Applied Quantitative Methods
for Trading and Investment

Edited by

Christian L. Dunis
Jason Laws
and
Patrick Naïm
Applied Quantitative Methods
for Trading and Investment
Wiley Finance Series

*Applied Quantitative Methods for Trading and Investment*
  Christian L. Dunis, Jason Laws and Patrick Naïm

  Michel Henry Bouchez, Ephraim Clark and Bertrand Groselambert

*Credit Derivatives Pricing Models: Models, Pricing and Implementation*
  Philipp J. Schönbucher

*Hedge Funds: A resource for investors*
  Simone Borla

*The Simple Rules: Revisiting the art of financial risk management*
  Erik Banks

*Option Theory*
  Peter James

*Risk-adjusted Lending Conditions*
  Werner Rosenberger

*Measuring Market Risk*
  Kevin Dowd

*An Introduction to Market Risk Management*
  Kevin Dowd

*Behavioural Finance*
  James Montier

*Asset Management: Equities Demystified*
  Shanta Acharya

*An Introduction to Capital Markets: Products, Strategies, Participants*
  Andrew M. Chisholm

*Hedge Funds: Myths and Limits*
  François-Serge Lhabitant

*The Manager’s Concise Guide to Risk*
  Jihad S. Nader

*Securities Operations: A guide to trade and position management*
  Michael Simmons

*Modeling, Measuring and Hedging Operational Risk*
  Marcelo Cruz

*Monte Carlo Methods in Finance*
  Peter Jäckel

*Building and Using Dynamic Interest Rate Models*
  Ken Kortanek and Vladimir Medvedev

*Structured Equity Derivatives: The Definitive Guide to Exotic Options and Structured Notes*
  Harry Kat

*Advanced Modelling in Finance Using Excel and VBA*
  Mary Jackson and Mike Staunton

*Operational Risk: Measurement and Modelling*
  Jack King

*Interest Rate Modelling*
  Jessica James and Nick Webber
Applied Quantitative Methods
for Trading and Investment

Edited by

Christian L. Dunis
Jason Laws
and
Patrick Naïm
3 Modelling the Term Structure of Interest Rates: An Application of Gaussian Affine Models to the German Yield Curve

Nuno Cassola and Jorge Barros Luís

Abstract

3.1 Introduction

3.2 Background issues on asset pricing

3.3 Duffie–Kan affine models of the term structure

3.4 A forward rate test of the expectations theory

3.5 Identification

3.6 Econometric methodology and applications

3.7 Estimation results

3.8 Conclusions

References

4 Forecasting and Trading Currency Volatility: An Application of Recurrent Neural Regression and Model Combination

Christian L. Dunis and Xuehuan Huang

Abstract

4.1 Introduction

4.2 The exchange rate and volatility data

4.3 The GARCH (1,1) benchmark volatility forecasts

4.4 The neural network volatility forecasts

4.5 Model combinations and forecasting accuracy

4.6 Foreign exchange volatility trading models

4.7 Concluding remarks and further work

Acknowledgements

Appendix A

Appendix B

Appendix C

Appendix D

Appendix E

Appendix F

Appendix G

References

5 Implementing Neural Networks, Classification Trees, and Rule Induction Classification Techniques: An Application to Credit Risk

George T. Albanis

Abstract

5.1 Introduction

5.2 Data description

5.3 Neural networks for classification in Excel

5.4 Classification tree in Excel
## Contents

5.5 See5 classifier 178  
5.6 Conclusions 191  
References 191  

6 Switching Regime Volatility: An Empirical Evaluation 193  
*Bruno B. Roche and Michael Rockinger*

Abstract 193  
6.1 Introduction 193  
6.2 The model 194  
6.3 Maximum likelihood estimation 195  
6.4 An application to foreign exchange rates 197  
6.5 Conclusion 206  
References 206  
Appendix A: Gauss code for maximum likelihood for variance switching models 208  

7 Quantitative Equity Investment Management with Time-Varying Factor Sensitivities 213  
*Yves Bentz*

Abstract 213  
7.1 Introduction 213  
7.2 Factor sensitivities defined 215  
7.3 OLS to estimate factor sensitivities: a simple, popular but inaccurate method 216  
7.4 WLS to estimate factor sensitivities: a better but still sub-optimal method 222  
7.5 The stochastic parameter regression model and the Kalman filter: the best way to estimate factor sensitivities 223  
7.6 Conclusion 236  
References 237  

8 Stochastic Volatility Models: A Survey with Applications to Option Pricing and Value at Risk 239  
*Monica Billio and Domenico Sartore*

Abstract 239  
8.1 Introduction 239  
8.2 Models of changing volatility 244  
8.3 Stochastic volatility models 246  
8.4 Estimation 250  
8.5 Extensions of SV models 261  
8.6 Multivariate models 263  
8.7 Empirical applications 265  
8.8 Concluding remarks 284  
Appendix A: Application of the pentanomial model 284
Appendix B: Application to Value at Risk 286
References 286

9 Portfolio Analysis Using Excel 293
Jason Laws
Abstract 293
9.1 Introduction 293
9.2 The simple Markovitz model 294
9.3 The matrix approach to portfolio risk 301
9.4 Matrix algebra in Excel when the number of assets increases 303
9.5 Alternative optimisation targets 308
9.6 Conclusion 310
Bibliography 311

10 Applied Volatility and Correlation Modelling Using Excel 313
Frédéric Bourgoin
Abstract 313
10.1 Introduction 313
10.2 The Basics 314
10.3 Univariate models 315
10.4 Multivariate models 324
10.5 Conclusion 331
References 332

11 Optimal Allocation of Trend-Following Rules: An Application of Theoretical Results 333
Pierre Lequeux
Abstract 333
11.1 Introduction 333
11.2 Data 333
11.3 Moving averages and their statistical properties 335
11.4 Trading rule equivalence 336
11.5 Expected transactions cost under assumption of random walk 338
11.6 Theoretical correlation of linear forecasters 340
11.7 Expected volatility of MA 341
11.8 Expected return of linear forecasters 342
11.9 An applied example 344
11.10 Final remarks 346
References 347

12 Portfolio Management and Information from Over-the-Counter Currency Options 349
Jorge Barros Luís
Abstract 349
12.1 Introduction 349
12.2 The valuation of currency options spreads 353
12.3 RND estimation using option spreads 355
12.4 Measures of correlation and option prices 359
12.5 Indicators of credibility of an exchange rate band 361
12.6 Empirical applications 365
12.7 Conclusions 378
References 379

13 Filling Analysis for Missing Data: An Application to Weather
Risk Management 381
Christian L. Dunis and Vassilios Karalis

Abstract 381
13.1 Introduction 381
13.2 Weather data and weather derivatives 383
13.3 Alternative filling methods for missing data 385
13.4 Empirical results 393
13.5 Concluding remarks 395
Appendix A 396
Appendix B 397
References 398

Index 401
**About the Contributors**

**George T. Albanis** is currently working at Hypovereinsbank – HVB Group. He obtained his PhD from City University Business School, London and holds a BSc in Economics from the University of Piraeus, Greece and Master’s degrees in Business Finance and in Decision Modelling and Information Systems from Brunel University, London. An experienced programmer, his interests are applications of advanced nonlinear techniques for financial prediction in fixed income and credit derivatives markets, and quantification of risk in financial modelling.

