Nonlinear Financial Econometrics

Markov Switching Models, Persistence and Nonlinear Cointegration

Edited by Greg N. Gregoriou
and Razvan Pascalau

Nonlinear Financial Econometrics: Markov Switching Models, Persistence and Nonlinear Cointegration

Also by Greg N. Gregoriou and Razvan Pascalau

FINANCIAL ECONOMETRICS MODELING: Derivatives Pricing, Hedge Funds and Term Structure Models

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Nonlinear Financial Econometrics: Markov Switching Models, Persistence and Nonlinear Cointegration

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First published in 2011 by
PALGRAVE MACMILLAN

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Palgrave Macmillan in the US is a division of St Martin's Press LLC, 175 Fifth Avenue, New York, NY 10010.

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ISBN: 978–0–230–28364–0 hardback

This book is printed on paper suitable for recycling and made from fully managed and sustained forest sources. Logging, pulping and manufacturing processes are expected to conform to the environmental regulations of the country of origin.

A catalogue record for this book is available from the British Library.

A catalog record for this book is available from the Library of Congress.

10 9 8 7 6 5 4 3 2 1
20 19 18 17 16 15 14 13 12 11

Printed and bound in Great Britain by
CPI Antony Rowe, Chippenham and Eastbourne

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Acknowledgments

We thank Lisa von Fircks and Renee Takken at Palgrave and the team at Newgen Imaging Systems. We also thank a handful of anonymous referees for the selection of papers for this book. Neither the contributors nor the publisher is held responsible for the contents of each chapter. The contents of each chapter remain the sole responsibility of each author.

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Abstracts

1 Valuing Equity when Discounted Cash-Flows are Markov

Jeremy Berkowitz

We derive new methods for valuing equity and a wide variety of other assets by assuming that both dividend payments and discount rates are Markov. Our approach does not require any particular model of the dynamics of dividend growth and is general enough to include most existing models of the term structure of interest rates. Dividend growth can be stationary or explosive, linear or nonlinear and can be modeled in discrete time or continuous time. We describe the relationship of our approach to existing methods of valuing stocks and present an application to S&P 500 index prices.

2 Markov Switching Mean-Variance Efficient Frontier Dynamics: Theory and International Evidence

Massimo Guidolin and Federica Ria

It is well known that regime switching models are able to capture the presence of rich non-linear patterns in the joint distribution of asset returns. After reviewing key concepts and technical issues related to specifying, estimating, and using multivariate Markov switching models in financial applications, in this chapter we map the presence of regimes in means, variances, and covariances of asset returns into explicit dynamics of the Markowitz mean-variance frontier. In particular, we show both theoretically and through an application to international equity portfolio diversification that substantial differences exist between bull and bear, regime-specific frontiers, both in statistical and in economic terms. Using Morgan Stanley Capital International (MSCI) investable indices, we characterize mean-variance frontiers and optimal portfolio strategies in bull periods, in bear periods, and in periods where high uncertainty exists on the nature of the current regime.

3 A Markov Regime-Switching Model of Stock Return Volatility: Evidence from Chinese Markets

Thomas C. Chiang, Zhuo Qiao and Wing-Keung Wong

This chapter presents a regime switching GARCH model (RS-GARCH) to examine the volatile behavior and volatility linkages among the four major segmented Chinese stock indices. We find evidence of a regime shift in the volatility of the four markets, and the RS-GARCH model appears to outperform the single regime GARCH model. The evidence suggests that B-share markets are more volatile and shift more frequently between high- and low-volatility states. B-share markets are found to be more sensitive to international shocks, while A-share markets seem immune to international spillovers of volatility. Also, volatility linkages among the four segmented markets are regime-dependent.

4 Nonlinear Persistence and Copersistence

Christian Gourieroux and Joann Jasiak

This chapter examines relationships between various forms of persistence in nonlinear transformations of stationary and nonstationary processes. We introduce the concept of persistence space that is used to define the degrees of persistence in univariate and multivariate time series. For illustration, we examine and compare persistence in a fractionally integrated process and in a beta mixture of AR(1) processes. We also propose the concept of persistence by trajectory that allows us to define nonlinear cointegration and discuss identification problems that arise in this context.

