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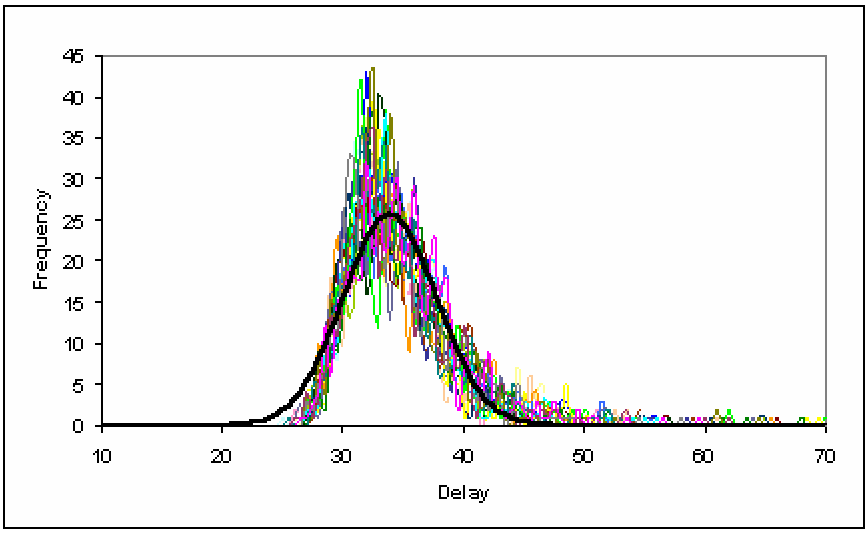
Thesis: "Testing for Causality in Variance: The case of the European Countries"



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To my father

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INTRODUCTION

In our days the importance of volatility modelling gains increasing attention. There are several reasons why volatility spillover plays an important role in the field of Economics and Finance. As Balasubramanyan (2004) underlines, the motivation underlying studies on volatility spillover is to understand how joint movements in volatility influence the distribution of portfolio returns as this gives implications for portfolio selection, derivative pricing and daily risk management. Bala and Premarante (2004) pinpoint that volatility process is significant on the determination of the cost of capital and on the assessment of investment and leverage decisions. In addition, Ng (2000) notes the necessity of the volatility process in the optimum allocation of assets, in the construction of international hedging strategies and finally in the development of capital controls or requirements.

The thesis has mainly two parts. The first part is the Econometric part, where we are trying to investigate the statistical properties of two methodologies that are used in the detection of Causality in Variance as well as in the Mean. Through several Monte Carlo simulations, we are trying to retrieve some conclusions concerning the empirical performance of these methodologies, using two Data Generating Processes, the GARCH and the FIGARCH model specifications. These methodologies are based on the estimation of the Cross Correlation Function for the squared standardised residuals. These residuals are obtained from the estimation of the univariate GARCH. The second part involves our empirical application. In this part we are trying to investigate the volatility as well as the return spillover among eighteen (18) countries of European Union (EU), based on the two methodologies, using both the GARCH and FIGARCH models.

The general structure of the thesis is the following: The Chapter 1 introduces us to the definition of the volatility as well as to its role in the field of Economics and Finance. In addition, we make a description of the GARCH family models. The second chapter is referred to the Causality in Variance Tests, those of Cheung & Ng and Hong, giving a description of these two methodologies. The third chapter is trying to define the long memory especially in volatility process and describe the FIGARCH model. In the fourth chapter we conduct three Monte Carlo simulations in order to examine the empirical performance of the two Tests and in the last part we present our empirical application. We include in the thesis also two appendices, which involve a number of Statistical Tables that were retrieved from the Causality Tests, obtaining the standardised residuals using the GARCH and the FIGARCH models. For brevity reasons we did not put all the statistical tables. All the tables are available from the author upon request.

To our knowledge, no research has been made, examining the empirical performance of the statistics of Cheung & Ng and Hong, using as Data Generating Processes the GARCH and FIGARCH models. Regarding the empirical application, we use a large sample of eighteen countries of the European Union examining the volatility as well as the return spillover of their corresponding stock market.

CHAPTER 1: FINANCIAL VOLATILITY AND ITS APPLICATIONS

1.1 Introduction to volatility and its role in the field of Economics and Finance

1.1.1 The Definition of volatility

It is useful to start with an explanation of what volatility is and to referred to its role in the field of Finance.

Volatility is a measure of dispersion around the mean or average return of a security. One way to measure volatility is by using the standard deviation, which denotes how tightly the price of a stock is grouped around the mean or moving average (MA). When the prices are tightly bunched together, the standard deviation is small. When the price is spread apart, we have a relatively large standard deviation. In other words, volatility refers to the spread of all likely outcomes of an uncertain variable. As described by modern portfolio theory (MPT), volatility creates risk that is associated with the degree of dispersion of returns around the average. The greater the chance of lower-than-expected return, the riskier the investment.

1.1.2 The role of volatility in the field of Economics and Finance

Financial markets and institutions play an important role in the economy by channelling funds from savers to investors. Some volatility in the prices of financial assets is a normal part of the process of allocating funds among competing uses. Excessive or extreme volatility of stock prices, interest rates, and exchange rates may be detrimental because such volatility may impair the smooth functioning of the financial system and adversely affect economic performance.

As far as stock market volatility is concerned**,** it can harm the economy of a country through a number of channels. Stock price volatility hinders economic performance through consumer spending. Stock price volatility may also affect business investment spending. Investors may perceive a rise in stock market volatility as an increase in the risk of equity investments. If so, investors may shift their funds to less risky assets. This reaction would tend to raise the cost of funds to firms issuing stock. Moreover, small firms and new firms might bear the brunt of this effect as investors gravitated toward the purchase of stock in larger, well-known firms. Extreme stock price volatility could also disrupt the smooth functioning of the financial system and lead to structural or regulatory changes.

In addition, like stock market volatility, extreme interest rate volatility may hurt economic performance and disrupt the smooth functioning of the financial system. One way in which interest rate volatility may harm the economy is through business investment spending. Investors may see an increase in the volatility of interest rates as an increase in the risk of holding bonds and other debt instruments. If investors shift their portfolios toward lower risk assets, firms may find it more costly to fund investment projects. The resulting fall in investment spending would reduce economic growth. Interest rate volatility could also have a direct impact on monetary policy. If higher rate volatility causes investors to change their investment portfolios, the demand for money may also change. To the extent that monetary policy is based on an assumed stable relationship between money and economic activity, changes in money demand due to rate volatility could complicate monetary policy. Greater interest rate volatility could also weaken the financial system if this volatility threatens the viability of financial intermediaries. Increased interest rate volatility is a serious problem for depository intermediaries, such as savings and loans that have long-term assets and short-term liabilities. An increase in interest rate volatility can lead to periodic liquidity crises for some of these institutions and may threaten the solvency of others. Regulatory actions, such as an increase in capital requirements, may be necessary to protect these institutions from increased volatility of interest rates.

Like volatility in the stock market and interest rates, exchange rate volatility may create uncertainty about future profits, which impairs long - term investment decisions. Companies involved in international trade may be reluctant to commit to long-term investment projects if they fear that exchange rate changes might significantly reduce profits. A second way that exchange rate volatility might impede international trade is through higher prices for exports and imports. If companies add a risk premium to the prices of internationally traded goods because of exchange rate uncertainty, consumers may reduce the amount of the higher priced goods they demand and slow the growth of world trade. Finally, exchange rate variability may alter international capital flows. Long-term capital flows may be reduced by greater exchange rate uncertainty, impeding the efficient flow of resources in the world economy. At the same time, increased exchange rate volatility may promote short-term, speculative capital flows. These speculative capital flows may complicate monetary policy. Central banks may be forced to intervene frequently in exchange markets or to adjust monetary policy to prevent these capital flows from having adverse effects on the domestic economy.

1.2 Modelling financial volatility

1.2.1 Introduction

Nowadays, the development in the financial econometrics requires the use of models that are able to model the attitude of investors not only towards expected returns but also towards the uncertainty - risk. This has as a result the construction of several models that are capable dealing with the volatility of the series, which we will present and analyse in this chapter. The ARCH - family models constitute one of the most important models, developed by outstanding econometricians.

Before proceeding to the analysis of these models, it would be better to refer first to one of the most puzzling issues of the behaviour of volatility, which is called volatility clustering. According to the latter, big changes in the returns of financial assets tend to be followed by other big changes and vice versa. The observations of earlier researchers have shown that economic as well as financial time series exhibit periods of high volatility followed by more tranquil periods of low volatility. In other words, there exist periods which are riskier than others and these risky periods are followed by periods with low volatility. Consequently the expected value of the magnitude of the disturbance terms is greater compared to others.

Therefore, in such cases the assumption of constant variance (homoskedasticity) is very limiting and as a result it is preferable to examine patterns that allow the variance to depend upon history. In other words, it is better to examine the conditional variance and not the unconditional variance which is the long – run forecast of the variance and can be still considered as constant. The models that we will present are focused on modelling the behaviour of conditional variance or the conditional heteroskedasticity.

Recent developments in financial econometrics suggest the use of nonlinear time series structures to model the attitude of investors toward risk and expected return. Precisely, **Bera and Higgins** (1993, p.315) remarked that "a major contribution of the ARCH literature is the finding that apparent changes in the volatility of economic time series may be predictable and as a result from a specific type of nonlinear dependence rather than exogenous structural changes in variables." **Campbell, Lo, and MacKinlay** (1997, p.481) argued that "it is both logically inconsistent and statistically inefficient to use volatility measures that are based on the assumption of constant volatility over some period when the resulting series moves through time." In the case of financial data, for example, large and small errors tend to occur in clusters, as we referred above. This suggests that returns are serially correlated. When dealing with nonlinearities, **Campbell, Lo, and MacKinlay** (1997) make the distinction between Linear Time Series and Nonlinear Time Series. Specifically, in Linear Time Series shocks are assumed to be uncorrelated but not necessarily identically independent distributed (iid).However, in Nonlinear Time Series shocks are assumed to be iid, but there is a nonlinear function relating the observed time series $\{X_t\}^{\infty}{}_{t=0}$ and the underlying shocks $\{u_t\}^{\infty}{}_{t=0}$

1.2.2 The ARCH model

The first model that proposed the concept of autoregressive heteroskedasticity was developed by **Robert F. Engle** in 1982 and constitutes the first step in the financial volatility forecasting. According to this model the variance of the residuals at time t depends on the squared error terms from past periods. Engle suggested that it is better to simultaneously model the mean and the variance of a series, when we suspect that the conditional variance is not constant. The conditional variance is a linear function of past squared residuals.

Considering the simple model $Y_t = a + \beta' X_t + u_t$, where X_t is a $k \times 1$ vector of explanatory variables and β is a $k \times 1$ vector of coefficients. We assume that u_t is white noise and it is independently distributed with a zero mean and a variance h_t or in mathematical notation $u_t / \Omega_t \sim iidN(0, h_t)$, where Ω_t is the information set.

Engle allows the variance of the residuals h_t to depend upon past information or to have heteroskedasticity, because the variance will change over time. One way of allowing for this is to have the variance depend on lagged periods of the squared error terms, as follows:

$$h_t = \gamma_0 + \gamma_1 u_{t-1}^2 + \gamma_2 u_{t-2}^2 + \ldots + \gamma_q u_{t-q}^2 = \gamma_0 + \sum_{j=1}^{q} \gamma_j u_{t-j}^2$$

This is the general ARCH (q) process.

Let's consider now the simple stationary model of the conditional mean of a series Y_t : $Y_t = a + \beta' X_t + u_t$ and decompose the u_t term in a systematic component and a random component as: $u_t = z_t h_t^{1/2}$ where z_t follows a standard normal distribution with zero means and variance one, and h_t is a scaling factor. In the basic ARCH (1) model we assume that $h_t = \gamma_0 + \gamma_1 u_{t-1}^2$. The process for y_t is now given by $y_t = a + \beta' x_t + z_t \sqrt{\gamma_0 + \gamma_1 u^2{}_{t-1}}$. From this expression it is easy to see that the mean of the residuals will be zero ($E(u_t) = 0$), because $E(z_t) = 0$. In addition, the unconditional (long – run) variance of the residuals will be given by the following formula: $Var(u_t) = E(z^2{}_t)E(h_t) = \frac{\gamma_0}{1-\gamma_1}$, which means that we need to impose the constraints $\gamma_0 > 0$ and $0 < \gamma_1 < 1$ in order to have stationarity.

An alternative form of the conditional (short – run) variance is $h_t = h(y_{t-1,}y_{t-2,}y_{t-3,}y_{t-4,}........., y_{t-p,}\gamma)$,where p denotes the order of the ARCH stochastic process and γ denotes a vector with unknown parameters. The regression ARCH models can be constructed assuming that the conditional mean of y_t is equal to $x_t \beta'$ and is a linear combination of lagged endogenous and exogenous variables that are all contained in the information set. In a more general formulation we can have the following

$y_t / \Omega_{t-1} \sim \ N(x_t \beta', h_t)$

$u_t = y_t - \beta' x_t$

$h_t = h(u_{t-1,}u_{t-2,}u_{t-3,}u_{t-4,}.........,u_{t-p,}\gamma)$

The ARCH regression model allow the conditional variance to be time varying and predictable. This plays an important role for studying a characteristic of forecasting procedures that has to do with the fact that the extent of uncertainty is a function of the time horizon that we use for conducting forecasts. This specification is also the mathematical representation of the empirical observation that the forecast errors tend to cluster through time and depending on their size.

We must underline that the intuition behind the ARCH (1) model is that the conditional (short – run) variance or volatility of the series is a function of the

immediate past values of the squared error term. In other words, the effect of each new shock z_t depends on the size of the shock in one lagged period. The ARCH process captures some of the properties of financial time series, such as the excess kurtosis of returns, the time varying volatility and the volatility clustering, that we referred to the introduction. The process is nonlinear in variance but linear in mean.
Before estimating ARCH (q) models it is important to check for the possible presence of ARCH effects in order to know which models require the ARCH estimation method instead of the OLS. The ARCH effects are used to denote the presence of autocorrelation in the second order moments process. The presence of ARCH effects has a relation with the efficient market hypothesis according to which the historical returns of financial assets cannot be used in order to achieve systematically abnormal returns in the future. The absence of autocorrelation in the returns means that there exist non linear relations governing the stochastic process of residuals which are in accordance with the efficiency of the markets. Non linearities in the innovations process can denote the presence of linear relations in the conditional (short - run) variance process of the errors. A possible source of volatility clustering effects is the autocorrelation in the news arrival process meaning that information arrives in the market, in clusters and not in uniformly distributed time points. This means that the stochastic process that describes the flow of information in the market is characterized by linear dependence with the quantity of information that reaches in the market.
Furthermore, extending the ARCH(1) process to ARCH(q) process which means adding additional, higher order lagged parameters as determinants of the variance of the residuals, we have the following expression: $h_t = \gamma_0 + \sum_{j=1}^{q} \gamma_j u_{t-j}{}^2$.

A significant remark is that ARCH (q) models are useful when the variability of the series is expected to change more slowly than in the ARCH(1) model. However, ARCH (q) models are quite often difficult to estimate, because they often yield negative estimates of the parameters γ_j s. To resolve this issue, a new model is introduced by Bollerslev (1986), which is the generalised ARCH (GARCH) model that we will analyse in the following section.
In the history of ARCH literature, interesting interpretations of process can be found. According to **Lamoureux and Lastrapes** (1990) the conditional heteroskedasticity may be caused by time dependence in the rate of information arrival to the market.

They use the daily trading volume of stock markets as a proxy for such information arrival, and confirm its significance. **Mizrach** (1990) associates ARCH models with the errors of the economic agents' learning processes. In this case, contemporaneous errors in expectations are linked with past errors in the same expectations, which is somewhat related with the old-fashioned "adaptable expectations hypothesis" in macroeconomics. Finally, the interpretation of **Stock** (1998) may be summarized by the argument that "any economic variable, in general, evolves an on 'operational' time scale, while in practice it is measured on a 'calendar' time scale. And this inappropriate use of a calendar time scale may lead to volatility clustering since relative to the calendar time, the variable may evolve more quickly or slowly" (Bera and Higgins, 1990, p.329; Diebold,1986].

1.2.3 The GARCH model

One of the drawbacks of the ARCH specification, according to Engle (1995), was that it looked more like a moving average specification rather than an autoregression. This is the reason that a new idea was emerged and was worked out by **Tim Bollerslev** (1986) concerning the inclusion of the lagged conditional variance terms as autoregressive terms, starting a new family of GARCH models. In other words, Bollerslev allowed on the one hand the past conditional variance to enter the conditional volatility ARCH model and on the other hand represent a new model reducing significantly the number of unknown parameters.

The general GARCH (p,q) model has the following form

$$Y_t = a + \beta' X_t + u_t$$

$$u_t / \Omega_t \sim iidN(0, h_t)$$

$$h_t = \gamma_0 + \sum_{i=1}^{p} \delta_i h_{t-i} + \sum_{j=1}^{q} \gamma_j u_{t-j}^{\ 2}$$

$\gamma_0 > 0$, $\gamma_j \geq 0$, j=1, 2 ,….q

$\delta_i \geq 0$, i=1,2,….p

$p \geq 0, q > 0$

Which denotes that the value of the variance scaling parameter h_t now depends both on past values of the shocks, which are captured by the lagged squared residual terms and on the past values of itself, which are captured by lagged h_t terms.

When p equals zero then the GARCH process is equivalent to an ARCH (q) process. If both p and q equal zero then $\{u_t\}$ is simply a white noise process. In contrast to the simple ARCH model where the conditional variance is a function of past realized volatility, in the GARCH specification the conditional is also a function of past conditional volatility which helps to formulate a better adapting learning mechanism for the volatility modeling procedure.

The simplest form of the GARCH (p,q) model is GARCH (1,1) model for which the variance equation has the following form $h_t = \gamma_0 + \delta_1 h_{t-1} + \gamma_1 u_{t-1}{}^2$. This model specification usually performs well and it is easy to estimate because it has only three parameters.

The conditional variance model for GARCH (1, 1) is expressed as following

$$h_t = \gamma_0 + \delta h_{t-1} + \gamma_1 u_{t-1}{}^2$$

Successive substitutions into the right – hand side gives

$$h_t = \gamma_0 + \delta h_{t-1} + \gamma_1 u_{t-1}{}^2$$

$$= \gamma_0 + \delta(\gamma_0 + \delta h_{t-2} + \gamma_1 u_{t-2}{}^2) + \gamma_1 u_{t-1}{}^2$$

$$= \gamma_0 + \gamma_1 u_{t-1}{}^2 + \delta\gamma_0 + \delta^2 h^2{}_{t-2} + \delta\gamma_1 u_{t-2}{}^2$$

$$= \gamma_0 + \gamma_1 u_{t-1}{}^2 + \delta\gamma_0 + \delta^2(\gamma_0 + \delta h_{t-3} + \gamma_1 u_{t-3}{}^2) + \delta\gamma_1 u_{t-2}{}^2$$

……………………….

$$= \frac{\gamma_0}{1-\delta} + \gamma_1(u_{t-1}{}^2 + \delta u_{t-2}{}^2 + \delta^2 u_{t-3}{}^2 + \ldots.)$$

$$= \frac{\gamma_0}{1-\delta} + \gamma_1 \sum_{j=1}^{\infty} \delta^{j-1} u^2{}_{t-j}$$

which shows that the GARCH (1,1) model is equivalent to an infinite order ARCH model with coefficients that decline geometrically.

There are many alternative specifications that model conditional volatility. One of them is the GARCH in mean or GARCH – M model, which allows the conditional mean to depend on its own conditional variance. This model has an application when, example, investors are risk averse and require a premium in order to buy a risk asset. That premium is a positive function of the risk. If the risk is captured by the volatility or by the conditional variance, then the conditional variance may enter the conditional mean function $Y_{t.}$

As a result, the GARCH- M (p,q) model is expressed as

$$Y_t = a + \beta' X_t + \vartheta h_t + u_t$$

$$u_t / \Omega_t \sim iidN(0, h_t)$$

$$h_t = \gamma_0 + \sum_{i=1}^{p} \delta_i h_{t-i} + \sum_{j=1}^{q} \gamma_j u_{t-j}^{\ 2}$$

An alternative expression of the GARCH- M (p,q) model is the following

$$Y_t = a + \beta' X_t + \vartheta \sqrt{h_t} + u_t$$

$$u_t / \Omega_t \sim iidN(0, h_t)$$

$$h_t = \gamma_0 + \sum_{i=1}^{p} \delta_i h_{t-i} + \sum_{j=1}^{q} \gamma_j u_{t-j}^{\ 2}$$

which relates the risk not with the variance series but with the standard deviation of the series.

These models have a number of financial applications, especially in the asset pricing, like the Capital Asset Pricing Models (CAPM).

Concluding our presentation of the ARCH / GARCH family of models we would like to mention a weakness of these parameterizations. This restriction lies on the fact that these models are symmetric. In other words, what matters is only the absolute value of the innovation and not its sign, as the residual term is squared. When we estimate an ARCH / GARCH model, a big positive shock will have exactly the same effect in the volatility of series as a big negative shock of the same magnitude. However, in the actual capital market, a negative shock in the market, which entails bad news for this market, have a greater impact on volatility, rather than a positive shock, which is related with good news.

Therefore, **Zakoian** (1990) and **Glosten**, **Joganathan** & **Runkle** (1993) introduced a new model which is called TGARCH model (Threshold GARCH model), in order to capture the asymmetries for determine and influence the conditional volatility. The conditional variance of the Threshold GARCH (p,q) model has the following form

$$h_t = \gamma_0 + \sum_{i=1}^{p} (\gamma_i + v_i d_{t-i}^{\ 2}) u^2{}_{t-i} + \sum_{j=1}^{q} \delta_j h_{t-j}$$

Another model that was introduced in order to capture the asymmetries in terms of positive and negative shocks, the exponential GARCH (EGARCH) model. This model was first developed by **Nelson (**1991). This new model allows for a different impact of good/bad news in volatility. In this specification we have two features. On the one hand negative shocks can have a stronger impact in the conditional Volatility forecast compared with positive shocks of the same magnitude and on the other hand powerful shocks have a bigger effect in the Volatility process compared with the effects of the same shocks when using the GARCH model.

The conditional variance equation of this model is given by:

$$\log(h_t) = \gamma + \sum_{j=1}^{q} \zeta_j \left| \frac{u_{t-j}}{\sqrt{h_{t-j}}} \right| + \sum_{j=1}^{q} \xi_j \frac{u_{t-j}}{\sqrt{h_{t-j}}} + \sum_{i=1}^{p} \delta_j \log(h_{t-i})$$

Since the left – hand side is the logarithm of the variance series, this makes the leverage effect exponential instead of quadratic and therefore the estimates of the conditional variance ate non – negative. The parameters ξs are used to test for asymmetries. If $\xi_1 = \xi_2 = ... = 0$, then the model is symmetric. If ξs are negative, then positive shocks (good news) generate less volatility than negative shocks (bad news).

CHAPTER 2: VECTOR AUTOREGRESSIVE (VAR) MODELS AND CAUSALITY TESTS

2.1 Vector Autoregressive models

In the field of Economics, there exist models where some variables are not only explanatory variables for a given dependent variable, but they are also explained by the variables that they are used to determine. This has as a result to have models of simultaneous equations, in which there are on the one hand variables that are endogenous and on the other hand variables that are exogenous or predetermined. However, this differentiation among variables was criticised by **Sims** (1980), who argued that if there exist simultaneity among the variables, then these variables should be treated in the same way and there should not be a distinction between endogenous and exogenous variables. Therefore, once this distinction is abandoned, all variables are treated as endogenous. This means that in its general reduced form, each equation has the same set of regressors which leads to the development of the VAR models.

The vector autoregression (VAR) model is one of the most successful, flexible and easy to use models for the analysis of multivariate time series. It is a natural extension of the univariate autoregressive model to dynamic multivariate time series. The VAR model has proven to be especially useful for describing the dynamic behaviour of economic and financial time series and for forecasting. It often provides superior forecasts to those from univariate time series models and elaborate theory-based simultaneous equations models. Forecasts from VAR models are quite flexible because they can be made conditional on the potential future paths of specified variables in the model.

In addition to data description and forecasting, the VAR model is also used for structural inference and policy analysis. In structural analysis, certain assumptions about the causal structure of the data under investigation are imposed, and the resulting causal impacts of unexpected shocks or innovations to specified variables on the variables in the model are summarized. These causal impacts are usually summarized with impulse response functions and forecast error variance decompositions.

Let $Y_t = (y_{1t} y_{2t}, ...y_{nt})'$ denotes a ($n \times 1$) vector denote of time series variables. The basic p-lag vector autoregressive (VAR (p)) model has the following form

$$Y_t = c + \Pi_1 Y_{t-1} + \Pi_2 Y_{t-2} + ...\Pi_p Y_{t-p} + u_t,\ t = 1,2,....T$$

where Π_i are $n \times n$ coefficient matrices and u_t is an (n×1) unobservable zero mean white noise vector process, serially uncorrelated or independent with time invariant covariance matrix Σ.

For example, a bivariate VAR (2) model equation by equation has the form

$$\begin{pmatrix} y_{1t} \\ y_{2t} \end{pmatrix} = \begin{pmatrix} c_1 \\ c_2 \end{pmatrix} + \begin{pmatrix} \pi_{11}^1 & \pi_{12}^1 \\ \pi_{21}^1 & \pi_{22}^1 \end{pmatrix} \begin{pmatrix} y_{1t-1} \\ y_{2t-1} \end{pmatrix} + \begin{pmatrix} \pi_{11}^2 & \pi_{12}^2 \\ \pi_{21}^2 & \pi_{22}^2 \end{pmatrix} \begin{pmatrix} y_{1t-2} \\ y_{2t-2} \end{pmatrix} + \begin{pmatrix} u_{1t} \\ u_{2t} \end{pmatrix}$$

Or

$$y_{1t} = c_1 + \pi_{11}^1 y_{1t-1} + \pi_{12}^1 y_{2t-1} + \pi_{11}^2 y_{1t-2} + \pi_{12}^2 y_{2t-2} + u_{1t}$$

$$y_{2t} = c_2 + \pi_{21}^1 y_{1t-1} + \pi_{22}^1 y_{2t-1} + \pi_{21}^2 y_{1t-2} + \pi_{22}^2 y_{2t-2} + u_{2t}$$

where $\text{cov}(u_{1t}, u_{2t}) = \sigma_{12}$ for t = s; 0 otherwise.

We can notice that each equation has the same regressors - lagged values of y_{1t} and y_{2t}. Hence, the VAR (p) model is just a seemingly unrelated regression model with lagged variables and deterministic terms as common regressors.

In lag operator notation, the VAR (p) is written as :

$\Pi(L)Y_t = c + u_t$ where $\Pi(L) = I_n - \Pi_1 L - ...... - \Pi_p L^p$ The VAR(p) is stable if the roots of $\det(I_n - \Pi_1 z - ...... - \Pi_p z^p) = 0$ lie outside the complex unit circle (have modulus greater than one), or, equivalently, if the eigenvalues of the companion matrix

$$F = \begin{pmatrix} \Pi_1 & \dots & \Pi_n \\ I_n & \dots & 0 \\ 0 & \ddots & \vdots \\ 0 & \cdots & 0 \end{pmatrix}$$

have modulus less than one. Assuming that the process has been initialized in the infinite past, then a stable VAR (p) process is stationary and ergodic with time invariant means, variances, and autocovariances.

If Y_t is covariance stationary, then the unconditional mean is given by

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

The mean-adjusted form of the VAR (p) is then

$$Y_t - \mu = \Pi_1(Y_{t-1} - \mu) + \Pi_2(Y_{t-2} - \mu) + ...\Pi_p(Y_{t-p} - \mu) + u_t$$

The basic VAR (p) model may be too restrictive to represent sufficiently the main characteristics of the data. In particular, other deterministic terms such as a linear time trend or seasonal dummy variables may be required to represent the data properly. Additionally, stochastic exogenous variables may be required as well. The general form of the VAR (p) model with deterministic terms and exogenous variables is given by $Y_t = \Pi_1 Y_{t-1} + \Pi_2 Y_{t-2} + ... + \Pi_p Y_{t-p} + \Phi D_t + GX_t + u_t$

where D_t represents an (l × 1) matrix of deterministic components, X_t represents an (m × 1) matrix of exogenous variables, and Φ and G are parameter matrices.

To sum up, we will analyse briefly the advantages and disadvantages of the VAR model. Precisely, the VAR model approach has some very good characteristics, as it is very simple and the econometricians do not need to worry about which variables are endogenous or exogenous. Estimating the model is a very simple procedure because each equation can be estimated with the OLS method, separately. According to **Mahmoud** (1984) and **McNees** (1986), the forecasts obtained from VAR models are in most cases better than those obtained from the far more complex simultaneous equation models.

Apart from the advantages, VAR models face several drawbacks. Firstly, they are a-theoretic since they are not based on any economic theory. Since the estimated parameters do not have any restrictions, 'everything causes everything'. However, statistical interference is often used in the estimated models. Another disadvantage constitutes the loss of degrees of freedom. If we suppose that we have a three – variable VAR model and we decide to include 12 lags for each variable in each equation, this will entail estimation of 36 parameters in each equation plus the equation constant. If the sample size is not sufficiently large, estimating that large a number of parameters will consume many degrees of freedom, creating problems in estimation. A third drawback is that the obtained coefficients of the VAR models are difficult to interpret since they totally lack any theoretical background. On the other hand, advocates of VAR models estimate so - called impulse response functions, which examine the response of the dependent variable in the VAR to shocks in the error terms. The difficult issue, here, is to defining the shocks.

2.2 Causality Tests

As we analysed in the first section, one of the good futures of VAR models is that they allow us to test for the direction of causality. Causality in econometrics is somewhat different to the concept in everyday use; it refers more to the ability of one variable to predict and as a result cause the other.

2.2.1 The Granger Causality Test

One of the most influential econometricians in the concept of Causality is **Clive Granger** (1969), who developed a relatively simple test that defined causality as follows: a random variable Y_t is said to Granger - cause X_t, if X_t can be predicted with greater accuracy by using past values of the Y_t variable rather than not using such past values, all other terms remaining unchanged.

In other words, the random variable Y_t causes X_{t+1} when the following relation is in effect, $\Pr ob(X_{t+1} \in A / \Omega_t) \neq \Pr ob(X_{t+1} \in A / \Omega_t - Y_t)$, with A being the set that contains all the possible values that X can take, and Ω being the information set (or σ-algebra) involving the maximum available information regarding the history of these two random variables. Thus a causal relation with direction from Y to X will exist when Y_t contains some kind of information regarding the values that X_{t+1} can take. The whole theory on Causality depends on the fundamental axiom that the past or the present can influence the future. We will analyze now the Granger Causality between two random variables. The Granger Causality Test for the case of two stationary variables Y_t and X_t, involves as a first step the estimation of VAR model, that we have discussed in the first section of this chapter and secondly the checking of the significance of the coefficients. In the field of Statistics and Econometrics the existence of deterministic relations is a Utopia and as a result it must be satisfied with the derivation of stochastic causal relations. So we will say that event A will possibly, but not certainly happen when event B is realized.

As originally specified, the general formalization of Granger (1969) causality for the case of two scalar-valued, stationary, and ergodic time series $\{X_t\}$ and $\{Y_t\}$ is defined as follows: We consider $F(X_t / I_{t-1})$ the conditional probability distribution of X_t, given the bivariate information set I_{t-1}, consisting of an Lx-length lagged vector of X_t : $X_{t-Lx}^{Lx} \equiv (X_{t-Lx}, X_{t-Lx+1}, ...X_{t-1})$ and an Ly-length lagged vector of $Y_t : Y_{t-Ly}^{Ly} \equiv (Y_{t-Ly}, Y_{t-Ly+1}, ...Y_{t-1})$

Given lags Lx and Ly, the time series $\{Y_t)$ does not strictly Granger cause $\{X_t\}$ if

$$F(X_t / I_{t-1}) = F(X_t /(I_{t-1} - Y_{t-Ly}^{Ly})), t = 1, 2, ...$$

If the equality in the above equation does not hold, then knowledge of past Y values helps to predict current and future X values, and Y is said to strictly Granger cause X. Similarly, a lack of instantaneous Granger causality from Y to X occurs if $F(X_t / I_{t-1}) = F(X_t /(I_{t-1} + Y_t)), t = 1, 2, ...,$ where the bivariate information set is modified to include the current value of Y. If the equality in the above equation does not hold, then Y is said to instantaneously Granger cause X.

As shown in the two above equations strict Granger causality relates to the past of one time series influencing the present and future of another time series, whereas, instantaneous causality relates to the present of one time series influencing the present of another time series. Due to problems in distinguishing between instantaneous causality and instantaneous feedback, we consider only strict Granger causality.

Apart from the specification of the Granger Causality Test that we referred above, it is important to analyze in a few lines the problems that occur during the examination of causal relations. The frequency of the empirical data that sometimes cannot be exclusively determined by the researcher and depends also on the nature and availability of this kind of data can in some occasions lead to misleading results regarding the type of Causality. In addition, the omission of important exogenous explanatory variables from the econometric models used during the Causality tests can lead once more to biased results. Finally, the time period in which we measure a certain variable may differ from the time period that an event that led this variable to take the measured value, has been realized. This happens especially in the field of Finance. In the following section we will introduce briefly an alternative test, the Sims Causality Test.

2.2.2 The Sims Causality Test

An alternative test for causality was proposed by Sims (1980). Sims made use of the fact that in any general notion of causality it is not possible for the future to cause the present and suggests estimating the following VAR model:

$$Y_t = a_1 + \sum_{i=1}^{n} \beta_i x_{t-i} + \sum_{j=1}^{m} \gamma_j y_{t-j} + \sum_{\rho=1}^{k} \zeta_\rho x_{t+\rho} + u_{1t}$$

$$X_t = a_2 + \sum_{i=1}^{n} \theta_i x_{t-i} + \sum_{j=1}^{m} \delta_j y_{t-j} + \sum_{\rho=1}^{k} \xi_\rho y_{t+\rho} + u_{2t}$$

The new approach is that apart from lagged values of x and y, there exist also leading values of x included in the first equation and similarly leading values of y in the second equation. Examining only the first equation, if Y_t causes X_t then we will expect that there is some relationship between y and the leading values of x.

2.3 Causality in Variance Tests

2.3.1 Introduction to Causality in Variance Tests

During the last two decades, a great deal of attention has been paid to modelling the dynamic properties of volatility. An important strand of this research has analysed volatility spillovers, particularly across financial series. **Morgenstern** (1959) first investigated if financial market crises spill over to other countries. The modelling of spill over effects has subsequently been developed primarily through correlation analysis based on GARCH models, including **King and Wadhwani** (1990), **Lin, Engle and Ito** (1994), **Susmel and Engle** (1994), **Ng** (2000) and **Billio** & **Pelizzon** (2003). These papers estimate parametric models to examine specific formulations for the spillover effects, while **Cheung and Ng** (1996) and **Hong** (2001) that we will analyse in this chapter develop general causality-in-variance tests within this framework. In addition, **Comte & Lieberman** (2000) give two new definitions as far as the causality in variance is concerned. The first one is of a Granger-type and the second one is a linear version of the Granger non causality through projections on Hilbert spaces. Both definitions acquire a more mathematical structure regarding the multivariate ARMA processes with GARCH-type errors. They show that second-order noncausality leads to exact testable restrictions on the parameters of the general class of VARMA models with GARCH-type errors. In principle, then, any of the likelihood-based tests, such as the Likelihood Ratio Test, the Lagrange Multiplier Test and the Wald Tests can be conducted in order to detect the existence and the direction of any causal relations in the second moments. They have used daily returns of dually listed stocks in the Tel Aviv and New York stock exchange as well as the returns of the general index of the Tel Aviv stock market from June 1988 until March 1998. Owning to the non overlapping trading in the two equity markets, it is possible to investigate the effects of the Volatility of the American stock market on the Israeli market and they proved the existence of a statistically important causal relation in the volatilities of the two markets.

In the previous decade there has been increasing interest in the causation in conditional variance across various financial asset price movements. The causality in variance has both economic and statistical significance. We must underline that changes in variance are said to reflect the arrival of information and the extent to which the market evaluates and assimilates new information. **Ross** (1989) shows that in a no-arbitrage economy the variance of price changes is directly related to the rate of information flow to the market. Under this framework, we can interpret the transmission of volatility as a result of information transmission among the markets or other variables. A good understanding of the origins and transmission intensity of shocks is necessary for many financial decisions, including optimal asset allocation, the construction of global hedging strategies, as well as the development of various regulatory requirements, like capital requirements or capital controls. If two capital markets are informationally efficient then it will not be expected to observe any volatility spillovers between them. The observed interactions among the international markets are not of the intensity and power that one would expect, because of the low cost of information, the globalization of the financial markets and the simplicity of conducting financial transactions in various different places around the world. We must not however surge to decide whether the capital markets are efficient. The absence of volatility spillovers may in fact be attributed to the varying construction methods of the stock indices used in empirical studies or to differences in industrial structures and foreign exchange policies across the different international markets.

2.3.2 The Cheung & Ng Test

This methodology was proposed by **Cheung & Ng** (1996) for testing the null hypothesis of non causality in Variance between two time series. The test is based on the residual cross-correlation function (CCF), which was first introduced by **Haugh** (1976) and afterwards by **McLeod and Li** (1983). According to them, a two stage methodology for testing the interdependence between two covariance stationary time series with homoscedastic errors is designed. The first stage involves the estimation of univariate time-series models that allows for time variation in both conditional means and conditional variances. In the second stage the resulting series of squared residuals standardized by conditional variances are constructed. The cross-correlation function (CCF) of these squared-standardized residuals is then used to test the null hypothesis of no causality in variance.

Cheung & Ng (1996) have developed a technique based on the two step CCF approach. In the first step they estimate univariate ARMA / GARCH models and obtain the squared standardized innovations and in the second step they estimate the CCF and test for the significance of the various cross correlation coefficients being able in this way to detect any possible volatility spillovers between the two series studied. They also analysed the effect of causality in mean, if any, by simply using the standardized residuals instead of their squares, as input in the CCF, on tests for causality in variance and the interaction between the tests for causality in mean and variance. Depending on model specifications, causation in mean can exist with or without the presence of causality in variance and vice versa.

The concept of causation in the second moment (in variance) can be viewed as a natural extension of the Granger causality in mean, that we referred to. We consider two stationary and egordic time series X_t and Y_t, and two information sets that are generated as following

$$I_t = \{X_{t-j}, j \geq 0\}$$

$$J_t = \{X_{t-j}, Y_{t-j}, j \geq 0\}$$

which means that $I_t \subseteq J_t$. Y_t is said to Granger cause X_{t+1} if exists the following relation

$$E\{(X_{t+1} - \mu_{x,t+1})^2 / I_t\} \neq E\{(X_{t+1} - \mu_{x,t+1})^2 / J_t\}$$

where $\mu_{x,t+1}$ is the mean of X_{t+1} conditioned on the σ –algebra I_t.

There exists feedback in variance when X causes Y and simultaneously Y causes X.

There is instantaneous causality in variance if

$$E\{(X_{t+1} - \mu_{x,t+1})^2 / J_t\} \neq E\{(X_{t+1} - \mu_{x,t+1})^2 / J_t + Y_{t+1}\}$$

As in the case of causality in mean, the concepts defined in the above two relations are too general to be empirically testable. This is the reason why additional structure is required in order to make the general causality concept applicable in practice. This will be done in the framework of specific econometric models.

$X_t = \mu_{X,t} + h_{x,t}^{0.5}\varepsilon_t$

$Y_t = \mu_{Y,t} + h_{y,t}^{0.5}\zeta_t$

where $\{\varepsilon_t\}$ and $\{\zeta_t\}$ are two independent white noise processes with zero mean and unit variance. Their conditional means and variances are given by the following relations

$$\mu_{z,t} = \sum_{i=1}^{\infty} \phi_{z,i}(\theta_{z,\mu}) Z_{t-i}$$

$$h_{z,t} = \phi_{z,0} + \sum_{i=1}^{\infty} \phi_{z,i}(\theta_{z,h})\{(Z_{t-i} - \mu_{z,t-i})^2 - \phi_{z,0}\}$$

where

- $\theta_{z,w}$ is a $p_{z,w} \times 1$ parameter vector
- W = μ, h and Z= X, Y
- $\phi_{z,i}(\theta_{z,\mu})$ is a uniquely defined function of $\theta_{z,\mu}$
- $\phi_{z,i}(\theta_{z,h})$ is a uniquely defined function of $\theta_{z,h}$
- $\mu_{z,t} = \sum_{i=1}^{\infty} \phi_{z,i}(\theta_{z,\mu}) Z_{t-i}$ is the ARMA model
- $h_{z,t} = \phi_{z,0} + \sum_{i=1}^{\infty} \phi_{z,i}(\theta_{z,h})\{(Z_{t-i} - \mu_{z,t-i})^2 - \phi_{z,0}\}$ is the GARCH model

We can now obtain the squared standardised innovations by estimating the above models. Let U_t and V_t be the squares of standardized innovations, with the following relations

$U_t = ((X_t - \mu_{x,t})^2 / h_{x,t}) = \varepsilon_t^2$

$V_t = ((Y_t - \mu_{y,t})^2 / h_{y,t}) = \zeta_t^2$

These residuals will be used in the next step as inputs for the estimation of the Cross Correlation Function. The CCF is calculated through the sample cross correlation coefficients. For example the sample cross correlation at lag k, $r_{uv}(k)$ is computed from the following equation

$$r_{uv}(k) = C_{uv}(k)\{C_{uu}(0)C_{vv}(0)\}^{-1/2}$$

with

- $C_{uu}(0)$ constitutes the sample variance of U

- $C_{vv}(0)$ constitutes the sample variance of V
- $C_{uv}(k)$ constitutes the kth lag sample cross covariance at lag k
- $C_{uv}(k) = T^{-1}\sum (U_t - \overline{U})(V_{t-k} - \overline{V}), k = 0, \pm 1, \pm 2, ...$

Given now the assurance that the second order moments of the squared standardized innovations are existent and finite and in combination with the hypothesis that these two residual series are independent we will have that

$$\begin{pmatrix} \sqrt{T}r_{uv}(k) \\ \sqrt{T}r_{uv}(k^{'}) \end{pmatrix} \sim AN\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{pmatrix} 1 & 0 \\ 1 & 0 \end{pmatrix}, k \neq k^{'}$$

Consequently a proper Causality in Variance test can be constructed. Owning to that the squared standardized residuals U_t and V_t are not observable, we should use their estimators. This means that we will finally use the sample estimators of the CCF $\hat{r}_{uv}(k)$ in order to test the null hypothesis of non Causality in Variance. Therefore we will have that $\hat{\theta}_z \equiv \{\hat{\theta}_{z,\mu}, \hat{\theta}_{z,h}, \hat{\phi}_{z,0}\}$ is the consistent estimator of the parameter $\theta_z^0 \equiv \{\theta_{z,\mu}^0, \theta_{z,h}^0, \phi_{z,0}^0\}$ and $Z = X, Y$, $\theta^0 = (\theta_x^0, \theta_y^0)$, $\hat{\theta} = (\hat{\theta}_x^0, \hat{\theta}_y^0)$ and $\theta = (\theta_x, \theta_y)$

Then $\hat{r}_{uv}(k)$ is defined as

$\hat{r}_{uv}(k) = r_{uv}(k)$ with $\theta = \hat{\theta}$

All the above results in combination with the fact that the asymptotic distribution of the CCF estimator is already known, the following test statistics can be constructed which follow either the standard normal or the chi-square distribution.

- One test statistic that we can use is the following:

  $S_N = \sqrt{T}\,\hat{r}_{uv}(k)$ which follows the standard normal distribution N(0,1)

The above test statistic is used to test the significance of a cross correlation coefficient at a specified lag.

- Another test statistic that we can use is the following:

  $S = T\sum_{i=j}^{k} \hat{r}_{uv}(i)^2$ which follows a chi-square distribution with (k - j + 1) degrees

of freedom

Using the above test function we can check for the joint existence of Causality from lag j up to lag k. We must underline that the choice of the values of indicators j and k will depend from the exact form of the alternative hypothesis. When we do not know in advance the direction of Causality it is preferable to conduct a bidirectional test setting -j = k = m. In the opposite case that we want to test for a specific direction in Causality for example whether y causes χ then we should set j =1 and k = m. It is also necessary to note the importance of the correct specification of the ARMA / GARCH models. In order to test whether a proper specification has been done a usual post estimation test is that based on the **Ljung-Box** Q-statistics (1978) on the standardized and squared standardized residuals.

- A third test statistic which is optimized for using with smaller samples is the following

  $S_M = T\sum_{i=j}^{k} \omega_i \hat{r}_{uv}(i)^2$ to attain a more accurate small-sample approximation to

the chi- square distribution, where $\omega_i = (T+2)/(T-|i|)$

- Finally, a fourth test statistic given by

  $S^* = T\sum_{k=-m}^{m-j}[\sum_{k=-m}^{m-j}\hat{r}_{uv}(k+i)]^2, i = 0,1,....m-1$ can be used to detect certain cross-correlation samples.

The existence of causality in mean violates the independence assumption and hence may affect the CCF test. Whether the causality in mean (variance) has any potential effect on the test for causality in variance (mean) depends on the model specification. For example, in a GARCH model, the conditional variance is driven by the squared innovations. As the causality in mean is associated with causality in the innovation term, it is likely that the former can have an effect on the size of the causality-in-variance test. Its conditional mean, however, does not necessarily depend on the variance. Hence the causality in variance may have a possible, but smaller, effect on the causality-in-mean test. The conditional mean of a GARCH-in mean model, on the other hand, is a function of the conditional variance. In this case the causality in variance is likely to have a potentially larger impact on the causality-in-mean test.

The Cheung & Ng methodology does not demand the simultaneous modeling of inter and intra series dynamics that renders it much easier to use. In addition, there exists a greater degree of uncertainty in regard with the correct specification of a multi dimensional model as well as with the asymptotic properties of its Maximum Likelihood Estimators. This methodology is robust to nonsymmetric, leptokurtic and nonnormal errors as well as to distributional assumption. In conclusion, it would be of interest to develop causality – in – variance test in a multivariate framework.

To sum up, Cheung and Ng (1996) test and Granger (1969)-type regression-based test can be viewed as uniform weighting because they give equal weighting to each lag. Specifically, Cheung and Ng (1996) test is based on the sum of finitely many squared sample cross-correlations, which has a null asymptotically chi –square distribution. This test is relatively simple and convenient to implement, and can provide valuable information in building multivariate GARCH models.

