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PHD TANATTRIN BUNNAG

Guidelines for Econometrics and Application. Emphasis on Tourism and Financial Economics

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BOOK SERIES
SOCIO-ECONOMICS RESEARCH, INNOVATION AND TECHNOLOGIES

GUIDELINES FOR ECONOMETRICS AND APPLICATION. EMPHASIS ON TOURISM AND FINANCIAL ECONOMICS

Tanattrin BUNNAG

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From the Author

This book was prepared by the author, who saw the importance of econometric principles, which have played an essential role in explaining their significance in academics and can be applied in various circles. It may or may not be related to economics; this book can be opened the world of analytics.

Introductory and advanced econometrics are two levels of study within the field of econometrics, which focuses on the application of statistical and mathematical methods to analyze economic data. Main key topics are covered by the two parts of this book:

Part I. Introductory and Advanced Econometrics

- Introduction
- Regression Model
- Univariate Time Series: Linear Models
- Stationarity and Unit Roots Tests
- Univariate Time Series: Volatility Models
- Multivariate Time Series Analysis
- Multivariate GARCH models.

Part II. Econometrics Tools Application for Cases Studies of Tourism and Financial Economics

This part of the book applies principles in econometrics derived from all before seven chapters from Part I, in tourism and financial economics. The author has published research papers in scientific journals and updated the information to suit changing times. The author has used the program EVIEWS to analyze and can read more manuals at www.eviews.com. Some people may find it difficult because they do not understand how to use it. This book can help you to understand it.

- Tourist Demand Using VECM and Cointegration;
- Modelling the Growth Rate and Volatility in International Tourist Arrivals;
- Volatility transmission, Comovements, and Spillovers Models with applications to Financial Economics.

Moreover, this book is intended for undergraduate and graduate-level students, including researchers interested in economic analysis. Econometric tools can be applied to real situations. The econometric tools range from essential to advanced levels, including writing explanations, testing economic theory, forecasting, and making policy recommendations. Emphasis is placed on financial and tourism economics.

However, this book was made possible thanks to RITHA Publishing, allowing the author to follow his dreams. I thank my advisor during my doctoral studies, including my colleagues and students who have completed this book. This book will be helpful and can be used for further development and benefit the reader the next.

Finally, thanks to the contributors who contributed to the successful implementation of this book.

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PART I - Introductory and Advanced Econometrics

Chapter 1 Introduction in Econometrics

Chapter 2 Regression Model

Chapter 3 Univariate Time Series: Linear Models

Chapter 4 Stationarity and Unit Roots Tests

Chapter 5 Univariate Time Series: Volatility Models

Chapter 6 Multivariate Time Series Analysis

Chapter 7 Multivariate GARCH Models

In this Part I, there are 7 chapters which focus lies in comprehending the essence of econometrics, ranging from its fundamental principles to its more sophisticated facets. The overarching aim is to equip readers with the understanding needed to effectively apply econometric techniques for prediction and analysis. Through this comprehensive journey, readers will gain the necessary knowledge to harness econometrics as a powerful tool for making informed predictions and conducting thorough analyses.

Keywords: econometrics; regression model; linear models; unit roots tests; volatility models; multivariate time series analysis; multivariate GARCH volatility; hedging.

JEL Classification: C01; C53; C58.

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Chapter 1

Introduction in Econometrics

What is econometrics?

It was interpreted as econometrics means "economic measurement." Although measurement is an essential part of econometrics, the scope of econometrics is much broader. It is based upon the development of statistical methods for estimating economic relationships, testing economic theories, and evaluating and implementing government and business policy. The most common application of econometrics is forecasting important microeconomic and macroeconomic variables.

Econometrics combines economic theory, mathematical economics, and statistics, but it is distinct from each branch of science. Economic theory makes statements or hypotheses that are primarily qualitative. For instance, the microeconomic theory states that other things remain the same; a commodity's price reduction is expected to increase the quantity demanded of that commodity. But the approach needs to provide a numerical measure of the relationship between the two; that does not tell how much will go up or down due to an inevitable change in the commodity's price. It is the job of an econometrician to provide such numerical statements.

The main concern of mathematical economics is to express economic theory in mathematical form (equations) without regard to measurability or empirical verification of the approach. Both economic theory and mathematical economics state the same relationships. The economic theory uses verbal exposition, but mathematical economics employs mathematical symbolism. Neither allows for random elements that affect the relationship and make it stochastic. Furthermore, they do not provide numerical values for the coefficients of the connections. Although econometrics presupposes the expression of economic relationships in mathematical forms, like mathematical economics, it does not assume that financial relationships are exact (deterministic).

Economic statistics mainly collect, process, and present financial data in charts and tables. It is primarily a descriptive aspect of economics. However, it needs to explain the development of the various variables and measure the parameters of economic relationships. Econometrics is the application of statistical and mathematical techniques to analyze economic data to verify or refute economic theories. In this respect, econometrics is distinguished from

The structure of economic data

Economic data sets come in a variety of types. The most important data structures encountered in applied work are the following:

- Cross-sectional data: a sample of individuals, households, firms, cities, states, countries, or other units, taken at a given time.
- Time series data consists of observations on a variable or several variables over time; examples of time series data include stock prices.
- Pooled Cross Section data have both cross-sectional and time series features. A pooled cross-section is analyzed much like a standard cross-section, except that we often need to account for secular differences in the variables across time.
- Panel data: This type of pooled data in which the same cross-sectional units (say, individuals, firms, or countries) are surveyed over time. It consists of a time series for each cross-sectional member in the data set. Hence, the critical feature distinguishing panel data from a pooled cross-section is that the same cross-sectional units are followed over a given period.

Each data structure has its strengths and considerations for econometric analysis. The choice of appropriate econometric models and techniques depends on the specific data structure and research objectives. Econometric methods for cross-sectional data, time series data, pooled cross-section data, and panel data have been developed to accommodate the unique characteristics and dependencies associated with each structure.

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Chapter 2

Regression Model

This chapter starts with an introduction to linear regression analysis, estimation, and inference methods. Regression analysis is a widely used tool in econometrics. They are used to describe and evaluate the relationship between economic variables and perform forecasting tasks. This chapter provides only a short and brief description of the main tools used in regression analysis. More detailed discussion and more profound theoretical background can be found in Greene (2000), Hamilton (1994), Hayashi (2000), Verbeek (2014), Mills (1999), and Zivot and Wang (2006).

Linear regression model

Linear regression analysis is a fundamental and widely used statistical technique in econometrics. It is a powerful tool for examining the relationship between dependent and independent variables, quantifying the impact of predictors on the outcome variable, and making predictions or forecasts.

In linear regression analysis, the goal is to model the linear relationship between a dependent variable (also known as the response or outcome variable) and one or more independent variables (also known as predictors or explanatory variables). The relationship is represented by a linear equation that estimates the average effect of changes in the independent variables on the dependent variable.

Consider the linear regression model:

$$Y_i = \beta_1 + \beta_2 X_{2i} + \dots + \beta_k X_{ki} + u_i = X_i'\beta + u_i,\ i = 1,\dots,n \qquad 2.1.$$

where: $X_i = [1, X_{2i}, \dots, X_{ki}]'$ is a $k \times 1$ vector of explanatory variables, $\beta = (\beta_1, \dots, \beta_k)'$ is a $k \times 1$ vector of coefficients, and u_i is a random error term. In matrix form, the model is expressed as:

$$Y = X\beta + u \qquad 2.2.$$

where:: Y and β are $n \times 1$ vectors and X is an $n \times k$ matrix.

The standard assumptions of the linear regression model are:

The least squares estimation problem to minimize:

$$S(\theta) = \sum_{i=1}^{n} \left(Y_i - F(X_i, \theta)\right)^2,$$

becomes nonlinear. The first-order conditions are given by:

$$\frac{\partial S(\theta)}{\partial \theta_j} = -2 \sum_{i=1}^{n} \left(Y_i - F(X_i, \theta)\right) \frac{\partial F}{\partial \theta_j}. \qquad 2.5.$$

This gives a set of nonlinear normal equations in θ. The nonlinear least squares (NLS) estimator $\grave{\theta}_{NLS}$ is the minimizing value of (2.5).

In EViews, the Nonlinear Least Squares method implements the same OLS. The only difference is that the model in the Equation specification box should be entered as a mathematical expression instead of a list of variables. for example,

$$y = \mathrm{eex}\left(c(1)^* x\right) + \left(c(2)^* z + 4\right)^\wedge 2$$

When using nonlinear regression models, it is important to carefully consider the choice of functional form and interpret the estimated coefficients appropriately. Interpreting the estimation output, residual diagnostic, and inference can be performed like for the OLS regression. Researchers should also assess the goodness of fit of the model and assess the statistical significance of the estimated parameters. Inference techniques, such as hypothesis testing and confidence intervals, can still be applied in nonlinear regression to evaluate the significance and precision of the estimated parameters.

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Chapter 3

Univariate Time Series: Linear Models

Time series is a sequence of numerical data in which observations are measured at a particular instant in time. For example, the observation frequency can be annual, quarterly, monthly, daily, etc. The main goal of time series analysis is to study the data dynamics. It involves studying the patterns, trends, and dynamics within the data to understand its behaviour and make forecasts or predictions for future time points.

