Sensitivity and Simulation Analysis of Granger Causality: An Empirical Investigation

By

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To

All those who seek knowledge to reach at the truth.

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Abstract

Centrality of causality in Economics dates back at least to Hume and Adam Smith. Hume's work on exploring relationship between money and prices, and Smith's book "An Inquiry into the Nature and Causes of the Wealth of Nations" are the clear manifestations of the importance of causality in economics. Later on with the development of statistical tools like correlation and regression in the early 20th century, the issue of causal inference has become more important than before. In the second half of the 20th century, with the introduction of Granger causality, it was considered that the issue of causality could simply be resolved by using statistical tools. A lot of literature in economics in the last two three decades is based on this concept of causality despite some thoughtful criticism on this technique by economists. In this thesis, we have made an effort to analyse the mis(use) of Granger causality on empirical grounds so that one can understand what are the pros and cons of Granger causality .By using published papers in refereed journals, we analyse whether Granger causality helps in establishing any causal direction? Our analysis suggests that causal relationships established through Granger causality are not robust with respect to sample range, lag length selection, base year change etc which is against the basic Axiom C proposed by Granger(1980) that all causal relationships should maintain the same direction. Moreover, Monte Carlo and Bootstrap simulation evidence also indicate that Granger causality results are misleading, and the valid causal relationship can probably be determined only if the whole population, all the relevant variables and true model are known. We conclude that no short cut procedure, merely based upon statistical techniques can be considered as a final word on causality .Nevertheless, concept of structural causality, an idea borrowed from the idea of Simon, Hendry and Hoover, works well and it can be considered a preferred approach for testing causality because it is based on extra statistical information which comes through past historical events and helps in introducing asymmetry in the relationship.

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Chapter 1
Introduction

Economists and econometricians have long been studying the issue of causality and causal laws, i.e., the issue of identifying a causal relation between an outcome and a set of factors that may have determined this outcome. The time-series notion of Granger (-Sims) causality is based on the idea that cause must precede effect, and that a factor cannot cause another variable if it does not contribute to the conditional distribution (or expectation) of the variable given in the past. This concept has become very influential in time series and macro-econometric modelling. It also plays a role in the concepts of exogeneity developed by Engle et al. (1983). An entirely different strand of literature on causal inference and treatment effects originated from the work of Rubin (1974). In this literature, causal effects are usually defined in terms of a comparison between the potential outcomes on the same unit, measured at the same time, but exposed to different treatments. Since only one of these two potential outcomes can be observed, the causal effect is considered essentially as a problem of inference with missing data.[1]

Determination of causal relationship between economic variables is the bread and butter of economic analysis. "The elucidation of causal relationships among a set of variables is one of the major goals of empirical research. It has long been recognized that finding of high correlation among variables does not in any necessary sense establish that they are causally related. Variables may be functionally related yet be uncorrelated and perhaps more often, they may be correlated yet not causally related. The former effect arises because correlation is a measure of linear association

[1] Journal of Econometrics (2006, June)

only; the latter because of common association of each with additional factors." (Pierce and Haugh, 1976).

Recently one of the most debated topics is how to determine the nature of relationship among different variables e.g. between export and economic growth, money and economic growth, energy consumption and GDP, FDI and Pollution, etc. So far, there has been very little consensus. Central question in this debate is whether strong economic performance is driven by these variables or these variables are driven by the economic growth. This question of determining causal pattern between these variables and economic growth is very important for policy makers' decisions about the appropriate growth and development strategies and policies to adopt.

It has been established fact that there is strong correlation between these variables and economic growth. Many investigate whether this association can be translated into causal relationship. This has been an area of research where there is strong controversy. Many researchers have used Granger causality to determine the direction of causation among these variables. Despite the fact that Granger definition which is based on a criterion of predictability is not in agreement with other definitions of causality, yet its wide use in the economic literature makes it important.

In this study we are going to analyze the mis(use) of Granger causality and to explore whether Granger causality can be used for determining such causal relationships. Most of the researchers, without studying the proper context, have misused Granger causality. Many of them shift from simple predictive analysis to policy analysis while interpreting the results.

One could find isolated sentences like:

"It's a measure of precedence rather causation," (Maddala)

“No technique has been misused in the last twenty years as much as this Granger Causality” (Pagan1989)

Granger himself did not make wrong claims but did use the wrong terminology and often economists shift from their descriptive and predictive analysis to the policy related conclusions while interpreting their results.

There are many articles in recent years on the use of Granger Causality and in most of these articles causality has been determined among economic variables .The procedure they use is clearly in contradiction to what Granger himself had warned. Granger (1980) writes,

“However, it should be said that some of the recent writers on this topic, because they have not looked at the original papers, have evolved somewhat unclear and incorrect forms of this definition”.

Maddala and Kim (Unit Roots, Cointegration, and Structural change) write “A better term for Granger causality is precedence. But like the Mad Hatter in Alice in Wonderland. Granger has chosen the word *causality* for precedence. Although he has amply made it clear in several papers what exactly the term means, some of the literature on Granger causality has used results from causality tests to infer causality, as it is commonly understood. An example that drives home what exactly Granger causality implies is the statement*: The weatherman's prediction about rain (Granger) causes the rain". (Page188-189)*

Pagan (1989) remarked “There was a lot of high powered analysis of this topic, but I came away from a reading of it with the feeling that it was one of the most unfortunate turnings for econometrics in the last two decades, and it has probably generated more nonsense results than anything else during that time.”

All this is sufficient to show that there is need for some comprehensive study on Granger causality. While investigating performance of Granger causality as a test of causality we have the following objectives in mind.

1.1 Objectives

First, to have empirical investigation of the sensitivity of Granger causality with respect to lag selection, sample length, frequency selection, base change, temporal aggregation etc. Although some studies point out lag selection problems for causal relationship but these are few in number and issue specific. Our empirical analysis is based on several data sets which are obtained from some recently published papers. Our empirical analysis suggests that causal law established by this procedure is very fragile and does not meet robustness criterion. Moreover, different causality methods (discussed in Chapter three) are not robust and causality results vary from one method to the other.

Secondly, to discuss the issue that results obtained from Granger causality testing indicate causation when we have mere association among the variables. For this we have carried out Monte Carlo simulation. Power of different causality methods has been determined through Monte Carlo simulation when there is mere association and no causation.

Thirdly, to determine how causality tests behave when both the true model and all relevant variables are known. For this we have carried out Bootstrap simulation.

Finally, an alternative test of structural causality (idea borrowed from Simon (1953), Hendry (1995) and Hoover (2001)) has been suggested. This concept of testing causality has also been applied to two data sets which were used while analysing Granger causality empirically. This method provides clear evidence in favour of export led growth in case of India. Such evidence was either missing or provided mixed results previously. Similarly, no causality exists between energy and GDP for Shanghai when tested through this structural causality approach.

1.2 Outline

Chapter two is about the review of literature on causality. An overview of different approaches in causality has been given there. We have briefly reviewed causality in economics in the second half of the last century with a major focus is on Granger causality. Zellner (1979) has given in detail review of Granger causality. A debate on whether Granger causality is a test of structural causality or not has also been given .This difference will also be useful in evaluating whether Granger causality can be used for the policy analysis or not.

Chapter three is about different methods for determining Granger causality. Brief outline of all the causality methods in use along with the conditions in which they can be applies is also given. For example, Granger causality test proposed by Granger (1969) can only be used when series are stationary. Toda and Yamamoto (1995) procedure is applicable whether nonstationary series are cointegrated or not. Error correction model (Engle and Granger 1987) can be used when there is cointegration. Other two methods which are not used frequently are Sims and Hsiao methods.

Chapter four is mainly about the issue of sensitivity of the Granger causality with respect to: lag length, sample range, base year change, causality testing method etc. In this chapter we have analyzed the data of four published papers and tried to explain that why there is no consensus on the direction of causality. This chapter is divided into three sections. In the beginning of each section, we have given a brief review of the problem under investigation in order to show that there is lack of consensus on the direction of causality from one study to another. In the next part of each section, an empirical analysis of Granger causality is presented which shows sensitivity of Granger causality direction and lack of robustness of the results.

In chapter five, simulation study of Granger causality has been carried out in order to evaluate the performance of Granger causality when actually the two series are jointly caused by the third variable. Six data generating processes have been considered and results for different causality tests are compared. Results show that Granger causality methods are unable to detect spurious causality. These methods show causality when there is only association among the variables. In the second part of chapter four, bootstrap simulation has been carried out by assuming that both the true model and the relevant variables are known. In this case it has been found that Granger causality is a useful procedure for detecting causal direction.

In the last chapter, we have described that how one should test causal direction. A method for detecting structural causality has been proposed and applied to the two different data sets used in chapter four. This structural causality tests indicate that causal direction runs from export to economic growth of India and there is no causality between energy consumption and economic growth of Shanghai. In the last chapter we summarize and conclude our findings.

Chapter2

Review of Literature on Causality

Debate on Causality in economics dates backs to Hume (1752) when he explored the relationship between money and prices. Title of Adam Smith's book "An Enquiry into the Nature and Causes of the Wealth of Nations" provides sufficient evidence that causality concept is crucial in Economics. Other economists like Ricardo and Stuart Mill were also explicitly involved in causality issues.

The philosophical debate of causality issues can be found in the work of David Hume. Hume defines it as: "we may define a cause to be an object, followed by another, and where all the other objects similar to the first one are followed by objects similar to the second. Or in other words where, if the first object had not been, the second never had existed." Hume believed that causal events were ontologically reducible to non-causal events, and causal relations were not directly observable, but could be known by means of the experience of constant conjunctions and by the construction of general laws.[2]

Early development of econometrics was mainly based on differentiating between causal relations and empirical regularities. But later on the former was not given much weight (may be due to lack of proper definition of causality) in econometrics text books and almost all focus shifted towards observing empirical regularities (Correlations) and analysing them. Currently there are three main approaches on the issue of causality in economics.

The first one is the probabilistic approach to causality developed by Patrick Suppes (1970). According to Suppes, an event A causes prima facie an event B if the conditional probability of B given A is greater than B alone, and A occurs before B.

[2] Alessio Monets "Causality and Econometrics: Some Philosophical underpinnings"

Granger (1969) proposed a definition of testing causality in time series on statistical grounds and this is the most widely used definition these days. We shall discuss it shortly. Third approach is that of structural causality which states that causality can not be detected from observed data until and unless there is structural change. We think that causality is important but can not be detected easily. For this one needs to explore data intensively.

In the early 20th century causal inference and development in statistical tools like correlation and regression were linked. It was fairly understood that, unlike correlation, regression has a natural direction; the regression of Y on X does not produce coefficient estimates that are the algebraic inverse of those from the regression of X on Y. The direction of regression should respect the direction of causation[3].

Despite the fact that regression has natural direction, yet there is nothing in the data that reveals which direction is the correct-each is observationally equivalent. Later on issue of simultaneity and problem of identification were pursued rigorously until the treatment to these problems by Cowles Commission, and the issue of causality was set aside. In the second half of the 20th century, two major approaches (one by Herman Wold and the other by Herbert Simon) on the issue of causality emerged.

2.1 Wold's Approach

Herman Wold's process analysis based on temporal precedence (an idea similar to that of Hume) for introducing asymmetry of causality ultimately led to the development of Granger Causality.

[3] Hoover(2006)

There has been lot of controversy about causality and related concepts in Philosophy, and Wold (1954) states that haze surrounding causality has spread over to other fields, among them economics and econometrics. Wold (1954) concentrated on different points regarding causality. He pointed out that concept of causality is important for all sciences. He explored that controversies are not hidden in concept of "causality" but in concept of "causal laws". He also gave a definition of causality with respect to "controlled experiment". Different statistical methods in experimental and non-experimental settings are discussed with distinction in descriptive and explanatory analysis. According to Wold to understand the definition of causation one of the supreme tools is "Controlled Experiment". In simple words "one or more variables are under experimenter's control and for suitably chosen values of these variables, he observes one or more other variables in whose values he is interested. Then if, the experiment reveals that an observed variable varies, systematically, as the controlled variables are allowed to vary, this relation is a type of "Causal Relation". The controlled variables are called cause variables and observed variables are called dependent or effect variables. The relationship "$Y = F(X)$" is then defined as causal if it is theoretically permissible to regard the variables as involved in a fictive controlled experiment with $X_1, X_2, \ldots X_n$ for cause variable and Y for effect variable. In the philosophical discussion of causality, one of the many ways of trying to avoid difficulties is to remove the word "causality" from the vocabulary, and to replace it with some uncommitted term, for example, "functional relation" or "predictability". It is clear, however, that the difficulties can not be solved in this way for if scientific analyses are stripped of all terms with causal content, nothing would remain but description and formalism."[4]

[4] Wold (1954), "Causality and Econometrics".

Wold tries to explain how causality and predictability are different. In experimental studies, the intimation of results between cause and effect process itself is a simple regression problem. Thanks to the controlled variation of cause variables, the neutralization of disturbances by means of randomization, and the independence between observations that can be achieved at least approximately, the regression analysis becomes a matter of streamlined routine. The resulting estimates of regression coefficients are unbiased, and the sampling errors can be evaluated with exactitude; if the disturbances have normal distributions the estimates are even of optimal efficiency and their confidence intervals can be evaluated. For the study of interaction between causal factors, ANOVA provides a specialized regression technique.

In observational studies, the estimation of causal relations by the use of regression analysis is hampered by the fact that randomization is not available. For example consider the current methods for estimating income elasticity on the basis of family budget data. Let $\log(d) = \alpha + \beta \log \mu + Z$ be the logarithmic regression of butter expenditure d upon income μ, the regression being found on the hypothesis that butter has a demand function with income elasticity constant and proportional to β. In symbols, the hypothesis is

$$\log(d) = \alpha + \beta \log \mu \text{ or } \log(d) = \alpha + \beta \log \mu + u$$

where u is the random effect of factors other than income.

We notice the essential difference between the Fisher randomization in a controlled experiment and the random selection of observation units in a sampling survey. Since the data do not come from a randomized experiment in Fisher's sense, income may be correlated with influencing factors, and such correlation will in general impair the causal interpretation. The deviation between b and β is known as an error of specification. To overcome these errors, other variable (the family size, the social stratum etc) need to be included and use multiple regression analysis. So Wold concludes that in observational studies statistical techniques are useful only if subject matter theory is also taken into account.

There is another debate that causality should be taken as one's personal belief. Wold (1960) described that no one has "monopoly rights in defining causality". He stressed on the point that the main challenge is how to explain and analyze this concept and this is not necessary to use the word "causality" at all. Many other investigators have also pointed out that to replace word "causality" with some other words would not solve the purpose.

So from all above discussion it is clear that a definition of causality seems to be simpler in experimental studies than in observational studies. Controlled experiments can serve the purpose for defining the causal laws. But in observational studies like economics it's a very difficult task.

2.2 Simon's Approach

Simon (1953) (or Cowles Commission) on the other hand showed that causality could be found for structural models not only between exogenous and endogenous variables, but also among the endogenous variables themselves.

Simon (1953) in "causal ordering and identifiably" pointed out that notion of causality is a deductive logical concept relation to model's characteristics not to empirical features of the world that require statements of inductive logic. Indeed, Simon (P-51) states, "It is the aim of this chapter…. to provide a clear and rigorous basis for determining when a causal ordering can be said to hold between two variable or groups of variables in a model (and not the real world), and the concepts to be defined all refer a model _ a system of equations and not to the “real” world the model purports to describe”. Obviously, a law that is causal in Simon’s sense needs not to be causal in Feigl’s (“Feigl’s causal law is sure predictability according to a law”, Zellner (1979)) that is law may be incapable of predicting “real world” outcomes. Such a law would not be termed causal in an inductive empirical sense.

Jeffrey (1967) applied his causal concept to non-experimental data in the field of astronomy and geophysics. According to Jeffery we should adopt same and uniform criteria for testing causal laws irrespective of subjects. Otherwise, we shall go to explain “what we want to believe.” And our analysis would be inadequate and results obtained from such an analysis would not represent the actual picture of the data. He applied his causal concept to non experimental data from astronomy and geophysics. According to Jeffery, there must be uniform standard of velocity for all hypotheses, irrespective of subject. Different laws may hold in different subjects, but they must be tested by the same criteria; otherwise we have no guarantee that our decision will be those warranted by the data and not merely the result of inadequate analysis or of believing what we want to believe.

Hicks, Zellner and Simon, while discussing causal link, emphasize the relevance of a sound economic theory. Hicks(1979) accepts static or equilibrium theory as sufficient for use, while Simon(1970) suggests that a statement that is logically connected to the general framework of systematic economics is much likely to be considered causal than one that stands alone. Zellner (1979) agrees to Feigl’s definition who says the classified (or purified) concept of causation is defined in terms of prediction according to a law.

Nelson and Schwartz (1982) studied the sampling distributions of alternative tests in the context of a bivariate time series model that includes independence, one-way causation, and feedback as special cases. We are aware that the concept of causation developed by Granger (1969) is a purely predictive one and may not in some circumstances coincide with the concepts of causation discussed by philosophers of science.

2.3 Granger Causality

Granger (1969) among econometrician, statisticians and philosophers provide an analysis of causation for time series data in terms of predictability. Granger definition of causality is based on two assumptions. First, that future cannot predict the past, thus strict causality can only occur with the past causing the present or future. Secondly, it is assumed that it is only meaningful to discuss causality for a group of stochastic stationary variables. The intuitive meaning of Granger causality is focused on the predictability of a time series X_t "if some other series Y_t contains information in the past terms that helps in the prediction of X_t and if the information is contained in no other series used in the predictor then Y_t is said to Cause X_t".[5]

Economists as well as philosophers and statisticians don't have the same understanding of causality. Economists who have attempted to define the meaning of causation in economics include Simon (1953), Hicks (1979), and Zellner (1979). Most of the authors emphasize the difference between a mere association and the deeper sub-class of association that might be called causal relationship.[6]

Granger proposed a workable definition of causality for the time series data. While differentiating between correlation and causation Granger write "A mere association between a pair of economic variables, such as correlation or a non-independent joint distribution, is insufficient to determine a causation, partly because

[5] Granger(1969)
[6] Granger 1969

such associations are symmetric between the variables, the extent to which X is correlated to Y, or can be explained by Y, is exactly the same as Y is correlated, or is explained by X. It is generally thought that causation is a non-symmetric relationship and there are various ways in which asymmetry can be introduced, the most important of which are controllability, a relevant theory, outside knowledge and temporal." While trying to make his definition operational, Granger gives the impression that purely statistical criteria can be employed in defining causality. Here we shall discuss the Granger definition of causality and see that why other economists reject his definition.

Let U_t be all the information in the universe accumulated since time t-1 and let U_t-Y_t denote all this information apart from specified series $Y_{t.}$ The general definition of "causality' given by Granger

Definition 1. Causality If $\sigma^2\left(X/u\right) < \sigma^2\left(X/\overline{u-y}\right)$

, we say that y is causing x, denoted by y $\Rightarrow$x if we were better able to predict x_t, using all available information than if the information apart from y_t had been used.

Definition 2. Feedback. If

$$\sigma^2\left(X/\bar{u}\right) < \sigma^2\left(X/\overline{u-y}\right)$$

$$\sigma^2\left(Y/\bar{u}\right) < \sigma^2\left(Y/\overline{u-x}\right)$$

We say feedback is occurring, which is denoted as $Y_t \Leftrightarrow X_t$, i.e. feedback is said to occur when X_t is causing Y_t and also Y_t is causing X_t.

Definition 3. Instantaneous Causality

If $\sigma^2\left(X/\bar{u},\bar{\bar{y}}\right) < \sigma^2\left(X/\bar{u}\right)$, we say that instantaneous causality $Y_t \Rightarrow X_t$ is occurring. In other words, the current value of X_t is better "predicted" if the present value of y_t is included in the "perdition" than if it is not.

Definition 4:- Causality Lag.

If $Y_t \Rightarrow X_t$, we define the (integer) causality lag m to be the least value of K such that σ^2 (X/U-Y(k) < σ^2 (X/U-Y(k+1). Thus knowing the values Y_t-U, j= 0, 1,... m-1 will be of no help in improving the prediction of X_t. (Granger, 1969).

Granger writes, in the alternative theory to be discussed here, the stochastic nature of the variables and the direction of the flow of time will be central features. The theory, in fact, not relevant for non-stochastic variables and will rely entirely on the assumption that the future cannot cause the past.

2.4 Zellner's Criticism on Granger Causality

Zellner, Hicks, Simon and many others strongly rejected this view. Simon disagrees with Granger that time precedence can be considered as the criteria for establishing causality and has quoted few examples (Charismas causes prices of toys to rise so cause is before the effect) in order to support the argument that in many cases cause can occur before the effect. Moreover he writes, "Surety of prediction is not a satisfactory definition of causality" and prediction is more closely related to association. So in a way Simon also differs from Feigl's definition "predictability according to a law" by saying that prediction is closer to association than causation.

According to Zellner causal laws are very useful because they are used not only to explain past data and experience but also future data and experience, which are usually not observed. *Zellner (1979) pointed out that "a causal law must be such* *that it explains past data and experience and give good and reliable predictions and if one tests these laws at different data sets, it provides consistent results"*

Zellner (1979) is very critical of Granger's definition of causality. He has compared different definitions of causality given by Feigl. Jeffrey, Simon, Ballack, Basman, Stortz, Wold etc. He agrees with Feigl's definition "predictability according to a law".

Zellner finds out many problems with the definition proposed by Granger.

First, as recognized by Granger (1969), "The one completely unreal aspect of the above definition is the use of the series U_t, representing all available information". In fact, this requirement makes the Granger definition non-operational and in violation of one of Jeffrey's (1967) rules for theories of scientific induction nearly, "Any rule must be applicable in practice. The existence of a thing or the estimate, "quantity must not involve an impossible experiment". In dealing with this problem Granger suggests replacing "all the information in the universe" with the concept of "all relevant information".

Second, Granger's definition of causality is unusual in that embedded in it is a particular confirmatory criterion, the variance of the forecast error of an unbiased least squares predictor. This confirmatory criterion is not applicable to processes that do not possess finite moments. Granger suggests using only linear system with parameters that must be estimated from finite sets of data, an "optimum" (in finite samples) linear unbiased predictor will not always be feasible.

Third, as regards the implied quadratic criterion involved in the use of unbiased predictors and variance of forecaster predicting errors, Granger (1969) writes,

"It can be argued that the variance is not the proper criterion to use to measure the closeness of a predictor P_t to the true value x_t certainly if some other criteria were used it may be possible to reach different conclusions about whether one series is causing another. The variance does seem to be a natural criterion to use in connection with linear predictors, as it is mathematically easy to handle and simple to interpret. If one uses this criterion, a better name might be causality in mean". Granger differs from Jeffrey and others on confirmatory criteria.

Fourth, Granger and Newbold failed to recognize explicitly the role of economic laws or theories in defining causality. They, perhaps inadvertently, give the impression that the concept of causality can be defined entirely in terms of statistical considerations, a point of view that is contrary to those of Feigl, Jeffreys, Basman, and others.

Fifth, Granger's definitions 2-4 are also subject to the criticism brought up in connection with his definition 1. In addition, since the two process x and y are not considered with the context of particular economic laws, it is hard to determine whether the modified, operational Granger concepts are indeed applicable and lead to unambiguous results.

On this latter point, Granger (1969) himself points out, "even for stochastic series, the definitions introduced may give apparently silly answers" (P-430). A perhaps more satisfactory position would be to define causality, as Feigl and other have, in terms of predictability according to a well-thought-out economic laws.

Lastly, Granger does not completely rule out the concept of instantaneous causality. Granger adopts a temporal asymmetrical view of cause and effect. As mentioned earlier, such a view is not compatible with certain physical science considerations and is not a necessary component of a definition of causality.

While summarising results Zellner conclude that Granger's definition of causality, his definition 1 above, is a non-operational confirmatory setting. The definition does not involve mention of laws, economic or otherwise. In fact, the conditions surrounding the definition and the suggestions for making the definition operational have important implications for the forms of laws for which least squares unbiased predictors are at least approximately optimal are not covered. Perhaps in principle such variables could be covered if definition 1 were broadened.

Granger (1980) “A general definition of causality is introduced and then specialized to become operational. By considering simple examples a number of advantages, and also difficulties, with the definition are discussed. Tests based on the definitions are then considered and the use of post-sample data emphasized, rather then relying on the same data to fit a model and use it to test causality. It is suggested that a Bayesian viewpoint should be taken in interpreting the results of these tests.”

Granger (1980) writes that attitudes towards causality differ widely from the defeatist one that it is impossible to define causality, let alone test for it, to the populist viewpoint that everyone has their own personal definition and so it is unlikely that a generally acceptable definition exists.

Granger (1980) is of the view that philosophical debate on causality will lead us nowhere. We personally agree with this point of view that one should focus on what is going on in practice. He then introduces another axiom to make his definition clear.

“Axiom C. All usual relationships remain constant in direction throughout time.”

In the next section he has given some definitions which are operational from his point of view. Granger disagree with Zellner that causality should only be considered in the context of some accepted theory.

Granger (1980) writes “Any true or correct law or theory is simply an observed constraint that is found to apply to these distribution functions, and so knowledge of it does not add to the assumed available information set. However, when trying to make the definition more operative, the use of some theory may well be helpful, depending on the quality of the theory and on its nature. For example, if the theory simply tells one that certain variables need to be included in the information set to be utilized, that is extremely useful. It is also helpful to be told that certain variables can safely be omitted from the information set, as this will greatly simplify the data analysis. However, there would be rather vague theories and, I suspect, are not what Zellner had in mind. If the theory is much more specific, such as; "interest changes do not cause change in production" or "money supply changes do cause changes in prices", then, if true, analysis of other possible causes would again be simplified. But such theories may be precisely what the causality test is designed to verify".

Zellner (1988) writes" Since the concept is widely used, it is important to have fruitful definition of it". Zellner while emphasizing on Feigl's definition points out that predictability means confirmed predictability not merely potential predictability and the forms of the law must be such that they are capable of explaining past data and experience and yield verifiable predictions of future data and experience.

Zellner (1988) explored the concepts of causality and causal laws. In his paper Zellner concluded that Feigl's definition of causality "predictability according to a law or set of laws" is the best one. In his paper many approaches are considered to produce causal laws. A more suitable and "preferred" approach is being discussed with an example of Friedman's work on theory of consumption function. Zellner argued that we need such approaches (as adopted by Friedman) to produce causal laws in economics. He raised the importance of sophisticatedly simple models and theories to produce causal laws. He compared complicated models and theories with simple models and theories and at the end suggested that we should use the latter approach. He pointed out that causal laws are very useful because they are used not only to produce the past data and experience but also the future data and experience which is not observed. Further, it has been emphasized, “causality and causal laws involve actually successful explanation and prediction of a wide range of data and experience. Further, posterior probabilities explicitly or perhaps implicitly evaluated can measure degrees of confidence that are associated with theories. When such probabilities are very high, reflecting much outstanding and broad-ranging performance in explanation and prediction, a theory can be termed a “causal law”.

Zellner (1988) has been very critical of VAR and MVARMA models for establishing any causal law. He says that mathematical, statistical and economic properties of these models are very difficult to be established. If these properties are not well understood, there is no secure basis for asserting that they can possibly be causal laws.