2.3.3 The Hong Test

The methodology developed by **Hong** (2001) constitutes an extensively modified version of the Cheung & Ng Test. Hong uses weighting functions inside the test functions. He states that there exists an inverse relation between the lag length and the weight that must be given to the corresponding cross correlation coefficient. In other words, larger weights are given to lower order lags.

Let's now assume that we have two strictly stationary time series

$\{Y_{1t,}Y_{2t}\}$ with $t \in (-\infty, +\infty)$.

Let's also consider the following information sets

- $I_{it}, i = 1,2$ which is the information set of time series $\{Y_{it}\}$ at period t
- $I_t = (I_{1t}, I_{2t})$

According to Granger,

- Y_{2t} is said to Granger cause Y_{1t} if $\Pr ob(Y_{1t} / I_{1t-1}) \neq \Pr ob(Y_{1t} / I_{t-1})$
- Y_{1t} is said to Granger cause Y_{2t}, if $\Pr ob(Y_{2t} / I_{1t-1}) \neq \Pr ob(Y_{2t} / I_{t-1})$

The null hypothesis is the non causality in variance between two time series

$H_0 : E\{(Y_{1t} - \mu_{1t}^0)^2 / I_{1t-1}\} = E\{(Y_{1t} - \mu_{1t}^0)^2 / I_{t-1}\} \equiv Var(Y_{1t} / I_{t-1})$

and the alternative hypothesis is the following

$H_1 : E\{(Y_{1t} - \mu_{1t}^0)^2 / I_{1t-1}\} = E\{(Y_{1t} - \mu_{1t}^0)^2 / I_{t-1}\} \neq Var(Y_{1t} / I_{t-1})$

The three different possible types of causal relations in Variance are the following :

1. Unidirectional Volatility Spillover

If H_0 is accepted then Y_{2t} does not Granger causes in variance Y_{1t}

If H_0 is rejected then Y_{2t} Granger causes in variance Y_{1t}

2. Feedback in Variance

If Y_{1t} Granger causes in variance Y_{2t} and H_0 Y_{2t} Granger causes in variance Y_{1t}

3. Instaneous Causality in Variance

$E\{(Y_{1t}-\mu_{1t}^0)^2 / I_{t-1}\} \neq E\{(Y_{1t}-\mu_{1t}^0)^2 / I_{1t-1}, I_{2t}\}$

Let's now continue with the procedure of Hong test. Consider the disturbance processes $\varepsilon_{it} = Y_{it} - \mu_{it}^0, i = 1,2$ where $\mu_{it}^0 = E(Y_{it} / I_{t-i})$.

The underlying generating mechanism of residuals is $\varepsilon_{it} = \xi_{it}(h_{it}^0)^{0.5}$ where h_{it}^0 is the conditional volatility and $\{\xi_{it}\}$ is an innovation process (standardised residuals). Specifically,

- For $\{\xi_{it}\}$, $E(\xi_{it} / I_{it-1}) = 0$ a.s. and $E(\xi^2{}_{it} / I_{it-1}) = 1$ a.s.
- For $\varepsilon_{it} = \xi_{it}(h_{it}^0)^{0.5}$, $E(\varepsilon_{it} / I_{it-1}) = 0$ a.s. and $E(\varepsilon^2{}_{it} / I_{it-1}) = 1$ a.s.

Therefore, the null and alternative hypothesis can be rewritten in the following forms:

$H_0 : Var(\xi_{1t} / I_{it-1}) = Var(\xi_{1t} / I_{t-1})$

$H_1 : Var(\xi_{1t} / I_{it-1}) \neq Var(\xi_{1t} / I_{t-1})$

We can test H_0 by checking if ξ_{2t} Granger – cause ξ_{1t} in variance with respect to I_{t-1}

Analytically,

- If H_0 is accepted then ξ_{2t} does not Granger causes in variance ξ_{1t}
- If H_0 is rejected then ξ_{2t} Granger causes in variance ξ_{1t}

The model specifications that will be used throughout the tests are the following:

- Conditional mean: $\mu_{it}^0 = \mu_{it}^0(b_i^0), i = 1,2$
- Conditional variance: $h_{it}^0 = \omega_i^0 + \sum_{j=1}^{q} a_{ij}^0 \varepsilon_{it-j}^2 + \sum_{j=1}^{q} \beta_{ij}^0 h_{it-j}^0$, which follows a GARCH (p,q) process
- The Vector Stochastic Process : $\{Y_t\}_{t\geq 1}$, where $Y_t = (Y_{1t}, Y_{2t})'$
- $\hat{\theta}_i = (\hat{b}_i', \hat{\omega}_i, \hat{a}_i', \hat{\beta}_i',)'$ is the consistent estimator of $\theta_i = (b_i^{0'}, \omega_i^0, a_i^{0'}, \beta_i^{0'})$, where

$\beta_i = (\beta_{1i}^0, \ldots \beta_{pi}^0)'$ and $a_i = (a_{1i}^0, \ldots a_{pi}^0)'$

From the estimation of the above models we can obtain the centralized squared standardized innovations.

- $\hat{u}_t \equiv u_t(\hat{\theta}_1) = (\hat{\varepsilon}_{1t}^2 / \hat{h}_{1t}) - 1$
- $\hat{v}_t \equiv v_t(\hat{\theta}_2) = (\hat{\varepsilon}_{2t}^2 / \hat{h}_{2t}) - 1$

where $\hat{\varepsilon}_{it} \equiv \varepsilon_{it}(\hat{\theta}_i)$, $\hat{h}_{it} \equiv h_{it}(\hat{\theta}_i)$ respectively.

$\varepsilon_{it}(\hat{\theta}_i)$ is the estimator of $\varepsilon_{it}(\theta_i) = Y_{it} - \mu_{it}(b_i)$

where $h_{it}(\theta_i) = \omega_i + \sum_{j=1}^{q} a_{ij}\varepsilon_{it-j}^2(\theta_i) + \sum_{j=1}^{q} \beta_{ij} h_{it-j}(\theta_j)$.

These residuals will be subsequently used as input for the estimation of CCF. The cross correlation function that was proposed by Cheung & Ng is calculated through the following procedure $\hat{\rho}_{uv}(j) = \{\hat{C}_{uu}(0)\hat{C}_{vv}(0)\}^{-1/2}\hat{C}_{uv}(j)$, where the sample cross – covariance function

$$\hat{C}_{uv}(j) = \begin{cases} T^{-1}\sum_{t=j+1}^{T} \hat{u}_t \hat{v}_{t-j}, \; j \geq 0 \\ T^{-1}\sum_{t=-j+1}^{T} \hat{u}_{t+j} \hat{v}_t, \; j < 0 \end{cases}$$

and $\hat{C}_{uu}(0) = T^{-1}\sum_{t=1}^{T} \hat{u}_t^2$, $\hat{C}_{vv}(0) = T^{-1}\sum_{t=1}^{T} \hat{v}_t^2$.

The key feature of volatility clustering is that a high volatility “today” tends to be followed by another high volatility “tomorrow”, and a low volatility “today” tends to be followed by another low volatility “tomorrow”, as we discussed in the first chapter. Recent past volatility often has greater impact on current volatility than distant past volatility. In general, this property carries over to volatility spillover between two assets or markets: the current volatility of an asset or market is more affected by the recent volatility of the other asset or market than by the remote past volatility of that asset or market.

Hong has claimed that the volatility transmission between two variables gradually weakens as the time distance between them increases. This is the reason why new tests statistics has been introduced in order to include the appropriate weights in accordance with the time. The weighting scheme depends on specific kernel functions:

a. Truncated : $k(z)=\begin{cases}1,|z|\le 1\\0, otherwise\end{cases}$

b. Bartlett : $k(z)=\begin{cases}1-|z|,|z|\le 1\\0, otherwise\end{cases}$

c. Daniell : $k(z)=\sin(\pi z)/\pi z, -\infty<z<+\infty$

d. Parzen : $k(z)=\begin{cases}1-6z^2+6|z|^3, |z|\le 1\\2(1-|z|)^3, 0.5<|z|\le 1\\0, otherwise\end{cases}$

e. Quadratic Spectral : $k(z)=\dfrac{3}{\sqrt{5}(\pi z)^2}\{\sin(\pi z)/\pi z-\cos(\pi z)\}, -\infty<z<+\infty$

f. Tukey – Hanning : $k(z)=\begin{cases}\frac{1}{2}(1+\cos(\pi z)), |z|\le 1\\0, otherwise\end{cases}$

The proposed test statistic is the following

$Q_1=\{T\sum_{j=1}^{T-1}k^2(j/M)\hat{\rho}_{uv}^2(j)-C_{1T}(k)\}^{1/2}/\{2D_{1T}(k)\}^{1/2}$, which has an asymptotic N(0,1) distribution, where

$C_{1T}(k)=\sum_{j=1}^{T-1}(1-j/T)k^2(j/M)$ and

$D_{1T}(k)=\sum_{j=1}^{T-1}(1-j/T)\{1-(j+1)/T\}k^4(j/M)$

The values obtained through the above test must be compared with upper tailed standard normal distribution critical values. A slightly modified version of aforementioned test function that is asymptotically equivalent is the following

$Q^*=\{T\sum_{j=1}^{T-1}(1-j/T)^{-1}k^2(j/M)\hat{\rho}_{uv}(j)-C_{1T}^*(k)\}/\{2D^*{}_{1T}(k)\}^{1/2}$, where

$C_{1T}^*(k)=\sum_{j=1}^{T-1}k^2(j/M)$ and

$$D^*_{1T}(k) = \sum_{j=1}^{T-1} \{1-(T-j)^{-1}\} k^4(j/M)$$

To conclude with the test statistics, another test statistic that is usually is used when we do not have any ex ante information in regard with the direction of causal relation is the following:

$Q_2 = \{T \sum_{j=1-T}^{T-1} k^2(j/M)\hat{\rho}^2_{uv}(j) - C_{2T}(k)\}^{1/2} / \{2D_{2T}(k)\}^{1/2}$,which has an asymptotic N(0,1) distribution, where

$C_{2T}(k) = \sum_{j=1-T}^{T-1} (1-|j|/T)k^2(j/M)$ and

$$D_{2T}(k) = \sum_{j=1-T}^{T-1} (1-|j|/T)\{1-(|j|+1)/T\}k^4(j/M)$$

The values obtained using the above test statistic must once be compared with the critical values that correspond to the upper tail of a standard normal distribution.

2.4 Literature Review on Causality

We will refer briefly to several studies that examined the concept of causality in the first and second moment. We will first introduce the studies from **Engle, Ito & Lin** (1990) and **Hamao, Masulis & Ng** (1990), who found that volatility in one market tends to continue after that market closes, producing volatility in markets opening several hours later even though these markets are geographically distant. **Engle, Ito and Lin** (1990) used four observations per day on the Japanese yen/U.S. dollar exchange rate and reported evidence in favour of a spillover effect in volatility between the different market locations, whereas **Hamao, Masulis and Ng** (1990) found a causal effect in the variance from the U.S. to the Japanese stock market only, and not conversely. Before referring to these studies, it is important to introduce the heat wave and the meteor shower hypothesis. According to the heat wave hypothesis, volatility has only country-specific autocorrelations, while on the other hand the meteor shower hypothesis allows volatility spillovers across markets. Specifically:

Engle, Ito & Lin (1990) attribute the Volatility Clustering pattern observed in economic and financial time series in two factors. On the one hand there exists the autocorrelation in the news arrival process which describes the flow of new information in the market that comes in clusters. On the other hand, the violation of the efficient market hypothesis which entails the existence of heterogeneous expectations and the use of inside information contribute negatively in a persistent turbulence in the market after a shock. An absence of Volatility transmission means that a market has local characteristics and influences only the domestic market. An existence of Volatility spillover can be attributed to competitive policies of the central banks, to the distribution of expectations or fears of a market in other markets and maybe to changes in common fundamental factors. Engle, Ito & Lin use daily data on the exchange rate Dollar/Yen exchange rate running from October 1985 till September 1986. Specifically, they decomposed the daily change in Exchange rate, in four individual changes in four important international foreign exchange markets, the markets of Pacific, Tokyo, London and New York. These markets are opened in non overlapping time periods. They founded volatility spillovers across these four markets.

Hamao, Masulis & Ng (1990) have studied the short-run interdependence of prices and price volatility across three major international stock markets of Tokyo, London and New York and examined the transmission mechanisms of the conditional first and second moment in common stock prices across these international stock markets. Specifically, they examined the daily and intraday stock-price activity over a three-year period running from April 1985 to March 1988. They divided daily close-to-close returns into their close-to-open and open-to-close components and analyzed separately the spillover effects of price volatility in foreign markets on the opening price in the domestic market and on prices after the opening of trading. They utilized the autoregressive conditionally heteroskedastic ARCH family of statistical models to explore these pricing relationships and found that daily stock returns measured from close-to-open and open-to-close to be approximated by a GARCH (1,1) in Mean model. They concluded that volatility spillovers could represent a causal phenomenon across markets that trade sequentially and could reflect global economic changes that can currently alter stock-return volatility across international stock markets. As far as the three international stock markets are concerned, they found that on the one hand there exist price volatility spillovers from New York to Tokyo, London to Tokyo, and New York to London, but on the other hand, however, they have not found any price volatility spillover effects in the reverse relation.

Lin et al (1991) use a signal extraction model with GARCH processes to study the interaction of the US and the Japanese stock markets. Their findings suggest that price and volatility spillovers are generally reciprocal, in the sense that the two markets influence each other.

In addition, two studies, the one from **Baillie & Bollerslev** (1991) and the second from **Ito, Engle & Lin** (1992), which the latter constitutes an extension of **Engle, Ito & Lin** (1990), found similar results concerning the transmission of volatility. They argued that volatility behaves as a 'meteor shower', owning to its similarity to the pattern of meteor showers and are contrary to the more natural expectation that the volatility would instead continue in the same market the next day, which is the heat wave hypothesis.

Baillie & Bollerslev (1991) have examined four (4) foreign exchange spot rate series, recorded on an hourly basis for a six-month period (January 1986 till July 1986) in 1986, using a GARCH model specification with hourly dummy variables in order to model the volatility apparent in the percentage nominal return of each currency. The use of hourly data allows both currency specific and market specific factors to be clearly identified. For the conditional mean specification they have chose a moving average parameterization that is compatible with the efficient market hypothesis. They concluded that for each exchange rate, the volatility appears to be highly serially correlated. This is in accordance with the meteor shower hypothesis, where the news is transmitted through time and different market locations.

Ito, Engle & Lin (1992) have examined the intra-daily volatility of the yen/dollar exchange rate from 1979 to 1988 which correspond to different degrees of international policy coordination and have tested for heat wave vs. meteor shower effects. Precisely, they examined the volatility of the yen/dollar exchange rate during the period 1979-1988 in order to disentangle the causes of meteor showers and proposed a decomposition of volatility into components due to heat waves and to meteor showers, measuring separate contribution of heat wave and meteor shower characteristics in the volatility of financial markets. According to them the meteor shower phenomenon constitutes a failure of the market to fully make use of its information and may signal a violation of the market efficiency. They examined the role of the cooperative policies of central banks in the creation of meteor shower effects. They used a GARCH model specification and collected data concerning the intra-daily yen/dollar exchange rate from 1 February 1979 to 23 December 1988. The final conclusion of this study is that the volatility of the exchange rates has the characteristics of a meteor shower to its similarity to the pattern of meteor showers which are transmitted across the various markets as the globe turns.

Despite the extensive investigation of the linkages and interactions of major stock markets, no attempt has been made to investigate the possibility that the quantity of news *(i.e.* the size of an innovation), as well as the quality *(i.e.* the sign of an innovation) may be important determinants of the degree of volatility spillovers across markets.

In terms of foreign stocks markets, **Koutmos** (1992) found a significant leverage effect in the stock returns of Canada, France and Japan stock markets. The evidence that volatility in the US and other stock markets is responding asymmetrically to own past innovations suggests that volatility spillovers themselves may be asymmetric, in the sense that negative innovations in a given market produce a higher volatility spill over in the next market to trade, than do positive innovations of an equal magnitude.

After three years, **Koutmos & Booth** (1995) have analyzed the transmission mechanism in the first and second moment of returns across the New York, Tokyo and London stock market. Using an extended multivariate Exponential Generalized Autoregressive Conditionally Heteroskedastic (EGARCH) model, they described the asymmetric impact of good and bad news on volatility. They collected daily open-to-close returns for the basic index of each of the three markets, for the period from September 1986 until December 1993. They found evidence of price spillovers from New York to Tokyo and London, and from Tokyo to London. More extensive and reciprocal, however, were the second moment interactions. They documented significant volatility spillovers from New York to London and Tokyo, from London to New York and Tokyo and from Tokyo to London and New York. In all instances the volatility transmission mechanism is asymmetric. For example negative innovations in a given market increase volatility in the next market to trade considerably more than positive innovations. In other words, stock markets are sensitive to news originating in other markets, especially when the news has negative sign.

Karolyi (1995) has studied the relationship between the US and Canadian equity markets, using the fact that the markets are open contemporaneously to circumvent the problems associated with non-synchronicity of trading and the associated correlation of price innovations.

Brailsford (1996) examined links between the volatility of the US stock market and the volatility of the Australian and New Zealand markets using the univariate GARCH framework of Hamao et al. (1990).

Booth, Martikainen & Tse (1997) have provided new evidence on the price and volatility spillovers among the four Scandinavian (Nordic) stock markets of Denmark, Norway, Sweden and Finland. They have applied the Exponential Generalized Autoregressive Conditionally Heteroskedastic (EGARCH) model and have collected data for the main index of each of the stock market for a six year period from May 1988 until June 1994. They found evidence for volatility transmission from Sweden to Finland with a weaker pattern observed in the reverse direction. These spillovers may reflect the longstanding economic and cultural ties between these two countries.

Hu, Chen, Fok & Huang (1997) have examined the transmission effects of volatility among the two developed markets and four emerging markets in the South China Growth Triangular using Cheung and Ng's causality in variance test. They analyzed index returns of equity markets for a 4 year period, from October 1992 through February 1996. The indices they used were from the stock market of Taiwan, Tokyo, New York, Hong Kong and Shanghai. They have provided evidence of the existence of volatility transmission from Tokyo to New York and a bidirectional causal relation in the second moment between the Hong Kong and US stock market. The information received from the Cheung and Ng's causality in variance test has contributed to the construction of econometric models. Including the effect of volatility transmission in the models, this has as a result the reduction of the degree of volatility persistence. In other words, foreign information is an important source of return volatility for emerging markets. Finally, geographic proximity and economic ties between two countries do not necessarily lead to a strong relationship in volatility across markets.

The results of the investigation of **Tse** (1998), that we will analyze now, are in contrast to **Hamao, Masulis & Ng** (1990) and **Engle, Ito & Lin** (1990) who found volatility spillovers between stock markets. Precisely, **Tse** (1998) has analyzed the information transmission mechanism between Japan and the US financial markets and tested the hypothesis that domestic market efficiently adjusts to foreign information. They collected data for 3-month interest rate futures contracts in Eurodollars and Euro Yen traded in Tokyo and Chicago, respectively, from the period June 1990 through July 1996. These two financial markets, according to Tse, they do not suffer from non- lead to spurious results as far as volatility spillovers are concerned. He used a two dimensional constant correlation EGARCH model in order to examine the Volatility linkages between the markets and the contemporaneous correlations for the investigation of the information transmission mechanism. He argued that the markets are informationally linked by some global events, the information transmission is rapid and that previous daytime foreign information, which is efficiently reflected in the open price of the domestic market, does not affect the volatility of the domestic market. To put it simply, Tse underlined that volatility clustering of changes thoroughly stems from domestic information.

Earlier studies such as that of **Comte & Lieberman** (2000), that we analysed in previous section and **Brooks & Henry** (2000), continue their investigation in the causality in variance and volatility spillovers, showing its importance in the field of Econometrics and Finance.

Brooks & Henry (2000) have modelled the transmission of shocks between the US, Japanese and Australian equity markets. They have used parametric and non-parametric techniques, in order to test for the existence of linear and non-linear transmission of volatility across these markets. Precisely, they used the non-parametric test for non-linear Granger causality of Hiemstra and Jones (1994) in order to detect possible ties across the three markets. They collected weekly data from US, Japanese and Australian stock markets for the period from 1980 to 1998. They found evidence for the presence of causal relations from the U.S. and Japan to Australia However, little evidence is found regarding the reverse causality between the two markets. The asymmetry of the estimated variance - covariance matrix of returns implies that both the magnitude as well as the sign of the innovation in returns determines the spillover.

Kanas and Kouretas (2002) investigated the existence of causal relations in the first and second moments of the exchange rates among four (4) Latin American markets, the market of Argentina, Brazil, Mexico and Chile. They collected monthly data running from 1976 till 1993.They used the Cheung & Ng test for Causality in Variance. Firstly, they used EGARCH models in order to capture the leverage effects of Volatility shocks as well as to investigate whether the presence of Causality in Variance can influence the existence of causal relations in the mean. They found that causality in variance can have a significant impact in causality in mean results in the case of a GARCH in mean (GARCH – M) or EGARCH in mean specification model. They generated data characterized from causality in variance and they used two specifications for the conditional mean model before studying for mean transmissions: 1. the GARCH term is included in the mean model and 2. The GARCH term is not included in the mean model. They concluded that there exist causal relations among the mean as well as the volatilities between the aforementioned markets inside each country and across the different markets. They proposed as a specification model for Volatility the Exponential GARCH (EGARCH) that has the possibility to model the asymmetric effects of shocks in Volatility.

Sola, Spagnolo & Spagnolo (2002) proposed an alternative way of detecting the transmission of high volatility periods from one economy to another. Using a parameterization of the Markov switching model which allows for four possible states of nature, they tested whether a country leads the other in and out of a period of high volatility. They underlined the fact that a crisis and as a result its transmission is better characterized as a sporadic event, rather than a structural relationship between stock markets as in a multivariate GARCH. They examined an empirical application of this procedure to three emerging markets recently affected by severe financial crises, the markets of Thailand, South Korea and Brazil for the period from January 1980 to January 2001, estimating two bivariate models. They have found that Thailand leads South Korea and therefore the volatility spillovers appear to be unidirectional following the onset of the crisis, running from the markets in turmoil (Thailand) to the other (South Korea). Only weak sign of evidence of volatility spillover was found between South Korea and Brazil.

In the same year, **Caporale, Pittis & Spagnolo** (2002) investigated the causality relations among variances in four East Asian countries. They used daily data from the financial markets of Japan, Indonesia, South Korea and Thailand for the period from January 1987 to January 2000. They introduced a bivariate GARCH–BEKK specification for testing for the existence of a relationship between the variances among these financial markets. Hypothesis testing is performed on the models using the likelihood ratio test. They found evidence of volatility spillovers in all four countries. In the period before crisis, for Indonesia and Thailand, they found unidirectional positive spillovers in the second moment, from stock markets to foreign exchange markets. On the other hand, Japan and South Korea markets are in line with the portfolio approach. In the post-crisis period in the case of Korea and Japan we have the same approach as it was in the pre-crisis period; the variance appears to become bidirectional for Indonesia and Thailand. In addition, they have conducted

Monte Carlo experiments to estimate the Type-I error probability of the likelihood ratio test, using artificial time series generated according to a multivariate model.

Pantelidis & Pittis (2004) investigated the effects of neglected causality in mean, on the finite sample properties of a variety tests regarding the causality in variance and focused on the interactions between causality in mean and causality in variance and more specifically on the effects of the former on testing for the latter. They made several critics in the field of tests concerning the causality in variance. Such tests are those of Cheung & Ng (1996) and Hong (2001). They stated that the above tests on the one hand are designed to detect the presence of causality in variance, but on the other hand do not account for any causality in mean, simultaneously. Using the Monte Carlo simulations they concluded that the tests for causality in variance suffer from size distortions when strong causality-in-mean effects do not have been taken into account. As a result, any conditional mean effects should be filtered out by a model that allows for the presence of causality in mean before any inferences on causality in variance are drawn.

Malik (2005) examined the relationship between the volatility of the British Pound and the volatility of the Euro, denominated in terms of Dollar, according to the exchange rates. According to his research, Malik found that Euro is more volatile than BP both at the hourly and daily frequencies. The higher volatility of euro than BP has important implications for many other financial markets.

Dijk, Osborn & Sensier (2005) examined the size properties of causality-in-variance tests in the presence of structural breaks in volatility. They made several critiques concerning the methods that are used from Cheung & Ng and Hong. They insisted of taking pre – tests for the series concerning the structural changes in volatility and recommended that causality-in-variance tests of Cheung & Ng and Hong should be applied only after such pre-testing for breaks in volatility. This is the reason why they conducted a Monte Carlo study in which they generated data that represent the above characteristics. They made several tests. First they ignored the structural breaks in volatility and found that this has only minor effects when just one of the series experiences a volatility change. On the other hand, simultaneous changes in volatility lead to substantially larger size distortions, with the distortion declining as the time interval between breaks increases.

Beltratti & Morana (2006) noted the potential bias of the estimation of volatility owning to the use of noisy proxies.

Finally, **Inagaki** (2007) examined the volatility spillover between the British pound and the euro, denominated in terms of dollar. He made one step more from Malik who investigated the relationship of the volatility of British pound and Euro. Inagaki gave weight to causality in variance, which is directly related to volatility spillover and obtained the following empirical results, using the residual cross-correlation approach. Firstly, he found evidence of existence of strong simultaneous interaction between the British pound and the euro. Secondly, observed that the Euro Granger-causes the British pound in mean, whereas the British pound does not Granger-cause the euro in mean. Finally, he argued that the Euro Granger-causes the British pound in variance, whereas the British pound does not Granger-cause the euro in variance. In other words, the euro mean and volatility has a one-sided impact on the British pound volatility. From a theoretical viewpoint, the mostly strong explanation from the above findings is that volatility interaction corresponds to information transmission. With regard to this, British pound traders pay attention to information derived from the euro and that euro traders also pay attention to information derived from the British pound.

CHAPTER 3: FRACTIONAL INTEGRATION & LONG MEMORY PROCESS

3.1 Introduction to long and short memory

The concept that economic time series may exhibit long-range dependence has been a hypothesis of many early theories of the trade and business cycles. Such theories were often motivated by the distinct but non-periodic cyclical patterns that typified plots of economic aggregates over time. Economic data often display cycles of many periods some that seem nearly as long as the span of the sample. In the frequency domain such times series are said to have power at the low frequencies. So common was this particular feature of the data that **Granger** (1966) dubbed it the "typical spectral shape of an economic variable".

Nature's predilection towards long-range dependence has been well-documented in the natural sciences such as hydrology, meteorology, and geophysics and to the extent that the ultimate sources of economic uncertainty are natural phenomena like weather or sunspots, it is also possible that long-term memory in economic time series.

Among the first to have considered the impact of persistent statistical dependence in asset prices was **Mandelbrot** (1971), who argued that the random walk and martingale models of speculative prices may not be realizable through arbitrage in the presence of long-term memory. Since then, several empirical studies have stated the possibility of such persistence in financial asset prices. For example, **Greene & Fielitz** (1977) have found long-range dependence in the daily returns of many securities listed on the New York Stock Exchange. In addition, more recent investigations have uncovered anomalous behaviour in long-horizon stock returns.

The presence of long-memory components in asset returns has important implications for many of the applications used in modern financial economics. For example, optimal consumption/savings and portfolio allocation decisions may become extremely sensitive to the investment horizon if stock returns were long-range dependent. Problems also arise in the pricing of derivative securities such as options and futures via martingale methods, since long-term memory is inconsistent with the martingale property. Traditional tests of the Capital Asset Pricing Model and the Arbitrage Pricing Theory are no longer valid since standard methods of statistical inference do not apply to time series displaying such persistence. The conclusions of more recent tests of "efficient" markets or stock market rationality also hang precariously on the presence or absence of these non-periodic cycles in asset returns.

A simple generalization of a statistic for testing forms of long-range dependence was first proposed by the English hydrologist **Harold Edwin Hurst** (1951). This statistic, called the "rescaled range" or "range over standard deviation" or "R/S" statistic, has subsequently been refined by **Mandelbrot** (1972, 1975) and others in several important ways.

Before developing a method of detecting long-term memory the distinction between long range and short-range statistical dependence must be made precise and clear. One of the most widely used concepts of short - range dependence (short memory) is the notion of "strong-mixing" due to **Rosenblatt** (1956), a measure of the decline in statistical dependence of two events separated by successively longer spans of time. Specifically, a time series is strong mixing if the maximal dependence between any two events becomes trivial as more time elapses between them. By controlling the rate at which the dependence between past and future events declines, it is possible to extend the usual laws of large numbers and central limit theorems to dependent sequences of random variables. Such mixing conditions have been used extensively by **White** (1982), **White and Domowitz** (1984), and **Phillips** (1987) for example to relax the assumptions that ensure consistency and asymptotic normality of various econometric estimators. According to **Phillips** (1987), these conditions are satisfied by many stochastic processes including all Gaussian finite-order stationary ARMA models. Moreover, the inclusion of a moment condition also allows for heterogeneously distributed sequences, such as those exhibiting unconditional heteroscedasticity, an especially important extension in view of the apparent instabilities of financial time series.

In contrast to the short memory of "weakly dependent" [i.e., mixing] processes, natural phenomena often display long-term memory in the form of non-periodic cycles. This has lead several authors, most notably Mandelbrot, to develop stochastic models that exhibit dependence even over very long time spans, such as the fractionally integrated time series models of **Mandelbrot and Van Ness** (1968), **Granger and Joyeux** (1980), and **Hosking** (1981). These stochastic processes possess autocorrelation functions that decay at much slower rates than those of weakly dependent processes, and violate the conditions of strong-mixing.

3.2 Properties of Financial Data

3.2.1 Long memory processes

Long memory processes are studied either in the time domain or in the frequency domain. In the time domain long memory is manifested through a hyperbolically decaying autocorrelation function. It is important to note at this point the importance of using large sample sizes in order for the long memory pattern to be observable in the graphs we use. In frequency domain the same information can be extracted from the spectrum of the variable under study.

A stationary process Y_t is called a stationary process with long memory if its autocorrelation function (ACF), $\rho(k)$, has asymptotically the following hyperbolic rate of decay $\sum_{k=-n}^{n} |\rho(k)| \rightarrow \infty$ as $n \rightarrow \infty$, where ρ (k) denotes the autocorrelation coefficient in lag k. This means that correlations at long lags are not negligible. In fact such a series is a stochastic mixture of a non unit root series with a simultaneously impressive persistence feature. For historical consistency we must also briefly refer to the Hurst Exponents, which are a different measure of the Long Memory property of a financial time series. Values of this parameter between 1/2 and 1 are indicative of this kind of persistence. In the above mentioned models the propagation of shocks to the mean occurs at a hyperbolic rate of decay when 0 < d < 1 and this is the main difference with the invertible and stationary ARMA models in which we observe an exponential rate of decay. This behaviour differs also, from the infinite memory ARIMA models in which a shock persists for an infinite horizon.

Daily prices P_t are normally found to be I (1), which is a consequence of the efficient-market hypothesis; that is $E(P_{t+1} / I_t) = P_t$, where I_t denotes the information set available at time t. Although the logs of returns $R_t = \ln(P_t / P_{t-1})$ are then I (0), their power transformation displays long memory.

3.2.2 Modelling long memory in volatility – FIGARCH Model

To begin with, the contemporaneous aggregation of stable GARCH (1, 1) as well as the weakly dependent information flow processes may play an important role in the long memory in volatility. Recent studies have shown that structural changes can induce a long range dependence in the second order moments process. Fractional integration is a way in order to describe the long range dependence. The GARCH models that were analysed in previous chapters account for volatility persistence but have the feature that this persistence decays relatively fast. There is a general consensus that the volatility of financial assets returns is stationary and on the same time strongly persistent. However, there are fewer consensuses on the causes of this persistence. One the one hand, studies attributes this volatility clustering to the unevenness of the news arrival process, which means that the long run persistence may occur due to the aggregation of a large number of heterogeneous auto correlated news arrival processes On the other hand, research has shown that volatility persistence may be attributed to the persistence in the trading volume which is also known to exhibit long memory properties. This explanation considers the information arrival process to influence the Volatility through trading decisions. This means that long memory is transmitted to the Volatility process and is not an internal feature of the latter.

It is known that the IGARCH specification model provides an unrealistically high degree of persistence in Volatility shocks. Volatility shocks in this parameterization persist to an infinite prediction horizon something that it is far from being realistic. The excessively high degree of persistence seems contrary to the economic intuition. A frequent argument in support of the fractional integrated models is that the distinction between I(0) and I(1) can be too restrictive especially when we use high frequency data. There is a continuously increasing number of studies that report the presence of autocorrelation in the squared or absolute returns.

This is now, when a new member of the Heteroscedastic family of models is emerged from and it is called Fractionally Integrated Generalized Autoregressive Conditional Heteroscedasticity Model (FIGARCH). The FIGARCH model specification was developed by **Baillie, Bollerslev & Mikkelsen** (1996) and combines many of the features of the fractionally integrated processes for the mean, with the regular GARCH model for the conditional variance. In addition, FIGARCH model implies an asymptotic consistency of its Maximum Likelihood Estimator in contrast to the ARFIMA models. As in the case of the conventional GARCH models, we consider a discrete time real-valued stochastic GARCH process $\{\varepsilon_t\}$, where $\varepsilon_t \equiv z_t \sigma_t$. Furthermore, $E_{t-1}(z_t) = 0$ and $Var_{t-1}(z_t) = 1$ constitute important properties of the z_t

standardized innovations process and $E_{t-1}(.)$ and $Var_{t-1}(.)$ constitute operators that depend on the same information set .

The classic GARCH (p,q) model is given from the equation $\sigma_t^2 = \omega + \alpha(L)\varepsilon_t^2 + \beta(L)\sigma_t^2$ where

- $\alpha(L) \equiv \alpha_1 L + \alpha_2 L^2 + ... + a_q L^q$ and

$\beta(L) \equiv \beta_1 L + \beta_2 L^2 + ... + \beta_q L^q$ are the Lag Polynomials, where L denotes the

The integrated GARCH (IGARCH) model is given by the following equation:

$\phi(L)(1-L)\varepsilon_t^2 = \omega + [1-\beta(L)]v_t$, where

- $\phi(L) \equiv \dfrac{[1-\alpha(L)-\beta(L)]}{(1-L)}$ is of order m-1.

The FIGARCH model is obtained by replacing the first difference operator with the fractional differencing operator. The fractional differencing operator $(1-L)^d$ has a binomial expansion which can be expressed in terms of the hyper geometric function:

$$(1-L)^d = F(-d,1,1;L) = \sum_{k=0}^{00} \Gamma(k-d)\Gamma(k+1)^{-1}\Gamma(-d)^{-1}L^k \equiv \sum_{k=0}^{00} \pi_k L^k$$

with Γ(.) denoting the Gamma function.

As a result the FIGARCH (p, d, q) process is defined as

$\phi(L)(1-L)^d \varepsilon_t^2 = \omega + [1-\beta(L)]v_t$ and d takes the following numbers:0 < d < 1.

All the roots of the corresponding polynomials lie outside the unit circle. This model can alternatively be expressed as :

$$[1-\beta(L)]\sigma_t^2 = \omega + \left[1-\beta(L)-\phi(L)(1-L)^d\right]\varepsilon_t^2$$

The conditional volatility of ε_t is obtained from the following infinite order ARCH representation:

$$\sigma_t^2 = \frac{\omega}{[1-\beta(1)]} + \left\{1 - \frac{\phi(L)(1-L)^d}{[1-\beta(L)]}\right\}\varepsilon_t^2 = \frac{\omega}{[1-\beta(1)]} + \lambda(L)\varepsilon_t^2$$

The FIGARCH process is not weakly stationary as is the case with the IGARCH processes because the second moment of ε_t is not finite. However both processes are strictly stationary for $0 \le d \le 1$. The persistence of Volatility can be expressed in terms of the impulse response coefficients of the optimal forecasts for the conditional Variance $\gamma_k \equiv \frac{\partial E_t\left(\varepsilon_{t+k}^2\right)}{\partial v_t} - \frac{\partial E_t\left(\varepsilon_{t+k-1}^2\right)}{\partial v_t}$.

We then modify the equation given for the FIGARCH Model in the equivalent form:

$\left(1-L\right)\varepsilon_t^2 = \frac{\omega}{\left(1-L\right)^{d-1}\phi(L)} + \frac{\left[1-\beta(L)\right]}{\left(1-L\right)^{d-1}\phi(L)} v_t \equiv \zeta + \gamma(L) v_t$ and we obtain the impulse response coefficients. To assess now the long term impact of shocks in the Volatility process we compute the limit of the cumulative impulse response weights.

$$\gamma(1) = \lim_{k \to 00} \sum_{i=0}^{k} \gamma_i = \lim_{k \to 00} \lambda_k = F(d-1,1,1;1)\phi(1)^{-1}\left[1-\beta(1)\right]$$

- γ_i is the impulse response weight and
- λ_k is the cumulative impulse response weight

For $0 \le d < 1$, we have $F(d-1,1,1;1) = 0$ and in the long memory FIGARCH model, with 0 < d < 1 the limit of the cumulative impulse response weights will tend to zero. This means that eventually any volatility shock will die out in a long term horizon. Whereas shocks to the GARCH process die out at a fast exponential rate, for the FIGARCH model, λ_k will eventually be dominated by a hyperbolic rate of decay.

For d = 1 the FIGARCH model becomes an IGARCH and this means that any shock will persist forever.

Finally the Maximum likelihood estimator of the parameters of the FIGARCH (p,d,q) can be obtained by the maximization of the log likelihood function:

$$\log L\left(\theta;\varepsilon_1,\varepsilon_2,...,\varepsilon_T\right) = -\frac{T}{2}\log\left(2\pi\right) - \frac{T}{2}\log\left(\sigma_t^2\right) - \frac{1}{2}\sum_{t=1}^{T}\left[\frac{\varepsilon_t^2}{\sigma_t^2}\right]$$

3.3 Literature Review on Long Memory Processes

We will refer briefly to several studies that examined the concept of long memory in the first and second moment. We will first introduce the studies from **Lo** (1991) and **Cheung** (1993), who made an attempt to test the long run memory.

To begin with, **Lo (**1991) has introduced a test for long run memory that is robust to short range dependence. It is an extension of the so called "rescaled range" or "range over standard deviation" or "R/S statistic. The study area of Lo includes also a distinction between the short range and long range statistical dependence by introducing the concept of mixing conditions. He conducts a Monte Carlo experiment in order to investigate the finite sample size and power properties of the test statistic that he has used. Finally using daily and monthly observations of the CRSP value and equal weighted indexes, running from July 1962 to December 1987, Lo is trying to find any possible long memory in the mean of specific time series. He found no evidence of long range dependence in any of these indexes which entails that it does not exist any long term memory for the U.S. Stock returns, as far as their first moments are concerned.

Cheung (1993) has used the semi nonparametric Geweke-Porter-Hudak test in order to detect long memory in exchange rates. In addition, he used fractionally integrated autoregressive moving average models (ARFIMA) in order to examine the dynamic relationship of the exchange rates. He collected weekly data of the exchange rates for the British Pound, the Deutsche Mark, the Swiss Franc, the French Franc and Japanese Yen, capturing a period from January 1974 to December 1989. He underlined a drawback of the ARFIMA model specification, because they do not incorporate the conditional heteroscedasticity pattern which is observed in the foreign exchange rates. He concluded that there exists long memory in the exchange rates. Cheung is trying to explain the reasons of the existence of Long Memory in the foreign exchange rates. He underlines on the one hand that Purchasing Power Parity (PPP) plays an important role due to the relationship of the exchange rates with the corresponding national prices. On the other hand, he notes that several macroeconomic fundamentals may be fractionally integrated.

From 1996, **Baillie, Bollerslev, Mikkelsen** and **Andersen** have made several studies concerning the volatility spillover in several equity markets, by introducing long memory processes as well as fractional integration. We will develop briefly some of their outstanding studies.

Baillie, Bollerslev & Mikkelsen (1996) have proposed a new class of models, the fractionally integrated generalized autoregressive conditional heteroscedasticity processes (FIGARCH), which we analysed in the previous section. They underlined that the FIGARCH models capture the long run dependencies observed in the autocorrelation functions of squared and absolute returns of various financial time series. The shocks in these processes die out at hyperbolic rate that is determined from the value of the long memory/fractional differencing parameter. Monte Carlo experiments have proven that Quasi Maximum Likelihood Estimator (QMLE) has very good finite sample properties and it is also argued to be asymptotically consistent. The FIGARCH model developed in this paper may obviously be extended to other parametric ARCH formulations, including the asymmetric EGARCH model develop by **Nelson** (1991) for modelling stock return volatility and the permanent-transitory components model recently proposed by **Engle** and **Lee** (1993). Baillie, Bollerslev & Mikkelsen collected daily observations for Deutschmark-US dollar exchange rates from March 1979 till December 1992 and tried to find any presence of long memory in the second moment. They have tried to explain the reasons of long memory characteristics in the stock market volatility by the aggregation of several different auto correlated news arrival processes. Finally, they concluded that the long run dynamics of the series are better modelled by the fractional differencing parameter

In the same year, **Baillie** (1996) has provided a survey and review of the major econometric work concerning the long memory processes, fractional integration, and their applications in the field of economics and finance. He noted that theoretical and simulation work has generally been disappointing on the performance of the parametric and semi parametric estimators, despite their credibility as they allow short memory effects to be neglected. In addition, the identifiability of high-order ARFIMA models often appears problematic according to several empirical studies and simulation evidence. In some cases the estimated value of d appears sensitive owning to the parameterization of the high-frequency components of the series, and in other cases the confidence interval of the fractional differencing estimate d may include the unit root.

A year later **Andersen & Bollerslev** (1997) analysed the information arrival of the volatility process by rationalizing this behaviour and underlined that several sudden bursts of volatility may have short-run as well as long-run components. They collected intradaily five-minute Deutschemark - U.S. Dollar returns and estimated the degree of long memory in volatility. They found that at low intradaily frequencies the frequency spectrum is approximately log-linear which entails long memory in Volatility. It is also shown that the fractional differencing operator constructed from the estimated d, is able to filter out all the long run dependencies in the conditional variance process and by this way he they found a hyperbolically decaying autocorrelation function, which indicates the presence of long memory in the exchange rates volatility.

Bollerslev & Mikkelsen (1999) have analysed the dynamic relationship of the stock market volatility, by examining its long term dependence, indirectly inferring to the degree of fractional integration in an equity market. The data constitute financial options' prices on the S&P 500 composite index from the Chicago Board of Options Exchange (CBOE) running a period from January 1991 until September 1993. They executed a Monte Carlo simulation in order to estimate the theoretical daily and weekly leaps prices, by generating a number of different paths for the simulated prices. They compared the observed leaps prices with their corresponding simulated by using the EGARCH, IEGARCH, FIGARCH, and FIEGARCH model specifications for the volatility process. They concluded that the FIEGARCH model tends to produce the most accurate daily and weekly prices by computing the low average pricing errors and keep up with the presence of long memory in the stock market volatility.

Baillie, Cecen & Han (2000) have provided a survey concerning the relationship of the FIGARCH model specification with the time series dynamics of the Deutschemark / US dollar spot exchange rate returns. They collected daily data running from March 1979 to December 1998 (4.989 Observations) as well as 30-minute data from January 1996 till January 1997. They found similar values of the estimated long memory volatility parameters across the low and high frequencies. Long memory is an intrinsic feature of the system and is not caused by exogenous shocks or regime switches. In addition, Baillie, Cecen and Han compared the FIGARCH model with the GARCH model specification, using the Wald test. These tests confirm the superiority and robustness of the long memory volatility model. Finally, they concluded that the FIGARCH models can be used successfully in the dynamics of the returns series irrespectively of the frequency of the data used in the estimations.

Szilard & Laszlo (2001) have developed a multivariate diagonal FIGARCH model in order to understand the concept of long memory and the fractional differencing to a multivariate framework. They used a common structure on the long memory components for overcoming the difficulties occurring during the estimation. It is argued that the market efficiency implies similar long range behaviour in the volatility of these series. They conducted a Monte Carlo simulation for testing the QMLE estimator, which is robust to distributional assumptions. In addition, they made an empirical application by modelling the daily volatility of the German mark, British pound and Japanese Yen against the U.S. dollar via a trivariate model specification. They collected daily spot rates of the above exchange rates running a period from July 1981 until January 2001.

Vilasuso (2002) compared three specifications models: the GARCH, the IGARCH and the FIGARCH model specification, conducting an empirical application. He collected daily US dollar denominated spot exchange rates which are the Canadian dollar, the French franc, the German mark, the Italian lira, the Japanese yen and the British pound. The sample period spans from March 1979 through December 1997. He underlined that FIGARCH captures more adequately the volatility dynamics of the exchange rates. Afterwards, Vilasuso conducted out-of-sample forecasts of the models running a period from January 1998 to December 1999 and concluded that the FIGARCH model generates superior out-of-sample forecasts.

Banerjee & Urga (2005) have analysed the breakthroughs in the field of the Long Memory process in Financial Time Series and underlined the relationship between the Long Memory and the Structural Breaks. They divided the estimation methods in two categories and analysed the pros and cons of these two estimation methods. The first category is the **"semi parametric"** method, like the GPH Test in which we are interested in the parameter d. The second category is the **"parametric"** method, like the FIGARCH or ARFIMA, which involve the complete estimation of models. An advantage of the parametric method is its efficiency in contrast to the semi parametric. However, the parametric method is computationally demanding and prone to misspecification. To conclude with, the authors found evidence in the dependence of the estimates of the long memory parameters on the number of regime switches and where they occur in the sample. Processes with infrequent regime switching may generate a long memory effect in the autocorrelation function.

A year later, **Caglayan & Jiang** (2006) have proposed the bivariate Constant Conditional Correlation ARFIMA-FIGARCH model specifications in order to analyse the long memory properties in the mean and variance of inflation and output growth as well their causal relations. They collected monthly data of consumer price index (CPI) and industrial production index (IPI) series from February 1957 till May 2005. Firstly, they conducted Monte Carlo simulations, computing the biases, the root mean square errors and the standard errors of the various models parameters. The results are satisfactory and concluded that QMLE estimators of these models are close to their true values. Secondly, they estimated the bivariate ARFIMA-CCC-FIGARCH model assuming a constant correlation coefficient structure. The fractional differencing parameters in the first and the second moments of the series are very similar to those obtained from the estimation of the univariate models suggesting that both inflation and output growth exhibit long memory in the mean and conditional volatility. Finally the researchers examine the bidirectional causal relations between the means and variances of inflation and output growth. They found that inflation causes higher inflation volatility and a reduction in output growth. The output growth causes an increase in inflation and inflation volatility.