5 Fractionally Integrated Models for Volatility: A Review

Dean Fantazzani

Many empirical studies have showed the extreme degree of persistence of shocks to the conditional variance process, whose effects can take a considerable time to decay. Therefore the distinction between stationary and unit root processes seems to be far too restrictive. Indeed, the propagation of shocks in a stationary process occurs at an exponential rate of decay (so that it only captures the short-memory), while for an unit root process the persistence of shocks is infinite. Fractional models have been recently proposed in the financial literature to fill the gap between short and complete persistence. The main motivation to use these kinds of models is that the propagation of shocks occurs at a slow hyperbolic rate of decay, as opposed to the exponential decay associated with the stationary and invertible ARMA class of processes, or the infinite persistence resulting from non-stationary processes. We review the main developments of this growing field of research, trying to highlight the main advantages and disadvantages of the approaches proposed so far.

6 An Explanation for Persistence in Share Prices and their Associated Returns

Derek Bond and Kenneth A. Dyson

The question of whether the returns on shares exhibit long memory has attracted considerable attention. Recently several studies have also raised the possibility that some share prices could exhibit long memory. As well as exploring the financial implications of such findings – namely: potential, exploitable, profitable inefficiencies in the market – it is also important to consider whether the apparent long memory is caused by nonlinearity. This chapter does this using tests based on the semi-parametric estimator of the fractional integration parameter'd' suggested by Smith (2005), Shimotsu (2006), Perron and Qu (2008).

7 Nonlinear Shift Contagion Modeling: Further Evidence from High Frequency Stock Data

Mohamed El Hedi Arouri, Fredj Jawadi, Waël Louhichi and Duc Khuong Nguyen

This chapter investigates the contagion hypothesis for the French and German stock markets using a combination of a Switching Transition Error Correction model and a Generalized Autoregressive Conditional Heteroscedasticity (STEC-GARCH) model. The main advantage of this double nonlinear error-correction modeling is to specify a time-varying process that apprehends the dynamic evolution of the contagion and reproduces its speed, its extreme regimes as well as its intermediate states, by taking into account the possible linkages between these markets. More importantly, these techniques capture two kinds of nonlinearity: nonlinearity in the mean and nonlinearity in the variance. Applying this modeling on the intraday data of the CAC40 and DAX100 indices over the pre-crisis period (2004–2006) and the post-crisis period (2007–2009), our results indicate significant shift contagion between studied markets. There is also evidence of nonlinear time-varying error correcting-mechanism toward the long-run equilibrium.

8 Sparse-Patterned Wavelet Neural Networks and Their Applications to Stock Market Forecasting

Jack Penm and R.D. Terrell

Wavelet neural networks combine the theories of wavelet analysis and neural networks. This Chapter proposes construction approaches to develop sparse-patterned wavelet neural networks, which demonstrate the 'presence and absence' restrictions on the coefficients of a subset time-series system. To demonstrate the effectiveness of the proposed nonlinear approaches, the developed sparse-patterned wavelet neural networks are applied to stock market forecasting.

9 Nonlinear Cointegration and Nonlinear Error Correction Models: Theory and Empirical Applications for Oil and Stock Markets

Mohamed El Hedi Arouri, Fredj Jawadi and Duc Khuong Nguyen

This chapter aims to present the recent developments of nonlinear cointegration and nonlinear error correction models (nonlinear cointegration regressions, attractors, mixing tests, nonlinear cointegration tests, threshold cointegration models and nonlinear ECM) that were introduced by Escribano and Mira (2002) [*Journal of Time Series Analysis*, Vol. 23, 509–522] and to discuss their applications in the field of empirical finance and energy studies. We also provide evidence regarding their superiority over useful linear cointegration tools. After pointing out the limitations of linear cointegration models at the theoretical level, we apply both linear and nonlinear cointegration techniques to reproduce the short- and long-term empirical linkages between oil and world stock markets over the last three decades. Our findings show several intriguing facts. Indeed, while linear modeling models fail to apprehend the significant relationship between oil and stock markets and, rather, conclude with their segmentation, the hypothesis of financial and oil market integration is not rejected regarding nonlinear cointegration models. More interestingly, this cointegration relationship between oil and world stock markets yields an on-going process that is partially activated, only per regime when oil price deviations against the world market are away from the equilibrium and exceed some threshold.