**Yves Bentz** is Vice President with Crédit Suisse First Boston, specialising in high frequency equity trading strategies and statistical arbitrage. He was previously a quantitative trader with Morgan Stanley and with Beaghton Capital Management in London where he developed automated equity and derivatives trading strategies. Yves holds a PhD from the University of London (London Business School). He has published several research papers on factor modelling and nonlinear modelling, in particular stochastic parameter models and nonparametric statistics and their applications to investment management.

**Monica Billio** is Associate Professor of Econometrics at Università Ca’ Foscari of Venice. She graduated in Economics at Università Ca’ Foscari di Venezia and holds a PhD degree in Applied Mathematics from the Université Paris IX Dauphine. Her fields of interest are simulation-based methods and the econometrics of finance.

**Frédéric Bourgoin** is an Associate Portfolio Manager in the Active Fixed Income Portfolio Management Team at Barclays Global Investors in London where he is involved in the development of the active bond and currency strategies, as well as the risk management systems. Prior to joining BGI, he was a risk manager and quantitative analyst at Portman Asset Management. Frédéric holds a Post-Graduate Degree in Finance from ESSEC Business School and an MSc in Econometrics and Mathematical Economics from Panthéon-Sorbonne University in Paris.

**Neil Burgess** is a Vice President in the Institutional Equity Division at Morgan Stanley where he works in the area of quantitative programme trading, leading and coordinating new developments in trading systems and strategies for equities and equity derivatives between Europe and the USA. He obtained his PhD from London University. He has published widely in the field of emerging computational techniques and has acted as a
programme committee member for international conferences: Forecasting Financial Markets, Computational Finance and Intelligent Data Engineering and Learning.

**Nuno Cassola** holds a PhD in Economics from the University of Kent at Canterbury. He worked as an Associate Professor at the Technical University of Lisbon from 1992 until 1994. He then joined the Research Department of the Banco de Portugal in 1994 where he became Head of the Monetary and Financial Division in 1996. In 1999 he joined the European Central Bank in Frankfurt where he is currently Principal Economist in the Monetary Policy Stance Division of the Monetary Policy Directorate.

**Christian L. Dunis** is Girobank Professor of Banking and Finance at Liverpool Business School, and Director of its Centre for International Banking, Economics and Finance (CIBEF). He is also a consultant to asset management firms, a Visiting Professor of International Finance at Venice International University and an Official Reviewer attached to the European Commission for the Evaluation of Applications to Finance of Emerging Software Technologies. He is an Editor of the *European Journal of Finance* and has published widely in the field of financial markets analysis and forecasting. He has organised the Forecasting Financial Markets Conference since 1994.

**Xuehuan Huang** graduated from Liverpool Business School with an MSc in International Banking and Finance and from China’s Shenzen University with a BA in Business Management. After working as an auditor with Ernst & Young, she is currently a financial analyst at Bayer DS European headquarters.

**Vassilios Karalis** is an Associate Researcher at the Centre for International Banking, Economics and Finance of Liverpool Business School (CIBEF). Vassilios holds an MSc in International Banking and Finance from Liverpool Business School and a BSc in Mathematics with specialisation in probabilities, statistics and operational research from the University of Ioannina, Hellas.

**Jason Laws** is a Lecturer in International Banking and Finance at Liverpool John Moores University. He is also the Course Director for the MSc in International Banking, Economics and Finance at Liverpool Business School. He has taught extensively in the area of investment theory and derivative securities at all levels, both in the UK and in Asia. Jason is also an active member of CIBEF and has published in a number of academic journals. His research interests are focused on volatility modelling and the implementation of trading strategies.

**Pierre Lequeux** joined the Global Fixed Income division of ABN AMRO Asset Management London in 1999. As Head of Currency Management, he has responsibility for the quantitative and fundamental currency investment process. He was previously Head of the Quantitative Research and Trading desk at Banque Nationale de Paris, London branch, which he joined in 1987. Pierre is also an Associate Researcher at the Centre for International Banking, Economics and Finance of Liverpool Business School (CIBEF) and a member of the editorial board of *Derivatives Use, Trading & Regulation*.

**Jorge Barros Luís** is Head of Credit Risk Modelling with Banco Português de Investimento. Previous positions include Economist at the European Central Bank and Banco de Portugal, Chief-Economist at Banif Investimento and Adviser to the Minister of Finance and to the Secretary of State for the Treasury of the Portuguese Government. Jorge holds
a PhD in Economics from the University of York and has published several papers on yield curve modelling and information extraction from option prices.

Patrick Naïm is an engineer of the Ecole Centrale de Paris. He is the founder and chairman of Elseware, a company specialised in the application of nonlinear methods to financial management problems. He is currently working for some of the largest French institutions and coordinating research projects in the field at a European level.

Bruno B. Roche is Head of Research in the Global Management Research group of a major multinational company where he leads a specialist team whose role is to provide world class expertise, methodologies, technologies and knowledge management in multiple areas which have a global critical impact (e.g. financial markets, risk management and advertising effectiveness). He is also a Researcher at the Solvay Business School at the University of Brussels.

Michael Rockinger is Professor of Finance at the HEC School of Business of the University of Lausanne. He has been scientific consultant at the French Central Bank for many years. He is also affiliated with CEPR and FAME. Previously, Michael taught Finance at all levels at HEC-Paris. His research interests are various, one of them is the modelling of asset prices. Michael earned his PhD in Economics at Harvard University. He is also a graduate in Mathematics from the Swiss Federal Institute of Technology (EPFL) and holder of a Master’s degree from the University of Lausanne.