In the same year, **Morana** (2006) has investigated the dynamic relationship of the Deutsche mark-US dollar exchange rate in the volatility process. He underlined the importance of the structural breaks in the volatility process. The author conducted an empirical application, which its dataset consists of daily as well as high frequency observations for the DM / US exchange rate, which span from January 1972 to December 1997, including and a sub – sample. He firstly estimated with the FIGARCH model and compared the results which were obtained by using the aforementioned low and high frequency data. He found that in the daily data the estimates for the long memory parameter are of smaller size when the short sample is considered rather than when the longer sample is used, which entails the fact that structural changes may induce the long memory in the volatility process in. In the case of high frequency data the estimation for the long memory parameter is once more lower for the sub-sample than the corresponding estimate for the longer sample. In other words, the FIGARCH models are sensitive to the length of the dataset.

CHAPTER 4: MONTE CARLO STUDY

4.1 Introduction

At this chapter we will analyse the finite sample properties of the Causality in Variance Tests and specifically those of Cheung & Ng and Hong. We have conducted several simulation experiments. We will present three discrete Monte Carlo designs. In each of them we make use of two different sample sizes, a small sample size and a large sample size. The small sample size which entails low frequency data is used for the field of Macroeconomics, whereas the big sample size which entails high frequency data is used for the field of Finance.

The small sample size consists of 200 observations and the big sample size consists of 1000 observations. The initial value for the conditional volatility process was set equal to the unconditional long term variance. For all the Monte Carlo designs we have chosen to generate 1000 Replications. The Distribution for the underlying Innovations Process is the Standard Normal distribution.

Before proceeding to the Monte Carlo Designs, it is essential to explain some econometric definitions:

- **Type I Error:** the error of rejecting a null hypothesis when it is actually true.
- **Type II Error:** the error of failing to reject a null hypothesis when it is in fact not true.

The Null Hypothesis is the No Causality in Variance and the Alternative Hypothesis is Causality in Variance in the first lag.

4.2 Monte Carlo Designs

Before analysing the following Designs, we will refer to our model, specifying the parameters:

$$\begin{pmatrix} y_{1t} \\ y_{2t} \end{pmatrix} = \begin{pmatrix} c_1 \\ c_2 \end{pmatrix} + \begin{pmatrix} \pi_{11} & \pi_{12} \\ \pi_{21} & \pi_{22} \end{pmatrix} \begin{pmatrix} y_{1t-1} \\ y_{2t-1} \end{pmatrix} + \begin{pmatrix} u_{1t} \\ u_{2t} \end{pmatrix}$$

where $c_1 = c_2 = \pi_{11} = \pi_{12} = \pi_{21} = \pi_{22} = 0$.

In addition the residuals $u_{it} = \xi_{it}(h_{it}^{0})^{0.5}$ where ξ_{it} follows Standard Normal Distribution N(0,1)

Regarding now the GARCH specification:

$$h_{1t} = \gamma_1 + \delta_1 h_{2t-1} + \gamma_2 u_{1t-1}{}^2$$

$$h_{2t} = \gamma_2 + \delta_2 h_{1t-1} + \gamma_3 u_{2t-1}{}^2$$

where $\gamma_1 = \gamma_2 = \gamma_2 = 0.1, \delta_1 = 0.5$ and $\delta_2 = 0$

Regarding the FIGARCH specification

$$h_{1t} = \omega_1 + \beta_1 h_{1t-1} + \left(1 - \beta_1 L - (1-\phi_1)(1-L)^{d_1}\right) u_{1t}^2 + \gamma_1 h_{2t-1}$$

$$h_{2t} = \omega_2 + \beta_2 h_{2t-1} + \left(1 - \beta_2 L - (1-\phi_2)(1-L)^{d_2}\right) u_{2t}^2 + \gamma_2 h_{1t-1}$$

$$(1-L)^d = F(-d,1,1;L) = \sum_{k=0}^{00} \Gamma(k-d)\Gamma(k+1)^{-1}\Gamma(-d)^{-1} L^k \equiv \sum_{k=0}^{00} \pi_k L^k$$

where $\omega_1 = \omega_2 = \beta_1 = \beta_2 = \phi_1 = \phi_2 = 0.1$, $\gamma_1 = 0.5$, $\gamma_2 = 0$ and $d_1 = d_2 = 0.75$

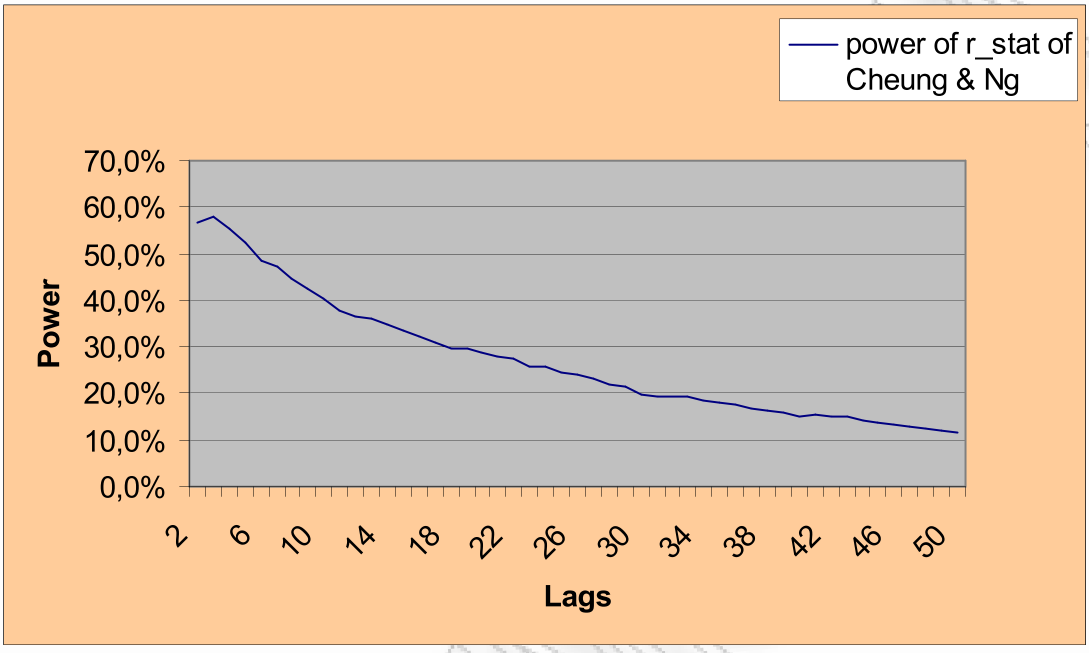
The Monte Carlo Designs are the following:

4.2.1 First Monte Carlo Design

The Data Generating Process is a VAR (1) - GARCH (1, 1) model. The estimator process is a VAR (1) - GARCH (1, 1) model specification. Finally we calculate the empirical power and the empirical size at specific lags of the Causality in Variance Tests of Cheung & Ng and Hong, presenting them with a graph, at 5% and 10 % significance level. The Null Hypothesis is No Volatility Spillover and the alternative Hypothesis is Unidirectional Volatility Spillover in the first (1st) lag. In addition, the Direction of the Unidirectional Tests is from Series 2 to Series 1.

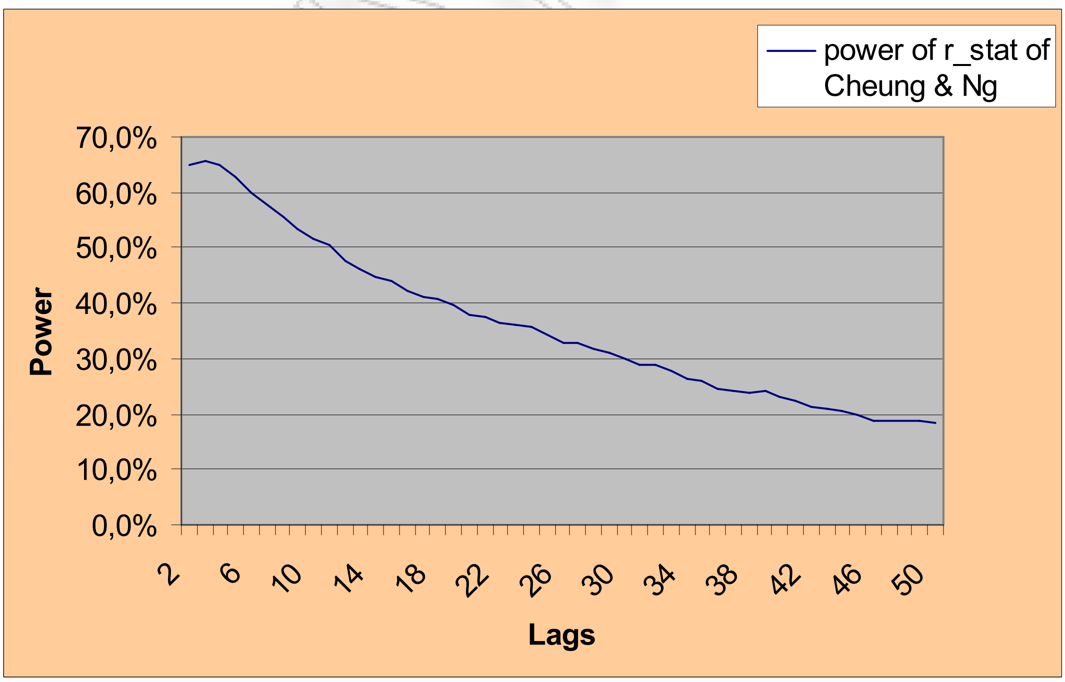
Graphs 4A
Small Sample

Empirical Power, Causality in Variance Test of Cheung & Ng, N(0,1), Sample Size: 200 observations., DGP: VAR(1)-GARCH(1,1), Estimation: VAR(1) – GARCH(1,1) Replications: 1000, Nominal Size: 5%



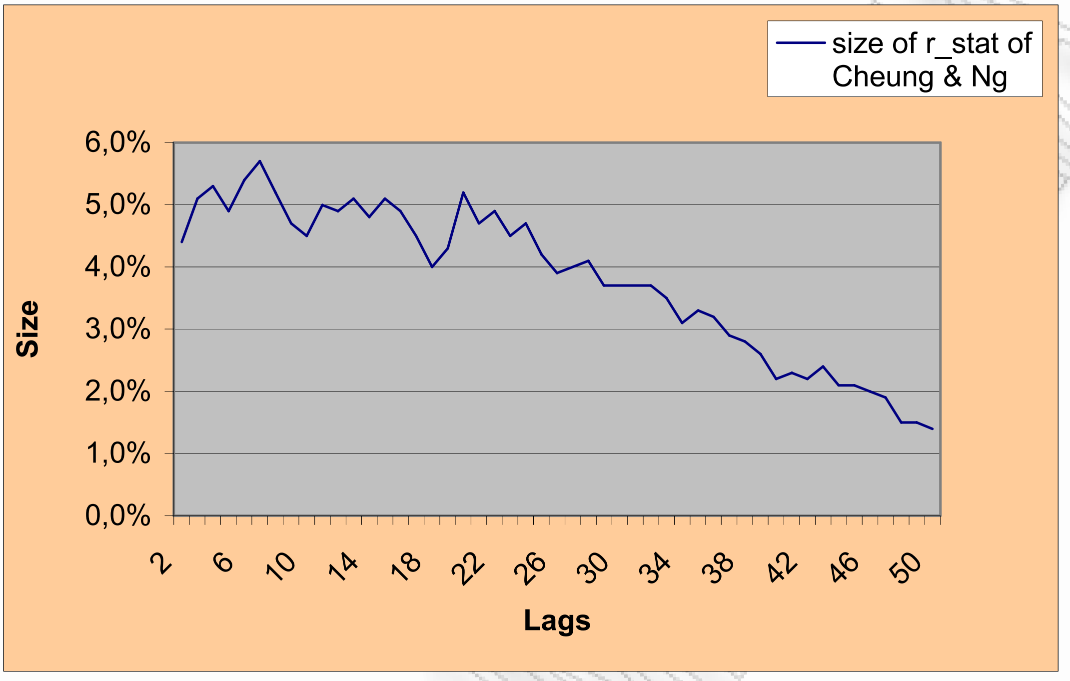
Small Sample

Empirical Power, Causality in Variance Test of Cheung & Ng, N(0,1), Sample Size: 200 observations., DGP: VAR(1)-GARCH(1,1), Estimation: VAR(1) – GARCH(1,1), Replications: 1000, Nominal Size: 10%



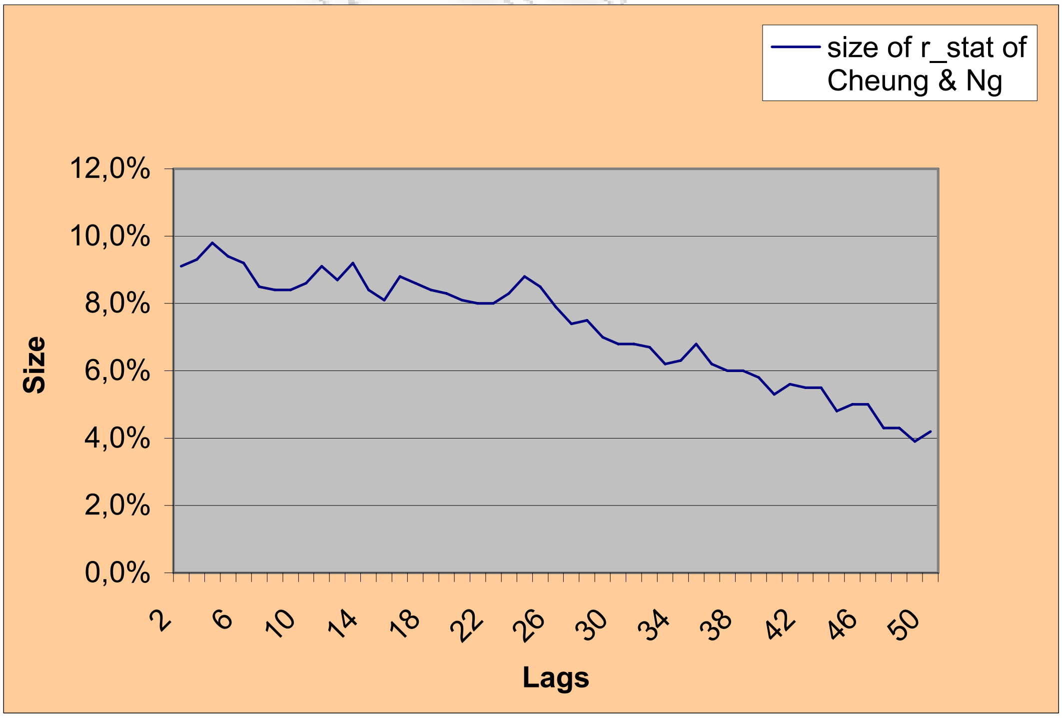
Graphs 4A (continued)
Small Sample

Empirical Size, Causality in Variance Test of Cheung & Ng, N(0,1), Sample Size: 200 observations., DGP: VAR(1)-GARCH(1,1), Estimation: VAR(1) – GARCH(1,1) Replications: 1000, Nominal Size: 5%



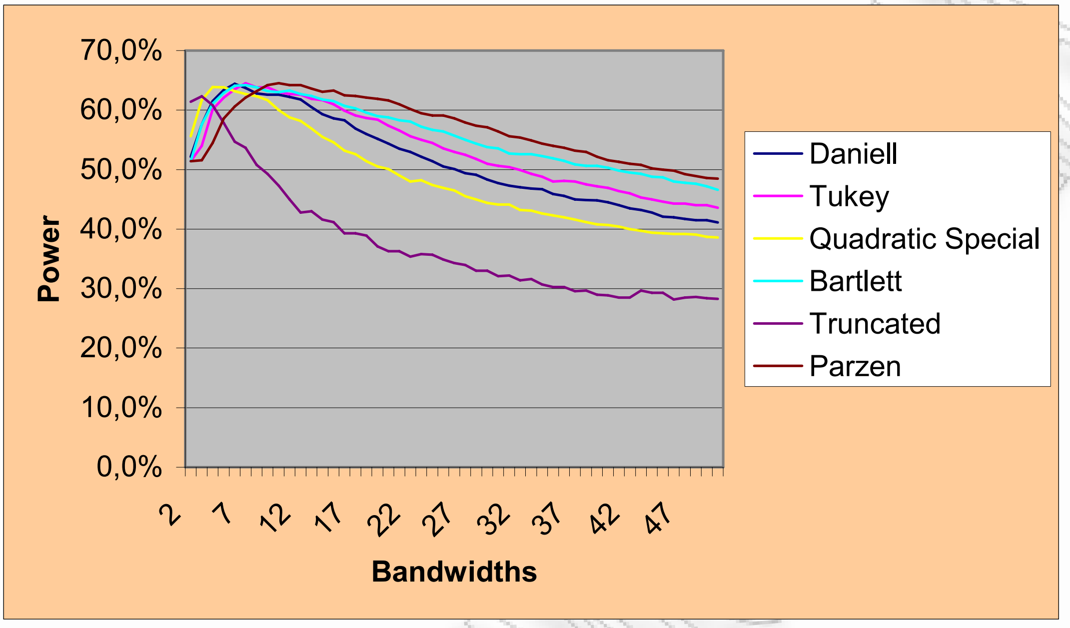
Small Sample

Empirical Size, Causality in Variance Test of Cheung & Ng, N(0,1), Sample Size: 200 observations., DGP: VAR(1)-GARCH(1,1), Estimation: VAR(1) – GARCH(1,1), Replications: 1000, Nominal Size: 10%



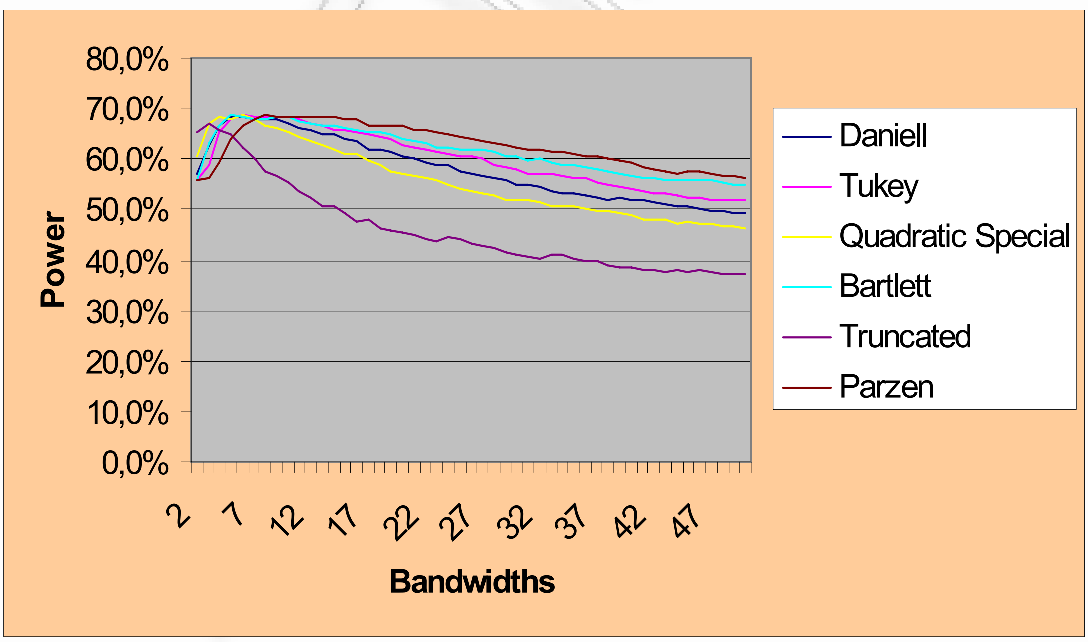
Graphs A (continued)
Small Sample

Empirical Power, Causality in Variance Test of Hong, N(0,1), Sample Size: 200 observations., DGP: VAR(1)-GARCH(1,1), Estimation: VAR(1) – GARCH(1,1),Replications: 1000, Nominal Size: 10%



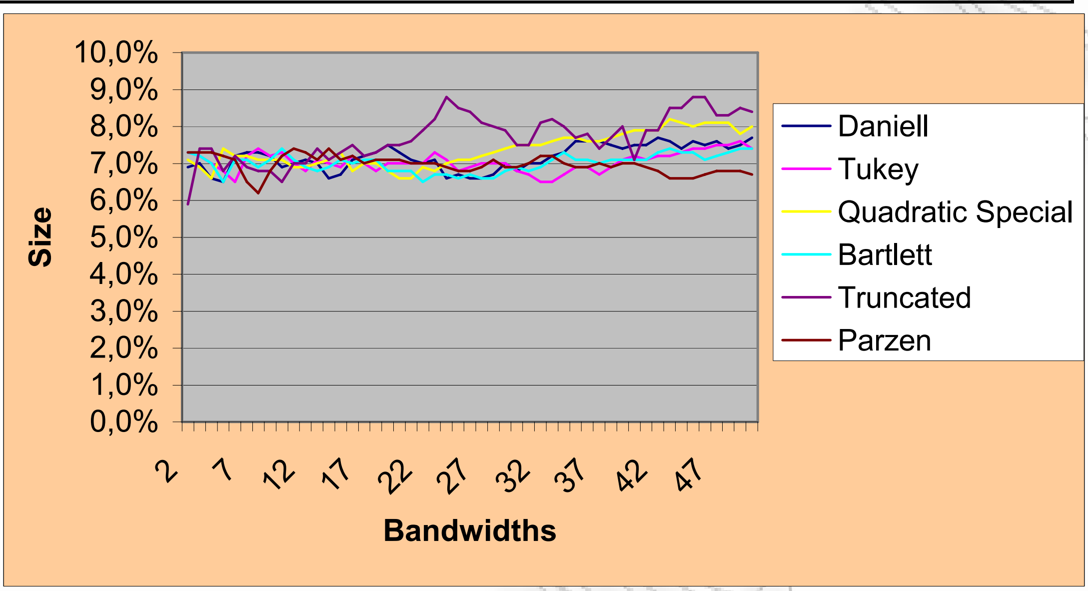
Small Sample

Empirical Power, Causality in Variance Test of Hong, N(0,1), Sample Size: 200 observations., DGP: VAR(1)-GARCH(1,1), Estimation: VAR(1) – GARCH(1,1),Replications: 1000, Nominal Size: 10%



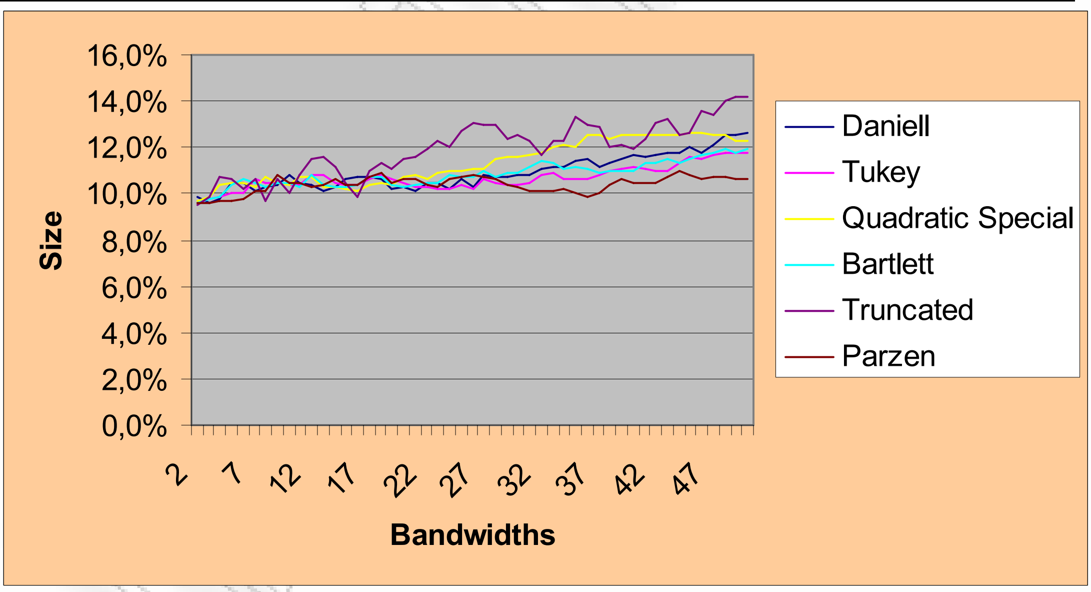
Graphs 4A(continued)
Small Sample

Empirical Size, Causality in Variance Test of Hong, N(0,1), Sample Size: 200 observations., DGP: VAR(1)-GARCH(1,1), Estimation: VAR(1) – GARCH(1,1), Replications: 1000, Nominal Size: 5%



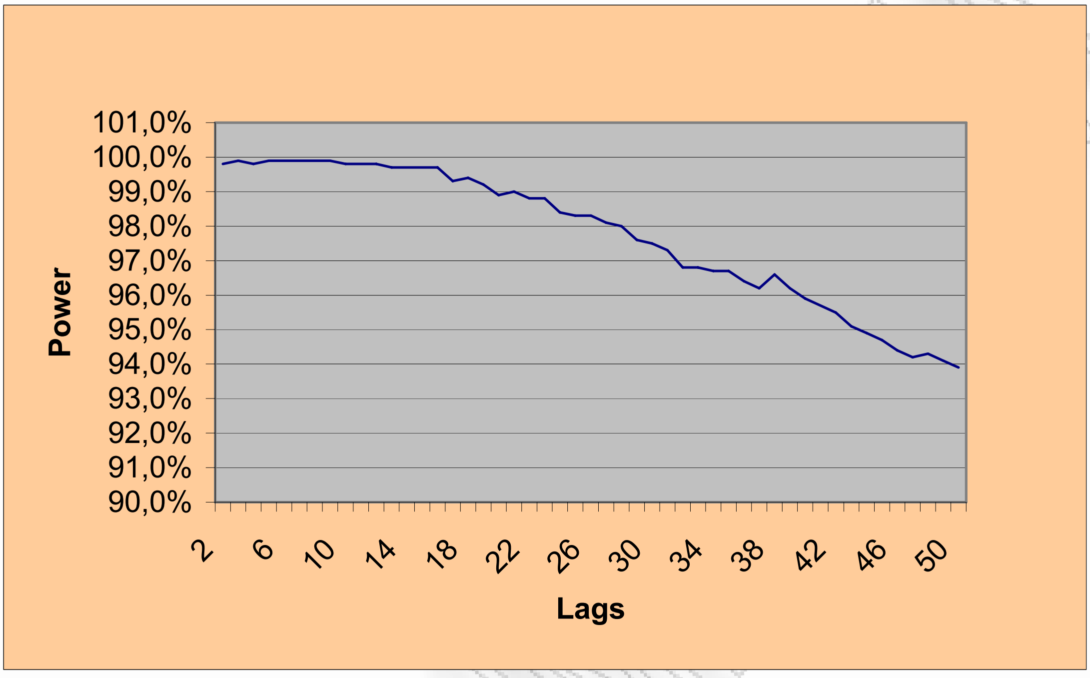
Small Sample

Empirical Size, Causality in Variance Test of Hong, N(0,1), Sample Size: 200 observations., DGP: VAR(1)-GARCH(1,1), Estimation: VAR(1) – GARCH(1,1) ,Replications: 1000, Nominal Size: 10%



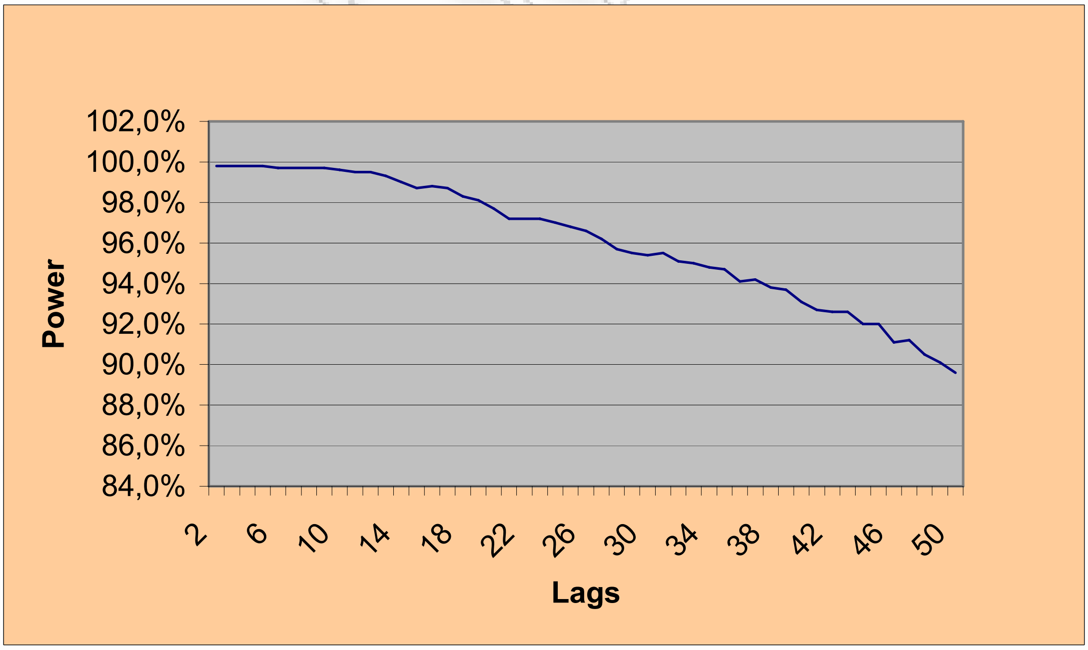
Graphs 4A(continued)
Large Sample

Empirical Power, Causality in Variance Test of Cheung & Ng, N(0,1), Sample Size: 1000 observations., DGP: VAR(1)-GARCH(1,1), Estimation: VAR(1) – GARCH(1,1), Replications: 1000, Nominal Size: 5%



Large Sample

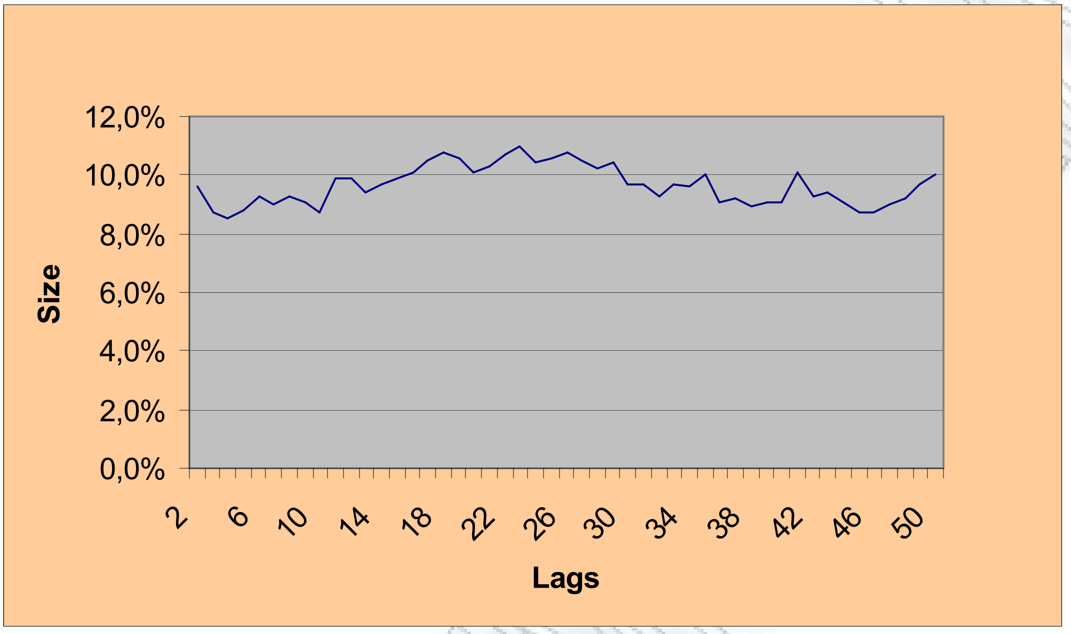
Empirical Power: Causality in Variance Test of Cheung & Ng, N(0,1), Sample Size: 1000 observations., DGP: VAR(1)-GARCH(1,1), Estimation: VAR(1) – GARCH(1,1), Replications: 1000, Nominal Size: 10%



Graphs 4A(continued)

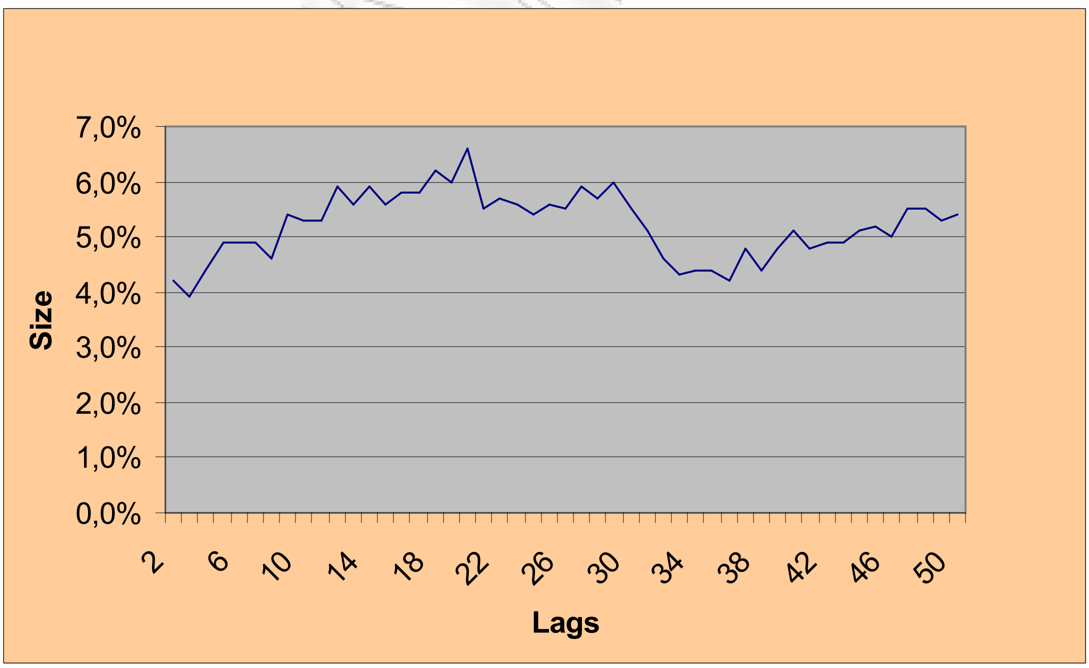
Large Sample

Empirical Size, Causality in Variance Test of Cheung & Ng, N(0,1), Sample Size: 1000 observations., DGP: VAR(1)-GARCH(1,1), Estimation: VAR(1) – GARCH(1,1), Replications: 1000, Nominal Size: 5%



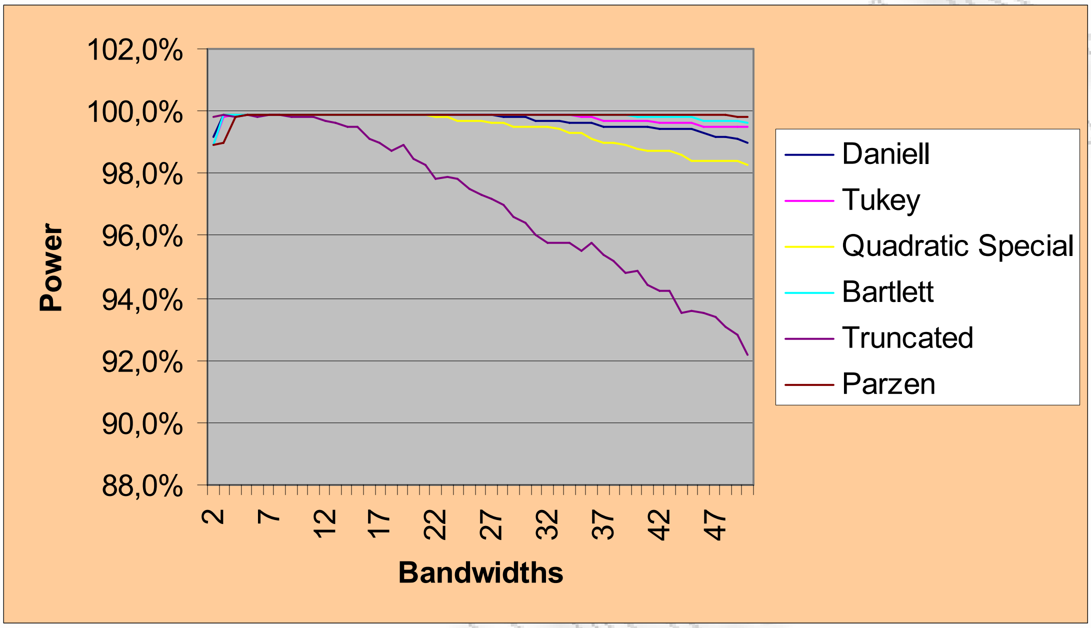
Large Sample

Empirical Size, Causality in Variance Test of Cheung & Ng, N(0,1), Sample Size: 1000 observations., DGP: VAR(1)-GARCH(1,1), Estimation: VAR(1) – GARCH(1,1), Replications: 1000, Nominal Size: 10%



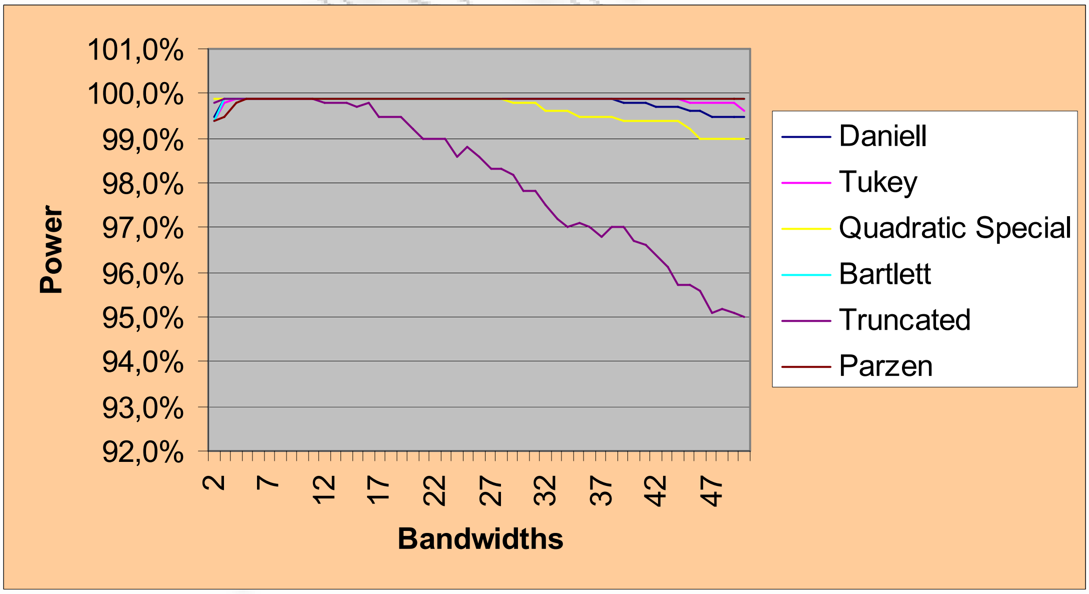
Graphs 4A(continued)
Large Sample

Empirical Power, Causality in Variance Test of Hong, N(0,1), Sample Size: 1000 observations., DGP: VAR(1)-GARCH(1,1), Estimation: VAR(1) – GARCH(1,1), Replications: 1000, Nominal Size: 5%



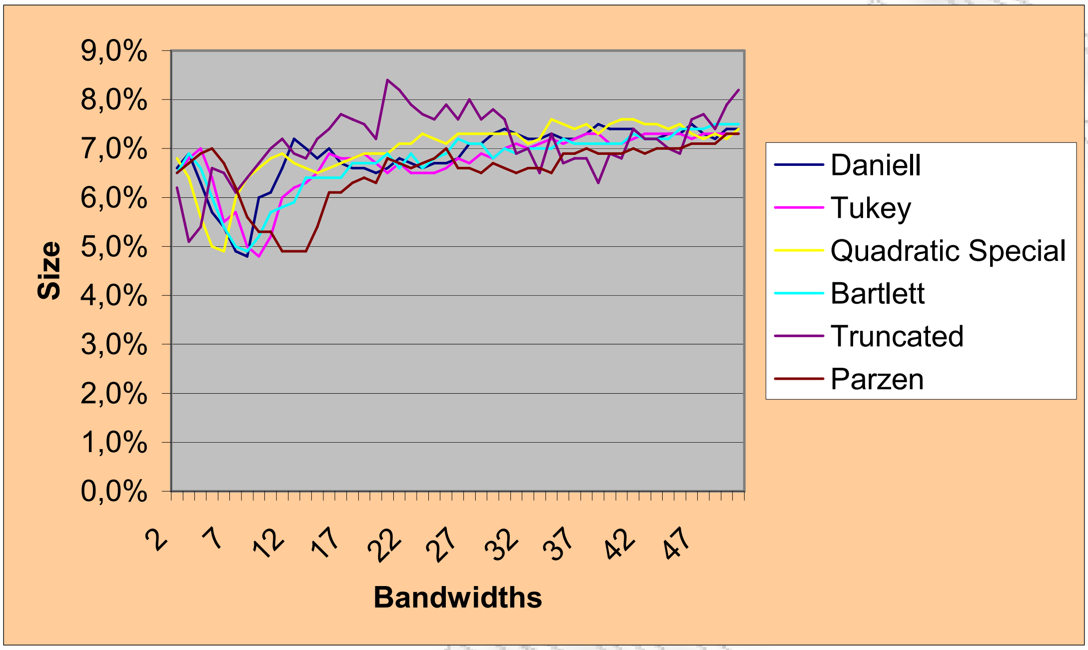
Large Sample

Empirical Power, Causality in Variance Test of Hong, N(0,1), Sample Size: 1000 observations., DGP: VAR(1)-GARCH(1,1), Estimation: VAR(1) – GARCH(1,1), Replications: 1000, Nominal Size: 10%



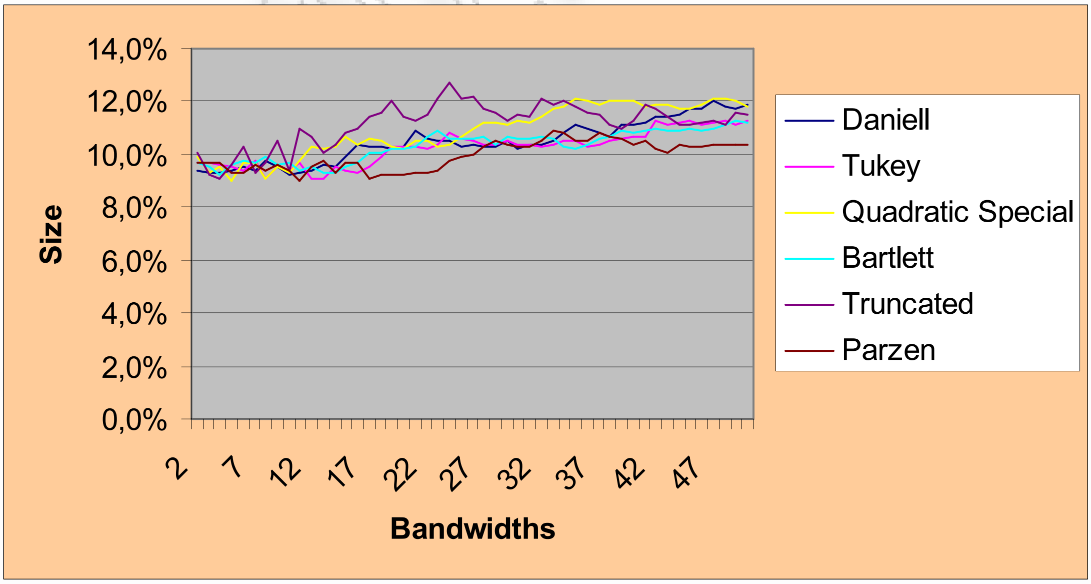
Graphs 4A(continued)
Large Sample

Empirical Size, Causality in Variance Test of Hong, N(0,1), Sample Size: 1000 observations., DGP: VAR(1)-GARCH(1,1), Estimation: VAR(1) – GARCH(1,1), Replications: 1000, Nominal Size: 5%



Large Sample

Empirical Size, Causality in Variance Test of Hong, N(0,1), Sample Size: 1000 observations., DGP: VAR(1)-GARCH(1,1), Estimation: VAR(1) – GARCH(1,1), Replications: 1000, Nominal Size: 10%

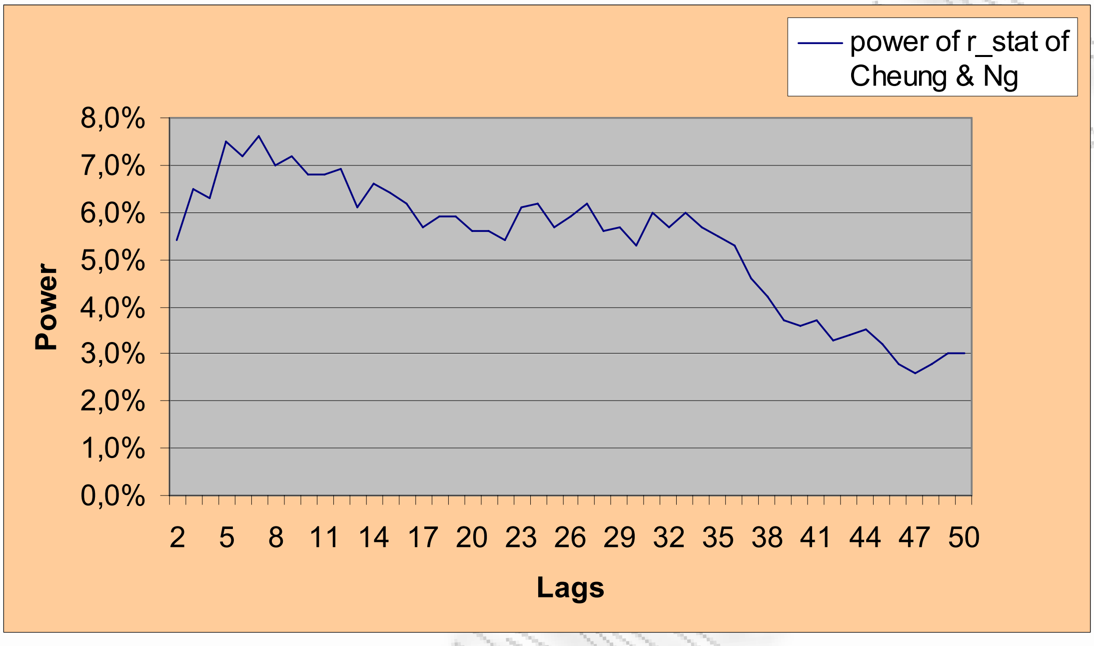


4.2.2 Second Monte Carlo Design

The Data Generating Process is a VAR (1) - FIGARCH (1, d, 1) model. The estimator process is a VAR (1) - GARCH (1, 1) model specification. Finally we calculate the empirical power and the empirical size at specific lags of the Causality in Variance Tests of Cheung & Ng and Hong, presenting them with a graph, at 5% and 10 % significance level. The Null Hypothesis is No Volatility Spillover and the alternative Hypothesis is Unidirectional Volatility Spillover in the first (1^{st}) lag. In addition, the Direction of the Unidirectional Tests is from Series 2 to Series 1.

