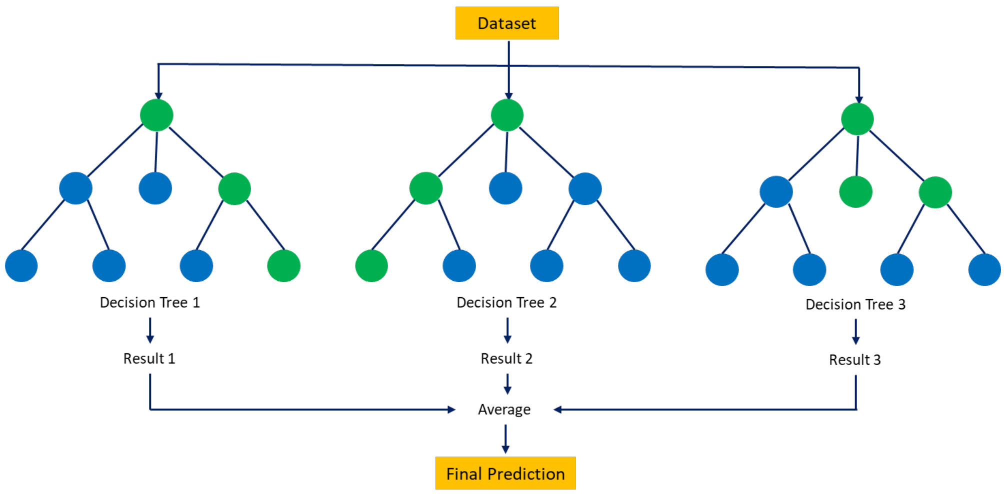

Figure A1. Random Forest.

It is particularly effective in high-dimensional and noisy financial datasets and provides feature importance measures that enhance interpretability. Additionally, it is robust to multicollinearity and missing data.

However, RF can be computationally intensive and less interpretable than simpler models. It may also struggle with extrapolation and can exhibit bias toward variables with more categories or continuous values.

Appendix B.6. Long Short-Term Memory

Long Short-Term Memory (LSTM) is a specialized Recurrent Neural Network (RNN) designed to model sequential and time-dependent data. It overcomes traditional RNN limitations (e.g., vanishing gradients) through memory cells and gating mechanisms (input, forget, and output gates), enabling it to capture both short- and long-term dependencies. The following mathematical equations work in concert to allow LSTM to learn which information to store, forget, or pass through to the next time step.

Forget Gate f_t:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$

Input Gate i_t:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$

New Information $\tilde{C}_t$:

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$$

Cell State C_t:

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t$$

Output Gate o_t:

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$

Hidden State h_t:

$$h_t = o_t \odot \tanh(C_t)$$

where

x_t is input to the current timestamp t;
σ is the sigmoid activation function;
W is the weight matrix associated with the gate;
b is the bias associated with the gate;
$[h_{t-1}, x_t]$ denotes the concatenation of the current input and the previous hidden state;
h_t is the hidden state of the current timestamp;
h_{t-1} is the hidden state of the previous timestamp;
C_t is the cell state of the current timestamp;
C_{t-1} is the cell state of the previous timestamp;
$\tilde{C}_t$ is the new information to be passed to the cell state;
tanh is the activation function that gives an output from -1 to +1;
$\odot$ denotes the Hadamard product (element-wise product/multiplication) operator.

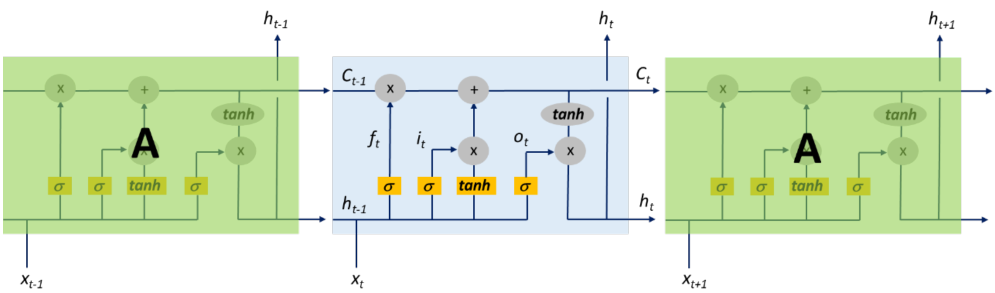

Figure A2. Long Short-Term Memory (repeating module with four interacting layers), source: Babs (2018) (https://colah.github.io/posts/2015-08-Understanding-LSTMs/, accessed on 22 March 2025).

LSTM is particularly powerful for time series forecasting, as it can learn complex temporal patterns, trends, and cyclical behaviors. It processes sequences of data, maintaining an internal state that evolves over time.

Despite its strengths, LSTM requires large datasets, extensive computational resources, and careful hyperparameter tuning. It is also sensitive to noisy data and structural changes in financial markets. Its "black-box" nature limits interpretability, which can be a disadvantage in investment decision-making contexts.

Appendix B.7. Artificial Neural Networks

Artificial Neural Networks (ANNs) are flexible computational models inspired by the human brain, consisting of interconnected layers of neurons. They can approximate complex linear and non-linear relationships using activation functions such as Rectified Linear Unit (ReLU), sigmoid, or tanh. ANN structure consists of:

- Input Layer. This is the entry point of the network, where the raw data or features are fed in. Each neuron in this layer represents a distinct feature of the input dataset.
- Hidden Layer(s). These layers handle the core computations and learning tasks. Comprising numerous neurons, they apply mathematical operations to the input data, enabling the network to identify and learn intricate patterns.
- Output Layer. This layer generates the network's final output, which could be a classification, prediction, or other outcomes derived from the processed input data.

The output is determined by an activation function that adds non-linearity to the model.

- Sigmoid. Maps input values to a range of 0 to 1, making it ideal for binary classification problems.
- ReLU. Outputs the input value if it is positive; otherwise, it outputs zero. ReLU is popular because it is simple and helps reduce the vanishing gradient issue.
- Tanh (Hyperbolic Tangent): Maps input values to a range from -1 to 1, offering a smooth gradient that supports learning.