Domenico Sartore is Full Professor of Econometrics at Università Ca’ Foscari di Venezia. Previously he taught at the University of Milan and the University of Padua. At present, he is President of the economics and finance consultancy GRETA (Gruppi di Ricerca Economica Teorica ed Applicata) in Venice. His field of interest is the econometrics of finance, where he has published many papers.

Mark Williams is an Associate Researcher at the Centre for International Banking, Economics and Finance of Liverpool Business School (CIBEF). Mark holds an MSc in International Banking and Finance from Liverpool Business School and a BSc in Economics from Manchester Metropolitan University.
Preface

*Applied Quantitative Methods for Trading and Investment* is intended as a quantitative finance textbook very much geared towards *applied* quantitative financial analysis, with detailed empirical examples, software applications, screen dumps, etc. Examples on the accompanying CD-Rom detail the data, software and techniques used, so that contrary to what frequently happens with most textbook examples, they clarify the analysis by being reasonably easily reproducible by the reader.

We expect this book to have a wide spectrum of uses and be adopted by financial market practitioners and in universities. For the former readership, it will be of interest to quantitative researchers involved in investment and/or risk management, to fund managers and quantitative proprietary traders, and also to sophisticated private investors who will learn how to use techniques generally employed by market professionals in large institutions to manage their own money. For the latter, it will be relevant for students on MSc, MBA and PhD programmes in Finance where a quantitative techniques unit is part of the course, and to students in scientific disciplines wishing to work in the field of quantitative finance.

Despite the large number of publications in the field of computational finance in recent years, most of these have been geared towards derivatives pricing and/or risk management.¹ In the field of financial econometrics, most books have been subject specific,² with very few truly comprehensive publications.³ Even then, these books on financial econometrics have been in reality mostly *theoretical*, with empirical applications essentially focused on validating or invalidating economic and financial theories through econometric and statistical methods.

What distinguishes this book from others is that it focuses on a wide spectrum of methods for modelling financial markets in the context of *practical financial applications*. On top of “traditional” financial econometrics, the methods used also include *technical analysis* systems and many *nonparametric tools* from the fields of data mining and artificial intelligence. Although we do not pretend to have covered all possible methodologies,

---

we believe that the wide breadth of potential methods retained in this manual is highly
desirable and one of its strengths. At the same time, we have been careful to present even
the most advanced techniques in a way that is accessible to most potential readers, mak-
ing sure that those interested in the practical utilisation of such methods could skip the
more theoretical developments without hindering comprehension, and concentrate on the
relevant practical application: in this respect, the accompanying CD-Rom should prove
an invaluable asset.

An applied book of this nature, with its extensive range of methodologies and applica-
tions covered, could only benefit from being a collaborative effort of several people with
the appropriate experience in their field. In order to retain the practitioner’s perspective
while ensuring the methodological soundness and, should we say, academic respectability
of the selected applications at the same time, we have assembled a small team of quantita-
tive market professionals, fund managers and proprietary traders, and academics who have
taught applied quantitative methods in finance at the postgraduate level in their respective
institutions and also worked as scientific consultants to asset management firms.

As mentioned above, the range of applications and techniques applied is quite large.
The different applications cover foreign exchange trading models with three chapters,
one using technical analysis, one advanced regression methods including nonparametric
Neural Network Regression (NNR) models and one a volatility filter-based system relying
on Markov switching regimes; one chapter on equity statistical arbitrage and portfolio
immunisation based on cointegration; two chapters on stock portfolio optimisation, one
using Kalman filtering techniques in the presence of time-varying betas and the other using
matrix algebra and Excel Solver to derive an optimal emerging stock market portfolio;
one chapter on yield curve modelling through the use of affine models; one chapter on
credit classification with decision trees, rule induction and neural network classification
models; two chapters on volatility modelling and trading, one using Excel to compute both
univariate and multivariate GARCH volatility and correlation in the stock market, the other
using straddle strategies based on GARCH and Recurrent Network Regression (RNR) to
build a forex volatility trading model; one chapter on Value at Risk (VaR) and option
pricing in the presence of stochastic volatility; one chapter on the information contained
in derivatives prices through the use of risk-neutral density functions and, finally, one
chapter on weather risk management when confronted with missing temperature data.

The first part of the book is concerned with applications relying upon advanced mod-
elling techniques. The applications include currencies, equities, volatility, the term struc-
ture of interest rates and credit classification. The second part of the book includes
three chapters where the applications on equities, VaR, option pricing and currency trad-
ing employ similar methodologies, namely Kalman filter and regime switching. In the
final part of the book there are five chapters where a variety of financial applications
ranging from technical trading to missing data analysis are predominantly implemented
using Excel.

In the following we provide further details on each chapter included in the book.

1. “Applications of Advanced Regression Analysis for Trading and Investment” by
C. L. Dunis and M. Williams: this chapter examines the use of regression models
in trading and investment with an application to EUR/USD exchange rate forecast-
ing and trading models. In particular, NNR models are benchmarked against some
other traditional regression-based and alternative forecasting techniques to ascertain
their potential added value as a forecasting and quantitative trading tool. In addition to evaluating the various models out-of-sample from May 2000 to July 2001 using traditional forecasting accuracy measures, such as root-mean-squared errors, models are also assessed using financial criteria, such as risk-adjusted measures of return. Transaction costs are also taken into account. Overall, it is concluded that regression models, and in particular NNR models, do have the ability to forecast EUR/USD returns for the period investigated, and add value as a forecasting and quantitative trading tool.

2. “Using Cointegration to Hedge and Trade International Equities” by A. N. Burgess: this chapter analyses how to hedge and trade a portfolio of international equities, applying the econometric concept of cointegration. The concepts are illustrated with respect to a particular set of data, namely the 50 equities which constituted the STOXX 50 index as of 4 July 2002. The daily closing prices of these equities are investigated over a period from 14 September 1998 to 3 July 2002 – the longest period over which continuous data is available across the whole set of stocks in this particular universe. Despite some spurious effects due to the non-synchronous closing times of the markets on which these equities trade, the data are deemed suitable for illustration purposes. Overall, depending on the particular task in hand, it is shown that the techniques applied can be successfully used to identify potential hedges for a given equity position and/or to identify potential trades which might be taken from a statistical arbitrage perspective.