This chapter introduces basic time series models for estimating and forecasting data. Further details about the theory of time series analysis can be found in Hamilton (1994), Greene (2000), Enders (2004), Tsay (2002), and others. There are various basic time series models that are commonly used for estimating and forecasting data. Here are a few examples:

- Autoregressive (AR) Model: The autoregressive model describes a time series by regressing its current value on its past values. It assumes that the current value depends linearly on its own lagged values. The AR model is denoted as AR(p), where 'p' represents the number of lagged values considered in the regression equation.
- Moving Average (MA) Model: The moving average model focuses on the relationship between the current value of a time series and the past prediction errors. It assumes that the current value depends linearly on the error terms from previous time points. The MA model is denoted as MA(q), where 'q' represents the number of lagged prediction errors considered in the equation.
- Autoregressive Moving Average (ARMA) Model: The ARMA model combines the autoregressive and moving average models. It incorporates both the autoregressive terms and the moving average terms to capture the dynamics of the time series. The ARMA model is denoted as ARMA(p, q), where 'p' represents the number of autoregressive terms and 'q' represents the number of moving average terms.
- Autoregressive Integrated Moving Average (ARIMA) Model: The ARIMA model extends the ARMA model by incorporating differencing to achieve stationarity in the data. It is suitable for time series data that exhibit trends or non-stationarity. The ARIMA model is denoted as ARIMA(p, d, q), where 'p' represents the number of autoregressive terms, 'd' represents the order of differencing, and 'q' represents the number of moving average terms.

Estimation of ARMA processes

$\mathrm{ARMA}(p,q)$ models are generally estimated using the maximum likelihood technique. An often, ignored aspect of the maximum likelihood estimation of $ARMA(p,q)$ models is the treatment of initial values. These initial values are the first p values of Y_t and q values of ε_t in (3.1). The exact likelihood utilizes the stationary distribution of the initial values in constructing the likelihood. The conditional likelihood treats the p initial values of Y_t as fixed and often sets the q initial values of ε_t to zero. The exact maximum likelihood estimates (MLE) maximize the exact log-likelihood, and the conditional MLE maximizes the conditional log-likelihood. The exact and conditional MLEs are asymptotically equivalent but can differ substantially in small samples, especially for models that are close to being non-stationary or non-invertible.

The conditional MLEs are equivalent to the least squares estimates for pure AR models. Model Selection Criteria Before an $\mathrm{ARMA}(p,q)$ may be estimated for a time series Y_t, the AR and MA orders p and q must be determined by visually inspecting the autocorrelation and partial autocorrelation functions for Y_t. A first-order autoregressive model is appropriate if the autocorrelation function decays smoothly, and the partial autocorrelations are zero after one lag. Alternatively, a first-order moving average process would seem reasonable if the autocorrelations were zero after one lag and the partial autocorrelations decayed slowly toward zero.

Alternatively, statistical model selection criteria may be used. The idea is to fit all $ARMA(p,q)$ models with orders p and q and choose the values of p and q, which minimizes model selection criteria:

$$AIC(p,q) = \ln\left(\grave{\sigma}^2(p,q)\right) + \frac{2}{T}(p+q)$$

$$BIC(p,q) = \ln\left(\grave{\sigma}^2(p,q)\right) + \frac{\ln(T)}{T}(p+q)$$

where: $\grave{\sigma}^2(p,q)$ is the MLE of $\mathrm{var}[\varepsilon_t] = \sigma^2$ without a degrees of freedom correction from the $ARMA(p,q)$ model.

To estimate and forecast data using time series models, various techniques are employed, such as maximum likelihood estimation, least squares estimation, or state space models. These techniques involve estimating the parameters of the models based on historical data and using them to make predictions for future time points.

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Chapter 4

Stationarity and Unit Roots Tests

Many time series, like exchange rate levels of stock prices, appear non-stationary. However, new statistical issues arise when analyzing non-stationary data. For example, unit root tests detect the presence and form of non-stationarity. Detecting non-stationarity is crucial because it affects the modelling and analysis of time series data.

This chapter reviews the main concepts of the non-stationarity of time series and describes some tests for time series stationarity. More information about such tests can be found in Hamilton (1994), Dickey and Fuller (1979), Enders (2004), Harris (1995), and Verbeek (2008).

A non-stationary time series is called integrated if it can be transformed by first differencing once or a very few times into a stationary process. The order of integration is the minimum number of times the series needs to be first differenced to yield a stationary series. An integrated order 1-time series is denoted by I(1). A stationary time series is said to be integrated of order zero, I(0).

There are two principal methods of detecting non-stationarity:

▪ Visual inspection of the time series graph and its correlogram provide initial insights into the presence of non-stationarity. In a non-stationary series, the mean and variance may change over time, and there may be trends, cycles, or irregular patterns. The correlogram can reveal persistent autocorrelation at various lags, indicating potential non-stationarity. However, visual inspection alone may not provide definitive evidence of non-stationarity and requires further statistical testing.

- Formal statistical tests of unit roots. Unit root tests are statistical tests used to formally assess non-stationarity. These tests examine whether a time series has a unit root, which indicates the presence of a stochastic trend or non-stationarity. The most commonly used unit root tests include the Augmented Dickey-Fuller (ADF) test and the Phillips-Perron (PP) test.

(KPSS). The KPSS test is another widely used unit root test that evaluates non-stationarity from a different perspective.

Unlike the ADF and PP tests, which test for the presence of a unit root, the KPSS test examines the null hypothesis of stationarity. It tests whether a time series is trend-stationary, meaning it exhibits a constant mean and variance over time, with or without a deterministic trend component. The KPSS test provides a test statistic and critical values to determine whether the null hypothesis of stationarity can be rejected, indicating the presence of non-stationarity.

Kwiatkowski, Phillips, Schmidt, and Shin (1992) derive their test by starting with the model:

$$Y_t = \alpha + \beta t + \mu_t + u_t$$
$$\mu_t = \mu_{t-1} + \varepsilon_t,\ \varepsilon_t \sim WN\left(0,\sigma_\varepsilon^2\right)$$

where u_t is $I(0)$ and may be heteroskedastic.

The null hypothesis that Y_t is $I(0)$ is formulated as $H_0\!:\sigma_\varepsilon^2 = 0$, which implies that μ_t is a constant. Although not directly apparent, this null hypothesis also means a unit moving average root in the ARMA representation of ΔY_t. The KPSS test statistic is the Lagrange multiplier (LM) or score statistic for testing $\sigma_\varepsilon^2 = 0$ against the alternative that $\sigma_\varepsilon^2 > 0$ and is given by:

$$KPSS = \left(\frac{1}{T^2}\sum_{t=1}^{T} \grave{S}_t^2\right)/\grave{\lambda}^2$$

where $\grave{S}_t = \sum_{j=1}^{t} \grave{u}_j$, $\grave{u}_t$ is the residual of a regression Y_t on t and $\grave{\lambda}_t^2$.

Critical values from the asymptotic distributions must be obtained by simulation methods. The stationary test is a one-sided right-tailed test so that one rejects the null of stationarity at the α level if the KPSS test statistic is greater than the $100(1-\alpha)$ quantile from the appropriate asymptotic distribution.

These tests provide evidence for or against the presence of a unit root but do not necessarily imply the form of non-stationarity or the appropriate transformation needed to achieve stationarity. The interpretation of unit root test results should be done carefully, considering other factors such as economic theory, the nature of the data, and the objectives of the analysis.

Overall, the combination of visual inspection and formal statistical tests of unit roots provides a comprehensive approach to detecting non-stationarity in time series data and guiding the selection of appropriate modelling techniques.

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Chapter 5

Univariate Time Series: Volatility Models

In this chapter 5, we have considered approaches to modeling the conditional mean of a univariate time series. However, many areas of financial theory are concerned with the second moment of time series - conditional volatility as a proxy for risk. In this chapter, we introduce time series models that represent the dynamics of conditional variances. In particular, we consider two widely used classes of models for modelling volatility: the Autoregressive Conditional Heteroscedasticity (ARCH) model and its extension, the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model.

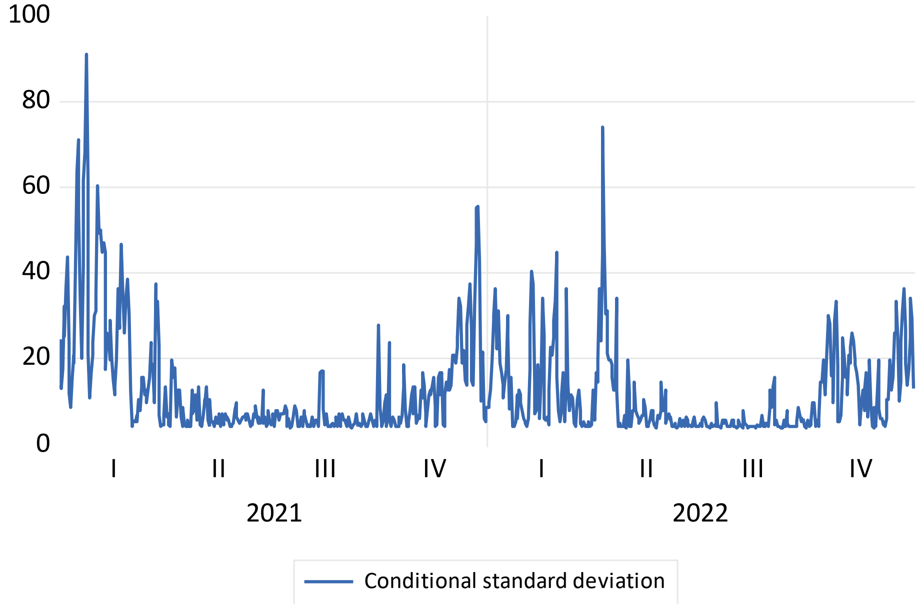
These models and their extensions provide a framework for capturing and analysing the dynamics of conditional variances in time series data, particularly in financial markets where volatility plays a crucial role. They offer valuable insights into the patterns, persistence, and asymmetries of volatility, allowing for more accurate risk management, option pricing, and forecasting in financial applications.

In this regard, the reader is also referred to Engle (1982), Bollerslev (1987), Nelson (1991), Hamilton (1994), Enders (2004), and Zivot and Wang (2006). These research works have significantly contributed to the development and understanding of time series analysis. They have shaped the literature and influenced subsequent research in the field, providing valuable insights and methodologies for modelling and analysing financial and economic time series data.