During training, ANN uses backpropagation to adjust the weights based on the error between predicted and actual values, iteratively minimizing the loss function. Weight parameters determine the connections' strength between nodes. Versatile ANN can recognize patterns and model complex, non-linear relationships in data, making them versatile tools for predicting future values based on historical patterns where intricate interactions among predictors are common.

The equation for a single node can be expressed as follows:

$$y = f\left(b + \sum_{i=1}^{n} x_i \cdot w_i\right)$$

where

y is the node's output;
f is the activation function (ReLU, sigmoid, or tanh) applied to the weighted sum of inputs;
b is the bias term;
x is input value to the node;
w is the corresponding weight;
n is the number of inputs from the incoming layer.

In multilayer network architectures, each layer's output functions as input for subsequent layers, creating sequential computational chains. During training processes, these weights and biases undergo iterative updates through backpropagation utilizing gradient descent methodologies to minimize a specified loss function, typically the mean squared error for regression applications.

However, ANNs require careful design of network architecture (layers, neurons, activation functions) and are highly sensitive to data preprocessing and hyperparameter selection. They often require large datasets and are prone to overfitting.

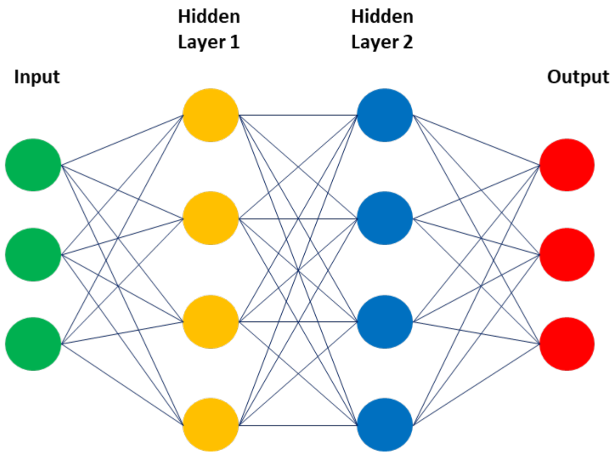

Figure A3. Artificial Neural Network.

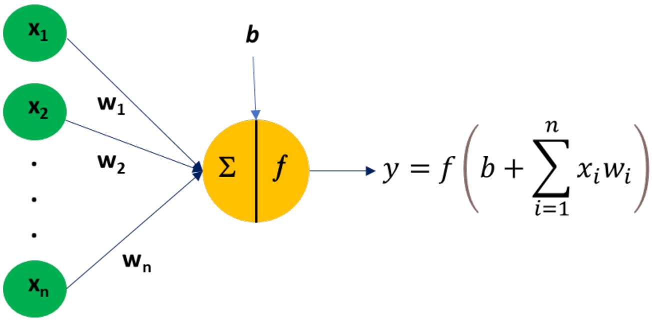

Figure A4. ANN input, node, function, and output, source: Babs (2018).

A key limitation is their lack of interpretability, as the internal decision-making process is not easily understood. Additionally, training can be computationally expensive and time-consuming.

Appendix C. Detailed Relevant Test Results

Table A2. Augmented Dickey–Fuller test statistics.

Market	ADF Statistics		*p*-Value		Stationary	
	Global	NZ	Global	NZ	Global	NZ
NZX 50	−74.0724	−73.1123	0.000	0.000	Yes	Yes
ASX 200	−14.4372	−21.0159	7.46×10^{-27}	0.000	Yes	Yes
Nikkei 225	−47.3223	−18.4117	0.000	2.18×10^{-30}	Yes	Yes
S&P 500	−18.9790	−18.6058	0.000	2.07×10^{-30}	Yes	Yes
U.S. Tr. Yield	−13.1497	−14.1077	1.38×10^{-24}	2.55×10^{-26}	Yes	Yes

Table A3. Ljung-Box test on squared returns (Lag 20).

Market	LB Statistics		*p*-Value		ARCH Effects	
	Global	NZ	Global	NZ	Global	NZ
NZX 50	3651.31	3658.53	0.0000	0.0000	Present	Present
ASX 200	8968.71	8845.68	0.0000	0.0000	Present	Present
Nikkei 225	4443.59	4141.14	0.0000	0.0000	Present	Present
S&P 500	8887.42	8855.56	0.0000	0.0000	Present	Present
U.S. Tr. Yield	4796.94	4702.96	0.0000	0.0000	Present	Present

Table A4. Model-specific lag order.

Lag	Global Trading Days			NZ Trading Days		
	AIC	BIC	HQIC	AIC	BIC	HQIC
1	−45.2372	−45.2046	−45.2259	−45.1902	−45.1570	−45.1787
2	−45.3011	−45.2414 *	−45.2804	−45.2496	−45.1887 *	−45.2285
3	−45.3068	−45.2200	−45.2767	−45.2544	−45.1659	−45.2237
4	−45.3142	−45.2002	−45.2747	−45.2627	−45.1466	−45.2224
5	−45.3305	−45.1893	−45.2815 *	−45.2791	−45.1353	−45.2292 *
6	−45.3321	−45.1637	−45.2737	−45.2806	−45.1092	−45.2211
7	−45.3434	−45.1478	−45.2756	−45.2912	−45.0920	−45.2221
8	−45.3462	−45.1235	−45.2690	−45.2936	−45.0667	−45.2149
9	−45.3532 *	−45.1033	−45.2665	−45.2998	−45.0452	−45.2115
10	−45.3525	−45.0754	−45.2565	−45.3036 *	−45.0213	−45.2057

Note: * highlights the minimum.

Table A5. Johansen cointegration test.