8

Sparse-Patterned Wavelet Neural Networks and Their Applications to Stock Market Forecasting

Jack Penm and R.D. Terrell

8.1 Introduction to Wavelet analysis

A new approach adopted in this chapter is to apply sparse-patterned wavelet neural networks to simulate emerging stock market price movements. The approach is based on wavelet analysis, which is a relatively new and quite powerful mathematical tool for non-linear financial econometrics. Like conventional Fourier time series analysis, it involves the projection of a time-series onto an orthogonal set of components: in the case of Fourier analysis sine and cosine functions; and in the case of wavelet analysis wavelets. A critical difference is that wavelet analysis exhibits the characteristics of the local behavior of the function, whereas Fourier analysis presents the characteristics of the global behavior of the function. Compared to Fourier analysis, wavelet analysis offers several advantages. Fourier analysis decomposes a given function into sinusoidal waves of different frequencies and amplitudes. This is an effective approach when the given function is stationary. However, when the characteristics at each frequency change over time or there are singularities, Fourier analysis will give us the average of the changing frequencies over the whole function, whereas wavelet analysis can tell us how a given function changes from one time period to the next. It does this by matching a wavelet function, of varying scales and positions, to that function. Wavelet analysis is also more flexible, in that we can choose a specific wavelet to match the type of function we are analyzing. Contrary to Fourier analysis, the basis involved is fixed to be sine or cosine waves.

The continuous wavelet transform (CWT) is used to transform a function, $f(x) \in L^2(R^d)$, that is defined over continuous time. Hence, we have

$$w(a,t) = \int_{R^d} f(x) a^{-\frac{d}{2}} \psi\left(\frac{x-t}{a}\right) dx, \tag{8.1}$$

where the parameters $a \in R_+$ and $t \in R^d$ are dilation and translation parameters respectively. Those parameters are used for creating the wavelet family where both vary continuously. The idea of the transform is, for a given d times translation td times and a given dilation λ and of the mother wavelet ψ, to make the wavelet functions best preserve all the information from $f(\cdot)$.

Then we can recover $f(\cdot)$ from its CWT using the following inverse transform:

$$f(x) = \frac{1}{C_\psi} \int_0^\infty a^{-(d+1)} \int_{R^d} w(a,t) a^{-\frac{d}{2}} \psi\left(\frac{x-t}{a}\right) dt\, da.$$

In reality, all time-series observations are collected discretely. Therefore, there exists a need to use the discrete wavelet transform to undertake time-series analysis in a discrete case.

We can then recover $f(\cdot)$ from its discrete wavelet transform using the following inverse transform:

$$f(x) = \sum_i w_i a_i^{-\frac{d}{2}} \psi\left(\frac{x-t_i}{a_i}\right).$$

Multi-resolution analysis (MRA) provides an ability of discrete wavelet transformation to decompose a time-series into a high-frequency wavelet coefficient (W) component and a low-frequency residual (U) component. The high-frequency W indicates the dynamic characteristics, and the low-frequency U shows the trend characteristics. The low-frequency U component will then be decomposed into the next level high-frequency W and low-frequency U. The decomposition process will repeat until the final level U becomes smooth and stationary. Figure 8.1 shows a wavelet decomposition tree (WDT) to describe this process. MRA outlines the wavelet decomposition tree approach to decompose the original time-series to many level W components and a final level U component. Those level W components and the final level U component can then follow the inverse WDT approach to reconstruct the original time-series. The original time-series variable X will then be decomposed to many W

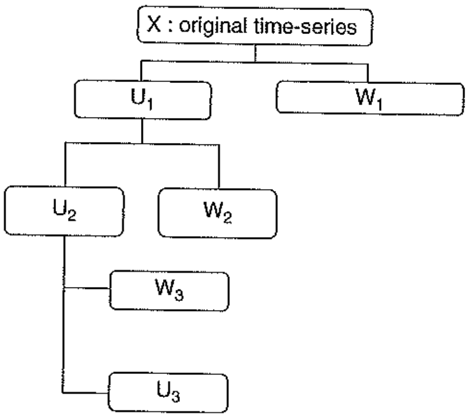

Figure 8.1 A wavelet decomposition tree

variables and one U variable by using MRA and WDT analysis. Those new W and U variables will facilitate modeling and forecasting, and improve predictability.