The ARCH models

Besides a time-varying conditional mean of time series, most also exhibit changes in volatility regimes, especially applicable to many high-frequency macroeconomic and economic time series. While modeling such time series, we cannot use homoscedastic models. The simplest way to allow volatility to vary is to model conditional variance using a simple autoregressive (AR) process.

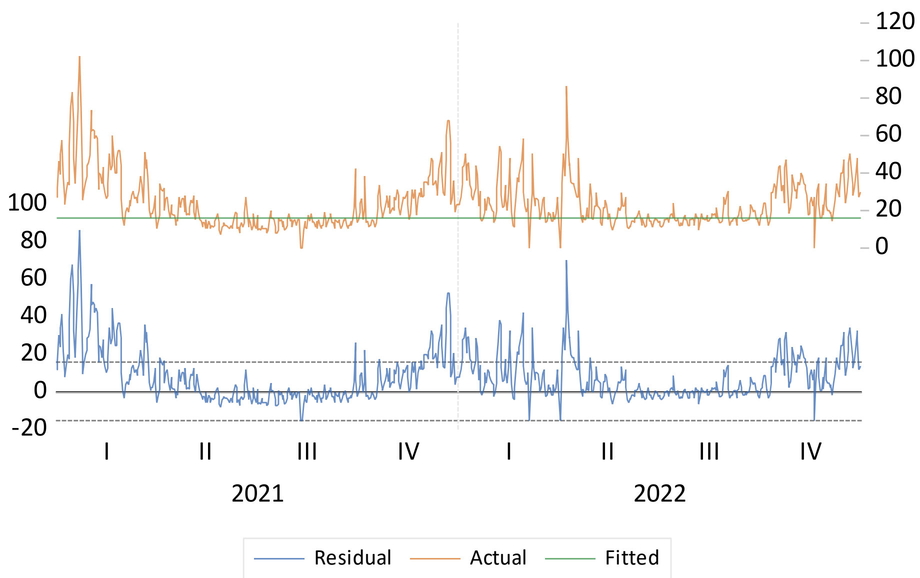
Figure 5.2. Plot of the simulated GARCH process



GARCH model estimation

This section illustrates how to estimate a GARCH model, assuming that μ_{it} follows normal or Gaussian distribution conditional on history, the prediction error.

Figure 5.3: Histogram of the simulated GARCH process



Forecasting the conditional volatility for h periods ahead can be done by a recursion:

$$\sigma_{t+h|t}^2 = \alpha_0 + \alpha_1 \sigma_{t+h-1|t}^2 + \dots + \alpha_p \sigma_{t+h-p}^2,$$

where: $\sigma_{t+j}^2 = u_{t+j}^2$ for $j \leq 0$.

The h-period ahead variance forecast for a $GARCH(1,1)$ model is:

$$\sigma_{t+1|t}^2 = \alpha_0 \left[\sum_{i=0}^{h-1} \left(\alpha_1 + \beta_1\right)^i \right] + \left(\alpha_1 + \beta_1\right)^h \sigma_t^2 .$$

Once a GARCH model is estimated and the parameters are obtained, forecasting the conditional variance involves a recursive process. The general steps for forecasting the conditional variance from a GARCH model are as follows:

- Obtain initial values: To initiate the forecasting process, initial values for the conditional variance need to be specified. Typically, these initial values are set equal to the estimated conditional variance from the last available data point.
- Forecast the next period's conditional variance: Using the estimated GARCH parameters and the previous period's conditional variance, the next period's conditional variance can be forecasted. The GARCH model equations are applied recursively to calculate the forecasted conditional variance.
- Repeat the process: The forecasted conditional variance from step 2 becomes the input for the next period, and the forecasting process is repeated iteratively to obtain forecasts for subsequent periods.

Continuing this iterative process, future values of the conditional variance can be forecasted over the desired forecast horizon. These forecasts provide valuable information about the expected volatility of returns and can be used for risk management, option pricing, and portfolio optimization, among other applications.

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Chapter 6

Multivariate Time Series Analysis

Multivariate time series analysis involves the analysis and modelling of multiple time series variables that are observed simultaneously over time. It allows for the examination of the relationships, dependencies, and interactions between multiple variables, providing a more comprehensive understanding of the dynamics and patterns within the data. Here are some key aspects and methods used in multivariate time series analysis:

- Vector Autoregression (VAR): VAR models are commonly used in multivariate time series analysis. A VAR model represents each variable in the system as a linear function of its lagged values and the lagged values of all other variables in the system. VAR models capture the simultaneous and lagged dependencies among the variables and can be used for forecasting, impulse response analysis, and variance decomposition.
- Granger Causality. A statistical concept used to assess the causal relationship between variables in a multivariate time series. It determines whether the past values of one variable help in predicting another variable beyond its own past values. Granger causality tests can provide insights into the direction and strength of causal relationships among the variables.
- Cointegration: A concept that deals with the long-term relationship between non-stationary time series variables. It identifies whether a linear combination of variables is stationary, implying a stable long-term relationship. Cointegration analysis is important when dealing with variables that exhibit unit roots (non-stationarity) and helps in analysing the long-run equilibrium relationships between variables.

The vector autoregression model is one of the most potent multivariate time series. It is a natural extension of the univariate autoregressive model to the multivariate case.

In this chapter, we cover concepts of VAR modeling, non-stationary multivariate time series, and cointegration. A more detailed discussion can be found in Hamilton (1994), Harris (1995), Enders (2004), Tsay (2002), and Zivot and Wang (2006). These references, are valuable resources that provide in-depth explanations, examples, and applications in

Granger causality tests are widely used in various fields, including economics, finance, and social sciences, to explore relationships between variables and understand the direction of information flow. They provide valuable insights into the potential causal dynamics among variables and help inform decision-making and policy analysis.

Impulse Response and Variance Decompositions

As in the univariate case, a $VAR(p)$ process can be represented as a vector moving average (VMA) process:

$$\mathbf{Y}_t = \mu + \mathbf{u}_t + \Psi_1 \mathbf{u}_{t-1} + \Psi_2 \mathbf{u}_{t-2} + \dots$$

where: the $k \times k$ moving average matrices Ψ_s are determined recursively using (6.3).

The elements of coefficient matrices Ψ_s mean effects of $\mathbf{u}_{t-s}$ shocks on $\mathbf{Y}_t$. The (i, j)-th element, ψ_{ij}^s, of the matrix Ψ_s is interpreted as the impulse response:

$$\frac{\partial Y_{i,t+s}}{\partial u_{j,t}} = \frac{\partial Y_{i,t}}{\partial u_{j,t-s}} = \psi_{ij}^s,\ i, j = 1, \dots, T.$$

Sets of coefficients $\psi_{ij}(s) = \psi_{ij}^s,\ i, j = 1, \dots, T$ are called the impulse response functions. It is possible to decompose the h-step-ahead forecast error variance into the proportions due to each shock u_{jt}. The forecast variance decomposition determines the proportion of the variation Y_{jt} due to the shock u_{jt} versus shocks of other variables u_{it} for $i \neq j$.

Table 6.1. Key questions addressed by Impulse response function and variance decomposition

Tools	Impulse Response Function (IRF)	Variance Decomposition
Purpose	▪ Analyse dynamic responses of variables to a shock	▪ Quantify the contribution of variables to forecast variance
Questions	▪ How does a shock in one variable affect other variables?	▪ How much does each variable contribute to forecast error?
	▪ What is the duration and magnitude of the response?	▪ What is the relative importance of each variable's shock?
	▪ Are the responses symmetric or asymmetric?	
	▪ Are there any lead-lag relationships among the variables?	
	▪ How do the effects of shocks evolve over time?	
	▪ Do shocks die out or persist in the system?	
	▪ What are the dynamic interactions and dependencies among variables?	

It checks whether the smallest $k - r_0$ eigenvalues are statistically different from zero. For example, if $\operatorname{rank}(\Pi) = r_0$, then $\hat{\lambda}_{r_0+1}, \ldots, \hat{\lambda}_k$ should all be close to zero, and $LR_{\text{trace}}\ (r_0)$ should be small. In contrast, if $\operatorname{rank}(\Pi) > r_0$, then some of $\hat{\lambda}_{r_0+1}, \ldots, \hat{\lambda}_k$ will be non-zero (but less than 1), and $LR_{\text{trace}}\ (r_0)$ should be large.

We can also test $H_0: r = r_0$ against $H_1: r_0 = r_0 + 1$ using so-called the maximum eigenvalue statistic:

$$LR_{\max}(r_0) = -T \log\left(1 - \hat{\lambda}_{r_0+1}\right).$$

Critical values for the asymptotic distribution of $LR_{\text{trace}}\ (r_0)$ and $LR_{\max}\ (r_0)$ statistics are tabulated in Osterwald-Lenum (1992) for $k - r_0 = 1, \ldots, 10$. To determine the number of cointegrating vectors, first test $H_0: r_0 = 0$ against the alternative $H_1: r_0 > 0$. If this null is not rejected, then it is concluded that there are no cointegrating vectors among the k variables in Y_t . If $H_0: r_0 = 0$ is rejected, then there is at least one cointegrating vector. In this case, we should test $H_0: r_0 \leq 1$ against $H_1: r_0 > 1$. If this null is not rejected, we say there is only one cointegrating vector. If the null is rejected, there are at least two cointegrating vectors. Therefore, we test $H_0: r_0 \leq 2$ and so on until the null hypothesis is not rejected.

In small samples, tests are biased if asymptotic critical values are used without a correction. Reinsel and Ahn (1992) and Reimars (1992) suggested small sample bias correction by multiplying the test statistics with $T - kp$ instead of T in constructing the likelihood ratio tests.

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Chapter 7

Multivariate GARCH Models

Modeling volatility in financial time series has been the object of much attention ever since the introduction of the Autoregressive Conditional Heteroskedasticity (ARCH) model in the seminal paper of Engle (1982). Subsequently, numerous variants and extensions of ARCH models have been proposed. A large body of this literature has been devoted to univariate models; for example, Bollerslev et al. (1994).