Dataset	Deterministic Term	Lag	Trace Test			Maximum Eigenvalue Test		
			$r \leq 0$	$r \leq 1$	$r \leq 2$	r = 0	r = 1	r = 2
Global	No deterministic (0)	1	45.2911	25.6121	10.2208	19.6789	15.3913	8.3700
			(47.8545)	(29.7961)	(15.4943)	(27.5858)	(21.1314)	(14.2639)
		2	45.1709	24.7580	10.1972	20.4130	14.5608	7.9959
			(47.8545)	(29.7961)	(15.4943)	(27.5858)	(21.1314)	(14.2639)
	Constant (1)	1	45.7055	23.2544	11.4275	22.4511	11.8269	9.2829
			(55.2459)	(35.0116)	(18.3985)	(30.8151)	(24.2522)	(17.1481)
		2	44.9923	23.3239	9.8117	21.6684	13.5122	7.8550
			(55.2459)	(35.0116)	(18.3985)	(30.8151)	(24.2522)	(17.1481)
NZ	No deterministic (0)	1	44.9764	25.4574	10.0871	19.5190	15.3703	8.2804
			(47.8545)	(29.7961)	(15.4943)	(27.5858)	(21.1314)	(14.2639)
		2	44.8598	24.5889	10.1235	20.2709	14.4654	7.9094
			(47.8545)	(29.7961)	(15.4943)	(27.5858)	(21.1314)	(14.2639)
	Constant (1)	1	45.4743	23.0694	11.3587	22.4049	11.7106	9.2735
			(55.2459)	(35.0116)	(18.3985)	(30.8151)	(24.2522)	(17.1481)
		2	44.7564	23.1343	9.7755	21.6222	13.3587	7.8740
			(55.2459)	(35.0116)	(18.3985)	(30.8151)	(24.2522)	(17.1481)

Notes: 1. Values in parentheses represent 5% critical values. All test statistics are below their respective critical values. 2. Deterministic term specifications: (0) = No deterministic term in the model; (1) = Constant term only included in the model. The choice affects the critical values used for hypothesis testing, with specification (1) being more realistic for financial time series that typically have non-zero means.

Table A6. Granger causality test (*p*-values).

	Cause	Effect				
		NZX 50	ASX 200	Nikkei 225	S&P 500	U.S. Tr. Yield
Global	NZX 50	n.a.	0.0	0.0	0.0	0.0
	ASX 200	0.011193	n.a.	0.047121	0.0	0.0
	Nikkei 225	0.007285	0.0	n.a.	0.0	0.0
	S&P 500	0.096898	0.000169	0.42373	n.a.	0.0
	U.S. Tr. Yield	0.016105	0.012702	0.270557	0.373458	n.a.
NZ	NZX 50	n.a.	0.0	0.0	0.0	0.0
	ASX 200	0.01774	n.a.	0.059913	0.0	0.0
	Nikkei 225	0.002791	0.0	n.a.	0.0	0.0
	S&P 500	0.056015	0.000034	0.297978	n.a.	0.0
	U.S. Tr. Yield	0.014439	0.015908	0.282418	0.155732	n.a.

Appendix D. Additional GVAR Results

Table A7. Second-lag models with global trading days dataset.

Variables	$\widehat{NZX50_t}$	$\widehat{ASX200_t}$	$\widehat{Nikkei225_t}$	$\widehat{SP500_t}$
$NZX50_{t-1}$	0.0058	0.0081	0.0509 †	0.0025
	(0.0136)	(0.0179)	(0.0264)	(0.0244)
$ASX200_{t-1}$	0.0161	−0.2536 ***	−0.0786 ***	−0.0422 *
	(0.0111)	(0.0145)	(0.0215)	(0.0198)
$Nikkei225_{t-1}$	−0.0118	−0.0337 ***	−0.1527 ***	0.0187
	(0.0072)	(0.0094)	(0.0139)	(0.0128)
$SP500_{t-1}$	0.2615 ***	0.4491 ***	0.6038 ***	−0.0887 ***
	(0.0071)	(0.0093)	(0.0138)	(0.0127)
$NZX50_{t-2}$	−0.0007	0.0408 *	−0.0362	0.0330
	(0.0131)	(0.0173)	(0.0255)	(0.0235)
$ASX200_{t-2}$	0.0355 ***	−0.0049	0.0151	0.0043
	(0.0108)	(0.0142)	(0.0209)	(0.0193)
$Nikkei225_{t-2}$	−0.0220 **	−0.0306 ***	−0.0315 *	−0.0173
	(0.0069)	(0.0091)	(0.0134)	(0.0123)
$SP500_{t-2}$	0.0311 ***	0.1958 ***	0.1788 ***	0.0002
	(0.0086)	(0.0113)	(0.0167)	(0.0154)
$US10Y_t$	0.0066 *	0.0591 ***	0.0701 ***	0.1496 ***
	(0.0033)	(0.0043)	(0.0063)	(0.0058)
Constant	0.0003 ***	0.0000	0.0000	0.0003 *
	(0.00008)	(0.00011)	(0.00016)	(0.00014)
Observations	6201	6201	6201	6201
Adj. R^2	0.1957	0.2914	0.2496	0.1062
Residual Std. Error	0.0063	0.0083	0.0123	0.0113
F-statistic	168.7 ***	284.3 ***	230.1 ***	82.87 ***

Standard errors in parentheses. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.10$.

Table A8. Fifth-lag models with global trading days dataset.