I have issued the following challenge; demonstrate that a complicated model in any area of science has performed well in explanation and prediction. To date, I have not heard any……….In summary, it has been emphasized that causality and causal laws involve successful explanation and prediction of a wide range of data and experience.[7]

Sims is of the view that Granger Causality has very healthy contribution in the literature and we have started making subtle distinctions between terms like exogeneity, causality etc which were previously absent. Sims criticizes Schewert for suggesting Granger Causality only for forecasting. He says that it must be used for policy analysis. Feigl’s definition predictability according to a law” according to

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[7] For more detail Zellner1988

Sims, is so general that Simon causal ordering and Granger Causality are special cases of this definition. Sims writes "The point is that there certainly is more than one notion of "Causality" in economics, all are logically related, and it sometimes happens that they coincide. Economists have not simply been in error to think that economic reasoning about what is causally prior may be helpful in deciding which variables belong on the right hand side of a regression. Granger's definition helps us understand what such reasoning involves and what its pitfalls may be."

Feige and Pierce point out that Sims (1972) show that Granger causality is equivalent to testing for exogeneity in econometrics. This is not correct as Granger (1980) himself pointed out that Granger causality is a property of DGP where as exogeneity is a property of the model. Hendry also disagree with Sims on accepting Granger causality as tantamount to exogeneity. They have compared different procedures, which imply different results. They have shown that Granger causality is very sensitive both to seasonal adjustment and prefiltering which are used to make the series stationary.

Geweke (1984) took issue with the remark of Zellner (1984, pp.71) "The Weiner-Granger definition involves a special form of predictability but no mention of economic laws. In this regard it is devoid of subject matter considerations, including subject matter theory, and thus is in conflict with other's definitions, including Feigl's that do mention both predictability and law."[8]

Pratt and Schlaifer (1988) raise the issue that a law with factors X and concomitants Z specifies a distribution given Z of a potential value Y_x that is defined for each X whether or not it is observed. An observed distribution of Y given X and Z agrees with the law if and only if, given Z, the observed X is independent of Y_x or,

[8] Basman(1988)

equivalently, of the joint effect of U_x of excluded variables on Y_x. To establish such independence in non-experimental data requires exhaustive exploration of the effect of concomitants, causal and non-causal assumptions; R^2 and F are irrelevant. They showed how the model-free theory applies to linear models, time series, and simultaneous equations, and pointed out its Bayesian implications.

Basman (1988), discussed the problem of observational equivalence (of alternative econometric equation systems on the same data), as a practical obstacle to econometrician's success in applying definitions of 'causality' by Simon (1953), Stortz and Wold (1960), and Granger (1969) to economic time-series.

Poirier (1988), proposed a concrete operational definition of 'causal relationship' in terms of a Bayesian model occurrence framework, in which exogeneity, predictability, lawfulness and replication play crucial roles.

Rubin (1998), focused to make sense of observational studies, including clinical trials with problems like non-compliance. The approach focuses on the concept of 'potential outcome, some of which are observed while others are unobserved: what would have happened if the person had not smoked, if he had received a different treatment, etc? This is an example of the counterfactual approach where one considers outcomes that would have resulted if some other treatment or risk factor had actually been occurring than that which did occur. This corresponds well with the notion of causality that is common in medicine: what difference would it make if the decisions of individuals or doctors were different?

Holland (1988) raised similar points in non-experimental data using path models for causal inference. According to Holland the model is important to derive the analysis instead of the data. He defined the causal effect as "In fact, given a set of covariates, the mean response over the "treatments" group minus the mean over the "controls" must be assumed equal to causal effect being estimated."

Pearl (2000) in his book vigorously opposed the attitude ultimately traceable to the philosopher David Hume- that the most we can learn from data are its associations summarized in the likelihood function and that, consequently, it is impossible systematically to infer or use causal relations. Pearl is, in contrast, a causal optimist. He defends a notion of causal structure that goes beyond probabilistic association. Each link in a casual structure is a stable and autonomous physical relationship that can be changed without changing other links. Pearl admires the econometrics of the Cowles Commission and, especially, the work of Simon. Pearl is a leader in the graph-theoretic approach to causal analysis, whose other contributors include Glymour, Scheines, Spirtes and colleagues at Carnegie-Mellon University. In a causal graph, causal linkages are shown as arrows running from causal variables to effect variables. Econometric systems are easily rendered into causal graphs. The mathematics of graph theory allows the implication of a causal structure for probability distributions to be readily worked out. The key notion is what Pearl calls d-separation, essentially the idea that a set of causes intervening between two variables or a set of parent causes of two variables induces a relationship of conditional independence between them. (p_412.)

Adam et al (2003), worked on causality in panel data. They focus on first order Markov process, in which only the most recent history conveys information:

$$f\left(Y_t \middle| Y_{t-1}\right) \equiv f\ \left(Y_t \middle| Y_{t-1}\right) \equiv f_1\left(Y_{1t} \middle| Y_{t-1}\right) .. f_2\left(Y_{2t} \middle| Y_{1t-1}, Y_{t-1}\right) .... f_k\left(Y_{kt} \middle| Y_{1t} ... Y_{k-1,t}, Y_{t-1}\right)$$

Above model can be extended to higher order Markov chain process. Model above is valid for given history Y_{t-1}, if it is the true conditional distribution of Y_t given this history. According to Adams et al (2003), term 'f' is a structural or causal model or a (probabilistic) law, for Y_t relative to a family of histories if it has the invariance property. It is valid for each history in the family. Operationally, this means that, within specified domain, "f" has the transferability property; it remains valid following policy interventions that alter the marginal distribution of Y_{t-1}. By including temporal or spatial variables in Y, it is possible to weaken invariance requirements to fit almost any application. So proposed models should be as generic as possible however, it may be necessary in some application to model. There is a difference between conventional definition of a causal model and current definition of causal model. According to former, causal model or probabilistic law requires that "f" be valid, having a property of invariance under proposed interventions for universe of possible histories, for details see pearl (2000). But according to later definition, a causal model or probabilistic law requires that "f" is valid model for a family of history (not universe of histories) i.e. it has invariance property for each history relative to this particular family. It is more difficult to show that a proposed model, which is using a given history inductively, would be causal for universe of histories. In Adam et al (2003) further issues about latent variables, measurement, sample characteristics, descriptive statistics, construct variables, relative risk, model of incidence, models of association simulation and some alternative scenarios are also discussed.

Rubin (2004), worked on randomized experiments which is remarkable. The concept of causality was originated from randomized experiments. Rubin's work on causality is known as "Rubin's causal model" (R.C.M) because he pointed out that causal inference is the problem of missing data. In order to check the observed data, he used different mathematical modeling techniques for assigning the different treatments. Many other economists agreed with this approach.

According to Rubin (2004), the causal inference is basically the comparison of potential outcome of a variable, on the same unit measured at the same time. Suppose Y is outcome variable and $Y_{(0)}$ is the value of outcome variable when it is exposed to treatment "0" and $Y_{(1)}$ is the value of outcome variable when it is exposed to treatment "1". Only one of these two outcomes can be observed and that outcome would be the unit which received the effect of treatment. As causal model is the difference between these potential outcomes i.e. $Y_{(1)} - Y_{(0)}$. This approach is consistent with views of other economists such as Agrist et al (1996, P-969) "Without potential outcomes, causal inference is exceedingly difficult and often misleading." According to Rubin the assignment mechanism is then a stochastic rule for assigning treatments to units and thereby revealing $Y_{(0)} - Y_{(1)}$ for each unit. This assignment mechanism can depend on other measurements. If these other measurements are observed values, then the assignable mechanism is ignorable, if the given observed value is one of the missing values, then it is non-ignorable. All form of statistical inference for causal effects, whether Bayesian or frequents, require the posting of an assignment mechanism.

Heckman (2003) argued that instead of having interest in concept of causality we should be interested that either empirically determined relationship can be used for valid forecast of certain policies. He argued that if a person used a conventional Cowle's approach (an organization for the development of econometrics) in estimation and formulation of the models, then he needs strong assumptions, which are difficult to fulfil. So he may choose another approach. This approach moves towards the "focused policy". "Under the specific given set of policies, what information are required, is the main theme of this approach. Under such policy questions, less information are required which can be obtained from given data set by credible identifying assumption". [9]

To differentiate the two approaches, Heckman (2003) writes "if a policy which has been implemented in the past in an environment which is identical to the present environment then such policy may provide a feedback between X_t and Y_t in a deterministic general linear model. So in this context, the historical data on X_t can be used to predict the variation in X_t. Association between X_t and Y_t will accurately forecast the changing policies. But problem arises when the current environment do not match the historical environment, in this context we can not use the previous policies and we will have to make the adjustment for the changed environment on the basis of information obtained from the particular or specific precise policy being investigated. For this situation, we need different combination of parameters. The whole notion of invariance should be defined under a class of new proposed policies in current environment.

In the article "Causality in Crisis?", Freedman "For nearly a century, investigators in the social sciences have used regression model to deduce cause and affect relationships from the patterns of association. Path models and automated research procedures are more recent developments. In my view, this enterprise has not been successful. The models tend to neglect the difficulties in establishing causal relations, and the mathematical complexities tend to obscure rather than clarify the assumptions on which analysis is based.

Formal statistical inference is, by its nature, conditional. If maintained hypothesis A, B, C…hold, then H can be tested against data. However, if A,B,C,… remain in doubt, so most inferences about H. Causal scrutiny of maintained

[9] Heckman(2003)

hypothesis should therefore be a critical part of empirical work----a principle honored more often in the breach than the observance”(Freedman 1997)

Freedman argues that many treatments of regression seem to take for granted that investigators knows the relevant variables, then causal order, and the functional form of the relationships among them; measurement of the independent variables are assumed to be without error. Indeed, Gauss developed and used regression in physical science context where these conditions hold, at least to a very good approximation.

According to Freedman in social science cause and effects relationship can not be disentangled as most of the time above mentioned assumptions are hard to satisfy. Freedman writes that for descriptive and prediction analysis, regression technique is very useful but he has not seen a single case where use of regression model has discovered any causal relationship.

Freedman while discussing Yule’s regression model for regression writes “Yule was looking for the ‘Hook’s law of Poverty’. Nature ran an experiment, with lots of variation over time and geography, and Yule analyzed the results. Regression was needed to control for the confounding effects of change in population and age structure. The equations were held to show that, other things being equal, changes in the outrelief ratio create corresponding changes in the number of paupers.

He is of the view that Yule failed to recognize the underlying mechanism of regression theory. He missed many important variables from the data. There are some noticeable inconsistencies in Yule’s coefficients, overtime and across the various kinds of geography. Nor are the signs of the coefficients entirely reasonable. These inconsistencies may not be themselves be fatal, but certainly raise the question of whether the equations hold true for any well defined population of times and places. If the coefficients do not have a life their own-----outside Yule’s particular data set----

---they can not be used to answer the question of the form," What would happen if you change the out relief ratio?"

Freedman (1991) justified that regression models being used in social sciences is not appropriate to infer cause and affect relationships. He presented the work of Snow on cholera as a successful story to find causation from non-experimental data. He also described many other examples in which regression modeling was being used to make causal arguments. In particular, this paper "suggests that statistical technique can seldom be an adequate substitute for good design, relevant data, and testing predictions against reality in a variety of settings."

Freedman (1997) discussed many modeling techniques, which convert association to causation. He argued that "the models tend to neglect the difficulties in establishing causal relations and the mathematical complexities tend to obscure rather than to clarify the assumptions on which analysis is based." Different uses of regression modeling are being discussed in this paper and some difficulties are pointed out to find causation from regression.

Freedman (1999) pointed out that while using regression modelling the slope is often used to predict how dependent variable would respond if some one intervenes and changes explanatory variable. He pointed out that this is possible or legitimate, when data come from experimental source; with observational studies the inference is often shaky because of confounding, measurement errors, causal ordering, lack of prior knowledge of the relevant variables and the functional form of the relationship among them. Actual picture of the technique is that theory should be or must be such that the variables of interest are permissible to treat them theoretically like fictive controlled variables. Regression modelling is often used to infer causation with the help of association in observational studies. Association is necessary condition but not sufficient for causation. Although, regression analysis deals with the dependence of one variable on one or more than one variables, it does not imply causation.

When we are going to make inferences about causality through regression modeling from patterns of association, we require strong assumptions. These assumptions are of two kinds, (i) Statistical assumptions (ii) Casual assumptions. The statistical assumptions are as usual. The causal assumptions are assumption of stability, assumption of exogeneity and assumption of invariance of error distribution under set of proposed interventions.

"To make casual inferences, it must be assumed that equations are stable under proposed interventions and this is hard to establish in observed data. A statistical assumption like independence is also problematic to fulfil in observational settings."(Freedman, 2004).

Freedman (2004) pointed out that to infer causation from pattern of association through modeling we need strong statistical and causal assumptions. He also stressed on logical basis of inferring causation from regression. The assumption of invariance is being discussed in detail through different examples in this paper.

Huasman (2003) pointed out that structural approach of model estimation is the best approach. He suggested, "Structural estimation is the best (and really only) method to answer questions of causality and exogeneity. Statistical inference is best done within an explicit framework of identification and consistent estimation. Structural models are usually a necessary approach to make reliable inference about causality."

Freedman argued that path models and structural models are later "refinements" of the regression technique. A "Path model" is a recursive system of regression equation, in which the dependent variables from some equations are used as explanatory variables in later equations. He justified that there are many problems, which are common in regression modeling and path modeling approach. For example the problem of an "elaborate theory", "specification form" and the problem of "assumptions" which are not derived from relevant theory. Freedman argued "this technique is not always appropriate to find cause and effect relationships."

SGS (Spirtes, Glymour, and Scheines, 1993) have proposed computerized algorithms, which are helpful in searching for path models. Using the algorithms, "SGS claim to make rigorous causal inferences from association. Further they explored that their methods which combine graph theory, statistics and computer science were supposed to allow quick, virtually automated conversion of statistical association to causation."

Hoover (2001) while giving some reflections on the history of causality in econometrics mentions that in the first half of the last century, causal analysis was a fundamental organizing principle animating the development of econometrics. Later on this issue was ignored altogether or discussed as separable topic Granger causality. He highlights the long existing tension between econometrics as instrument of structural articulation and econometrics as an instrument of statistical description by giving some evidence from the intersection of the traditions of demand measurement and business cycle analysis.

> "Despite the inroads of dynamic approaches, the static, equilibrium demand theory suggested that price and quantity stood in a relationship of mutual influence that could be represented by simultaneous equations. Simultaneity is closely related to the identification problem, and business-cycle analysis with its emphasis on dynamics and time suggests a possible solution to it. But is time the essence of causation? In Chapter 6, we examined reasons to doubt

that it is Econometrician of the 1930s and 40s also debated these issues. If time order is rejected as non-fundamental, then how causal asymmetry should be represented? Is mutual causation acceptable? Wold (ch. 41) argued that causes must be asymmetrical and built into economic models before they are estimated. The Cowles Commission was ready to admit simultaneity. Herbert Simon's "Causal Ordering and Identifiability" (1953b), the article that is one of the principal sources for the structural account defended here, was the last gasp of causality in the cowls econometric tradition. After that, identification became a staple of the received view, but causality is hardly mentioned. Why?

We can offer only conjectures. First, Wold had opposed models involving simultaneity in favour of "explicit causal chains." Wold's causal chains were similar to vector autoregressions or to Nancy Cartwright's time-ordered causal systems (Chapter 6, system (6.3)), except that he permitted contemporaneous variables to be related. But Wold Banished simultaneity: If X_t appeared on the right-hand side of a regression with Y_t on the left-hand side, then Y_t must not appear on the right-hand side of a regression with X_t on the left-hand side, Which is cause and which is effect must always be indicated. But Wold lost the debate. Second, What Simon (1953b) showed was that a linear system of equations was identified if and only if it is was causally ordered. This equivalence worked against causal analysis identification seemed to be the more pressing problem to econometricians focused on the problems of estimation. Equivalence meant that, in some respects, causality could be ignored without loss. And identification itself had non-causal roots in the problem of the measurement of demand. Causal language simply faded away.

Finally, for reasons that may have to do with larger trends in the philosophy of science, econometricians became shy of anything that smacked of metaphysics – in a sense a return to Hume. Despite being the champion of explicit causal chains, Wold (p. 465) argued that it was better to replace the adjective "causal" with "explanatory'" Nor was (or is) Wold alone: Haavelmo (p.481), Simon (1953a, p. 56), and, more recently, David Hendry (Hendry et al. 1990, p. 184) explicitly deny either the existence of truth or of causal relationship independent of our own causal representations. [4] Why would authors, each of whom subscribes to a conception of econometrics that make most sense in light of realist metaphysics, be reluctant to endorse a realist interpretation of causality?

One possibility is simply Zeitgeist: the logical positivism that dominated the philosophy of science from the 1930s to the 1950s was strongly antimetaphysical. Such intellectual trends tend to diffuse slowly, so that, despite a turn away from the doctrine in philosophy, logical positivism continues to exercise some influence in economics.

A second possibility is the rise of the notation of economic modeling. We take the idea of a model as so central to the practice of economics that we forget that the dominance of model building is relatively new (Hendry and Morgan 1995, p . 68; Morgan 1997, 1999, 2000). Models are self-evidently artifacts, our creations, not given in the world. It is easy to forget that their empirical usefulness is constrained by the need to stand in an appropriately representative relationship with the world.

A third possibility has to do with observational equivalence, which was not only well known to Simon (See Chapter 2 earlier in this book) but to his predecessors and contemporaries as well (e.g., see Frisch, p. 417; Koopmans, p. 551) understood, as did Simon, that Koopmans's pessimism was warranted only if the econometrician could not consider interventions that, to use the language of Chapter 2, Section 2, altered parameters. So long as econometricians took a narrow view of the information that they could legitimately bring to bear on quantitative analysis the resolution of causal questions seemed doubtful and causal language pointless.

After the 1950s, statistical methods in economics divided into two separate streams. The Cowles Commission tradition, now free of causal language, dominated the mainstream textbooks. Wold Continued to advocate explicit causal chains into the early 1960s, but Robert Basmann ((1965) landed the decisive blow when he showed that any explicit causal –chain model could be recast as an observationally equivalent simultaneous model. Despite the absorption of much of empirical business-cycle into the Cowles Commission framework, the older time-Series statistics associated with the theoretical business-cycle analysis of the first half of the twentieth century developed on a separate track. The work of the statisticians Box and Jenkins (1970) and of the econometricians C. W. J. Granger and Paul Newbold (1977) was particularly influential.

By 1966, Simon was more clearly a realist; see Simon and Rescher (1966)

Time-series econometricians revived causality as an important topic in econometrics. The central figure is Granger (1969). Granger suggested a data-based technique for deciding whether two variables were causally linked. Causality was thus reduced to the outcome of a statistical test rather than serving as an organizing category for econometrics in general, as it had in the early history of the discipline. Inevitably, however, the discussions of causality became linked to larger issues. Christopher Sims (1972) popularized Granger-Causality tests among economists when he applied them to the causal linkage between money and income. Sims's analysis was equivocal. On the one hand, it appeared to be addressed to the old question, much discussed after Hume (see Chapter 1, Section 1) of whether control over money yielded control over GDP. On the other hand, Sims packaged the test as an effort to determine from the data whether or not they were exogenous in a sense meant to be relevant to the discussions of exogeneity that were important in the structural econometrics of the 1940s and 1950s. Since Sims's (1972) article, many of the issues that were important in the early discussions are on the table once more." Hoover [2001]

2.5 Causation and Cointegration

Granger1988 examines the relationship between causation and cointegration. If a pair of I(1) series are cointegrated, there must be causation in at least one direction. An implication is that some tests of causation based on different series may have missed one source of causation. Secondly he considers that whether instantaneous causality is needed or not. Lastly, he suggested that causality tests should be considered for policy evaluation with care.

Granger (1988) "Suppose that X_t, Y_t are both I(1), without trends in mean, so that their changes are both I(0) and with zero means. Then it will be typically true that any linear combination of X_t, Y_t will also be I(1). However, it is possible that there will exist a constant such that $Z_t = X_t - A Y_t$ is I(0). This would happen for instance, if

$$X_t = Aq_t + Z_{1t},$$

And $$Y_t = q_t + Y_{1t},$$

Where q_t is I(0) and $X_{t,}$ Y_t are both I(0). When this occurs $X_{t,}$ Y_t are said to be cointegrated. Clearly, not all pairs of I(1) series have this property. If $X_{t,}$ Y_t are both I(1) but are cointegrated, then there will be generated by an "error correction" model taking the form

$$\Delta X_t=\gamma_1 Z_{t-1}+\text{lagged } \Delta X_t,\ \Delta Y_t+\epsilon_{1t},$$

And

$$\Delta Y_t=\gamma_2 Z_{t-1}+\text{lagged } \Delta X_t,\ \Delta Y_t+\epsilon_{2t},$$

where one of $\gamma_{1,}$ $\gamma_2\neq0$ and $\epsilon_{1t,}$ ϵ_{2t} are finite order moving averages.

Thus, changes in the variables $X_{t,}$ Y_t are partly driven by the previous value of Z_t. It can be shown that line X-AY=0 can be considered to be" equilibrium" or "attractor" for the system in the phase-space, where X_t is plotted against $Y_{t,}$ so that Z_t can be interpreted as the extent to which system is out of equilibrium. A consequence of error correction model is that either $D(X_t)$ or $D(Y_t)$ (or both) must be caused by Z_{t-1} which is itself a function of X_{t-1}, $Y_{t-1.}$

In error correction model there are two possible sources of causation of X_t by Y_{t-j}, either through the Z_{t-1} term, if $\gamma_1\neq0$, or through the lagged $D(Y_t)$ terms, if they are present in the equation. While discussing instantaneous causality Granger says that correlation can only be considered as causation if there is some extra knowledge which could break correlation symmetry. If, for example, one 'knows' that X_t can not cause Y_t(instantaneously or otherwise), then the symmetry is broken. This "extra knowledge" can come from economic theory or a belief in exogeneity.

Granger mentions three possible reasons for instantaneous causality:

i) There is true instantaneous causality in an economic system so that some elements in the system reach without any measurable time delay to changes in some other elements.

ii) There is no true instantaneous causality, but the finite time delay between cause and effect is small compared to time interval over which data is collected. Thus, the apparent causation is due to temporal aggregation.

iii) There is a jointly caused variable ω_{t-1}, that causes both X_t, Y_t but is not included in the information set, possibly because it is not observed.

So he is of the view that true instantaneous causality in economics never occurs and possibility of a missing variable is always there, therefore, there is no need to define instantaneous causality .Moreover, instantaneous causality among flow variables can not occur. Only temporal aggregation may be the realistic or plausible and well-known reason for observing apparent instantaneous causation and so need no further discussion.

2.6 Causality and Exogeneity

There is a close connection between Granger causality and exogeneity of variables in simultaneous equation estimation (Engle et al., 1983). From an econometric standpoint, there are different degrees of exogeneity (Engle and Hendry, 1993). We now distinguish three types of exogeneity: weak, strong and super. To keep the exposition simple, suppose we consider only two variables, Y_t and X_t, and further we regress Y_t on X_t. We say that X_t is weakly exogenous if Y_t also does not explain X_t. Further X_t is said to be strongly exogenous if current and lagged Y values do not explain it (i.e. no feedback relationship). And X_t is super-exogenous if the parameters in the regression of Y on X do not change even if the X values change, that is, the parameter values are invariant to changes in the values(s) of X. The reason for distinguishing the three types of exogeneity is that "In general, weak exogeneity is all that is needed for estimating and testing, strong exogeneity is necessary for forecasting and super exogeneity for policy analysis (Hall and Mark, Applied Econometric techniques, (1992, p. 100). Now consider bivariate system in granger causality, if a variable, say 'X' Granger cause another variable 'Y' but 'Y' does not Granger cause 'X' then variable 'X' is said to be strongly exogenous. In other words, strong exogeneity rests on non-causality or the absence of feedback between X and Y. if we are talking about weak exogeneity, it can be shown that Granger causality is neither necessary nor sufficient to establish exogeneity. On the other hand, Granger causality is necessary but not sufficient for strong exogeneity.

Hendry (1995) also mentions the same problem as that was mentioned by Zellner that Granger causality requires the universe of information and practically we have very limited information sets. Secondly, most empirical tests have been conditional on a host of untested assumptions about other aspects of the model within which the tests were conducted including parameter constancy, homoscedasticity, linearity in the associated data space, and fixed lag lengths. Among other drawbacks to the concept is dependence on temporal ordering, so that a 'contemporaneous causality' needs a separate construct.

Hendry suggests that if in a conditional distribution $D_{y/z}(y_t/z_{t,}X_{t-1,}\Phi_1)$there is a non zero dependence of y_t on z_t, where z_t is superexogenous for $\psi=f(\Phi_1)$, and Φ_2 has changed without affecting conditional relationship between y_t and z_t, then z_t is deemed to cause the resultant change in y_t.

He bases this invariance under intervention concept by quoting Simon, Hoover and Nancy Cartwright (1989). He says that given invariance under intervention of this form, the response of y_t to z_t is the same for different sequences $\{z_t\}$, and could sustain policy changes if z_t were under government control. Conversely, an absence of invariance could vitiate the proposed policy.

Hamilton (1995) has mentioned an example which clearly indicates that in a forward looking behaviour, Granger Causality runs in the opposite direction. He writes

“If an investor buys one share of a stock for the price P_t at date t, then at t+1 the investor will receive D_{t+1} in dividend and be able to sell the stock for P_{t+1}. The ex post rate of return from the stock (denoted r_{t+1}) is defined by

$(1+ r_{t+1})P_t=P_{t+1}+D_{t+1}$

A simple model of stock prices holds that the expected rate of return for the stock is a constant at all dates:

$(1+r)P_t=E_t(P_{t+1}+D_{t+1})$

$$\begin{bmatrix} Pt \\ Dt \end{bmatrix} = \begin{bmatrix} d/r \\ -d/r \end{bmatrix} + \begin{pmatrix} 0 & 0 \\ 1+r & 0 \end{pmatrix} \begin{bmatrix} Pt-1 \\ Dt-1 \end{bmatrix} + \begin{bmatrix} \delta ut/(1+r) \\ ut+vt \end{bmatrix}$$

….

After solving these equations he has written bivariate VAR model as

$$\begin{bmatrix} Pt \\ Dt \end{bmatrix} = \begin{bmatrix} d/r \\ -d/r \end{bmatrix} + \begin{pmatrix} 0 & 0 \\ 1+r & 0 \end{pmatrix} \begin{bmatrix} Pt-1 \\ Dt-1 \end{bmatrix} + \begin{bmatrix} \delta ut/(1+r) \\ ut+vt \end{bmatrix} .$$

Thus stock prices Granger –cause dividends, though dividends fail to Granger-cause stock prices. Hence, in this model, Granger causation runs in the opposite direction from the true causation. Dividends fail to “Granger-cause” prices, even though investor’ perceptions of dividends are the sole determinant of stock prices. On the other hand prices do “Granger-cause” dividends, even though the market’s evaluation of the stock in reality has no effect on the dividend process.

In general, time series that reflect forward looking behaviour, such as stock prices and interest rates, are often found to be excellent predictors of many key economic time series. This clearly does not mean that these series reflect the market’s best information as to where GNP or inflation might be headed. Granger causality tests for such series may be useful for assessing the efficient markets view or investigating whether markets are concerned with or are able to forecast GNP or inflation, but should not be used to infer a direction of causation. Hamilton thinks that if there is strict exogeneity then it is possible to determine the direction of causation by applying Granger Causality.