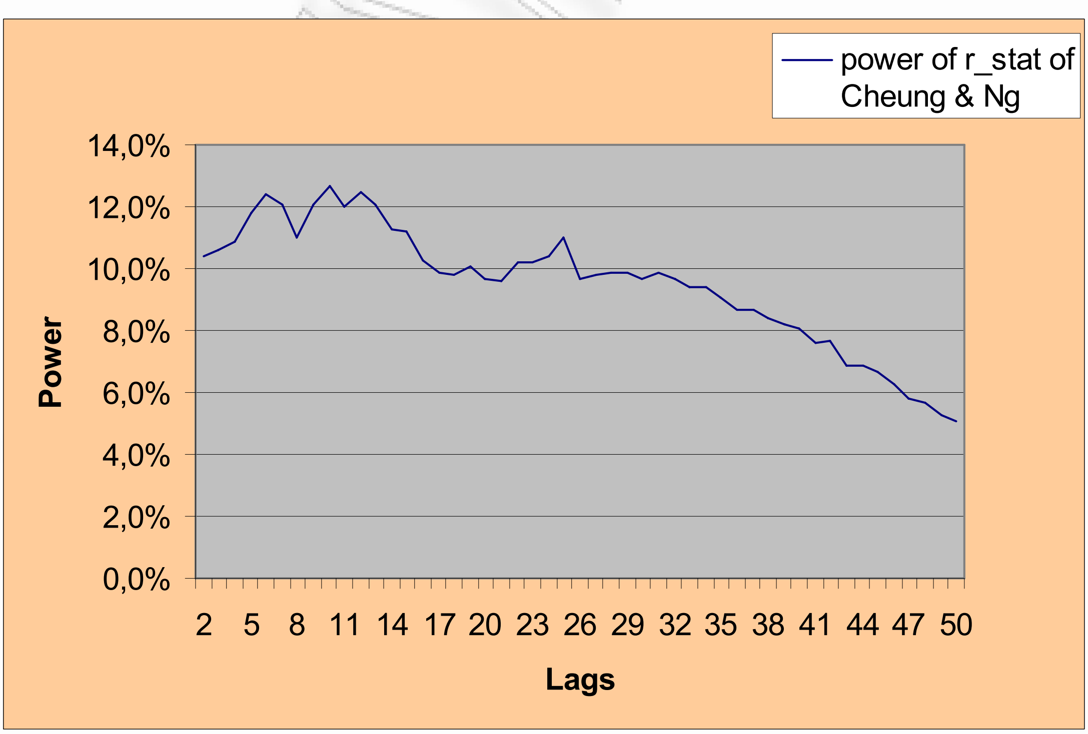
Graphs 4B
Small Sample

Empirical Power, Causality in Variance Test of Cheung & Ng, N(0,1), Sample Size: 200 observations., DGP: VAR(1) – FIGARCH(1,d,1), Estimation: VAR(1)- GARCH(1,1), Replications: 1000, Nominal Size: 5%



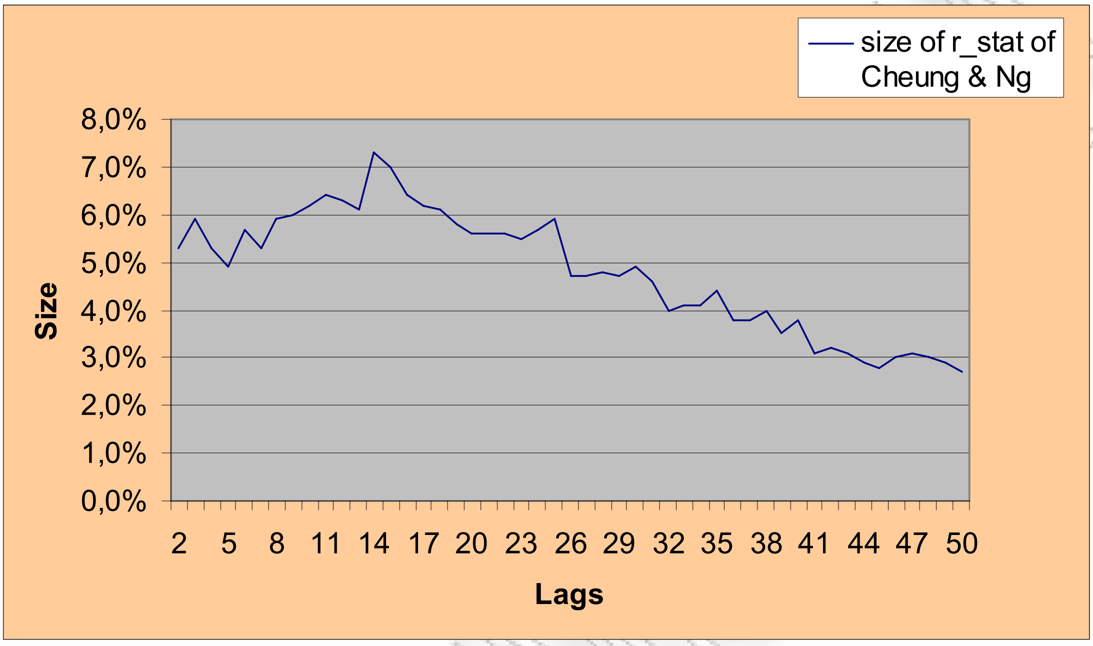
Small Sample

Empirical Power, Causality in Variance Test of Cheung & Ng, N(0,1), Sample Size: 200 observations., DGP: VAR(1) – FIGARCH(1,d,1), Estimation: VAR(1)- GARCH(1,1), Replications: 1000, Nominal Size: 10%



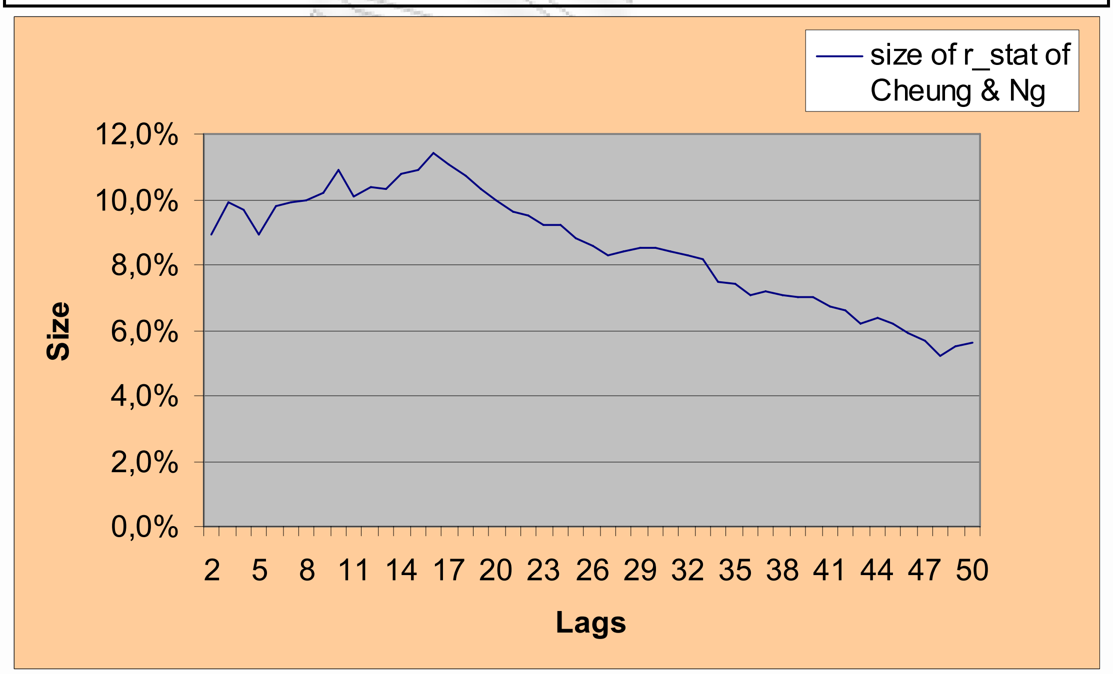
Graphs 4B(continued)
Small Sample

Empirical Size, Causality in Variance Test of Cheung & Ng, N(0,1), Sample Size: 200 observations., DGP: VAR(1) – FIGARCH(1,d,1), Estimation: VAR(1)- GARCH(1,1), Replications: 1000, Nominal Size: 5%



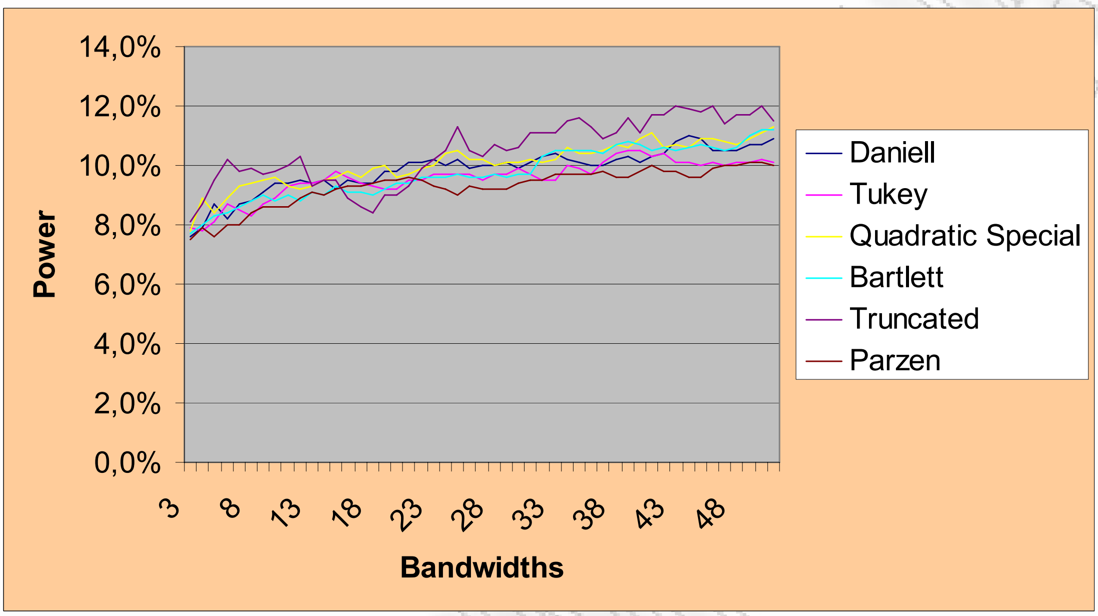
Small Sample

Empirical Size, Causality in Variance Test of Cheung & Ng, N(0,1), Sample Size: 200 observations., DGP: VAR(1) – FIGARCH(1,d,1), Estimation: VAR(1)- GARCH(1,1), Replications: 1000, Nominal Size: 10%



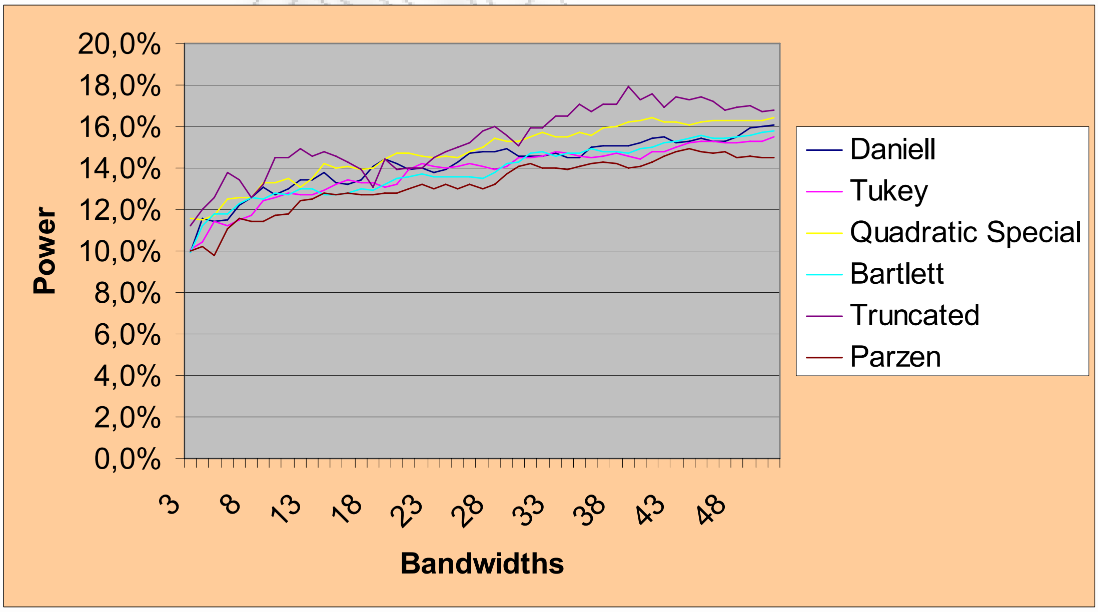
Graphs 4B(continued)
Small Sample

Empirical Power, Causality in Variance Test of Hong, N(0,1), Sample Size: 200 observations., DGP: VAR(1) – FIGARCH(1,d,1), Estimation: VAR(1)- GARCH(1,1) ,Replications: 1000, Nominal Size: 10%



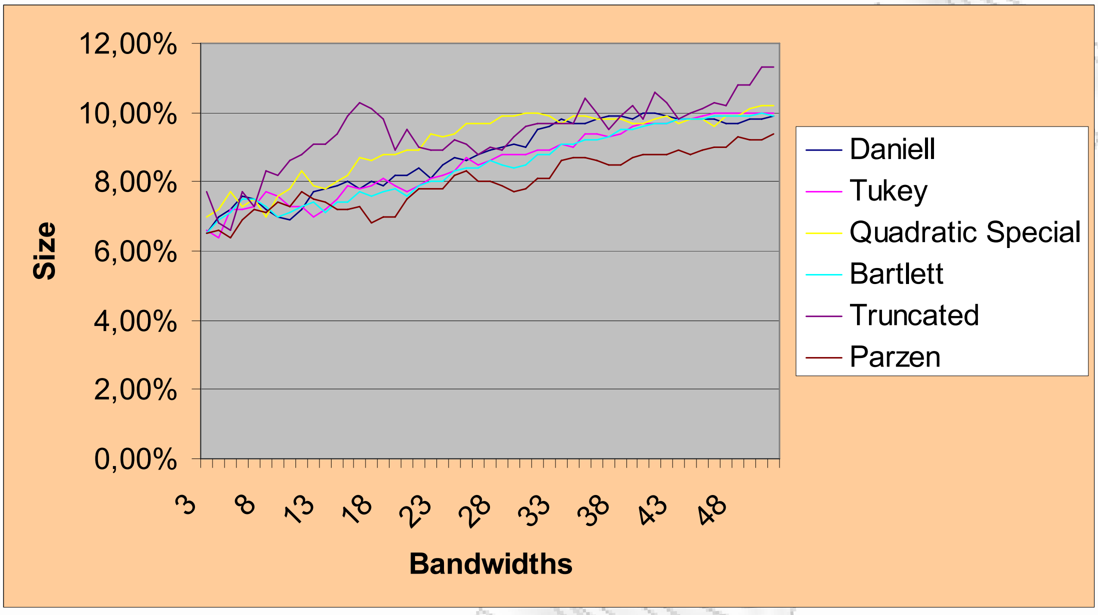
Small Sample

Empirical Power, Causality in Variance Test of Hong, N(0,1), Sample Size: 200 observations., DGP: VAR(1) – FIGARCH(1,d,1), Estimation: VAR(1)- GARCH(1,1) ,Replications: 1000, Nominal Size: 10%



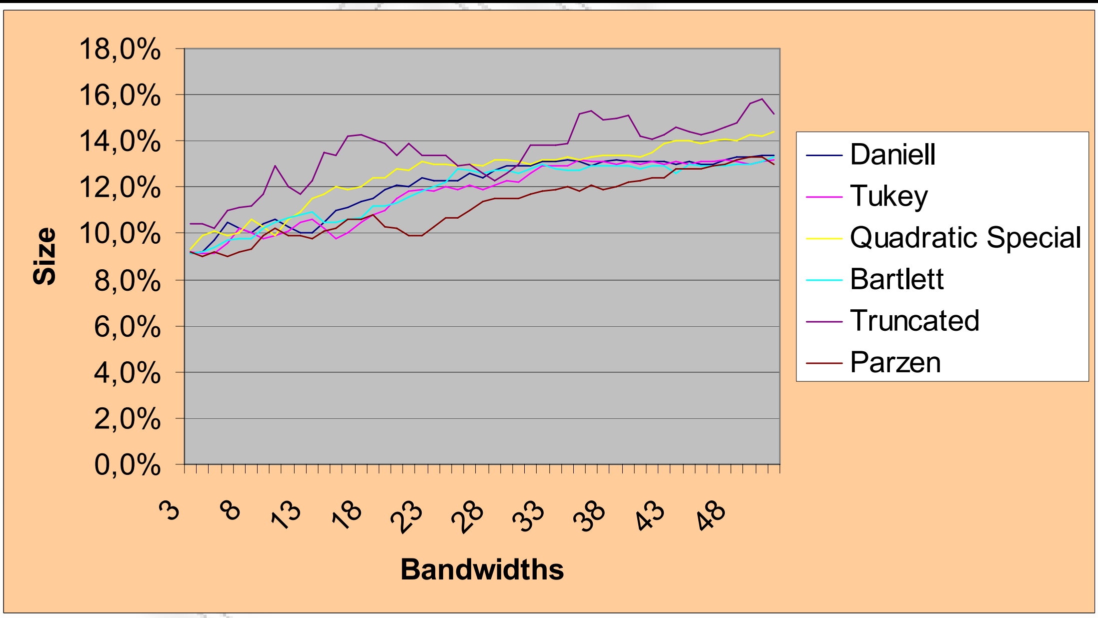
Graphs 4B(continued)
Small Sample

Empirical Size, Causality in Variance Test of Hong, N(0,1), Sample Size: 200 observations., DGP: VAR(1) – FIGARCH(1,d,1), Estimation: VAR(1)- GARCH(1,1), Replications: 1000, Nominal Size: 5%



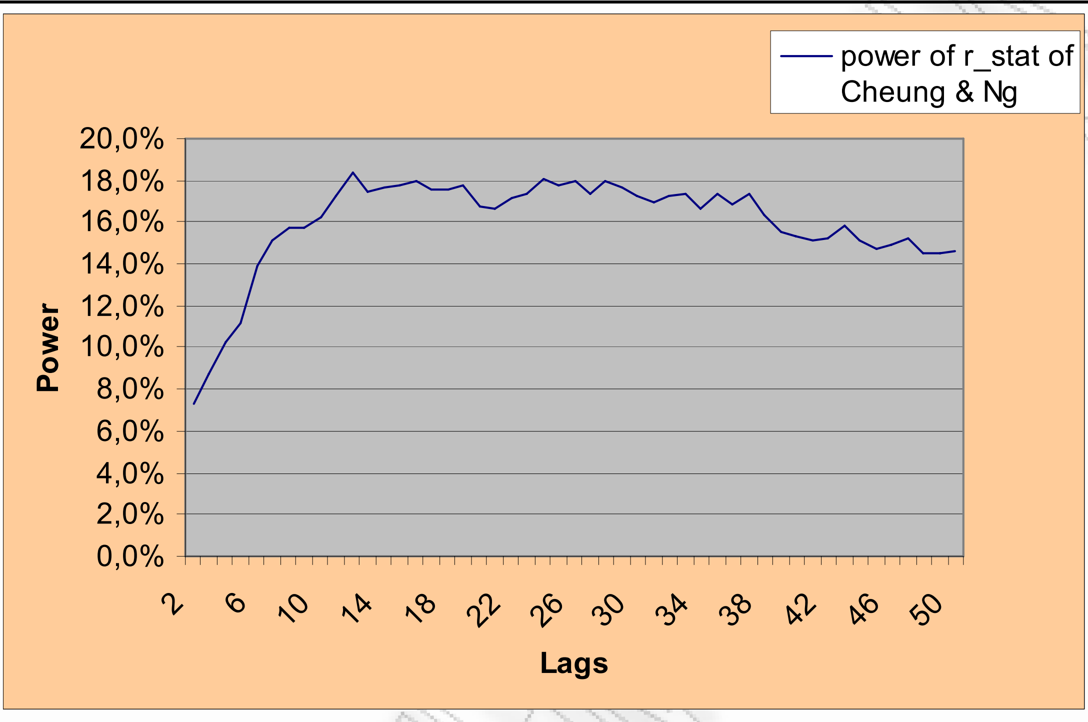
Small Sample

Empirical Size, Causality in Variance Test of Hong, N(0,1), Sample Size: 200 observations., DGP: VAR(1) – FIGARCH(1,d,1), Estimation: VAR(1)- GARCH(1,1), Replications: 1000, Nominal Size: 10%



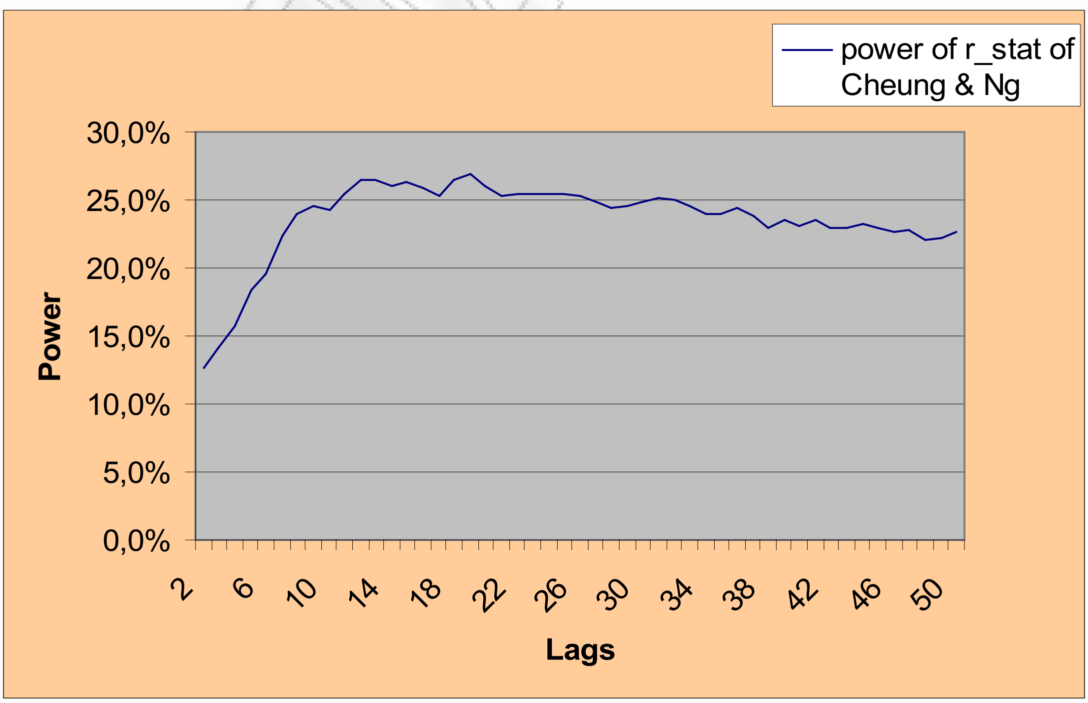
Graphs 4B(continued)
Large Sample

Empirical Power, Causality in Variance Test of Cheung & Ng, N(0,1), Sample Size: 1000 observations., DGP: VAR(1) – FIGARCH(1,d,1), Estimation: VAR(1)- GARCH(1,1), Replications: 1000, Nominal Size: 5%



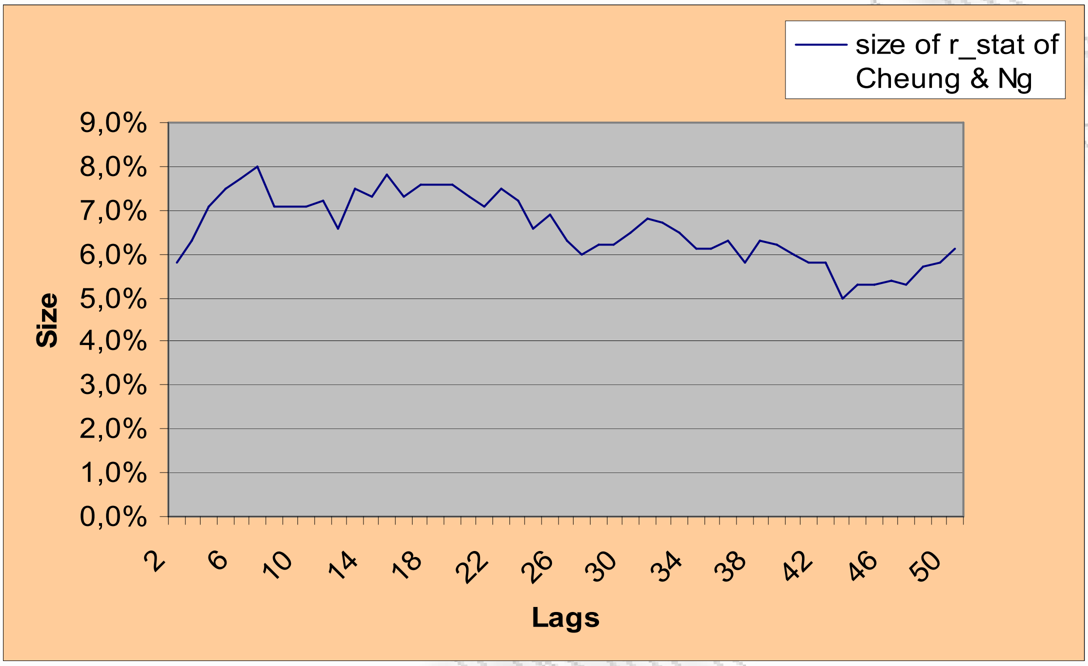
Large Sample

Empirical Power, Causality in Variance Test of Cheung & Ng, N(0,1), Sample Size: 1000 observations., DGP: VAR(1) – FIGARCH(1,d,1), Estimation: VAR(1)- GARCH(1,1), Replications: 1000, Nominal Size: 10%



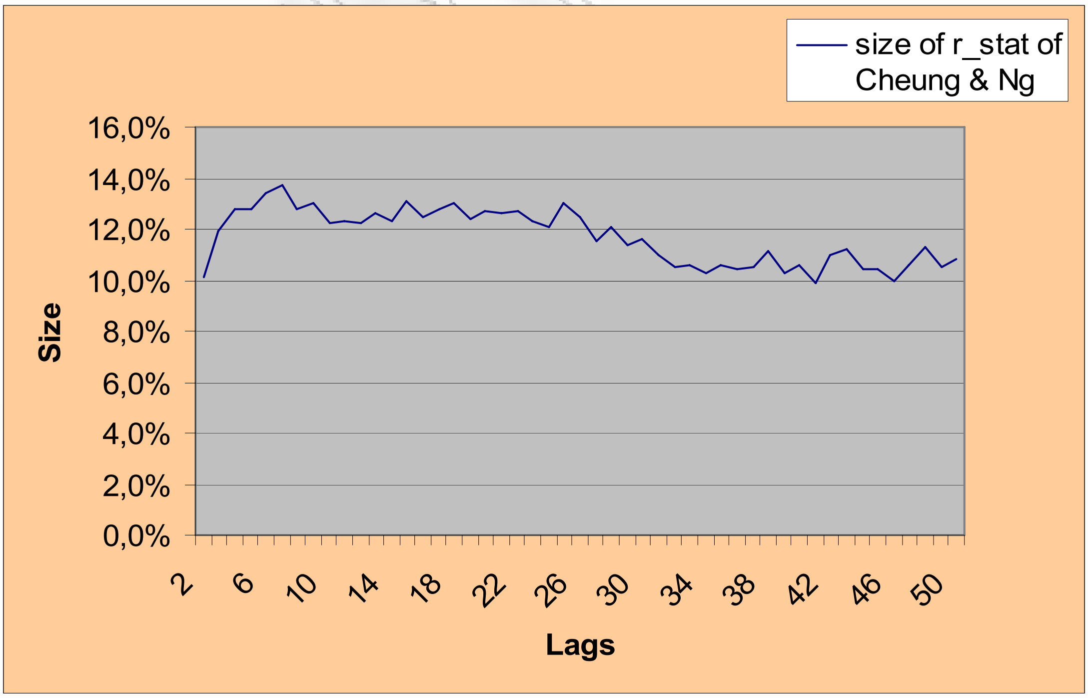
Graphs 4B(continued)
Large Sample

Empirical Size, Causality in Variance Test of Cheung & Ng, N(0,1), Sample Size: 1000 observations., DGP: VAR(1) – FIGARCH(1,d,1), Estimation: VAR(1)- GARCH(1,1), Replications: 1000, Nominal Size: 5%



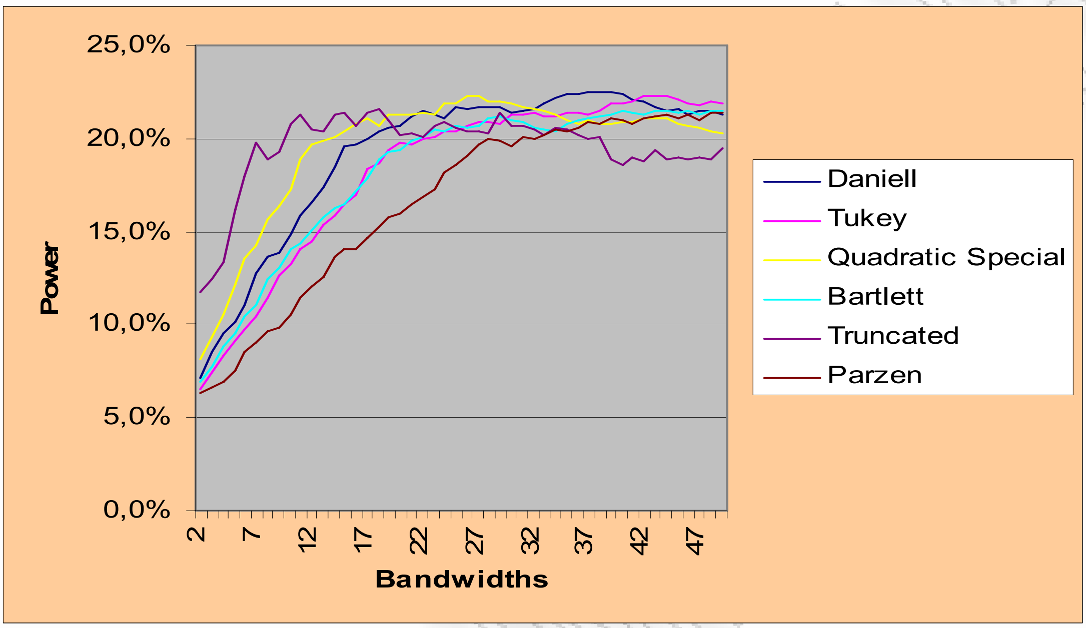
Large Sample

Empirical Size, Causality in Variance Test of Cheung & Ng, N(0,1), Sample Size: 1000 observations., DGP: VAR(1) – FIGARCH(1,d,1), Estimation: VAR(1)- GARCH(1,1), Replications: 1000, Nominal Size: 10%



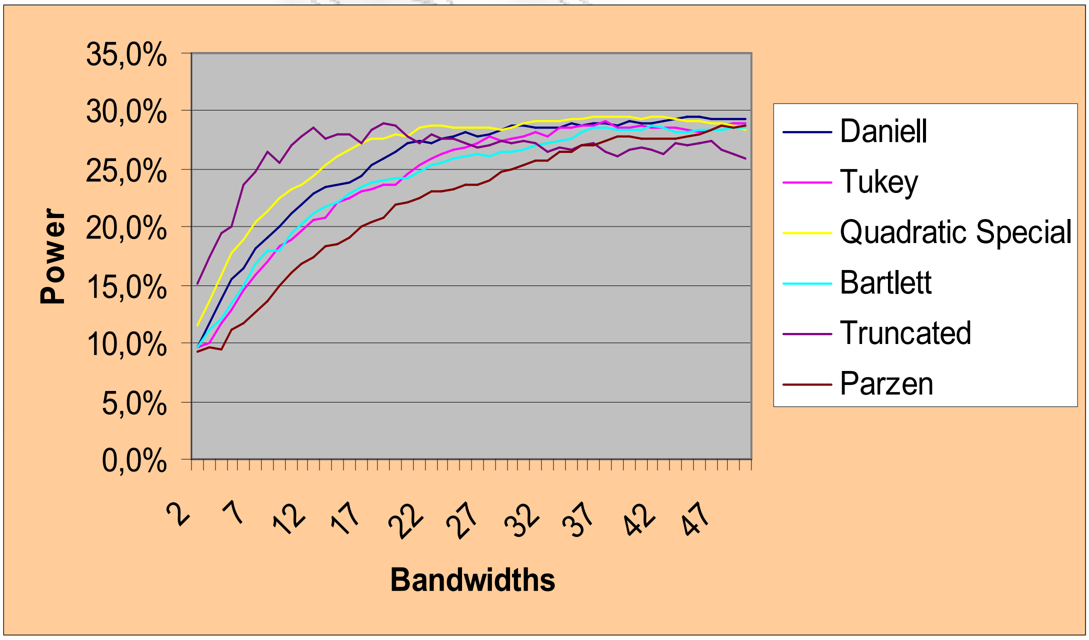
Graphs 4B(continued)
Large Sample

Empirical Power, Causality in Variance Test of Hong, N(0,1), Sample Size: 1000 observations., DGP: VAR(1) – FIGARCH(1,d,1), Estimation: VAR(1)- GARCH(1,1), Replications: 1000, Nominal Size: 5%



Large Sample

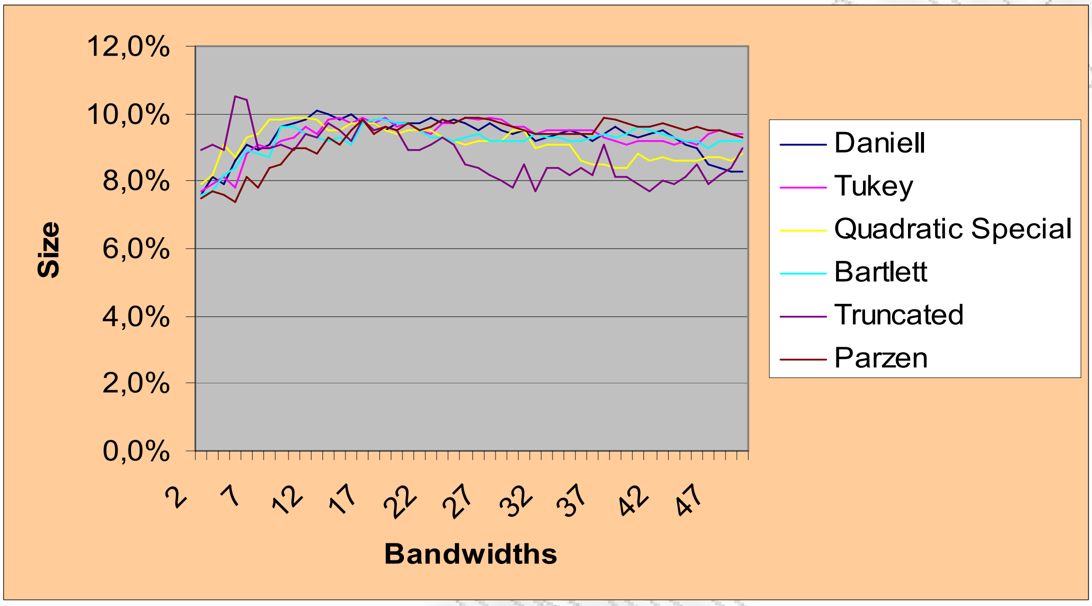
Empirical Power, Causality in Variance Test of Hong, N(0,1), Sample Size: 1000 observations., DGP: VAR(1) – FIGARCH(1,d,1), Estimation: VAR(1)- GARCH(1,1), Replications: 1000, Nominal Size: 10%



Graphs 4B (continued)

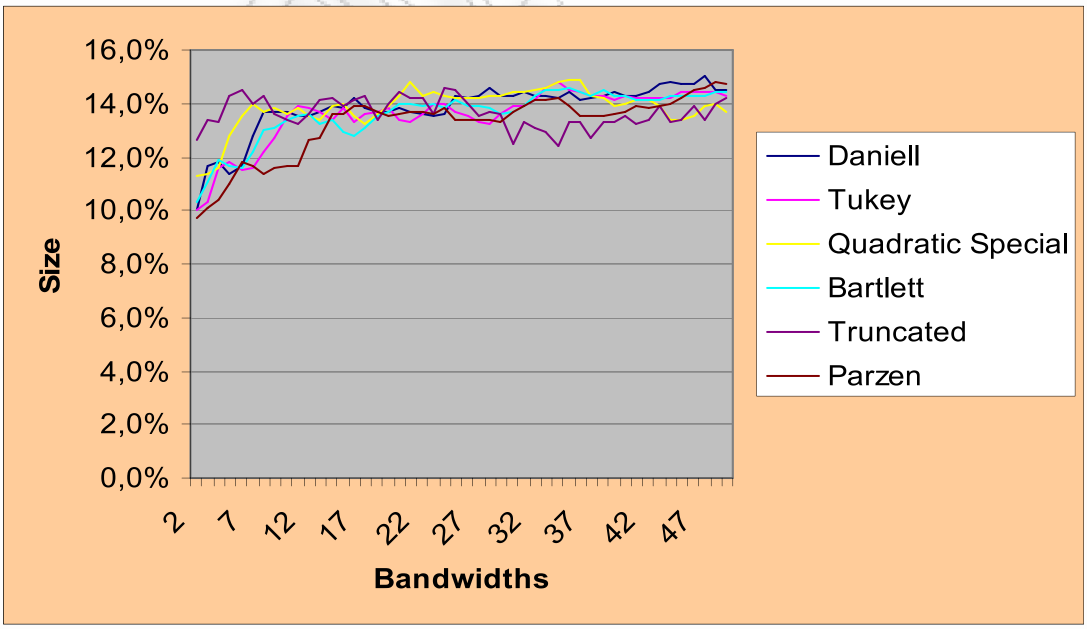
Large Sample

Empirical Size, Causality in Variance Test of Cheung & Ng, N(0,1), Sample Size: 1000 observations., DGP: VAR(1) – FIGARCH(1,d,1), Estimation: VAR(1)- GARCH(1,1), Replications: 1000, Nominal Size: 5%



Large Sample

Empirical Size, Causality in Variance Test of Cheung & Ng, N(0,1), Sample Size: 1000 observations., DGP: VAR(1) – FIGARCH(1,d,1), Estimation: VAR(1)- GARCH(1,1), Replications: 1000, Nominal Size: 10%

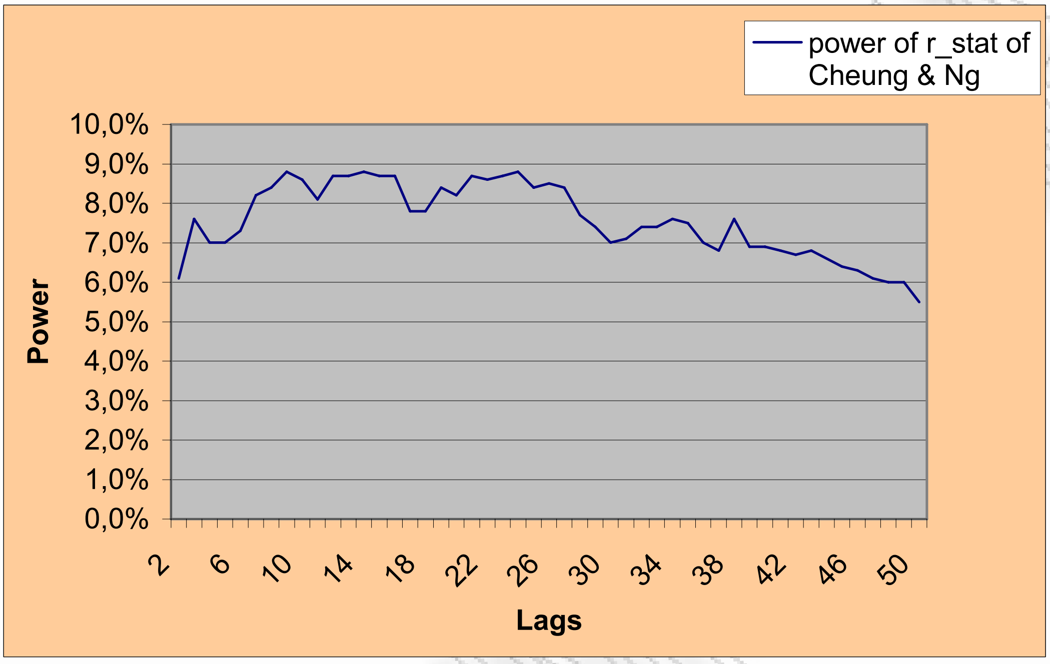


4.2.3 Third Monte Carlo Design

The Data Generating Process is a VAR (1) - FIGARCH (1, d, 1) model. The estimator process is a VAR (1) - FIGARCH(1,d, 1) model specification and finally we calculate the empirical power and the empirical size at specific lags of the Causality in Variance Tests of Cheung & Ng and Hong, presenting them with a graph, at 5% and 10 % significance level. The Null Hypothesis is No Volatility Spillover and the alternative Hypothesis is Unidirectional Volatility Spillover in the first (1^{st}) lag. In addition, the Direction of the Unidirectional Tests is from Series 2 to Series 1.