Variables	$\widehat{NZX50_t}$	$\widehat{ASX200_t}$	$\widehat{Nikkei225_t}$	$\widehat{SP500_t}$
$NZX50_{t-1}$	0.0045	0.0108	0.0516 †	0.0062
	(0.0136)	(0.0178)	(0.0264)	(0.0244)
$ASX200_{t-1}$	0.0115	−0.2704 ***	−0.0962 ***	−0.0411 *
	(0.0113)	(0.0148)	(0.0219)	(0.0202)
$Nikkei225_{t-1}$	−0.0120 †	−0.0376 ***	−0.1552 ***	0.0157
	(0.0072)	(0.0094)	(0.0139)	(0.0129)
$SP500_{t-1}$	0.2647 ***	0.4561 ***	0.6109 ***	−0.0885 ***
	(0.0071)	(0.0093)	(0.0138)	(0.0127)
$NZX50_{t-2}$	−0.0134	0.0194	−0.0597 *	0.0258
	(0.0136)	(0.0178)	(0.0264)	(0.0244)
$ASX200_{t-2}$	0.0265 *	−0.0414 **	−0.0123	0.0040
	(0.0116)	(0.0152)	(0.0225)	(0.0208)
$Nikkei225_{t-2}$	−0.0270 ***	−0.0451 ***	−0.0491 ***	−0.0174
	(0.0073)	(0.0095)	(0.0141)	(0.0130)
$SP500_{t-2}$	0.0382 ***	0.2193 ***	0.2016 ***	0.0030
	(0.0091)	(0.0119)	(0.0177)	(0.0163)
$NZX50_{t-3}$	−0.0101	−0.0227	0.0530 *	−0.0025
	(0.0136)	(0.0178)	(0.0264)	(0.0244)
$ASX200_{t-3}$	−0.0018	−0.0366 *	−0.0135	0.0111
	(0.0116)	(0.0152)	(0.0225)	(0.0208)
$Nikkei225_{t-3}$	0.0015	−0.0043	−0.0373 **	0.0184
	(0.0073)	(0.0095)	(0.0141)	(0.0130)
$SP500_{t-3}$	0.0265 **	0.0803 ***	0.0729 ***	0.0051
	(0.0094)	(0.0123)	(0.0182)	(0.0168)

Table A8. *Cont.*

Variables	$\widehat{\text{NZX50}_t}$	$\widehat{\text{ASX200}_t}$	$\widehat{\text{Nikkei225}_t}$	$\widehat{\text{SP500}_t}$
NZX50_{t-4}	−0.0091	0.0372 *	0.0241	0.0609 *
	(0.0136)	(0.0178)	(0.0264)	(0.0244)
ASX200_{t-4}	−0.0112	−0.0703 ***	−0.0620 **	−0.0067
	(0.0114)	(0.0149)	(0.0221)	(0.0204)
Nikkei225_{t-4}	−0.0058	−0.0121	−0.0271 †	−0.0125
	(0.0072)	(0.0095)	(0.0141)	(0.0130)
SP500_{t-4}	0.0219 *	0.0541 ***	0.0374 *	−0.0267
	(0.0093)	(0.0123)	(0.0182)	(0.0168)
NZX50_{t-5}	−0.0323 *	−0.0460 **	−0.0455 †	−0.0285
	(0.0131)	(0.0172)	(0.0255)	(0.0235)
ASX200_{t-5}	0.0411 ***	0.0083	0.0010	0.0009
	(0.0108)	(0.0141)	(0.0210)	(0.0194)
Nikkei225_{t-5}	0.0023	0.0096	0.0183	−0.0071
	(0.0069)	(0.0090)	(0.0134)	(0.0124)
SP500_{t-5}	0.0317 ***	0.0644 ***	0.0661 ***	−0.0265 †
	(0.0088)	(0.0116)	(0.0172)	(0.0159)
US10Y_t	0.0059 †	0.0587 ***	0.0696 ***	0.1496 ***
	(0.0033)	(0.0043)	(0.0063)	(0.0059)
Constant	0.00029 ***	0.00001	0.00001	0.00030 *
	(0.00008)	(0.00011)	(0.00016)	(0.00014)
Observations	6198	6198	6198	6198
Adjusted R^2	0.2014	0.3014	0.2544	0.1071
Residual Std. Error	0.00629	0.00824	0.01221	0.01129
F-statistic	75.43 ***	128.30 ***	101.70 ***	36.41 ***

Standard errors in parentheses. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.10$.

Table A9. Second-lag models with NZ trading days dataset.

Variables	$\widehat{\text{NZX50}_t}$	$\widehat{\text{ASX200}_t}$	$\widehat{\text{Nikkei225}_t}$	$\widehat{\text{SP500}_t}$
NZX50_{t-1}	0.0109	0.0011	0.0369	−0.0068
	(0.0138)	(0.0182)	(0.0267)	(0.0246)
ASX200_{t-1}	0.0170	−0.2491 ***	−0.0799 ***	−0.0513 **
	(0.0112)	(0.0148)	(0.0217)	(0.0200)
Nikkei225_{t-1}	−0.0140 *	−0.0312 ***	−0.1558 ***	0.0120
	(0.0073)	(0.0096)	(0.0141)	(0.0130)
SP500_{t-1}	0.2652 ***	0.4427 ***	0.5961 ***	−0.0889 ***
	(0.0072)	(0.0095)	(0.0140)	(0.0129)
NZX50_{t-2}	0.0051	0.0397 **	−0.0470 †	0.0181
	(0.0133)	(0.0175)	(0.0257)	(0.0236)
ASX200_{t-2}	0.0324 ***	0.0009	0.0139	−0.0028
	(0.0110)	(0.0144)	(0.0212)	(0.0195)
Nikkei225_{t-2}	−0.0235 ***	−0.0287 ***	−0.0324 **	−0.0067
	(0.0070)	(0.0093)	(0.0136)	(0.0125)
SP500_{t-2}	0.0285 ***	0.1881 ***	0.1868 ***	0.0225
	(0.0087)	(0.0115)	(0.0168)	(0.0155)
US10Y_t	0.0075 **	0.0604 ***	0.0713 ***	0.1481 ***
	(0.0033)	(0.0044)	(0.0064)	(0.0059)
const	0.000313 ***	0.000049	0.000085	0.000279 †
	(0.000082)	(0.000108)	(0.000159)	(0.000146)
Observations	6069	6069	6069	6069
Adj. R^2	0.1979	0.2824	0.2443	0.1057
Residual Std. Error	0.00637	0.00839	0.01231	0.01133
F-statistic	167.3 ***	266.3 ***	218.9 ***	80.65 ***

Standard errors in parentheses. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.10$.