Simon (1998) chapter III of his book, a concept of causality that corresponds to the intuitive use of that term in scientific discussion is given. Causality is an asymmetrical relation among certain variables, or subsets of variables, in a self contained structure. There is no necessary connection between the asymmetry of this relation and asymmetry in time. Though, an analysis of the causal structure of dynamical systems in econometrics and physics shows that lagged relations can generally be interpreted as causal relations. (p_73).In models specifying which variables are excluded from which equations, the concept of causality has been shown to be intimately connected with the concept of identifiability, although the conditions under which a self-contained structure possesses a nontrivial causal structure are somewhat weaker than the conditions under which it is completely identifiable

Demiralp and Hoover (2003) provided an accessible introduction to graph–theoretic methods for causal analysis. Building on the work of Swanson and Granger (1997, 92 357-367, Journal of the American Statistical Association,), and generalizing to a larger class of models, they showed how to apply graph-theoretic methods to selecting the causal order for a structural vector auto regression (SVAR). They evaluate the PC (Causal search) algorithm in a Monte Carlo study. The PC algorithm uses tests of conditional independence to select among the possible causal orders- or at least to reduce the admissible causal orders to a narrow equivalence class. Our findings suggest that graph-theoretic methods may prove to be a useful tool in the analysis of SVARs. "A study of the operational meaning of the causal ordering (or of the concept of "structural "equations) appears to require a metalanguage that permits discussion of the relations between the structure and an experimenter who has direct control over some of the parameters of the structure. As the brief discussion of the nonlinear case implies, the distinction between parameters and variables can be disregarded if the former are regarded as exogenous variables (determined by a larger system) with respect to the latter. In this case the experimenter must be regarded as being able to relax or alter particular equations in this larger system. (p_74).

2.7 Structural causality and Granger causality[10]

"The upshot of these examples is that Granger-causality is not necessary for structural causality. It might appear that Granger-causality is a sufficient condition for structural causality, but this turns out to be true only in the linear case. Consider the case in which prices appear to Granger-cause money because the public is better able to predict the implications of monetary policy for future inflation than is the econometrician and the public's expectations are unobservable. Nonlinearities of the type introduced by rational expectations undermine the correspondence between Granger-causality and structural causality. We are going to discuss that how Granger causality is different from structural causality when economic agents are using rational expectation. This analysis is based on Cagan's convergence model. General money demand function is given as follows

$$m_t - p_t = \delta + \beta y_t - \alpha\left(r_t + ({}_t p^e_{t+1} - p_t)\right) + \nu_t \qquad (2.1)$$

where subscripts index time, m_t is the nominal money stock, p_t is the general price level, y_t is real GDP, r_t is the real rate of interest, ${}_tp^e_{t+1}$ is the

[10] This is adapted from Hoover(2001).

expectation at time t of the price level at time t+1, so that $({}_tp^e_{t+1} - p_t)$ is (approximately) the rate of inflation between times t and t+1, and v_t is an independent random error term. All variables except r_t are in natural logarithms, and the coefficients α, β, δ>0. Hoover mentions that the special case of a hyperinflation implies that the inflation rate is so large relative to changes in real interest rates and real incomes that it would be reasonable to impound these variables as constants in a causal field

Equation (2.1) can then be rewritten as

$$m_t - p_t = \delta + \beta \bar{y} - \alpha\left(\bar{r} + ({}_t p^e_{t+1} - p_t)\right) + v_t \qquad (2.2)$$

where bars and the omission of time subscripts indicates that the variables take on constant values. The demand for money was given in equation (2.2) can be written in more compact form as follows

$$m_t - p_t = \mu - \alpha\left({}_t p^e_{t+1} - p_t\right) + v_t \qquad (2.3)$$

With the addition of a stochastic growth term, θ_{t-1}, to the money-supply rule, model becomes

$$m_{t+1} = \lambda + \theta_{t+1} + m_t + \varepsilon_{t+1} \qquad (2.4)$$

where $\lambda = ({}_tp^e_{t+1} - p_t)$

θ_{t+1} is assumed to be an identically distributed serially independent random variable, uncorrelated with any other random term in the model.

If it is assumed that θ_{t+1} is unobservable at time t, then it can be grouped with the error term ε_{t+1}, and the solution to the model for prices repeats equation (3.9)

$$p_t = m_t - \mu + \alpha\lambda + v_t \qquad (2.5)$$

Substitute equation (4) lagged once into (5) to yield [11]

$$p_t = (1+\alpha)\lambda + m_{t-1} - \mu + (\theta_t + \varepsilon_t + \nu_t) \tag{2.6}$$

Equations (2.5) and (2.6) form a system of reduced-form equations. By inspection, it is obvious that money Granger-causes prices, but prices do not Granger-cause money in this system.

But now let us suppose that the public is better informed that the econometrician: The public knows θ_{t+1} and earlier realizations at time t, although not realizations at time t+2.2 and later, while the econometrician is ignorant of all realizations. A reasonable conjecture for the rate of inflation (analogue to equation (3.8)) is

$$\left({}_t p_{t+1}^e - p_t\right) = \lambda + \frac{\theta_{t+1}}{1+\alpha}. \tag{2.7}$$

We confirm that this is the rational expectation of inflation. First, substitute (2.7) into (2.6) and rearrange to get an expression for current prices:

$$p_t = m_t - \mu + \alpha\left(\lambda + \frac{\theta_{t+1}}{1+\alpha}\right) + \nu_t. \tag{2.8}$$

Next take expectations of actual inflation conditional on information available at time t based on the current and future price levels determined by equation (7.11):

$$E\left(P_{t+1} - p_t \middle| \Omega_t\right) = E(m_{t+1} - \mu + \alpha\left(\lambda + \frac{\theta_{t+2}}{1+\alpha}\right) + \nu_{t+1} - \left(m_t - \mu + \alpha\left(\lambda + \frac{\theta_{t+1}}{1+\alpha}\right) + \nu_t\right)$$

$$= E\left(m_{t+1} - m_t + (\lambda + \alpha\left(\frac{\theta_{t+2} - \theta_{t+1}}{1+\alpha}\right) + \nu_{t+1} - \nu_t\right)$$

$$= \lambda + \theta_{t+1} - \frac{\alpha\theta_{t+1}}{1+\alpha} = \lambda + \frac{\theta_{t+1}}{1+\alpha} \tag{2.9}$$

this is what we conjectured. The terms involving θ_{t+2} drop out under the expectations operator because θ_t is mean zero and the public has advanced knowledge of its realizations only one period ahead.

$$\theta_{t+1} = (1+\alpha)\left[\frac{p_t - m_t + u - \nu_t}{\alpha} - \lambda\right] \quad (2.10)$$

Substitute equation (2.10) into (2.7), simplify, and rearrange to yield the reduced form for the money stock:

$$m_{t+1} = \left[\left(\frac{1-\alpha}{\alpha}\right)\mu - \alpha\lambda\right] - \left(\frac{1}{\alpha}\right)m_t + \left(\frac{1+\alpha}{\alpha}\right)p_t - \left[\left(\frac{1+\alpha}{\alpha}\right)\nu_t + \varepsilon_{t+1}\right] \quad (2.11)$$

Thus, even though prices at time t do not cause money at time t+1, according to the structural account, they nonetheless Granger-cause money. The behaviour of current prices is a way in which public's superior knowledge of the future course of money is made observable to econometricians. Current prices serve as a proxy for the values of θ_{t+1}, which the econometricians can not observe. In the end, we must conclude that whatever uses Granger-causality has a measure of incremental predictability; it is neither necessary nor sufficient for structural causality in a range of cases important to macroeconomics."(Hoover 2001)

So from all this discussion it becomes clear that Granger causality which has been widely used by many researchers as test of causality and using the results obtained from this for policy recommendations needed to be explored in detail. To have an investigation of this issue we have carried out empirical investigation of Granger causality.

Chapter 3
Methods for Testing Causality

Different methods for Granger causality tests are given in this chapter. These methods are Granger Causality method, Sims method, Finite Prediction Error (FPE), Error Correction model, Toda and Yamamoto (1995) procedure .All these methods have their own pros and cons but all these test the same causality as was suggested by Granger (1969).

3.1 Granger Causality test (1969)

A particularly simple approach to test for Granger causality is to regress the current value of the time series Y_t against the past values of the time series X_t in the presence of lagged values of Y_t.

Assume a particular autoregressive having lag length k, and estimate the following unrestricted equation by ordinary least squares (OLS):

$$Y_t = \alpha_0 + \sum_{i=1}^{k} \alpha_i Y_{t-i} + \sum_{j=1}^{k} \beta_j X_{t-j} + u_t \tag{3.1}$$

$$H_{0a} : \beta_1 = \beta_2 = \cdots = \beta_k = 0$$

To see if jointly the coefficients associated with the X's are statistically significant, we conduct an F-test to test the null hypothesis. Now run the following restricted equation through OLS:

$$Y_t = \alpha_0 + \sum_{i=1}^{k} \alpha_i Y_{t-i} + u_t \tag{3.2}$$

Compare their respective sum of squared of residuals from (3.1) and (3.2), we have the following F-statistic (Wald statistic):

$$F = \frac{(SSR_{restricted} - SSR_{unrestricted})/k}{SSR_{unrestricted}/(T-2k-1)} \sim F_{k,\,T-2k-1} \tag{3.3}$$

If the F- statistic is greater than the specified critical value, then reject the null hypothesis that *X* does not Granger-cause *Y*, i.e., X does Granger-cause Y. Similarly regressing X on its own past values and past values of Y, i.e.

$$X_t = \alpha_0 + \sum_{i=1}^{k} \alpha_i Y_{t-i} + \sum_{j=1}^{k} \beta_j X_{t-j} + e_t \tag{3.4}$$

$$H_{0b} : \alpha_1 = \alpha_2 = \cdots = \alpha_k = 0$$

To see if jointly the coefficients associated with the Y's are statistically significant, we conduct an F-test to test the null hypothesis. Now run the following restricted equation through OLS:

$$X_t = \alpha_0 + \sum_{i=1}^{k} \alpha_i X_{t-i} + u_t \tag{3.5}$$

Compare their respective sum of squared of residuals from (3.4) and (3.5) by using the F-statistic (3.3), then we have the following four possible cases,

(i) If H_{0a} is accepted and H_{0b} is rejected then there exists unidirectional causality from 'Y' to 'X'.

(ii) If H_{0a} is rejected and H_{0b} is accepted then there exists unidirectional causality from 'X' to 'Y'.

(iii) If both H_{0a} *and* H_{0b} are rejected then there exists bi-directional causality (feedback) between 'X' and 'Y'.

If both H_{0a} *and* H_{0b} are accepted then 'X' and 'Y' are independent.

It is to be noted that Granger test is based on assumption that the variables 'X' and 'Y' are stationary and u_t *and* e_t are uncorrelated. So in all of the above equations we assume that the variables are stationary at levels and u_t *and* e_t are uncorrelated. The lag length in above equations can be selected where residuals are whitenoise. However if the variables are integrated of order one then first differencing of the variables is required. Now in multivariate case we use the first differences of each variable, if they are integrated of order one i.e. I (1), then we run the following equations to test causality between three variables,

$$\Delta Y_t = \alpha + lagged(\Delta Y_t, \Delta X_t, \Delta Z_t) + e_t \tag{3.6}$$

$$\Delta X_t = \alpha + lagged(\Delta Y_t, \Delta X_t, \Delta Z_t) + e_t \tag{3.7}$$

$$\Delta Z_t = \alpha + lagged(\Delta Y_t, \Delta X_t, \Delta Z_t) + e_t \tag{3.8}$$

where 'Δ' is the first difference operator defined as $\Delta Y_t = Y_t - Y_{t-1}$. Now test the associated null hypothesis by assuming that 'e_t' is white noise process in above three equations. Nevertheless, it is said that by taking the first difference of the variable actual causal processes is taken away, therefore, Granger causality test proposed above is not valid in such cases .Error Correction Mechanism or Toda and Yamamoto procedure should be used in these situations.

3.2 Sims Test (1972)

According to Sims, one can regress Y on past and future values of X, and if causality runs from X to Y only, future values of X in the regression should have coefficients insignificantly different from zero as a group (Sims; 1972). So Sims argues that "future cannot cause current or past". This concept of causality here refers to the lagged and lead relationship between economic variables.

In Sims test, we regress a variable Y on past and future values of variable X. if X granger cause Y then the coefficients of the future values of X are equal to zero. Therefore, to apply Sims test, we run the following regression while testing from X to Y:

$$Y_t = \alpha_0 + \sum_{i=1}^{m} a_{1i} X_{t-i} + \sum_{j=1}^{n} b_{1j} X_{t+j} + v_{1t} \tag{3.9}$$

Here we test the following null hypothesis by using the F-test (2.3):

$$H_0 : b_{11} = b_{12} = ... = b_{1n} = 0$$

If H_0 is accepted then X cause Y otherwise X does not cause Y.

Similarly to test causality from Y to X we use the following regression line:

$$X_t = \alpha + \sum_{i=1}^{m} a_{2i} Y_{t-i} + \sum_{j=1}^{n} b_{2j} Y_{t+j} + v_{2t} ,$$

and test

$$H_0 : b_{21} = b_{22} = ... = b_{2n} = 0 \tag{3.10}$$

It is to be noted that error term in above equations are assumed to be white noise processes and both the variables are assumed to be stationary. If any of the variables in above equation is non-stationary at levels but integrated of order one then it is used in first differencing form in Sims test. The main problem with Sims test is existence of autocorrelation among residuals. Sims suggested that using the filter $(1-0.75L)^2$ where 'L' is lag operator, one can avoid the autocorrelation problem.

Thus in Sims test each variable like Y_t is replaced by $Y_t^* = Y_t - 1.5Y_{t-1} + 0.5625Y_{t-2}$ to avoid the problem of autocorrelation. But it is questionable that whether every series becomes stationary with this filter. Therefore, issue of non-stationarity is serious both in Sims and Granger causality method.

3.3 Hsiao (1981) Final Prediction Error (FPE) Method:

Hsiao (1981) suggested a two step procedure of combining Granger's causality test with Akaike Final Prediction Error (FPE) criterion. This method which uses an optimality criterion of minimizing the mean square prediction error eliminates the uncertainty in the choice of significance level, apparently because it is more generous in including additional variables than the conventional significance level. Hsiao (1981) proposes a two step procedure. In the first step we treat the dependent variable Y as a one dimensional autoregressive process. Initially, we regress a variable only on its own lagged values. So in first step we estimate the following autoregressive equation having the form:

$$Y_t = \alpha_0 + \sum_{i=1}^{M} a_{1i} Y_{t-i} + v_{1t} \tag{3.11}$$

Now here select 'm' as large as possible. Then compute the FPE for each regression in the following way:

$$FPE(m) = \frac{T+m+1}{T-m-1} Q(m) \Big/ T \tag{3.12}$$

where 'T' is the number of observations used, 'm' is the order of lags varying from 1 to M and Q (m) is the associated sum of squared residuals.

The specific value of m, say m^* is the optimal lag length which produces the lowest FPE. In step two we treat 'Y' as dependent variable with the order of lags set at m^* and 'X' as an independent variable with the order of lags varying from 1 to N. Then we estimate the regression of the form:

$$Y_t = \alpha_1 + \sum_{i=1}^{m^*} a_{1i} Y_{t-i} + \sum_{j=1}^{N} b_{1j} X_{t-j} + v_{2t} \tag{3.13}$$

The corresponding two dimensional FPE is:

$$FPE(m, n) = \frac{T+m^*+n+1}{T-m^*-n-1} Q(m, n) \Big/ T \tag{3.14}$$

where 'n' is the order of lags on 'X'. Once again, the optimum 'n' say 'n^*' is chosen to minimize FPE (m, n).

We then conclude that X Granger causes Y if $FPE(m^*, n^*) < FPE(m^*)$. By repeating the same procedure for the following equations we can test Granger causality among three variables.

Restricted equation	Unrestricted equation	
$Y_t = a_1 + lagged(Y_t) + v_{2t}$	$Y_t = a_1 + lagged(Z_t, Y_t) + v_{2t}$	(3.15)

$$Y_t = a_1 + lagged(Y_t) + v_{2t} \qquad Y_t = a_1 + lagged(X_t, Y_t) + v_{2t} \tag{3.16}$$

$$Z_t = a_2 + lagged(Z_t) + v_{3t} \qquad Z_t = a_2 + lagged(Z_t, Y_t) + v_{3t} \tag{3.17}$$

$$Z_t = a_3 + lagged(Z_t) + v_{4t} \qquad Z_t = a_3 + lagged(Z_t, X_t) + v_{4t} \tag{3.18}$$

$$X_t = a_4 + lagged(X_t) + v_{5t} \qquad X_t = a_4 + lagged(Z_t, X_t) + v_{5t} \tag{3.19}$$

$$X_t = a_5 + lagged(X_t) + v_{6t} \qquad X_t = a_5 + lagged(Y_t, X_t) + v_{6t} \tag{3.20}$$

Now run the above unrestricted and restricted equations and note the corresponding minimum FPE for specified values of m and n and draw conclusions. In all of the above equations errors are assumed to be white noise and variables used are assumed to be stationary at levels.

3.4 Error Correction Mechanism

First of all one needs to know whether underlying variables are stationary or not. If they are stationary then one can apply standard Granger causality testing procedure. Nevertheless, if they are nonstationary then each variable should be tested for stationarity using Augmented Dickey Fuller (ADF) test to determine the order of integration. If they are integrated of the same order then one can proceed further for carrying out the test of cointegration. Most commonly used methods for testing cointegration are Granger method and Johansen method.

If the variables are found to be cointegrated, this implies that there is long run relationship among the variables. This is called error correction mechanism. As standard Granger and Sims methodology do not include this error correction term, so they lead to misleading results. Therefore, error correction models are formulated as follows.

By introducing error correction terms in the above equations, it is said that an additional channel of causality is opened up. Coefficients of lagged value of the error term determine the significance of long run relationship whiles coefficients of lagged independent variables measure short run dynamics.

According to Granger representation theorem, if two variables X and Y are cointegrated, then the relationship between the two variables can be expressed as ECM. So when two variables are found to be cointegrated, i.e. they have long run equilibrium relationships (of course in the short run there may be disequilibrium), then it is better to use Error Correction Model (ECM).

Consider an ECM model in three variables case,

$$\Delta Y_t = \alpha_0 + b_0 u_{t-1} + \sum_{i=1}^{p} \delta_{1i} \Delta Y_{t-i} + \sum_{j=1}^{p} \theta_{1j} \Delta X_{t-j} + \sum_{k=1}^{p} \lambda_{1k} \Delta Z_{t-k} + w_{1t} \tag{3.21}$$

$$\Delta X_t = \alpha_1 + b_1 u_{t-1} + \sum_{i=1}^{p} \delta_{2i} \Delta Y_{t-i} + \sum_{j=1}^{p} \theta_{2j} \Delta X_{t-j} + \sum_{k=1}^{p} \lambda_{2k} \Delta Z_{t-k} + w_{2t} \tag{3.22}$$

$$\Delta Z_t = \alpha_2 + b_2 u_{t-1} + \sum_{i=1}^{p} \delta_{3i} \Delta Y_{t-i} + \sum_{j=1}^{p} \theta_{3j} \Delta X_{t-j} + \sum_{k=1}^{p} \lambda_{3k} \Delta Z_{t-k} + w_{3t} \tag{3.23}$$

where 'Δ' is the first difference operator defined as $\Delta Y_t = Y_t - Y_{t-1}$.

In above three equations 'u_t' is defined as $u_t = y_t - \alpha_1 x_t - \beta_1 z_t$ and it is assumed that the error terms w_{1t}, w_{2t} *and* w_{3t} are white noise. Thus by including error correction term in above equations, ECM introduce an additional channel through which Granger Causality could be detected. In the above ECM there are two possible sources of causation. Changes in X_t are partly driven by u_{t-1} and also lagged values of the two variables Y_t and Z_t. For example in equation (3.21) we say 'X' Granger causes 'Y' if $b \neq 0$ or $\theta_{11} = \theta_{12} = ...\theta_{1p} \neq 0$. Thus conducting F-test to test the null hypothesis that 'X' does not granger causes 'Y' in equation (3.21) is equivalent to test the hypothesis by using F-test (3.3):

$H_{0a} : \theta_{11} = \theta_{12} = ...\theta_{1p} = 0$

and using t-test to test the hypothesis:

$H_{0b}: b = 0$

If either of the null hypothesis H_{0a} or H_{0b} is rejected then 'X' Granger cause 'Y'. If both the hypotheses are accepted then we say that 'X' does not Granger cause 'Y'. It is to be noted that the error correction term 'u_{t-1}' represents the long term impact of one variable on the other variable. Where, the short run impact of one variable on another variable is measured by using the lagged values of the variable.

Thus, when two or more than two variables are cointegrated then it is better to use Error Correction Model (ECM) rather than using simple VAR model in first differencing to avoid the misleading results.

3.5 Toda and Yamamoto method (1995)

This method shows how we can estimate vector autoregressive (VAR) model formulated in levels and test general restrictions on the parameter matrices even if the process may be integrated or cointegrated of an arbitrary order. As Granger test and ECM approach are based on prior knowledge about the integration and cointegration properties of a series. But, in most applications, it is not known a priori whether the variables are integrated, cointegrated or (trend) stationary. Consequently pre-tests for a unit root(s) and cointegration in the economic time series are usually required before estimating a VAR model in which statistical inferences are conducted.

A different procedure, developed by Toda and Yamamoto (1995) utilizes a modified Wald test for restrictions on the parameters of a VAR (k) model (where k is the lag length in the system). Toda and Yamamoto (1995) proved that this test has an asymptotic χ^2 distribution when a VAR (k+$d_{\max}$) model is estimated (where $d_{\max}$ is the maximal order of integration suspected to occur in the system). The advantage of this procedure is that it does not require knowledge of cointegration properties of the system. This test can be done even if there is no cointegration and/or the stability and rank conditions are not satisfied. (Zapta and Rambaldi; 1997)

Consider the following VAR (k+ $d_{\max}$) model in three variables case:

$$Y_t = \alpha_0 + \sum_{i=1}^{k} \delta_{1i} Y_{t-i} + \sum_{j=k+1}^{d_{\max}} \alpha_{1j} Y_{t-j} + \sum_{j=1}^{k} \theta_{1j} X_{t-j} + \sum_{j=k+1}^{d_{\max}} \beta_{1j} X_{t-j} + w_{1t} \qquad (3.24)$$

$$X_t = \alpha_1 + \sum_{i=1}^{k} \delta_{2i} Y_{t-i} + \sum_{j=k+1}^{d_{\max}} \alpha_{2j} Y_{t-j} + \sum_{j=1}^{k} \theta_{2j} X_{t-j} + \sum_{j=k+1}^{d_{\max}} \beta_{2j} X_{t-j} + w_{2t} \qquad (3.25)$$

where the error terms w_{1t} *and* w_{2t} across the different equations and within equation are uncorrelated, $d_{\max}$ is the maximum order of integration.

The lag length in above three equations can be determined by using Akaike Information Criterion (AIC) and Schwarz Bayesian criterion (SBC).In equation (3.24) 'X' granger causes 'Y' provided that $\theta_{1j} \neq 0 \; \forall_j$. We can test the following null hypothesis in equation (3.24) and (3.25) by using modified Wald statistic:

$H_0 : \theta_{11} = \theta_{12} = ... = \theta_{1k} = 0$ (X does not Granger cause Y)

$H_0 : \alpha_{11} = \alpha_{12} = ... = \alpha_{1k} = 0$ (Y does not Granger cause X)

Chapter 4
Sensitivity of Granger Causality

The literature on causality is full of controversies. Even the meaning of the term itself is disputed .It is needless to say that causality concept is difficult to formalize .Therefore; we shall analyze Granger causality on empirical grounds. Our analysis largely avoids the quagmire of the philosophy of scientific literature which promises much but we think that it may be of little value in practice for an economist. We have analysed Granger causality empirically to find out that whether causal directions determined by this procedure are robust.

It is very interesting to see that causal direction determined by Granger causality is unstable. For the same set of variables under study causal direction determined from this technique varies from one study to the other even when analysed for the same country. Even if we ignore the debate whether Granger causality is a test of structural causality or not, the results obtained from different causality tests[12] are against the basic axiom proposed by Granger "Axiom C; All usual relationships remain constant in direction throughout time"[13] . This rapidly changing behaviour of direction of causality brings it closer to correlation rather than causation. Because correlation is just an association and associations get its nature changed with minor alterations. On the other hand causal relation is the one which is time tested and should not change its direction even under interventions.

As discussed in chapter two that Granger Causality is deficient on many aspects as a definition of causality but its wide use for drawing causal inferences has made it necessary to analyse it. Although experienced and advanced users of econometrics know the problems in Granger Causality yet common user often misuse

[12] Mentioned in Chapter Three.
[13] Granger (1980)

it and apply it for making causal inferences. Purpose of this chapter is to show that Granger causality is sensitive to minor changes like lag length, sample range, base year change etc. Moreover different causality methods discussed in Chapter3 lead to different causal results.

For example, whether the choice of lag length by the rule of thumb or arbitrary. Not surprisingly, models selected by different statistical criteria yield contradictory conclusions concerning the Granger causal ordering for bivariate cases.
Similarly results for different sample ranges have been tested. The choice for sample range is mainly arbitrary .Nevertheless, in some cases it is based on the evidence of some structural change evident from the graph and also by applying statistical test for structural change. Similarly different causality tests yield different results.
This objective of analyzing the sensitivity of Granger causality has been achieved by selecting few recently published papers from different areas of Economics. These papers mainly deal with the causal hypothesis for export economic growth, energy growth and Saving Growth.

Firstly, the choice of these areas for an empirical investigation of Granger causality is based on the fact that these areas are of utmost importance for the economic development of a country. Although there are many other areas which are important but we think that to have an empirical analysis of causality tests, the three areas we have selected will be sufficient to serve our purpose.

In the first section of the paper we shall analyse energy-growth issue. Increase in the aggregate level of the demand for energy in the last couple of decades makes it important to study the relationship between energy and economic growth for making decision whether energy conservation policies could be opted without having compromise on economic growth. Moreover, energy is also basic input in most of the industrial activities and is of central importance to economic activity.

Enter in the race today or prepare yourself to join it tomorrow if you want to be the part of the race. This is the message which we get from globalisation. So if someone wants to be a part of global economy one has to go for the policy of openness of the economy. So there is no more question on the openness of the economy but whether to go for it right now through export oriented polices or have economic growth first and then openness. For this export led growth or growth led export is widely studied issue in the last two decades. Arguments in both of the cases are very strong. We shall discuss it in the second section of the chapter.

Saving causes economic growth or vice versa is important from the investment point of view. We shall discuss it in the third section of the paper.

Secondly the choice for selection of these papers is based on the availability of the data, their year of publication i.e. not earlier than 2000 and the application of Granger causality tests in a straightforward way along with the policy implications. These papers are as follow:

Wolde Yemane, Rufael (2004) "Disaggregated industrial energy consumption and GDP: the case of Shanghai, 1952-1999" published in Energy Economics.

Love, J. and Chandra, R. (2004) "Testing Export-Led Growth in India, Pakistan and Sri Lanka Using a Multivariate Framework" published in The Manchester School.