MRA outlines the wavelet decomposition tree approach to decompose the original time-series to many level W components and a final level U component. The redundant Haar wavelet transform is adopted in the wavelet decomposition tree, with the following relations at the k-th point of the j-th level.

$$U_j(k) = 0.5\left(U_{j-1}(k) + U_{j-1}(k - 2^{j-1})\right); \quad W_j(k) = U_{j-1}(k) - U_j(k) \tag{8.2}$$

where U is the residual and W are the wavelet coefficients.

We observe that the Haar wavelet function is asymmetric and resembles a step function. Haar wavelets have an ability to overcome weaknesses of symmetric wavelets and effectively capture the scale characteristics of a time-series which will be modeled for forecasting purposes. The time-series will be decomposed to high- and low-frequency components. Those high- and low-frequency components can then follow the inverse WDT approach to reconstruct the original time-series.

This chapter is organized as follows. Section 8.2 outlines the construction of sparse-patterned wavelet neural networks, which demonstrate the 'presence and absence' restrictions on the coefficients of subset time-series systems, including full-order systems. To demonstrate the effectiveness of the proposed non-linear financial econometrics approaches, Section 8.3 presents an application to illustrate the practical use of the proposed sparse-patterned wavelet neural networks, which models the relationship between financial time-series, and then undertakes forecasting. In this example, the relationship between the Taiwanese stock market index and the Taiwanese future market index is used. A brief summary is provided in Section 8.4.

8.2 Sparse-patterned Wavelet neural networks

Wavelet neural networks combine the theories of wavelets analysis and neural networks. A three-layer wavelet neural network generally consists of a feed-forward neural network, with one hidden layer. A neural network is a non-linear statistical data modeling tool composed of highly interconnected nodes that can model complex relationships between inputs and outputs. A neural network processes information and generates some form of response based upon the relationship identified within a panel data system, using both time-series and cross-section data. Each elementary node of a neural network can receive input signals from other nodes, which activates the algorithmic procedure in each node to transform the input signal into an output signal to other nodes. These nodes are arranged in a series of layers that connect nodes in different layers, but not with nodes within the same layer. Thus, these nodes are usually divided into the input layer, the output layer and one or more hidden layers. The input layer receives the inputs while the final layer is the output layer, as it provides the target output signal. The hidden layers are any layers that lie between the input and output layers.

Neural networks also exist as computer-based systems operating many non-linear computational units or nodes interconnected by links with adjustable weights. Multi-layer networks with one or more hidden layers allow neural networks to classify functions that are not linearly separable. Historically, neural networks were not used extensively until they could solve non-linear problems. Several pruning algorithms for performance improvement have been proposed to eliminate non-significant connections.

Conventionally linear time-series approaches have been adopted in modelling financial time-series in econometrics. However, the modeling power of linear approaches is weak in relation to the complexities of financial markets. This chapter focuses on non-linear models to improve performance in modeling and simulation. It is proposed that non-linear models, in particular wavelet neural networks, have the ability to improve the performance of modeling and simulate the movements of financial variables, including equity market indicators. These networks have the flexibility to account for potentially complex nonlinear relationships which cannot be fully captured by linear models.

Subset time-series models are often necessary when variables exhibit some form of periodic behavior, such as strong seasonality. If the underlying true process has a subset structure, the suboptimal full-order model specification can give rise to inefficient estimates and inferior projections. It is also possible that zero coefficients could exist in time-series models, particularly when periodic responses are likely. Conventional neural networks have difficulty when used for practical modeling of subset time-series systems, as they cannot demonstrate the 'presence and absence' restrictions on the coefficients of a system.