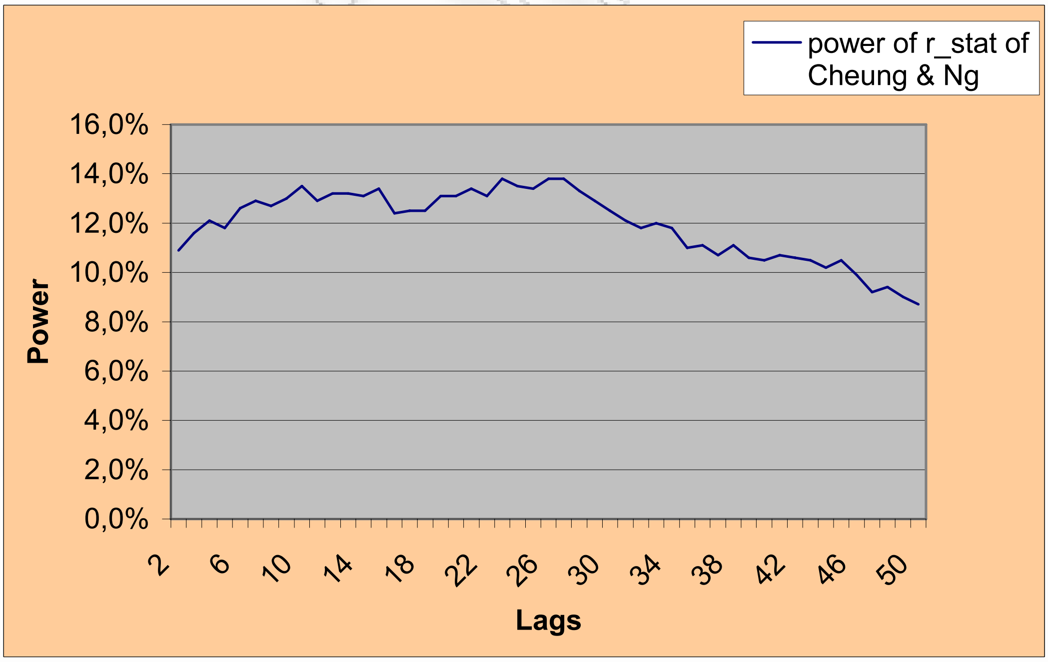
Graphs 4C
Small Sample

Empirical Power, Causality in Variance Test of Cheung & Ng, N(0,1), Sample Size: 200 observations., DGP: VAR(1) – FIGARCH(1,d,1), Estimation: VAR(1)- FIGARCH(1,d,1), Replications: 1000, Nominal Size: 5%



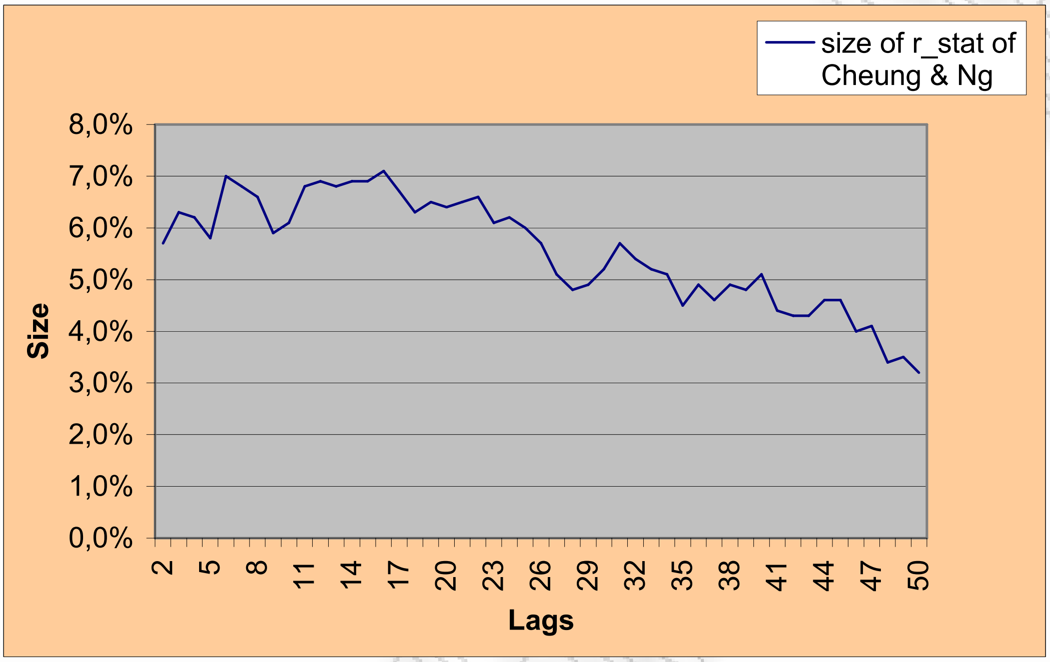
Small Sample

Empirical Power, Causality in Variance Test of Cheung & Ng, N(0,1), Sample Size: 200 observations., DGP: VAR(1) – FIGARCH(1,d,1), Estimation: VAR(1)- FIGARCH(1,d,1), Replications: 1000, Nominal Size: 10%



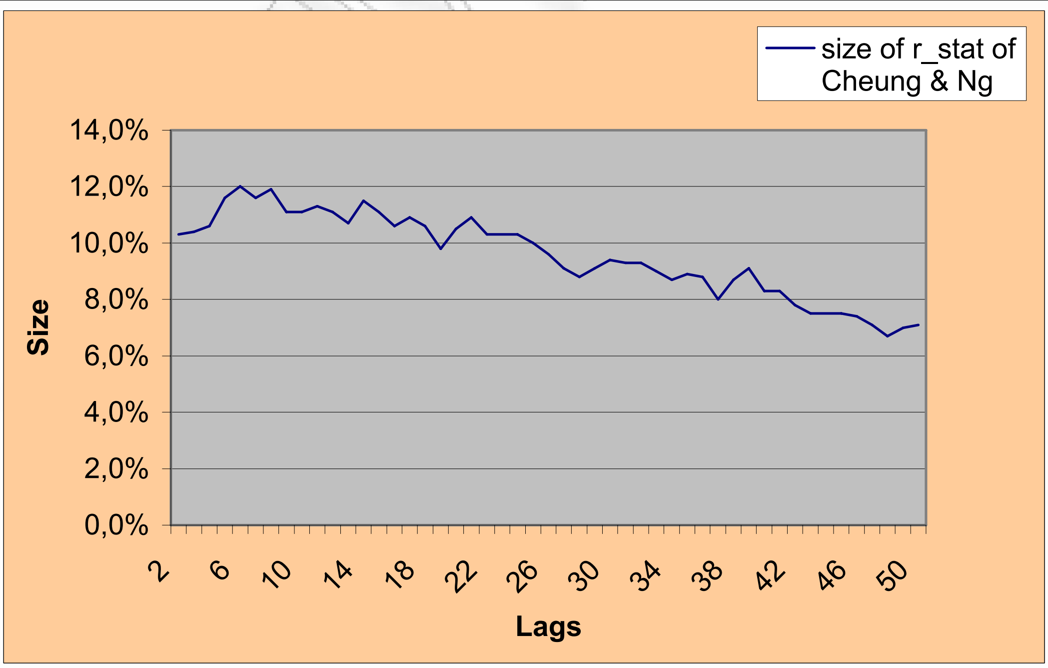
Graphs 4C(continued)
Small Sample

Empirical Size, Causality in Variance Test of Cheung & Ng, N(0,1), Sample Size: 200 observations., DGP: VAR(1) – FIGARCH(1,d,1), Estimation: VAR(1)- FIGARCH(1,d,1), Replications: 1000, Nominal Size: 5%



Small Sample

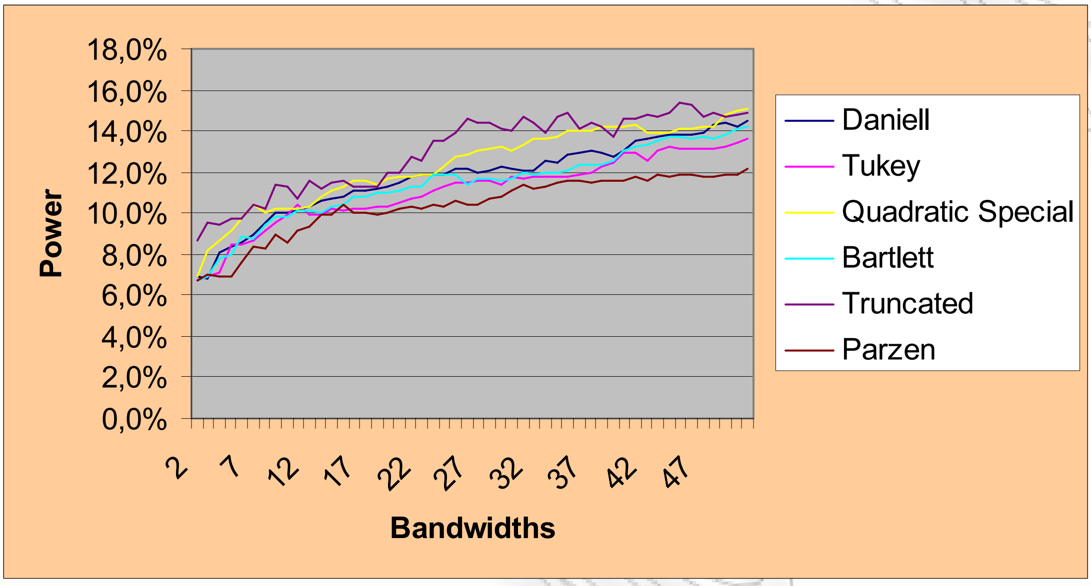
Empirical Size, Causality in Variance Test of Cheung & Ng, N(0,1), Sample Size: 200 observations., DGP: VAR(1) – FIGARCH(1,d,1), Estimation: VAR(1)- FIGARCH(1,d,1), Replications: 1000, Nominal Size: 10%



Graphs 4C→(continued)

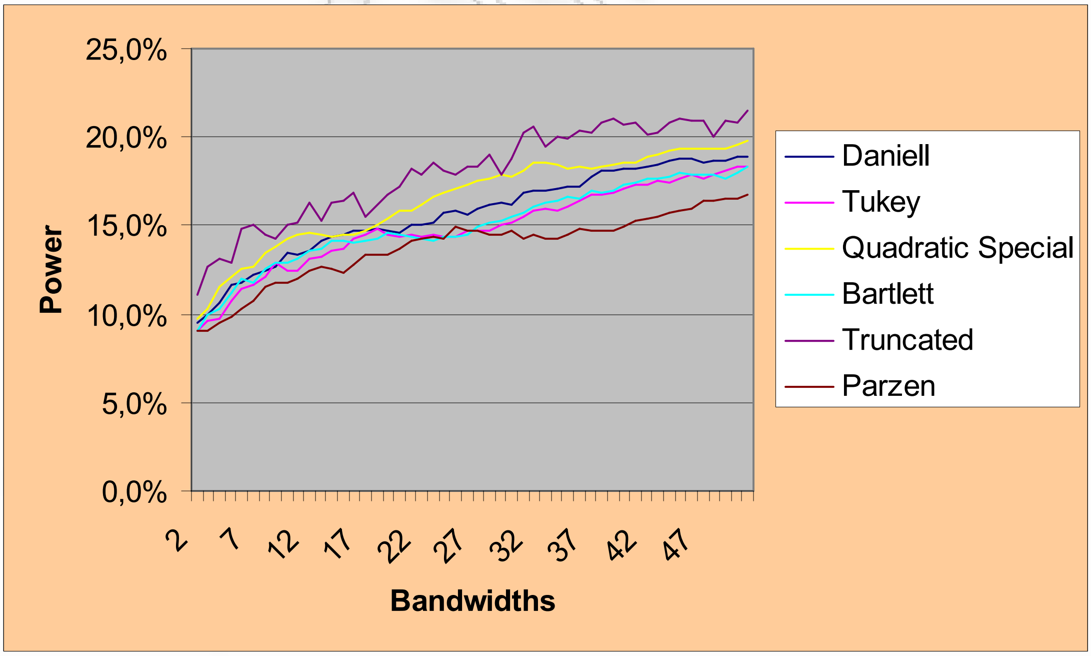
Small Sample

Empirical Power, Causality in Variance Test of Hong, N(0,1), Sample Size: 200 observations., Replications: 1000, DGP: VAR(1) – FIGARCH(1,d,1), Estimation: VAR(1)- FIGARCH(1,d,1) Nominal Size: 5%



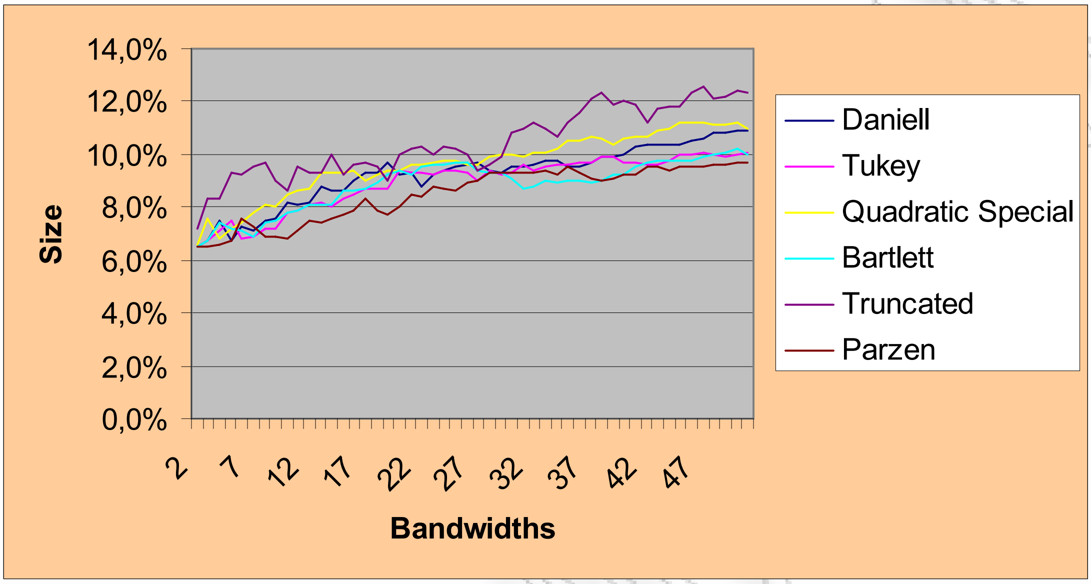
Small Sample

Empirical Power, Causality in Variance Test of Hong, N(0,1), Sample Size: 200 observations., Replications: 1000, DGP: VAR(1) – FIGARCH(1,d,1), Estimation: VAR(1)- FIGARCH(1,d,1) Nominal Size: 10%



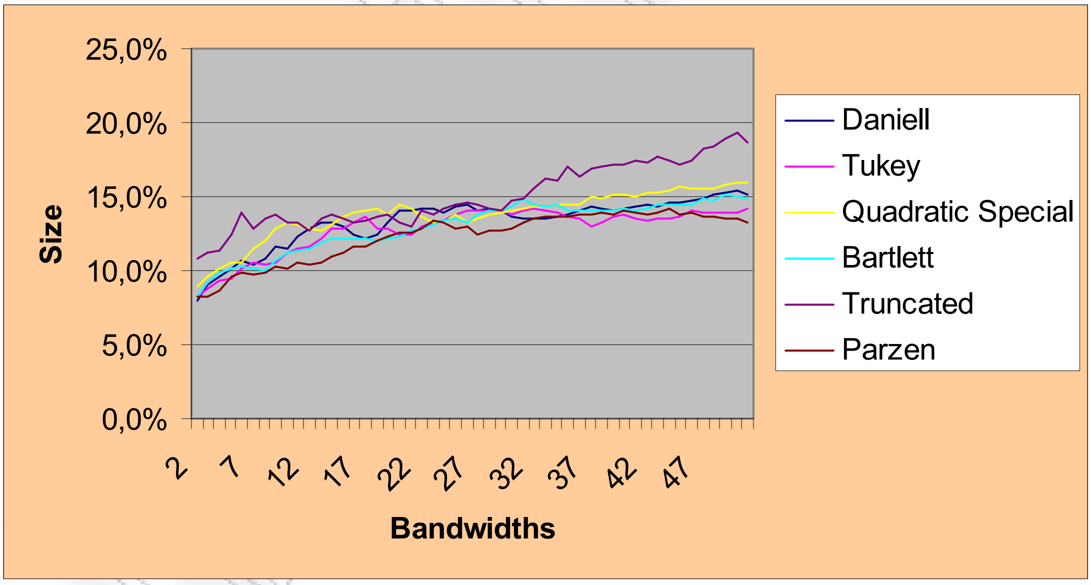
Graphs 4C (continued)
Small Sample

Empirical Size, Causality in Variance Test of Hong, N(0,1), Sample Size: 200 observations., DGP: VAR(1) – FIGARCH(1,d,1), Estimation: VAR(1)- FIGARCH(1,d,1),Replications: 1000, Nominal Size: 5%



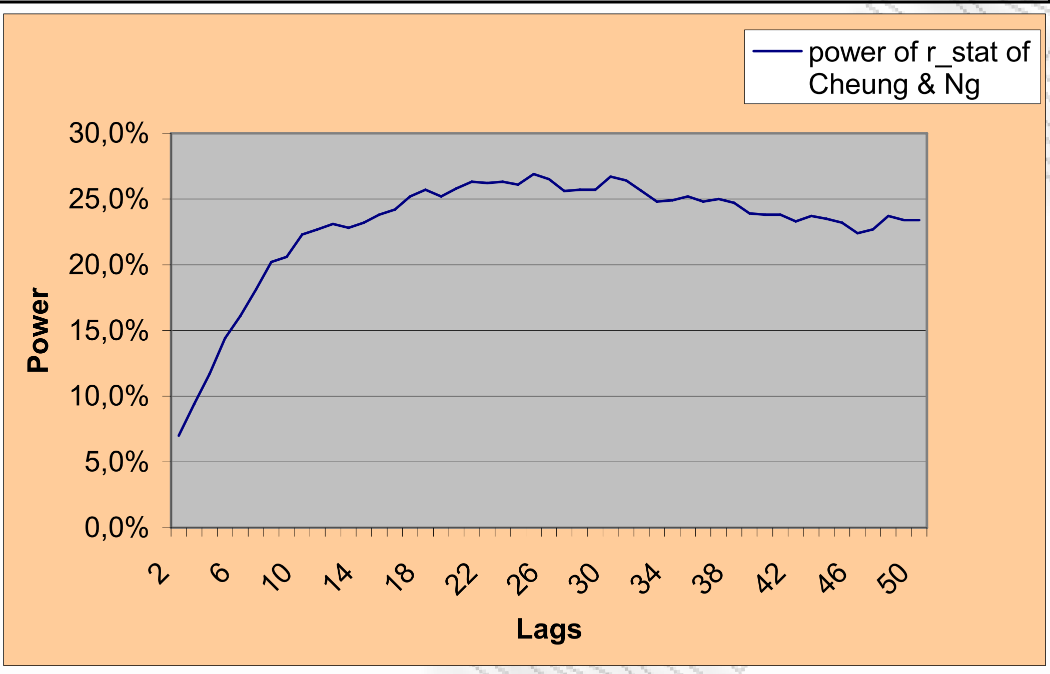
Small Sample

Empirical Size, Causality in Variance Test of Hong, N(0,1), Sample Size: 200 observations., DGP: VAR(1) – FIGARCH(1,d,1), Estimation: VAR(1)- FIGARCH(1,d,1), Replications: 1000, Nominal Size: 10%



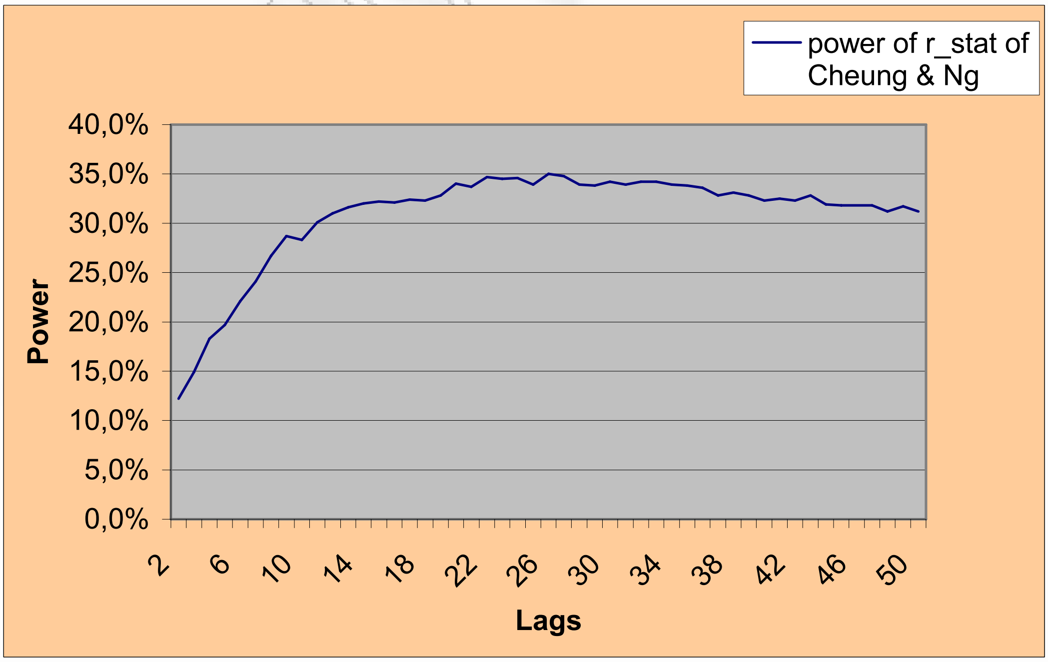
Graphs 4C (continued)
Large sample

Empirical Power, Causality in Variance Test of Cheung & Ng, N(0,1), Sample Size: 1000 observations., DGP: VAR(1) – FIGARCH(1,d,1), Estimation: VAR(1)- FIGARCH(1,d,1), Replications: 1000, Nominal Size: 5%



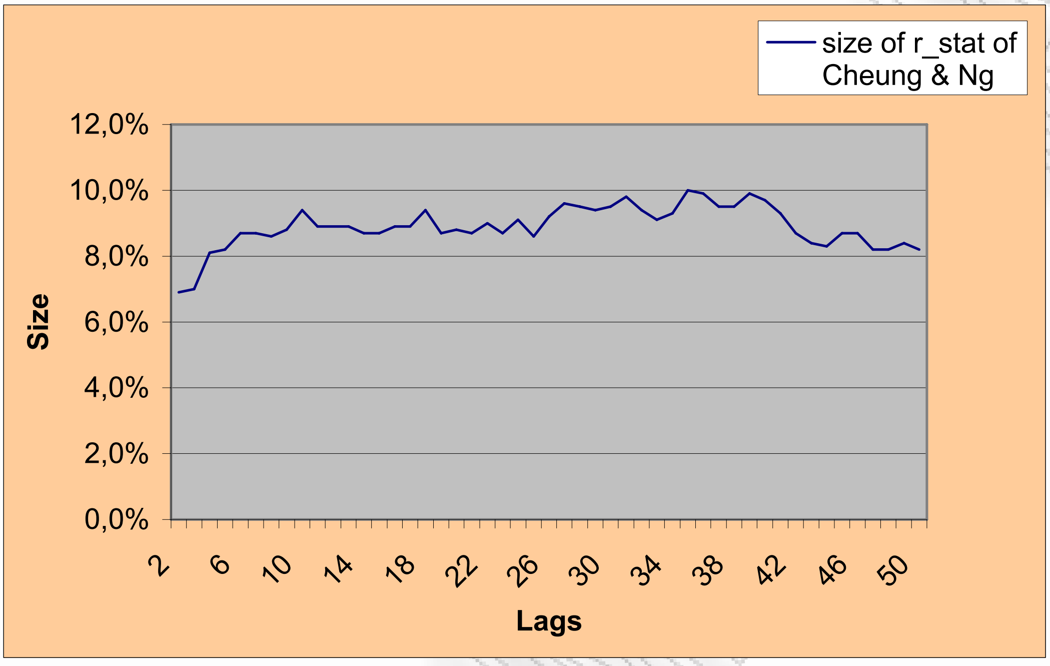
Large sample

Empirical Power, Causality in Variance Test of Cheung & Ng, N(0,1), Sample Size: 1000 observations., DGP: VAR(1) – FIGARCH(1,d,1), Estimation: VAR(1)- FIGARCH(1,d,1), Replications: 1000, Nominal Size: 10%



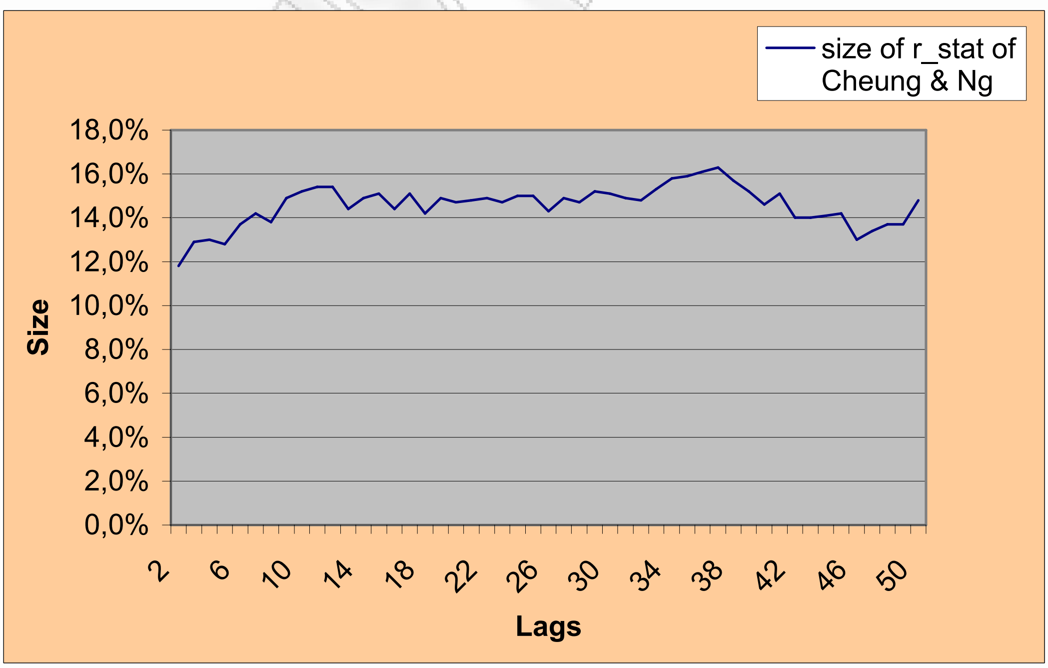
Graphs 4C (continued)
Large sample

Empirical Size, Causality in Variance Test of Cheung & Ng, N(0,1), Sample Size: 1000 observations., DGP: VAR(1) – FIGARCH(1,d,1), Estimation: VAR(1)- FIGARCH(1,d,1), Replications: 1000, Nominal Size: 5%



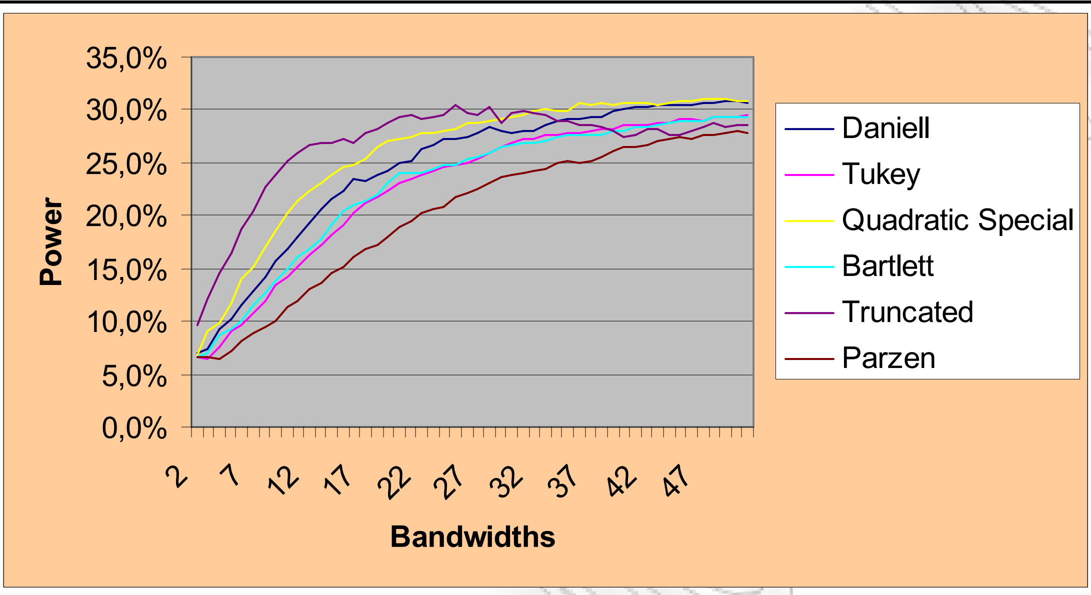
Large sample

Empirical Size, Causality in Variance Test of Cheung & Ng, N(0,1), Sample Size: 1000 observations., DGP: VAR(1) – FIGARCH(1,d,1), Estimation: VAR(1)- FIGARCH(1,d,1), Replications: 1000, Nominal Size: 10%



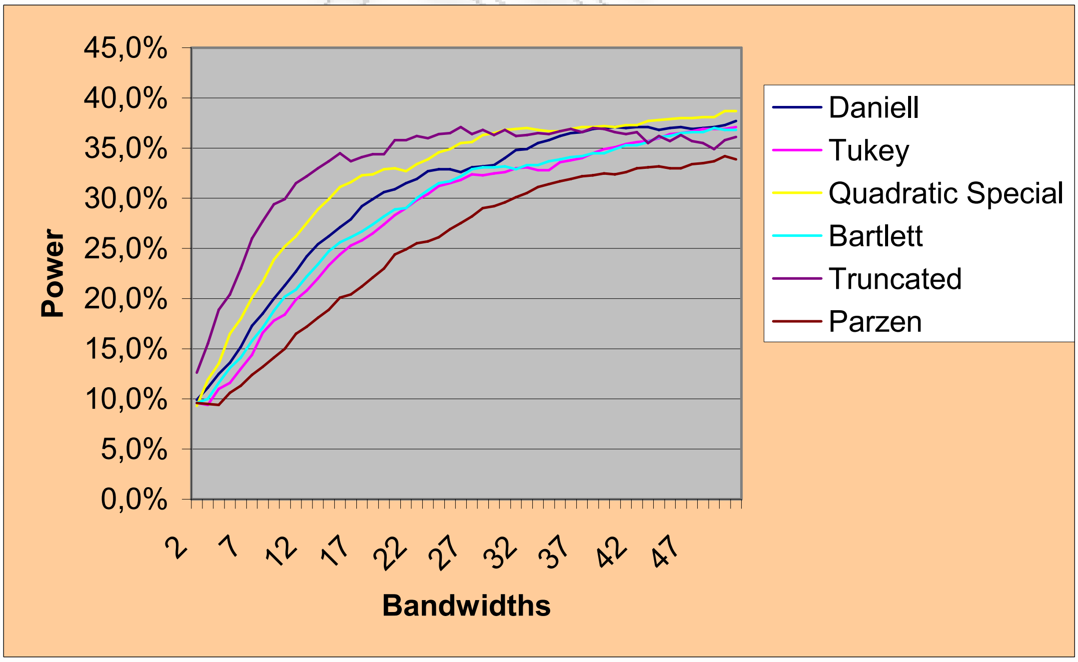
Graphs 4C (continued)
Large sample

Empirical Power, Causality in Variance Test of Hong, N(0,1), Sample Size: 1000 observations., DGP: VAR(1) – FIGARCH(1,d,1), Estimation: VAR(1)- FIGARCH(1,d,1), Replications: 1000, Nominal Size: 5%



Large sample

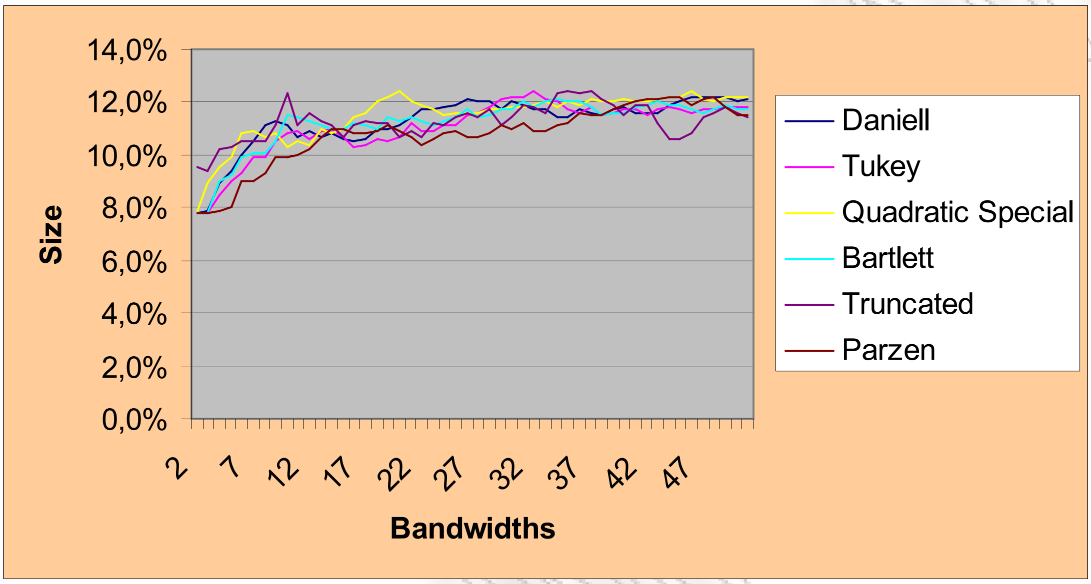
Empirical Power, Causality in Variance Test of Hong, N(0,1), Sample Size: 1000 observations., DGP: VAR(1) – FIGARCH(1,d,1), Estimation: VAR(1)- FIGARCH(1,d,1), Replications: 1000, Nominal Size: 10%



Graphs 4C (continued)

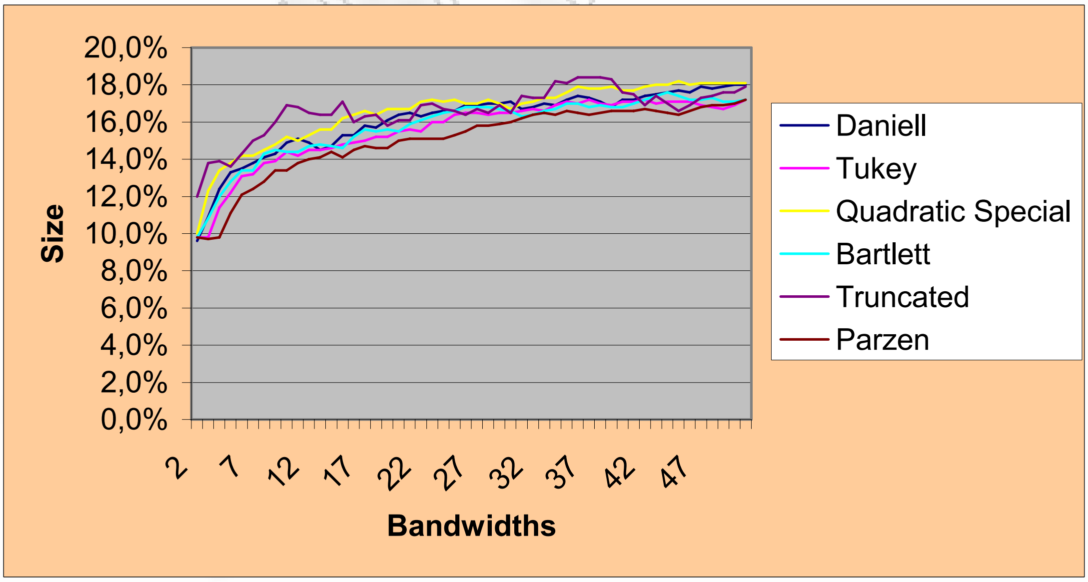
Large sample

Empirical Size, Causality in Variance Test of Hong, N(0,1), Sample Size: 1000 observations., DGP: VAR(1) – FIGARCH(1,d,1), Estimation: VAR(1)- FIGARCH(1,d,1), Replications: 1000, Nominal Size: 5%



Large sample

Empirical Size, Causality in Variance Test of Hong, N(0,1), Sample Size: 1000 observations., DGP: VAR(1) – FIGARCH(1,d,1), Estimation: VAR(1)- FIGARCH(1,d,1), Replications: 1000, Nominal Size: 10%



4.3 Analysis of the three Monte Carlo Designs

The goal of our analysis is to analyse the finite sample properties of Causality in Variance Tests and specifically those of Cheung & Ng and Hong, using two sample sizes. Let's first separate our analysis in the two sample sizes and in the two Causality Tests.

Causality Test of Cheung & Ng / small sample: Let's first analyse these statistics in macroeconomic series. This is the reason we first use a small sample (low frequency data). First we generated data which do not have long memory in volatility (DGP: GARCH (1st Monte Carlo Design)) and estimated them with the GARCH model specification. The Null Hypothesis is No Causality in Volatility and the Alternative Hypothesis is Causality in Volatility in the first (1st) lag. Afterwards we found the empirical size and power of the statistics of the Causality in Variance Tests. We remarked that the empirical size as well as the empirical power of the Cheung & Ng's statistics exhibits a good empirical performance in both nominal size of 5% and 10%, After these results, we made a second simulation experiment, generating data that have long memory in volatility (DGP: FIGARCH (2nd Monte Carlo Design)) and estimated them with the GARCH model specification. The Null Hypothesis is No Causality in Volatility and the Alternative Hypothesis is Causality in Volatility in the first (1st) lag. Afterwards we found the empirical size and power of the statistics of the Causality in Variance Tests. We remarked that the empirical size of the Cheung & Ng's statistics exhibits a good empirical performance in both nominal size of 5% and 10%. We discerned that these statistics do not exhibit a good empirical power which ranges in low levels, across the lag length. To be more precise, from the graphs 4A in the previous section, we noted that the empirical power of the statistics of Cheung & Ng fluctuates in high levels and in a difference of 50% in the first simulation compared to the results of the second simulation. Till now, we can assume that the statistics of Cheung & Ng, exhibit a good performance when they are used in data which do not present long memory in volatility. In addition, these statistics perform poorly when it is taken into account the long memory in volatility. This is the reason why we proceeded to a third simulation experiment, where we generated data which have long memory in the second moment and estimated them not with the GARCH specification, but with the FIGARCH model specification. The Null Hypothesis is No Causality in Volatility and the Alternative Hypothesis is Causality in Volatility in the first (1st) lag. Afterwards we found the empirical size and power of the statistics of the Causality in Variance Tests. We remarked that the empirical size of the Cheung & Ng's statistics exhibits a relatively good empirical performance in both nominal sizes of 5% and 10% (a small upward distortion of the size). Let's now see the performance of the empirical power. As we can see from the graphs 4C, the statistics do not exhibit a good empirical power, as it ranges in low levels. However, the empirical power of the statistics in the third simulation ranges in highest values than the empirical power of the statistics in the second simulation, a difference which ranges from 5% to 6%. The statistics of Cheung & Ng have better empirical performance when the FIGARCH model is used when data present long memory in volatility. Let's analyse the results in a larger sample, analysing these statistics in financial series:

Causality Test of Cheung & Ng / large sample: We made the same procedure as described above, but now we used a larger sample, a sample of 1000 observations rather than only 200(small sample). Conducting the first simulation it is undeniable that the statistics of Cheung & Ng exhibit a very good empirical performance owning the high value that power takes across the lag length(99 -100%) and the small values of the size in both nominal sizes. In the second simulation (DGP: FIGARCH(1,d,1) and the estimation GARCH(1,1)), we remarked a small upward distortion of the size in the Causality Test in both nominal sizes 5% and 10%, however we can say that the statistics of Cheung & Ng exhibit a relatively good empirical performance regarding the size. On the contrary, we remarked a small increase in the value of the power. In the third simulation (DGP: FIGARCH(1,d,1) and the estimation FIGARCH(1,d,1)) we remarked also a small upward distortion of the size. However, the increase of the power was bigger than the power found in the second simulation in the Test in both nominal sizes. Finally, the empirical performance of the statistics regarding the power is better, compared to the performance of the statistics of the second simulation that we have conducted.

Causality Test of Hong / small sample: First we generated data which do not have long memory in volatility (DGP: GARCH (1st Monte Carlo Design)) and estimated them with the GARCH model specification and we found the empirical size and power of the statistics of the Causality in Variance Tests. We remarked that the empirical size as well the empirical power of the Hong's statistics exhibits a good empirical performance in both nominal size of 5% and 10%. After these results, we made a second simulation experiment, generating data that present long memory in volatility (DGP: FIGARCH (2nd Monte Carlo Design)) and estimated them with the GARCH model specification. The Null Hypothesis is No Causality in Volatility and the Alternative Hypothesis is Causality in Volatility in the first (1st) lag. Afterwards we found the empirical size and power of the statistics of the Causality in Variance Tests. We remarked that the empirical size of the Hong's statistics exhibits a relatively good empirical performance, but a little oversized, in both nominal size of 5% and 10%. In addition, we discerned that these statistics do not exhibit a good empirical power which ranges in low levels. From the graphs 4A in the previous section, we noted that the empirical power of the statistics of Hong fluctuates in high levels and in a difference of 55% compared to the results found in the second simulation. Till now, we can assume that the statistics of Hong exhibit a good performance when the DGP is a GARCH model and the estimation is performed also by the GARCH specification model. However, these Tests perform poorly when it is taken into account the long memory in volatility. This is the reason why we proceeded to a third simulation experiment. In our third simulation experiment we generated data which have long memory in the second moment and estimated them with the FIGARCH model specification. We remarked that the empirical size of the Hong's statistics exhibits a relatively good empirical performance in both nominal size of 5% and 10%. Let's now see the performance of the empirical power. As we can see from the graphs 4C, the statistics do not exhibit a good empirical power, as it ranges in low levels. However, the empirical performance of the statistics regarding the power is better, compared to the performance of the statistics of the second simulation that we have conducted. The difference ranges from 5% - 6%. The statistics of Hong have better empirical performance when the FIGARCH model, instead of the GARCH model is used in data which present long memory in volatility. Let's analyse the results in a larger sample, analysing these statistics in financial series:

Causality Test of Hong / large sample: We made the same procedure as described above, but now we use a larger sample, a sample of 1000 observations rather than only 200(small sample). Conducting the first simulation, we remarked that the statistics of Cheung & Ng exhibit a very good empirical performance owning to the high value that power takes across the lag length(99 -100%) and the small values of the size in both nominal sizes. In the second simulation (DGP: FIGARCH(1,d,1) and the estimation GARCH(1,1)), we remarked a small upward distortion of the size of the Causality Test in both nominal sizes 5% and 10%. However, we remarked a small increase in the value of the power. In the third simulation (DGP: FIGARCH (1, d, 1) and the estimation FIGARCH (1, d, 1)) we remarked also a small distortion of the size. However, the increase of the power was bigger than the power found in the second simulation in the Test in both nominal sizes. Finally, the empirical performance of the statistics regarding the power is better, compared to the performance of the statistics of the second simulation that we have conducted.

4.4 Conclusive Remarks

From the above analysis (4.2) we can assert that for the macroeconomic series (low frequency data), the Causality in Variance Tests Cheung & Ng and Hong, which use the GARCH model specification for modelling the (conditional) volatility, exhibit a relatively good empirical performance. Taken into consideration an important property of volatility, the long memory, these two Causality Tests perform poorly. When we replace the GARCH model with that of FIGARCH, these statistics exhibit a poor empirical performance for the macroeconomic series. On the other hand, these Tests exhibit a good empirical performance for the financial series (high frequency data). Taking now into consideration the long memory in volatility, these two Causality Tests perform poorly. However, replacing now the GARCH with the FIGARCH model specification, we remark a better empirical performance compared to the corresponding, regarding the macroeconomic series.

CHAPTER 5: EMPIRICAL APPLICATION: CAUSALITY IN MEAN AND VARIANCE FOR 18 COUNTRIES OF THE EUROPEAN UNION

5.1 Data

The data consist of monthly observations of the aggregate (general) stock price index, as well as the consumer price index (CPI) of 18 countries of the European Union. Table 5A shows a table of these countries, with their abbreviations. The data are being retrieved from the database DataStream. The sample period runs from January 1973 to March 2009.

Using the CPI, we obtained the monthly real stock prices, by dividing the period's nominal stock price index by the corresponding consumer price index. Afterwards we obtained the real stock returns using the percentage change (log difference) of the real stock prices over a given period.

a/a	Country	Abbreviation
1	Belgium	Bl
2	Czech Republic	Cz
3	Cyprus	Cy
4	Denmark	Dk
5	Estonia	Es
6	France	Fr
7	Germany	Ger
8	Greece	Gr
9	Hungary	Hu
10	Ireland	Ir
11	Italy	It
12	Netherlands	Nth
13	Portugal	Port
14	Slovakia	Slvk
15	Slovenia	Slvn
16	Spain	Sp
17	Sweden	Sw
18	United Kingdom	UK

Table 5A

5.2 Empirical Analysis of the Results

Our goal is on the one hand to detect any causality in mean and on the other hand any volatility spillover (causality in variance) concerning the real stock returns among the European countries. In other words we detect the dynamic relationship in mean and volatility of the 18 European stock markets, using the corresponding real stock returns. With the aid of the non – parametric causality tests that we analysed in

Chapter 2, the Causality Test of Cheung & Ng and the Causality Test of Hong, we have the results. Now, we have to underline that we first estimated the financial time series of the real stock returns using the **GARCH** and the **FIGARCH** model specifications for modelling the conditional variance. Afterwards obtaining the residuals from the two model specifications, we estimated the cross correlation function. In **APPENDIX A** we present a number of the statistical tables of the causality in mean and variance of Cheung & Ng and Hong, using the GARCH model. In **APPENDIX B** we present a number of the statistical tables of the causality in variance of Cheung & Ng and Hong, using the FIGARCH model. We provide only the table of causality in variance as far as the FIGARCH model is concerned, because we want to see the impact of the long memory in volatility. *For brevity reasons we cannot put all the statistical tables in our dissertation. These tables are available from the author upon request*. With the aid of **Matlab,** we retrieve the results**.** *The matlab code is available from the author upon request.*

In the following pages we present nine (9) cumulative tables for the results:

- Table 5B presents the **Cumulative Table** of Causality in **Mean** among the 18 European Countries of EU, according to **r statistic** of the Causality Test of **Cheung &Ng**, using the **GARCH** Model
- Table 5C presents the **Cumulative Table** of Causality in **Variance** among the 18 European Countries of EU, according to **r statistic** of the Causality Test of **Cheung &Ng**, using the **GARCH** Model
- Table 5D presents the **Cumulative Table** of Causality in **Mean** among the 18 European Countries of EU, according to **S statistic** of the Causality Test of **Cheung &Ng**, using the **GARCH** Model
- Table 5F presents the **Cumulative Table** of Causality in **Variance** among the 18 European Countries of EU, according to **S statistic** of the Causality Test of **Cheung &Ng**, using the **GARCH** Model
- Table 5F presents the **Cumulative Table** of Causality in **Mean** among the 18 European Countries of EU, according to **kernel functions** of the Causality Test of **Hong**, using the **GARCH** Model
- Table 5G presents the **Cumulative Table** of Causality in **Variance** among the 18 European Countries of EU, according to **kernel functions** of the Causality Test of **Hong**, using the **GARCH** Model

- Table 5H presents the **Cumulative Table** of Causality in **Variance** among the 18 European Countries of EU, according to **r statistic** of the Causality Test Of **Cheung &Ng**, using the **FIGARCH** Model
- Table 5I presents the **Cumulative Table** of Causality in **Variance** among the 18 European Countries of EU, according to **S statistic** of the Causality Test of **Cheung &Ng**, using the **FIGARCH** Model
- Table 5J presents the **Cumulative Table** of Causality in **Variance** among the 18 European Countries of EU, according to **kernel functions** of the Causality Test of **Hong**, using the FIGARCH Model

It is important to refer to the construction of the cumulative tables. We took note to the biggest statistic which rejects the Null Hypothesis of the No Causality in Mean and in Variance

Regarding the Appendices, the tables of Cheung & Ng are two. The **first table** presents the r statistic for 30 lags. The indicators of the r statistic show the direction of the one country to the other and the symbol m is referred to the mean and the symbol v is referred to volatility. The **second table** provide us with S statistic. The indicators of the S statistic are the same with the indicators of the r statistic. On the other hand, the tables of Hong are also two. The **first table** presents the statistics of three kernel functions (Quadratic, Bartlett and Truncated) for the **causality in mean**. The **second table** presents the statistics of three kernel functions (Quadratic, Bartlett and Truncated) for the **causality in variance**. The indicators of these kernel functions show the direction of the one country to the other. *For brevity reasons we did not put the other three kernel functions Daniell, Parzen and Tukey*. *These data are available from the author upon request.*

Cumulative Table of Causality in Mean among the 18 European Countries of EU, according to r statistic of the Causality Test of Cheung &Ng,using the GARCH Model

MEAN	Belgium	Czech	Cyprus	Denmark	Estonia	France	Germany	Greece	Hungary
Belgium		x	→(*)	x	→(*)	→(***)	→(**)	→(**)	x
Czech	x		→(*)	→(***)	x	→(***)	→(**)	→(**)	x
Cyprus	x	→(*)		x	x	x	x	→(**)	x
Denmark	x	→(**)	x		x	→(***)	→(**)	x	→(**)
Estonia	x	x	x	x		→(***)	x	x	x
France	→(**)	x	→(*)	→(**)	x		→(**)	→(**)	→(**)
Germany	→(*)	→(**)	→(**)	x	→(***)	→(***)		→(*)	→(***)
Greece	x	x	x	x	→(***)	→(**)	x		→(**)
Hungary	x	x	→(*)	→(**)	→(**)	→(***)	x	x	
Ireland	→(***)	x	x	→(**)	→(**)	x	x	x	x
Italy	→(**)	x	→(**)	→(**)	x	→(***)	→(**)	→(**)	x
Netherlands	x	x	x	→(**)	x	→(***)	→(***)	→(*)	→(**)
Portugal	→(**)	x	x	x	x	→(***)	x	x	→(**)
Slovakia	x	→(**)	→(*)	→(**)	→(**)	→(***)	→(***)	→(***)	→(*)
Slovenia	→(*)	x	x	→(**)	x	→(**)	→(***)	→(**)	→(***)
Spain	→(***)	→(***)	→(***)	→(***)	→(***)	→(***)	→(***)	→(***)	→(***)
Sweden	→(**)	x	x	→(***)	x	→(***)	→(***)	→(***)	→(***)
UK	→(**)	→(**)	x	→(**)	→(**)	→(***)	→(**)	→(***)	→(*)

Table 5Ba

MEAN	Ireland	Italy	Netherlands	Portugal	Slovakia	Slovenia	Spain	Sweden	UK
Belgium	→(***)	→(**)	→(**)	→(**)	→(***)	→(*)	x	x	x
Czech	→(***)	→(**)	→(***)	→(***)	x	→(**)	→(**)	→(**)	x
Cyprus	→(***)	→(*)	→(***)	→(**)	x	x	x	→(***)	→(**)
Denmark	→(***)	x	→(**)	→(*)	→(**)	x	→(**)	x	x
Estonia	→(***)	x	x	→(**)	→(**)	→(**)	→(**)	→(**)	x
France	→(***)	→(**)	→(**)	→(*)	x	x	→(**)	x	x
Germany	→(***)	x	→(**)	→(**)	→(**)	x	x	→(**)	x
Greece	→(***)	→(**)	x	→(**)	→(*)	→(**)	→(**)	→(***)	x
Hungary	→(***)	→(*)	x	x	→(***)	x	x	x	x
Ireland		→(**)	x	x	x	x	x	x	x
Italy	→(***)		→(**)	x	→(***)	x	→(**)	→(*)	x
Netherlands	→(***)	→(**)		→(***)	→(**)	x	→(**)	→(**)	x
Portugal	→(***)	x	→(**)		→(**)	x	x	x	x
Slovakia	→(***)	x	→(***)	x		→(**)	x	x	→(***)
Slovenia	→(**)	→(**)	→(**)	→(**)	x		x	→(**)	→(***)
Spain	→(***)	→(***)	→(***)	→(***)	→(***)	x		→(***)	→(***)
Sweden	→(***)	→(**)	→(**)	→(**)	→(**)	x	→(**)		→(***)
UK	→(***)	x	→(**)	→(**)	→(**)	→(*)	→(**)	→(**)	

Table 5Bb

Annotation	
x	no relation
*	10% significance level
**	5% significance level
***	1% significance level
	first lags(1-15)
	last lags(16-30)
→	direction

As we can see from the above tables the stock market of United Kingdom plays a significant role to the majority of the stock markets, regarding the return spillover. In neighbour countries, such as Spain – Portugal, we remark a unidirectional return spillover in the first lags in a 1% nominal size, from Spain to Portugal. In another pair of countries, that of Greece – Cyprus, it is noted a unidirectional spillover in the first lags from Cyprus to Greece. The same remark is pinpointed regarding the Scandinavian countries Sweden – Denmark, where the stock market of Sweden influences the stock market of Denmark, in the case of returns (causality in mean). It is interesting a group of countries, Czech Republic, Hungary, Estonia, Slovakia and Slovenia, which constitutes emerging economies. Their stock markets are not strongly influenced from the majority of the markets of the other countries. It will be interesting what happens regarding their volatility spillover to "control" countries, as the United Kingdom. Finally, we can pinpoint that the stock market of Spain plays an important role to the other markets, as we can see from the Tables 5Ba, 5Bb. To enhance this remark we must underline that its stock market influences, in the returns, all the rest of stock markets under examination, except from that of Slovenia. Large stock markets, such that of France and Germany are strongly influenced even from small exchange stock markets. The above analysis was made according to the r statistic of the Causality Test of Cheung & Ng, regarding the causality in mean.