Titus, Awokuse, O. (2003) "Is the export-led growth hypothesis valid for Canada?" published in Canadian Journal of Economics.

Anoruo, E. and Ahmad, Y. (2001) “Causal Relationship between Domestic Savings and Economic Growth: Evidence from Seven African Countries” published in African Development Bank.

We shall now analyse these papers one by one in order to highlight the issue that Granger Causality does not meet the criteria of a causal law. Brief introduction and review of literature is given at the beginning of every case study to mention that results are very conflicting on the direction of causality even when they are analysed for the same country.

4.1 Energy Consumption and GDP Growth Causal Analysis

4.1.1 Introduction:

Energy is a key source of economic growth because many production and consumption activities involve energy as a basic input. Energy is one of the most important inputs for the economic development. From a physical viewpoint, the use of energy drives economic productivity and industrial growth and is central to the operation of any modern economy. Barney & Franzi (2002) argue that energy is responsible for at least half of the industrial growth in a modern economy while representing less than one tenth of the costs of production.

Some analysts argue that growth in energy use directly causes growth in GDP. The nature of causal relationship between Energy consumption and Economic growth is one of the hotly debated issues. The energy crises in the 1970’s and consequently higher energy prices slowed down the economic growth. Since the end of the 1970s, the relationship between energy consumption and economic growth has been studied extensively using modern advances in the time series econometric.

Many studies suggest that energy consumption has a high positive correlation with economic growth. Whether economic growth precedes energy consumption or energy consumption boosts the economic growth has been examined in a number of studies, yet empirical evidence is mixed and conflicting.

From policy perspective, the causality in either direction between energy consumption and economic growth may have a significant impact upon energy conservation policies. The energy conservation measures may or may not be taken depending upon the direction of the causality (Rufael, 2006). For example the unidirectional causality from economic growth to energy consumption imply a less energy-dependent economy, therefore, energy conservation policy has no affect on economic growth. But causality from energy consumption to economic growth implies that in energy-dependent economy energy conservation policies may harm the economic growth. No- causality in either direction means energy conservation policy does not affect economic growth. Finally bi-directional causality indicates the high level of economic activity and energy consumption mutually influences each other. Energy consumption and economic growth are highly dependent and energy conservation measures may negatively affect economic growth.

The pioneering study was by Kraft and Kraft (1978).They utilized Sims (1972) approach to find the causal relationship between gross energy inputs and Gross National Product (GNP) for USA using the annual data over the period of 1947 – 1974. They found an evidence of unidirectional causality running from GNP to energy consumption so economic activity may influence energy consumption and energy consumption has no causal influence on economic growth. So energy conservation policy has no impact on economic growth.

Akarca and Long (1980) used the same data over the period of 1947 – 1972 and failed to support the Kraft (1978) results and found no causality between energy consumption and economic growth. So there is no consensus in the causal direction even for the same country with data slightly different i.e. one is using 1947-1972 and another is using 1947-1974. Just use of two more observations has changed the results.

Yu and Jin (1992) used monthly data over the period 1974:1 – 1990:4 for USA and examined the causal relationship between energy consumption, GNP and employment. They do not find any causality between energy consumption and economic growth .They support Akarca and Long (1980) results. Earlier studies of energy-growth relationships focused on the U.S economy; later on these were extended to other countries.

Soytas and Sari (2002)) consider top ten emerging markets. For G-7 countries cointegrating relationship exist. For Turkey, France, Germany and Japan results indicate that in the long run unidirectional causality is from energy consumption to GDP. For Italy and Korea long run unidirectional causality from GDP to energy consumption and for Argentina and Turkey short run bi-directional causality is detected.

Masih (1999) investigate the causal and cointegrated relationship between the total energy consumption and real income of six Asian countries; India, Pakistan, Malaysia, Singapore, Philippines and Indonesia. For India, Pakistan and Indonesia there is cointegrating relationship between the energy consumption and income. For India flow of causality is from energy consumption to income so shortage of energy affects the economic growth and for Pakistan there is mutual causality.

Asafu-Adjaye (2000 found the unidirectional Granger causality running from energy consumption to GDP) for India and in the long run there is unidirectional Granger causality running from energy and price to income.

Aqeel and Butt (2001) for Pakistan consider total energy consumption as well as different component of energy consumption that are Oil, Gas, Coal, Electricity consumption and have checked their causality with economic growth. They found no cointegrating relationship between the variables and there is unidirectional causality running from electricity to economic growth and also from economic growth to the total energy consumption and economic growth to Oil consumption.

Ghosh (2002) found no long run equilibrium relationship between electricity consumption and economic growth for India but found the unidirectional Granger causality running from Economic growth to electricity consumption.

Morimoto and Hope (2004) examined the impact of electricity supply on economic growth in Sri Lanka and found unidirectional causality running from electricity supply to economic growth; therefore, power shortage in Sri Lanka has serious impact on country economic growth.

Bhattacharya (2004) investigated the causality between energy consumption and Economic growth in India and the result of Engle- Granger cointegration combined with standard Granger causality test shows the bi-directional causality between energy consumption and Economic growth.

All these studies and many others bring forward mixed results. Purpose of presenting this brief survey is to show that how Granger causality is widely used in order to study the relationship between energy and economic growth. There is hardly any paper in which attention has been paid to Granger's concept of the extra statistical information[14] in order to break the symmetry between energy and economic growth relationship.

[14] Extra Statistical information means controllability, some natural happening or any other information which could be useful in determining the direction of causality.

Why do these conflicting results arise? Why do results differ when investigated by some other researcher? What we want to establish here is that these causality tests fail to establish causal laws because they are based on associations. Associations get changed with slight changes as it is already mentioned in the beginning of the chapter.

4.1.2 Data and Results

For this purpose we have selected Rufael's (2004) paper and we are thankful to him for providing us data. Rufael (2004) used modified version of Granger causality proposed by Toda and Yamamoto (1995) to examine the causal relationship between different types of industrial consumption and income in Shanghai for 1952-1999.[15] Shanghai which is the richest and fastest growing city in China with the per capita income of $3720 as compared to national average per capita income of $780. There is unidirectional Granger causality running from Electricity, Coal, Coke and total energy consumption to income so reducing energy consumption cause poor economic performance. This implies that energy conservation policies can be implemented without having any slowdown to the economic growth. But no causality between Oil consumption and income supports the neutrality hypothesis meaning that Oil consumption and income are independent. Increase or decrease in Oil consumption has no effect on income. Oil conservation policy does not affect economic growth.

We have replicated the results of Rufael's (2004) paper and our results match with that of the results reported in the paper. These results are reported in the first column of table 4.1. Nevertheless, we shall show how sensitive these results are to slight changes in the data and they fail to maintain causal direction.

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[15] Toda and Yamamoto procedure is given in Ch 2

Results are not only sensitive with respect to sample range but also with respect to lag length. Why do these results contradict? Lets have a look at the graphs. Causal analysis is given in table 4.1 and table 4.2.

Graphical Analysis

Time series plot of all the series hardly indicate any relationship among them. From the Figure 4.1 it is obvious that there are unusual values from 1959-1963. This is the reason that we shall split data into two ranges i-e 1965-1999 and 1952-1999.If we discard the values in the range from 1959-1964 any causal relationship can hardly be established but otherwise we have found that all energy variables are causing economic growth except oil. Oil consumption is increasing very rapidly but it’s very surprising that it has not caused GDP growth or vice versa. Another feature of the data which deserves special attention that for the first data range 1952-1999 (table 4.2) and the third data range 1952-1990 (table 4.2) does not show much difference. This is all because the extreme values in the range 1959-1964 are included in both of the cases. The results and their interpretation are given below.

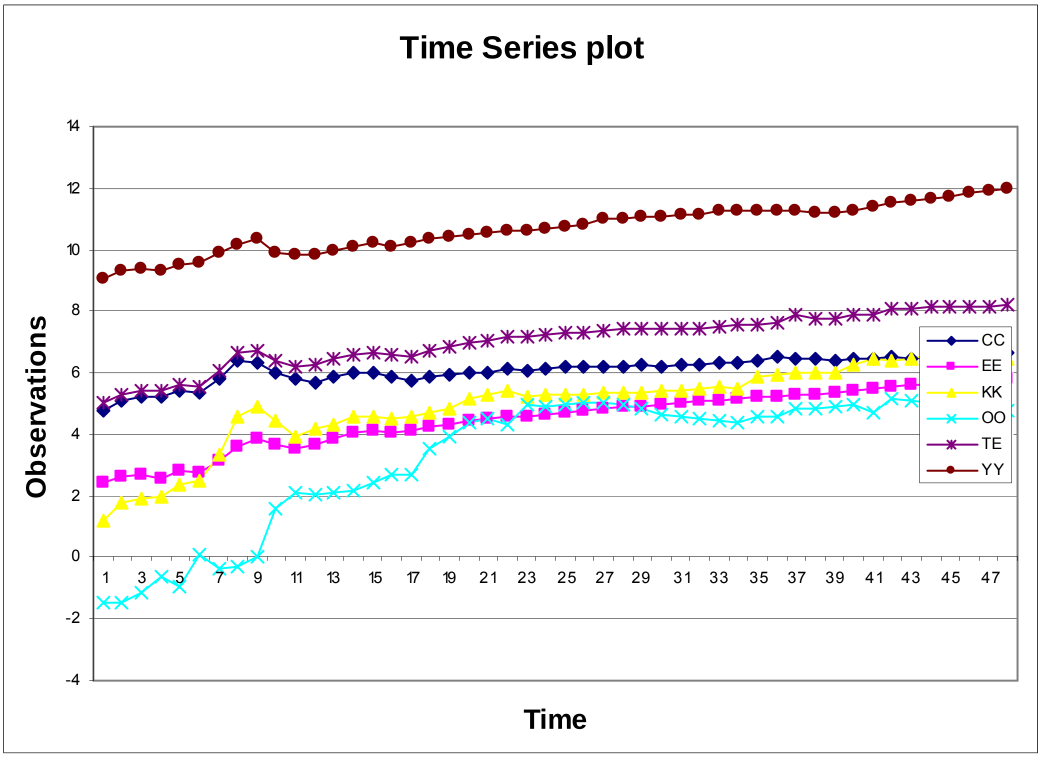

Figure4.1

In the first column of table (4.1) we have the results which match with those of the original paper but in the second column results are completely different.

Table 4.1 (Toda and Yamamoto Procedure)

Results of Causality from 1952-1999(at lag length 4)		
Source	1952-1999(lag4)	1965-1999(Lag4)
CC ⇒ YY	0.000016	0.305372
YY⇒CC	0.222	0.324841
KK⇒YY	0.0019	0.730152
YY⇒KK	0.3525	0.957640
TE⇒YY	0.0032	0.919491
YY⇒TE	0.2461	0.244372
OO⇒YY	0.8968	0.861737
YY⇒OO	0.6975	0.153969
EE⇒YY	0.0018	0.899251
YY⇒EE	0.1050	0.541047

Note: CC, EE, KK, OO, TE and YY are the logs of coal, electricity, coke, oil, total energy consumption and real GDP respectively. The numbers in the table are the p-values.

These results are by Toda and Yamamoto (T&Y) procedure for two different sample ranges but lag length remains same. One could easily observe that for the data set 1952-1999 there is a strong indication that all the energy sources are granger cause of economic growth but OO. In case of second data set there is no such evidence available so it's hard to conclude that energy consumption causes economic growth or for even that matter it always precede economic growth.

A causal law should be the one that is time tested and should not change its nature by slight alterations in the data set.

As the above results are based on T&Y procedure and the author has used ADF (GLS) to find the order of integration and it was observed that all series are I(1). Now if we apply simple ADF test we find no evidence of non-stationarity therefore we have also used Granger method for finding the direction of causation. These results are as follows:

P- Values are given for three different data ranges and for three different lag lengths. Results keep on changing with these variations. For example results for cc⇒yy are very interesting to observe for the 1965-1999 period. They are highly significant for this period and change with lag length while in other cases results are not very significant for this particular period. Similarly comparisons can be made with T&Y procedure.

Table 4.2 (Granger Causality)

Pair wise Granger Causality Tests				
	Sample Range	1952 1999	1965-1999	1952-1990
Source	Lags:	Probability	Probability	Probability
CC⇒YY	4	0.000	0.018	0.000
CC⇒YY	3	0.00061	0.50	0.0031
CC⇒YY	2	0.009	0.53	0.018
YY⇒CC	4	0.009	0.068	0.056
YY⇒CC	3	0.013	0.007	0.071
YY⇒CC	2	0.01	0.002	0.06
EE⇒YY	4	0.002	0.27	0.002
EE⇒YY	3	0.07	0.33	0.14
EE⇒YY	2	0.46	0.33	0.61
YY⇒EE	4	0.182	.56	0.306
YY⇒EE	3	0.212	0.72	0.34
YY⇒EE	2	0.14	0.89	0.21
KK⇒YY	4	0.003	0.53	0.003
KK⇒YY	3	0.0015	0.33	0.003
KK⇒YY	2	0.39	0.49	0.46
YY⇒KK	4	0.196	0.74	0.30
YY⇒KK	3	0.3	0.77	0.3
YY⇒KK	2	0.24	0.75	0.34
TE⇒YY	4	0.004	0.017	0.003
TE⇒YY	3	0.024	0.183	0.03
TE⇒YY	2	0.62	0.29	0.56
YY⇒TE	4	0.321	0.25	0.34
YY⇒TE	3	0.22	0.14	0.31
YY⇒TE	2	0.19	0.31	0.25
OO⇒YY	4	0.95	0.93	0.624
OO⇒YY	3	0.634	0.96	0.18
OO⇒YY	2	0.33	0.72	0.08
YY⇒OO	4	0.80	0.24	0.703
YY⇒OO	3	0.685	0.103	0.47
YY⇒OO	2	0.82	0.27	0.52

Note: ⇒ stands for casual direction: CC, EE, KK, OO, TE and YY are the logs of coal, electricity, coke, oil, total energy consumption and real GDP, respectively. The numbers in the table are the p-values.

4.2 Export Growth Causal Analysis for Major economies of South Asia

We have considered the same variables as that of Love and Chandra (2004) in order to show that how our results are different from those of Love and Chandra despite the fact that we have same source of the data and defined the variables in the same manner except that the base year is different. In our case base year is 2000 rather than 1995 as was used by Love and Chandra.

In the following section some brief analysis of export economic growth relationship by highlighting conflicting results about Export Led Growth (ELG) and Growth Led Export (GLE) hypothesis and the sensitivity of causal relationship has been given.

4.2.1 Introduction

There is little consensus on the nature of relationship between exports and national output. A central question in this debate is whether strong economic performance is export led or growth driven. This question of determining causal pattern between export and growth is very important for policy makers' decisions about the appropriate growth and development strategies and policies.

There is strong correlation between export and economic growth. Many investigate whether this association can be translated into causal relationship. Early cross-sectional studies (e.g. Michaely1970s; Blassa 1978; Heller and Porter, 1978; Tyler, 1981; Feder, 1983), suggested that export promotes overall economic growth. But to determine causal relationship between the export growth and the GDP growth within a country requires a time series analysis. Using Granger causality many researchers have tried to determine the direction of causality.

There could be three possible relations between the economic growth and the export namely: Export led growth, growth driven export and two way relationship that I term feedback. Early work on this started in the second half of 1970's (Michael 1997; Blassa, 1978; Tyler, 1981; Kormeudi and Meguire, 1985). But all this work on export led growth hypothesis was for static cross-country comparison. In these studies it was presumed export causes economic growth and output growth used to be regressed on the export growth along with additional variables like growth of labour force. There was a priori assumption that export is exogenous and the economic growth an endogenous variable and that export would cause economic growth if its coefficient comes out to be statistically significant. Possible simultaneity between export and economic growth had been ignored and OLS was simply used to determine the statistical significance of export growth variable, if it happened so causality from export growth to economic growth was established.

Kravis (1970) pointed out that this is dynamic process: as he puts it, is exports handmaiden or the engine of growth? To address this dynamic question, economists started using time series data to investigate these hypothesis for single countries and there are a number of papers in 80s and 90s (Jung and Marshall, 1985; Chow, 1987; Serletis, 1992; Kunst and Marin, 1989; Marin, 1992; Afxention and Serletis, 1991; Reizman et al; 1996).While discussing that whether ELG or Growth led export hypotheses, Irene Henriques and Sadrosky (1996) write that the proponents of ELG argue that growth of export has a stimulating influence across the economy as a whole in the form of technological spill over and other externalities. Models by Grosman and Helpman (1991), Riveria-Batiz and Romer (1991), and Romer (1991) posit that expanded international trade increases the number of specialized imports, increasing growth rates as economics become open to international trade.

In contrast to the above point of view, Giles and Williams (2000) summaries GLE view as "Bhagwati (1988) postulates that Growth led export are likely, unless antitrade bias results from the growth-induced supply and demand. Neoclassical trade theory supports this notion, as it suggests that other factors aside from exports are responsible for output growth (e.g. primary input growth and/ or factor productivity growth). GLE orthodoxy is justified by, for instance, Lancaster (1980) and Krugman (1984); economic growth leads to enhancement of skills and technology, with this increased efficiency creating a comparative advantage for the country that facilitates exports, Market failure, with subsequent government intervention, may also result in GLE."

"There are two views in presence on the economic foundations linking exports and GDP. First, there is a Keynesian view, which is that exports, being an important component of aggregate demand and largely determined by foreign variables cause GDP. This view is fairly standard among macroeconomists. Second, there is a neoclassical view, which is also the standard international trade theory approach, that in a small open economy, exports are supply determined: domestic factor endowments and technology determine production possibility frontier. Given the terms-of-trade and tastes, the output mix, the consumption mix, and exports and imports are determined by the principle of comparative advantage. In such a framework an increase in domestic factor endowments or an improvement in technology shift the production possibility curve outward and increase GDP. Under these conditions, one would expect the supply of exports to grow as well. According to the neoclassical view GDP and exports tend to be caused by the same factor (i.e. factor endowments, technology, and the terms of trade)"

Kaldor (1967) said that higher economic growth naturally leads to faster imports growth, and that ultimately necessitate greater export growth to avoid the balance of payment deficits that could hinder future economic growth. Greater export growth is made possible by an important outcome of economic growth – increased productivity. The important linkage from productivity and exports is discussed next. Kaldor (1967) noted Productivity increases lead to low unit costs resulting, an improved competitiveness that makes it easier to increase sales abroad. In Kaldor's arguments, productivity increases can arise as economic growth allows greater utilization of economics of scale. In Veron's (1966) product cycle theory, economics of scale may be exploited through mass production for a manufacturing product to commitment on product standards. The originating country (that is developing the product) is also hypothesized to export more during the maturing period. This occurs due to there being increasing demand in other countries for the product when the cost of procuring and shipping the product from the originating country to the others is cheaper than producing the product in those countries.

Jung and Marshall (1985) carried out analysis for ELG or GLE for 37 countries. Jung and Marshall (1985) analyze the relationship between the growth rate of real experts and the growth rate of real output, for 37 developing countries. Depending on Granger causality, Jung and Marshall find evidence for the export led growth in only 4 out of the 37 countries: Indonesia, Egypt, Cost Rica and Ecuador.

They claim that "ELG is not very strong as was claimed by previous studies. Jung and Marshall claim that in all the previous studies where ELG hypothesis hold are based on the argument that export growth is causally prior to output growth. They write "such an approach contains a serious methodological weakness. Although the hypothesis of export promotion clearly implies a correlation between real export and real GNP growth, so do other hypothesis with quite different implications. Whether export growth may lead to out put growth, an equally plausible hypothesis is that output growth causes export growth.

All this discussion is sufficient to argue that causality between export and growth may run in any direction or there can be feedback mechanism. Jung and Marshal (1985) while testing for direction of causality say that in the absence of any statistical tools they rely on the temporal predictability and consider it as an indication of causation for export-growth causal analysis. This temporal predictability could be spurious and one needs to see whether it survives test of robustness i-e. Does not change with slight changes in data, lag length, base period change? I have shown that this predictive analysis is often spurious and very sensitive to minor changes which should be unusual in time series data.

All empirical investigations are based on the hope that only in this way one can find causal direction between these variables. This is exactly what has been implied in Granger causality. It tries to address the issue of causality merely on statistical ground.

Bahmani – Dskoce et al (1991) examine 20 less developed countries (LDCs), all of which are also studies by Jung and Marshall. The two papers reach at different results for most of the countries but Indonesia. Our study is restricted for major economies of South Asian region which include Bangladesh, India, Pakistan and Sri Lanka.

There are very few studies on this subject for **South Asia**. Nevertheless, there are some studies for the case of India (Love (1992), Dhawan and Biswal (1999), Chandra (2000)) .Love and Chandra (2004) studied this relationship for India, Pakistan and Sri Lank and Love and Chandra (2005) for the whole South Asian Region. There is hardly any consensus for either ELG or GLE for India. Most of these researchers have extended their studies to multivariate framework. For example, Dhawan and Biswal (1999) investigate ELG for India by using three variables; real

GDP, real exports and terms of trade by constructing VAR models. They conclude that the causality from exports to GDP appears to be short run phenomena.

Asafu – Adjaye and Chakraborty (1999) consider these variables; exports, real output and import for India but find no evidence of the existence of causal relationship.

Love and Chandra (2004) have studied causal relationship between real output, real GDP and terms of trade for the three South Asian countries. They have applied "Error Correction Mechanism" procedure to investigate the causal relationship. They found bidirectional causality between real exports and real income in India, export – led growth in Pakistan and a non-causality result for Sri Lanka. Interestingly Love and Chandra (2005) find contradictory results from their last year paper for Pakistan, India and Sri Lanka by using the same co-integration and error corrections modeling approach and their data source is also the same. Nevertheless, they have extended their studies for the whole South Asian region. We have shown that Granger causality fails in establishing any causal law among the export growth and is highly sensitive to very minor changes.

4.2.2 Data and Results

We have used yearly data for India (1955-2002), Pakistan (1970-2003), Sri Lanka (1955-2002) on GDP, Export, Unit Value of Export and Imports, and GDP deflator from the International Financial Statistics website ifs.apdi.net.

The variables I have used are real export, real GDP and real terms of trade. A term of trade variable is not available for Bangladesh, so I have excluded it from our study. Y is used for real GDP which is obtained as the ratio of GDP to GDP deflator, X (real export) is obtained as the ratio of export value of goods and services to unit value of export, and tt (terms of trade) is defined as the ratio of unit value of exports to unit value of import. All the data are annual and variables are in log form.

The first step was to see whether variables are stationary or not because the procedure mentioned below needs to augment the equation by the maximum order of integration. Therefore unit root tests by using ADF tests have been carried and their results for all the three countries are reported in the table named ADF test for unit root. The lag length selection in applying ADF test is determined by making the residuals serially independent. To carryout Granger causality testing we have used Toda and Yamamoto procedure which is given in chapter 3.

Appendix is attached for results in detail. All analysis has been carried out using EVIEWS package.

Table 4.3, 4.4 and 4.5 are Augmented Dickey Fuller Tests for unit root testing for Pakistan, India and Sri Lanka respectively. In all the three countries all the variables are first difference stationary but export in case of Pakistan. Therefore, for Pakistani data there is no need for testing cointegration because for cointegrating relationship all variables should be integrated of the same order.

Table 4.6 and 4.7 are Granger causality results by Toda and Yamamoto procedure for two different sample ranges for Pakistan. Export seems to Granger cause economic growth for the sample range (1970-2003) in table 4.6 but the two lag selection criteria contradict .Which criteria to use is crucial and obviously lead to different results. Results in table 4.7 (1974-2003) indicate no causality from export to economic growth at all lags. Results for causal direction from Y to X are not reported because for both sample range data does not support any causality from economic growth to export.

Terms of trade, which are considered by many researchers as an important variable to be included in the model while studying export output relationship, does not play any significant role in predicting export or economic growth.

Johansen cointegration test has been carried out both for Indian and Sri Lankan data but there is no long run relationship observed. So we have used the Toda and Yamamoto causality testing for these two countries. Results can be interpreted for India and Sri Lanka as that of Pakistan .In a gist what we observe that results keep on changing with change of sample range, lag length and base year change .We have used data with year 2000 as base year and our results are different than those of Chandra and Love (2004) despite the fact that all things are the same but base year.

Similarly for multivariate case results seem sensitive with respect to lag length for the case of Pakistan .In case of India results show no such sensitivity in multivariate case.

ADF Tests for Unit Roots

Table 4.3 Pakistan 1970-2003

Test Statistics			95% critical values	
Variable	**Levels**	**First Differences**	**Levels**	**First Differences**
LRX	-4.079(1)		-3.58	
LRY	-0.4787(1)	- 4.36(0)	-3.55	-2.9558
LRTT	-2.436(1)	-5.23(0)	-2.9558	-2.9591

Table 4.4 India 1955-2002

Test Statistics			95% critical values	
Variable	**Levels**	**First Differences**	**Levels**	**First Differences**
LRX	-0.3540(1)	-6.1432(0)	-3.51	-2.9256
LRY	-0.9874 (1)	-7.11(0)	-3.51	-2.9256
LRTT	-1.6658(3)	-5.87(2)	-2.93	-2.93

Table 4.5 Sri Lanka 1965-1997

Test Statistics			95% critical values	
Variable	**Levels**	**First Differences**	**Levels**	**First Differences**
LRX	-1.5273(4)	-3.3205(3)	-3.58	-3.567
LRY	-3.1515(2)	-6.2855(0)	-3.58	-2.963
LRTT	-2.496(2)	-5.17(1)	-2.963	-2.9627

Table 4.6 Results for Pakistan 1970-2003

Causal Direction	Lag Length	P-Value	AIC	SC
X⇒Y	(2,2)	0.0174	-5.1070	-4.878
X⇒Y	(2,3)	0.4955	-5.1359	-4.8584
X⇒Y	(3,3)	0.5607	-5.077	-4.7537

Table 4.7 Results for Pakistan 1974-2003

Causal Direction	Lag Length	P-Value	AIC	SC
X⇒Y	(2,2)	0.7524	-5.096	-4.8584
X⇒Y	(2,3)	0.7720	-5.079	-4.7920
X⇒Y	(3,3)	0.850	-5.011	-4.6752
X⇒Y	(3,4)	0.574	-5.2142	-4.8271
X⇒Y	(3,3)	0.850	-5.011	-4.6752

Table 4.8   Results for Pakistan in Multivariate Framework

Lag2	GDP	Export	TOT
GDP	_____	0.0266	0.8197
Export	0.3586	_______	0.1996
TOT	0.7071	0.0458	_______

Lag3

GDP	_____	0.7226	0.6455
Export	0.6390	_______	0.3592
TOT	0.4532	0.0039	_______

The numbers in the table are the p-values. AIC stands for Akaike Information Criteria and SC for Schwartz criteria.