3. “Modelling the Term Structure of Interest Rates: An Application of Gaussian Affine Models to the German Yield Curve” by N. Cassola and J. B. Luís: this chapter shows that a two-factor constant volatility model describes quite well the dynamics and the shape of the German yield curve between 1986 and 1998. The analysis supports the expectations theory with constant term premiums and thus the term premium structure can be calculated and short-term interest rate expectations derived from the adjusted forward rate curve. The analysis is carried out in Matlab and the authors include all of the files with which to reproduce the analysis. Their findings will be of interest to risk managers analysing the shape of the yield curve under different scenarios and also to policy makers in assessing the impact of fiscal and monetary policy.

4. “Forecasting and Trading Currency Volatility: An Application of Recurrent Neural Regression and Model Combination” by C. L. Dunis and X. Huang: this chapter examines the use of nonparametric Neural Network Regression (NNR) and Recurrent Neural Network (RNN) regression models for forecasting and trading currency volatility, with an application to the GBP/USD and USD/JPY exchange rates. The results of the NNR and RNN models are benchmarked against the simpler GARCH alternative and implied volatility. Two simple model combinations are also analysed. Alternative FX volatility forecasting models are tested out-of-sample over the period April 1999–May 2000, not only in terms of forecasting accuracy, but also in terms of trading efficiency: in order to do so, a realistic volatility trading strategy is implemented, using FX option straddles once mispriced options have been identified. Allowing for transaction costs, most trading strategies retained produce positive returns. RNN models appear as the best single modelling approach, yet model combination which has the best overall performance in terms of forecasting accuracy fails to improve the RNN-based volatility trading results.
5. “Implementing Neural Networks, Classification Trees, and Rule Induction Classification Techniques: An Application to Credit Risk” by G. T. Albanis: this chapter shows how to implement several classification tools for data mining applications in finance. Two freely available softwares on classification neural networks and decision trees, respectively, and one commercial software for constructing decision trees and rule induction classifiers are demonstrated, using two datasets that are available in the public domain. The first dataset is known as the Australian credit approval dataset. The application consists of constructing a classification rule for assessing the quality of credit card applicants. The second dataset is known as the German credit dataset. The aim in this application is to construct a classification rule for assessing the credit quality of German borrowers. Beyond these examples, the methods demonstrated in this chapter can be applied to many other quantitative trading and investment problems, such as the determination of outperforming/underperforming stocks, bond rating, etc.

6. “Switching Regime Volatility: An Empirical Evaluation” by B. B. Roche and M. Rockinger: this chapter describes in a pedagogical fashion, using daily observations of the USD/DEM exchange rate from October 1995 to October 1998, how to estimate a univariate switching model for daily foreign exchange returns which are assumed to be drawn in a Markovian way from alternative Gaussian distributions with different means and variances. The application shows that the USD/DEM exchange rate can be modelled as a mixture of normal distributions with changes in volatility, but not in mean, where regimes with high and low volatility alternate. The usefulness of this methodology is demonstrated in a real life application, i.e. through the profit performance comparison of simple hedging strategies.

7. “Quantitative Equity Investment Management with Time-Varying Factor Sensitivities” by Y. Bentz: this chapter describes three methods used in modern equity investment management for estimating time-varying factor sensitivities. Factor models enable investment managers, quantitative traders and risk managers to model co-movements among assets in an efficient way by concentrating the correlation structure into a small number of factors. Unfortunately, the correlation structure is not constant but evolves in time and so do the factor sensitivities. As a result, the sensitivity estimates have to be constantly updated in order to keep up with the changes. The first method, based on rolling regressions, is the most popular but also the least accurate. The second method is based on a weighted regression approach which overcomes some of the limitations of the first method by giving more importance to recent observations. Finally, a Kalman filter-based stochastic parameter regression model is shown to optimally estimate nonstationary factor exposures.

8. “Stochastic Volatility Models: A Survey with Applications to Option Pricing and Value at Risk” by M. Billio and D. Sartore: this chapter analyses the impact on Value at Risk and option pricing of the presence of stochastic volatility, using data for the FTSE100 stock index. Given the time-varying volatility exhibited by most financial data, there has been a growing interest in time series models of changing variance in recent years and the literature on stochastic volatility models has expanded greatly: for these models, volatility depends on some unobserved components or a latent structure. This chapter discusses some of the most important ideas, focusing on the simplest forms of the techniques and models available. It considers some motivations for stochastic volatility models: empirical stylised facts, pricing of contingent assets
and risk evaluation, and distinguishes between models with continuous and discrete volatility, the latter depending on a hidden Markov chain. A stochastic volatility estimation program is presented and several applications to option pricing and risk evaluation are discussed.

9. “Portfolio Analysis Using Excel” by J. Laws analyses the familiar Markovitz model using Excel. This topic is taught on Finance degrees and Master’s programmes all over the world, increasingly through the use of Excel. The author takes time out to explain how the spreadsheet is set up and how simple short-cuts can make analysis of this type of problem quick and straightforward. In the first section of the chapter the author uses a two-variable example to show how portfolio risk and return vary with the input weights, then he goes on to show how to determine the optimal weights, in a risk minimisation sense, using both linear expressions and matrix algebra. In the second part of the chapter the author extends the number of assets to seven and illustrates that using matrix algebra within Excel, the Markovitz analysis of an $n$-asset portfolio is as straightforward as the analysis of a two-asset portfolio. The author takes special care in showing how the correlation matrix can be generated most efficiently and how within the same framework the optimisation objective can be modified without fuss.

10. “Applied Volatility and Correlation Modelling Using Excel” by F. Bourgoin. The originality of this chapter lies in the fact that the author manages to implement a range of univariate and multivariate models within the software package, Excel. This is extremely useful as a large proportion of finance practitioners, students and researchers are familiar with this package. Using S&P500 return data the author generates one-step-ahead forecasts of volatility using the J.P. Morgan RiskMetrics model, the J.P. Morgan RiskMetrics model with optimal decay, a GARCH(1,1) model with and without a variance reduction technique and finally using the GJR model to account for asymmetric reaction to news. A comparison of forecasts is made and some useful insights into the efficacy of the models highlighted. In the second part of the chapter the author uses return data on the DAX30 and CAC40 to model the correlation structure using a number of models. As with the univariate approach this includes the J.P. Morgan RiskMetrics model with and without optimal decay, a GARCH model with and without variance reduction and finally the so-called “Fast GARCH” model of which the author has previously made significant contributions to the literature.