Cumulative Table of Causality in Variance among the 18 European Countries of EU, according to r statistic of the Causality Test of Cheung &Ng,using the GARCH Model

VOLATILITY	Belgium	Czech	Cyprus	Denmark	Estonia	France	Germany	Greece	Hungary
Belgium		x	→(***)	x	x	x	x	x	x
Czech	x		→(***)	x	x	→(***)	→(**)	→(***)	x
Cyprus	→(***)	→(***)		→(**)	→(**)	x	x	→(**)	x
Denmark	x	x	x		x	x	→(***)	x	x
Estonia	x	x	→(***)	x		x	→(**)	x	x
France	x	x	→(*)	→(***)	x		x	→(***)	x
Germany	x	x	→(***)	x	x	x		x	x
Greece	x	x	→(**)	x	x	→(***)	→(***)		→(**)
Hungary	x	x	→(**)	x	→(**)	x	→(**)	→(**)	
Ireland	x	x	→(***)	→(**)	x	→(***)	x	→(*)	x
Italy	→(*)	x	→(**)	→(**)	x	→(***)	→(***)	→(**)	→(**)
Netherlands	→(**)	x	x	x	→(***)	x	x	x	x
Portugal	x	→(***)	→(**)	→(***)	x	→(***)	→(**)	x	x
Slovakia	→(***)	x	→(***)	x	→(**)	→(***)	→(***)	x	→(**)
Slovenia	→(***)	x	→(***)	→(*)	→(**)	→(***)	→(*)	→(***)	→(**)
Spain	x	→(***)	→(***)	→(**)	→(*)	→(**)	→(***)	x	→(***)
Sweden	x	x	→(***)	→(**)	x	→(**)	x	x	→(***)
UK	→(*)	→(***)	→(***)	x	→(***)	→(**)	→(***)	→(*)	→(*)

Table 5Ca

VOLATILITY	Ireland	Italy	Netherlands	Portugal	Slovakia	Slovenia	Spain	Sweden	UK
Belgium	→(***)	→(*)	→(**)	x	→(***)	→(***)	x	x	→(**)
Czech	→(***)	→(***)	→(***)	x	→(**)	→(**)	→(***)	→(***)	x
Cyprus	→(***)	→(***)	→(**)	→(***)	→(***)	→(**)	x	→(***)	x
Denmark	→(**)	x	→(***)	→(**)	→(***)	x	→(***)	→(*)	x
Estonia	x	x	x	x	x	→(**)	→(**)	x	x
France	→(***)	→(**)	→(*)	x	x	→(***)	→(**)	x	→(***)
Germany	→(***)	x	→(**)	→(***)	→(***)	x	→(***)	x	x
Greece	→(**)	→(**)	→(***)	→(***)	x	x	→(***)	x	→(***)
Hungary	→(**)	→(*)	x	→(***)	x	x	x	x	x
Ireland		x	→(***)	→(**)	x	x	→(**)	x	x
Italy	→(***)		→(**)	x	→(***)	→(*)	x	→(***)	→(***)
Netherlands	x	x		→(***)	x	x	→(***)	x	x
Portugal	→(***)	x	x		→(**)	→(**)	→(***)	x	x
Slovakia	x	→(***)	→(**)	x		x	x	x	x
Slovenia	→(***)	→(**)	→(**)	→(**)	→(***)		→(**)	→(***)	x
Spain	→(***)	x	→(***)	→(***)	x	x		→(***)	x
Sweden	→(***)	x	→(**)	x	→(***)	x	→(***)		x
UK	→(***)	→(***)	→(**)	→(**)	→(***)	→(*)	→(*)	→(***)	

Table 5Cb

Annotation	
x	no relation
*	10% significance level
**	5% significance level
***	1% significance level
(light blue)	first lags(1-15)
(grey)	last lags(16-30)
→	direction

Tables 5Ca, 5Cb presents the causality in variance according to r statistic of Causality Test of Cheung & Ng. A first remark is that volatility spillover is not as detected as return spillover does. As we show in the previous chapter, the Causality in Variance Test of Cheung & Ng performs poorly when the long memory in volatility is taken into consideration. It is clear that the UK influences the majority of stock markets and is not influenced strongly by the others, in the case of volatility. This is in agreement with the previous analysis regarding the returns spillover. The group of countries Czech Republic, Hungary, Estonia, Slovakia and Slovenia takes now a more regional character in the volatility spillover. They are influenced by a small number of markets, but this influence is presented in the last lags. In other words they are not influenced directly. Regarding the pair of countries Greece - Cyprus, we can see a bidirectional volatility spillover, with the stock market of Greece to influence directly (in the first lags) that of Cyprus in a nominal size of 5%. The stock market of Spain continues to “cause” directly, regarding the volatility, a large number of stock markets, in a nominal size 1%, but not in such a large number as in the return spillover,

Cumulative Table of Causality in Mean among the 18 European Countries of EU, according to S statistic of the Causality Test of Cheung &Ng,using the GARCH Model

MEAN	Belgium	Czech	Cyprus	Denmark	Estonia	France	Germany	Greece	Hungary
Belgium		x	→(**)	x	x	x	x	x	x
Czech	→(***)		→(***)	→(***)	x	→(***)	→(***)	→(***)	→(***)
Cyprus	x	x		→(***)	x	x	x	→(***)	→(**)
Denmark	x	x	→(***)		x	→(***)	→(***)	→(***)	→(***)
Estonia	x	x	→(***)	→(***)		→(***)	→(***)	→(***)	→(***)
France	x	x	→(***)	x	x		x	→(***)	x
Germany	x	x	→(***)	x	x	→(***)		→(***)	x
Greece	x	x	→(***)	→(***)	x	→(***)	→(***)		x
Hungary	→(***)	→(**)	→(***)	→(***)	x	→(***)	→(***)	→(***)	
Ireland	→(***)	x	→(***)	x	x	→(***)	→(***)	→(***)	x
Italy	x	x	→(***)	x	x	→(***)	→(***)	→(***)	x
Netherlands	x	x	x	x	x	x	x	x	x
Portugal	x	x	→(***)	x	x	→(***)	→(***)	→(***)	x
Slovakia	→(***)	→(***)	x	→(***)	→(***)	→(***)	→(***)	x	x
Slovenia	x	x	→(**)	x	x	x	x	x	x
Spain	→(***)	→(*)	→(***)	→(***)	x	x	x	→(***)	x
Sweden	x	x	→(***)	→(***)	x	→(***)	→(***)	→(***)	x
UK	x	→(***)	→(***)	x	x	→(***)	→(***)	→(***)	x

Table 5Da

MEAN	Ireland	Italy	Netherlands	Portugal	Slovakia	Slovenia	Spain	Sweden	UK
Belgium	x	x	→(***)	→(***)	x	x	x	x	x
Czech	→(***)	→(***)	→(***)	→(***)	→(***)	x	→(***)	→(***)	→(***)
Cyprus	→(***)	→(***)	→(***)	→(***)	x	x	→(***)	→(***)	→(***)
Denmark	→(***)	→(***)	→(***)	→(***)	x	x	x	x	x
Estonia	→(***)	→(***)	→(***)	→(***)	x	x	→(***)	→(***)	x
France	→(***)	x	x	x	x	x	x	x	x
Germany	→(***)	→(***)	→(***)	x	x	x	x	x	x
Greece	x	x	x	x	x	x	x	x	x
Hungary	→(***)	→(***)	→(***)	→(***)	x	x	→(***)	x	x
Ireland		→(***)	→(***)	→(***)	x	x	→(***)	→(***)	x
Italy	→(***)		x	x	x	x	→(***)	→(***)	x
Netherlands	→(***)	→(***)		→(***)	x	x	→(***)	x	→(***)
Portugal	→(***)	→(***)	→(***)		x	x	→(***)	→(**)	→(***)
Slovakia	x	x	x	x		→(***)	x	x	x
Slovenia	x	x	x	x	→(***)		x	x	x
Spain	→(***)	→(***)	→(***)	→(***)	x	x		→(***)	→(***)
Sweden	→(***)	→(***)	→(***)	→(***)	x	x	→(***)		→(***)
UK	→(***)	→(***)	→(***)	→(**)	x	x	→(***)	→(***)	

Table 5Db

Annotation	
x	no relation
*	10% significance level
**	5% significance level
***	1% significance level
→	direction

The above tables are referred to the S statistic of the Causality Test of Cheung & Ng. In other words, S statistic examines in which lag causality is pinpointed. The results are similar to those from the r statistics of Cheung & Ng Test. However, we remark a bidirectional return spillover regarding the stock markets of Greece and Cyprus. This happens also in pair of neighbour countries, between Spain and Portugal. UK continues to have a "control" stock market.

<u>Cumulative Table of Causality in Variance among the 18 European Countries of EU, according to S statistic of the Causality Test of Cheung &Ng,using the GARCH Model</u>

VOLATILITY	Belgium	Czech	Cyprus	Denmark	Estonia	France	Germany	Greece	Hungary
Belgium		x	x	x	x	x	x	x	x
Czech	x		→(***)	→(***)	x	x	x	→(**)	x
Cyprus	x	→(***)		→(***)	x	x	x	→(***)	x
Denmark	x	x	x		x	x	→(***)	x	x
Estonia	x	→(***)	→(***)	x		→(***)	x	x	x
France	x	x	→(***)	→(***)	x		x	→(*)	x
Germany	x	x	→(***)	x	x	x		x	x
Greece	x	x	→(***)	x	x	→(***)	→(***)		→(***)
Hungary	x	x	→(***)	x	x	x	x	x	
Ireland	x	x	→(***)	x	x	→(***)	x	x	x
Italy	x	x	→(***)	→(***)	x	→(***)	→(***)	x	→(***)
Netherlands	x	x	x	x	x	x	→(***)	x	x
Portugal	x	x	x	x	x	x	→(***)	x	x
Slovakia	x	x	x	x	x	x	x	x	→(***)
Slovenia	x	x	x	x	x	x	→(***)	→(***)	→(**)
Spain	x	→(***)	x	→(***)	x	→(***)	→(***)	x	→(***)
Sweden	x	x	x	→(***)	x	x	→(***)	x	x
UK	x	x	→(***)	x	x	x	→(***)	→(***)	x

Table 5Ea

VOLATILITY	Ireland	Italy	Netherlands	Portugal	Slovakia	Slovenia	Spain	Sweden	UK
Belgium	x	x	x	x	x	x	x	x	x
Czech	→(***)	→(***)	→(***)	→(***)	x	x	→(***)	→(***)	→(***)
Cyprus	→(***)	→(***)	→(***)	→(***)	x	x	x	x	x
Denmark	x	x	→(***)	x	→(***)	x	x	→(**)	x
Estonia	→(***)	x	x	→(**)	x	x	x	x	x
France	→(***)	x	x	→(**)	x	x	→(***)	x	→(***)
Germany	x	x	→(***)	x	→(***)	x	x	x	→(***)
Greece	→(***)	→(***)	x	→(***)	x	x	→(***)	→(***)	x
Hungary	x	→(***)	x	→(**)	x	x	→(***)	x	x
Ireland		→(***)	x	→(***)	x	x	→(***)	x	→(***)
Italy	→(***)		→(***)	→(***)	x	x	→(***)	→(***)	→(***)
Netherlands	x	x		x	x	x	→(***)	x	x
Portugal	→(***)	x	→(***)		x	x	→(***)	→(***)	x
Slovakia	x	→(***)	x	x		x	x	x	x
Slovenia	x	→(***)	→(***)	→(***)	→(***)		x	x	x
Spain	→(***)	x	x	→(***)	x	x		→(***)	→(***)
Sweden	x	x	x	x	x	x	→(***)		→(***)
UK	→(***)	x	x	x	x	x	→(***)	→(***)	

Table 5Eb

Annotation	
x	no relation
*	10% significance level
**	5% significance level
***	1% significance level
→	direction

Let's now see what happens in the case of volatility spillover. As Tables 5Ea, 5Eb indicate, which present the volatility spillover according to S statistic of Cheung & Ng Test, the results are not differed compared to the corresponding r statistic. The emerging countries continue to have a more regional character. We can see a strong bidirectional volatility spillover between the two Scandinavian countries, Denmark and Sweden and between Greece and Cyprus. It is clear also the leading stock market of the UK. However, it is also important to underline from an econometric point of view, that the causality in the second moment is not detected in the same level as causality in the first moment.

Cumulative Table of Causality in Mean among the 18 European Countries of EU, according to kernel functions of the Causality Test of Hong, using the GARCH Model

MEAN	Belgium	Czech	Cyprus	Denmark	Estonia	France	Germany	Greece	Hungary
Belgium		x	x	x	→(*)	→(***)	x	x	x
Czech	x		→(*)	→(*)	x	→(***)	x	x	x
Cyprus	x	→(*)		x	→(*)	x	x	x	x
Denmark	x	x	x		x	→(***)	x	x	x
Estonia	x	x	x	x		→(***)	x	x	x
France	x	x	x	x	x		x	x	x
Germany	x	x	→(**)	x	→(*)	→(***)		→(*)	→(**)
Greece	x	x	→(**)	x	x	x	x		x
Hungary	x	x	→(***)	→(***)	x	→(***)	x	x	
Ireland	→(***)	x	x	x	x	x	x	x	x
Italy	→(**)	x	x	x	x	→(***)	→(**)	x	x
Netherlands	x	x	x	x	x	→(***)	→(***)	→(**)	→(**)
Portugal	x	x	x	x	x	→(***)	x	x	→(**)
Slovakia	x	x	x	x	x	→(**)	→(***)	→(***)	→(*)
Slovenia	→(**)	x	x	→(**)	x	x	→(***)	x	→(***)
Spain	→(***)	→(***)	→(***)	→(***)	→(***)	→(***)	→(***)	→(***)	→(***)
Sweden	→(***)	x	x	→(***)	x	→(***)	→(***)	→(***)	→(***)
UK	→(**)	x	x	x	x	→(***)	→(**)	→(***)	x

Table 5Fa

MEAN	Ireland	Italy	Netherlands	Portugal	Slovakia	Slovenia	Spain	Sweden	UK
Belgium	→(***)	x	x	→(***)	x	x	x	x	x
Czech	→(***)	→(*)	→(**)	→(**)	x	x	x	x	x
Cyprus	→(***)	→(*)	x	→(**)	x	x	x	→(***)	→(**)
Denmark	→(***)	x	x	→(**)	x	x	x	x	x
Estonia	→(***)	x	x	x	x	x	x	x	x
France	→(***)	x	x	x	x	x	x	x	x
Germany	→(***)	x	x	x	x	x	x	x	x
Greece	→(***)	x	x	x	→(*)	x	→(**)	x	x
Hungary	→(***)	→(*)	x	x	→(***)	x	x	x	x
Ireland		x	x	x	x	x	x	x	x
Italy	→(***)		x	x	→(***)	x	→(**)	→(*)	x
Netherlands	→(***)	x		→(***)	→(**)	x	→(**)	→(**)	x
Portugal	→(***)	x	→(**)		→(**)	x	x	x	x
Slovakia	→(**)	x	→(***)	x		x	x	x	→(***)
Slovenia	→(**)	→(**)	→(**)	x	x		x	→(**)	→(***)
Spain	→(***)	→(***)	→(***)	→(***)	→(***)	x		→(***)	→(***)
Sweden	→(***)	→(**)	→(**)	→(**)	→(**)	x	→(**)		→(**)
UK	→(***)	x	→(**)	→(*)	→(**)	→(*)	x	→(**)	

Table 5Fb

Annotation	
x	no relation
*	10% significance level
**	5% significance level
***	1% significance level
	first banwidths(1-15)
	last bandwidths(16-30)
→	direction

The above Tables 5Fa, 5Fb present the statistics of Hong, using six kernel functions. We remind that the Causality Test of Hong differs from that of Cheung & Ng. Cheung & Ng Test employs a uniform weighting of the lags. Hong introduces a non – uniform, flexible weighting scheme for the cross correlation at each lag, using the six kernel functions that we referred in chapter 2. We can remark that UK stock market constitutes a "control" market. Ireland's stock market is influenced immediately by all the under examination markets, regarding the return spillover. Sweden "causes" directly the Denmark stock market in a 1% nominal size. This is in agreement with the results retrieved from the Causality Test of Cheung & Ng. However, we can remark a difference, regarding the countries Greece and Cyprus, where the causality in mean stays strongly unidirectional, but now from Greece to Cyprus in 5% nominal size, in contrast to the indication from the r statistic of Cheung & Ng. It is also clear that the emerging economies, Czech Republic, Hungary, Estonia, Slovakia and Slovenia have both regional and a European character, with the regional to be stronger than the European character.

<u>Cumulative Table of Causality in Variance among the 18 European Countries of EU, according to kernel functions of the Causality Test of Hong, using the GARCH Model</u>

VOLATILITY	Belgium	Czech	Cyprus	Denmark	Estonia	France	Germany	Greece	Hungary
Belgium		x	→(***)	x	x	x	x	x	x
Czech	x		→(***)	x	x	→(**)	x	x	x
Cyprus	→(***)	→(***)		→(**)	→(**)	x	x	→(**)	x
Denmark	x	x	x		x	x	→(*)	x	x
Estonia	x	x	→(**)	x		x	x	x	x
France	x	x	x	→(**)	x		x	→(***)	x
Germany	x	x	→(***)	x	x	x		x	x
Greece	x	x	x	x	x	→(***)	x		→(**)
Hungary	x	x	→(***)	x	x	x	x	x	
Ireland	x	x	→(***)	→(*)	x	→(***)	x	→(*)	x
Italy	x	x	→(**)	x	x	→(***)	→(**)	x	→(**)
Netherlands	x	x	x	x	→(**)	x	x	x	x
Portugal	x	x	→(**)	x	x	x	x	x	x
Slovakia	x	x	x	x	x	→(***)	→(***)	x	x
Slovenia	x	x	x	x	→(*)	x	→(*)	x	x
Spain	x	→(***)	→(***)	→(**)	→(*)	→(**)	→(***)	x	→(***)
Sweden	x	x	x	→(***)	x	x	x	x	→(***)
UK	x	→(***)	→(***)	x	→(***)	→(**)	→(***)	→(*)	x

Table 5Ga

VOLATILITY	Ireland	Italy	Netherlands	Portugal	Slovakia	Slovenia	Spain	Sweden	UK
Belgium	→(***)	x	x	x	x	x	x	x	→(**)
Czech	→(***)	→(***)	x	x	x	x	→(***)	→(**)	x
Cyprus	x	x	→(**)	→(**)	→(*)	x	x	→(**)	x
Denmark	→(***)	x	x	x	x	x	x	→(**)	x
Estonia	x	x	x	x	x	→(**)	x	x	x
France	→(***)	x	x	x	x	→(***)	→(**)	x	→(***)
Germany	→(***)	x	x	→(***)	→(***)	x	→(***)	x	x
Greece	→(**)	x	→(***)	x	x	x	→(***)	x	→(***)
Hungary	→(**)	→(*)	x	x	x	x	x	x	x
Ireland		x	→(***)	x	x	x	→(**)	x	x
Italy	→(***)		x	x	→(***)	→(*)	x	→(***)	x
Netherlands	x	x		→(***)	x	x	→(***)	x	x
Portugal	→(***)	x	x		x	x	x	x	x
Slovakia	x	→(***)	→(**)	x		x	x	x	x
Slovenia	x	→(**)	→(**)	x	→(***)		→(**)	→(***)	x
Spain	→(***)	x	→(***)	→(***)	x	x		→(***)	x
Sweden	→(***)	x	x	x	x	x	→(***)		x
UK	→(***)	x	→(**)	x	x	x	x	→(***)	

Table 5Gb

Annotation	
x	no relation
*	10% significance level
**	5% significance level
***	1% significance level
	first banwidths(1-15)
	last bandwidths(16-30)
→	direction

Let's now see what happens in the causality in volatility. According to tables 5Ga, 5Gb, generally speaking, we can remark a similarity in the results. However, some differences are also pinpointed. From an econometric point of view the volatility spillover is not strongly detected as in the case of returns spillover. This is in accordance with the previous test. From the empirical viewpoint, the emerging economies continue to have a strong regional character in the volatility spillover, as it was also indicated in the test of Cheung & Ng. The UK stock market is unquestionably the strongest market in Europe. We can pinpoint a unidirectional causality in variance from Cyprus to Greece, but not very strongly. Regarding the Scandinavian countries, Denmark and Sweden, we can see a strong and direct bidirectional volatility spillover between these two countries. Regarding, the two neighbour countries, Spain and Portugal, we can underline a direct unidirectional volatility spillover from Spain to Portugal in 1% nominal size, which is in agreement with the Cheung & Ng's Causality Test.

Cumulative Table of Causality in Variance among the 18 European Countries of EU,according to r statistic of the Causality Test Of Cheung &Ng,using the FIGARCH Model

VOLATILITY	Belgium	Czech	Cyprus	Denmark	Estonia	France	Germany	Greece	Hungary
Belgium		→(**)	→(***)	x	x	→(*)	→(***)	→(***)	→(**)
Czech	→(**)		x	x	→(***)	→(***)	→(**)	→(**)	x
Cyprus	x	→(***)		→(***)	→(***)	→(**)	→(**)	→(**)	x
Denmark	x	x	→(***)		x	x	x	x	x
Estonia	→(**)	x	→(*)	→(*)		x	→(***)	→(***)	x
France	→(**)	→(*)	→(**)	→(**)	x		→(**)	→(***)	x
Germany	→(*)	x	x	x	x	x		→(**)	x
Greece	x	→(*)	x	x	x	→(**)	→(***)		→(***)
Hungary	→(***)	x	→(***)	x	→(**)	x	x	→(*)	
Ireland	x	x	→(***)	→(*)	x	→(**)	→(**)	→(*)	→(**)
Italy	→(**)	→(***)	x	x	x	→(***)	→(***)	→(**)	x
Netherlands	→(**)	x	x	x	x	x	→(***)	→(***)	x
Portugal	x	x	x	x	→(*)	→(***)	→(***)	→(**)	→(**)
Slovakia	x	→(***)	x	x	→(***)	→(**)	x	x	→(**)
Slovenia	→(***)	x	x	→(*)	→(***)	→(**)	→(***)	→(**)	→(**)
Spain	→(**)	→(***)	→(**)	→(*)	x	→(**)	→(***)	x	→(*)
Sweden	x	x	→(***)	→(***)	x	x	→(***)	→(*)	→(*)
UK	→(**)	→(**)	→(**)	x	x	→(***)	→(***)	→(**)	→(**)

Table 5Ha

VOLATILITY	Ireland	Italy	Netherlands	Portugal	Slovakia	Slovenia	Spain	Sweden	UK
Belgium	→(*)	→(***)	→(***)	→(***)	→(***)	→(*)	x	→(**)	x
Czech	x	→(**)	→(**)	→(***)	→(**)	→(*)	→(**)	→(***)	x
Cyprus	x	→(***)	→(**)	x	→(**)	x	x	→(**)	x
Denmark	→(***)	x	→(**)	x	x	x	x	→(***)	x
Estonia	→(**)	x	→(***)	→(***)	x	x	→(**)	x	x
France	→(***)	x	→(***)	x	→(**)	→(**)	→(**)	→(***)	→(***)
Germany	→(***)	x	→(***)	→(**)	x	x	→(***)	→(***)	→(**)
Greece	→(**)	→(**)	→(***)	→(***)	x	x	→(***)	→(***)	→(**)
Hungary	→(***)	x	→(***)	→(***)	→(***)	→(**)	x	x	x
Ireland		x	→(***)	→(**)	x	x	x	x	x
Italy	→(***)		→(***)	→(*)	x	→(***)	→(**)	→(***)	→(***)
Netherlands	→(***)	x		→(***)	x	x	→(**)	→(**)	x
Portugal	→(***)	→(*)	→(***)		x	→(**)	→(***)	→(***)	x
Slovakia	x	x	x	x		→(**)	x	→(*)	x
Slovenia	→(**)	→(**)	→(***)	x	→(**)		→(**)	→(***)	→(***)
Spain	→(***)	→(**)	→(***)	→(**)	x	x		→(***)	→(**)
Sweden	→(***)	x	→(***)	x	→(*)	x	→(**)		→(**)
UK	→(**)	→(**)	→(***)	→(**)	x	x	→(***)	→(***)	

Table 5Hb

Annotation	
x	no relation
*	10% significance level
**	5% significance level
***	1% significance level
	first lags(1-15)
	last lags(16-30)
→	direction

Now, we made a step forward. We would like to take account the long memory in the volatility process. Relying on the results from the Monte Carlo simulations, we show that both Causality Tests exhibit a good empirical performance in financial time series. As our series in this empirical application are financial, we used instead of the GARCH specification the FIGARCH specification for taking due note of the long memory in volatility. From the econometric perspective, it is obvious that the causality in volatility is more powerful using the FIGARCH model rather than the GARCH model, comparing the tables 5Ha, 5Hb with 5Ca, 5Cb, respectively. Belgium stock market is influenced by a larger number of markets than in the case of using the GARCH specification. The stock markets of emerging economies stay as markets with a more regional character regarding the volatility spillover. However, we must underline that these countries are now influenced by a large number of stock markets in a non – immediate effect. It is a remark that we did not see in the case of Cheung & Ng, with the GARCH model. UK stock market remains the "control" market, as it influences directly and indirectly the majority of the European stock markets.

However, it is noted that it is influenced by three more countries, where in the case of GARCH specification it has not been shown. Another example is the stock market of Cyprus, which a larger number of the under examination markets have immediate or not, effect at this market.

<u>Cumulative Table of Causality in Variance among the 18 European Countries of EU, according to S statistic of the Causality Test of Cheung &Ng,using the FIGARCH Model</u>

VOLATILITY	Belgium	Czech	Cyprus	Denmark	Estonia	France	Germany	Greece	Hungary
Belgium		X	X	X	X	X	X	→(***)	X
Czech	X		→(***)	→(***)	X	→(***)	→(***)	→(**)	X
Cyprus	X	X		X	X	X	X	→(***)	X
Denmark	X	X	→(***)		X	X	X	X	X
Estonia	X	→(**)	X	→(**)		→(***)	→(***)	→(**)	X
France	X	X	→(***)	→(***)	X		→(***)	X	X
Germany	X	X	X	→(***)	X	X		X	X
Greece	X	X	X	X	X	→(***)	→(***)		→(**)
Hungary	X	X	X	X	X	X	X	X	
Ireland	X	X	→(***)	X	X	→(***)	X	X	X
Italy	X	X	X	X	X	→(***)	X	X	→(***)
Netherlands	X	X	X	X	X	X	X	X	X
Portugal	X	X	X	→(***)	→(**)	X	→(***)	X	X
Slovakia	X	X	→(***)	X	X	X	X	X	X
Slovenia	X	X	X	X	X	X	→(***)	→(***)	→(***)
Spain	X	→(***)	X	→(***)	X	X	→(***)	X	X
Sweden	X	X	→(***)	→(***)	X	X	X	X	X
UK	X	X	→(**)	X	X	→(**)	→(***)	→(**)	X

Table 5Ia

VOLATILITY	Ireland	Italy	Netherlands	Portugal	Slovakia	Slovenia	Spain	Sweden	UK
Belgium	X	X	X	X	X	X	X	X	X
Czech	→(***)	→(***)	→(***)	X	X	X	→(***)	→(***)	→(***)
Cyprus	X	→(***)	→(***)	→(***)	X	X	→(***)	→(***)	→(***)
Denmark	X	X	→(***)	X	→(***)	X	X	→(***)	X
Estonia	X	X	X	→(**)	X	X	X	X	X
France	→(***)	X	→(***)	X	X	X	→(***)	→(***)	X
Germany	X	X	→(***)	X	→(***)	X	X	→(***)	X
Greece	→(***)	→(**)	→(***)	→(***)	→(**)	X	→(***)	→(***)	→(***)
Hungary	X	X	X	X	X	X	X	X	X
Ireland		→(***)	X	X	X	X	X	X	X
Italy	→(***)		→(***)	X	X	X	→(***)	→(***)	X
Netherlands	X	X		X	X	X	X	X	X
Portugal	→(***)	X	→(***)		X	X	→(***)	→(***)	X
Slovakia	X	X	X	X		X	X	X	X
Slovenia	X	→(***)	→(**)	→(***)	→(***)		→(***)	X	→(***)
Spain	→(***)	X	→(***)	→(***)	→(***)	X		→(***)	→(***)
Sweden	X	X	→(***)	X	→(***)	X	X		X
UK	→(*)	→(**)	→(***)	→(*)	X	X	→(***)	→(***)	

Table 5Ib

Annotation	
x	no relation
*	10% significance level
**	5% significance level
***	1% significance level
→	direction

As Tables 5Ia, 5Ib, from the perspective preview the causality in volatility is more powerful using the FIGARCH model rather than using the GARCH specification. The direction of the causality in variance remains the same with that of Cheung & Ng Test. However, as was noted previously, we can see some markets that were influenced by or influence other markets

Cumulative Table of Causality in Variance among the 18 European Countries of EU, according to kernel functions of the Causality Test of Hong, using the FIGARCH Model

VOLATILITY	Belgium	Czech	Cyprus	Denmark	Estonia	France	Germany	Greece	Hungary
Belgium		→(**)	x	x	x	x	→(**)	→(***)	→(**)
Czech	x		x	x	x	→(***)	→(**)	→(**)	x
Cyprus	x	→(***)		x	→(**)	x	→(**)	→(**)	x
Denmark	x	→(***)	x		x	→(*)	x	x	x
Estonia	x	x	→(**)	→(**)		x	→(***)	x	x
France	x	x	x	→(*)	x		→(**)	x	x
Germany	x	x	x	x	x	x		x	x
Greece	x	x	x	x	x	→(**)	→(***)		x
Hungary	x	x	→(***)	x	x	x	x	x	
Ireland	x	x	→(***)	→(*)	x	→(**)	x	→(**)	x
Italy	x	x	x	x	x	→(***)	x	x	x
Netherlands	x	x	x	→(**)	x	x	→(***)	x	x
Portugal	x	x	→(***)	x	→(*)	→(***)	→(***)	x	x
Slovakia	x	x	x	x	x	→(*)	x	x	x
Slovenia	→(***)	x	x	x	→(***)	x	x	x	x
Spain	x	→(***)	→(*)	x	x	→(***)	→(***)	x	x
Sweden	x	x	→(***)	x	x	x	→(**)	x	x
UK	→(**)	x	→(**)	x	x	→(***)	→(***)	→(*)	x

Table 5Ja

VOLATILITY	Ireland	Italy	Netherlands	Portugal	Slovakia	Slovenia	Spain	Sweden	UK
Belgium	→(*)	x	x	→(***)	→(*)	x	x	→(**)	x
Czech	x	→(***)	→(**)	→(***)	x	x	→(***)	→(**)	x
Cyprus	x	→(**)	→(**)	x	→(**)	x	x	→(***)	x
Denmark	→(***)	x	→(**)	x	x	x	x	→(***)	x
Estonia	x	x	x	→(***)	x	x	x	x	x
France	→(***)	x	x	x	x	→(***)	x	→(***)	x
Germany	→(***)	x	→(***)	→(**)	x	x	→(***)	→(***)	x
Greece	→(**)	x	→(***)	x	x	x	→(***)	→(***)	→(**)
Hungary	→(***)	x	→(***)	x	→(***)	x	x	x	x
Ireland		x	→(**)	x	x	x	x	x	x
Italy	→(***)		→(**)	→(**)	x	→(***)	x	→(***)	x
Netherlands	→(***)	x		→(***)	x	x	→(***)	→(***)	x
Portugal	→(***)	→(*)	→(***)		x	x	→(***)	→(***)	x
Slovakia	x	x	x	x		x	x	→(**)	x
Slovenia	x	x	x	x	→(**)		→(**)	→(**)	x
Spain	→(***)	→(*)	→(***)	→(***)	x	x		→(***)	x
Sweden	→(***)	x	→(**)	x	→(**)	x	→(**)		x
UK	x	→(**)	→(***)	→(***)	x	x	→(***)	→(***)	

Table 5Jb

Annotation	
x	no relation
*	10% significance
**	5% significance
***	1% significance
	first lags - banwidths(1-15)
	last lags - bandwidths(16-30)
→	direction

We can support also that in the case of the Test of Hong, using the FIGARCH model the remarking results regarding the direction and the influence of the causality are in accordance with Hong's Test using the GARCH specification, but this influence is stronger in this case. In case we used daily data instead of monthly data in the case of FIGARCH the difference of the empirical performance of the two tests using the GARCH and the FIGARCH models would be stronger in the second specification.

5.3 Concluding Remarks of the Results

Let's now summarize the analysis of the previous empirical results (section 5.2) in a more general way. Our empirical analysis has three dimensions. The first dimension is the analysis of the dynamic relationship among the stock markets of the countries of the European Union, regarding the causality in mean and variance. This analysis is based on the cumulative tables that were emerged from the statistical tables of the Causality Tests of Cheung & Ng and Hong, using the GARCH and the FIGARCH model specifications. A number of them are presented in APPENDICES A & B. The second dimension involves the record of some differences regarding the methodology, concerning the two Causality Tests. Finally we will refer to the empirical performance of these tests, using the two model specifications, in a way based on our empirical results.

To begin with, it is essential to refer to some characteristics of the stock European markets. The exchanges stock markets of Paris, Frankfurt, Milan, and London represent four of the world's major centres for the trading and distribution of both domestic and international equities, let alone of the European stock market exchanges. Specifically, France, Germany and Italy are viewed as 'core' European economies having been members of the Exchange Rate Mechanism (ERM) since its inception in 1979, and the European common currency – the Euro - since 1999. However, the UK, Denmark and Sweden are members of the EU, but they are not members of the Euro.

Let's now begin with our analysis. We can strongly remark that the UK exchange stock market influences the majority of the European stock markets both in mean and volatility. We can see some exceptions, regarding the Czech Republic, Denmark, Estonia, Hungary, Slovakia and Slovenia stock markets, where we cannot find any causality, unidirectional or bidirectional, or we can find a volatility spillover from UK to the aforementioned stock markets in the last lags. However, we cannot deny that the UK stock market constitute a "control market" and one of the world's and as a result of European stock markets. The above remarks emerge from the two causality tests that we analysed in previous chapters. On the other hand, this market is hardly influenced by other markets. We can see bidirectional causality both in mean and volatility only between France – UK, Spain – UK, Sweden – UK stock markets, where this causality is presented in the first lags (bandwidths) in a 1% nominal significance level.

Another remark is that some geographically neighbour countries, such as Spain – Portugal and Sweden – Denmark have bidirectional causality. This is logical taking into consideration that, generally, neighbour markets have same regulatory and policy systems. Specifically, we can remark a stronger causality both in mean and volatility from the Spanish and Swedish stock market to the stock markets of Portugal and Denmark respectively. By stronger causality we mean immediate causality, causality presented in first lags. However, we cannot omit the inverse relationship, where the causality in mean and variance is presented mainly in the last lags. These remarks are emerged from both the Cheung & Ng as well as Hong Causality Tests.

An additional important observation is that a group of stock markets, the markets of Czech Republic, Cyprus, Denmark, Estonia, Hungary, Slovakia and Slovenia do not have a close relationship with the other European markets. It is remarkable, that the aforementioned stock markets on the one hand do not influence especially in volatility the majority of the rest European markets and one the other hand are not being influenced immediately or at all, by "strong" stock markets, those of Paris, Frankfurt, Milan, and London. An important issue is that the stock market of Hungary differs from the other markets of this "group", as it is the only one that has a relation in both in mean and volatility by more markets in contrast to the others at the same group. It may seem that Hungary will be integrated first on the highest level with the "old" European Union countries. However, Czech Republic has not the same impact as Hungary, although they are considered as the most advanced transition economies with a common history among the emerging economies' countries. We have to underline that these countries have both a regional and European character concerning the return spillovers. On the contrary to the volatility spillover that has mainly a more regional character. Someone could say that this enchases the diversification of a portfolio of an investor, in case he could expand his investments at these emerging economies.

Regarding the Germany stock market, it does not have such a strong impact to the other markets, neither in mean nor in volatility, as UK has, although it is undeniable that it constitutes one of the strongest stock markets all over the world. An explanation to the above remark is that German stock market involves a large number of financial powerhouse companies. In other words, it constitutes a banking based market.

Moreover, we can see bidirectional returns and volatility spillovers regarding the stock market of Spain with the rest of the European countries. It means that there exists a bidirectional flow process of the news regarding the Spanish stock Market with the other European markets. Another substantial remark is that Ireland's stock market is influenced by all the other European stock markets, both in the first and second moment. The inverse direction does not exist. Regarding now the stock market of Cyprus and Greece, we remark bidirectional causality in volatility according to the r and S statistic of Cheung & Ng. However, the Causality Test of Hong detects causality in variance only unidirectional, from Cyprus to Greece. The above discernment concerns the estimation by the GARCH model. On the contrary all the statistics of the Causality Test of Cheung & Ng as well as of Hong, estimating our financial data using the FIGARCH model, indicate a unidirectional volatility spillover from Cyprus to Greece, which is in agreement with the statistics of the Causality Test of Hong, using the GARCH model.

At this point, it is important to move to the second and third dimension of our empirical analysis, regarding the differences of the two causality tests, using the two model specifications. First, it is important to mention that the description of the methodologies, on the one hand those of the two causality tests and on the other hand those of the model specifications, are analysed at the second and third chapters respectively. Secondly, from a general pattern of the cumulative tables, it is undeniable that the return spillover is obviously more detected than the volatility spillover. However, the causality in variance is more powerful using the FIGARCH model rather than using the GARCH model. The fact that causality in mean is more detected than the causality in volatility can be attributed from the potential bias affecting the estimates of the conditional volatility owning to the use of noisy volatilities approximations. In addition, the reason why the causality in variance is more detected using the FIGARCH model rather than using the GARCH model, can be explained from the fact that the GARCH model constitutes a short – non persistent memory process, which means that it does not focus on the presence of long memory in volatility, in contrast to the FIGARCH model specification which constitutes a persistent - long memory process. In APPENDICES A & B we provide some examples. To be more precise in the case of Belgium – Greece when we examine the Causality Test of Hong, using the GARCH specification, we do not remark any volatility spillover. However, taking into consideration the long memory in volatility by using the FIGARCH model, we can remark a strong volatility spillover from Belgium to Greece. Another example is that of Spain - Portugal, where in the first case we find volatility spillover from Spain to Portugal, while in the second case it appeared also a volatility spillover from Portugal to Spain. More examples are shown in cumulative tables, as well as in the two Appendices. The above remarks have been shown in the previous chapter, conducting a number of Monte Carlo simulations. Comparing now the two causality tests, we could say that the Causality Test of Hong is more "severe" to the Causality Test of Cheung & Ng. This reason is attributed owning to the use of kernel functions by the Hong's Test which weights the lags regarding the volatility persistence, the so called "bandwidths".

CONCLUSION

As we noted in the Introduction, the thesis involves two parts, the Econometric Part and the Empirical part.

In the Econometric part of our dissertation we conducted a number of Monte Carlo simulations in order to examine the empirical performance of the Causality in Variance Tests of Cheung & Ng and Hong, employing a small sample (low frequency data) and a large sample (high frequency data). Macroeconomic series are related with small samples, while the financial series with large samples. First, we studied the effects of volatility spillover in the empirical size and power of the Causality in Variance Tests. We show that both Tests exhibit a good empirical size and power in both samples. In this point we must underline that in the financial time series these two Causality Tests exhibit a better empirical power compared to the empirical power when macroeconomic series are used. Next, we tried to analyse the effects of long memory in volatility in the properties of these two tests. Specifically, we have observed that under the presence of long memory in the volatility process, these tests present a good empirical size. However, in terms of empirical power, these tests perform poorly. In addition, they present a different behaviour in terms of empirical power between the two samples. The empirical power of these tests in macroeconomic data is dramatically lower than the empirical power in financial data. Generally speaking, we can assume that these tests under the presence of long memory in volatility perform poorly. This is now where we made a step. We replaced the estimator GARCH model that is used by the two tests with that of the FIGARCH specification. We remarked, on the one hand a very small upward distortion of the empirical size and on the other hand a different behaviour in terms of empirical power between the two samples. In the macroeconomic series, we can observe a distortion of the power. However, in financial series, we can remark a good empirical power of both Causality Tests.

In the empirical part, we took the real stock returns of eighteen countries of the European Union, examining the dynamic relationship of these European stock markets both in mean and in volatility. We employed the two Causality Tests of Cheung & Ng, using for the modelling of conditional variance the GARCH and the FIGARCH models. In brief, we remarked that the stock market of the United Kingdom constitutes a "control" market which influences the majority of stock markets both in the first and the second moment. In addition, emerging economies such as Czech Republic, Estonia, Hungary, Slovakia and Slovenia have both a regional and European character in mean. However in volatility are taking a more regional character, as they are not influenced by a large number of stock markets, some of them very “strong”. As a result these countries constitute significant investing places for investors for the diversification of their portfolio. The above remarks are in accordance with the existing literature. An additional important issue is that we confirmed our results from the Monte Carlo simulation in this empirical application. For example, in the case of Belgium – Greece when we used the Causality Test of Hong, introducing the GARCH specification, we did not remark any volatility spillover. However, taking into consideration the long memory in volatility by using the FIGARCH model, we remarked a strong volatility spillover from Belgium to Greece. Another example is that of Spain - Portugal, where in the first case we found evidence of volatility spillover from Spain to Portugal, while in the second case it appeared also a volatility spillover from Portugal to Spain.

To conclude with, more research is needed for examining the empirical performance of the two aforementioned Causality Tests.