Table 4.9   Results for India 1955-2002

Causal Direction	Lag Length	P-Value	AIC	SC
X⇒Y	(2,2)	0.0547	-4.23	-4.03
X⇒Y	(2,3)	0.1346	-4.24	-3.99
X⇒Y	(2,4)	0.3361	-4.17	-3.88
X⇒Y	(3,3)	0.097	-4.2662	-3.98
X⇒Y	(1,3)	0.1049	-4.2661	-4.06
X⇒Y	(1,2)	0.038	-4.2389	-4.079

Table 4.10   Results for India   1955-1998

Causal Direction	Lag Length	P-Value	AIC	SC
X⇒Y	(2,2)	0.0317	-4.187	-3.9806
X⇒Y	(2,3)	0.0653	-4.201	-3.9504
X⇒Y	(3,3)	0.0437	-4.2390	-3.9465

Table 4.11 India in Multivariate Framework

Results for the data range 1955-2002

Source	Lag	GDP	X	TOT
GDP	2		0.201	0.621
	3		0.118	0.868
	4		0.306	0.935
X	2	0.293		0.049
	3	0.084		0.114
	4	0.367		0.200
TOT	2	0.346	0.360	
	3	0.402	0.306	
	4	0.254	0.218	

The numbers in the table are the p-values.

Table 4.12 Results for Sri Lanka 1965-1997

Causal Direction	Lag Length	P-Value	AIC	SC
X⇒Y	(2,2)	0.6152	-2.2268	-1.996
X⇒Y	(2,3)	0.6308	-2.169	-1.889
X⇒Y	(2,4)	0.8112	-2.07	-1.741
X⇒Y	(3,3)	0.6278	-2.1059	-1.779
X⇒Y	(1,3)	0.5419	-2.2033	-1.97
X⇒Y	(1,2)	0.307	-2.2695	-2.0845

From Y to X 1965-1997

Causal Direction	Lag Length	P-Value	AIC	SC
Y⇒X	(2,2)	0.889	-0.9224	-0.6911
X⇒Y	(1,2)	0.687	-0.9820	-0.7970
X⇒Y	(3,3)	0.992	-0.7508	-0.4239
X⇒Y	(2,3)	0.9959	-0.8169	-0.5367

Table 4.13 Results for Sri Lanka 1970-1997

Causal Direction	Lag Length	P-Value	AIC	SC
X⇒Y	(2,2)	0.6432	-2.183	-1.945
X⇒Y	(2,3)	0.6426	-2.1344	-1.85
X⇒Y	(2,4)	0.8347	-2.063	-1.73
X⇒Y	(3,3)	0.6278	-2.063	-1.73
X⇒Y	(1,3)	0.5513	-2.1632	-1.925
X⇒Y	(1,2)	0.2889	-2.220	-2.030

4.2.3 Comparison of Different Causality Methods[16]

Different studies use different causality tests and in this section we have used more than one method (where applicable). The objective of using more than one causality test is to compare the results of different causality methods with respect to lag length, sample time period and functional form of the model . We observe that causal direction varies from one approach to the other. We have compared most commonly used methods which are Granger causality test, Error Correction Mechanism (Granger 1987), and Toda and Yamamoto

Results for India

In table 4.14 we summarize the results of bivariate version of different causality tests. Granger and TY test only favour the export led growth hypothesis. Granger and T&Y tests provide different results implying sensitivity of the granger causality under different lag length. All other null hypotheses of non-causality are accepted at 5% significance level.

In table 4.14 we summarize and compare the results of different causality tests in multivariate framework. Granger test only support the export led growth hypothesis. TY test show insignificant results. While ECM under lag length one and two shows that real income (Y) and terms of trade (Z) granger causing real exports

[16] Courtesy to Mr.Yousaf , one of my student for helping me in this section.

(X) in the long run. Further ECM at lag length one shows that real exports (X) and real income (Y) cause terms of trade (Z) in the long run.

Table 4.14 Comparison in Multivariate Case for testing Granger Causality, India (1950-2002)

Null Hypothesis	Granger test		TY test		Error Correction Model			
	Lag length		Lag length		Lag length			
	P-values							
	One	Two	Two	Four	One	EC term	Two	EC term
X does not granger cause Y	0.041	0.0880	0.0637	0.3215	0.0723	0.5619	0.1956	0.1813
Z does not granger cause Y	0.213	0.540738	0.2616	0.7542	0 .3054		0.5602	
Y does not granger cause X	0.2371	0.188188	0.3014	0.2985	0.2978	0.0023	0.0629	0.00023
Z does not granger cause X	0.67935	0.4850	0.9979	0.2465	0.6394		0.88956	
Y does not granger cause Z	0.3018	0.284153	0.66730	0.1716	0.1771	0.00370	0.2286	0.6790
X does not granger cause Z	0.7083	0.064431	0.2394	0.0645	0.6628		0.26840	

Now we present the results for India covering the time period (1950-1990). In table 4.15 the results of two causality tests are presented by using multivariate version of these tests. T&Y test shows that real export (X) is significant in terms of trade (Z) equation by using lag length three. While the results of ECM indicates that real export (X) and real income (Y) granger causes terms of trade (Z). By observing the above results we can say that granger causality is sensitive to time period covered.

Table 4.15 Comparison in Multivariate Case for testing Granger Causality, India (1950-1990)

Null Hypothesis	TY test		Error Correction Model	
	Lag length		Lag length	
	Two	Three	One	EC term
	P-values			
X does not granger cause Y	0.1180	0.3033	0.24496	0.999
Z does not granger cause Y	0.0804	0.32008	0.0964	
Y does not granger cause X	0.4207	0.3945	0.7570	0.821
Z does not granger cause X	0.4308	0.92356	0.4189	
Y does not granger cause Z	0.3464	0.4108	0.2958	0.0000
X does not granger cause Z	0.0844	0.00762	0.0549	

Results for Pakistan

From ADF test for unit root, it is observed that real export X is stationary at level and real GDP and terms of trade are stationary at first difference. So we apply Granger causality and T&Y procedure. Granger test indicates that export causes economic growth. T&Y test, that uses the modified Wald test statistic, shows that export growth (X) variable is significant in terms of trade (Z) equation. Thus, we observe that the results of the two tests vary while using different causality tests and different lag lengths. In table 4.17 we compare the results of the different causality tests in multivariate framework. Granger causality test by using lag length one and two showing significant results in favour of export led growth hypothesis. While Granger test with lag length two and T&Y test with lag length three showing that export growth (X) is significant in terms of trade equation.

Table 4.16 Comparison in bivariate Case for testing Granger Causality, Pakistan (1970-2003)

Null Hypothesis	Granger test		T&Y test	
	Lag length		Lag length	
	one	two	three	four
	P-values			
X does not granger cause Y	0.0389	0.024782	0.3324	0.3931
Y does not granger cause X	0.5191	0.9922	0.9846	0.9678
X does not granger cause Z	0.6690	0.036172	0.001522	0.00075
Z does not granger cause X	0.9563	0.20147	0.2054	0.31739
Y does not granger cause Z	0.1483	0.7187	0.5319	0.1666
Z does not granger cause Y	0.2840	0.53259	0.8477	0.43578

Table 4.17 Comparison in Multivariate Case for testing Granger Causality, Pakistan (1970-2003)

Null Hypothesis	Granger test		T&Y test	
	Lag length		Lag length	
	One	Two	Three	Five
	P-values			
X does not granger cause Y	0.0494	0.037979	0.29689	0.26430
Z does not granger cause Y	0.3555	0.6446	0.82536	0.29150
Y does not granger cause X	0.5219	0.864	0.902632	0.92023
Z does not granger cause X	0.9127	0.1984	0.23612	0.30704
Y does not granger cause Z	0.1172	0.695	0.755127	0.18429
X does not granger cause Z	0.433	0.044075	0.017008	0.08114

Now we split data into time period 1970-1998 to observe that whether causal direction sustains for this time period or not. Both T&Y and ECM methods in table 4.18 show no support for export led growth hypothesis. In T&Y test only export variable is significant in terms of trade equation. The results of ECM showing that in both short run and long run exports(X) and real income (Y) granger causes terms of trade (Z).

Table 4.18 Comparison in Multivariate Case for testing Granger Causality, Pakistan (1970-1998)

<table>
<tr><td rowspan="4">Null Hypothesis</td><td colspan="2">T&Y test</td><td colspan="2">Error Correction Model</td></tr>
<tr><td colspan="2">Lag length</td><td colspan="2">Lag length</td></tr>
<tr><td>Three</td><td>Five</td><td>three</td><td>EC term</td></tr>
<tr><td colspan="4">P-values</td></tr>
<tr><td>X does not granger cause Y</td><td>0.51773</td><td>0.8416</td><td>0.990</td><td rowspan="2">0.273</td></tr>
<tr><td>Z does not granger cause Y</td><td>0.86304</td><td>0.48509</td><td>0.6340</td></tr>
<tr><td>Y does not granger cause X</td><td>0.66174</td><td>0.9704</td><td>0.9619</td><td rowspan="2">0.419</td></tr>
<tr><td>Z does not granger cause X</td><td>0.46044</td><td>0.94279</td><td>0.5287</td></tr>
<tr><td>Y does not granger cause Z</td><td>0.52335</td><td>0.6110</td><td>0.034</td><td rowspan="2">0.0118</td></tr>
<tr><td>X does not granger cause Z</td><td>0.00586</td><td>0.3420</td><td>0.0042</td></tr>
</table>

Results for Sri Lanka

T&Y test shows lack of causality among variables in either direction by using lag length two and three. Summary of the results for Sri Lanka is given in Table 4.19 and Table 4.20.

Table 4.19 Comparison in a bivariate Case for testing Granger Causality: Sri Lanka (1965-1997).

Null Hypothesis	Granger test		TY test	
	Lag length		Lag length	
	one	two	Two	three
	P-values			
X does not granger cause Y	0.5781	0.634334	0.8803	0.953755
Y does not granger cause X	0.9533	0.981354	0.9699	0.989076
X does not granger cause Z	0.0218	0.205340	0.0624	0.247141
Z does not granger cause X	0.0421	0.164624	0.0721	0.316979
Y does not granger cause Z	0.7451	0.852582	0.7945	0.999752
Z does not granger cause Y	0.7502	0.948302	0.9191	0.901953

Table 4.20 Comparison in a Multivariate Case for testing Granger Causality, Sri Lanka

<table>
<tr><th rowspan="4">Null Hypothesis</th><th colspan="2">Granger test (1965-1997)</th><th colspan="2">T&Y test (1965-1997)</th><th colspan="2">TY test (1965-1990)</th><th colspan="2">ECM(1965-997)</th></tr>
<tr><th colspan="2">Lag length</th><th colspan="2">Lag length</th><th colspan="2">Lag length</th><th colspan="2">Lag length</th></tr>
<tr><th>One</th><th>Two</th><th>Two</th><th>Three</th><th>Two</th><th>Three</th><th>Two</th><th>EC term</th></tr>
<tr><th colspan="8">P-values</th></tr>
<tr><td>X does not granger cause Y</td><td>0.499</td><td>0.606</td><td>0.933</td><td>0.965</td><td>0.489</td><td>0.703</td><td>0.987</td><td rowspan="2">0.1651</td></tr>
<tr><td>Z does not granger cause Y</td><td>0.612</td><td>0.877</td><td>0.911</td><td>0.969</td><td>0.854</td><td>0.920</td><td>0.672</td></tr>
<tr><td>Y does not granger cause X</td><td>0.801</td><td>0.880</td><td>0.759</td><td>0.939</td><td>0.626</td><td>0.852</td><td>0.831</td><td rowspan="2">0.6608</td></tr>
<tr><td>Z does not granger cause X</td><td>0.044</td><td>0.170</td><td>0.256</td><td>0.874</td><td>0.117</td><td>0.6133</td><td>0.402</td></tr>
<tr><td>Y does not granger cause Z</td><td>0.020</td><td>0.120</td><td>0.069</td><td>0.290</td><td>0.096</td><td>0.359</td><td>0.536</td><td rowspan="2">0.0170</td></tr>
<tr><td>X does not granger cause Z</td><td>0.001</td><td>0.032</td><td>0.0105</td><td>0.047</td><td>0.076</td><td>0.329</td><td>0.157</td></tr>
</table>

We observe that the varying results show that causality conclusions are sensitive to the different causality tests used, to the lag length specification of the model.

4.2.4 Conclusion

Most of the work on export led growth hypothesis is either based on cross country regression or time series analysis using Granger causality for the individual country. In the former case it was presumed that export causes economic growth and output growth used to be regressed on export growth. In the latter case economists used granger causality tests to determine the direction of causality without any assumption that which variable is the cause of another. But most of these causal relationships are mainly derived from associations which exist among variables like export, income, terms of trade etc. Whether these associations can be translated into causal relations is a very gigantic task which can not simply be determined from applying Granger causality tests. A causal relationship is the one which is not sensitive to small changes in the data and is time tested. Correlation structure on the other hand is very sensitive to structural changes or to slight changes in the data. This is exactly what has happened in our case. This sensitivity of correlation structure probably explains that why results differ from one study to another on Export-Growth relationship.

We are thus led to the conclusion that the empirical results are highly sensitive to the use of data at varying sample range, lag length, base year change etc. So we are left with uncomfortable result that a major substantive hypothesis, albeit boldly formulated, is by and large not substantiated by our empirical findings. There is very weak evidence that in some cases export helps in predicting economic growth as is shown in table 4-6. We have shown in this section that ELG hypothesis can not be established in the case of South Asia. So the general conclusion that developing countries like those of the SAARC region should promote export oriented policies by exploiting all available resources can be made on the common observation rather on these types of causal analysis.

4.3 Export led growth hypothesis for Canada

We are thankful to T.O. Awokuse for providing us data set. We have analyzed this data set at two different sample ranges. Problem of aggregation which may occur if we analyze this data at annual frequency has been skipped from the analysis.

Lags are set 5 because max order of integration for all the variables is one and secondly Awokuse selected lag length equal to 5.

Table 4.21 1961:1 2004:4

Lag Length 5

Source	Y	X	L	K	IP	TOT
Y	___	0.0795	0.0541	0.7985	0.0000	0.8685
X	0.2177	_____	0.0421	0.0932	0.0055	0.0906
L	0.0192	0.0096	0.4300	______	0.0001	0.5278
K	0.8910	0.9525	0.2801	_______	0.9264	0.9061
IP	0.0767	0.2514	0.0339	0.3928	______	0.9792
TOT	0.8647	0.2042	0.8299	0.9603	0.5708	_______

Table 4.22 Data range1961:1 2000:4

Source	Y	X	L	K	IP	TOT
Y	______	0.1612	0.1515	0.0029	0.0011	0.9894
X	0.0096	______	0.2196	0.0350	0.0414	0.6188
L	0.0504	0.0937	_______	0.0193	0.0023	0.5551
K	0.3511	0.3236	0.0075	______	0.0593	0.3936
IP	0.0593	0.3936	0.1164	0.0090	_______	0.8233
TOT	0.9224	0.0054	0.8394	0.2518	0.4445	______

One can observe clear differences in these two above tables which indicate that it’s not possible to find the direction of causation with the help of Granger causality. For example in case of data 1961:1 2000:4 we don't find any evidence that export or employment is causing the real GDP but these two seem to Granger cause for the data range 1961:1 2004:4. Similarly gross capital formation is Granger causing real GDP for the data set 1961:1 2000:4 but not for the other. This means that results change so quickly it is hardly possible to design any meaningful policy. Or in other words Granger causality is not an appropriate technique to determine the direction of causation and any policy implemented on the basis of this technique will not lead us to anywhere.

4.4 Saving Economic Growth Causal Analysis

4.4.1 Introduction

In this section we have analysed the results for seven African countries on Saving Economic Growth. We have recently seen a paper accepted in Economic Bulletin by Mohan but due to non availability of data related to some of the we have not been able to analyse it .Mohan (2006) like other conventional users of Granger causality has tried to trace the direction of causation from simple Granger test without keeping in mind the true sense of Granger causality. This actually verifies our point of view that Granger causality is misused in Economics and has very serious repercussions for the policy makers.

Mohan (2006) writes that "Mavarotas and Kelly (2001) used Toda and Yamamoto method to test for Granger causality. Using data for India and Sri Lanka, the relationship among gross domestic product, gross domestic savings and private saving was examined in this study. The authors found no causality between GDP growth and private savings in India. However, bi-directional causality was found for Sri Lanka". Sinha (1999) found unidirectional causality from growth rate of gross domestic savings to economic growth rate. Which of these two studies for Sri Lanka should be taken as benchmark by the policy is an open ended question.

Similarly for Korea results of Mohan (2006) are different than those of Baharrumshah et al. (2003). Latter find no evidence for direction of causality and the former find it from GDP growth to saving growth. Why these results differ?

"Policy makers, including the World Bank, have long advocated policies that lead to higher savings in order to boost economic growth for developing countries. The question that may arise is whether high savings actually promote economic growth, especially for countries with nascent economies. The recent financial crisis witnessed by the East Asian countries has cast further doubt on the viability of the earlier growth models. Prior to the crisis, a number of Asian leaders, world leaders, as Ill as economists, praised the region's high savings rate, which was among the highest in the world. The idea seemed to be that a high saving rate would engender economic growth and thus reduce the region's reliance on the foreign capital for its economic development projects. This assertion proved to be wrong because despite the impressive savings rate among East Asian countries, their economies still collapsed and their dependency on foreign capital never abated"[17]

4.4.2 Data and Results

There are seven African countries whose data is analyzed in this paper. Our Augmented Dickey fuller test results are almost the same as that of the paper. As far as the issue of long run binding relationship between economic growth and saving is concerned I do not find any evidence of cointegration. I have used both Granger and Johansen procedure to test for cointegration. Results of Granger Causality are reported in table 4.24. Residuals in all of these cases are nonstationary at 5% and 1% level of significance and the graph of these residuals is displayed in the appendix.

[17] (Anoruo and Ahmad 2001)

Due to absence of any cointegrating relationship we have applied Toda and Yamamoto procedure and have not found any Granger causality evidence but South Africa. Only in case of South Africa there is an evidence of GDP causing savings. In all other cases there is no such evidence. More important to note is that in case of South Africa it's the saving which is Granger causing GDP and not vice versa .This verifies the previously established theory and does say nothing as is claimed in the introduction of the paper by the authors. However, our purpose in this paper is to show the sensitivity of the Granger Causality results. There is only Granger causal relationship for only one country of the African countries but even this does not stand for causal law because as we break this data into two parts mainly on the basis of Chow structural break point tests (e.g. 1975). Results show no Granger Causality for these two separate parts of data set. All this is sufficient to show that Granger causality can produce nonsense results if I go in depth data analysis.

Graph for the residuals obtained by regressing growth on saving for different countries are reported below to indicate that all these seem not to i.i.d which means that there is no cointegrating relation among these variables.

Table 4.23 Results of ADF test

ADF Test Statistic	
RCIV	-2.745483
RCOG	-2.867973
RKEN	0.041045
RNGA	-1.065291
RZAF	-2.338062
RZMB	-3.641579
RGHA	-1.236053

CIV: Cote de Ivories Coast COG: Congo

KEN: Kenya NGA: Nigeria ZAF: South Africa ZMB: Zambia GHA: Ghana

As the variables are not cointegrated but all are non-stationary at level so we have applied Toda and Yamamoto procedure for testing causality. There is no causality between saving and economic growth in five countries and there is weak evidence on Nigeria that saving causes economic growth. For South Africa there is feedback relationship between saving and economic growth but results are not robust in case of South Africa over different sample periods.

Table 4.24 Results of Toda and Yamamoto Procedure

Country	Sample Range	Causal Direction	p-value
COG	1960-1997	G→S	0.2848
	1960-1997	S→G	0.3547
CIV	1960-1997	G→S	0.2168
	1960-1997	S→G	0.8147
GHA	1960-1997	G→S	0.4078
	1960-1997	S→G	0.0721
KEN	1960-1997	G→S	0.6767
	1960-1997	S→G	0.3073
NGA	1960-1997	G→S	0.7692
	1960-1997	S→G	0.0589
SA	1960-1975	S→G(2,2)	0.0000
	1960-1975	S→G(3,3)	0.0012
	1976-1997	G→S (3,3)	0.4331
	1976-1997	G→S(2,2)	0.1412
ZMB	1960-1997	S→G	0.2033
	1960-1997	G→S	0.8889

CIV: Cote de Ivories Coast   COG: Congo

KEN: Kenya   NGA: Nigeria   ZAF: South Africa   ZMB: Zambia

GHA: Ghana

From the results and the discussion about them, we can easily verify that most of the researchers have started misusing Granger Causality either knowingly or unknowingly. Conflicting results are the hallmark of these studies. Same data sets when analysed by a different researcher yields different results which is against the basic essence of Granger causality. Axiom C (Granger 1980) of Granger causality says that direction of the relationship should not change. This naïve approach of detecting causal direction has very serious implications for the policy makers and the subject of economics.

Chapter5

Monte Carlo and Bootstrap simulation Evidence on Granger Causality

Testing Granger causality in the time series econometrics has been very common since the Granger introduced this concept in 1969. Monte Carlo simulation studies on causality are carried out in order to determine the power of different causality tests. We have also conducted simulation experiment in order to test the performance of Granger causality. But our experiments differ from other studies in two ways. One, that we have test causality in presence of a confounding variable. Secondly we have done Bootstrap simulation in order to observe the performance of Granger causality when it is assumed that true model is known and all the relevant variables under study are also known.

There are number of methods used for testing causality in time series data depending upon the properties of variables in use. For stationary variables Granger (1969) proposed the method discussed in chapter three. If the series are non-stationary then the two used methods for testing causality are Error Correction Mechanism(if the series are cointegrated Granger(1988)) and the other one is Toda and Yamamoto(1995) .These methods are described in Chapter three in detail.

Zapata and Rambaldi (1997), Dolado and Lutkepohl (1996), Yamada and Toda (1998), Clark and Mirza (2006) have conducted simulation experiments in order to compare different methods used for causality testing.

All these papers have presumed that Granger Causality is a test of causality and have compared the efficiency at different sample sizes. They differ only in either lag selection procedure or on the size of Monte Carlo experiment.

Clark and Mirza (2006) “The simulation experiment of Toda and Phillips [6], though extensive are limited to trivariate VAR [1] DGPs with lag order either specified correctly or overestimated by a fixed order. Dolado and Lutkepohl [4] undertake a small Monte Carlo involving a bivariate VAR [2] system with i.i.d errors; they assume that the VAR order is either unknown or over specified. Zapata and Rambaldi [7] examine GNC within bivariate and trivariate systems, but they limit attention to DGPs that are sufficiently 'cointegrated' in the sense of Toda and Philips [6, 9] so that either GNC has a standard limiting distribution; we consider situations in which non-standard asymptotic distributions result."

It is clear from all this above discussion that no one has tested Granger causality in the presence of a confounding variable which is often the case in

economic theory that two variables seems cause of one or the other but the hidden variable is the real cause which derives both the variables in a particular direction. We have conducted Monte Carlo simulation experiments where we have introduced a third variable which is mainly the cause of the other two variables. We have tested causality between the two variables by keeping the real cause out of the model. We have applied Granger Causality method for stationary variables. Then we have compared ECM and Toda and Yamamoto for nonstationary variables.

We have carried out Bootstrap simulation for the data on Shanghai discussed in Chapter four. From this bootstrap simulation we infer that if one assumes that the true data generating process is known and we have knowledge of all relevant variables in the model, then Granger causality is powerful test for determining direction of causality and its results are given at the end of this chapter.

Granger causality tests are based on Wald statistics for testing Granger non causality. In unrestricted VAR, the test involves nuisance parameters and non standard distribution (Toda and Phillips (1993)). Toda and Yamamoto (1995) propose a method that is to estimate unrestricted VAR whose order is k+d, where k is the true order and d is the highest degree of integration in the system.

Zapata and Rambaldi (1997) use the Monte Carlo simulation to check the performance of three tests for Granger non causality. These include two Wald tests, using VAR at level and Vector error correction model and a likelihood ratio test proposed by Mosconi and Giannini (1992). Zapata and Rambaldi use six data generation processes, which include four bivariate and two trivariate models. Their Monte Carlo evidence show that likelihood ratio test performs best as compared to Wald tests.

Clarke and Mirza (2006) studied three Granger non causality testing strategies. In their Monte Carlo simulation, they use ten data generating processes of bivariate and trivariate system. Zapata and Rambaldi (1997) assume that lag order is either correctly specified or over/under specified, while Clarke and Mirza (2006) use two selection criteria (finite prediction error and Schwarz criteria) for estimating the lag length. They also use three pretesting strategies (co integration testing) and examine the impact of these strategies on Granger non causality test and find that wrong estimation of co integration rank at the prior stage can result in over rejection of the true non causality null hypothesis. Their Monte Carlo evidence show that the pretesting strategy proposed by Ahn and Reinsel (1990) perform well and in this strategy for estimation of lag length Schwarz criterion perform well.

Toda and Phillips (1994) introduce some sequential testing procedure for testing Granger Causality and compare these procedures with level VAR and difference VAR. They assume that lag order is either known or overestimated by a fixed order. They show that these sequential procedures perform well when sample size is large but in small sample size neither of the tests performs well.

5.1 Monte Carlo Experiments and the Results

We have considered six DGP_s .The criteria used for the first four DGP_s were: coefficients for all the three variables generated are such that their sum is less than one in each equation to maintain the assumption of stationarity which is basic assumption of Granger causality test. DGP (1) and DGP (2) differ only for the hidden variable to capture the effect that whether any change in this variable changes the causal structure between the other two variables. Similarly DGP (3) and DGP (4) differ only in case of third variable. This bivariate analysis has been carried out because of their application in Economics e.g. Export-Growth causal analysis, Energy- Growth relationship and in other studies of economic dynamics with pairs of variables. But there might be the case that it's Capital Formation or Money supply which is affecting both economic growth and export and these variables show causal relationship just because these both are associated with one of these third variable. If export and growth are genuine cause of each other it means any change in the level of Capital formation or money supply should not affect this causal structure.

We have defined the GDP as follows

$$X_t=\Pi_1 X_{t-1}+ \Pi_2 X_{t-2}+\epsilon_t \qquad (5.1)$$

X is a (3 x 1) column vector, Π_i is a square matrix (3x3) and ϵ is a vector of order 3 x 1. ϵ_{it} are generated independently from normal distribution with mean 0 and standard deviation 0. Initial values of all the three variables are zeros.

DGP 1

$$\pi_1 = \begin{bmatrix} -0.581 & 0 & 0.71 \\ 0 & 0.02 & 0.83 \\ 0 & 0 & 0.90 \end{bmatrix} \qquad \pi_2 = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & -0.43 \\ 0 & 0 & -0.80 \end{bmatrix}$$

DGP 2

$$\pi_1 = \begin{bmatrix} -0.581 & 0 & 0.71 \\ 0 & 0.02 & 0.83 \\ 0 & 0 & 0.60 \end{bmatrix} \qquad \pi_2 = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & -0.43 \\ 0 & 0 & -0.30 \end{bmatrix}$$

DGP 3

$$\pi_1 = \begin{bmatrix} -0.581 & 0 & 0.171 \\ 0 & 0.02 & 0.83 \\ 0 & 0 & 0.90 \end{bmatrix} \qquad \pi_2 = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & -0.43 \\ 0 & 0 & -0.80 \end{bmatrix}$$

DGP 4

$$\pi_1 = \begin{bmatrix} -0.581 & 0 & 0.171 \\ 0 & 0.02 & 0.83 \\ 0 & 0 & 0.60 \end{bmatrix} \qquad \pi_2 = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & -0.43 \\ 0 & 0 & -0.30 \end{bmatrix}$$

For Toda and Yamamoto procedure we have used nonstationary series and DGP_s are as follows;

DGP 5

$$\pi_1 = \begin{bmatrix} 0.50 & 0 & 1 \\ 0 & 1 & 1 \\ 0 & 0 & 1 \end{bmatrix} \qquad \pi_2 = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & -0.5 \\ 0 & 0 & 0 \end{bmatrix}$$

DGP 6

$$\pi_1 = \begin{bmatrix} 0.50 & 0 & 1 \\ 0 & 1 & 1 \\ 0 & 0 & 0.50 \end{bmatrix} \qquad \pi_2 = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & -0.5 \\ 0 & 0 & 0.50 \end{bmatrix}$$

In all the models there is no causality either from X→Y or Y→X but these two variables are caused by Z.