11. “Optimal Allocation of Trend-Following Rules: An Application Case of Theoretical Results” by P. Lequeux uses sophisticated Excel modelling tools to determine what should be the optimal weighting of trading rules to maximise the information ratio. The trading rules utilised in the chapter are moving average trading rules ranging in order from 2 to 117 days and they are applied to a sample of five currency pairs (USD–JPY, EUR–USD, GBP–USD, USD–CAD and AUD–USD) over the period 15/02/1996 to 12/03/2002. The analysis could however be applied to any financial asset and any linear trading rule. In the applied example the author attempts to determine ex-ante what would be the optimal weighting between moving averages of order 2, 3, 5, 9, 32, 61 and 117 to maximise the delivered information ratio. To assist in understanding, the model has been programmed into a spreadsheet to give the reader the possibility to experiment. The results show that in four currency
pairs out of five the optimal weighting procedure is superior, when measured by the information ratio, to an equally weighted basket of trading rules.

12. “Portfolio Management and Information from Over-the-Counter Currency Options” by J. B. Luís: this chapter looks at the informational content of risk-reversals and strangles derived from OTC at-the-money forward volatilities. Three empirical applications of the literature are presented: one on the EUR/USD, followed by the analysis of implied correlations and the credibility of the Portuguese exchange rate policy during the transition to the EMU, and of the Danish exchange rate policy around the euro referendum in September 2000. This chapter is supported by the necessary Excel files to allow the reader to validate the author’s results and/or apply the analysis to a different dataset.

13. “Filling Analysis for Missing Data: An Application to Weather Risk Management” by C. L. Dunis and V. Karalis: this chapter analyses the use of alternative methods when confronted with missing data, a common problem when not enough historical data or clean historical data exist, which will typically be the case when trying to develop a decision tool either for a new asset in a given asset class (say a recently issued stock in a given company sector) or for a new asset class as such (for instance weather derivatives). The application to weather data derives from the fact that most weather derivatives pricing methodologies rely heavily on clean data. The statistical imputation accuracy of different filling methods for missing historical records of temperature data is compared: the Expectation Maximisation (EM) algorithm, the Data Augmentation (DA) algorithm, the Kalman Filter (KF), Neural Networks Regression (NNR) models and, finally, Principal Component Analysis (PCA). Overall, it is found that, for the periods and the data series concerned, the results of PCA outperformed the other methodologies in all cases of missing observations analysed.

Overall, the objective of *Applied Quantitative Methods for Trading and Investment* is not to make new contributions to finance theory and/or financial econometrics: more simply, but also more practically, it is to enable its readers to make competent use of advanced methods for modelling financial markets.

We hope that, with the numerous files and software programs made available on the accompanying CD-Rom, it will constitute a valuable reference textbook for quantitative market professionals, academics and finance graduate students.

Many of the authors of chapters contained in this book have an affiliation to the Forecasting Financial Markets (FFM) conference which has been held each May since 1993. The editors of the text and several of the authors are members or associates of the Centre for International Banking, Economics and Finance (CIBEF) at Liverpool John Moores University. Details of both the conference and CIBEF may be found at www.cibef.com.

*February 2003*
Applications of Advanced Regression Analysis for Trading and Investment*

CHRISTIAN L. DUNIS AND MARK WILLIAMS

ABSTRACT

This chapter examines and analyses the use of regression models in trading and investment with an application to foreign exchange (FX) forecasting and trading models. It is not intended as a general survey of all potential applications of regression methods to the field of quantitative trading and investment, as this would be well beyond the scope of a single chapter. For instance, time-varying parameter models are not covered here as they are the focus of another chapter in this book and Neural Network Regression (NNR) models are also covered in yet another chapter.

In this chapter, NNR models are benchmarked against some other traditional regression-based and alternative forecasting techniques to ascertain their potential added value as a forecasting and quantitative trading tool.

In addition to evaluating the various models using traditional forecasting accuracy measures, such as root-mean-squared errors, they are also assessed using financial criteria, such as risk-adjusted measures of return.

Having constructed a synthetic EUR/USD series for the period up to 4 January 1999, the models were developed using the same in-sample data, leaving the remainder for out-of-sample forecasting, October 1994 to May 2000, and May 2000 to July 2001, respectively. The out-of-sample period results were tested in terms of forecasting accuracy, and in terms of trading performance via a simulated trading strategy. Transaction costs are also taken into account.

It is concluded that regression models, and in particular NNR models do have the ability to forecast EUR/USD returns for the period investigated, and add value as a forecasting and quantitative trading tool.

1.1 INTRODUCTION

Since the breakdown of the Bretton Woods system of fixed exchange rates in 1971–1973 and the implementation of the floating exchange rate system, researchers have been motivated to explain the movements of exchange rates. The global FX market is massive with

* The views expressed herein are those of the authors, and not necessarily those of Girobank.
an estimated current daily trading volume of USD 1.5 trillion, the largest part concerning
spot deals, and is considered deep and very liquid. By currency pairs, the EUR/USD is
the most actively traded.

The primary factors affecting exchange rates include economic indicators, such as
growth, interest rates and inflation, and political factors. Psychological factors also play a
part given the large amount of speculative dealing in the market. In addition, the movement
of several large FX dealers in the same direction can move the market. The interaction
of these factors is complex, making FX prediction generally difficult.

There is justifiable scepticism in the ability to make money by predicting price changes
in any given market. This scepticism reflects the efficient market hypothesis according
to which markets fully integrate all of the available information, and prices fully adjust
immediately once new information becomes available. In essence, the markets are fully
efficient, making prediction useless. However, in actual markets the reaction to new infor-
mation is not necessarily so immediate. It is the existence of market inefficiencies that
allows forecasting. However, the FX spot market is generally considered the most efficient,
again making prediction difficult.

Forecasting exchange rates is vital for fund managers, borrowers, corporate treasurers,
and specialised traders. However, the difficulties involved are demonstrated by the fact
that only three out of every 10 spot foreign exchange dealers make a profit in any given
year (Carney and Cunningham, 1996).

It is often difficult to identify a forecasting model because the underlying laws may
not be clearly understood. In addition, FX time series may display signs of nonlinearity
which traditional linear forecasting techniques are ill equipped to handle, often producing
unsatisfactory results. Researchers confronted with problems of this nature increasingly
resort to techniques that are heuristic and nonlinear. Such techniques include the use of
NNR models.

The prediction of FX time series is one of the most challenging problems in forecasting.
Our main motivation in this chapter is to determine whether regression models and, among
these, NNR models can extract any more from the data than traditional techniques. Over
the past few years, NNR models have provided an attractive alternative tool for researchers
and analysts, claiming improved performance over traditional techniques. However, they
have received less attention within financial areas than in other fields.