Table A10. Fifth-lag models with NZ trading days dataset.

Variables	$\widehat{\text{NZX50}_t}$	$\widehat{\text{ASX200}_t}$	$\widehat{\text{Nikkei225}_t}$	$\widehat{\text{SP500}_t}$
NZX50_{t-1}	0.0109	0.0029	0.0357	−0.0040
	(0.0138)	(0.0181)	(0.0267)	(0.0246)
ASX200_{t-1}	0.0125	−0.2606 ***	−0.0927 ***	−0.0466 *
	(0.0114)	(0.0150)	(0.0220)	(0.0203)
Nikkei225_{t-1}	−0.0150 *	−0.0356 ***	−0.1578 ***	0.0102
	(0.0073)	(0.0096)	(0.0141)	(0.0130)
SP500_{t-1}	0.2683 ***	0.4484 ***	0.6017 ***	−0.0900 ***
	(0.0072)	(0.0095)	(0.0140)	(0.0129)
NZX50_{t-2}	−0.0093	0.0208	−0.0680 *	0.0152
	(0.0138)	(0.0181)	(0.0267)	(0.0246)
ASX200_{t-2}	0.0228 †	−0.0276 †	−0.0058	0.0034
	(0.0117)	(0.0154)	(0.0227)	(0.0209)
Nikkei225_{t-2}	−0.0288 ***	−0.0405 ***	−0.0483 ***	−0.0034
	(0.0074)	(0.0097)	(0.0143)	(0.0132)
SP500_{t-2}	0.0365 ***	0.2075 ***	0.2063 ***	0.0207
	(0.0092)	(0.0121)	(0.0178)	(0.0164)
NZX50_{t-3}	−0.0159	−0.0333 †	0.0383	0.0048
	(0.0138)	(0.0181)	(0.0267)	(0.0246)
ASX200_{t-3}	−0.0025	−0.0237	−0.0048	0.0183
	(0.0117)	(0.0154)	(0.0226)	(0.0209)
Nikkei225_{t-3}	0.0042	−0.0084	−0.0403 **	0.0110
	(0.0074)	(0.0097)	(0.0143)	(0.0132)
SP500_{t-3}	0.0287 **	0.0653 ***	0.0598 **	−0.0112
	(0.0094)	(0.0124)	(0.0182)	(0.0168)
NZX50_{t-4}	−0.0065	0.0402 *	0.0176	0.0600 *
	(0.0138)	(0.0181)	(0.0267)	(0.0246)
ASX200_{t-4}	−0.0193 †	−0.0722 ***	−0.0607 **	−0.0023
	(0.0115)	(0.0151)	(0.0223)	(0.0206)
Nikkei225_{t-4}	−0.0063	−0.0073	−0.0042	−0.0135
	(0.0074)	(0.0097)	(0.0143)	(0.0131)
SP500_{t-4}	0.0253 **	0.0545 ***	0.0440 *	−0.0332 *
	(0.0094)	(0.0124)	(0.0182)	(0.0168)
NZX50_{t-5}	−0.0373 **	−0.0532 **	−0.0407	−0.0274
	(0.0133)	(0.0174)	(0.0257)	(0.0237)
ASX200_{t-5}	0.0428 ***	0.0112	0.0395 †	0.0085
	(0.0110)	(0.0144)	(0.0212)	(0.0196)
Nikkei225_{t-5}	0.0001	0.0055	−0.0057	−0.0078
	(0.0070)	(0.0092)	(0.0136)	(0.0125)
SP500_{t-5}	0.0326 ***	0.0606 ***	0.0551 **	−0.0152
	(0.0089)	(0.0117)	(0.0173)	(0.0159)
US10Y_t	0.0069 *	0.0603 ***	0.0705 ***	0.1479 ***
	(0.0033)	(0.0044)	(0.0064)	(0.0059)
Constant	0.000313 ***	0.000046	0.000063	0.000281 †
	(0.000082)	(0.000108)	(0.000159)	(0.000147)
Observations	6044	6044	6044	6044
Adj. R^2	0.2044	0.2912	0.2480	0.1060
Residual Std. Error	0.00634	0.00834	0.01228	0.01133
F-statistic	75.19 ***	119.70 ***	96.27 ***	35.24 ***

Standard errors in parentheses. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.10$.

References

Abe, M., & Nakayama, H. (2018). Deep learning for forecasting stock returns in the cross-section. In D. Phung, V. Tseng, G. Webb, B. Ho, M. Ganji, & L. Rashidi (Eds.), *Advances in knowledge discovery and data mining* (Vol. 10937). Springer. [CrossRef]

Alloul, F., & Ferrouhi, E. M. (2024). Macroeconomic indicators and stock market returns: A comparative analysis. *International Journal of Revenue Management*, *14*(4), 333–360. [CrossRef]

Amenc, N., & Le Sourd, V. (2003). *Portfolio theory and performance analysis*. Wiley. Available online: https://www.wiley.com/en-us/Portfolio+Theory+and+Performance+Analysis-p-9780470858752 (accessed on 8 February 2025).

Athey, S., & Imbens, G. (2019). Machine learning methods that economists should know about. *Annual Review of Economics*, *11*, 685–725. [CrossRef]

Babs, T. (2018, July 15). *The mathematics of neural networks.* Medium. Available online: https://medium.com/coinmonks/the-mathematics-of-neural-network-60a112dd3e05 (accessed on 1 March 2025).

Baek, S., Glambosky, M., & Mohanty, S. K. (2024). Macroeconomic shocks and stock market returns. *Applied Economics Letters*, *32*(5), 1601–1607. [CrossRef]

Beirne, J., & Gieck, J. (2014). Interdependence and contagion in global asset markets. *Review of International Economics*, *22*(4), 639–659. [CrossRef]

Belly, G., Boeckelmann, L., Graciano, C., Di Iorio, A., Istrefi, K., Siakoulis, V., & Stalla-Bourdillon, A. (2023). Forecasting sovereign risk in the euro area via machine learning. *Journal of Forecasting*, *42*(3), 657–684. [CrossRef]

Billio, M., Getmansky, M., Lo, A., & Pelizzon, L. (2012). Econometric measures of connectedness and systemic risk in the finance and insurance sectors. *Journal of Financial Economics*, *104*(3), 535–559. [CrossRef]

Bodie, Z., Kane, A., & Marcus, A. J. (2011). *Investments and portfolio management*. McGraw-Hill Education.