While modeling volatility of the returns has been the main center of attention, understanding the comovements of financial returns is of great practical importance. It is, therefore, essential to extend the considerations to multivariate GARCH (MGARCH) models. For example, asset pricing depends on the covariance of the assets in a portfolio, and risk management and asset allocation relate, for instance, to finding and updating optimal hedging positions.

Combining these needs has been difficult in the MGARCH literature. The first GARCH model for the conditional covariance matrices was the VEC model of Bollerslev, Engle, and Wooldridge (2015); see Engle, Granger, and Kraft (1984) for an ARCH version. This model is very general, and a goal of the subsequent literature has been to formulate more parsimonious models. Furthermore, since imposing positive definiteness of the conditional covariance matrix in this model is complex, developing models with this feature has been considered necessary. Likewise, constructing models in which the estimated parameters have direct interpretation has been viewed as beneficial.

Models

Consider a stochastic vector process $\{r_t\}$ with dimension $N \times 1$ such that $Er_t = 0$. Let $\mathscr{F}_{t-1}$ denote the information set generated by the observed series $\{r_t\}$ up to and including time $t-1$. We assume that $\{r_t\}$ is conditionally heteroskedastic:

$$r_t = H_t^{1/2}\eta_t. \quad 7.1.$$

Given the information set $\mathscr{F}_{t-1}$, where the $N \times N$ matrix $H_t = \left[h_{ijt}\right]$ is the conditional covariance matrix of r_t and η_t is an iid vector error process such that $E\eta_t\eta_t' = I$. This defines the standard multivariate GARCH framework, in which rt has no linear dependence structure $\{r_t\}$.

The interpretation of the extreme states is the following: At the beginning of the sample, $P_{(11)}$ and $P_{(21)}$ are the two extreme states between which the correlations vary according to the transition variable s_{1t} and similarly, $P_{(12)}$ and $P_{(22)}$ are the corresponding states at the end of the sample. The TVSTCCGARCH model allows the extreme states, constant in the STCC-GARCH framework, to be time-varying, which introduces extra flexibility when modeling long time series. The number of parameters, excluding the univariate GARCH equations, is $2N(N-1)+4$, which restricts the use of the model in very large systems.

The Regime Switching Dynamic Correlation (RSDC-) GARCH model introduced by Pelletier (2006) falls somewhere between the models with constant correlations and those with continuous correlations at every period. The model imposes constancy of correlations within a regime while the dynamics enter through switching regimes. Specifically,

$$P_t = \sum_{r=1}^{R} \Delta_{(t=r)} P_{(r)},$$

where: Δ_t is a (usually first-order) Markov chain independent of η_t that can take R possible values and is governed by a transition probability matrix Π, I is the indicator function, and $P_{(r)}$, $r = 1, \ldots, R$, are positive definite regime-specific correlation matrices. The correlation component of the model has $R\,N(N-1)/2 - R(R-1)$ parameters.

A version that involves fewer parameters is obtained by restricting the R possible states of correlations to be linear combinations of a state of zero correlations and that of possibly high correlations. Thus,

$$P_t = \left(1 - \lambda(\Delta_t)\right)I + \lambda(\Delta_t)P,$$

where: I is the identity matrix ('no correlations'), P is a correlation matrix representing the state of possibly high correlations, and $\lambda(\cdot):\{1, \ldots, R\} \to [0,1]$ is a monotonic function of Δ_t.

The number of regimes *R* is not a parameter to be estimated. The conditional correlation matrices are positively definite at each point in time by construction both in the unrestricted and restricted versions of the model. Pelletier (2006) recommends a two-step estimation if N is small. First, estimate the parameters of the GARCH equations and, second, conditionally, on these estimates, estimate the correlations and the switching probabilities using the EM algorithm of Dempster, Laird, and Rubin (1977).

Statistical properties

Statistical properties of multivariate GARCH models are only partially known. For the development of statistical estimation and testing theory, it would be desirable to have conditions for strict stationarity and ergodicity of a multivariate GARCH process and conditions for consistency and asymptotic normality of the quasi-maximum likelihood estimator. The available results establish these properties in special cases and sometimes under strong conditions.

Jeantheau (1998) considers the statistical properties and estimation theory of the ECCCGARCH model he proposes. He provides sufficient conditions for a weakly stationary and ergodic solution, which is also strictly stationary. This is done by assuming $E r_t r_t' < \infty$. It would be useful to have both a necessary and a sufficient condition for a strictly stationary solution, but this question remains open. Jeantheau (1998) also proves the strong consistency of the QML estimator for the ECCC-GARCH model.

Ling and McAleer (2003) complement Jeantheau's results and prove the asymptotic normality of the QMLE in the case of the ECCC-GARCH model. The sixth moment of $\boldsymbol{r}_t$ is required for the global asymptotic normality result $\boldsymbol{r}_t$. The statistical properties of the second-order model are also investigated by He and Teräsvirta (2004), who provide sufficient conditions for the existence of fourth moments, and, furthermore, give expressions for the fourth moment as well as the autocorrelation function of squared observations as functions of the parameters.

Comte and Lieberman (2003) study the statistical properties of the BEKK model. Relying on Boussama (1998) result, they give sufficient but not necessary conditions for strict stationarity and ergodicity. Applying Jeantheau's effects, they provide conditions for the strong consistency of the QMLE. Furthermore, they also prove the asymptotic normality of the QMLE, for which they assume the existence of the eighth moment of $\boldsymbol{r}_t$. The fourth-moment structure of the BEKK and VEC models is investigated by Hafner (2003), who gives necessary and sufficient conditions for the existence of the fourth moments and provides expressions for them. These expressions are not functions of the parameters of the model.

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PART II - Econometrics Tools Application for Cases Studies of Tourism and Financial Economics

Chapter 8 Tourist Demand Using VECM and Cointegration

Chapter 9 Modelling the Growth Rate and Volatility in International Tourist Arrivals

Chapter 10 Volatility transmission, Comovements, and Spillovers Models with applications to Financial Economics

Part II will be the application of principles and tools in econometrics. The problem with using econometric tools is that we have learned the principles but have yet to be able to apply them in practice for further research that needs to be studied or solved. Therefore, in this section, the author brings together peer-reviewed research to apply to the actual situation in terms of tourism, which is the case in Thailand, and finance and investment, which is linked to foreign markets. The results obtained can be used for practical purposes. They can provide policy recommendations to the government or relevant agencies.

We apply the econometrics tools to tourism and financial economics because the service sector and its operational efficiency are increasingly crucial in GDP creation and volatility generation in economic development. Efficient and growth-generating management of such vital elements of the service sector as tourism, financial instruments, and petroleum and other futures markets; must be balanced against concern for both stability (reductions in temporally predictable extreme fluctuations) and self-immunization against the vagaries of external natural, financial, petroleum-based. As service-sector markets are frequently co-integrated, it is also vital to determine whether an investment in one can offset downside risk in the others.

Econometric management was developed when agriculture was still the predominant sector of the economy in both GDP and employment. Ricardo's theory of surplus value and diminishing returns, Griliches', Nerlove, Koyck, Almon and others' breakthroughs in the estimation of stochasticity in yields and lagged dependence; measurement, and explanation of productive efficiency under technical change and inter-annual weather fluctuations; the stochastic frontier function; and the early applications of Box and Jenkins' ARIMA to the modelling of cobweb structures in the livestock sector all took real-world agricultural data as both their inspiration and data source.

Today, those fundamental econometric tools must not only be transferred to the service sector; they must be improved through further methodological advances to reflect the unique features of each subsector and market: the consumer market (tourism), financial markets (financial instruments, stocks, petroleum, and other futures).

These special proceedings issue of the author proudly focuses on the publication of seminal contributions in each of these subsectors of the service economy from authors working in two subdivisions: consumer markets and financial markets.

Tourism

First, we study the relationship between four factors in the Japanese demand model, including the number of Japanese arrivals to Thailand, GDP per capita of Japanese tourists, the own price, and the cross price. It is a multivariate analysis that investigates dependence and interaction among variables in a multi-values process. One of the most potent methods of analysing multivariate time series is the vector autoregression model (VAR), and the extended models are the vector error correction model (VECM) and Cointegration.

Second, we analyse the volatility of Thailand's international tourist arrival growth rates. The variable of interest for policymakers was the tourist arrival growth rates at any given month, directly related to tourism revenue growth rates. In this study, we considered the volatility of Thailand's international tourist arrival growth rates by employing the GARCH and GJR models. GARCH and GJR models were widely used to manage financial and tourism risk exposure.

Third, we examined the international tourist arrivals volatility comovements and spillovers for Malaysian (GML), Japanese (GJP), British (GUK), and American (GUS) tourists. The three Multivariate GARCH models were employed: the VAR (5)-diagonal VECH and VAR (5)-diagonal BEKK.

Financial markets

First, we examined the oil futures and the carbon emissions futures volatility comovements and spillovers for crude oil, gasoline, and heat oil, as well as carbon emissions. The three Multivariate GARCH models, namely the VAR (3)-diagonal VECH, the VAR (3)-diagonal BEKK, and the VAR (3)-CCC, were employed. The empirical results showed that the VAR (3)-diagonal VECH estimates and the VAR (3)-CCC parameters were statistically significant in a case involving oil except for carbon emissions.

Second, we examined the COMEX market's precious metals volatility comovements and spillovers for gold, palladium, platinum, and silver. The results of the volatility analysis were used to calculate the optimal two-metal portfolio weights and hedging ratios. The three Multivariate GARCH models, namely the VAR (1)-diagonal VECH, the VAR (1)-diagonal BEKK, and the VAR (1)-CCC, were employed.