Typically, NNR models are optimised using a mathematical criterion, and subsequently
analysed using similar measures. However, statistical measures are often inappropriate
for financial applications. Evaluation using financial measures may be more appropriate,
such as risk-adjusted measures of return. In essence, trading driven by a model with a
small forecast error may not be as profitable as a model selected using financial criteria.

The motivation for this chapter is to determine the added value, or otherwise, of NNR
models by benchmarking their results against traditional regression-based and other fore-
casting techniques. Accordingly, financial trading models are developed for the EUR/USD
exchange rate, using daily data from 17 October 1994 to 18 May 2000 for in-sample
estimation, leaving the period from 19 May 2000 to 3 July 2001 for out-of-sample fore-
casting.\(^1\) The trading models are evaluated in terms of forecasting accuracy and in terms
of trading performance via a simulated trading strategy.

---

\(^1\) The EUR/USD exchange rate only exists from 4 January 1999: it was retropolated from 17 October 1994 to
31 December 1998 and a synthetic EUR/USD series was created for that period using the fixed EUR/DEM
conversion rate agreed in 1998, combined with the USD/DEM daily market rate.
Applications of Advanced Regression Analysis

Our results clearly show that NNR models do indeed add value to the forecasting process.

The chapter is organised as follows. Section 1.2 presents a brief review of some of the research in FX markets. Section 1.3 describes the data used, addressing issues such as stationarity. Section 1.4 presents the benchmark models selected and our methodology. Section 1.5 briefly discusses NNR model theory and methodology, raising some issues surrounding the technique. Section 1.6 describes the out-of-sample forecasting accuracy and trading simulation results. Finally, Section 1.7 provides some concluding remarks.

1.2 LITERATURE REVIEW

It is outside the scope of this chapter to provide an exhaustive survey of all FX applications. However, we present a brief review of some of the material concerning financial applications of NNR models that began to emerge in the late 1980s.

Bellgard and Goldschmidt (1999) examined the forecasting accuracy and trading performance of several traditional techniques, including random walk, exponential smoothing, and ARMA models with Recurrent Neural Network (RNN) models. The research was based on the Australian dollar to US dollar (AUD/USD) exchange rate using half hourly data during 1996. They conclude that statistical forecasting accuracy measures do not have a direct bearing on profitability, and FX time series exhibit nonlinear patterns that are better exploited by neural network models.

Tyree and Long (1995) disagree, finding the random walk model more effective than the NNR models examined. They argue that although price changes are not strictly random, in their case the US dollar to Deutsche Mark (USD/DEM) daily price changes from 1990 to 1994, from a forecasting perspective what little structure is actually present may well be too negligible to be of any use. They acknowledge that the random walk is unlikely to be the optimal forecasting technique. However, they do not assess the performance of the models financially.

The USD/DEM daily price changes were also the focus for Refenes and Zaidi (1993). However they use the period 1984 to 1992, and take a different approach. They developed a hybrid system for managing exchange rate strategies. The idea was to use a neural network model to predict which of a portfolio of strategies is likely to perform best in the current context. The evaluation was based upon returns, and concludes that the hybrid system is superior to the traditional techniques of moving averages and mean-reverting processes.

El-Shazly and El-Shazly (1997) examined the one-month forecasting performance of an NNR model compared with the forward rate of the British pound (GBP), German Mark (DEM), and Japanese yen (JPY) against a common currency, although they do not state which, using weekly data from 1988 to 1994. Evaluation was based on forecasting accuracy and in terms of correctly forecasting the direction of the exchange rate. Essentially, they conclude that neural networks outperformed the forward rate both in terms of accuracy and correctness.

Similar FX rates are the focus for Gençay (1999). He examined the predictability of daily spot exchange rates using four models applied to five currencies, namely the French franc (FRF), DEM, JPY, Swiss franc (CHF), and GBP against a common currency from 1988 to 1994. The research was based on half hourly data from 1990 to 1994. They conclude that neural networks outperformed the forward rate both in terms of accuracy and correctness.

2 A brief discussion of RNN models is presented in Section 1.5.
1973 to 1992. The models include random walk, GARCH(1,1), NNR models and nearest neighbours. The models are evaluated in terms of forecasting accuracy and correctness of sign. Essentially, he concludes that non-parametric models dominate parametric ones. Of the non-parametric models, nearest neighbours dominate NNR models.

Yao et al. (1996) also analysed the predictability of the GBP, DEM, JPY, CHF, and AUD against the USD, from 1984 to 1995, but using weekly data. However, they take an ARMA model as a benchmark. Correctness of sign and trading performance were used to evaluate the models. They conclude that NNR models produce a higher correctness of sign, and consequently produce higher returns, than ARMA models. In addition, they state that without the use of extensive market data or knowledge, useful predictions can be made and significant paper profit can be achieved.

Yao et al. (1997) examine the ability to forecast the daily USD/CHF exchange rate using data from 1983 to 1995. To evaluate the performance of the NNR model, “buy and hold” and “trend following” strategies were used as benchmarks. Again, the performance was evaluated through correctness of sign and via a trading simulation. Essentially, compared with the two benchmarks, the NNR model performed better and produced greater paper profit.

Carney and Cunningham (1996) used four data sets over the period 1979 to 1995 to examine the single-step and multi-step prediction of the weekly GBP/USD, daily GBP/USD, weekly DEM/SEK (Swedish krona) and daily GBP/DEM exchange rates. The neural network models were benchmarked by a naive forecast and the evaluation was based on forecasting accuracy. The results were mixed, but concluded that neural network models are useful techniques that can make sense of complex data that defies traditional analysis.

A number of the successful forecasting claims using NNR models have been published. Unfortunately, some of the work suffers from inadequate documentation regarding methodology, for example El-Shazly and El-Shazly (1997), and Gençay (1999). This makes it difficult to both replicate previous work and obtain an accurate assessment of just how well NNR modelling techniques perform in comparison to other forecasting techniques, whether regression-based or not.

Notwithstanding, it seems pertinent to evaluate the use of NNR models as an alternative to traditional forecasting techniques, with the intention to ascertain their potential added value to this specific application, namely forecasting the EUR/USD exchange rate.

1.3 THE EXCHANGE RATE AND RELATED FINANCIAL DATA

The FX market is perhaps the only market that is open 24 hours a day, seven days a week. The market opens in Australasia, followed by the Far East, the Middle East and Europe, and finally America. Upon the close of America, Australasia returns to the market and begins the next 24-hour cycle. The implication for forecasting applications is that in certain circumstances, because of time-zone differences, researchers should be mindful when considering which data and which subsequent time lags to include.