DGP (5) is like DGP (8) of Clark and Mirza (2006) and there is cointegration between these two variables. The difference is once again the same that the third variable Z is kept outside while testing causality between X and Y. DGP (6) differs from DGP(5) only in Z.

We have applied Granger Causality procedure for the first four DGP_s and Toda and Yammamoto (1995) for the DGP(5) and DGP(6).Results for the first four DGP_s are given in Table 1 and for the DGP(5) and DGP(6) in Table 2.

In all cases 5000 samples of size T+K+100 were generated with the fist 100 observations discarded in order to address initial value problem which were assumed to be zeros for all the variables. For each DGP, six sample sizes were included; T=30, 60, 90,120,240 and 480. Lags for each DGP are set at one, two and three for the first four DGPs and for the remaining two lags are set at two and three. Correlation summary for the first four DGPs at sample size 30 and 60 is given in table 3 and 4 respectively. These tables show that whenever there is high correlation chances of causality between two variables are higher than the case of low correlation.

In the body of both the tables 1 and 2, the number shows the cases for which variables show causality. The headings of the table are self explanatory. The errors are i.i.d from normal with mean 0 and variance 1. The symbol→ means causal direction.

The experiments written using R-programming language were performed for almost a period of 200 hours. Time varied from 30 minutes to 3 hours depending on the sample size and lag length used in the DGP.

Results for the DGP (1) show that at all lags and at all the sample sizes y causes x at least 50% of the time except at lag 3 for T=30. Y causes X more than 80% of the time for most of the lags at different sample sizes. This implies that power of Granger causality test is very low in all such cases. For X→Y there is weak evidence of causality only at lag 1 for all the sample sizes. For lags two and three, X also seems causing Y and once again power of causality test is very low.

As discussed above that in case of DGP (2), only difference is in Z which is generated differently. By changing this Z, causal structure between X and Y gets changed in general and particularly at small sample sizes. If we observe carefully there was nothing but low correlation between X and Y this time which shows less degree of causation between X and Y. Similar kind of differences can be observed for DGP(3) and DGP(4).

Causal law is the one which is time tested and does not change with slight changes. Correlation on the other hand is very sensitive to minor changes in the data. In all these DGP_s, there was the association between X and Y due to Z. Such associations get their nature changed when there is change in the real cause of that association.

Table 2 for the DGP (5) and DGP (6) also show similar findings as those of table 1. Only at small sample size there is evidence of non causality .At large sample size results are not different from that of Granger causality. Both the tests have very low power and fail to identify the true causal structure. Therefore, we are not in a position to suggest that which of these two methods is preferable for testing Causality under the presence of a confounding variable.

Table 3 and 4 are the correlation summaries of different DGP_s for sample size 30 and 60 respectively. Other tables are not given due to space limitations. However, correlation structures remain almost the same for higher sample size. Correlation tables show that chances of causality from $Y \rightarrow X$ are very high when there is high correlation.

All this is sufficient to show that these causality tests which are based on prediction do not detect causal relation until and unless all the confounders are under control which is probably possible only in experimental studies and not in observational studies. There is still a long way to go to work on this topic of causality which is bread and butter of empirical economics. Freedman (1995) "Indeed, casual inference requires a lot of skill, intelligence and hard work. Natural variation needs to be identified. Data must be collected. Confounders need to be considered. Alternative explanations have to be tested.” Theory must support to find true causes and one must go deeper into the problem rather statistical analysis.

5.2 Bootstrap Simulation

For bootstrap simulation we have picked two variables data of Rufael (2004) " “Disaggregated industrial energy consumption and GDP: the case of Shanghai, 1952-1999” Energy Economics. The two variables are GDP and Coal data of shanghai and if it is assumed that they are related as follows:

$$Y_t = \alpha_0 + \sum_{i=1}^{k} \alpha_i Y_{t-i} + \sum_{j=1}^{k} \beta_j X_{t-j} + u_t \qquad (5.2)$$

where Y is GDP and X is the coal. Lags are set at three.

We have done bootstrapping by resampling regression residuals by having sample sizes of 1000, 5000 and 10,000. Our results indicate that Granger causality detects this causality 90.7%, 90.28% and 90.16% for 1000, 5000 and 10000 repetition respectively. Obviously magnitude of the parameters of X will matter but one may say that in presence of two variables when model is known Granger causality is a useful device. All this bootstrap has been done using Microsoft Excel. We have calculated F-Statistics and its critical value at 5% level of significance with 3 and 36 is 3.28. Summary of these results is given in Appendix A-4.1.We have also carried out this bootstrap simulation by using “R” and results are given in the Appendix 4.2.

Table 5.1 Monte Carlo Simulation Results

DGP	Causal Direction	T=30	T=60	T=90	T=120	T=240	T=480
1	Lag1						
	Y→X	0.55	0.86	0.97	0.99	1.00	1.00
	X→Y	0.04	0.04	0.04	0.04	0.04	0.05
	Lag=2						
	Y→X	0.54	0.85	0.96	0.99	1.00	1.00
	X→Y	0.12	0.20	0.29	0.36	0.61	0.90
	Lag=3						
	Y→X	0.32	0.67	0.86	0.95	1.00	1.00
	X→Y	0.14	0.29	0.43	0.58	0.90	1.00
	Lag1						
2	Y→X	0.16	0.28	0.41	0.52	0.82	0.98
	X→Y	0.04	0.05	0.05	0.05	0.04	0.05
	Lag=2						
	Y→X	0.11	0.20	0.28	0.36	0.65	0.93
	X→Y	0.05	0.07	0.07	0.08	0.11	0.17
	Lag=3						
	Y→X	0.09	0.16	0.24	0.30	0.56	0.88
	X→Y	0.05	0.07	0.08	0.10	0.16	0.30
	Lag1						
3	Y→X	0.17	0.30	0.43	0.55	0.84	0.99
	X→Y	0.03	0.03	0.03	0.03	0.03	0.03
	Lag=2						
	Y→X	0.06	0.26	0.38	0.48	0.79	0.97
	X→Y	0.15	0.08	0.08	0.09	0.11	0.15
	Lag=3						
	Y→X	0.12	0.25	0.36	0.45	0.79	0.98
	X→Y	0.05	0.06	0.07	0.08	0.13	0.23
4	Lag1						
	Y→X	0.06	0.08	0.10	0.12	0.18	0.32
	X→Y	0.04	0.05	0.04	0.05	0.04	0.05
	Lag=2						
	Y→X	0.06	0.07	0.08	0.10	0.15	0.25
	X→Y	0.05	0.05	0.05	0.05	0.06	0.06
	Lag=3						
	Y→X	0.05	0.07	0.08	0.08	0.12	0.22
	X→Y	0.05	0.05	0.05	0.05	0.05	0.07

Table 5.2

DGP	Causal Direction	T=30	T=60	T=90	T=120	T=240	T=480
5	Lag=2						
	Y→X	0.2166	0.4618	0.6398	0.77	0.9748	0.9998
	X→Y	0.1382	0.2948	0.459	0.5984	0.8988	0.9948
	Lag3						
	Y→X	0.182	0.102	0.1326	0.1692	0.3016	0.5582
	X→Y	0.1378	0.0766	0.105	0.1288	0.222	0.421
	Lag=2						
6	Y→X	0.0662	0.4048	0.6096	0.746	0.9766	1
	X→Y	0.057	0.3096	0.4762	0.6152	0.921	0.9988
	Lag=3						
	Y→X	0.1008	0.1938	0.3096	0.4134	0.723	0.9626
	X→Y	0.1006	0.2094	0.3186	0.4236	0.7614	0.976

Table 5.3 Correlation between X and Y T=30

DGP		Lag 1	Lag2	Lag3
1	Minimum	-.2640	-0.2996	-0.1681
	Ist Qu	0.3862	0.3935	0.3964
	Median	0.5030	0.5077	0.5063
	Mean	0.4912	0.4940	0.4932
	3rd Qu:	0.6090	0.6061	0.6030
	Max.:	0.8831	0.8765	0.8659
	Y→X	2765	2679	1590
	X→Y	182	606	688
2	Minimum	-0.3158	-0.3351	-0.2633
	Ist Qu	0.2103	0.2126	0.2183
	Median	0.3233	0.3279	0.3309
	Mean	0.3164	0.3181	0.3207
	3rd Qu:	0.4319	0.4315	0.4328
	Max.:	0.7850	0.7620	0.7739
	Y→X	798	563	432
	X→Y	218	256	273
3	Minimum	-0.42417	-0.47646	-0.4231
	Ist Qu	0.05386	0.05892	0.0614
	Median	0.16209	0.16251	0.1608
	Mean	0.15635	0.15767	0.1581
	3rd Qu:	0.26021	0.26104	0.2620
	Max.:	0.59631	0.59170	0.6072
	Y→X	846	734	586
	X→Y	139	313	262
4	Minimum	-0.46310	-0.51303	-0.46296
	Ist Qu	-0.02518	-0.02488	-0.02141
	Median	0.09015	0.09157	0.09645
	Mean	0.08891	0.08965	0.09326
	3rd Qu:	0.20905	0.20572	0.20838
	Max.:	0.64655	0.59205	0.60153
	Y→X	298	293	266
	X→Y	218	235	252

Table 5.4 Correlation **between X and Y** **T=60**

DGP		Lag 1	Lag2	Lag3
1	Minimum	-0.01514	-0.001962	-0.08676
	Ist Qu	0.42695	0.424447	0.42671
	Median	0.50608	0.505698	0.50941
	Mean	0.49859	0.498162	0.50029
	3^{rd} Qu:	0.57941	0.578065	0.58067
	Max.:	0.82651	0.819613	0.81296
	Y→X	4316	4244	3337
	X→Y	179	1021	1450
2	Minimum	-0.1076	-0.2142	-0.1839
	Ist Qu	0.2458	0.2443	0.2443
	Median	0.3245	0.3223	: 0.3242
	Mean	0.3182	0.3183	0.3193
	3^{rd} Qu:	0.3966	0.3976	0.3978
	Max.:	0.6751	0.6806	0.6557
	Y→X	1403	1002	795
	X→Y	240	327	349
3	Minimum	-0.30981	-0.2538	-0.30894
	Ist Qu	0.08708	0.0872	0.08645
	Median	0.16034	0.1594	0.16115
	Mean	0.15694	0.1567	0.15805
	3^{rd} Qu:	0.22976	0.2300	0.23059
	Max.:	0.57761	0.5208	0.51735
	Y→X	1524	1316	1238
	X→Y	148	403	318
4	Minimum	-0.361166	-0.375629	-0.35673
	Ist Qu	0.009214	0.009514	0.01010
	Median	0.092567	0.090323	0.09090
	Mean	0.089627	0.089788	0.09075
	3^{rd} Qu:	0.170107	0.171444	0.17147
	Max.:	0.489873	0.580160	0.48374
	Y→X	407	364	336
	X→Y	239	258	243

Chapter 6
Analysis of Structural Causality
6.1 Introduction

In all the previous chapters what has been observed is that there are serious problems associated with Granger Causality. In this chapter we shall propose an alternative way for testing causality. Structural causality is critical but not easily detected and Granger causality basically ignores this aspect of causality altogether. In this chapter we shall give a brief outline of testing for causal structure and apply it on ELG data for India to show how one should actually test causality. There is no simple rule for establishing causality and the effort made in this chapter basically borrows idea from Simon(1953), Hendry(1995) and Hoover(2001). The advantage of structural causality over other approaches is that it incorporates all possible information before reaching at a causal result and is not merely based on Statistical technique. Nevertheless, we can not determine the magnitude of the effect of causal variable on the dependent variable is one of the limitations. In our opinion to resolve this latter issue is not possible at least by the statistical means. Since results are based on the observational data and we must be careful in interpreting results as we have intervened so can not be the same.

6.2 Method for Detecting Structural Causality

Given a bivariate series (X, Y) there are three possibilities for causality: (1) X &Y are jointly determined, (2) first X is determined and then Y is calculated from some equation like $Y = a + bX + u$, or (3) first Y is determined and then X is calculated from some equation like $X = c + d Y + v$. All the three possibilities are observationally equivalent – data series generated by (1), (2) & (3) will be identical in all respects and hence it is impossible to detect causality by looking at the data *as* *long as there is no structural change.* Thus in a stable environment, it is impossible to tell whether Y causes X or whether X causes Y or whether there is mutual bi-directional causality. When there is some structural change, it will reveal the causal patterns provided that we look carefully. For example, suppose that the variance of X increases. If Y is caused by X, then there will be no change in the conditional distribution of Y given X. However, the conditional distribution of X given Y will change. Also the joint distribution of X and Y will change. So of the three possibilities listed above, only the causally correct one – number (2) – will stay the same after the structural change. From this we learn that causally correct relationships can survive certain types of structural change. This information can be used to differentiate between models which are causally correct and those which are not in period of structural change. In periods where we have stability and no structural changes, even models with incorrect causality will perform well. This idea is propagated by Simon(1953).

To prove the above mentioned instance let us assume a very simple two variable problem:

Let

$$x=\alpha+\varepsilon \tag{6.1}$$

$$y=\beta+\gamma * x+\nu \tag{6.2}$$

Where $\varepsilon \sim n.i.i.d(0,\sigma_\varepsilon{}^2)$ and $\nu \sim n.i.i.d(0,\sigma_\nu{}^2)$

ε and ν are independent i-e Covariance(ε,ν)=0. Now we find four probability distributions namely conditional of x given y, Marginal of x, Conditional of y given x and marginal of y.

For this we find mean and variance E(X)=α V(X)=$\sigma_\varepsilon{}^2$

$$E(\mathrm{y}) = \beta + \gamma\alpha,\ V(\mathrm{y}) = \gamma^2\sigma\varepsilon^2 + \sigma_\nu{}^2 \tag{6.3}$$

Covariance(X,Y)=$\gamma\sigma_\varepsilon{}^2$
Now for conditional distribution of X we have

$$E(\mathrm{x}|\mathrm{y} = y) = \alpha + \left(\gamma\sigma\varepsilon^2 / \left(\gamma^2\sigma\varepsilon^2 + \sigma_\nu{}^2\right)\right) * \left(\mathrm{y} - \beta - \gamma\alpha\right) \tag{6.4}$$

$$= \alpha\sigma_\nu{}^2 - \beta\gamma\sigma_\nu{}^2 + \left(\gamma\sigma\varepsilon^2 / \left(\gamma^2\sigma\varepsilon^2 + \sigma_\nu{}^2\right)\right) * \mathrm{y}$$

$$Var(\mathrm{x}|\mathrm{y} = y) = \sigma\varepsilon^2\sigma_\nu{}^2 / \left(\gamma^2\sigma\varepsilon^2 + \sigma_\nu{}^2\right) \tag{6.5}$$

So the conditional distribution of X given Y=y is given as

$$f(\mathrm{x}\Big|\mathrm{y} = y) = N\left(\alpha\sigma_\nu{}^2 - \beta\gamma\sigma_\nu{}^2 + \left(\gamma\sigma\varepsilon^2 / \left(\gamma^2\sigma\varepsilon^2 + \sigma_\nu{}^2\right)\right) * \mathrm{y}, \sigma\varepsilon^2\sigma_\nu{}^2 / \left(\gamma^2\sigma\varepsilon^2 + \sigma_\nu{}^2\right)\right)$$

(6.6)

$$E\left(\mathrm{y}|\mathrm{x} = x\right) = \beta + \gamma\alpha + \left(\gamma\sigma\varepsilon^2 / \left(\sigma\varepsilon^2\right)\right)\left(\mathrm{x} - \alpha\right)$$

$$= \beta + \gamma\mathrm{x} \tag{6.7}$$

$$Var(\mathrm{y}\Big|\mathrm{x} = x) = \left(\gamma^2\sigma\varepsilon^2 + \sigma_\nu{}^2\right)\left(1 - \left(\gamma\sigma\varepsilon^2\right)^2 / \left(\gamma^2\sigma\varepsilon^2 + \sigma_\nu{}^2\right)\sigma\varepsilon^2\right)$$

$$= \sigma_\nu{}^2 \tag{6.8}$$

Conditional distribution of Y given X=x is

$$g(\mathrm{y}|\mathrm{x} = x) = N\left(\beta + \gamma\mathrm{x}, \sigma_\nu{}^2\right) \tag{6.9}$$

Marginal distribution of X is

$$f(X)=N(\alpha,\ \sigma_\varepsilon{}^2) \tag{6.10}$$

Marginal distribution of Y is

$$h\left(y\right) = N\left(\beta + \gamma\alpha, \gamma^2\sigma_\varepsilon{}^2 + \sigma_\nu{}^2\right) \tag{6.11}$$

So from these four distributions one may judge that if there is any change in parameters of the first equation. For example economic crisis of a country demands that there should be a change in policy and sudden major decisions are made which change the value of the parameter α or variability parameter of the first equation, then either α or σ_ε^2 changes. Then $f(\mathrm{x})$ and $f(\mathrm{x}|\mathrm{y})$ will change and also one may notice that $h(\mathrm{y})$ will also change. The only stable distribution is $g(\mathrm{y}|\mathrm{x})$.

Now if there is change in β or σ_v^2 $g(\mathrm{y}|\mathrm{x})$ and $h(\mathrm{y})$ will change and there is also a change in $f(\mathrm{x}|\mathrm{y})$, but $f(\mathrm{x})$ will remain unchanged. Hence in case of intervention when X is causing Y the joint probability distribution $g(\mathrm{y}|\mathrm{x}) * f(\mathrm{x})$ will remain invariant where as $f(\mathrm{x}|\mathrm{y}) * h(\mathrm{y})$ will no more be invariant. So the first partition recapitulates true underlying processes while the second not. Had the causal direction been reversed, second partition would have behaved in a similar manner.

This approach for testing causality requires lot of investigation in the underlying economic mechanism not only on theoretical grounds but also in historical prospective. How to find the period of intervention is a question of considerable importance.

Extra statistical information as the clear shift change in government policies, minutes of the Central Bank's monetary policy etc, signals an intervention in the investment policies, money-supply process respectively. Purely statistical or econometric information is unlikely to be sufficient to identify an intervention. Hoover (2001) mentions that this intervention should be traced in historical prospective and then statistical tests should also be carried out to validate that whether intervention is there. Hoover (2001) and Freedman (1991) seems to be in close agreement over this issue. Freedman also pointed out that determining causal direction requires an in depth knowledge of the problem at hand. Once one has been able to find the time of intervention in one of the variable, then further analysis can be carried out by looking at the conditional and marginal distributions of the variable.

6.3 Simulated Data

Now we are going to apply this above mentioned idea on a simulated series. Causality has been tested between two variables x and y where

$x = 1 + e_i$ and $y = 2 + 0.8 * x + e_j$: both random errors are N(0,1) and covariance is zero between these two error terms. We have generated 100 observations on X and Y, and from these 100 observations we can not make a decision that whether its X which is causing Y or vice versa as the slope of the two lines is the same in both of the cases. Nevertheless, if there is any structural change in any one of the variables and somehow we get some idea of that structural change, then as per our theory we can see the behavior of four probability distributions. True causal relation would remain stable but the other one would become unstable.

To observe the behavior of these probability distributions we have changed the values of second half of the X variable and X_i=1+e_i where e_i ~N(0,1) for i=1,2,…,50 and X_{i+50}=1+e_{i+50} where e_i ~ N(2,3). The regression line in both of the conditional distributions is the same but when we split our data into parts that is before and after the change in x, then $f(x|y)$ becomes unstable but $g(y|x)$ remains stable. Both the marginal of x and y are unstable .This as per our definition indicates that it is x which is causing y and not vice versa. So observationally x and y are equivalent but extra statistical information may lead us to trace the causal pattern.

The four distributions namely $f(x|y), g(y|x)$, $f(x)$ and $h(y)$ are given as follows;.

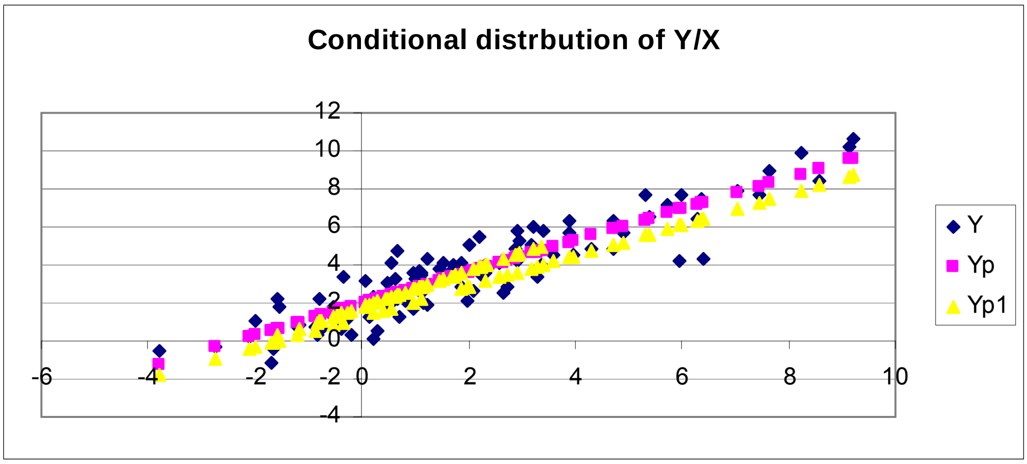

Figure 6.1a

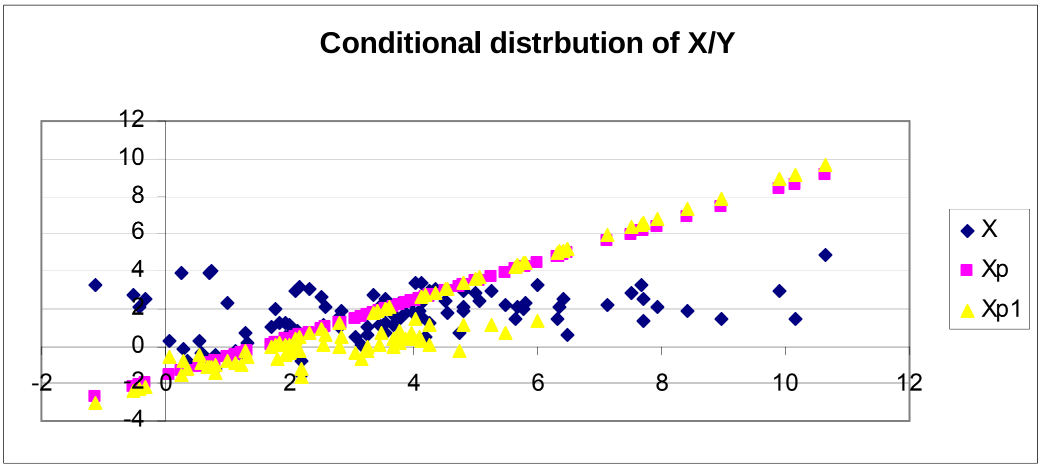

Figure 6.1b

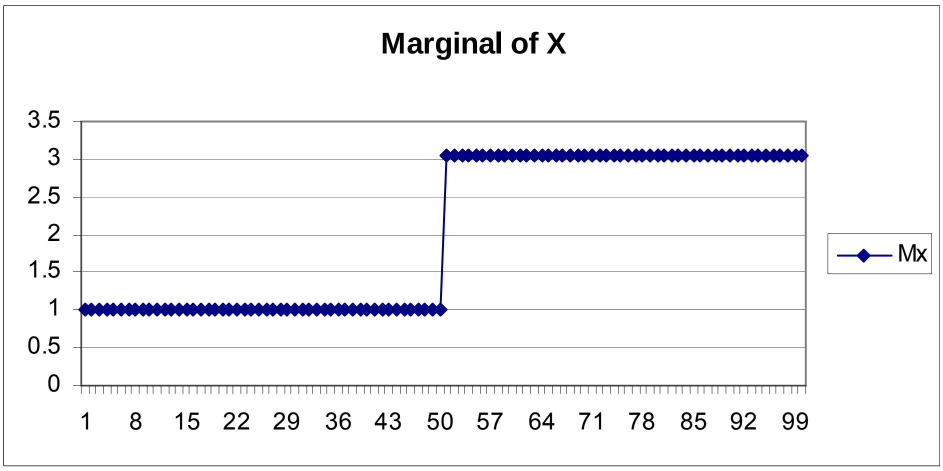

Figure6.1c

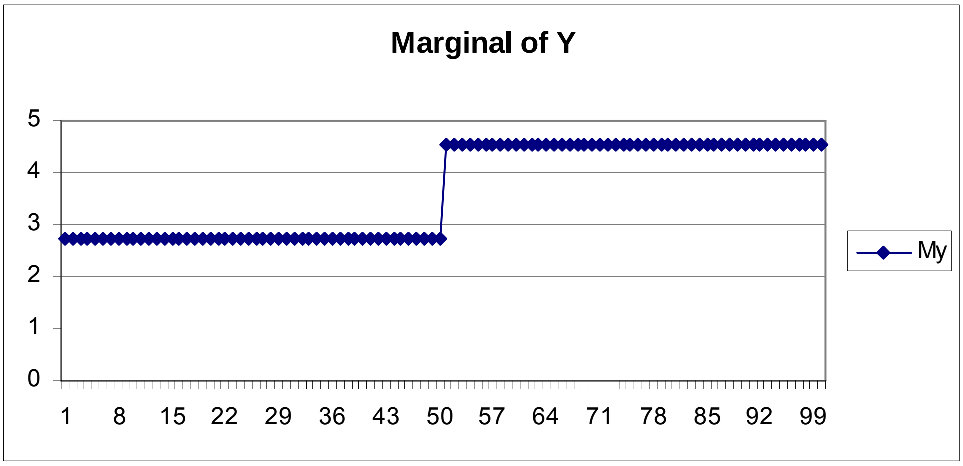

Figure 6.1d

We are going to implement this idea of finding the direction of causality to the export led growth ELG for the Indian data and the electricity-GDP growth data of Shanghai. Both of these data sets are already discussed in chapter 4.

6.4 Structural Causality Test for Export-Growth Data for India

The controversy about ELG or GLE is already given in chapter four. There are very strong arguments which are put forward to support ELG hypothesis theoretically. From a demand side perspective, sustained demand growth in a small domestic economy can not maintained permanently since domestic demand exhausts very soon. On the contrary, export markets are limitless and hence there is no need for any restriction on output. Thus export can serve as a catalyst for income growth, as a component of aggregate demand.[18]

In addition to this direct demand side effect, export expansion may have an indirect affect by providing foreign exchange which allows for having more capital import.[19]This increase in capital goods in turn boosts economic growth by raising the level of capital formation. As Chuang (1998) argues that capital goods import from technological advanced countries may increase productivity and thereby growth,

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[18] Agosin (1999)
[19] Reizman, Summers, and Whiteman (1996)

since knowledge and technology is embodied in equipment and machinery and therefore transferred through international trade.