Third, we study the petroleum futures volatility comovements and spillovers for crude oil, gasoline, heat oil, and natural gas. The results of volatility analysis were used to calculate the optimal two-petroleum portfolio weights and hedging ratios. The three Multivariate GARCH models, namely the VAR (1)-diagonal VECH, the VAR (1)-diagonal BEKK, and the VAR (1)-CCC, were employed.

The content provides cutting-edge insights for the academic econometrician, practical forecasting tools, private decision-making, and policy recommendations for fostering vigorous research.

Keywords: multivariate time series; volatility transmission; comovement and spillover; multivariate GARCH

JEL Classification: C51; C52; C54; C55; C58.

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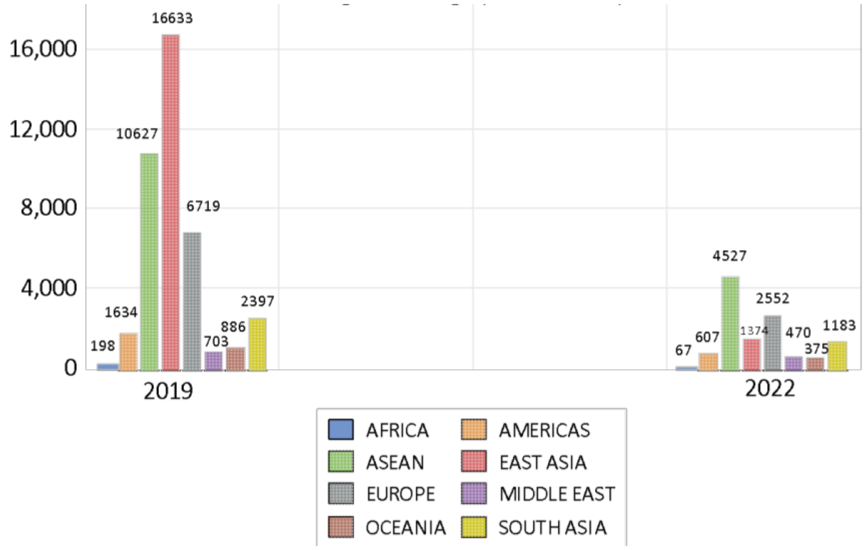
Chapter 8

Tourist Demand Using VECM and Cointegration[1]

The importance of tourism is a source of income for the country. For Thailand, tourism revenue is proportional to 15% of the GDP. Tourism revenue turns over in the country is more than 8 billion baht per year. We receive income from the travel of Thai tourists and foreign tourists entering Thailand, so the Thai government prioritizes tourism (Tourism Authority of Thailand, 2023a).

However, the purpose of this study focused on the study of foreign tourists, which this study needs to be revised. The data (Tourism Authority of Thailand, 2023b) showed that foreign tourists from Figure 8.1 in 2022 compared arrivals from different world regions in 2019 and 2022. Primarily the number of arrivals was proportionally less for all areas except for arrivals from Eastern Asia. And from Figure 8.2, it can be seen that tourists in East Asia are still important, especially Chinese and Japanese tourists;

Figure 8.1. Tourists to Thailand (2019 and 2022), region of origin



Source: https://www.thaiwebsites.com, 2023

Figure 8.2. Tourist arrivals by nationality in 2022

[1] This chapter is based on the findings of the published paper (Bunnag, 2014)

Period	S.E.	LOGNOJ	LOGGDPJ	LOGRPJ	LOGCPJ
1	0.084	2.039	7.077	90.882	0.000
2	0.116	1.708	4.273	88.983	5.034
3	0.134	3.270	4.609	86.753	5.366
4	0.149	4.504	4.212	86.629	4.652
5	0.167	5.366	3.921	86.704	4.008
6	0.182	6.694	3.658	86.008	3.638
7	0.198	9.078	3.470	84.204	3.247
8	0.213	10.634	3.353	83.118	2.893
9	0.229	11.872	3.212	82.279	2.635
10	0.244	13.176	3.016	81.381	2.424
4. ∆LOGCPJ					
Period	S.E.	LOGNOJ	LOGGDPJ	LOGRPJ	LOGCPJ
1	0.120	9.85E-05	4.217	21.881	73.900
2	0.191	0.511	2.500	40.154	56.833
3	0.262	0.582	2.582	50.324	46.510
4	0.336	0.871	1.910	55.706	41.511
5	0.386	0.985	1.480	58.178	39.355
6	0.423	1.152	1.254	58.734	38.857
7	0.455	1.426	1.088	59.545	37.939
8	0.485	1.825	0.968	60.177	37.028
9	0.513	2.250	0.868	60.523	36.356
10	0.542	2.791	0.794	60.896	35.518

We can conclude the relationships in the short run of various variables in the Japanese tourist demand model. It shows the relationship as follows: It produces a relationship called the income elasticity of demand and the own price elasticity of demand, equal to 3.281 and -0.505, respectively. In addition, the percentage change of GDP per capita of Japanese tourists has a negative relationship with the percentage change in the own price. Finally, the percentage change of the cross-price has a positive relationship with the percentage change of the own price.

In the long run, the number of Japanese tourist arrivals has a positive relationship with the GDP per capita of Japanese tourists, and the own price also has a positive relationship with the cross price. This conclusion is expected to be useful to the government and the private sector in tourism management for Japanese tourists.

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Chapter 9

Modelling Volatility and Growth Rate in International Tourist Arrivals

This chapter examined the volatility of international tourist arrival growth rates to Thailand using monthly time series data from 1991-2022, being an updated version of our previous research published[1], and the timing of such data will cover the impact of the Covid-19 pandemic, amplifying the effect of volatility. The variable of interest for policymakers was the tourist arrival growth rates at any given month, directly related to tourism revenue growth rates.

In the studies presented in sub-chapter 9.1 and 9.2 considered the volatility of Thailand's international tourist arrival growth rates by employing the GARCH and GJR models. GARCH and GJR models were widely used to manage financial and tourism risk exposure. Considering the number of tourist arrivals and the growth rate, it was found that most tourists were from Malaysia and Japan. Therefore, this study could compare the USA and the UK in making policy because of the difference in tourism volatility. The GARCH model generated relatively accurate tourism volatility forecasts from this study, except for Japan and the USA volatility. In addition, the GJR model developed fairly accurate tourism volatility forecasts except for Malaysia and the UK volatility.

The sub-chapter 9.3 examined the international tourist arrivals volatility comovements and spillovers for Malaysian (GML), Japanese (GJP), British (GUK), and American (GUS) tourists. The data used in this study was the monthly data from 1985 to 2022, and the two Multivariate GARCH models were employed, namely the VAR (5)-diagonal VECH and the VAR (5)-diagonal BEKK. The empirical results overall showed that the estimates of the VAR (5)-diagonal VECH parameters were statistically significant in the case of GML with GUS and GJP with GUS except in the case of GML with GJP, GML with GUK, GJP with GUK, and GUK with GUS. This indicates that the short-run persistence of shocks on the dynamic conditional correlations was greatest for GML with GJP, while the largest long-run persistence of shocks to the conditional correlations for GML with GUS.

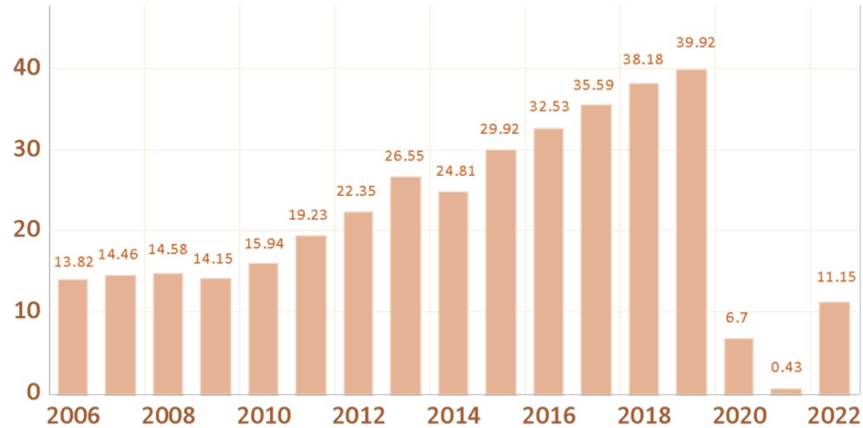
[1] This sub-chapter is based on the findings of the published paper of Bunnag (2016).

like Bangkok, Phuket, and Pattaya resulted in environmental degradation and strained infrastructure.

The number of tourists visiting Thailand increased from 35.35 million in 2017 to 38.28 million in 2018 and 39.92 million in 2019. The increase in visitors from 2018 to 2019 was limited to 4.24%, less than Thai authorities expected. The ever-rising number of tourists arriving ended abruptly from March 2020 onwards. 2020 saw only 6,702,396 tourists, almost all coming in the year's first three months. No tourists were allowed in from March 2020 to the end of August 2020. After that, in the last three months of 2020, 10,822 tourists arrived under exceptionally stringent conditions.

Lots of people in the hospitality sector have lost their jobs. As 2020, 2021 was a dismal year with few visitors arriving, but Thailand had the opening of the country as of 1 November 2021. This appears to have been an audacious move since, at the time of the initiative's announcement, a new wave of Covid-19 was hitting the country hard, much more so than during the initial infections in 2020. But it likely needed to be done since many people have a significantly reduced income, and the government needs more resources to continue providing for them. However, the impact of this relaxation of travel conditions was limited, with little effect on the number of arrivals. Except for the last three months of 2021, monthly appearances were between 5,000 and 20,000 each month, which is a deficient number for Thailand. Figure 9.1. shows that more tourists started coming during the last quarter of 2021. Things improved, especially from the middle of 2022, when most restrictions were lifted.