Breiman, L. (2001). Random forests. *Machine Learning*, *45*(1), 5–32. [CrossRef]

Brinson, G., Hood, L., & Beebower, G. (1986). Determinants of portfolio performance. *Financial Analysts Journal*, *42*(4), 39–44. [CrossRef]

Buchwalter, B., Diebold, F. X., & Yilmaz, K. (2026). Clustered network connectedness: A new measurement framework with application to global equity markets. *Journal of Econometrics*, *104*(3), 106243. [CrossRef]

Chiang, T. C. (2023). Real stock market returns and inflation: Evidence from uncertainty hypotheses. *Finance Research Letters*, *53*, 103606. [CrossRef]

Chiang, T. C. (2024). Inflation expectations, U.S. categorical equity market uncertainty and real stock returns: Evidence from global markets. *Financial Economics Letters*, *3*(4), 37. [CrossRef]

Choi, D., Jiang, W., & Zhang, C. (2019). Alpha go everywhere: Machine learning and international stock returns. *The Review of Asset Pricing Studies*, *15*(3–4), 288–331. [CrossRef]

Chudik, A., & Pesaran, H. (2016). Theory and practice of GVAR modeling. *Journal of Economic Surveys*, *30*(1), 165–197.

Costola, M. (2013). *Essays in financial econometrics* [Doctoral dissertataion, Universita Degli Studi di Padova]. Available online: https://www.research.unipd.it/handle/11577/3423452 (accessed on 5 March 2025).

Coulombe, P., Leroux, M., Stevanovic, D., & Surprenant, S. (2022). How is machine learning useful for macroeconomic forecasting? *Journal of Applied Econometrics*, *37*(5), 920–964. [CrossRef]

Cuadro-Saez, L., Fratzscher, M., & Thimann, C. (2009). Transmission of emerging market shocks to global equity markets. *Journal of Empirical Finance*, *16*(1), 2–17. [CrossRef]

Časta, M. (2023). Inflation, interest rates and the predictability of stock returns. *Finance Research Letters*, *58*, 104380. [CrossRef]

Damodaran, A. (2012). *Investment philosophies: Successful strategies and the investors who made them work* (2nd ed.). Wiley.

Dassanayake, W., & Jayawardena, C. (2017). Determinants of stock market index movements: Evidence from New Zealand stock market. In *6th national conference on technology and management (nctm) 2017.* IEEE. [CrossRef]

Dees, S., Di Mauro, F., Pesaran, M., & Smith, L. (2007). Exploring the international linkages of the euro area: A global VAR analysis. *Journal of Applied Econometrics*, *22*(1), 1–38. [CrossRef]

Diebold, F., & Yilmaz, K. (2013). *Measuring the dynamics of global business cycle connectedness* (Working Paper No. 13-070). PIER. [CrossRef]

Dogah, K., & Premaratne, G. (2021). Dynamic interconnectedness and risk contagion among asian financial markets. *The Singapore Economic Review*, *69*(8), 2475–2520. [CrossRef]

Drucker, H., Burges, C. J., Kaufman, L., Smola, A., & Vapnik, V. (1997). Support vector regression machines. *Advances in Neural Information Processing Systems*, *9*, 155–161.

Efron, B., Hastie, T., Johnstone, I., & Tibshirani, R. (2004). Least angle regression. *The Annals of Statistics*, *32*(2), 407–499. [CrossRef]

Eickmeier, S., & Ng, T. (2011). *How do credit supply shocks propagate internationally? A GVAR approach* (Discussion Paper Series 1 No. 2011/27). Deutsche Bundesbank. [CrossRef]

Elkamhi, R., Lee, J., & Sadik, S. (2021). Bridging the gap between strategic allocation and investment risk. *The Journal of Portfolio Management*, *47*(6), 89–100. [CrossRef]

Eun, C. S., & Shim, S. (1989). International transmission of stock market movements. *Journal of Financial and Quantitative Analysis*, *24*(2), 241–256. [CrossRef]

Fabozzi, F., Focardi, S., Rachev, S., & Arshanapalli, B. (2014). *The basics of financial econometrics: Tools, concepts, and asset management applications*. Wiley. [CrossRef]

Fischer, T., & Krauss, C. (2018). Deep learning with long short-term memory networks for financial market predictions. *European Journal of Operational Research*, *270*(2), 654–669. [CrossRef]

Fraser, P., McAlevey, L., & Tayler, M. (2008). The New Zealand market's relationship with Australia and pacific-basin share markets: Is New Zealand converging with Australia? *Applied Financial Economics*, *18*, 451–462. [CrossRef]

Frijns, B., Gilbert, A., & Tourani-Rad, A. (2010). The dynamics of price discovery for cross-listed shares: Evidence from Australia and New Zealand. *Journal of Banking & Finance*, *34*(3), 498–508. [CrossRef]

Frijns, B., Gilbert, A., & Tourani-Rad, A. (2015). The determinants of price discovery: Evidence from US-Canadian cross-listed shares. *Journal of Banking & Finance*, *59*, 457–468. [CrossRef]

Galesi, A., & Lombardi, M. (2009). *External shocks and international inflation linkages: A global var analysis* (Working Paper Series No. 1062). European Central Bank. [CrossRef]

Gan, C., Lee, M., Au Yong, H., & Zhang, J. (2006). Macroeconomic variables and stock market interactions: New Zealand evidence. *Investment Management & Financial Innovations*, *3*(4), 89–101.