In order to increase the modeling and analysis power of neural networks to be applied to subset time-series systems including full-order systems, Penm and Terrell (2003) and Chen, Penm and Terrell (2006) incorporate two types of connection (synapse), namely inhibitor arc and switchable connection, to the neural network structure. Constraints on the connection strength (synaptic weights) are imposed on the extended network structure. The inhibitor arc is connected to neural network theory from Petri nets, and the associated connection strength for all these inhibitor arcs is constrained to zero at all times. The switchable connection is obtained from switching theory, and the strength is switchable between zero and non-zero at any time. Further, O'Neill, Penm and Penm (2007), Penm and Terrell (2003) and Chen, Penm and Terrell (2006) have extended the relevance of multi-layered neural networks and so more effectively model a greater array of decomposed wavelet functions to construct wavelet neural networks. In order to increase estimation power of a wavelet neural network, the input layer variables comprise high-frequency wavelet coefficient variables and low-frequency residual variables.

This approach thus recognizes that many connections between nodes in layers are unnecessary and can be deleted to construct sparse-patterned wavelet neural networks. Those inhibitor arcs – reflecting inhibitive synapses – in patterned wavelet neural networks focus zero strength at all times to node connections. The patterned network also allows for connections between nodes in layers that have variable strengths at different points of time by introducing additionally excitatory arcs – reflecting excitatory synapses.

Also, the innovative and sophisticated learning algorithm we have developed (Penm and Terrell, 2003; Chen, Penm and Terrell, 2006) is simple to use and can avoid cumbersome matrix inversion, and therefore results in better numerical accuracy. Patterned neural networks with inhibitor arcs and switchable connections are intuitively the most direct approach to increasing the estimation power of neural networks. These extensions provide neural networks with an ability to estimate sequentially changing panel data systems with a subset structure. This dynamic sparse-pattern illustrates the 'presence and absence' restrictions on the coefficients of the panel system, and can update the specification each time a new observation becomes available. This specification is superior to the conventional static one in which all synapses are considered to be excitatory, as no 'absence' restrictions are imposed on the coefficients. The sparse-patterned network approach reveals that both the modeling and simulation performance of patterned neural networking can be improved by the chosen optimal specification, using model selection criteria.

Figure 8.2 indicates the structure of a polynomial network with a single hidden-layer for the predictor of a time-series system, where all y(t), u(t) and w(t) denote input neuron vectors.

If the neural input-vector y(t) includes the first-order and second-order terms $y_1(t)$, $y_2(t)$, $y_1(t)y_2(t)$, $y_1^2(t)$ and $y_2^2(t)$, a three-layered polynomial neural network can be constructed. The hidden-node transfer function in this network consists of a quadratic regression polynomial of two variables used by the group method of data handling (GMDH) algorithm.

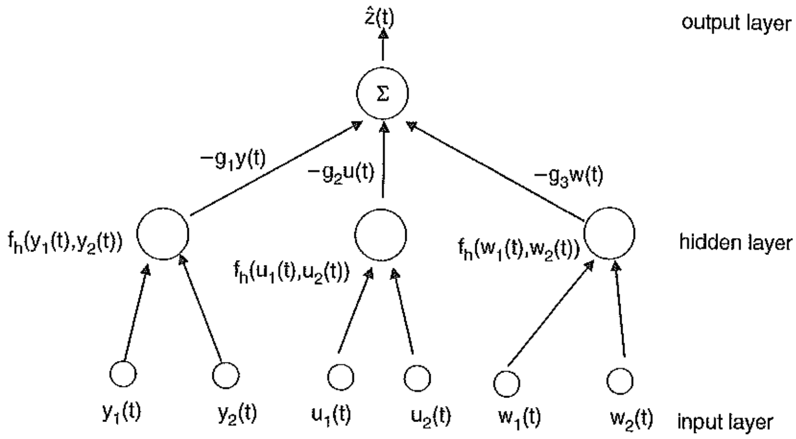

Figure 8.2 A neural network with a single hidden-layer for a time-series system with input vectors y(t), u(t) and w(t)