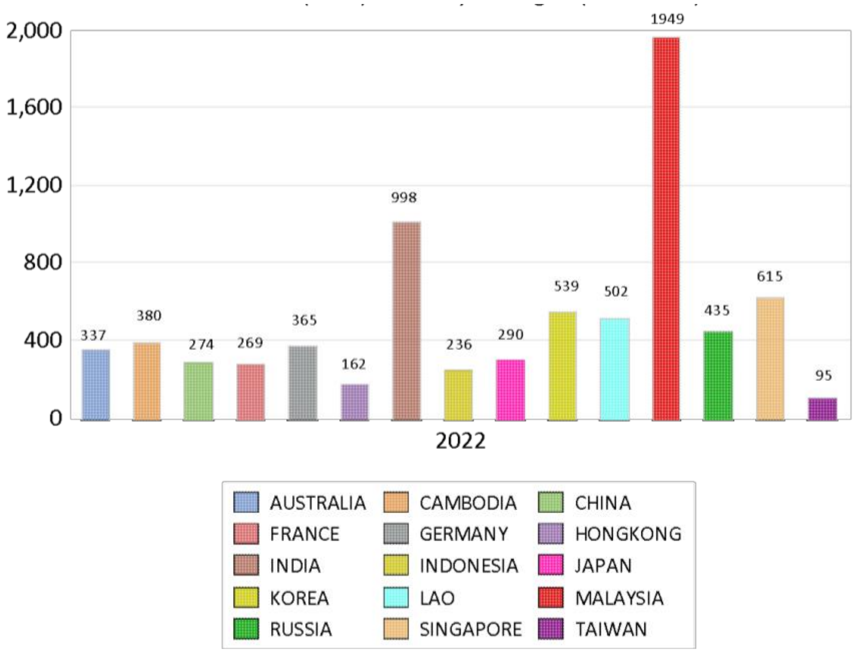
Figure 9.1. International Tourist Arrivals to Thailand, 2006 – 2022 (millions)



Source: The Tourism Authority of Thailand (2023)

From Figure 9.3, during COVID-19, the number of these tourists declined. However, the cumulative number of such tourists is still significant, especially Malaysian and Japanese tourists. Considering the number of tourist arrivals and the growth rate, it was found that most tourists are from Malaysia and Japan. Therefore, this study can compare the USA and the UK for making policies because of the difference in tourism volatility.

Figure 9.3. Tourist arrivals by nationality in 2022, thousands



Source: www.thaiwebsites.com (2023)

9.1.1. Related Literature Review for Volatility Analysis

In volatility analysis, Michael McAleer et al. (2005) studied a risk management framework of daily tourist tax revenues for the Maldives using value at risk (VaR) to measure the risk from the growth of the number of tourist arrivals affecting the environment. The GARCH (1,1) and the GJR(1,1) were used to forecast the required conditional volatilities.

Shareef and McAleer (2007) showed how the GARCH (1,1) model and the GJR (1,1) model could be used to measure the conditional volatility in monthly international tourist arrivals to six SITEs, namely Barbados, Cyprus, Dominica, Fiji, Maldives, and Seychelles, and to appraise the implications of conditional volatility of SITEs for modelling tourist arrivals. For the logarithm of monthly international tourist arrivals, the estimates of the conditional volatility using GARCH (1,1) and GJR (1,1) was highly satisfactory. The conditions to ensure the positivity of the conditional variance were met for all six SITEs, except for Maldives. It was worth noting that

which minimizes some model selection criteria. Model selection criteria for VAR (p) could be based on Akaike (AIC), Schwarz-Bayesian (BIC), and Hannan-Quinn (HQ) information criteria.

Before constructing the conditional mean, the first thing to do is find the right VAR model's lag, as shown in Table 9.14. From the various criteria are found to be selected lag that 8, 5, 1, and 2, respectively. Most of them will choose lag 5. Therefore, lag 5 should be suitable for the conditional mean. After all, multivariate conditional volatility models are already estimated. In the next step, we must explain each model's results and select the best model.

Table 9.14. Lag order selection

Lag	LR	FPE	AIC	SC	HQ
0	NA	3.49e+08	31.020	31.064	31.038
1	168.148	2.35e+08	30.627	30.846*	30.714
2	87.835	1.99e+08	30.462	30.857	30.619*
3	53.750	1.86e+08	30.394	30.965	30.621
4	48.473	1.77e+08	30.340	31.087	31.087
5	30.995	1.76e+08*	30.337*	31.259	30.704
6	24.340	1.79e+08	30.354	31.452	30.791
7	22.541	1.83e+08	30.375	31.648	30.882
8	36.264*	1.76e+08	30.352	31.801	30.929

Note: * indicates lag order selected: LR (Sequential modified test statistic,) FPE (Final prediction error), AIC (Akaike information criterion), SC (Schwarz information criterion), HQ (Hannan-Quinn information criterion).

The VAR (5)-diagonal VECH estimates of the conditional correlation between the volatilities of the growth rates of international tourist arrivals based on estimating the univariate GARCH (1,1) model for each international tourist are given in Table 9.15 (see APPENDIX 1 Chapter 9 – subchapter 9.3.3). The estimates of the VAR (5)-diagonal VECH parameters that θ_1 and θ_2 are statistically significant in the case of $\rho_{(GML\_GUS)}$, and $\rho_{(GJP\_GUS)}$ except in the case of $\rho_{(GML\_GJP)}$, $\rho_{(GML\_GUK)}$, $\rho_{(GJP\_GUK)}$ and $\rho_{(GUK\_GUS)}$. This indicates that the short-run persistence of shocks on the dynamic conditional correlations is greatest for GML with GJP at 0.159 (θ_1), while the largest long-run persistence of shocks to the conditional correlations is 0.887 ($\theta_1 + \theta_2$) for GML with GUS.

The VAR (5)-diagonal BEKK estimates of the conditional correlation between the volatilities of the growth rates of international tourist arrivals are given in Table 9.16 (see APPENDIX 1 Chapter 9 – subchapter 9.3.3). The estimates of the diagonal BEKK parameters

Chapter 10

Volatility transmission, Comovements, and Spillovers Models with Applications to Financial Economics

This chapter will apply the volatility model to study and analyse risks in financial assets (volatility transmission, comovements, and spillover models), especially energy financial instruments, including precious metals, and risk management to benefit investors in portfolio management. Finally, the ultimate aim is the least volatility and to make a profit to investors.

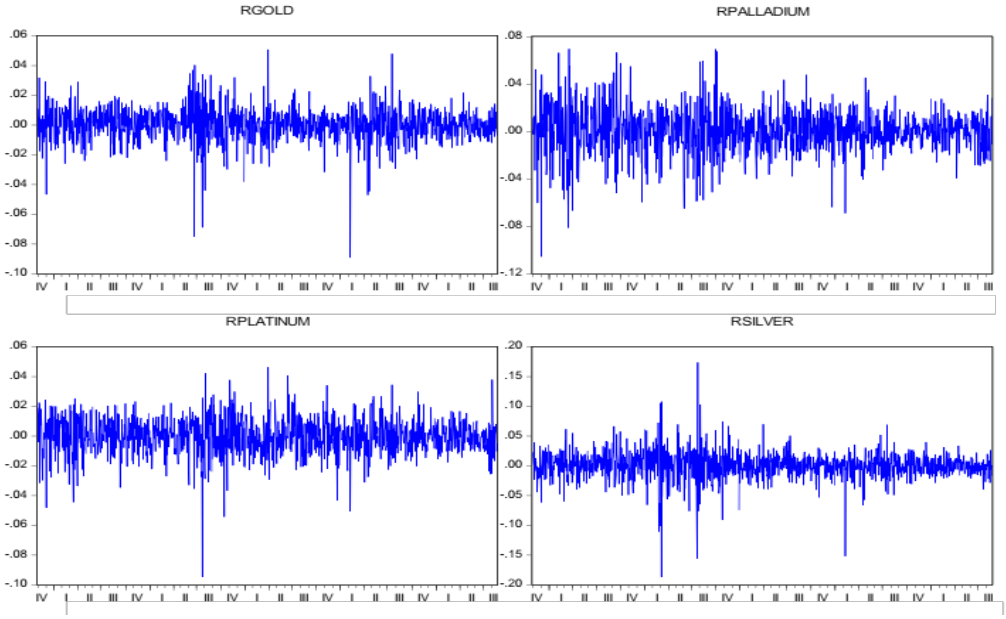
10.1 Volatility Transmission in Oil Futures Markets and Carbon Emissions Futures[1]

This sub-chapter examined the oil futures and the carbon emissions futures volatility comovements and spillovers for crude oil, gasoline, and heat oil, as well as carbon emissions. The data used in this study was the daily data from 2017 to 2022. The three Multivariate GARCH models, namely the VAR (3)-diagonal VECH, the VAR (3)-diagonal BEKK, and the VAR (3)-CCC, were employed. The empirical results showed that the estimates of the VAR (3)-diagonal VECH and the VAR (3)-CCC parameters were statistically significant in a case involving oil except for carbon emissions. This indicates that the short-run persistence of shocks on the dynamic conditional correlations was greatest for RGASOLINE with RHEATOIL, while the largest long-run persistence of shocks to the conditional correlations for RCRUDE with RGASOLINE. At the same time, the VAR (3)-diagonal BEKK parameters were statistically significant in all cases. This indicates that the short-run persistence of shocks on the dynamic conditional correlations is greatest for RHEATOIL with RCO2, while the largest long-run persistence of shocks to the conditional correlations for RCRUDE with RCO2 and RHEATOIL with RCO2.

Finally, we would choose the best model by considering the value of log-likelihood, AIC, SIC, and HQ. For the value of these figures, we should select the VAR (3)-diagonal BEKK model in volatility analysis of the oil futures and the carbon emissions futures returns. In addition, oil futures volatility impacts carbon emissions futures volatility.

[1] This sub-chapter is based on the findings of the published paper of Bunnag (2015).