In any time series analysis it is critical that the data used is clean and error free since the learning of patterns is totally data-dependent. Also significant in the study of FX time series forecasting is the rate at which data from the market is sampled. The sampling frequency depends on the objectives of the researcher and the availability of data. For example, intraday time series can be extremely noisy and “a typical off-floor trader...
would most likely use daily data if designing a neural network as a component of an overall trading system” (Kaastra and Boyd, 1996: 220). For these reasons the time series used in this chapter are all daily closing data obtained from a historical database provided by Datastream.

The investigation is based on the London daily closing prices for the EUR/USD exchange rate. In the absence of an indisputable theory of exchange rate determination, we assumed that the EUR/USD exchange rate could be explained by that rate’s recent evolution, volatility spillovers from other financial markets, and macro-economic and monetary policy expectations. With this in mind it seemed reasonable to include, as potential inputs, other leading traded exchange rates, the evolution of important stock and commodity prices, and, as a measure of macro-economic and monetary policy expectations, the evolution of the yield curve. The data retained is presented in Table 1.1 along with the relevant Datastream mnemonics, and can be reviewed in Sheet 1 of the DataAppendix.xls Excel spreadsheet.

### Table 1.1 Data and Datastream mnemonics

<table>
<thead>
<tr>
<th>Number</th>
<th>Variable</th>
<th>Mnemonics</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>FTSE 100 – PRICE INDEX</td>
<td>FTSE100</td>
</tr>
<tr>
<td>2</td>
<td>DAX 30 PERFORMANCE – PRICE INDEX</td>
<td>DAXINDEX</td>
</tr>
<tr>
<td>3</td>
<td>S&amp;P 500 COMPOSITE – PRICE INDEX</td>
<td>S&amp;P500COM</td>
</tr>
<tr>
<td>4</td>
<td>NIKKEI 225 STOCK AVERAGE – PRICE INDEX</td>
<td>JAPDOWA</td>
</tr>
<tr>
<td>5</td>
<td>FRANCE CAC 40 – PRICE INDEX</td>
<td>FRACAC40</td>
</tr>
<tr>
<td>6</td>
<td>MILAN MIB 30 – PRICE INDEX</td>
<td>ITMIB30</td>
</tr>
<tr>
<td>7</td>
<td>DJ EURO STOXX 50 – PRICE INDEX</td>
<td>DJS50I</td>
</tr>
<tr>
<td>8</td>
<td>US EURO-$ 3 MONTH (LDN:FT) – MIDDLE RATE</td>
<td>ECUSD3M</td>
</tr>
<tr>
<td>9</td>
<td>JAPAN EURO-$ 3 MONTH (LDN:FT) – MIDDLE RATE</td>
<td>ECJP3M</td>
</tr>
<tr>
<td>10</td>
<td>EURO EURO-CURRENCY 3 MTH (LDN:FT) – MIDDLE RATE</td>
<td>ECEUR3M</td>
</tr>
<tr>
<td>11</td>
<td>GERMANY EURO-MARK 3 MTH (LDN:FT) – MIDDLE RATE</td>
<td>ECWGM3M</td>
</tr>
<tr>
<td>12</td>
<td>FRANCE EURO-FRANC 3 MTH (LDN:FT) – MIDDLE RATE</td>
<td>ECFFR3M</td>
</tr>
<tr>
<td>13</td>
<td>UK EURO-£ 3 MONTH (LDN:FT) – MIDDLE RATE</td>
<td>ECUK£3M</td>
</tr>
<tr>
<td>14</td>
<td>ITALY EURO-LIRE 3 MTH (LDN:FT) – MIDDLE RATE</td>
<td>ECIL3M</td>
</tr>
<tr>
<td>15</td>
<td>JAPAN BENCHMARK BOND-RYLD.10 YR (DS) – RED. YIELD</td>
<td>JPBRYLD</td>
</tr>
<tr>
<td>16</td>
<td>ECU BENCHMARK BOND 10 YR (DS) ‘DEAD’ – RED. YIELD</td>
<td>ECBRYLD</td>
</tr>
<tr>
<td>17</td>
<td>GERMANY BENCHMARK BOND 10 YR (DS) – RED. YIELD</td>
<td>EDBRYLD</td>
</tr>
<tr>
<td>18</td>
<td>FRANCE BENCHMARK BOND 10 YR (DS) – RED. YIELD</td>
<td>FRBRYLD</td>
</tr>
<tr>
<td>19</td>
<td>UK BENCHMARK BOND 10 YR (DS) – RED. YIELD</td>
<td>UKMBRYLD</td>
</tr>
<tr>
<td>20</td>
<td>US TREAS. BENCHMARK BOND 10 YR (DS) – RED. YIELD</td>
<td>USBD10Y</td>
</tr>
<tr>
<td>21</td>
<td>ITALY BENCHMARK BOND 10 YR (DS) – RED. YIELD</td>
<td>ITBRYLD</td>
</tr>
<tr>
<td>22</td>
<td>JAPANESE YEN TO US $ (WMR) – EXCHANGE RATE</td>
<td>JAPAYE</td>
</tr>
<tr>
<td>23</td>
<td>US $ TO UK £ (WMR) – EXCHANGE RATE</td>
<td>USDOLLR</td>
</tr>
<tr>
<td>24</td>
<td>US $ TO EURO (WMR) – EXCHANGE RATE</td>
<td>USEURSP</td>
</tr>
<tr>
<td>25</td>
<td>Brent Crude-Current Month, fob US $/BBL</td>
<td>OILBREN</td>
</tr>
<tr>
<td>26</td>
<td>GOLD BULLION $/TROY OUNCE</td>
<td>GOLDBLN</td>
</tr>
<tr>
<td>27</td>
<td>Bridge/CRB Commodity Futures Index – PRICE INDEX</td>
<td>NYFECRB</td>
</tr>
</tbody>
</table>

---

3 EUR/USD is quoted as the number of USD per euro: for example, a value of 1.2657 is USD1.2657 per euro. The EUR/USD series for the period 1994–1998 was constructed as indicated in footnote 1.
All the series span the period from 17 October 1994 to 3 July 2001, totalling 1749 trading days. The data is divided into two periods: the first period runs from 17 October 1994 to 18 May 2000 (1459 observations) used for model estimation and is classified in-sample, while the second period from 19 May 2000 to 3 July 2001 (290 observations) is reserved for out-of-sample forecasting and evaluation. The division amounts to approximately 17% being retained for out-of-sample purposes.