The general connection between the mean-corrected input and output vectors of a hidden-node is represented by

$$f_h(y_1(t), y_2(t)) = h_{11}y_1(t) + h_{12}y_2(t) + h_{13}y_1(t)y_2(t) + h_{14}y_1^2(t) + h_{15}y_2^2(t),$$

where $y_i(t), i = 1,2,$ are the input variables, and h_{1i}, $i = 1,2,\ldots,5$ are zero or non-zero coefficients. For an output-vector z(t) with three neural input-vectors, y(t), u(t) and w(t), the prediction vector $\hat{z}(t)$ will be:

$$\hat{z}(t) = -g_1 y(t) - g_2 u(t) - g_3 w(t), \tag{8.3}$$

where $y(t) = \left[y_1(t) \quad y_2(t) \quad y_1(t)y_2(t) \quad y_1^2(t) \quad y_2^2(t)\right]'$,

$u(t) = \left[u_1(t) \quad u_2(t) \quad u_1(t)u_2(t) \quad u_1^2(t) \quad u_2^2(t)\right]'$,

$w(t) = \left[w_1(t) \quad w_2(t) \quad w_1(t)w_2(t) \quad w_1^2(t) \quad w_2^2(t)\right]'$, and

$g_i = \left[h_{i,1} h_{i,2} \cdots h_{i,5}\right]$, $i = 1, 2$ and 3.

If any $h_{i,j} = 0, j = 1,2,3,4,5,$ and $i = 1,2$ and 3 is missing, (8.3) becomes a time-series system without full-order. If an input vector, say u(t), in (8.3) is missing, (8.3) becomes a subset time-series system. In this case, the hidden unit operating $f_h(u_1(t), u_2(t))$ becomes inoperative and the corresponding incoming and outgoing arcs become inhibitive. The resulting neural network will be a sparse-patterned neural network.

Sparse-patterned neural networks with inhibitor arcs and switchable connections are intuitively the most direct approach to increasing the modelling power of neural networks. These extensions provide neural networks with an ability to model sequentially changing time series systems with a subset structure.

Section 8.3 presents an application of sparse-patterned wavelet neural networks with input layer variables, comprising those high-frequency wavelet coefficient variables and low-frequency residual variables, decomposed from wavelet decomposition. The application concerns prediction relationships between the stock and futures markets.

8.3 Empirical application to stock market forecasting

This section gives an illustration of the practical use of the proposed sparse-patterned wavelet neural network. The three-layer patterned wavelet neural network described in Section 8.2 can be used to model the relationship between financial time-series, and then undertake forecasting. In this example, the relationship between the Taiwanese stock market index and the Taiwanese future market index is used. A future contract is one of the most important hedging instruments for the underlying asset. Stock index futures have many attractive hedging benefits for a trader who wishes to trade the underlying stock portfolio corresponding to the index. In Taiwan the stock market at the Taiwanese Stock Exchange is an important East Asia emerging market, and the main stock market indicator is the Taiwanese equity index (TAIEX). The index is calculated on the basis of market capitalization of the constituent stocks traded on the Taiwanese Stock Exchange. The Taiwanese Futures Exchange offers a futures contract on the TAIEX. This contract is available on a quarterly expiry date and is known as the TAIEX Futures contract (TX).

There is already a considerable literature examining the relationship between stock and future market prices. The literature has either examined the theoretical relationship between the markets through models such as the cost-of-carry, or examined the causality between the markets through lead-lag relationships, cointegrating tests or bi-variate spillover models. The general findings confirm a strong causality between the markets. This relationship is not unexpected given the pricing relationship between the markets and the fact that the basis reduces to zero at the maturity of the future contract. However, there has been debate about the direction of causality, with the evidence generally indicating that the futures market leads the stock market. In particular, Penm and Terrell (2003) have examined the lead-lag relationship between stock index futures and cash index prices in Australia, and document that the futures price is a leading indicator for the spot, when spot prices move together under market-wide movements.