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APPENDIX A

Statistical Tables (GARCH)

Introduction

We present the statistical tables for the causality in mean and variance among the 18 European countries. We first provide a table of these countries together with their abbreviations.

a/a	Country	Abbreviation
1	Belgium	Bl
2	Czech Republic	Cz
3	Cyprus	Cy
4	Denmark	Dk
5	Estonia	Es
6	France	Fr
7	Germany	Ger
8	Greece	Gr
9	Hungary	Hu
10	Ireland	Ir
11	Italy	It
12	Netherlands	Nth
13	Portugal	Port
14	Slovakia	Slvk
15	Slovenia	Slvn
16	Spain	Sp
17	Sweden	Sw
18	United Kingdom	UK

In addition we must note that the tables of Cheung & Ng are two. The **first table** presents the r statistic for 30 lags. The indicators of the r statistic show the direction of the one country to the other and the symbol m is referred to the mean and the symbol v is referred to volatility. The **second table** provide us with S statistic. The indicators of the S statistic are the same with the indicators of the r statistic. On the other hand, the tables of Hong are also two. The **first table** presents the statistics of three kernel functions (Quadratic, Bartlett and Truncated) for the **causality in mean**. The s**econd table** presents the statistics of three kernel functions (Quadratic, Bartlett and Truncated) for the **causality in variance**. The indicators of these kernel functions show the direction of the one country to the other. For brevity reasons we did not put the other three kernel functions Daniell, Parzen and Tukey. These data would be available from the author upon request.

We provide only a small number of the statistical tables for brevity reasons. All statistical tables are available from the author upon request.

Belgium - France

Causality in Mean & Variance between Belgium – France, according to r statistic of Causality Test of Cheung & Ng

Table I

Lags	$r_{Bl\_Fr,m}$	$r_{Fr\_Bl,m}$	$r_{Bl\_Fr,v}$	$r_{Fr\_Bl,v}$
1	2,693***	1,365	0,392	0,312
2	0,068	0,674	-0,820	-0,816
3	-0,726	0,053	-1,256	-1,253
4	-0,061	-0,571	0,940	0,969
5	0,464	2,137**	-0,099	-0,092
6	0,870	0,027	-0,183	-0,193
7	0,399	1,007	0,030	0,017
8	0,360	1,893*	-0,994	-0,995
9	-0,183	-0,286	-0,105	-0,105
10	-0,477	-0,909	-0,169	-0,156
11	-1,531	-1,471	1,055	1,059
12	-0,138	-0,243	-0,127	-0,141
13	0,370	0,997	0,141	0,139
14	0,126	0,580	-0,935	-0,935
15	0,557	0,042	-0,717	-0,698
16	-0,812	-0,884	0,384	0,414
17	0,599	0,310	0,963	0,958
18	-0,190	-0,398	0,314	0,296
19	-0,712	-0,013	-0,601	-0,591
20	1,057	-0,388	-0,063	-0,071
21	-0,710	0,309	-1,090	-1,090
22	1,294	0,669	-0,437	-0,433
23	0,430	-0,455	-0,451	-0,454
24	-1,172	-0,795	0,533	0,539
25	0,356	-0,276	-0,206	-0,202
26	0,509	-0,319	-0,119	-0,123
27	0,740	0,261	0,143	0,162
28	-1,325	-0,866	0,979	0,982
29	-1,271	-1,000	-0,059	-0,072
30	-1,029	-0,523	0,343	0,343

Notes: The Null Hypothesis (Ho) denotes No Causality in Mean and Variance. The Alternative Hypothesis (H1) denotes Causality in Mean and Variance. The '*'indicates significance at the 10%, the '**' indicates significance at the 5% and the '***' indicates significance at the 1% level

Causality in Mean & Variance between Belgium – France, according to S statistic of Causality Test of Cheung & Ng

Table II

$S_{Bl\_Fr,m}$	4,76
$S_{Fr\_Bl,m}$	8,00
$S_{Bl\_Fr,v}$	-15,68
$S_{Fr\_Bl,v}$	-15,75

See Notes at Table I

Causality in Mean between Belgium – France, according to the kernel functions of Causality Test of Hong

Table III

Bandwidth	QuadraticBl_Fr	BartlettBl_Fr	TruncatedBl_Fr	QuadraticFr_Bl	BartlettFr_Bl	TruncatedFr_Bl
1	4,462***	NaN	4,523***	0,603	NaN	0,633
2	4,357***	4,523***	2,722***	0,564	0,633	0,184
3	3,709***	4,222***	2,055**	0,343	0,524	-0,253
4	3,084***	3,807***	1,445*	0,115	0,356	-0,449
5	2,579***	3,425***	1,064	0,087	0,190	0,802
6	2,188**	3,083***	0,929	0,154	0,144	0,457
7	1,861**	2,793***	0,654	0,256	0,173	0,457
8	1,586*	2,544***	0,411	0,365	0,209	1,152
9	1,361*	2,325**	0,176	0,468	0,264	0,892
10	1,177	2,127**	0,013	0,558	0,330	0,842
11	1,020	1,946**	0,361	0,630	0,391	1,115
12	0,884	1,788**	0,164	0,685	0,449	0,900
13	0,762	1,652**	0,008	0,722	0,503	0,908
14	0,652	1,531*	-0,160	0,743	0,550	0,781
15	0,552	1,420*	-0,256	0,748	0,589	0,597
16	0,461	1,318*	-0,275	0,741	0,621	0,582
17	0,381	1,223	-0,349	0,723	0,644	0,436
18	0,310	1,134	-0,480	0,697	0,661	0,312
19	0,247	1,051	-0,515	0,664	0,671	0,166
20	0,191	0,972	-0,434	0,628	0,676	0,056
21	0,141	0,898	-0,465	0,589	0,674	-0,058
22	0,097	0,830	-0,284	0,548	0,669	-0,103
23	0,060	0,767	-0,369	0,506	0,659	-0,186
24	0,028	0,709	-0,242	0,463	0,646	-0,192
25	0,002	0,656	-0,331	0,420	0,630	-0,290
26	-0,019	0,608	-0,393	0,376	0,613	-0,379
27	-0,035	0,563	-0,404	0,332	0,593	-0,470
28	-0,047	0,521	-0,211	0,288	0,573	-0,444
29	-0,056	0,482	-0,044	0,245	0,551	-0,375
30	-0,061	0,447	0,033	0,203	0,528	-0,424

See Notes at Table I

Causality in Mean between Belgium – France, according to the kernel functions of Causality Test of Hong

Table IV

Bandwidth	QuadraticBl_Fr	BartlettBl_Fr	TruncatedBl_Fr	QuadraticFr_Bl	BartlettFr_Bl	TruncatedFr_Bl
1	-0,611	NaN	-0,602	-0,652	NaN	-0,643
2	-0,629	-0,602	-0,580	-0,669	-0,643	-0,612
3	-0,594	-0,636	-0,205	-0,633	-0,677	-0,234
4	-0,486	-0,588	-0,193	-0,519	-0,627	-0,198
5	-0,451	-0,519	-0,477	-0,478	-0,555	-0,482
6	-0,485	-0,484	-0,705	-0,506	-0,515	-0,709
7	-0,549	-0,487	-0,912	-0,566	-0,515	-0,916
8	-0,623	-0,517	-0,821	-0,636	-0,542	-0,824
9	-0,697	-0,556	-0,996	-0,709	-0,578	-1,000
10	-0,768	-0,597	-1,151	-0,778	-0,617	-1,155
11	-0,835	-0,642	-1,028	-0,843	-0,660	-1,030
12	-0,896	-0,686	-1,172	-0,903	-0,703	-1,172
13	-0,951	-0,728	-1,304	-0,958	-0,743	-1,304
14	-1,001	-0,769	-1,236	-1,007	-0,783	-1,237
15	-1,045	-0,809	-1,248	-1,051	-0,822	-1,255
16	-1,085	-0,846	-1,336	-1,091	-0,858	-1,337
17	-1,122	-0,881	-1,255	-1,127	-0,892	-1,258
18	-1,155	-0,914	-1,345	-1,161	-0,924	-1,351
19	-1,186	-0,944	-1,377	-1,192	-0,954	-1,385
20	-1,215	-0,972	-1,477	-1,220	-0,982	-1,485
21	-1,242	-1,000	-1,338	-1,248	-1,009	-1,345
22	-1,268	-1,026	-1,394	-1,273	-1,035	-1,403
23	-1,292	-1,050	-1,445	-1,298	-1,059	-1,453
24	-1,316	-1,072	-1,476	-1,322	-1,081	-1,483
25	-1,339	-1,094	-1,550	-1,345	-1,102	-1,557
26	-1,362	-1,114	-1,626	-1,367	-1,123	-1,632
27	-1,384	-1,134	-1,697	-1,390	-1,143	-1,702
28	-1,406	-1,154	-1,589	-1,412	-1,162	-1,594
29	-1,428	-1,173	-1,657	-1,433	-1,181	-1,661
30	-1,449	-1,192	-1,701	-1,455	-1,200	-1,704

See Notes at Table I

Belgium - Greece

Causality in Mean & Variance between Belgium – Greece, according to r statistic of Causality Test of Cheung & Ng

Table I

Lags	$r_{Bl\_Gr,m}$	$r_{Gr\_Bl,m}$	$r_{Bl\_Gr,v}$	$r_{Gr\_Bl,v}$
1	2,203**	0,256	0,109	0,098
2	2,108**	0,588	1,348	1,350
3	1,459	0,118	1,390	1,381
4	-0,323	-0,107	0,131	0,131
5	-0,895	1,780*	0,471	0,464
6	1,775*	1,126	-1,389	-1,391
7	0,515	0,545	0,038	0,038
8	1,420	-0,503	-0,271	-0,272
9	-0,101	-0,061	-1,208	-1,213
10	-1,964**	-0,505	-1,111	-1,110
11	-1,391	0,509	-1,187	-1,186
12	0,709	-0,121	-1,058	-1,055
13	-0,235	-0,216	-0,286	-0,286
14	0,112	0,647	-1,069	-1,066
15	0,198	-0,384	0,827	0,828
16	-0,354	-0,292	0,093	0,088
17	-0,520	-0,209	-0,808	-0,806
18	0,674	-0,131	0,312	0,314
19	-0,257	-0,035	0,252	0,253
20	0,873	0,507	0,173	0,175
21	0,066	-0,739	1,309	1,306
22	0,202	-0,049	-0,667	-0,664
23	-0,596	-0,409	1,031	1,032
24	0,099	-1,228	0,770	0,762
25	0,382	0,187	-0,500	-0,500
26	0,222	-0,522	0,205	0,206
27	0,222	-0,003	-0,296	-0,296
28	-1,345	-0,762	0,844	0,842
29	-1,865*	-0,055	-0,701	-0,701
30	0,078	-0,604	-0,486	-0,485

Notes: The Null Hypothesis (Ho) denotes No Causality in Mean and Variance. The Alternative Hypothesis (H1) denotes Causality in Mean and Variance. The '*'indicates significance at the 10%, the '**' indicates significance at the 5% and the '***' indicates significance at the 1% level

Causality in Mean & Variance between Belgium – Greece, according to S statistic of Causality Test of Cheung & Ng

Table II

$S_{Bl\_Gr,m}$	29,85
$S_{Gr\_Bl,m}$	-5,77
$S_{Bl\_Gr,v}$	-12,27
$S_{Gr\_Bl,v}$	-12,48

See Notes at Table I

Causality in Mean between Belgium – Greece, according to the kernel functions of Causality Test of Hong

Table III

Bandwidth	QuadraticBl_Gr	BartlettBl_Gr	TruncatedBl_Gr	QuadraticGr_Bl	BartlettGr_Bl	TruncatedGr_Bl
1	2,952***	NaN	2,791***	-0,700	NaN	-0,665
2	3,141***	2,791***	3,772***	-0,733	-0,665	-0,796
3	3,694***	3,319***	3,595***	-0,857	-0,755	-1,054
4	3,768***	3,645***	2,825***	-1,008	-0,858	-1,263
5	3,654***	3,737***	2,501***	-1,006	-0,967	-0,395
6	3,528***	3,699***	2,981***	-0,923	-1,000	-0,257
7	3,407***	3,647***	2,597***	-0,843	-0,963	-0,412
8	3,319***	3,601***	2,748***	-0,794	-0,911	-0,560
9	3,271***	3,555***	2,388***	-0,779	-0,868	-0,754
10	3,244***	3,509***	3,010***	-0,789	-0,841	-0,869
11	3,219***	3,472***	3,144***	-0,815	-0,828	-0,973
12	3,189***	3,452***	2,956***	-0,854	-0,827	-1,123
13	3,154***	3,441***	2,69***	-0,904	-0,836	-1,256
14	3,110***	3,432***	2,445***	-0,961	-0,852	-1,302
15	3,056***	3,418***	2,224**	-1,021	-0,873	-1,401
16	2,995***	3,398***	2,037**	-1,082	-0,899	-1,507
17	2,926***	3,371***	1,892**	-1,144	-0,928	-1,615
18	2,851***	3,339***	1,795**	-1,204	-0,959	-1,724
19	2,774***	3,303***	1,632*	-1,264	-0,993	-1,830
20	2,695***	3,263***	1,608*	-1,321	-1,028	-1,884
21	2,616***	3,221***	1,452*	-1,376	-1,065	-1,884
22	2,539***	3,176***	1,311*	-1,428	-1,102	-1,980
23	2,464***	3,130***	1,233	-1,477	-1,139	-2,043
24	2,393***	3,083***	1,101	-1,524	-1,176	-1,870
25	2,326**	3,034***	0,998	-1,568	-1,212	-1,954
26	2,263**	2,985***	0,884	-1,610	-1,247	-1,994
27	2,206**	2,935***	0,776	-1,649	-1,280	-2,079
28	2,153**	2,885***	0,965	-1,686	-1,313	-2,064
29	2,105**	2,834***	1,427*	-1,721	-1,344	-2,143
30	2,061**	2,786***	1,318*	-1,755	-1,375	-2,161

See Notes at Table I

Causality in Mean between Belgium – Greece, according to the kernel functions of Causality Test of Hong

Table IV

Bandwidth	QuadraticBl_Gr	BartlettBl_Gr	TruncatedBl_Gr	QuadraticGr_Bl	BartlettGr_Bl	TruncatedGr_Bl
1	-0,660	NaN	-0,706	-0,661	NaN	-0,707
2	-0,607	-0,706	-0,058	-0,608	-0,707	-0,056
3	-0,285	-0,534	0,378	-0,286	-0,534	0,369
4	-0,097	-0,318	-0,009	-0,101	-0,319	-0,016
5	-0,038	-0,184	-0,238	-0,043	-0,187	-0,247
6	-0,029	-0,138	0,109	-0,035	-0,142	0,103
7	-0,048	-0,114	-0,150	-0,055	-0,119	-0,156
8	-0,071	-0,098	-0,355	-0,078	-0,103	-0,360
9	-0,086	-0,099	-0,169	-0,092	-0,105	-0,171
10	-0,085	-0,108	-0,051	-0,092	-0,114	-0,054
11	-0,075	-0,113	0,104	-0,081	-0,119	0,101
12	-0,063	-0,113	0,186	-0,069	-0,119	0,181
13	-0,053	-0,107	0,029	-0,059	-0,112	0,025
14	-0,046	-0,098	0,123	-0,052	-0,104	0,117
15	-0,042	-0,089	0,117	-0,048	-0,095	0,111
16	-0,041	-0,079	-0,029	-0,047	-0,085	-0,035
17	-0,042	-0,071	-0,031	-0,048	-0,076	-0,036
18	-0,045	-0,064	-0,142	-0,051	-0,070	-0,148
19	-0,050	-0,059	-0,253	-0,055	-0,065	-0,259
20	-0,054	-0,057	-0,364	-0,060	-0,063	-0,369
21	-0,060	-0,057	-0,135	-0,066	-0,063	-0,141
22	-0,065	-0,060	-0,156	-0,071	-0,065	-0,163
23	-0,070	-0,062	-0,053	-0,076	-0,068	-0,060
24	-0,074	-0,064	-0,038	-0,081	-0,070	-0,047
25	-0,079	-0,066	-0,085	-0,086	-0,072	-0,094
26	-0,084	-0,067	-0,167	-0,090	-0,073	-0,176
27	-0,089	-0,069	-0,236	-0,095	-0,075	-0,245
28	-0,094	-0,071	-0,184	-0,100	-0,077	-0,193
29	-0,099	-0,073	-0,170	-0,106	-0,079	-0,179
30	-0,104	-0,075	-0,199	-0,111	-0,082	-0,208

See Notes at Table I

Czech – Ireland

Causality in Mean & Variance between Czech – Ireland, according to r statistic of Causality Test of Cheung & Ng

Table I

Lags	$r_{Cz\_Ir,m}$	$r_{Ir\_Cz,m}$	$r_{Cz\_Ir,v}$	$r_{Ir\_Cz,v}$
1	2,498**	-0,48	-0,84	-0,84
2	1,654*	0,53	-0,34	1,50
3	-0,63	0,32	0,34	-0,58
4	-0,97	0,89	0,22	-0,08
5	0,070	0,155	0,167	0,819
6	0,921	-0,487	-0,166	0,601
7	0,368	-0,062	0,579	-0,134
8	0,785	0,920	-0,083	0,195
9	-0,889	0,003	0,097	-0,305
10	-0,106	-0,204	0,586	-0,498
11	2,335**	-0,962	3,361***	-0,593
12	0,155	-1,149	0,656	-0,160
13	1,771*	0,458	1,496	1,512
14	-0,733	1,124	0,093	-0,519
15	1,213	0,040	1,322	-0,111
16	2,745***	-0,143	1,731*	0,178
17	0,707	-1,572	-0,020	0,228
18	1,782*	-0,125	0,877	-0,237
19	-0,543	-0,678	-0,648	-0,133
20	-0,259	0,276	2,163**	-0,448
21	2,283**	0,287	1,727*	-0,754
22	-0,178	-0,099	0,365	-0,185
23	2,787***	-0,870	3,074***	-0,111
24	-0,628	-0,348	0,601	-0,181
25	-0,160	-0,812	0,442	0,679
26	1,019	0,149	0,977	-0,223
27	-1,095	0,213	-0,071	-0,170
28	1,263	-1,023	0,905	0,283
29	-1,138	-0,806	-0,282	-0,307
30	-0,785	-1,575	0,032	-0,339

Notes: The Null Hypothesis (Ho) denotes No Causality in Mean and Variance. The Alternative Hypothesis (H1) denotes Causality in Mean and Variance. The '*'indicates significance at the 10%, the '**' indicates significance at the 5% and the '***' indicates significance at the 1% level

Causality in Mean & Variance between Czech – Ireland, according to S statistic of Causality Test of Cheung & Ng

Table II

$S_{Cz\_Ir,m}$	159,96***
$S_{Ir\_Cz,m}$	-59,33
$S_{Cz\_Ir,v}$	189,72***
$S_{Ir\_Cz,v}$	-8,98

See Notes at Table I

Causality in Mean between Czech – Ireland, according to the kernel functions of Causality Test of Hong

Table III

Bandwidth	QuadraticCz_Ir	BartlettCz_Ir	TruncatedCz_Ir	QuadraticIr_Cz	BartlettIr_Cz	TruncatedIr_Cz
1	3,838***	NaN	3,778***	-0,587	NaN	-0,547
2	3,922***	3,77***	3,580***	-0,620	-0,547	-0,743
3	3,886***	3,969***	2,699***	-0,781	-0,652	-0,974
4	3,579***	3,907***	2,345***	-0,896	-0,763	-0,908
5	3,233***	3,738***	1,799**	-0,990	-0,845	-1,119
6	2,922***	3,538***	1,624*	-1,077	-0,912	-1,238
7	2,630***	3,335***	1,289*	-1,164	-0,978	-1,412
8	2,391***	3,141***	1,133	-1,246	-1,045	-1,346
9	2,197**	2,960***	1,045	-1,318	-1,107	-1,503
10	2,056**	2,794***	0,786	-1,380	-1,164	-1,637
11	1,970**	2,642***	1,796**	-1,431	-1,220	-1,560
12	1,930**	2,517***	1,542*	-1,471	-1,272	-1,404
13	1,925**	2,424***	1,9718**	-1,500	-1,316	-1,496
14	1,948**	2,355***	1,845**	-1,520	-1,353	-1,365
15	1,997**	2,305**	1,917**	-1,534	-1,384	-1,495
16	2,068**	2,268**	3,171***	-1,547	-1,411	-1,614
17	2,157**	2,250**	3,031***	-1,559	-1,435	-1,262
18	2,257**	2,253**	3,401***	-1,573	-1,456	-1,381
19	2,365***	2,270**	3,236***	-1,589	-1,473	-1,415
20	2,478***	2,298**	3,042***	-1,605	-1,487	-1,514
21	2,592***	2,332***	3,760***	-1,622	-1,500	-1,608
22	2,705***	2,370***	3,567***	-1,638	-1,512	-1,711
23	2,817***	2,413***	4,690***	-1,654	-1,525	-1,684
24	2,925***	2,463***	4,557***	-1,668	-1,538	-1,763
25	3,029***	2,520***	4,373***	-1,680	-1,551	-1,751
26	3,128***	2,581***	4,362***	-1,691	-1,565	-1,841
27	3,221***	2,643***	4,381***	-1,701	-1,578	-1,924
28	3,308***	2,706***	4,466***	-1,710	-1,592	-1,848
29	3,388***	2,769***	4,505***	-1,717	-1,606	-1,834
30	3,462***	2,831***	4,444***	-1,724	-1,620	-1,539

See Notes at Table I

Causality in Variance between Czech – Ireland, according to the kernel functions of Causality Test of Hong

Table IV

Bandwidth	QuadraticCz_Ir	BartlettCz_Ir	TruncatedCz_Ir	QuadraticIr_Cz	BartlettIr_Cz	TruncatedIr_Cz
1	-0,253	NaN	-0,203	-0,156	NaN	-0,204
2	-0,304	-0,203	-0,585	-0,071	-0,204	0,506
3	-0,526	-0,348	-0,838	0,163	0,024	0,151
4	-0,722	-0,498	-1,061	0,143	0,139	-0,216
5	-0,897	-0,636	-1,256	0,043	0,132	-0,285
6	-1,024	-0,764	-1,427	-0,075	0,082	-0,435
7	-1,181	-0,882	-1,494	-0,199	0,020	-0,660
8	-1,311	-0,988	-1,645	-0,333	-0,050	-0,852
9	-1,363	-1,084	-1,783	-0,463	-0,126	-1,011
10	-1,323	-1,174	-1,833	-0,578	-0,207	-1,119
11	-1,216	-1,258	0,624	-0,676	-0,287	-1,194
12	-1,080	-1,294	0,503	-0,762	-0,366	-1,337
13	-0,936	-1,274	0,778	-0,838	-0,442	-0,989
14	-0,792	-1,221	0,579	-0,909	-0,511	-1,079
15	-0,646	-1,151	0,744	-0,974	-0,571	-1,215
16	-0,497	-1,073	1,146	-1,036	-0,624	-1,339
17	-0,343	-0,988	0,961	-1,097	-0,675	-1,453
18	-0,185	-0,900	0,932	-1,156	-0,723	-1,560
19	-0,024	-0,813	0,842	-1,214	-0,770	-1,670
20	0,135	-0,729	1,518*	-1,270	-0,816	-1,742
21	0,292	-0,647	1,875**	-1,326	-0,861	-1,747
22	0,442	-0,562	1,733**	-1,381	-0,906	-1,843
23	0,585	-0,476	3,174***	-1,435	-0,949	-1,939
24	0,719	-0,387	3,060***	-1,488	-0,992	-2,028
25	0,844	-0,291	2,926***	-1,540	-1,034	-2,044
26	0,960	-0,192	2,922***	-1,592	-1,076	-2,126
27	1,065	-0,093	2,770***	-1,643	-1,117	-2,208
28	1,161	0,004	2,754***	-1,692	-1,157	-2,280
29	1,247	0,099	2,625***	-1,740	-1,197	-2,347
30	1,324*	0,191	2,490***	-1,787	-1,236	-2,409

See Notes at Table I

Czech – United Kingdom

Causality in Mean & Variance between Czech – United Kingdom according to r statistic of Causality Test of Cheung & Ng

Table I

Lags	$r_{Cz\_UK,m}$	$r_{UK\_Cz,m}$	$r_{Cz\_UK,v}$	$r_{UK\_Cz,v}$
1	1,168	-0,264	-1,238	-0,422
2	-0,921	1,086	0,619	2,596***
3	1,244	-1,517	0,773	0,343
4	0,524	0,256	-0,626	-0,559
5	0,118	0,489	-0,244	-0,321
6	2,010**	0,477	-0,668	-0,265
7	0,490	0,392	0,050	-0,096
8	-1,289	-2,135**	0,318	-0,325
9	0,519	1,187	0,890	-0,348
10	2,089**	-0,338	2,390**	0,526
11	1,219	-0,924	0,157	0,046
12	0,670	0,671	0,103	-0,567
13	0,354	-1,487	-0,752	0,583
14	0,495	-0,052	-0,377	-0,051
15	1,965**	0,217	0,540	-0,698
16	1,004	0,219	-0,020	-0,574
17	1,098	-0,229	-0,462	-0,182
18	0,111	-0,982	0,874	-0,393
19	0,597	0,125	3,041***	-0,456
20	0,592	-0,453	1,080	2,385**
21	1,165	0,352	-0,017	-0,538
22	2,153**	-0,220	1,684*	0,113
23	0,154	-0,146	-0,579	-0,287
24	0,001	-0,833	0,203	-0,354
25	1,788*	-0,284	0,123	-0,377
26	0,260	-1,086	0,194	0,158
27	0,412	0,290	0,189	0,188
28	-0,043	-0,230	-0,508	-0,074
29	-1,563	-2,040**	0,331	0,781
30	-0,121	-1,670*	-0,959	-0,131

Notes: The Null Hypothesis (Ho) denotes No Causality in Mean and Variance. The Alternative Hypothesis (H1) denotes Causality in Mean and Variance. The '*'indicates significance at the 10%, the '**' indicates significance at the 5% and the '***' indicates significance at the 1% level

Causality in Mean & Variance between Czech – United Kingdom according to S statistic of Causality Test of Cheung & Ng

Table II

$S_{Cz\_UK,m}$	179,87***
$S_{UK\_Cz,m}$	-89,92
$S_{Cz\_UK,v}$	69,66***
$S_{UK\_Cz,v}$	6,89

See Notes at Table I

Causality in Mean between Czech – United Kingdom, according to the kernel functions of Causality Test of Hong

Table III

Bandwidth	QuadraticCz_UK	BartlettCz_UK	TruncatedCz_UK	QuadraticUK_Cz	BartlettUK_Cz	TruncatedUK_Cz
1	0,267	NaN	0,269	-0,642	NaN	-0,661
2	0,253	0,269	0,124	-0,636	-0,661	-0,367
3	0,252	0,239	0,344	-0,437	-0,607	0,256
4	0,229	0,249	0,050	-0,242	-0,447	-0,103
5	0,196	0,247	-0,262	-0,205	-0,325	-0,325
6	0,209	0,203	0,694	-0,248	-0,279	-0,512
7	0,248	0,192	0,453	-0,263	-0,279	-0,694
8	0,321	0,217	0,622	-0,244	-0,306	0,307
9	0,404	0,250	0,431	-0,202	-0,315	0,417
10	0,493	0,282	1,238	-0,150	-0,291	0,211
11	0,583	0,324	1,323*	-0,104	-0,256	0,195
12	0,668	0,381	1,180	-0,064	-0,221	0,094
13	0,744	0,443	0,982	-0,032	-0,190	0,377
14	0,810	0,501	0,826	-0,010	-0,160	0,190
15	0,867	0,550	1,405*	0,001	-0,131	0,025
16	0,919	0,596	1,401*	0,000	-0,106	-0,129
17	0,968	0,643	1,439*	-0,014	-0,088	-0,272
18	1,013	0,689	1,258	-0,037	-0,076	-0,239
19	1,057	0,733	1,150	-0,067	-0,070	-0,377
20	1,100	0,773	1,048	-0,101	-0,067	-0,474
21	1,141	0,808	1,129	-0,135	-0,069	-0,580
22	1,181	0,839	1,772**	-0,169	-0,074	-0,694
23	1,218	0,870	1,618*	-0,201	-0,083	-0,808
24	1,253	0,901	1,468*	-0,229	-0,095	-0,805
25	1,283*	0,932	1,848**	-0,253	-0,110	-0,902
26	1,310*	0,962	1,715**	-0,274	-0,127	-0,817
27	1,333*	0,992	1,605*	-0,290	-0,145	-0,908
28	1,352*	1,022	1,473*	-0,304	-0,164	-1,000
29	1,368*	1,050	1,727**	-0,314	-0,183	-0,450
30	1,380*	1,076	1,604*	-0,322	-0,203	-0,122

See Notes at Table I

Causality in Variance between Czech – United Kingdom, according to the kernel functions of Causality Test of Hong

Table IV

Bandwidth	QuadraticCz_UK	BartlettCz_UK	TruncatedCz_UK	QuadraticUK_Cz	BartlettUK_Cz	TruncatedUK_Cz
1	0,357	NaN	0,391	-0,335	NaN	-0,583
2	0,316	0,391	-0,027	0,048	-0,583	2,527***
3	0,127	0,275	-0,177	1,212	0,438	1,718**
4	-0,040	0,156	-0,361	1,559*	1,083	1,260
5	-0,175	0,049	-0,616	1,541*	1,334*	0,856
6	-0,326	-0,056	-0,714	1,388*	1,403*	0,524
7	-0,477	-0,158	-0,924	1,198	1,382*	0,231
8	-0,579	-0,255	-1,084	0,993	1,314*	0,003
9	-0,610	-0,349	-1,056	0,803	1,223	-0,193
10	-0,602	-0,437	0,142	0,629	1,120	-0,332
11	-0,591	-0,492	-0,061	0,464	1,014	-0,520
12	-0,590	-0,511	-0,249	0,305	0,907	-0,622
13	-0,591	-0,517	-0,304	0,157	0,803	-0,713
14	-0,586	-0,516	-0,441	0,024	0,702	-0,866
15	-0,570	-0,515	-0,539	-0,092	0,605	-0,913
16	-0,541	-0,515	-0,687	-0,191	0,512	-0,987
17	-0,501	-0,517	-0,786	-0,275	0,424	-1,113
18	-0,454	-0,523	-0,777	-0,347	0,339	-1,210
19	-0,402	-0,532	0,775	-0,408	0,258	-1,292
20	-0,347	-0,533	0,826	-0,462	0,180	-0,394
21	-0,292	-0,522	0,675	-0,509	0,110	-0,473
22	-0,240	-0,503	1,018	-0,551	0,051	-0,595
23	-0,191	-0,477	0,929	-0,590	-0,001	-0,700
24	-0,147	-0,447	0,797	-0,628	-0,048	-0,793
25	-0,108	-0,413	0,666	-0,664	-0,091	-0,879
26	-0,073	-0,379	0,545	-0,701	-0,130	-0,981
27	-0,042	-0,346	0,429	-0,737	-0,167	-1,077
28	-0,016	-0,314	0,353	-0,772	-0,203	-1,174
29	0,005	-0,284	0,257	-0,807	-0,237	-1,174
30	0,023	-0,257	0,290	-0,842	-0,270	-1,265

See Notes at Table I

Cyprus – Greece

Causality in Mean & Variance between Cyprus – Greece
according to r statistic of Causality Test of Cheung & Ng

Table I

Lags	$r_{Cy\_Gr,m}$	$r_{Gr\_Cy,m}$	$r_{Cy\_Gr,v}$	$r_{Gr\_Cy,v}$
1	0,540	0,751	0,918	-0,356
2	1,165	1,549	-0,766	0,275
3	-0,546	-0,007	1,555	2,576**
4	-1,415	-1,010	0,009	1,036
5	2,063**	1,053	0,313	0,055
6	0,820	-0,230	1,000	0,127
7	0,272	0,944	1,758*	2,382**
8	0,080	-0,741	1,510	0,062
9	-0,644	-0,683	-0,024	0,562
10	2,053**	1,547	0,681	0,861
11	1,190	-0,139	0,835	1,473
12	1,780*	1,084	1,330	-0,639
13	-0,905	1,959*	0,090	0,757
14	0,314	-0,614	0,049	0,135
15	0,112	0,282	1,102	1,331
16	-1,056	-0,127	-0,750	-0,999
17	0,301	0,542	-0,026	0,373
18	2,032**	0,302	2,268**	2,228**
19	1,567	0,951	-0,270	-1,093
20	-0,521	-0,608	0,496	1,626
21	-0,076	-0,088	-0,769	0,673
22	1,603	0,014	-0,496	-0,230
23	0,357	0,202	0,284	-0,746
24	0,437	-0,482	1,195	0,064
25	-0,512	-0,069	0,837	0,754
26	-0,182	-0,208	0,712	0,329
27	-0,590	-0,586	0,744	0,293
28	0,114	0,831	-0,234	-0,506
29	1,055	0,100	-1,627	-0,108
30	0,507	-0,012	0,582	-0,359

Notes: The Null Hypothesis (Ho) denotes No Causality in Mean and Variance. The Alternative Hypothesis (H1) denotes Causality in Mean and Variance. The '*'indicates significance at the 10%, the '**' indicates significance at the 5% and the '***' indicates significance at the 1% level

Causality in Mean & Variance between Cyprus – Greece
according to r statistic of Causality Test of Cheung & Ng

Table II

$S_{Cy\_Gr,m}$	103,91***
$S_{Gr\_Cy,m}$	56,73***
$S_{Cy\_Gr,v}$	116,77***
$S_{Gr\_Cy,v}$	113,52***

See Notes at Table I

Causality in Mean between Cyprus – Greece, according to the kernel functions of Causality Test of Hong

Table III

Bandwidth	QuadraticCy_Gr	BartlettCy_Gr	TruncatedCy_Gr	QuadraticGr_Cy	BartlettGr_Cy	TruncatedGr_Cy
1	-0,112	NaN	-0,105	-0,609	NaN	-0,620
2	-0,150	-0,105	-0,274	-0,707	-0,620	-0,903
3	-0,111	-0,169	0,390	-0,422	-0,759	1,653**
4	-0,002	-0,102	-0,009	0,270	-0,413	1,487*
5	-0,023	-0,036	-0,285	0,653	0,038	1,031
6	-0,027	-0,031	-0,238	0,891	0,343	0,672
7	0,011	-0,052	0,397	1,062	0,517	1,978**
8	0,074	-0,052	0,744	1,192	0,663	1,624*
9	0,143	-0,017	0,482	1,296*	0,808	1,398*
10	0,196	0,031	0,362	1,368*	0,925	1,304*
11	0,231	0,074	0,310	1,407*	1,016	1,558*
12	0,253	0,109	0,507	1,426*	1,089	1,404*
13	0,271	0,140	0,312	1,437*	1,152	1,302*
14	0,288	0,168	0,131	1,449*	1,202	1,096
15	0,302	0,188	0,211	1,466*	1,240	1,264
16	0,315	0,203	0,160	1,489*	1,269	1,273
17	0,328	0,214	0,004	1,517*	1,292*	1,119
18	0,342	0,220	0,840	1,547*	1,311*	1,897**
19	0,355	0,228	0,696	1,577*	1,329*	1,942**
20	0,368	0,240	0,593	1,606*	1,351*	2,256**
21	0,380	0,254	0,558	1,631*	1,378*	2,168**
22	0,391	0,267	0,466	1,653**	1,407*	2,016**
23	0,400	0,280	0,350	1,669**	1,437*	1,960**
24	0,409	0,292	0,473	1,682**	1,467*	1,815**
25	0,417	0,303	0,471	1,689**	1,495*	1,773**
26	0,423	0,312	0,439	1,693**	1,521*	1,658**
27	0,429	0,321	0,418	1,692**	1,544*	1,545*
28	0,435	0,330	0,318	1,687**	1,565*	1,466*
29	0,439	0,337	0,644	1,679**	1,583*	1,351*
30	0,444	0,344	0,594	1,668**	1,598*	1,261

See Notes at Table I

Causality in Variance between Cyprus – Greece, according to the kernel functions of Causality Test of Hong

Table IV

Bandwidth	QuadraticCy_Gr	BartlettCy_Gr	TruncatedCy_Gr	QuadraticGr_Cy	BartlettGr_Cy	TruncatedGr_Cy
1	-0,483	NaN	-0,502	-0,248	NaN	-0,305
2	-0,447	-0,502	-0,160	-0,146	-0,305	0,516
3	-0,363	-0,420	-0,411	0,101	-0,046	0,018
4	-0,298	-0,394	0,030	0,132	0,069	0,043
5	-0,058	-0,357	1,128	0,117	0,089	0,096
6	0,185	-0,224	0,962	0,080	0,095	-0,176
7	0,325	-0,053	0,660	0,033	0,085	-0,169
8	0,415	0,087	0,384	-0,022	0,063	-0,252
9	0,505	0,184	0,246	-0,062	0,036	-0,344
10	0,598	0,245	1,047	-0,077	0,007	0,041
11	0,686	0,297	1,136	-0,074	-0,016	-0,155
12	0,764	0,356	1,618*	-0,060	-0,032	-0,075
13	0,835	0,422	1,563*	-0,039	-0,045	0,581
14	0,904	0,494	1,366*	-0,019	-0,047	0,472
15	0,971	0,564	1,167	-0,003	-0,037	0,310
16	1,036	0,627	1,203	0,008	-0,023	0,148
17	1,098	0,683	1,042	0,013	-0,009	0,050
18	1,157	0,731	1,664**	0,012	0,003	-0,079
19	1,212	0,775	1,951**	0,005	0,011	-0,049
20	1,261	0,822	1,830**	-0,008	0,017	-0,116
21	1,305*	0,869	1,669**	-0,026	0,021	-0,243
22	1,344*	0,915	1,974**	-0,049	0,022	-0,366
23	1,378*	0,959	1,8451**	-0,075	0,020	-0,476
24	1,406*	1,002	1,734**	-0,105	0,016	-0,548
25	1,429*	1,044	1,641**	-0,137	0,009	-0,654
26	1,447*	1,082	1,516*	-0,170	-0,001	-0,750
27	1,459*	1,117	1,449*	-0,204	-0,012	-0,792
28	1,467*	1,149	1,332*	-0,238	-0,026	-0,774
29	1,471*	1,178	1,399*	-0,272	-0,041	-0,865
30	1,471*	1,203	1,329*	-0,306	-0,057	-0,955

See Notes at Table I

Denmark – Sweden

Causality in Mean & Variance between Denmark –Sweden according to r statistic of Causality Test of Cheung & Ng

Table I

Lags	$r_{Dk\_Sw,m}$	$r_{Sw\_Dk,m}$	$r_{Dk\_Sw,v}$	$r_{Sw\_Dk,v}$
1	0,477	2,631***	0,441	-0,407
2	0,705	1,145	1,609	0,044
3	0,555	1,004	1,990**	-0,585
4	1,084	0,446	-1,516	-0,140
5	0,523	1,202	0,421	1,307
6	0,501	2,760***	-1,120	1,359
7	-1,124	0,031	2,052**	1,138
8	0,328	0,112	0,411	0,227
9	-0,728	1,312	-0,539	-0,760
10	1,118	0,877	0,014	1,023
11	-1,202	-0,388	-1,472	2,041**
12	-1,025	-0,408	1,706*	1,025
13	-0,025	0,490	1,578	1,659*
14	-0,732	-0,284	-0,430	-0,771
15	-1,153	-0,704	1,574	0,002
16	0,330	0,510	-0,502	-0,131
17	0,153	0,664	-1,480	-0,156
18	-0,148	-0,077	0,580	1,007
19	0,360	0,698	0,695	1,635
20	-1,146	-0,933	0,986	-0,338
21	1,002	-0,823	-0,730	-0,076
22	0,473	1,039	-0,203	-0,442
23	0,042	-0,159	-0,363	-0,841
24	0,191	-1,273	-1,489	0,723
25	0,708	-0,095	1,138	-0,898
26	-0,899	-0,094	-0,162	0,698
27	1,794*	0,562	-0,565	-0,960
28	-1,690*	-1,452	-0,838	-0,872
29	-0,637	-2,848***	-0,104	0,878
30	0,035	-0,451	-0,045	0,264

Notes: The Null Hypothesis (Ho) denotes No Causality in Mean and Variance. The Alternative Hypothesis (H1) denotes Causality in Mean and Variance. The '*'indicates significance at the 10%, the '**' indicates significance at the 5% and the '***' indicates significance at the 1% level

Causality in Mean & Variance between Denmark –Sweden according to r statistic of Causality Test of Cheung & Ng

Table II

$S_{Dk\_Sw,m}$	-1,58
$S_{Sw\_Dk,m}$	66,82***
$S_{Dk\_Sw,v}$	44,13**
$S_{Sw\_Dk,v}$	92,81***

See Notes at Table 1.1

Causality in Mean between Denmark – Sweden according to the kernel functions of Causality Test of Hong

Table III

Bandwidth	QuadraticDk_Sw	BartlettDk_Sw	TruncatedDk_Sw	QuadraticSw_Dk	BartlettSw_Dk	TruncatedSw_Dk
1	-0,575	NaN	-0,547	4,244***	NaN	4,236***
2	-0,595	-0,547	-0,636	4,225***	4,236***	3,170***
3	-0,699	-0,616	-0,800	3,926***	4,167***	2,608***
4	-0,749	-0,688	-0,622	3,459***	3,951***	1,987**
5	-0,784	-0,729	-0,783	3,169***	3,696***	1,938**
6	-0,818	-0,754	-0,928	3,106***	3,460***	3,752***
7	-0,854	-0,786	-0,776	3,127**	3,364***	3,223***
8	-0,890	-0,814	-0,946	3,153***	3,367***	2,784***
9	-0,911	-0,838	-0,995	3,160***	3,377***	2,825***
10	-0,922	-0,864	-0,873	3,140***	3,381***	2,652***
11	-0,928	-0,887	-0,720	3,090***	3,378***	2,364***
12	-0,929	-0,903	-0,663	3,018***	3,366***	2,110**
13	-0,928	-0,911	-0,828	2,933***	3,341***	1,896**
14	-0,931	-0,916	-0,874	2,841***	3,305***	1,669**
15	-0,940	-0,921	-0,764	2,744***	3,260***	1,540*
16	-0,954	-0,925	-0,890	2,644***	3,208***	1,377*
17	-0,972	-0,928	-1,024	2,541***	3,151***	1,260
18	-0,993	-0,933	-1,152	2,435***	3,090***	1,073
19	-1,015	-0,941	-1,254	2,329**	3,026***	0,981
20	-1,036	-0,951	-1,150	2,227**	2,960***	0,960
21	-1,054	-0,962	-1,102	2,132**	2,894***	0,910
22	-1,070	-0,974	-1,184	2,048**	2,828***	0,930
23	-1,082	-0,986	-1,298	1,975**	2,763***	0,781
24	-1,091	-0,999	-1,401	1,915**	2,700***	0,891
25	-1,097	-1,013	-1,429	1,867**	2,638***	0,748
26	-1,102	-1,028	-1,409	1,829**	2,579***	0,612
27	-1,107	-1,043	-1,026	1,799**	2,521***	0,527
28	-1,112	-1,057	-0,708	1,776**	2,464***	0,712
29	-1,118	-1,069	-0,756	1,759**	2,409***	1,772**
30	-1,124	-1,078	-0,861	1,746**	2,359***	1,663**

See Notes at Table I

Causality in Variance between Denmark – Sweden according to the kernel functions of Causality Test of Hong

Table IV

Bandwidth	QuadraticDk_Sw	BartlettDk_Sw	TruncatedDk_Sw	QuadraticSw_Dk	BartlettSw_Dk	TruncatedSw_Dk
1	-0,468	NaN	-0,571	-0,641	NaN	-0,591
2	-0,378	-0,571	0,407	-0,698	-0,591	-0,919
3	0,210	-0,276	1,572*	-0,879	-0,745	-1,017
4	0,821	0,159	1,844**	-1,025	-0,869	-1,228
5	1,155	0,567	1,400*	-1,070	-0,975	-0,862
6	1,385*	0,848	1,370*	-1,016	-1,037	-0,526
7	1,543*	1,024	2,172**	-0,958	-1,043	-0,394
8	1,637*	1,173	1,838**	-0,910	-1,015	-0,601
9	1,692**	1,306*	1,580*	-0,847	-0,980	-0,657
10	1,730**	1,408*	1,287*	-0,763	-0,952	-0,599
11	1,768**	1,477*	1,508*	-0,672	-0,928	0,150
12	1,808**	1,525*	1,876**	-0,580	-0,896	0,172
13	1,848**	1,567*	2,135**	-0,493	-0,850	0,547
14	1,886**	1,611*	1,921**	-0,413	-0,794	0,467
15	1,919**	1,654**	2,169**	-0,343	-0,732	0,279
16	1,947**	1,696**	1,987**	-0,283	-0,671	0,106
17	1,970**	1,736**	2,174**	-0,235	-0,615	-0,054
18	1,988**	1,774**	2,023**	-0,197	-0,566	-0,028
19	2,002**	1,810**	1,909**	-0,168	-0,524	0,287
20	2,011**	1,842**	1,886**	-0,145	-0,485	0,153
21	2,016**	1,870**	1,793**	-0,127	-0,449	0,007
22	2,015**	1,895**	1,625*	-0,112	-0,416	-0,100
23	2,008**	1,915**	1,480*	-0,100	-0,388	-0,120
24	1,997**	1,930**	1,673**	-0,091	-0,363	-0,168
25	1,980**	1,942**	1,717**	-0,084	-0,342	-0,169
26	1,960**	1,952**	1,568*	-0,079	-0,324	-0,217
27	1,937**	1,960**	1,469*	-0,076	-0,309	-0,198
28	1,911**	1,966**	1,432*	-0,074	-0,296	-0,203
29	1,883**	1,970**	1,296*	-0,074	-0,285	-0,205
30	1,854**	1,971**	1,165	-0,075	-0,275	-0,307

See Notes at Table I

France– United Kingdom

Causality in Mean & Variance between France – United Kingdom according to r statistic of Causality Test of Cheung & Ng