On theoretical grounds there are several possible channels through which exports can enhance productivity. A country can promote specialization in areas where it has comparative advantage through export expansion, and lead to reallocation of resources from the relatively inefficient non-trade sector to the more productive sector. Secondly, the growth of exports can increase productivity by offering larger economies of scale (Helpman and Krugman (1995).

Thirdly, total factor productivity may increase through dynamic spillover effects on the rest of the economy when there is export growth. The possible sources of these knowledge externalities include productivity enhancements resulting from increased competitiveness, more efficient management styles, and better forms of organizations, labor training, and knowledge about technology and intellectual markets (Chuang 1998). In short export growth has beneficial impact on output growth.[20]

On the other hand primary export is considered harmful for economic growth because such type of export does not provide any long term potential for knowledge spillovers, and an increase in primary exports can draw resources away from the externality-generating manufacturing sector (Matusuyama 1992). Moreover, primary exports are subject to extreme price and volume fluctuations. Increasing primary exports therefore lead to increasing GDP variability and macroeconomic uncertainty. High instability and uncertainty, may, in turn hamper efforts at economic planning and reduce quantity as well as efficiency of investments (Dawe 1996).

[20] For more detail Hertzer et al (2006)

There is strong correlation between export and economic growth. Many investigate whether this association can be translated into causal relationship. Early cross-sectional studies (e.g. Michaely1970s; Blasa 1978; Heller and Porter, 1978; Tyler, 1981; Feder (1983), suggested that export promotes overall economic growth. But to determine causal relationship between export growth and GDP growth within a country requires a time series analysis. By using Granger causality many researchers have tried to determine the direction of causality. As we have explored export economic growth data for India in chapter four and shown that Granger causality leads us to nowhere.

Now if explored historically, there are three major events in Indian History i-e 1965 war, 1979 economic crisis and 1990 economic crisis. We have applied chow structural breakpoint test on all these three points but results do not indicate significant structural change in real GDP. Then by considering the fact that Indian policy makers changed their policies of investment and went for opening their economy for investors in early 1990s which might led export to grow and then ultimately economic growth. Results of these policies have started materialising in mid 1990s and onward. But due to data constraint we have applied chow structural breakpoint test at 1990 and found that there is structural change. Therefore, we split data into two parts i-e 1955-1989 and 1990-2002. Although we are left with few observations in the second half but to get an idea of the four probability distributions i-e marginal of x, marginal of y, conditional of x given y and conditional of y given x, this is a useful exercise.

Table 6.1 ADF test India (1955-2002)

Variables	Test statistic		5% critical value	
	Levels	First difference	Levels	First difference
Y	1.260816(0)	-8.158184(0)	-2.9178	-2.9190
X	2.996876(0)	-7.030767(0)	-2.9178	-2.9190

Note: X and Y represent the log of real exports and log of real GDP respectively. Figures in parenthesis represent the number of lags that is included in ADF test.

Table 6.2 Chow Breakpoint Test

Year			
	1990	1979	1965
Export	0.018	0.274	0.3751
GDP	0.089	0.498	0.769

Table 6.3 Characterisation of Conditional and Marginal Distributions Regressions

Distributions	Year	Results
GDP Conditional	1955-2002	DY=0.483DY(−1)+ 0.2039DX(−1)
		(0.115) (0.056)
	1955-1989	DY=0.410DY(−1)+0.2189DX(−1)
		(0.0778) (0.1426)
	1990-2002	DY=0.7083DY(−1)+0.0946 DX(−1)
		(0.2238) (0.0926)
Export Conditional	1955-2002	DX=1.0564 DY(−1)+0.0.1533 DX(−1)
		(0.2943) (0.1437)
	1955-1989	DX=0.700DY(−1) −0.0001DX(−1)
		(0.318657) (0.174)
	1990-2002	DX=2.4148DY(−1)−0.1126DX(−1)
		(0.7665) (0.3172)
Export Marginal	1955-2002	DX=0.0611+0.058DX (−1)
		(0.016) (0.1533)
	1955-1989	DX=0.0480-0.151DX (−1)
		(0.016) (0.1786)
	1990-2002	DX=0.1281-0.0579DX (−1)

		(0.0426) (0.3147)
GDP Marginal	1955-2002	DY=0.0483−0.1476DY(−1)
		(0.0076) (0.1488)
	1955-1989	DY=0.0472-0.2481DY(-1)
		(0.0086) (0.174)
	1990-2002	DY=0.0492-0.0578DY(-1)
		(0.017) (0.3038)

where DY is the first difference of the real GDP, DX is the first difference of the real export. DY ((−1) and DX ((−1) denote the first lag of the DY and DX.

Following are the time plots for estimated values from the four distributions over different sample periods i-e the entire time period and then at two tranquil time periods.

Conditional distribution of $x \mid y = y$ **:**

X1F is for the whole data set, X2F is the for the data set 1955−1989 and X3F is for the data set 1990−2002

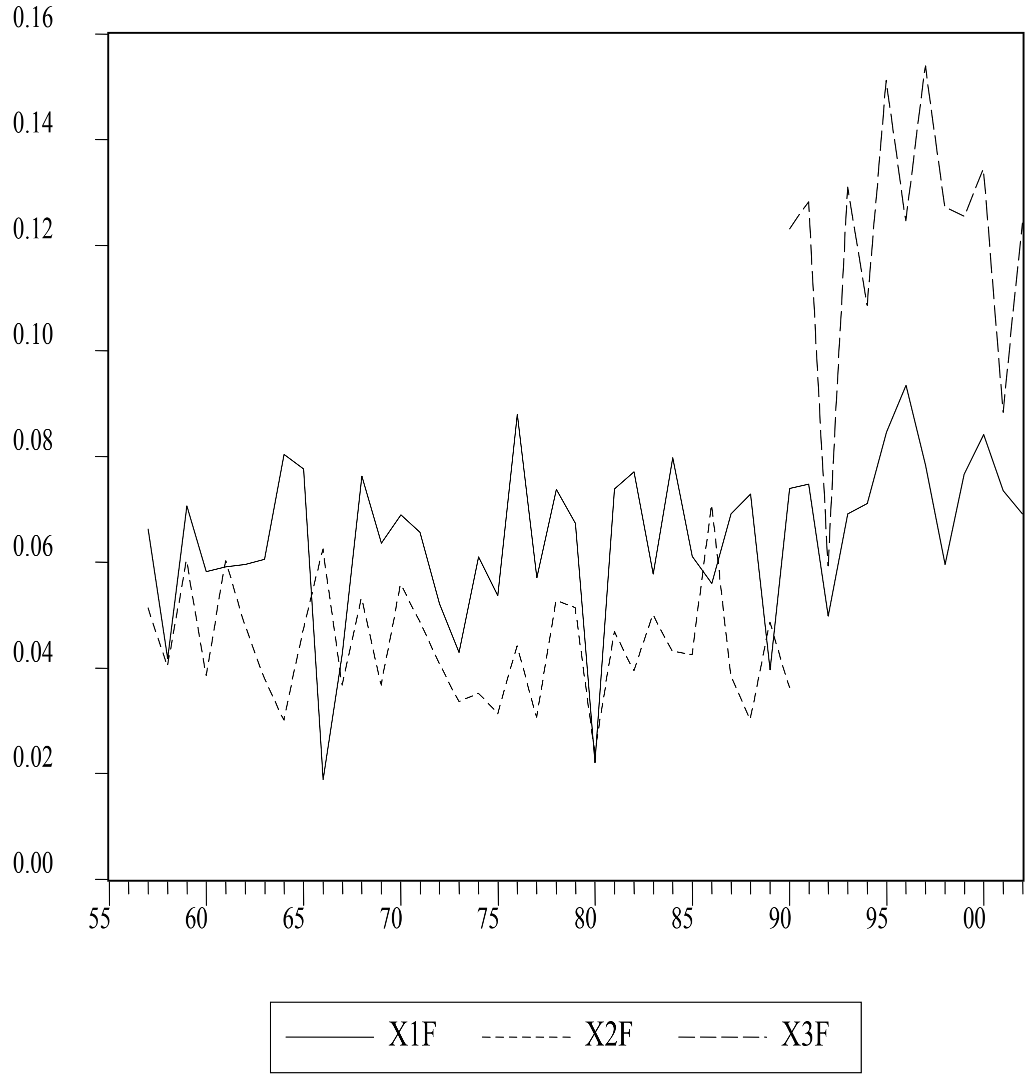

Figure 6.2a

Conditional distribution of Y/X=x:

Y1F is conditional distribution for the whole range. Y2F for range 1955−1989, Y3F for the range 1990−2002

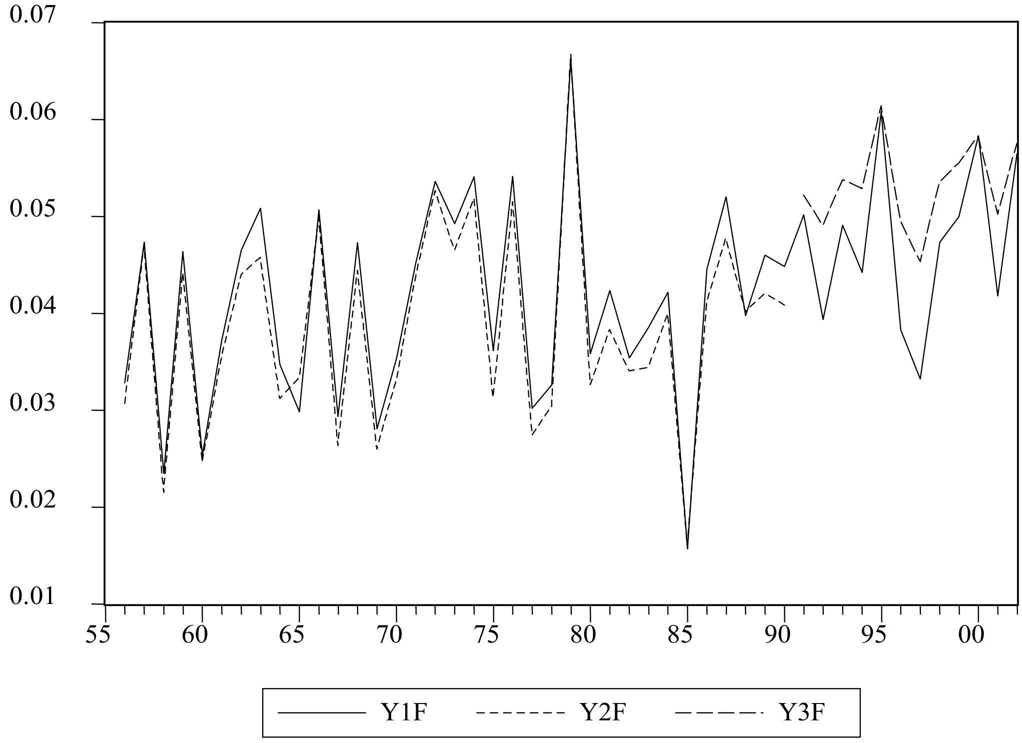

Figure 6.2b

Marginal of X and Y are as follows

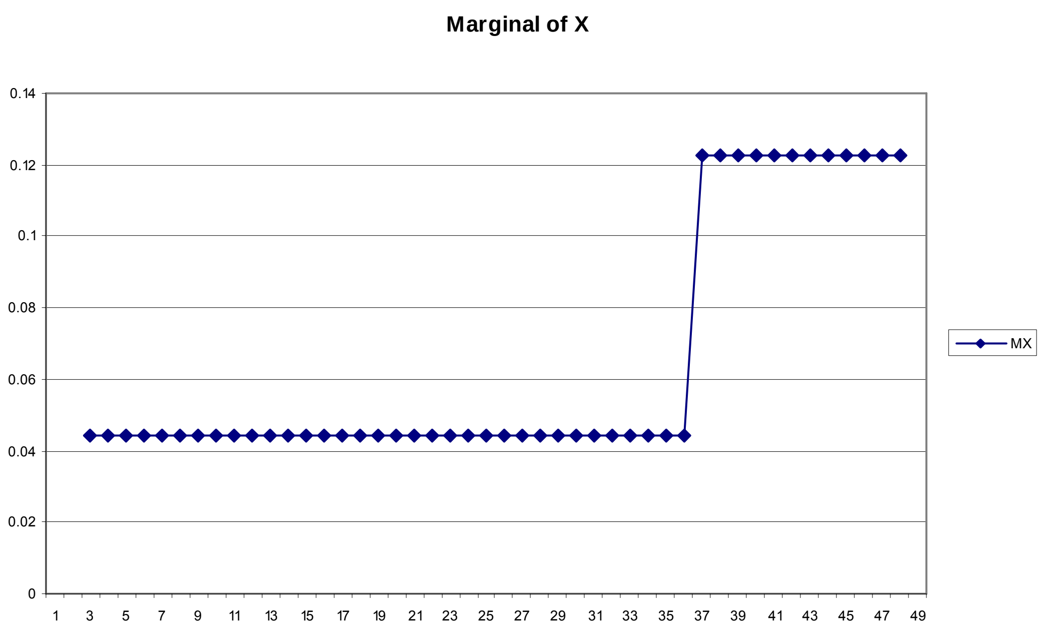

Figure6.2c

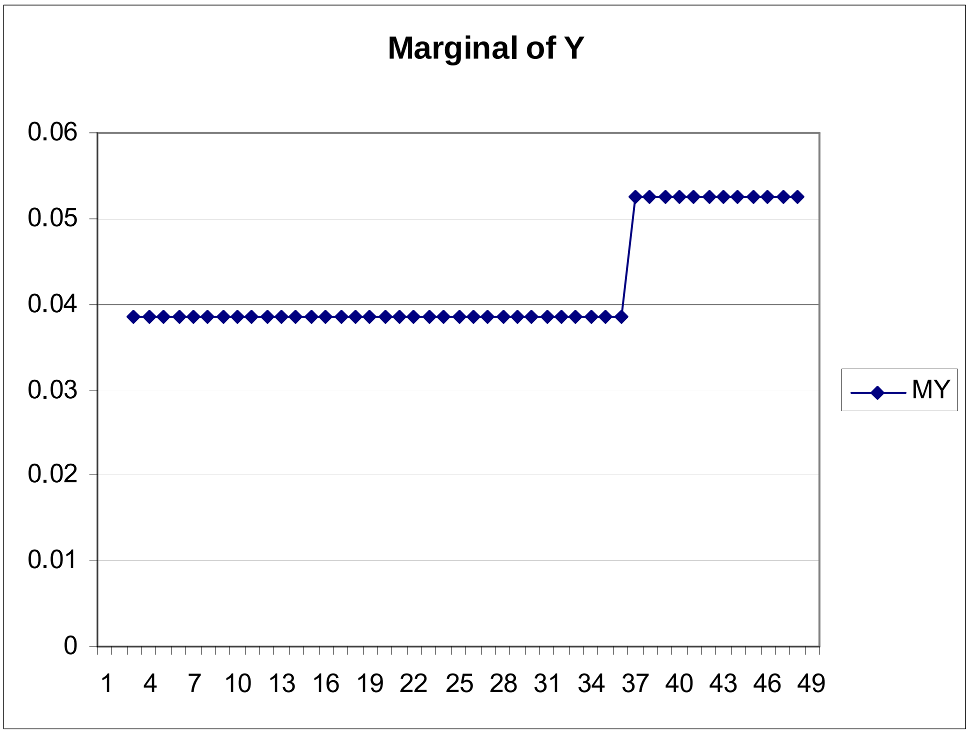

Fig 6.2d

So it is obvious that three distributions breakdown and only one remains stable, which implies that its X which is causing Y and not vice versa. Therefore, we may conclude that real export is a cause of economic growth. Moreover, the joint distribution f(x,y)=f(Y/X)f(X) shows that X is exogenous in the sense that parameters of the conditional distribution of Y given X are independent of the marginal distribution of X.

Thus, export expansion has beneficial impact on GDP for India. So, in future export growth should be future course of action for India to achieve sustainable economic growth. However, this test of structural causality provides only the direction of causality and what would be the magnitude of expansion in export growth to the economic growth need further investigation.

6.5 Structural Causality Test for Energy-GDP Data: Shanghai

Now we shall investigate the data on energy growth for Shanghai as discussed in Chapter four. We have found in chapter four that there is no causality between different energy consumption and economic growth if we exclude few unusual observations from our data. Now we shall apply the test of structural causality and try to find out that is there any evidence of causality. We have restricted ourselves in this case only to statistical evidence for finding periods tranquillity. We have selected only two variables electricity and economic growth, and split data into 1952-1965 and 1966-1999. Then we have calculated the two conditional and marginal distributions. The graph of two marginal distributions has been broken down over two different periods but both conditional distributions remain stable before and after the break, therefore we conclude that there is no causality between electricity and economic growth or we are unable to detect it even if it exists at all.

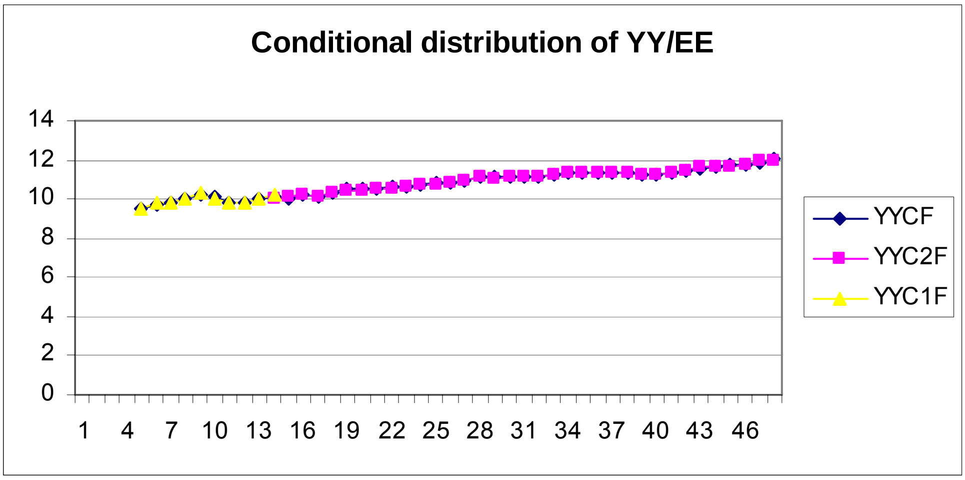

Fig.6.3a

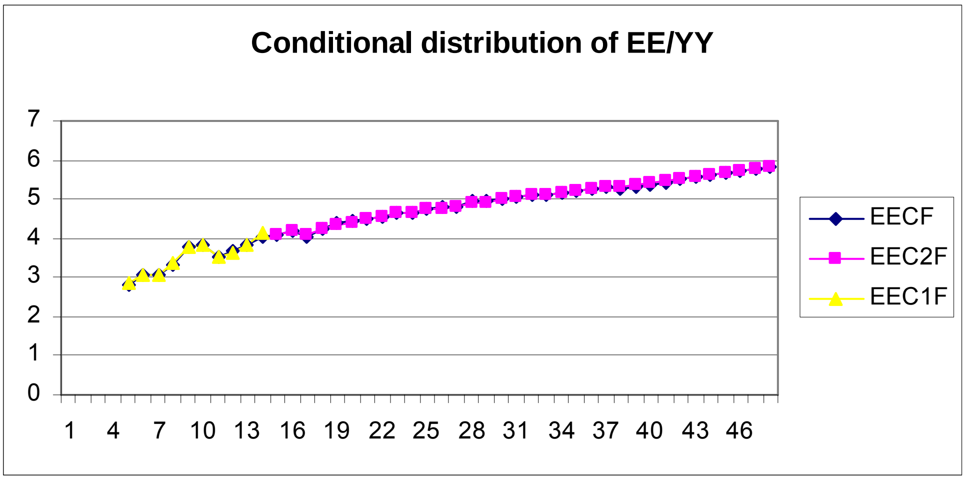

Fig. 6.3 b

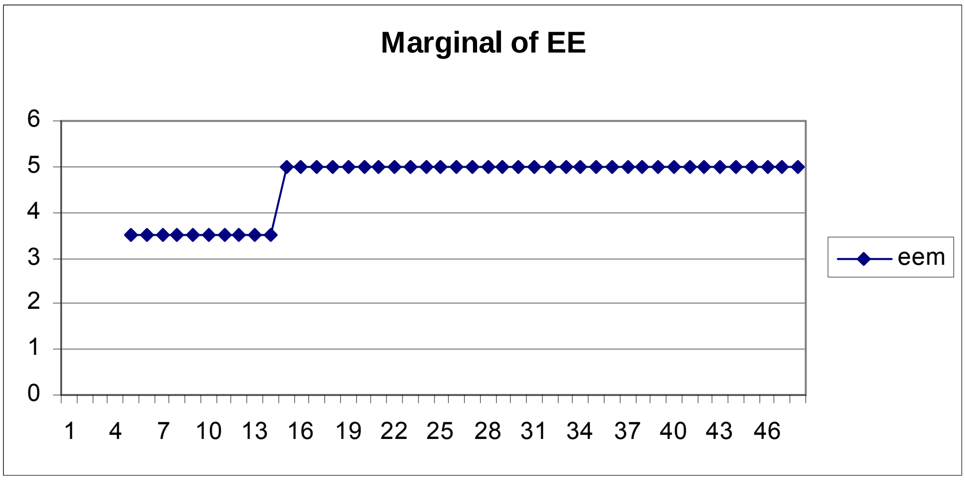

Fig. 6.3 c

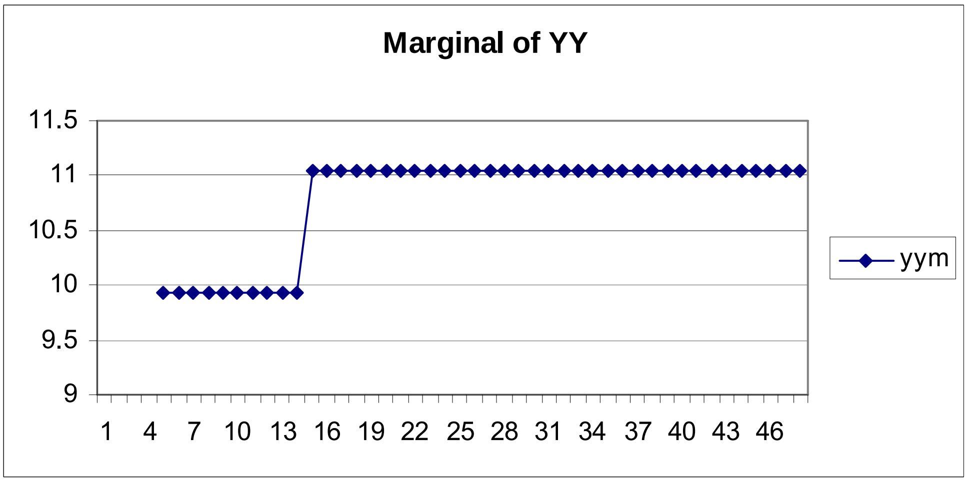

Fig. 6.3 d

Chapter 7
Results and Discussion

Causality is probably one of the most important issues in economics but in the absence of any formal testing procedure for detecting the causal relationship, it has been ignored by most of the researchers while doing their analysis. Granger causality is one of the most widely used methods for detecting causal direction. There are many objections on Granger causality by several economists and this debate of causality seems to be beyond a common economists' reach. Therefore, in this study we have analysed Granger causality test as test of causality on empirical grounds and found that Granger causality results are not robust .Our results are an interesting application of all the versions of Granger causality (all methods of testing for causality).Our results explain the reason for the varied evidence on the direction of causation from one study to another in the literature. Most of the researchers have ignored Granger's advice of introducing the extra statistical information to bring asymmetry in the relationship. Use of built in commands by several computer packages for testing Granger causality has produced nonsense results in most of the cases.

We have also compared three different causality tests (Granger causality, Toda and Yamamoto , Error Correction Mechanism) for the three South Asian countries and found that one may reach at a different causal direction depending upon the method one use. Moreover, all these methods lack in robustness and are sensitive to the lag length, sample period, base period change etc.

Our simulation results verify that Granger causality tests provide misleading results if all the relevant variables, true underlying model and population are not known. Moreover, whenever there is high correlation between the variables under study, there is high probability of having Granger causality relationship between the variables. This shows that it is the association among the variables which matters and not the genuine causal relationship. Because in stable economic environment all the models whether good or bad work fine because correlation among the variables remain stable. Causally correct model will be the one which does not change its behaviour even after the intervention while correlation structure will change its nature after such an intervention.

As regression of X on Y or vice versa are observationally equivalent so one can not detect causality from observed data; therefore, it becomes all the important to add some structure on the issue under study to get some evidence of causal relationship from the observed data. This structure can be imposed by having some information from chronological events and then verifying these events by statistical tests. If it is found that both history and statistical tests supports that there has been some structural change in one of the variable under study then it might be possible to find causal direction between the two variables as has been discussed in the last chapter. The approach we have used in the last chapter of our study for detecting causality incorporates economic theory, history of economic process, statistical information, and super exogeneity into account for reaching at a possible result. By using all this information we have found that there is causal direction from export to economic growth and not vice versa for the case of India. This is in agreement with the theory which is mainly postulated that openness of the economy leads to economic progress. In the end we would like to say that causality can not be detected by merely using statistical means and there is need to explore data intensively and careful functioning of the economic process might be useful in detecting causality.