We sampled the data on the TAIEX and TX daily between 27 January and 29 June 2008 ($T=98$), the TAIEX data being observed as the daily market closing index values, and the TX data being observed as the last traded price on each day in the June 2008 contract. We use $u(t) = \log(TAIEX_{t-1})$ and $w(t) = \log(TX_{t-1})$ to predict $y(t) = \log(TAIEX_t)$.

To demonstrate the usefulness of the proposed approach in a small sampling environment, forecasting for period $(T+1)$ is carried out by building a patterned wavelet neural network on the first T period, using three-layer neural networks. In the course of constructing the patterned network, the Haar wavelet function is adopted. Augmented Dickey-Fuller tests are selected to examine the most suitable scale to undertake wavelet decomposition. Further, the Wavelet Toolbox of Matlab is used to undertake wavelet transformation. For both u(t) and w(t), MRA and WDT analysis associated with a wavelet decomposition tree indicate that each time-series involved has been decomposed to seven high-frequency W components and a low- frequency R component. Therefore, a (16–16–1) wavelet neural network with 16 neuron variables in the input layer is initially constructed. The 'presence and absence' patterns, indicating switchable connections and inhibitor arcs, are then examined by using the model selection algorithm proposed in Penm and Terrell (2003). One-step ahead forecasts based on each selected optimal patterned network specification are undertaken for $T=93$ through $T=98$.

It is commonly agreed that accurate forecasting in share markets is a difficult task. The approach adopted here focuses on models which can valuably simulate share price movements. The trading profits gained from the outcome of these models can still be offset by stock market frictions, such as stamp duty costs, capital gain taxes and broker's fees.

For brevity, the forecast performance outcomes are summarized in Table 8.1. The forecast performances based on the full-order neural network with two neural variables, both u(t) and w(t), are also shown for comparison purposes. The root mean squares error (RMSE) denotes $\sqrt{\frac{1}{6}\sum_{i=93}^{98}(\hat{y}_i - y_i)^2}$, and Theil's inequality coefficient, $\sqrt{\frac{\sum(P_i - A_i)^2}{\sum A_i^2}}$, where (P_i, A_i) stands for a pair of predicted and observed changes. The RMSE error of the patterned wavelet neural network forecast is 28.05 percent of the prediction error of the full-order neural network forecast. The Theil's inequity coefficient is 0.0071 for the sparse-patterned wavelet neural network forecast, and 0.0118 for the full-order neural network forecast.

Of course, many other non-parametric econometric techniques and dynamic forgetting factor methods could play a significant role in stock

Table 8.1 Forecasting performance comparison – The sparse-patterned wavelet neural network forecast versus the full-order neural network forecast

Neural network	**RMSE over test period**	**RMSE improvement**	**Theil's inequality coefficient**
Patterned wavelet	0.005233	28.05%	0.0071
Full-order	0.006701	–	0.0118

market price simulations. The interest of this chapter is mainly to investigate how the model developed may be utilized to improve the accuracy of financial simulations of share prices by using the proposed sparse-patterned wavelet neural network approach. Possible approaches to improve the accuracy of forecast magnitude are being investigated by our researcher team.

8.4 Summary

In this chapter, a numerically robust specification approach has been developed to select the best specification of a sparse-patterned wavelet neural network. The proposed construction method is simple to use and can be applied to an M-layered wavelet neural network with hidden layer nodes in layer $m \in [1, M-2]$. Section 8.3 presents a case study to demonstrate the effectiveness of the proposed approach and widen the possible use of sparse-patterned wavelet neural networks in financial simulations and/or econometric forecasting.

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This book introduces new methods to value equity and model the Markowitz efficient frontier using Markov switching models. In particular, the book shows that there are substantial differences between 'bull' and 'bear' market efficient portfolios that need to be taken into account when building diversified portfolios. Also, the book proposes a new concept of persistence that may be used to define and better understand the concept of nonlinear cointegration. In addition, the book reviews the recent developments of using fractional integrated models to model stock market volatility and suggests a new explanation for the persistence observed in share prices and their associated returns. Lastly, the book develops a new procedure that involves using the bootstrap to build vector error correction models and as an application, investigates the nonlinear relationship between oil and stock markets, respectively.

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ISBN 978-0-230-28364-0

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Printed in Great Britain