Garcia-Vega, S., Zeng, X.-J., & Keane, J. (2020). Stock price prediction using kernel adaptive filtering within a stock market interdependence approach. *Expert Systems with Applications*, *160*, 113668. [CrossRef]

Gastineau, G., Olma, A., & Zielinski, R. (2007). Equity portfolio management. In J. Maginn, D. Tuttle, D. McLeavey, & J. Pinto (Eds.), *Managing investment portfolios: A dynamic process* (3rd ed.). Wiley.

Geraci, M., & Gnabo, J. (2018). Measuring interconnectedness between financial institutions with Bayesian time-varying vector autoregressions. *Journal of Financial and Quantitative Analysis*, *53*(3), 1371–1390. [CrossRef]

Greenwood-Nimmo, M., Nguyen, V., & Shin, Y. (2021). Measuring the connectedness of the global economy. *International Journal of Forecasting*, *37*(2), 899–919. [CrossRef]

Gu, S., Kelly, B., & Xiu, D. (2020). Empirical asset pricing via machine learning. *Review of Financial Studies*, *33*(5), 2223–2273. [CrossRef]

Hakkoum, H., Abname, I., & Idri, A. (2022). Interpretability in the medical field: A systematic mapping and review study. *Applied Soft Computing*, *117*, 108391. [CrossRef]

Halton, C. (2024, January 3). *Intermarket analysis: What it is and how it works.* Investopedia. Available online: https://www.investopedia.com/terms/i/intermarketanalysis.asp (accessed on 11 August 2025).

Hastie, T., Narasimhan, B., & Tay, J. (2023). Elastic net regularization paths for all generalized linear models. *Journal of Statistical Software*, *106*(1), 1–31. [CrossRef] [PubMed]

Hastie, T., Tibshirani, R., & Friedman, J. (2009). *The elements of statistical learning: Data mining, inference, and prediction* (2nd ed.). Springer. [CrossRef]

Hastie, T., Tibshirani, R., & Wainwright, M. (2015). *Statistical learning with sparsity: The lasso and generalizations*. CRC Press.

Haykin, S. (2009). *Neural networks and learning machines* (3rd ed.). Prentice Hall.

Heaton, J. B., Polson, N. G., & Witte, J. H. (2017). Deep learning for finance: Deep portfolios. *Applied Stochastic Models in Business and Industry*, *33*(1), 3–12. [CrossRef]

Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. *Neural Computation*, *9*(8), 1735–1780. [CrossRef] [PubMed]

Hoerl, A. E., & Kennard, R. W. (1970). Ridge regression: Biased estimation for nonorthogonal problems. *Technometrics*, *12*(1), 55–67. [CrossRef]

Holden, C., Jacobsen, S., & Subrahmanyam, A. (2014). The empirical analysis of liquidity. *Foundations and Trends in Finance*, *8*(4), 263–365. [CrossRef]

Ibbotson, R., & Kaplan, P. (2000). Does asset allocation policy explain 40, 90, or 100 percent of performance? *Financial Analysts Journal*, *56*(1), 26–33. [CrossRef]

James, G., Witten, D., Hastie, T., & Tibshirani, R. (2013). *An introduction to statistical learning*. Springer. [CrossRef]

Jiang, G. J., Xu, D., & Yao, T. (2009). The information content of idiosyncratic volatility. *Journal of Financial and Quantitative Analysis*, *44*(1), 1–28. [CrossRef]

Johnson, R., & Soenen, L. (2002). Asian economic integration and stock market comovement. *Journal of Financial Research*, *25*(1), 141–157. [CrossRef]

Kakran, S., Sidhu, A., Bajaj, P. K., & Dagar, V. (2023). Novel evidence from APEC countries on stock market integration and volatility spillover: A diebold and yilmaz approach. *Cogent Economics & Finance*, *11*(2), 2254560. [CrossRef]

Kass, R., & Raftery, A. (1995). Bayes factors. *Journal of the American Statistical Association*, *90*(430), 773–795. [CrossRef]

Kollias, C. (2024). Stock markets cycles and macroeconomic dynamics. *International Advances in Economic Research*, *30*, 255–278. [CrossRef]

Konate, S. (2024). *Interpretability of machine learning models for medical image analysis* [Doctoral dissertation, Queensland University of Technology]. Available online: https://eprints.qut.edu.au/248812/ (accessed on 8 September 2025).

Kotagiri, A. (2024). Demystifying machine learning by unravelling interpretability. In P. Whig, S. Sharma, S. Sharma, A. Jain, & N. Yathiraju (Eds.), *Practical applications of data processing, algorithms, and modeling.* IGI Global. [CrossRef]

Kumar, R. (2019). Does trade interdependency lead linkages between stock markets? A case of South Asian countries. *International Journal of Emerging Markets*, *15*(3), 490–506. [CrossRef]

Liang, K., & Yen, C. (2014). Dissecting the cycles: An intermarket investigation and its implications to portfolio reallocation. *International Review of Economics & Finance*, *33*, 39–51. [CrossRef]

Lin, H., & Quill, D. (2016). Information diffusion and the predictability of New Zealand stock market returns. *AFAANZ Accounting and Finance*, *56*, 749–785.

Liu, X., & Wang, X. (2023). Stock investment strategies with time-varying co-movements between energy market and global financial market. *Highlights in Business, Economics and Management*, *21*, 104847. [CrossRef]

Longin, F., & Solnik, B. (2001). Extreme correlation of international equity markets. *Journal of Finance*, *56*(2), 649–676. [CrossRef]

Maginn, J., Tuttle, D., McLeavey, D., & Pinto, J. (2007). The portfolio management process and the investment policy statement. In J. Maginn, D. Tuttle, D. McLeavey, & J. Pinto (Eds.), *Managing investment portfolios: A dynamic process* (3rd ed.). Wiley.