Figure 10.9. The four daily precious metal returns



The descriptive statistics are given in Table 10.9. The daily returns of silver (RSILVER) display the greatest variability with a mean of -4.81E-06%, a maximum of 0.1736%, and a minimum of -0.1869%. Furthermore, the skewness, the kurtosis, and the Jarque-Bera Lagrange multiplier statistics of all metal returns are statistically significant, implying that the distribution is not normal.

Table 10.9. Descriptive statistics

Returns	RGOLD	PALLADIUM	RPLATINUM	RSILVER
Mean	8.34E-05	0.000517	-0.000145	-4.81E-06
Median	0.000387	0.00136	0.0000	0.0000
Maximum	0.0507	0.0696	0.0461	0.1736
Minimum	-0.0891	-0.1053	-0.0946	-0.1869
Std. Dev.	0.0112	0.0189	0.0123	0.0238
Skewness	-0.8299	-0.3151	-0.5773	-0.6609
Kurtosis	10.0943	5.3072	6.6583	13.2650
Jarque-Bera	2687.414	289.6139	745.0484	5422.883

Besides, return series will be used to construct the conditional mean and variances next.

Unit Root tests

Standard econometric practice in the analysis of financial time series data begins with an examination of unit roots. The Augmented Dickey-Fuller (ADF) (Dickey and Fuller,1979) and Phillips-Perron (PP) (Phillips and Perron,1988) tests are used to test for all the precious metal returns under the null hypothesis of a unit root against the alternative hypothesis of stationarity. The results from unit root tests are presented in Table 10.10. The tests yield negative values in all cases for levels, such that the individual returns series reject the null hypothesis at the 1% significance level, so all returns are stationary.

Empirical results

An important task is to model the return series' conditional mean and variances. Therefore, the appropriate multivariate conditional volatility models given as VAR (1)-diagonal VECH, VAR (1)-diagonal BEKK, and VAR (1)-CCC models are estimated. The conditional mean comes from VAR (Vector Autoregression Model), which can display the source as follows.

Vector autoregression model

Let $Y_t = (Y_{1t}, Y_{2t}, ..., Y_{nt})'$ denote a $k \times 1$ vector of the precious metal return series variables. The basic vector autoregressive model of order p, VAR (p), is:

$$Y_t = c + \Pi_t Y_{t-1} + \Pi_2 Y_{t-2} + ... + \Pi_p Y_{t-p} + \mu_t, \qquad t = 1,...T, \tag{10.16}$$

where Π_t are $k \times k$ matrices of coefficients, c is a $k \times 1$ vector of constants, and μ_t is a $k \times 1$ unobservable zero mean white noise vector process with the covariance matrix $\sum$.

As in the univariate case with AR processes, we can use the lag operator to represent VAR (p):

$$\Pi(L)Y_t = c + \mu_t, \qquad \text{where} \qquad \Pi(L) = I_n - \Pi_1 L - ... - \Pi_p L^p$$

If we impose stationarity on Y_t in (10.16), the unconditional expected value is given by

$$\mu = (I_n - \Pi_1 - ... - \Pi_p)^{-1} c.$$

Lag Length Selection: A reasonable strategy for determining the lag length of the VAR model is to fit VAR (p) models with different orders $p = 0,..., p_{\max}$ and choose the value of p, which minimizes some model selection criteria. Model selection criteria for VAR (p) could be based on Akaike (AIC), Schwarz-Bayesian (BIC), and Hannan-Quinn (HQ) information criteria.

Before constructing the conditional mean, the first thing to do is find the right VAR model's lag, as shown in Table 10.11. From the various criteria are found to be selected lag that 1, 7, and 0. Most of them will choose lag 1. Therefore, we conclude that lag 1 should be suitable for the conditional mean. After all, multivariate conditional volatility models in this paper are already estimated. In the next step, we must explain each model's results and select the best model.

The VAR (1)-diagonal VECH estimates of the conditional correlation between the volatilities of the four precious metal returns based on estimating the univariate GARCH (1,1) model for each precious metal are given in Table 10.12. The VAR (1) - diagonal VECH parameter θ_1 and θ_2 estimates are statistically significant in all cases. This indicates that the short-run persistence of shocks on the dynamic conditional correlations is greatest for RGOLD with RSIL. At 0.068 (θ_1), the largest long-run persistence of shocks to the conditional correlations is 0.963 ($\theta_1 + \theta_2$) for RPAL, with RSIL.

The VAR (1)-diagonal BEKK estimates of the conditional correlation between the volatilities of the four precious metal returns are given in Table 10.13. The estimates of the diagonal BEKK parameters θ_1 and θ_2 are statistically significant in all cases. This indicates that the short-run persistence of shocks on the dynamic conditional correlations is greatest at 0.050 for RGOLD with RSIL., while the largest long-run persistence of shocks to the conditional correlations is 0.983 ($\theta_1 + \theta_2$) for RPAL with RSIL

Finally, Table 10.14 presents the VAR (1)-CCC model $p = q = r = s = 1$ estimates. The ARCH and GARCH estimates of the conditional variance between the four precious metal returns are statistically significant in all cases. The ARCH (α) estimates are generally small (less than 0.2), and the GARCH (β) estimates are generally high (more than 0.8) and close to one. Therefore, the long-run persistence ($\alpha + \beta$), is generally one, indicating a near-long memory process. This indicates a near-long memory process. In addition, $\alpha + \beta < 1$ all metals satisfy the second and log-moment conditions, which is sufficient for the QMLE (quasi-maximum likelihood) to be consistent and asymptotically normal. VAR (1)-CCC estimates the constant conditional correlation between RGOLD and RSIL, with the highest at 0.809. This indicates that the standardized shock on the constant conditional correlation for RGOLD with RSIL is 0.809.

Furthermore, we will choose the best model by considering the value of log-likelihood, AIC, SIC, and HQ. From Tables 10.12, 10.13, and 10.14, we found that the VAR (1)-diagonal VECH model is the highest log-likelihood equal to 15321.96. AIC and HQ are the lowest, equal to -25.159 and -25.080, respectively. Thus, we should choose the VAR (1)-diagonal VECH model in the volatility analysis of the precious metal returns. The results of this model are used to calculate the optimal two-metal portfolio weights and hedging ratios.

However, we can show the movement of the conditional covariance and the conditional correlation of the four precious metal returns in each model according to Figures 10.10, 10.11, 10.12, 10.13, and 10.14, respectively.

Multivariate GARCH diagnostic tests

The multivariate GARCH models consist of the VAR (1)-diagonal VECH, the VAR (1)-diagonal BEKK, and the VAR (1)-CCC model. We can diagnostic check on the system residuals to determine the estimator's efficiency according to Table 10.15. We found that system residuals have no autocorrelations up to lag 6 and are not normally distributed. Therefore, the estimators of the multivariate GARCH model are efficient.

Implications for portfolio designs and hedging strategies

We provide two examples for constructing optimal portfolio designs and hedging strategies using our best estimates of model VAR (1)-diagonal VECH for the four metals. The first example follows Kroner and Ng (1998) by considering a portfolio that minimizes risk without lowering expected returns. If we assume the expected returns to be zero, the optimal portfolio weight of one metal (or asset) to the other in a two-metal (asset) portfolio is given by:

$$w_{12,t} = \frac{h_{22,t} - h_{12,t}}{h_{11,t} - 2h_{12,t} + h_{22,t}} \qquad 10.17$$

and

$$w_{12,t} = \begin{cases} 0, & if \quad w_{12,t} < 0 \\ w_{12,t}, & if \quad 0 \le w_{12,t} \ge 1 \\ 1, & if \quad w_{12,t} > 1 \end{cases} \qquad 10.18$$

where $w_{12,t}$ is the weight of the first precious metal in one dollar portfolio of two precious metals at the time t, $h_{12,t}$ is the conditional covariance between metals 1 and 2, and $h_{22,t}$ is the conditional variance of the second metal in the one-dollar portfolio $1 - w_{12,t}$.

The average values of the $w_{12,t}$ based on VAR (1)-diagonal VECH estimates are reported in the first column of Table 10.16. For instance, the average value of $w_{12,t}$ a portfolio comprising gold and palladium, is 0.91. This suggests that the optimal holding of gold in one dollar of gold/palladium portfolio is 91 cents and 9 cents for palladium. These optimal portfolio weights indicate that investors should have more gold than palladium and other precious metals to minimize risk without lowering the expected return. Regarding the two metals, palladium and silver, the optimal portfolio should be 72% to 28%, and investors should have more palladium than silver.

We now follow the example given by Kroner and Sultan (1993) regarding risk-minimizing hedge ratios and apply it to our precious metals. A long (buy) position of one dollar taken in one precious metal should be hedged by a short (sell) position β_t in another precious metal t to minimize risk. The rule to have an effective hedge is to have an inexpensive hedge. The β_t is given by:

$$\beta_t = \frac{h_{12,t}}{h_{22,t}} \qquad 10.19$$

where β_t is the risk-minimizing hedge ratio for two precious metals; $h_{12,t}$ is the conditional covariance between metals 1 and 2; $h_{22,t}$ is the conditional variance of second metal.

The second column of Table 10.16 reports the average values β_t. The results show that the most effective hedging among all the precious metals is hedging long (buy) palladium position by shorting (selling) platinum. The least effective hedging among all the precious metals is hedging long (buy) gold position by shorting (selling) platinum.

This sub-chapter investigates volatility comovements and spillovers for gold, palladium, platinum, and silver. The results of volatility analysis are used to calculate the optimal two-metal portfolio weights and hedging ratios. In addition, this paper estimated three popular multivariate GARCH models, namely the VAR (1) - diagonal VECH, the VAR (1) - diagonal BEKK, and the VAR (1)-CCC model, for the four metal returns.

The empirical results showed that the multivariate GARCH parameter estimates are statistically significant in all cases. This indicates that the short-run persistence of shocks on the dynamic conditional correlations is greatest for RGOLD with RSILVER, while the largest long-run persistence of shocks to the conditional correlations for RPALLADIUM with RSILVER.