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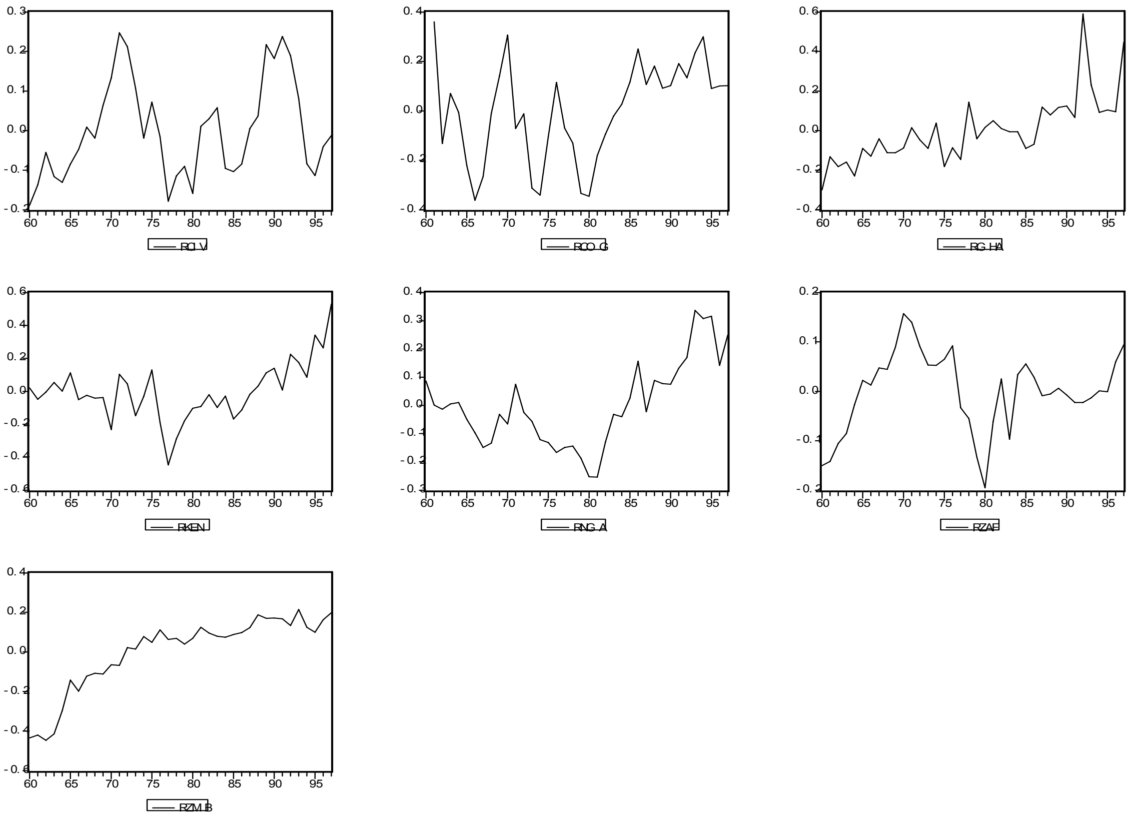
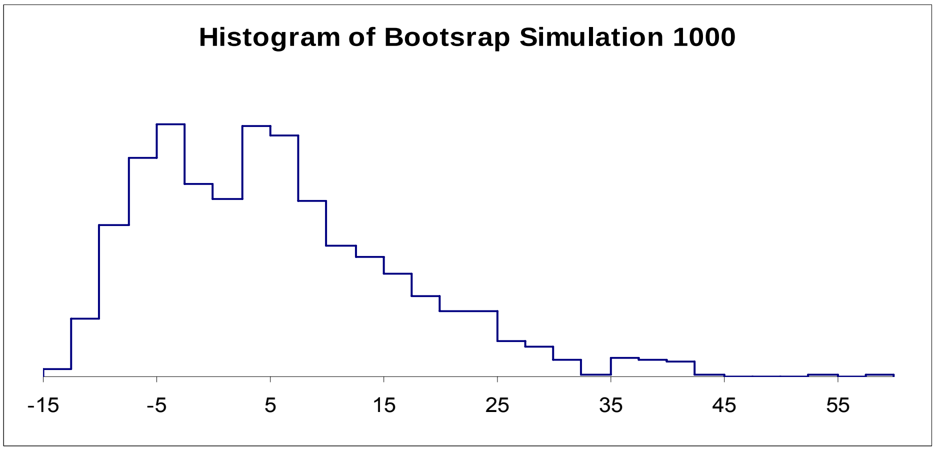
Appendix

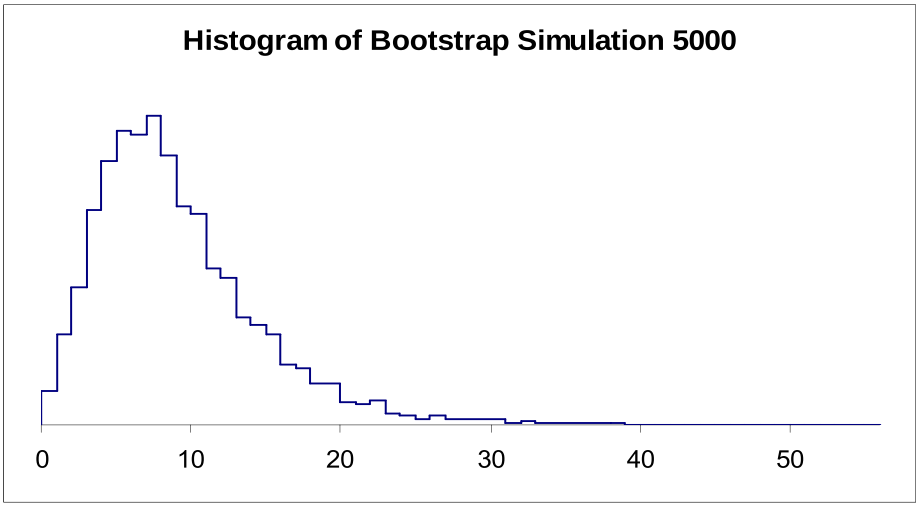
A-3.1 Time Plot of Residuals obtained from the regression of Granger Causality is as follows;

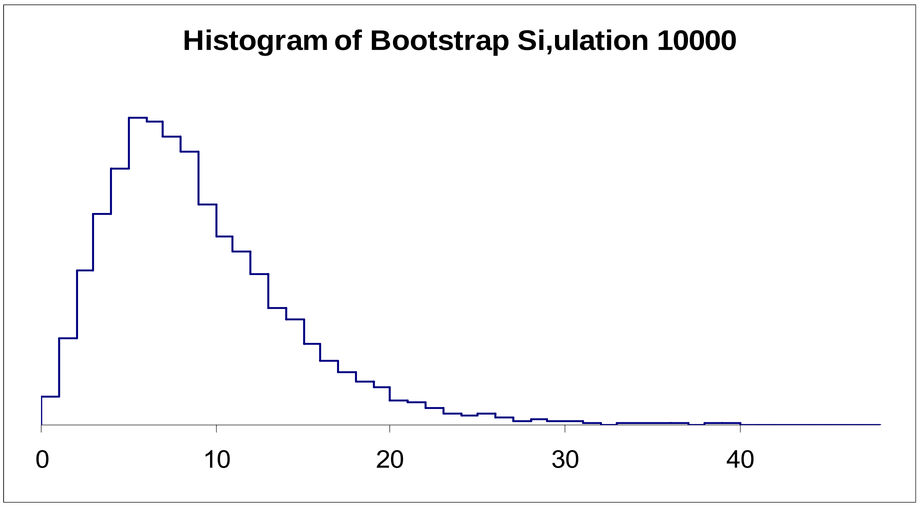


A-4.1 Result Summary of Bootstrap Simulation

Simulation Stats			
repetitions	1000	5000	10000
Average	5.617	9.168	9.085
SD	11.3128	5.6099	5.4264
Max	59.723	55.156	47.780
Min	-12.932	0.023	0.045







A-4.2 R code for Bootstrap simulation

Toda and Yamamoto

```
N=5000
m=48
p=m-11
A=array(0,dim=c(N,1))
B=array(0,dim=c(N,1))
C=array(0,dim=c(N,1))
D=array(0,dim=c(N,1))
E=array(0,dim=c(N,1))
yy=array(0,dim=c(m,1))
s1=array(0,dim=c(m,1))
yy1=array(0,dim=c(m,1))
cc=array(0,dim=c(m,1))
a=array(0,dim=c(m,1))
yy=t[1]
cc=t[2]
yy=ts(yy)
cc=ts(cc)
yy1=ts(yy1)
s1=ts(s1)
fm=dynlm(yy~(L(cc,1)+L(cc,2)+L(cc,3)+L(yy,1)+L(yy,2)+L(yy,3)))
a=resid(fm)
for (i in 1:N){
s1=sample(a,m,replace=TRUE)
for (j in 4:m){
yy1[j]= 0.96617*yy[j-1]+ 0.11012*yy[j-2]+ 0.03732*yy[j-3] +0.33453*cc[j-1]-
0.79764*cc[j-2]+ 0.27462*cc[j-3]+s1[j]

}
fm1=dynlm(yy1~(L(yy,1)+L(yy,2)+L(yy,3)+L(yy,4)+L(cc,4)))
fm2=update(fm,.~.+ (L(cc,1)+L(cc,2)+L(cc,3)))
A[i]=sum((fm1$residuals)^2)
 B[i]=sum((fm2$residuals)^2)
```

```
C[i]=(p*(A[i]-B[i])/ (3*(B[i])))
D[i]=pf(C[i],3,p,lower.tail=FALSE)

}
for( i in 1:N){if(D[i]<=0.05){E[i]=1}
 else{E[i]=0}
 }
sum(E)
[1] 2604
```

Granger Causality

```
N=5000
m=48
p=m-11
A=array(0,dim=c(N,1))
 B=array(0,dim=c(N,1))
C=array(0,dim=c(N,1))
D=array(0,dim=c(N,1))
E=array(0,dim=c(N,1))
yy=array(0,dim=c(m,1))
s1=array(0,dim=c(m,1))
yy1=array(0,dim=c(m,1))
cc=array(0,dim=c(m,1))
a=array(0,dim=c(m,1))
yy=t[1]
cc=t[2]
yy=ts(yy)
cc=ts(cc)
yy1=ts(yy1)
s1=ts(s1)
fm=dynlm(yy~(L(cc,1)+L(cc,2)+L(cc,3)+L(yy,1)+L(yy,2)+L(yy,3)))
a=resid(fm)
for (i in 1:N){
s1=sample(a,m,replace=TRUE)
for (j in 4:m){
yy1[j]= 0.96617*yy[j-1]+ 0.11012*yy[j-2]+ 0.03732*yy[j-3] +0.33453*cc[j-1]-
0.79764*cc[j-2]+ 0.27462*cc[j-3]+s1[j]

}
fm1=dynlm(yy1~(L(yy,1)+L(yy,2)+L(yy,3)))
fm2=update(fm,.~.+ (L(cc,1)+L(cc,2)+L(cc,3)))
A[i]=sum((fm1$residuals)^2)
 B[i]=sum((fm2$residuals)^2)
C[i]=(p*(A[i]-B[i])/ (3*(B[i])))
D[i]=pf(C[i],3,p,lower.tail=FALSE)
```

```
 }
 for( i in 1:N){if(D[i]<=0.05){E[i]=1}
 else{E[i]=0}
  }
sum(E)
[1] 3370
```

A 4.3 Monte Carlo Simulation for Granger Causality (DGP-1,2,3,4)

Simulation Program in R for Granger Causality

```
library(zoo)
library(quadprog)
library(stats)
library(tseries)
library(dynlm)
N=5000
n=131
m=31
p=m-3
A<-array(0,dim=c(N,1))
B<-array(0,dim=c(N,1))
C<-array(0,dim=c(N,1))
D<-array(0,dim=c(N,1))
E<-array(0,dim=c(N,1))
G=array(0,dim=c(N,1))
H<-array(0,dim=c(N,1))
I<-array(0,dim=c(N,1))
J=array(0,dim=c(N,1))
K=array(0,dim=c(N,1))
set.seed(006198)
for(i in 1:N){
x<-array(0,dim=c(n,1))
 y<-array(0,dim=c(n,1))
 z=array(0,dim=c(n,1))
 z1=array(0,dim=c(m,1))
 y1=array(0,dim=c(m,1))
 x1=array(0,dim=c(m,1))
 e1<-array(0,dim=c(n,1))
 e2<-array(0,dim=c(n,1))
 e3=array(0,dim=c(n,1))
 x<-ts(x)
 y<-ts(y)
 y1=ts(y1)
 x1=ts(x1)
 e1<-ts(e1)
 e2=ts(e2)
 z1=ts(z1)
 e3=ts(e3)
 for(j in 3:n){z[1]=0
 z[2]=0
```

```
e3[j]=rnorm(1,mean=0,sd=1)
z[j]=0.90*z[j-1]-0.80*z[j-2]+e3[j]
y[1]=0
y[2]=0
e2[j]=rnorm(1,mean=0,sd=1)
y[j]= 0.02*y[j-1]+0.83*z[j-1]-0.430*z[j-2]+e2[j]
x[1]<-0
x[2]=0
e1[j]<-rnorm(1,mean=0,sd=1)
x[j]=-0.583*x[j-1]+0.71*z[j-1]+e1[j]
}
for(k in 1:m)
{y1[k]=y[k+100]
x1[k]=x[k+100]
z1[k]=z[k+100]
}
fm=dynlm(x1~0+L(x1,1))
fm1=update(fm,.~.+L(y1,1))
fm2=dynlm(y1~0+L(y1,1))
fm3=update(fm2,.~.+L(x1,1))
A[i]<-sum((fm$residuals)^2)
B[i]<-sum((fm1$residuals)^2)
C[i]<-(p*(A[i]-B[i])/(B[i]))
D[i]= sum((fm2$residuals)^2)
E[i]= sum((fm3$residuals)^2)
F[i]= (p*(D[i]-E[i])/(E[i]))
I[i]=cor(x1,y1)
J[i]=pf(C[i],1,p,lower.tail=FALSE)
K[i]=pf(F[i],1,p,lower.tail=FALSE)}

summary(C)
summary(F)
summary(I)
for(i in 1:N){
 if(J[i]<=0.05){G[i]=1}
 else{G[i]=0}
 }
sum(G)
for(i in 1:N){
 if(K[i]<=0.05){H[i]=1}
 else{H[i]=0}
}
sum(H)
```

```
library(zoo)
library(quadprog)
library(stats)
library(tseries)
library(dynlm)
N=5000
n=131
m=31
p=m-3
A<-array(0,dim=c(N,1))
B<-array(0,dim=c(N,1))
C<-array(0,dim=c(N,1))
D<-array(0,dim=c(N,1))
E<-array(0,dim=c(N,1))
G=array(0,dim=c(N,1))
H<-array(0,dim=c(N,1))
I<-array(0,dim=c(N,1))
J=array(0,dim=c(N,1))
K=array(0,dim=c(N,1))
set.seed(006198)
for(i in 1:N){
x<-array(0,dim=c(n,1))
 y<-array(0,dim=c(n,1))
 z=array(0,dim=c(n,1))
 z1=array(0,dim=c(m,1))
 y1=array(0,dim=c(m,1))
 x1=array(0,dim=c(m,1))
 e1<-array(0,dim=c(n,1))
 e2<-array(0,dim=c(n,1))
 e3=array(0,dim=c(n,1))
 x<-ts(x)
 y<-ts(y)
 y1=ts(y1)
 x1=ts(x1)
 e1<-ts(e1)
 e2=ts(e2)
 z1=ts(z1)
 e3=ts(e3)
 for(j in 3:n){z[1]=0
 z[2]=0
 e3[j]=rnorm(1,mean=0,sd=1)
 z[j]=0.60*z[j-1]-0.30*z[j-2]+e3[j]
 y[1]=0
 y[2]=0
 e2[j]=rnorm(1,mean=0,sd=1)
 y[j]= 0.02*y[j-1]+0.83*z[j-1]-0.430*z[j-2]+e2[j]
 x[1]<-0
 x[2]=0
```

```
 e1[j]<-rnorm(1,mean=0,sd=1)
 x[j]=-0.583*x[j-1]+0.71*z[j-1]+e1[j]
 }
 for(k in 1:m)
 {y1[k]=y[k+100]
 x1[k]=x[k+100]
 z1[k]=z[k+100]
 }
 fm=dynlm(x1~0+L(x1,1))
 fm1=update(fm,.~.+L(y1,1))
 fm2=dynlm(y1~0+L(y1,1))
 fm3=update(fm2,.~.+L(x1,1))
 A[i]<-sum((fm$residuals)^2)
 B[i]<-sum((fm1$residuals)^2)
 C[i]<-(p*(A[i]-B[i])/(B[i]))
 D[i]= sum((fm2$residuals)^2)
 E[i]= sum((fm3$residuals)^2)
F[i]= (p*(D[i]-E[i])/(E[i]))
 I[i]=cor(x1,y1)
J[i]=pf(C[i],1,p,lower.tail=FALSE)
K[i]=pf(F[i],1,p,lower.tail=FALSE)}

summary(C)
summary(F)
summary(I)
for(i in 1:N){
  if(J[i]<=0.05){G[i]=1}
  else{G[i]=0}
  }
sum(G)
for(i in 1:N){
  if(K[i]<=0.05){H[i]=1}
  else{H[i]=0}
 }
 sum(H)
```

```
library(zoo)
library(quadprog)
library(stats)
library(tseries)
library(dynlm)
N=5000
n=131
m=31
p=m-3
A<-array(0,dim=c(N,1))
B<-array(0,dim=c(N,1))
C<-array(0,dim=c(N,1))
D<-array(0,dim=c(N,1))
E<-array(0,dim=c(N,1))
G=array(0,dim=c(N,1))
H<-array(0,dim=c(N,1))
I<-array(0,dim=c(N,1))
J=array(0,dim=c(N,1))
K=array(0,dim=c(N,1))
set.seed(006198)
for(i in 1:N){
x<-array(0,dim=c(n,1))
 y<-array(0,dim=c(n,1))
 z=array(0,dim=c(n,1))
 z1=array(0,dim=c(m,1))
 y1=array(0,dim=c(m,1))
 x1=array(0,dim=c(m,1))
 e1<-array(0,dim=c(n,1))
 e2<-array(0,dim=c(n,1))
 e3=array(0,dim=c(n,1))
 x<-ts(x)
 y<-ts(y)
 y1=ts(y1)
 x1=ts(x1)
 e1<-ts(e1)
 e2=ts(e2)
 z1=ts(z1)
 e3=ts(e3)
 for(j in 3:n){z[1]=0
 z[2]=0
 e3[j]=rnorm(1,mean=0,sd=1)
 z[j]=0.90*z[j-1]-0.80*z[j-2]+e3[j]
 y[1]=0
 y[2]=0
 e2[j]=rnorm(1,mean=0,sd=1)
 y[j]= 0.02*y[j-1]+0.83*z[j-1]-0.430*z[j-2]+e2[j]
 x[1]<-0
 x[2]=0
 e1[j]<-rnorm(1,mean=0,sd=1)
 x[j]=-0.583*x[j-1]+0.171*z[j-1]+e1[j]
```

```
 }
 for(k in 1:m)
 {y1[k]=y[k+100]
 x1[k]=x[k+100]
 z1[k]=z[k+100]
 }
 fm=dynlm(x1~0+L(x1,1))
 fm1=update(fm,.~.+L(y1,1))
 fm2=dynlm(y1~0+L(y1,1))
 fm3=update(fm2,.~.+L(x1,1))
 A[i]<-sum((fm$residuals)^2)
 B[i]<-sum((fm1$residuals)^2)
 C[i]<-(p*(A[i]-B[i])/(B[i]))
 D[i]= sum((fm2$residuals)^2)
 E[i]= sum((fm3$residuals)^2)
F[i]= (p*(D[i]-E[i])/(E[i]))
 I[i]=cor(x1,y1)
J[i]=pf(C[i],1,p,lower.tail=FALSE)
K[i]=pf(F[i],1,p,lower.tail=FALSE)}

summary(C)
summary(F)
summary(I)
for(i in 1:N){
  if(J[i]<=0.05){G[i]=1}
  else{G[i]=0}
  }
sum(G)
for(i in 1:N){
  if(K[i]<=0.05){H[i]=1}
  else{H[i]=0}
 }
 sum(H)
```

```
library(zoo)
library(quadprog)
library(stats)
library(tseries)
library(dynlm)
N=5000
n=131
m=31
p=m-3
A<-array(0,dim=c(N,1))
B<-array(0,dim=c(N,1))
C<-array(0,dim=c(N,1))
D<-array(0,dim=c(N,1))
E<-array(0,dim=c(N,1))
G=array(0,dim=c(N,1))
H<-array(0,dim=c(N,1))
I<-array(0,dim=c(N,1))
J=array(0,dim=c(N,1))
K=array(0,dim=c(N,1))
set.seed(006198)
for(i in 1:N){
x<-array(0,dim=c(n,1))
 y<-array(0,dim=c(n,1))
 z=array(0,dim=c(n,1))
 z1=array(0,dim=c(m,1))
 y1=array(0,dim=c(m,1))
 x1=array(0,dim=c(m,1))
 e1<-array(0,dim=c(n,1))
 e2<-array(0,dim=c(n,1))
 e3=array(0,dim=c(n,1))
 x<-ts(x)
 y<-ts(y)
 y1=ts(y1)
 x1=ts(x1)
 e1<-ts(e1)
 e2=ts(e2)
 z1=ts(z1)
 e3=ts(e3)
 for(j in 3:n){z[1]=0
 z[2]=0
 e3[j]=rnorm(1,mean=0,sd=1)
 z[j]=0.60*z[j-1]-0.30*z[j-2]+e3[j]
 y[1]=0
 y[2]=0
 e2[j]=rnorm(1,mean=0,sd=1)
 y[j]= 0.02*y[j-1]+0.83*z[j-1]-0.430*z[j-2]+e2[j]
 x[1]<-0
 x[2]=0
 e1[j]<-rnorm(1,mean=0,sd=1)
 x[j]=-0.583*x[j-1]+0.171*z[j-1]+e1[j]
```

```
}
for(k in 1:m)
{y1[k]=y[k+100]
x1[k]=x[k+100]
z1[k]=z[k+100]
}
fm=dynlm(x1~0+L(x1,1))
fm1=update(fm,.~.+L(y1,1))
fm2=dynlm(y1~0+L(y1,1))
fm3=update(fm2,.~.+L(x1,1))
A[i]<-sum((fm$residuals)^2)
B[i]<-sum((fm1$residuals)^2)
C[i]<-(p*(A[i]-B[i])/(B[i]))
D[i]= sum((fm2$residuals)^2)
E[i]= sum((fm3$residuals)^2)
F[i]= (p*(D[i]-E[i])/(E[i]))
I[i]=cor(x1,y1)
J[i]=pf(C[i],1,p,lower.tail=FALSE)
K[i]=pf(F[i],1,p,lower.tail=FALSE)}

summary(C)
summary(F)
summary(I)
for(i in 1:N){
  if(J[i]<=0.05){G[i]=1}
  else{G[i]=0}
  }
sum(G)
for(i in 1:N){
  if(K[i]<=0.05){H[i]=1}
  else{H[i]=0}
 }
 sum(H)
```

A4.3 Program for T&Y Procedure (DGP-5 and DGP-6)

```
library(zoo)
library(stats)
library(quadprog)
library(dynlm)
library(tseries)
N=5000
n=132
m=32
p=m-6
A=array(0,dim=c(N,1))
B=array(0,dim=c(N,1))
C=array(0,dim=c(N,1))
D=array(0,dim=c(N,1))
E=array(0,dim=c(N,1))
G=array(0,dim=c(N,1))
```

```
H=array(0,dim=c(N,1))
I=array(0,dim=c(N,1))
J=array(0,dim=c(N,1))
K=array(0,dim=c(N,1))
set.seed(006198)
for(i in 1:N){
x=array(0,dim=c(n,1))
 y=array(0,dim=c(n,1))
 z=array(0,dim=c(n,1))
 z1=array(0,dim=c(m,1))
 y1=array(0,dim=c(m,1))
 x1=array(0,dim=c(m,1))
 e1=array(0,dim=c(n,1))
 e2=array(0,dim=c(n,1))
 e3=array(0,dim=c(n,1))
 x=ts(x)
 y=ts(y)
 y1=ts(y1)
 x1=ts(x1)
 e1=ts(e1)
 e2=ts(e2)
 z1=ts(z1)
 e3=ts(e3)
 for(j in 3:n){z[1]=0
 z[2]=0
 e3[j]=rnorm(1,mean=0,sd=1)
  z[j]=z[j-1]+ e3[j]
  y[1]=0
  y[2]=0
  e2[j]=rnorm(1,mean=0,sd=1)
  y[j]= y[j-1]+z[j-1]-0.50*z[j-2]+e2[j]
  x[1]=0
  x[2]=0
  e1[j]=rnorm(1,mean=0,sd=1)
  x[j]=0.50*x[j-1]+z[j-1]+e1[j]
}
 for(k in 1:m)
 {y1[k]=y[k+100]
 x1[k]=x[k+100]
 z1[k]=z[k+100]
 }
 fm=dynlm(x1~0+L(x1,1)+L(x1,2)+L(y1,2))
 fm1=update(fm,.~.+L(y1,1))
 fm2=dynlm(y1~0+L(y1,1)+L(y1,2)+L(x1,2))
 fm3=update(fm2,.~.+L(x1,1))
 A[i]=sum((fm$residuals)^2)
 B[i]=sum((fm1$residuals)^2)
 C[i]=(p*(A[i]-B[i])/(B[i]))
 D[i]= sum((fm2$residuals)^2)
 E[i]= sum((fm3$residuals)^2)
```

```
F[i]= (p*(D[i]-E[i])/(E[i]))
 I[i]=cor(x1,y1)
J[i]=pf(C[i],1,p,lower.tail=FALSE)
K[i]=pf(F[i],1,p,lower.tail=FALSE)}
summary(C)
summary(F)
summary(I)
for(i in 1:N){
  if(J[i]<=0.05){G[i]=1}
  else{G[i]=0}
  }
sum(G)
for(i in 1:N){
  if(K[i]<=0.05){H[i]=1}
  else{H[i]=0}
 }
 sum(H)
```

```
library(zoo)
library(stats)
library(quadprog)
library(dynlm)
library(tseries)
N=5000
n=132
m=32
p=m-6
A<-array(0,dim=c(N,1))
B<-array(0,dim=c(N,1))
C<-array(0,dim=c(N,1))
D<-array(0,dim=c(N,1))
E<-array(0,dim=c(N,1))
G=array(0,dim=c(N,1))
H<-array(0,dim=c(N,1))
I<-array(0,dim=c(N,1))
J=array(0,dim=c(N,1))
K=array(0,dim=c(N,1))
set.seed(006198)
for(i in 1:N){
x<-array(0,dim=c(n,1))
 y<-array(0,dim=c(n,1))
 z=array(0,dim=c(n,1))
 z1=array(0,dim=c(m,1))
 y1=array(0,dim=c(m,1))
 x1=array(0,dim=c(m,1))
 e1<-array(0,dim=c(n,1))
 e2<-array(0,dim=c(n,1))
 e3=array(0,dim=c(n,1))
 x<-ts(x)
 y<-ts(y)
 y1=ts(y1)
 x1=ts(x1)
 e1<-ts(e1)
 e2=ts(e2)
 z1=ts(z1)
 e3=ts(e3)
 for(j in 3:n){z[1]=0
 z[2]=0
 e3[j]=rnorm(1,mean=0,sd=1)
  z[j]=0.5*z[j-1]+ 0.5*z[j-2]+e3[j]

  y[1]=0
  y[2]=0
  e2[j]=rnorm(1,mean=0,sd=1)
  y[j]= y[j-1]+z[j-1]-0.50*z[j-2]+e2[j]
  x[1]=0
  x[2]=0
  e1[j]=rnorm(1,mean=0,sd=1)
```

```
  x[j]=0.50*x[j-1]+z[j-1]+e1[j]
}
 for(k in 1:m)
 {y1[k]=y[k+100]
 x1[k]=x[k+100]
 z1[k]=z[k+100]
 }
 fm=dynlm(x1~0+L(x1,1)+L(x1,2)+L(y1,2))
 fm1=update(fm,.~.+L(y1,1))
 fm2=dynlm(y1~0+L(y1,1)+L(y1,2)+L(x1,2))
 fm3=update(fm2,.~.+L(x1,1))
 A[i]<-sum((fm$residuals)^2)
 B[i]<-sum((fm1$residuals)^2)
 C[i]<-(p*(A[i]-B[i])/(B[i]))
 D[i]= sum((fm2$residuals)^2)
 E[i]= sum((fm3$residuals)^2)
F[i]= (p*(D[i]-E[i])/(E[i]))
 I[i]=cor(x1,y1)
J[i]=pf(C[i],1,p,lower.tail=FALSE)
K[i]=pf(F[i],1,p,lower.tail=FALSE)}
summary(C)
summary(F)
summary(I)
for(i in 1:N){
  if(J[i]<=0.05){G[i]=1}
  else{G[i]=0}
  }
sum(G)
for(i in 1:N){
  if(K[i]<=0.05){H[i]=1}
  else{H[i]=0}
 }
 sum(H)
```