Maier-Paape, S., & Platen, A. (2016). Lead–lag relationship using a stop-and-reverse-minmax process. *Risks*, *4*(3), 27. [CrossRef]

Mauboussin, M., & Callahan, D. (2021). *Everything is a dcf model: A mantra for valuing cash-generating assets.* Consilient Observer, Morgan Stanley Investment Management. Available online: https://www.morganstanley.com/im/en-us/individual-investor/insights/consilient-observer/everything-is-a-dcf-model.html (accessed on 23 March 2026).

Molnar, C. (2022). *Interpretable machine learning* (2nd ed.). Lulu.com. Available online: https://christophm.github.io/interpretable-ml-book/ (accessed on 8 April 2025).

Murphy, J. (2004). *Intermarket analysis: Profiting from global market relationships*. Wiley Trading.

Narayan, P. K., & Smyth, R. (2005). Cointegration of stock markets between New Zealand, Australia, and the G7 economies: Searching for co-movement under structural change. *Australian Economic Papers*, *44*(3), 231–247. [CrossRef]

Ozgur, O., & Akkoc, U. (2021). Inflation forecasting in an emerging economy: Selecting variables with machine learning algorithms. *International Journal of Emerging Markets*, *17*(8), 1889–1908. [CrossRef]

Paramati, S. R., Gupta, R., & Hui, A. (2016). Trade and investment linkages and stock market long-run relationship. *Australian Economic Papers*, *55*(2), 149–169. [CrossRef]

Pekedis, M. (2020). Damage diagnosis of bolt loosening via vector autoregressive—Support vector machines. *Hittite Journal of Science and Engineering*, *7*(3), 169–179. [CrossRef]

Pesaran, H., Schuermann, T., & Weiner, S. (2004). modeling regional interdependencies using a global error-correcting macroeconometric model. *Journal of Business & Economic Statistics*, *22*(2), 129–162. [CrossRef]

Qiao, Z., Li, Y., & Wong, W. (2011). Regime-dependent relationships among the stock markets of the US, Australia, and New Zealand: A markov-switching VAR approach. *Applied Financial Economics*, *21*(24), 1831–1841. [CrossRef]

Raddant, M., & Kenett, D. (2016). *Interconnectedness in the global financial market* (Tech. Rep. No. 16-09). Office of Financial Research (OFR). [CrossRef]

Rasmussen, M. (2003). Quantitative portfolio construction and asset allocation. In *Quantitative portfolio optimisation, asset allocation and risk management.* Palgrave Macmillan. [CrossRef] [PubMed]

Rudin, C. (2019). Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead. *Nature Machine Intelligence*, *1*(5), 206–215. [CrossRef] [PubMed]

Sari, D. R., & Riyadi, S. (2025). Macroeconomics and stock market returns: A case study in the ASEAN region 2018–2024. *Brilliant International Journal of Management and Tourism*, *6*(1), 201–209. [CrossRef]

Schmidt, J., Cestonaro, T., & Bender, M. (2024). *Lead-lag relationships in market microstructure.* Behavioral & Experimental Finance eJournal. [CrossRef]

Schwarz, G. (1978). Estimating the dimension of a model. *Annals of Statistics*, *6*(2), 461–464. [CrossRef]

Sharpe, W., Chen, P., Pinto, J., & McLeavey, D. (2007). Asset allocation. In J. Maginn, D. Tuttle, D. McLeavey, & J. Pinto (Eds.), *Managing investment portfolios: A dynamic process* (3rd ed.). Wiley.

Shi, Y. (2022). What influences stock market co-movements between China and its Asia-Pacific trading partners after the global financial crisis? *Pacific-Basin Finance Journal*, *72*, 101722. [CrossRef]

Smola, A. J., & Schölkopf, B. (2004). A tutorial on support vector regression. *Statistics and Computing*, *14*(3), 199–222. [CrossRef]

Soydemir, G. (2000). International transmission mechanism of stock market movements: Evidence from emerging equity markets. *Journal of Forecasting*, *19*(3), 149–176. [CrossRef]

Swinkels, L., & Hoogteijling, T. (2022). *Forecasting stock crash risk with machine learning.* White Paper. Robeco. Available online: https://www.robeco.com/en/riam (accessed on 26 April 2025).

Tibshirani, R. (1996). Regression shrinkage and selection via the lasso. *Journal of the Royal Statistical Society: Series B*, *58*(1), 267–288. [CrossRef]

Uemoto, T., & Naito, K. (2022). Support vector regression with penalized likelihood. *Computational Statistics and Data Analysis*, *174*, 107522. [CrossRef]

Vapnik, V. N. (1998). *Statistical learning theory*. Wiley.

Varner, M. (2017). *Vector autoregressions with machine learning*. Honors Theses 216. Bates College Scarab. Available online: https://scarab.bates.edu/honorstheses/216 (accessed on 30 January 2025).

Weerasinghe, P. (2009). Trade policy openness and economic performance: Cross-country evidence. *Staff Studies (Central Bank of Sri Lanka)*, *35*(1), 33–61. [CrossRef]

Wein, A. (2022). The dynamics of risk: Implications for asset allocation strategies. *The Journal of Beta Investment Strategies*, *13*(1), 57–68. Available online: https://api.semanticscholar.org/CorpusID:247253505 (accessed on 9 March 2025). [CrossRef]

Wong, A., & Fong, T. (2011). Analysing interconnectivity among economies. *Emerging Markets Review*, *12*(4), 432–442. [CrossRef]

Zhang, R., & Jia, H. (2021). Production performance forecasting method based on multivariate time series and vector autoregressive machine learning model for waterflooding reservoirs. *Petroleum Exploration and Development*, *48*(1), 201–211. [CrossRef]

Zhao, Z., & Chen, W. (2021). Regional effect of monetary policy based on GVAR model and machine learning. *Journal of Intelligent & Fuzzy Systems*, *40*(4), 6567–6579. [CrossRef]

Zou, H., & Hastie, T. (2005). Regularization and variable selection via the elastic net. *Journal of the Royal Statistical Society, Series B: Statistical Methodology*, *67*(2), 301–320. [CrossRef]