Over the review period there has been an overall appreciation of the USD against the euro, as presented in Figure 1.1. The summary statistics of the EUR/USD for the examined period are presented in Figure 1.2, highlighting a slight skewness and low kurtosis. The Jarque–Bera statistic confirms that the EUR/USD series is non-normal at the 99% confidence interval. Therefore, the indication is that the series requires some type of transformation. The use of data in levels in the FX market has many problems, “FX price movements are generally non-stationary and quite random in nature, and therefore not very suitable for learning purposes... Therefore for most neural network studies and analysis concerned with the FX market, price inputs are not a desirable set” (Mehta, 1995: 191).

To overcome these problems, the EUR/USD series is transformed into rates of return. Given the price level $P_1, P_2, \ldots, P_t$, the rate of return at time $t$ is formed by:

$$R_t = \left( \frac{P_t}{P_{t-1}} \right) - 1$$

An example of this transformation can be reviewed in Sheet 1 column C of the oos_Naive.xls Excel spreadsheet, and is also presented in Figure 1.5. See also the comment in cell C4 for an explanation of the calculations within this column.

An advantage of using a returns series is that it helps in making the time series stationary, a useful statistical property.

Formal confirmation that the EUR/USD returns series is stationary is confirmed at the 1% significance level by both the Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) test statistics, the results of which are presented in Tables 1.2 and 1.3.

The EUR/USD returns series is presented in Figure 1.3. Transformation into returns often creates a noisy time series. Formal confirmation through testing the significance of

![Figure 1.1](image)

**Figure 1.1** EUR/USD London daily closing prices (17 October 1994 to 3 July 2001)

---

Applications of Advanced Regression Analysis

Figure 1.2  EUR/USD summary statistics (17 October 1994 to 3 July 2001)

Table 1.2  EUR/USD returns ADF test

<table>
<thead>
<tr>
<th>ADF test statistic</th>
<th>1% critical value^a</th>
<th>5% critical value</th>
<th>10% critical value</th>
</tr>
</thead>
<tbody>
<tr>
<td>−18.37959</td>
<td>−3.4371</td>
<td>−2.8637</td>
<td>−2.5679</td>
</tr>
</tbody>
</table>

^MacKinnon critical values for rejection of hypothesis of a unit root.

Augmented Dickey–Fuller Test Equation
Dependent Variable: D(DR USEURSP)
Method: Least Squares
Sample(adjusted): 7 1749
Included observations: 1743 after adjusting endpoints

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>DR_USEURSP(−1)</td>
<td>−0.979008</td>
<td>0.053266</td>
<td>−18.37959</td>
<td>0.0000</td>
</tr>
<tr>
<td>D(DR_USEURSP(−1))</td>
<td>−0.002841</td>
<td>0.047641</td>
<td>−0.059636</td>
<td>0.9525</td>
</tr>
<tr>
<td>D(DR_USEURSP(−2))</td>
<td>−0.015731</td>
<td>0.041288</td>
<td>−0.381009</td>
<td>0.7032</td>
</tr>
<tr>
<td>D(DR_USEURSP(−3))</td>
<td>−0.011964</td>
<td>0.033684</td>
<td>−0.355179</td>
<td>0.7225</td>
</tr>
<tr>
<td>D(DR_USEURSP(−4))</td>
<td>−0.014248</td>
<td>0.024022</td>
<td>−0.593095</td>
<td>0.5532</td>
</tr>
<tr>
<td>C</td>
<td>−0.000212</td>
<td>0.000138</td>
<td>−1.536692</td>
<td>0.1246</td>
</tr>
</tbody>
</table>

R-squared 0.491277  Mean dependent var.  1.04E-06
Adjusted R-squared 0.489812  S.D. dependent var.  0.008048
S.E. of regression 0.005748  Akaike info. criterion −7.476417
Sum squared resid. 0.057394  Schwarz criterion −7.457610
Log likelihood 6521.697  F-statistic 335.4858
Durbin–Watson stat. 1.999488  Prob(F-statistic) 0.000000
### Table 1.3 EUR/USD returns PP test

<table>
<thead>
<tr>
<th>PP test statistic</th>
<th>1% critical value&lt;sup&gt;a&lt;/sup&gt;</th>
<th>5% critical value</th>
<th>10% critical value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>-41.04039</strong></td>
<td><strong>-3.4370</strong></td>
<td><strong>-2.8637</strong></td>
<td><strong>-2.5679</strong></td>
</tr>
</tbody>
</table>

<sup>a</sup>MacKinnon critical values for rejection of hypothesis of a unit root.

- Lag truncation for Bartlett kernel: 7
- (Newey–West suggests: 7)
- Residual variance with no correction: 3.29E-05
- Residual variance with correction: 3.26E-05

**Phillips–Perron Test Equation**
Dependent Variable: D(DR\_USEURSP)
Method: Least Squares
Sample(adjusted): 3 1749
Included observations: 1747 after adjusting endpoints

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>DR_USEURSP(-1)</td>
<td>-0.982298</td>
<td>0.023933</td>
<td>-41.04333</td>
<td>0.0000</td>
</tr>
<tr>
<td>C</td>
<td>-0.000212</td>
<td>0.000137</td>
<td>-1.539927</td>
<td>0.1238</td>
</tr>
<tr>
<td><strong>R-squared</strong></td>
<td>0.491188</td>
<td>Mean dependent var.</td>
<td>-1.36E-06</td>
<td></td>
</tr>
<tr>
<td><strong>Adjusted R-squared</strong></td>
<td>0.490896</td>
<td>S.D. dependent var.</td>
<td>0.008041</td>
<td></td>
</tr>
<tr>
<td><strong>S.E. of regression</strong></td>
<td>0.005737</td>
<td>Akaike info. criterion</td>
<td>-7.482575</td>
<td></td>
</tr>
<tr>
<td><strong>Sum squared resid.</strong></td>
<td>0.057436</td>
<td>Schwarz criterion</td>
<td>-7.476318</td>
<td></td>
</tr>
<tr>
<td><strong>Log likelihood</strong></td>
<td>6538.030</td>
<td>F-statistic</td>
<td>1684.555</td>
<td></td>
</tr>
<tr>
<td><strong>Durbin–Watson stat.</strong></td>
<td>1.999532</td>
<td>Prob(F-statistic)</td>
<td>0.000000</td>
<td></td>
</tr>
</tbody>
</table>

![EUR/USD returns series](image_url)

**Figure 1.3** The EUR/USD returns series (18 October 1994 to 3 July 2001)