Table I

Lags	$r_{Fr\_UK,m}$	$r_{UK\_Fr,m}$	$r_{Fr\_UK,v}$	$r_{UK\_Fr,v}$
1	0,055	3,712***	-0,594	1,842*
2	-1,172	-0,292	0,314	-0,675
3	0,681	0,523	0,228	0,645
4	-0,371	1,579	-0,404	-0,565
5	-0,052	-0,711	0,245	-0,667
6	-0,670	0,402	0,895	1,076
7	1,246	0,359	0,643	-0,157
8	1,007	-0,137	-0,845	-1,742*
9	-0,051	0,219	2,148**	0,293
10	0,220	1,915*	2,668***	0,138
11	2,451**	1,461	-0,445	-0,038
12	0,242	-1,206	3,489***	0,378
13	-1,339	-1,225	0,981	-0,494
14	-0,303	1,086	-0,572	-0,966
15	0,020	0,829	1,150	-0,535
16	-0,830	-0,248	1,508	-0,080
17	-0,109	-0,751	-0,508	-0,526
18	0,535	0,067	0,524	-0,391
19	-0,242	-0,517	3,183***	-0,258
20	-0,731	0,697	0,161	1,920*
21	1,254	-0,308	-0,016	-0,033
22	-0,903	0,675	0,452	-0,435
23	0,842	-0,470	0,065	-1,110
24	-0,577	0,779	0,185	0,045
25	0,695	0,284	1,191	-0,233
26	-1,087	-0,683	-0,763	0,129
27	-0,748	1,046	-0,617	-1,686*
28	-2,217**	0,161	-0,419	-0,988
29	0,740	0,185	0,732	-0,186
30	-1,519	-0,364	0,206	-0,025

Notes: The Null Hypothesis (Ho) denotes No Causality in Mean and Variance. The Alternative Hypothesis (H1) denotes Causality in Mean and Variance. The '*'indicates significance at the 10%, the '**' indicates significance at the 5% and the '***' indicates significance at the 1% level

Causality in Mean & Variance between France – United Kingdom according to S statistic of Causality Test of Cheung & Ng

Table II

$S_{Fr\_UK,m}$	-45,64
$S_{UK\_Fr,m}$	141,04***
$S_{Fr\_UK,v}$	245,05***
$S_{UK\_Fr,v}$	-82,67

See Notes at Table I

Causality in Mean between France – United kingdom according to the kernel functions of Causality Test of Hong

Table III

Bandwidth	QuadraticFr_UK	BartlettFr_UK	TruncatedFr_UK	QuadraticUK_Fr	BartlettUK_Fr	TruncatedUK_Fr
1	-0,696	NaN	-0,706	9,035***	NaN	9,096***
2	-0,664	-0,706	-0,308	8,901***	9,096***	5,988***
3	-0,560	-0,619	-0,468	7,801***	8,670***	4,605***
4	-0,567	-0,570	-0,709	6,835***	7,964***	4,537***
5	-0,662	-0,583	-0,949	6,150***	7,386***	3,914***
6	-0,736	-0,633	-1,022	5,595***	6,932***	3,342***
7	-0,805	-0,697	-0,790	5,101***	6,536***	2,871***
8	-0,857	-0,750	-0,729	4,677***	6,177***	2,449***
9	-0,871	-0,784	-0,920	4,340***	5,847***	2,093**
10	-0,845	-0,811	-1,083	4,081***	5,540***	2,612***
11	-0,803	-0,839	0,072	3,884***	5,271***	2,753***
12	-0,753	-0,849	-0,118	3,731***	5,048***	2,748***
13	-0,701	-0,837	0,057	3,605***	4,863***	2,758***
14	-0,655	-0,813	-0,111	3,494***	4,708***	2,709***
15	-0,618	-0,784	-0,284	3,391***	4,575***	2,576***
16	-0,593	-0,755	-0,321	3,294***	4,460***	2,339***
17	-0,579	-0,728	-0,476	3,200***	4,356***	2,209**
18	-0,574	-0,706	-0,574	3,108***	4,259***	1,991**
19	-0,576	-0,688	-0,707	3,017***	4,168***	1,831**
20	-0,582	-0,675	-0,754	2,925***	4,080***	1,717**
21	-0,587	-0,666	-0,630	2,835***	3,995***	1,546*
22	-0,589	-0,661	-0,632	2,744***	3,913***	1,442*
23	-0,586	-0,657	-0,650	2,654***	3,832***	1,307*
24	-0,578	-0,655	-0,724	2,566***	3,752***	1,238
25	-0,566	-0,654	-0,773	2,478***	3,675***	1,094
26	-0,549	-0,654	-0,717	2,393***	3,599***	1,012
27	-0,528	-0,656	-0,752	2,309**	3,524***	1,025
28	-0,503	-0,658	-0,167	2,227**	3,451***	0,887
29	-0,477	-0,660	-0,211	2,146**	3,380***	0,754
30	-0,448	-0,659	-0,010	2,068**	3,310***	0,641

See Notes at Table I

Causality in Variance between France – United kingdom according to the kernel functions of Causality Test of Hong

Table IV

Bandwidth	QuadraticFr_UK	BartlettFr_UK	TruncatedFr_UK	QuadraticUK_Fr	BartlettUK_Fr	TruncatedUK_Fr
1	-0,507	NaN	-0,458	1,670**	NaN	1,705**
2	-0,554	-0,458	-0,775	1,623*	1,705**	0,938
3	-0,755	-0,599	-1,020	1,314*	1,562*	0,532
4	-0,932	-0,741	-1,179	1,001	1,356*	0,224
5	-1,054	-0,867	-1,351	0,740	1,158	0,029
6	-1,150	-0,980	-1,287	0,541	0,980	0,080
7	-1,233	-1,072	-1,346	0,419	0,835	-0,183
8	-1,236	-1,146	-1,327	0,332	0,712	0,356
9	-1,100	-1,204	-0,372	0,263	0,620	0,125
10	-0,861	-1,229	1,060	0,198	0,556	-0,096
11	-0,569	-1,189	0,847	0,129	0,501	-0,301
12	-0,256	-1,103	3,171***	0,057	0,447	-0,458
13	0,061	-0,966	3,057***	-0,018	0,391	-0,583
14	0,369	-0,783	2,832***	-0,095	0,334	-0,565
15	0,663	-0,584	2,814***	-0,169	0,278	-0,670
16	0,938	-0,385	2,977***	-0,236	0,222	-0,821
17	1,192	-0,190	2,774***	-0,297	0,168	-0,914
18	1,421*	-0,004	2,589***	-0,352	0,113	-1,025
19	1,627*	0,170	4,087***	-0,405	0,059	-1,144
20	1,809**	0,338	3,844***	-0,456	0,005	-0,659
21	1,969**	0,506	3,612***	-0,505	-0,046	-0,792
22	2,107**	0,667	3,425***	-0,550	-0,092	-0,890
23	2,225**	0,820	3,217***	-0,593	-0,135	-0,821
24	2,325**	0,963	3,024***	-0,630	-0,176	-0,943
25	2,408***	1,095	3,047***	-0,664	-0,213	-1,052
26	2,475***	1,216	2,949***	-0,692	-0,249	-1,162
27	2,529***	1,328*	2,826***	-0,717	-0,285	-0,860
28	2,571***	1,430*	2,681***	-0,739	-0,318	-0,833
29	2,603***	1,524*	2,591***	-0,757	-0,349	-0,939
30	2,625***	1,609*	2,438***	-0,772	-0,378	-1,046

See Notes at Table I

Germany– Italy

Causality in Mean & Variance between Germany –Italy according to r statistic of Causality Test of Cheung & Ng

Table I

Lags	$r_{Ger\_It,m}$	$r_{It\_Ger,m}$	$r_{Ger\_It,v}$	$r_{It\_Ger,v}$
1	0,900	2,065**	-0,777	0,004
2	1,041	1,020	0,162	-0,252
3	-0,234	0,110	0,271	-0,706
4	1,102	0,271	-0,572	0,180
5	0,442	0,596	-0,650	1,535
6	1,076	-0,125	-0,211	1,485
7	-0,353	-0,497	0,541	0,753
8	0,705	0,333	-0,048	-0,792
9	1,740*	-1,261	-0,077	-0,152
10	1,730*	1,482	-0,087	0,032
11	0,770	0,982	-1,663*	0,674
12	1,330	-0,003	-0,415	0,515
13	0,647	-0,967	0,034	-0,071
14	-1,418	-0,607	-0,868	-0,266
15	0,496	-1,145	-1,312	-0,554
16	-0,280	0,531	0,423	0,328
17	-0,825	-0,104	-0,910	-1,268
18	0,915	-1,520	-0,970	-0,589
19	-1,173	-1,124	-0,353	4,551***
20	-0,476	-2,231**	-0,829	2,439**
21	-0,383	0,503	-0,174	0,301
22	1,128	1,203	0,033	-1,002
23	0,800	1,328	-0,989	-0,188
24	-1,040	0,911	-0,313	-0,457
25	1,981**	0,264	-0,871	-0,576
26	-0,429	0,413	0,151	0,000
27	-0,876	0,258	-1,305	-0,565
28	-0,636	-1,994**	-0,073	0,404
29	-0,963	0,959	-0,860	0,052
30	-1,880*	0,282	1,283	-0,579

Notes: The Null Hypothesis (Ho) denotes No Causality in Mean and Variance. The Alternative Hypothesis (H1) denotes Causality in Mean and Variance. The '*'indicates significance at the 10%, the '**' indicates significance at the 5% and the '***' indicates significance at the 1% level

Causality in Mean & Variance between Germany –Italy according to S statistic of Causality Test of Cheung & Ng

Table II

$S_{Ger\_It,m}$	126,63***
$S_{It\_Ger,m}$	41,89*
$S_{Ger\_It,v}$	-247,48
$S_{It\_Ger,v}$	113,38***

See Notes at Table I

Causality in Mean between Germany– Italy according to the kernel functions of Causality Test of Hong

Table III

Bandwidth	QuadraticGer_It	BartlettGer_It	TruncatedGer_It	QuadraticIt_Ger	BartlettIt_Ger	TruncatedIt_Ger
1	-0,137	NaN	-0,133	2,303**	NaN	2,319**
2	-0,121	-0,133	-0,050	2,288**	2,319**	1,663**
3	-0,161	-0,114	-0,426	2,006**	2,257**	0,957
4	-0,246	-0,163	-0,290	1,610*	2,051**	0,503
5	-0,299	-0,217	-0,513	1,262	1,805**	0,248
6	-0,366	-0,264	-0,419	0,950	1,572*	-0,056
7	-0,426	-0,306	-0,621	0,687	1,360*	-0,251
8	-0,446	-0,345	-0,704	0,482	1,166	-0,455
9	-0,427	-0,387	-0,176	0,341	0,990	-0,285
10	-0,380	-0,415	0,290	0,243	0,836	0,006
11	-0,319	-0,416	0,194	0,164	0,713	0,003
12	-0,255	-0,397	0,350	0,094	0,618	-0,199
13	-0,194	-0,369	0,226	0,035	0,539	-0,199
14	-0,144	-0,335	0,418	-0,012	0,471	-0,308
15	-0,105	-0,300	0,270	-0,046	0,411	-0,234
16	-0,073	-0,265	0,102	-0,070	0,358	-0,350
17	-0,048	-0,232	0,050	-0,084	0,310	-0,507
18	-0,031	-0,205	0,027	-0,088	0,264	-0,263
19	-0,018	-0,181	0,096	-0,084	0,223	-0,206
20	-0,007	-0,161	-0,025	-0,074	0,186	0,450
21	0,002	-0,144	-0,152	-0,058	0,158	0,329
22	0,011	-0,130	-0,100	-0,038	0,138	0,398
23	0,020	-0,119	-0,144	-0,017	0,124	0,513
24	0,029	-0,110	-0,122	0,003	0,115	0,485
25	0,038	-0,104	0,314	0,022	0,112	0,348
26	0,048	-0,097	0,200	0,040	0,111	0,231
27	0,059	-0,089	0,172	0,056	0,111	0,104
28	0,070	-0,082	0,095	0,070	0,112	0,522
29	0,083	-0,074	0,092	0,084	0,114	0,510
30	0,096	-0,067	0,437	0,097	0,117	0,388

See Notes at Table I

Causality in Variance between Germany– Italy according to the kernel functions of Causality Test of Hong

Table IV

Bandwidth	QuadraticGer_It	BartlettGer_It	TruncatedGer_It	QuadraticIt_Ger	BartlettIt_Ger	TruncatedIt_Ger
1	-0,334	NaN	-0,280	-0,753	NaN	-0,708
2	-0,389	-0,280	-0,685	-0,806	-0,708	-0,969
3	-0,628	-0,439	-0,938	-0,950	-0,847	-0,995
4	-0,819	-0,599	-1,049	-1,064	-0,947	-1,204
5	-0,961	-0,731	-1,120	-1,059	-1,030	-0,643
6	-1,074	-0,837	-1,298	-0,968	-1,062	-0,233
7	-1,187	-0,929	-1,390	-0,867	-1,029	-0,329
8	-1,291	-1,013	-1,550	-0,805	-0,971	-0,398
9	-1,380	-1,092	-1,695	-0,736	-0,915	-0,604
10	-1,453	-1,168	-1,830	-0,697	-0,872	-0,795
11	-1,509	-1,243	-1,359	-0,719	-0,845	-0,872
12	-1,551	-1,308	-1,469	-0,784	-0,832	-0,983
13	-1,582	-1,358	-1,606	-0,855	-0,831	-1,138
14	-1,604	-1,400	-1,591	-0,899	-0,838	-1,271
15	-1,618	-1,439	-1,399	-0,904	-0,853	-1,352
16	-1,629	-1,471	-1,498	-0,868	-0,874	-1,465
17	-1,638	-1,497	-1,478	-0,795	-0,900	-1,310
18	-1,649	-1,520	-1,442	-0,696	-0,929	-1,379
19	-1,662	-1,539	-1,543	-0,579	-0,957	1,934**
20	-1,678	-1,556	-1,550	-0,451	-0,966	2,695***
21	-1,697	-1,572	-1,660	-0,320	-0,941	2,497***
22	-1,716	-1,587	-1,771	-0,189	-0,889	2,450***
23	-1,735	-1,602	-1,730	-0,064	-0,821	2,260**
24	-1,751	-1,617	-1,822	0,055	-0,743	2,105**
25	-1,764	-1,632	-1,814	0,165	-0,659	1,975**
26	-1,773	-1,647	-1,913	0,266	-0,574	1,804**
27	-1,778	-1,663	-1,772	0,357	-0,489	1,684**
28	-1,778	-1,678	-1,871	0,439	-0,407	1,548*
29	-1,775	-1,693	-1,868	0,511	-0,328	1,396*
30	-1,767	-1,708	-1,744	0,574	-0,252	1,294*

See Notes at Table I

Portugal – Spain

Causality in Mean & Variance between Portugal - Spain
according to r statistic of Causality Test of Cheung & Ng

Table I

Lags	$r_{Port\_Sp,m}$	$r_{Sp\_Port,m}$	$r_{Port\_Sp,v}$	$r_{Sp\_Port,v}$
1	1,050	9,599***	0,640	0,559
2	0,523	1,149	0,175	4,339***
3	-0,818	0,781	0,304	1,143
4	-0,170	1,293	-0,766	0,615
5	0,005	0,196	-0,370	-0,965
6	0,030	-1,032	1,162	-0,329
7	0,859	1,265	-0,630	0,464
8	-0,116	1,709*	-0,508	0,959
9	1,779*	0,028	0,122	1,193
10	0,228	1,156	0,769	-0,766
11	-0,620	1,494	0,993	-1,261
12	0,293	-0,725	3,607***	0,298
13	-1,047	-0,093	-0,166	0,435
14	0,298	0,720	-0,727	-0,965
15	0,197	1,071	0,999	-0,552
16	-0,214	0,003	2,163**	-0,679
17	-0,724	-1,292	0,665	0,945
18	-0,954	-0,537	1,745*	1,610
19	1,493	-2,123**	0,298	0,440
20	1,328	0,096	-0,864	0,855
21	0,021	0,215	0,563	-0,057
22	1,472	0,448	-0,904	-0,537
23	0,587	1,099	-1,451	-0,090
24	1,159	1,114	-1,503	-0,020
25	-0,341	-0,355	0,063	-0,105
26	0,218	0,955	-0,450	-0,699
27	-1,349	0,396	-0,230	0,651
28	-0,088	-0,011	-0,364	-0,296
29	1,346	-1,557	0,138	-0,789
30	-1,078	-0,093	1,552	-0,342

Notes: The Null Hypothesis (Ho) denotes No Causality in Mean and Variance. The Alternative Hypothesis (H1) denotes Causality in Mean and Variance. The '*'indicates significance at the 10%, the '**' indicates significance at the 5% and the '***' indicates significance at the 1% level

Causality in Mean & Variance between Portugal - Spain
according to S statistic of Causality Test of Cheung & Ng

Table II

$S_{Port\_Sp,m}$	83,63***
$S_{Sp\_Port,m}$	264,50***
$S_{Port\_Sp,v}$	109,11***
$S_{Sp\_Port,v}$	93,98***

See Notes at Table I

Causality in Mean between Portugal - Spain according to the kernel functions of Causality Test of Hong

Table III

Bandwidth	QuadraticPort_Sp	BartlettPort_Sp	TruncatedPort_Sp	QuadraticSp_Port	BartlettSp_Port	TruncatedSp_Port
1	0,037	NaN	0,076	64,738***	NaN	64,856***
2	-0,012	0,076	-0,309	64,142***	64,856***	46,120***
3	-0,188	-0,050	-0,384	58,100***	62,991***	37,580***
4	-0,344	-0,161	-0,675	51,723***	59,075***	32,859***
5	-0,503	-0,265	-0,919	46,590***	55,308***	29,149***
6	-0,669	-0,376	-1,127	42,571***	52,006***	26,691***
7	-0,800	-0,489	-1,109	39,392***	49,150***	24,934***
8	-0,888	-0,593	-1,283	36,831***	46,689***	23,872***
9	-0,939	-0,687	-0,680	34,72***	44,569***	22,321***
10	-0,970	-0,757	-0,855	32,956***	42,724***	21,306***
11	-0,998	-0,803	-0,942	31,430***	41,094***	20,637***
12	-1,030	-0,839	-1,085	30,095***	39,645***	19,711***
13	-1,063	-0,871	-1,015	28,91***	38,349***	18,788***
14	-1,095	-0,899	-1,147	27,873***	37,175***	18,060***
15	-1,122	-0,925	-1,280	26,935***	36,103***	17,524***
16	-1,145	-0,951	-1,405	26,087***	35,119***	16,832***
17	-1,164	-0,979	-1,439	25,316***	34,211***	16,495***
18	-1,181	-1,007	-1,404	24,615***	33,369***	15,954***
19	-1,195	-1,036	-1,148	23,973***	32,587***	16,169***
20	-1,205	-1,062	-0,981	23,382***	31,861***	15,643***
21	-1,210	-1,084	-1,107	22,835***	31,187***	15,158***
22	-1,212	-1,102	-0,885	22,325***	30,557***	14,728***
23	-1,210	-1,118	-0,954	21,848***	29,966***	14,482***
24	-1,205	-1,129	-0,869	21,399***	29,408***	14,259***
25	-1,198	-1,139	-0,970	20,975***	28,883***	13,886***
26	-1,190	-1,146	-1,078	20,573***	28,386***	13,648***
27	-1,180	-1,152	-0,925	20,191***	27,914***	13,315***
28	-1,170	-1,158	-1,035	19,830***	27,466***	12,978***
29	-1,159	-1,162	-0,889	19,487***	27,039***	12,996***
30	-1,149	-1,166	-0,836	19,162***	26,631***	12,685***

See Notes at Table I

Causality in Variance between Portugal - Spain according to the kernel functions of Causality Test of Hong

Table IV

Bandwidth	QuadraticPort_Sp	BartlettPort_Sp	TruncatedPort_Sp	QuadraticSp_Port	BartlettSp_Port	TruncatedSp_Port
1	-0,468	NaN	-0,417	0,307	NaN	-0,486
2	-0,519	-0,417	-0,780	1,449*	-0,486	8,650***
3	-0,738	-0,570	-1,007	5,122***	2,607***	7,209***
4	-0,897	-0,720	-1,016	6,489***	4,713***	6,039***
5	-1,015	-0,833	-1,181	6,773***	5,691***	5,397***
6	-1,039	-0,923	-0,970	6,636***	6,124***	4,683***
7	-1,087	-0,987	-1,056	6,352***	6,282***	4,139***
8	-1,150	-1,030	-1,171	6,044***	6,289***	3,867***
9	-1,180	-1,067	-1,335	5,753***	6,217***	3,765***
10	-1,150	-1,103	-1,353	5,481***	6,111***	3,494***
11	-1,062	-1,141	-1,286	5,226***	5,991***	3,478***
12	-0,930	-1,175	1,302*	4,990***	5,866***	3,156***
13	-0,775	-1,170	1,068	4,775***	5,741***	2,886***
14	-0,604	-1,116	0,950	4,581***	5,615***	2,784***
15	-0,426	-1,039	0,932	4,403***	5,489***	2,576***
16	-0,250	-0,953	1,592*	4,241***	5,366***	2,413***
17	-0,088	-0,858	1,461*	4,090***	5,244***	2,339***
18	0,059	-0,756	1,792**	3,948***	5,126***	2,568***
19	0,192	-0,652	1,606*	3,814***	5,014***	2,381***
20	0,314	-0,547	1,541*	3,686***	4,908***	2,295**
21	0,427	-0,445	1,410*	3,564***	4,808***	2,097**
22	0,532	-0,348	1,366*	3,446***	4,712***	1,955**
23	0,628	-0,257	1,526*	3,332***	4,620***	1,777**
24	0,713	-0,171	1,704**	3,221***	4,530***	1,606*
25	0,788	-0,089	1,539*	3,113***	4,442***	1,444*
26	0,853	-0,011	1,411*	3,009***	4,355***	1,360*
27	0,907	0,062	1,268	2,907***	4,270***	1,271
28	0,951	0,129	1,140	2,807***	4,187***	1,137
29	0,985	0,192	1,002	2,710***	4,105***	1,084
30	1,012	0,248	1,200	2,615***	4,025***	0,963

See Notes at Table I

Sweden– United Kingdom

Causality in Mean & Variance between Sweden - UK according to r statistic of Causality Test of Cheung & Ng

Table I

Lags	$r_{Sw\_UK,m}$	$r_{UK\_Sw,m}$	$r_{Sw\_UK,v}$	$r_{UK\_Sw,v}$
1	1,927*	1,940*	0,682	1,998**
2	-0,968	1,560	0,804	2,376**
3	0,318	0,174	1,288	2,976***
4	0,100	-0,430	-0,830	0,144
5	-0,698	-0,086	1,230	1,409
6	2,600***	1,299	0,088	-0,573
7	0,076	0,208	1,109	1,771*
8	0,891	-0,318	-0,595	-0,480
9	0,915	-0,482	0,057	-0,642
10	0,097	1,849*	2,277**	0,655
11	0,334	0,528	-0,587	-0,355
12	0,424	-0,407	1,198	1,423
13	-0,909	0,097	1,129	1,547
14	-0,270	0,225	-0,258	-0,204
15	-0,925	0,186	0,199	-0,277
16	-0,485	0,079	0,368	1,625
17	-0,601	-0,684	0,247	-0,896
18	-0,592	-0,492	0,253	0,257
19	0,515	-0,172	2,335**	1,136
20	0,449	-0,385	0,057	0,057
21	1,559	0,756	0,020	0,321
22	0,274	0,694	1,010	0,169
23	-0,036	-0,261	-0,401	-1,676*
24	0,557	2,495**	0,621	0,451
25	0,525	0,713	0,266	1,148
26	-1,486	-1,430	-1,568	-0,220
27	0,547	0,651	-0,513	1,222
28	-0,820	-0,853	-0,458	-0,855
29	0,089	-0,635	-1,177	-0,356
30	-0,023	0,408	-0,664	0,340

Notes: The Null Hypothesis (Ho) denotes No Causality in Mean and Variance. The Alternative Hypothesis (H1) denotes Causality in Mean and Variance. The '*'indicates significance at the 10%, the '**' indicates significance at the 5% and the '***' indicates significance at the 1% level

Causality in Mean & Variance between Sweden - UK according to r statistic of Causality Test of Cheung & Ng

Table II

$S_{Sw\_UK,m}$	68,18***
$S_{UK\_Sw,m}$	112,41***
$S_{Sw\_UK,v}$	126,89***
$S_{UK\_Sw,v}$	224,51***

See Notes at Table I

Causality in Mean between Sweden – UK according to the kernel functions of Causality Test of Hong

Table III

Bandwidth	QuadraticSw_UK	BartlettSw_UK	TruncatedSw_UK	QuadraticUK_Sw	BartlettUK_Sw	TruncatedUK_Sw
1	1,920**	NaN	1,935**	2,018**	NaN	1,970**
2	1,906**	1,935**	1,344*	2,098**	1,970**	2,123**
3	1,671**	1,868**	0,734	2,136**	2,160**	1,342*
4	1,286*	1,681**	0,288	1,877**	2,138**	0,879
5	1,033	1,458*	0,101	1,590*	1,994**	0,476
6	0,987	1,248	1,791**	1,339*	1,812**	0,644
7	1,034	1,158	1,399*	1,117	1,646**	0,345
8	1,087	1,162	1,267	0,944	1,504*	0,102
9	1,115	1,185	1,167	0,810	1,370*	-0,079
10	1,116	1,208	0,891	0,703	1,244	0,489
11	1,092	1,221	0,667	0,616	1,137	0,319
12	1,051	1,222	0,478	0,540	1,053	0,141
13	0,996	1,209	0,436	0,461	0,981	-0,053
14	0,931	1,188	0,251	0,375	0,914	-0,226
15	0,862	1,160	0,227	0,285	0,850	-0,390
16	0,792	1,127	0,092	0,196	0,786	-0,548
17	0,724	1,091	-0,012	0,112	0,722	-0,616
18	0,657	1,052	-0,111	0,036	0,658	-0,718
19	0,591	1,010	-0,220	-0,033	0,595	-0,852
20	0,526	0,968	-0,333	-0,093	0,532	-0,959
21	0,462	0,923	-0,081	-0,145	0,470	-0,994
22	0,401	0,879	-0,211	-0,191	0,409	-1,041
23	0,343	0,837	-0,347	-0,231	0,348	-1,150
24	0,288	0,796	-0,431	-0,267	0,289	-0,316
25	0,236	0,755	-0,516	-0,299	0,235	-0,368
26	0,187	0,714	-0,314	-0,326	0,187	-0,193
27	0,141	0,674	-0,394	-0,350	0,144	-0,257
28	0,098	0,636	-0,417	-0,371	0,108	-0,275
29	0,057	0,599	-0,533	-0,388	0,075	-0,337
30	0,019	0,564	-0,646	-0,402	0,046	-0,431

See Notes at Table I

Causality in Mean between Sweden – UK according to the kernel functions of Causality Test of Hong

Table IV

Bandwidth	QuadraticSw_UK	BartlettSw_UK	TruncatedSw_UK	QuadraticUK_Sw	BartlettUK_Sw	TruncatedUK_Sw
1	-0,387	NaN	-0,378	2,404***	NaN	2,134**
2	-0,413	-0,378	-0,442	2,6141***	2,134**	3,860***
3	-0,400	-0,426	-0,085	3,933***	2,875***	6,406***
4	-0,323	-0,395	-0,179	4,941***	3,848***	5,214***
5	-0,250	-0,349	0,011	5,352***	4,560***	4,997***
6	-0,218	-0,306	-0,274	5,478***	4,956***	4,381***
7	-0,227	-0,277	-0,183	5,463***	5,161***	4,655***
8	-0,235	-0,263	-0,328	5,367***	5,269***	4,175***
9	-0,212	-0,258	-0,542	5,228***	5,322***	3,812***
10	-0,168	-0,266	0,455	5,071***	5,328***	3,503***
11	-0,124	-0,263	0,301	4,917***	5,300***	3,165***
12	-0,085	-0,242	0,391	4,772***	5,246***	3,263***
13	-0,052	-0,214	0,443	4,636***	5,178***	3,435***
14	-0,026	-0,181	0,257	4,509***	5,109***	3,141***
15	-0,006	-0,148	0,078	4,388***	5,041***	2,878***
16	0,009	-0,119	-0,070	4,275***	4,970***	3,106***
17	0,021	-0,097	-0,223	4,168***	4,900***	2,997***
18	0,031	-0,082	-0,367	4,066***	4,834***	2,770***
19	0,038	-0,073	0,410	3,970***	4,768***	2,764***
20	0,043	-0,065	0,249	3,878***	4,704***	2,549***
21	0,046	-0,055	0,096	3,792***	4,641***	2,362***
22	0,047	-0,045	0,112	3,709***	4,578***	2,173**
23	0,047	-0,037	-0,006	3,631***	4,515***	2,426***
24	0,045	-0,029	-0,084	3,556***	4,452***	2,274**
25	0,041	-0,023	-0,206	3,483***	4,392***	2,296**
26	0,035	-0,018	0,028	3,412***	4,333***	2,132**
27	0,027	-0,015	-0,063	3,342***	4,275***	2,184**
28	0,019	-0,013	-0,158	3,273***	4,219***	2,128**
29	0,011	-0,011	-0,084	3,207***	4,165***	1,990**
30	0,002	-0,010	-0,143	3,142***	4,113***	1,856**

See Notes at Table I

APPENDIX B

Statistical Tables (FIGARCH)

Introduction

We present the statistical tables for the Causality in Varianceand variance among the 18 European countries. We first provide a table of these countries together with their abbreviations.

a/a	Country	Abbreviation
1	Belgium	Bl
2	Czech Republic	Cz
3	Cyprus	Cy
4	Denmark	Dk
5	Estonia	Es
6	France	Fr
7	Germany	Ger
8	Greece	Gr
9	Hungary	Hu
10	Ireland	Ir
11	Italy	It
12	Netherlands	Nth
13	Portugal	Port
14	Slovakia	Slvk
15	Slovenia	Slvn
16	Spain	Sp
17	Sweden	Sw
18	United Kingdom	UK

In addition we must note that the tables of Cheung & Ng are two. The **first table** presents the r statistic for 30 lags. The indicators of the r statistic show the direction of the one country to the other and the symbol v is referred to volatility. The **second table** provide us with S statistic. The indicators of the S statistic are the same with the indicators of the r statistic. On the other hand, the table of Hong is one. This **table** presents the statistics of three kernel functions (Quadratic, Bartlett and Truncated) for the **causality in variance**. The indicators of these kernel functions show the direction of the one country to the other. For brevity reasons we did not put the other three kernel functions Daniell, Parzen and Tukey. These data would be available from the author upon request.

We provide only a small number of the statistical tables for brevity reasons. All statistical tables are available from the author upon request.

Belgium - Greece

Causality in Variance between Belgium – Greece,
according to r statistic of Causality Test of Cheung & Ng

Table I

Lags	$r_{Bl\_Gr,v}$	$r_{Gr\_Bl,v}$
1	-1,488	0,377
2	3,370***	-1,084
3	0,850	-0,716
4	-0,767	-0,325
5	-0,417	-0,371
6	2,170**	-0,158
7	1,689*	0,214
8	-0,713	-0,661
9	1,368	0,267
10	0,516	0,134
11	-0,282	-0,279
12	0,904	-0,804
13	1,168	-0,603
14	0,118	0,792
15	-0,785	-0,493
16	-0,566	-0,290
17	-0,404	-0,270
18	0,251	0,373
19	-1,037	-0,647
20	1,237	0,153
21	-0,676	0,107
22	-0,733	-0,227
23	-0,269	-0,826
24	-0,031	1,106
25	0,029	-0,334
26	0,312	-0,772
27	-0,456	-0,408
28	-0,224	0,756
29	0,493	-0,621
30	1,079	-0,399

Notes: The Null Hypothesis (Ho) denotes No Causality in Variance. The Alternative Hypothesis (H1) denotes Causality Variance. The '*'indicates significance at the 10%, the '**' indicates significance at the 5% and the '***' indicates significance at the 1% level

Causality in Variance between Belgium – Greece,
according to S statistic of Causality Test of Cheung & Ng

Table II

$S_{Bl\_Gr,v}$	56,52***
$S_{Gr\_Bl,v}$	-50,62

See Notes at Table I

Causality in Variance between Belgium – Greece,
according to the kernel functions of Causality Test of Hong

Table III

Bandwidth	QuadraticBl_Gr	BartlettBl_Gr	TruncatedBl_Gr	QuadraticGr_Bl	TukeyGr_Bl	TruncatedGr_Bl
1	1,351*	NaN	0,886	-0,607	NaN	-0,609
2	2,022**	0,886	5,977***	-0,588	-0,609	-0,329
3	4,075***	2,682***	4,816***	-0,527	-0,589	-0,460
4	4,719***	3,831***	4,070***	-0,558	-0,538	-0,710
5	4,778***	4,314***	3,416***	-0,652	-0,517	-0,903
6	4,762***	4,478***	4,301***	-0,769	-0,536	-1,103
7	4,762***	4,551***	4,568***	-0,886	-0,583	-1,273
8	4,753***	4,626***	4,203***	-1,002	-0,647	-1,320
9	4,728***	4,690***	4,247***	-1,112	-0,720	-1,459
10	4,686***	4,736***	3,915***	-1,213	-0,796	-1,600
11	4,625***	4,765***	3,581***	-1,300	-0,871	-1,717
12	4,548***	4,773***	3,452***	-1,379	-0,945	-1,698
13	4,460***	4,763***	3,461***	-1,450	-1,016	-1,743
14	4,367***	4,743***	3,193***	-1,515	-1,084	-1,729
15	4,273***	4,714***	3,072***	-1,576	-1,149	-1,796
16	4,180***	4,678***	2,906***	-1,635	-1,211	-1,892
17	4,087***	4,637***	2,723***	-1,690	-1,268	-1,985
18	3,995***	4,591***	2,535***	-1,743	-1,321	-2,062
19	3,903***	4,540***	2,552***	-1,792	-1,371	-2,082
20	3,815***	4,487***	2,658***	-1,838	-1,418	-2,174
21	3,726***	4,433***	2,569***	-1,881	-1,462	-2,266
22	3,644***	4,380***	2,502***	-1,920	-1,504	-2,346
23	3,561***	4,328***	2,359***	-1,955	-1,544	-2,312
24	3,481***	4,277***	2,211**	-1,987	-1,583	-2,183
25	3,403***	4,225***	2,072**	-2,017	-1,620	-2,248
26	3,328***	4,174***	1,956**	-2,043	-1,656	-2,229
27	3,256***	4,123***	1,865**	-2,068	-1,691	-2,281
28	3,186***	4,071***	1,753**	-2,090	-1,724	-2,264
29	3,119***	4,019***	1,679**	-2,111	-1,757	-2,276
30	3,054***	3,968***	1,760**	-2,129	-1,788	-2,325

See Notes at Table I

Cyprus – Greece

Causality in Variance between Cyprus – Greece
according to r statistic of Causality Test of Cheung & Ng

Table I

Lags	$r_{Cy\_Gr,v}$	$r_{Gr\_Cy,v}$
1	0,120	0,666
2	0,419	1,295
3	-0,650	-0,570
4	-1,697*	-1,597
5	2,538**	0,304
6	-0,159	-0,553
7	-0,422	0,390
8	-0,608	-0,093
9	-0,853	-1,040
10	2,142**	0,245
11	2,324**	-0,952
12	0,623	0,391
13	-0,492	1,031
14	-0,457	-0,579
15	0,273	-1,194
16	0,430	-0,135
17	0,266	-0,559
18	-0,088	0,546
19	0,408	1,452
20	-0,336	-0,753
21	-0,097	0,103
22	1,405	-0,573
23	0,689	0,376
24	0,344	-0,352
25	-0,650	-0,224
26	-0,024	-0,635
27	0,141	0,178
28	-0,061	0,635
29	0,995	0,431
30	-0,135	0,051

Notes: The Null Hypothesis (Ho) denotes No Causality in Variance. The Alternative Hypothesis (H1) denotes Causality Variance. The '*'indicates significance at the 10%, the '**' indicates significance at the 5% and the '***' indicates significance at the 1% level

Causality in Variance between Cyprus – Greece
according to r statistic of Causality Test of Cheung & Ng

Table II

$S_{Cy\_Gr,v}$	54,96***
$S_{Gr\_Cy,v}$	-14,78

See Notes at Table I

Causality in Variance between Cyprus – Greece,
according to the kernel functions of Causality Test of Hong

Table III

Bandwidth	QuadraticCy_Gr	BartlettCy_Gr	TruncatedCy_Gr	QuadraticGr_Cy	BartlettGr_Cy	TruncatedGr_Cy
1	-0,729	NaN	-0,702	-0,362	NaN	-0,392
2	-0,769	-0,702	-0,909	-0,301	-0,392	0,083
3	-0,897	-0,821	-0,975	-0,181	-0,257	-0,200
4	-0,826	-0,912	-0,136	-0,077	-0,198	0,417
5	-0,415	-0,884	1,706**	0,004	-0,127	0,097
6	-0,001	-0,665	1,296233*	0,014	-0,057	-0,098
7	0,272	-0,381	1,002	-0,022	-0,025	-0,306
8	0,476	-0,144	0,804	-0,084	-0,024	-0,525
9	0,666	0,035	0,725	-0,152	-0,045	-0,446
10	0,856	0,168	1,598*	-0,219	-0,078	-0,622
11	1,035	0,284	2,597***	-0,284	-0,114	-0,584
12	1,190	0,415	2,403***	-0,343	-0,153	-0,718
13	1,314*	0,555	2,199**	-0,393	-0,191	-0,643
14	1,411*	0,690	2,007**	-0,438	-0,229	-0,725
15	1,482*	0,813	1,805**	-0,478	-0,264	-0,576
16	1,531*	0,921	1,640**	-0,511	-0,296	-0,715
17	1,561*	1,013	1,466*	-0,537	-0,326	-0,789
18	1,575*	1,090	1,291*	-0,559	-0,354	-0,860
19	1,577*	1,154	1,158	-0,580	-0,381	-0,587
20	1,570*	1,204	1,023	-0,601	-0,406	-0,606
21	1,555*	1,244	0,877	-0,624	-0,427	-0,724
22	1,534*	1,275	1,091	-0,648	-0,447	-0,780
23	1,509*	1,297*	1,037	-0,674	-0,465	-0,865
24	1,481*	1,316*	0,926	-0,701	-0,483	-0,949
25	1,451*	1,329*	0,873	-0,730	-0,501	-1,042
26	1,418*	1,339*	0,753	-0,758	-0,518	-1,072
27	1,385*	1,345*	0,641	-0,786	-0,536	-1,161
28	1,350*	1,347*	0,532	-0,812	-0,555	-1,185
29	1,315*	1,346*	0,589	-0,837	-0,573	-1,243
30	1,279	1,343*	0,490	-0,859	-0,592	-1,328

See Notes at Table I

Denmark – Sweden

Causality in Variance between Denmark –Sweden
according to r statistic of Causality Test of Cheung & Ng

Table I

Lags	$r_{Dk\_Sw,v}$	$r_{Sw\_Dk,v}$
1	2,783***	0,060
2	1,189	-0,372
3	0,713	-1,466
4	-1,282	-0,755
5	-0,461	0,963
6	-0,543	2,102**
7	1,594	0,752
8	1,005	-0,235
9	-0,721	-1,090
10	-0,222	1,093
11	-1,622	0,848
12	0,760	0,959
13	2,680***	1,004
14	0,715	-0,855
15	1,188	0,036
16	-0,568	-0,229
17	-1,831*	0,467
18	-0,281	0,937
19	1,081	0,271
20	0,923	-0,180
21	-0,252	-0,103
22	-0,958	-0,780
23	-0,358	-0,170
24	-1,135	0,585
25	0,592	-0,468
26	0,092	-0,033
27	-0,413	-1,124
28	-0,919	-0,201
29	0,117	1,194
30	0,508	1,399

Notes: The Null Hypothesis (Ho) denotes No Causality in Variance. The Alternative Hypothesis (H1) denotes Causality Variance. The ‘*’indicates significance at the 10%, the ‘**’ indicates significance at the 5% and the ‘***’ indicates significance at the 1% level

Causality in Variance between Denmark –Sweden
according to r statistic of Causality Test of Cheung & Ng

Table II

$S_{Dk\_Sw,v}$	52,66***
$S_{Sw\_Dk,v}$	55,51***

See Notes at Table I

Causality in Variance between Denmark – Sweden according to the kernel functions of Causality Test of Hong

Table III

Bandwidth	QuadraticDk_Sw	BartlettDk_Sw	TruncatedDk_Sw	QuadraticSw_Dk	BartlettSw_Dk	TruncatedSw_Dk
1	4,831***	NaN	4,825***	-0,733	NaN	-0,707
2	4,818***	4,825***	3,640***	-0,788	-0,707	-0,931
3	4,413***	4,757***	2,787***	-0,797	-0,833	-0,277
4	3,964***	4,481***	2,664***	-0,695	-0,804	-0,386
5	3,560***	4,212***	2,147**	-0,564	-0,730	-0,359
6	3,252***	3,971***	1,770**	-0,384	-0,674	0,699
7	3,021***	3,740***	2,083**	-0,219	-0,578	0,543
8	2,823***	3,545***	1,972**	-0,090	-0,452	0,279
9	2,660***	3,389***	1,763**	0,009	-0,343	0,325
10	2,544***	3,257***	1,473*	0,083	-0,255	0,371
11	2,474***	3,136***	1,790**	0,135	-0,182	0,309
12	2,443***	3,028***	1,647**	0,171	-0,121	0,298
13	2,440***	2,936***	2,885***	0,191	-0,071	0,307
14	2,455***	2,869***	2,711***	0,198	-0,028	0,263
15	2,481***	2,831***	2,728***	0,193	0,007	0,081
16	2,511***	2,809***	2,544***	0,179	0,035	-0,079
17	2,541***	2,796***	2,931***	0,156	0,055	-0,199
18	2,568***	2,792***	2,716***	0,125	0,067	-0,193
19	2,590***	2,795***	2,706***	0,088	0,073	-0,328
20	2,607***	2,800***	2,645***	0,045	0,074	-0,463
21	2,618***	2,808***	2,458***	0,000	0,070	-0,594
22	2,623***	2,815***	2,4217***	-0,047	0,062	-0,622
23	2,622***	2,820***	2,262**	-0,093	0,050	-0,742
24	2,614***	2,825***	2,294**	-0,138	0,035	-0,807
25	2,600***	2,827***	2,182**	-0,180	0,017	-0,888
26	2,582***	2,828***	2,023**	-0,219	-0,003	-1,000
27	2,559***	2,827***	1,895**	-0,255	-0,025	-0,917
28	2,534***	2,823***	1,873**	-0,288	-0,048	-1,018
29	2,506***	2,818***	1,732**	-0,318	-0,073	-0,912
30	2,477***	2,810***	1,632*	-0,345	-0,097	-0,732

See Notes at Table I

Portugal – Spain

Causality in Variance between Portugal - Spain
according to r statistic of Causality Test of Cheung & Ng

Table I

Lags	$r_{Port\_Sp,v}$	$r_{Sp\_Port,v}$
1	0,086	0,793
2	-0,399	2,062**
3	-0,745	2,445**
4	-0,740	0,576
5	-0,652	-0,998
6	-0,162	-0,901
7	-0,211	0,653
8	0,284	1,355
9	-0,657	1,391
10	1,541	-0,483
11	5,051***	-1,641*
12	3,940***	-0,027
13	0,132	0,513
14	-0,219	-0,766
15	1,863*	-1,382
16	2,744***	-1,079
17	0,421	1,299
18	1,243	0,969
19	-0,332	1,060
20	-1,036	1,174
21	-0,708	-0,596
22	-1,371	-0,693
23	-1,929*	0,357
24	-1,542	0,488
25	-0,426	-0,063
26	0,751	-0,008
27	0,331	0,040
28	-0,375	-0,473
29	0,721	-0,216
30	0,882	0,097

Notes: The Null Hypothesis (Ho) denotes No Causality in Variance. The Alternative Hypothesis (H1) denotes Causality Variance. The '*'indicates significance at the 10%, the '**' indicates significance at the 5% and the '***' indicates significance at the 1% level

Causality in Variance between Portugal - Spain
according to S statistic of Causality Test of Cheung & Ng

Table II

$S_{Port\_Sp,v}$	131,47***
$S_{Sp\_Port,v}$	92,14***

See Notes at Table I

Causality in Variance between Portugal - Spain
according to the kernel functions of Causality Test of Hong

Table III

Bandwidth	QuadraticPort_Sp	BartlettPort_Sp	TruncatedPort_Sp	QuadraticSp_Port	BartlettSp_Port	TruncatedSp_Port
1	-0,744	NaN	-0,703	-0,074	NaN	-0,262
2	-0,789	-0,703	-0,918	0,096	-0,262	1,459*
3	-0,920	-0,826	-0,929	1,145	0,309	3,253***
4	-0,971	-0,910	-0,963	1,957**	1,060	2,590***
5	-1,015	-0,964	-1,041	2,334***	1,620*	2,326**
6	-0,979	-1,007	-1,231	2,452***	1,944**	2,080**
7	-1,124	-1,053	-1,394	2,460***	2,127**	1,782**
8	-1,237	-1,105	-1,533	2,437***	2,221**	1,892**
9	-1,147	-1,163	-1,576	2,405***	2,267**	2,023**
10	-0,823	-1,222	-1,174	2,364***	2,294**	1,757**
11	-0,325	-1,270	4,260***	2,316**	2,309**	2,060**
12	0,271	-1,214	7,152***	2,266**	2,317**	1,777**
13	0,896	-0,994	6,698***	2,219**	2,321**	1,573*
14	1,512*	-0,667	6,293***	2,176**	2,317**	1,449*
15	2,096**	-0,298	6,572***	2,138**	2,305**	1,587*
16	2,635***	0,081	7,589***	2,105**	2,290**	1,582*
17	3,121***	0,466	7,244***	2,075**	2,273**	1,674**
18	3,556***	0,847	7,163***	2,044**	2,256**	1,632*
19	3,941***	1,215	6,849***	2,013**	2,240**	1,626*
20	4,283***	1,562*	6,716***	1,979**	2,225**	1,665**
21	4,585***	1,886**	6,502***	1,941**	2,211**	1,538*
22	4,850***	2,187**	6,520***	1,900**	2,198**	1,438*
23	5,081***	2,464***	6,829***	1,857**	2,184**	1,289*
24	5,279***	2,722***	6,925***	1,812**	2,169**	1,164
25	5,449***	2,963***	6,693***	1,763**	2,153**	1,010
26	5,590***	3,187***	6,529***	1,711**	2,135**	0,861
27	5,706***	3,396***	6,308***	1,656**	2,115**	0,718
28	5,800***	3,588***	6,102***	1,599*	2,092**	0,613
29	5,875***	3,765***	5,959***	1,540*	2,068**	0,487
30	5,933***	3,928***	5,858***	1,481*	2,041**	0,360

See Notes at Table I