In the next step, we will choose the best model by considering the value of log-likelihood, AIC, SIC, and HQ. Finally, we found that the best volatility and hedging ratios analysis model is the VAR (1)-diagonal VECH model. The results from these optimal portfolio weights based on the VAR (1)-diagonal VECH estimates suggest that investors should have more gold than palladium and other precious metals to minimize risk without lowering the expected return. Such results can help manage the volatility of precious metals for investors.

Table 10.10. Unit Root tests

Returns	Augmented Dickey-Fuller Test			
	Constant		Constant and Trend	
	I(0)	I(1)	I(0)	I(1)
RGOLD	-35.78***	-19.40***	-35.85***	-19.39***
RSILVER	-40.08***	-40.16***	-17.62***	-17.61***
RPLATINUM	-33.86***	-17.34***	-33.872***	-17.33***
RPALLADIUM	-34.89***	-17.86***	-34.90***	-17.85***
Returns	**Phillips-Perron Test**			
	Constant		Constant and Trend	
	I(0)	I(1)	I(0)	I(1)
RGOLD	-35.85***	-559.61***	-35.94***	-559.25***
RSILVER	-40.17***	-40.34***	-417.25***	-416.86***
RPLATINUM	-33.87***	-399.32***	-33.882***	-398.94***
RPALLADIUM	-35.01***	-387.25***	-35.033***	-386.97***

Note: *** denote significance at the 1% level

Table 10.11. Lag order selection

Lag	LR	FPE	AIC	SC	HQ
0	NA	3.33e-16	-24.286	-24.269*	-24.280
1	113.029	3.11e-16*	-24.353*	-24.269	-24.332*
2	14.492	3.16e-16	-24.339	-24.187	-24.282
3	18.577	3.19e-16	-24.328	-24.108	-24.245
4	16.192	3.24e-16	-24.315	-24.028	-24.207
5	18.238	3.27e-16	-24.304	-23.949	-24.170
6	23.029	3.30e-16	-24.297	-23.875	-24.138
7	39.359*	3.27e-16	-24.304	-23.814	-24.119
8	14.863	3.32e-16	-24.290	-23.733	-24.080

Note: * indicates lag order selected: LR= Sequential modified LR test statistic, FPE=Final prediction error, AIC=Akaike information criterion, SC=Schwarz information criterion, HQ=Hannan-Quinn information criterion

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List of Abbreviations

ADF	Augmented Dickey-Fuller test
AGDCC-GARCH	Asymmetric Generalized DCC-GARCH model
AIC	Akaike information criterion
ARCH	Autoregressive conditional heteroscedasticity model
ARMA	Generalization autoregressive-moving average model
BEKK	Baba-Engle-Kraft-Kroner model
BIC	Bayesian information criterion
CCC-GARCH	Constant Conditional Correlation model
DCC-GARCH	Dynamic Conditional Correlation model
DW	Durbin-Watson statistic
ECCC-GARCH	Exponential CCC-GARCH model
ECM	Error correction model
EGARCH	Exponential GARCH
GARCH	Generalized autoregressive conditional heteroskedasticity model
GARCH-M	GARCH-in-the-mean model
GFDCC-GARCH	Quadratic Flexible DCC-GARCH model
GJR	The Glosten-Jagannathan-Runkle GARCH model
GLS	Generalized least squares
HQ	Hannan-Quinn information criteria
KPSS	Kwiatkowski-Phillips-Schmidt-Shin test
MGARCH	Multivariate GARCH
MLE	The maximum likelihood estimates
NLS	Nonlinear least squares estimator
OLS	Ordinary least squares estimation
PGARCH	Power GARCH model
PP	Phillips and Perron tests

RMSE	The Root Mean Squared Error
RSS	Residual sum of squares
RSDC-GARCH	Regime Switching Dynamic Correlation GARCH model
SARMA	The seasonal generalization autoregressive-moving average model
STCC-GARCH	Smooth Transition Conditional Correlation GARCH model.
TGARCH	Threshold GARCH
TVCC-GARCH	Time-Varying Conditional Correlation model
TVSTCC-GARCH	Time-Varying Smooth Transition Conditional Correlation GARCH model
VAR	Vector Autoregression Model
VAR-BEKK	The Vector Autoregression -Baba-Engle-Kraft-Kroner model
VAR-CCC	The Vector Autoregression - Constant Conditional Correlation model
VAR-VECH	Vector Autoregression - Bollerslev, Engle, and Wooldridge model
VC-GARCH	Varying Correlation GARCH models
VEC-GARCH	Models of the conditional covariance matrix
VECM	Vector error correction model
VMA	Vector moving average process

List of Key Concepts

Analysis: Testing Economic Theory	Economists formulated the basic principles of the functioning of the economic system using verbal exposition and applying a deductive procedure.	… 10
Conditional Volatility	As a proxy for risk	… 34
Econometric model	A set of assumptions that approximately describes the behaviour of an economy (or a sector of an economy).	… 9
Forecasting	In formulating policy decisions, it is essential to be able to forecast the value of the economic magnitudes.	… 10
Multivariate GARCH models	They have numerous variants and extensions of ARCH models.	… 56
Multivariate time series analysis	It investigates dependence and interactions among variables in multi-values processes.	… 45
Regression analysis	They are used to describe and evaluate the relationship between economic variables and perform forecasting tasks.	… 14
Time series	It is a sequence of numerical data in which observations are measured at a particular instant in time.	… 21
Cointegration	Cointegration is a technique used to find a possible correlation between time series processes in the long term. Nobel laureates Robert Engle and Clive Granger introduced the concept of cointegration in 1987.	… 75
Granger causality	The Granger causality test is a statistical hypothesis test for determining whether one-time series helps forecast another, first proposed in 1969. The causality in economics could be tested by measuring the ability to predict the future values of a time series using prior values of another time series.	… 81
Impulse response functions	Impulse response functions help study the interactions between variables in a vector autoregressive model. They represent the reactions of the variables to shocks hitting the system. However, it is often unclear which shocks are relevant for studying specific economic problems.	… 82
Hedging strategies	Investors use hedging strategies to reduce their exposure to risk if an asset in their portfolio is subject to a sudden price decline. When correctly done, hedging strategies reduce uncertainty and limit losses without significantly reducing the potential rate of return.	… 152
Multivariate GARCH diagnostic test	It is a diagnostic check on the system residuals to determine the estimator's efficiency.	… 114

SARMA model	SARMA models help model seasonal time series, where the mean and other statistics for a given season are not stationary across the years. The SARMA model defined constitutes a straightforward extension of the nonseasonal autoregressive-moving average (ARMA).	… 93
SARMA-GARCH model	It is a combination of SARMA and GARCH model to provide estimation or volatility valuation (Univariate model).	… 93
SARMA-GJR model	It is a combination of SARMA and GJR model to provide estimation or volatility valuation (Univariate model).	… 93
Variance decomposition analysis	It is used to aid in interpreting a vector autoregression (VAR) model once it has been fitted. The variance decomposition indicates the amount of information each variable contributes to the other variables in the autoregression. It determines how much of the forecast error variance of each of the variables can be explained by exogenous shocks to the other variables.	… 84
VAR-the diagonal VECH model	It is a combination of Vector Autoregression and Bollerslev, Engle, and Wooldridge model to provide estimation or volatility valuation (Multivariate model).	… 106
VAR-the diagonal BEKK model	It is a combination of Vector Autoregression and Baba-Engle-Kraft-Kroner model to provide estimation or volatility valuation (Multivariate model).	… 106
VAR-CCC model	It is a combination of Vector Autoregression and Constant Conditional Correlation model to provide estimation or volatility valuation (Multivariate model).	… 121
Vector error correction model	It is a cointegrated VAR model. This idea of the Vector Error Correction Model (VECM) consists of a VAR model of the order p - 1 on the differences of the variables and an error-correction term derived from the known (estimated) cointegrating relationship.	… 78
Vector autoregression model	Vector autoregression (VAR) is a statistical model used to capture the relationship between multiple quantities as they change over time. VAR is a type of stochastic process model. VAR models generalize the single-variable (univariate) autoregressive model by allowing for multivariate time series.	… 112
Volatility model	A volatility model is defined by its first and second moment, referred to as the mean and variance equation.	… 96

"Guidelines for Econometrics and Application: Emphasis on Tourism and Financial Economics" is an essential resource that masterfully bridges the world of econometrics with the complicated domains of tourism and financial economics. In an era where the service sector plays an increasingly pivotal role in shaping economies and influencing their stability, this book stands as a beacon of insightful guidance for anyone interested in understanding and managing the complex interplay of economic forces.

What sets this book apart is its unwavering commitment to achieving a delicate balance between fostering growth and ensuring stability. The author advocates for the reduction of temporally predictable extreme fluctuations, a critical factor in achieving long-term economic sustainability. Moreover, it is emphasized the importance of self-immunization against external factors, such as natural disasters, financial crises, and petroleum market fluctuations, which can have far-reaching consequences on economies.

PhD Professor Laura Nicola-Gavrilă, Spiru Haret University, Romania

Publisher Manager

The author's side has gained expertise in applying specific volatility tools such as GARCH, EGARCH, multivariate GARCH such as CCC, VECH, and BEKK, as well as VAR-multivariate GARCH. Such tools can explain the risks, especially with more precise financial complexity, making such research reliable.

One of the book's key strengths lies in its comprehensive approach. The author recognizes that service-sector markets are often interconnected, and they skilfully navigate the complexities of co-integration. They delve into the intricate relationships between various investments within this sector, offering invaluable insights into how an investment in one area can mitigate downside risks in others. This holistic perspective is a valuable asset for investors, policymakers, and economists seeking to make informed decisions in an increasingly interdependent world.

PhD Pathairat Pastpipatkul, Faculty of Economics, Chiang Mai University, Thailand"