ELG hypothesis is valid for India: An Evidence from Structural Causality

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Abstract: - Causality is important for empirical analysis in economics but not easily detected. Therefore, it is always important that one should investigate the problem not only on statistical grounds but also add extra statistical information which may come from economic events happening over a time about the problem under study. This extra statistical information helps in introducing asymmetry in the relationship. Most of the studies are based on Granger Causality for determining causal direction between export and economic growth for individual countries. In this paper we use a method suggested by Hoover (2001) for detecting causality which incorporates extra statistical information, economic theory and statistical analysis. We apply this technique to a simulated data and also apply it to the export-led growth hypothesis for India. Our results indicate that there is unidirectional causality from export to economic growth.

Key Words: **Structural Causality, Conditional and Marginal probability distributions, Granger Causality, Export Led Economic Growth**

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1 Introduction

Debate on Causality in economics dates backs to David Hume 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(1776)" 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.[1] 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.

[1] 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. As per Granger criteria a variable X is said to cause the variable Y if by using X we are able to better predict Y than by not using X. Third approach is that of structural causality.In this paper we shall give a brief outline of testing for this approach. In order to show how one should test causality we test export led economic growth (ELG) or vice versa for Indian data. There is no simple rule for establishing causality and the effort made in this paper basically is in close agreement with Hoover's (2001)) idea of causality.

The first objective of this paper is to mention a procedure for testing causal direction in a simple way and applying it to a real data. Moreover we want to find causal direction from export to economic growth on the basis of a combination of factors i-e historical knowledge, economics, probability theory and regression analysis. So it is the first ever study where an alternative technique for finding causal direction has been used.

Section 2 discusses the procedure for testing causality. In section 3, an example based on simulated data and the issue of export-growth data for India has been discussed. In the end conclusions have been made.

2 Method for Detecting 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.

Let

$$x=\alpha+\varepsilon \tag{1.1}$$

$$y=\beta+\gamma * x+\nu \tag{1.2}$$

Where $\varepsilon : n.i.i.d(0,\sigma_{\varepsilon}^{2})$ 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)=σ_{ε}^{2}

$$E(y)=\beta+\gamma\alpha\ ,\ V(y)=\gamma^{2}\sigma\varepsilon^{2}+\sigma_{\nu}^{2} \tag{1.3}$$

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

$$E(\mathrm{x}|\mathrm{y}=y)=\alpha+\left(\gamma\sigma\varepsilon^{2}/\left(\gamma^{2}\sigma\varepsilon^{2}+\sigma_{v}^{2}\right)\right)*(\mathrm{y}-\beta-\gamma\alpha) \quad (1.4)$$

$$=\alpha\sigma_{v}^{2}-\beta\gamma\sigma_{v}^{2}+\left(\gamma\sigma\varepsilon^{2}/\left(\gamma^{2}\sigma\varepsilon^{2}+\sigma_{v}^{2}\right)\right)*\mathrm{y} \quad (1.5)$$

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

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

$$f(\mathrm{x}|\mathrm{y}=y)=N\left(\alpha\sigma_{v}^{2}-\beta\gamma\sigma_{v}^{2}+\left(\gamma\sigma\varepsilon^{2}/\left(\gamma^{2}\sigma\varepsilon^{2}+\sigma_{v}^{2}\right)\right)*\mathrm{y},\sigma\varepsilon^{2}\sigma_{v}^{2}/\left(\gamma^{2}\sigma\varepsilon^{2}+\sigma_{v}^{2}\right)\right) \quad (1.6)$$

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

$$=\beta+\gamma\,\mathrm{x} \quad (1.7)$$

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

$$=\sigma_{v}^{2} \quad (1.8)$$

Conditional distribution of Y given X=x is

$$g(\mathrm{y}|\mathrm{x}=x)=N\left(\beta+\gamma\,\mathrm{x},\sigma_{v}^{2}\right) \quad (1.9)$$

Marginal distribution of X is

$$f(X)=N(\alpha,\ \sigma^{\varepsilon^2}) \quad (1.10)$$

Marginal distribution of Y is

$$h(y)=N\left(\beta+\gamma\alpha,\gamma^{2}\sigma_{\varepsilon}^{2}+\sigma_{v}^{2}\right) \quad (1.11)$$

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.

For example clear shift and change in government policies signals an intervention in the investment policies, minutes of the Central Bank's monetary policy may indicate money-supply process. These are sources for extra statistical information. 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.

So in a gist we state that for finding an evidence of causal direction one should proceed as follows;

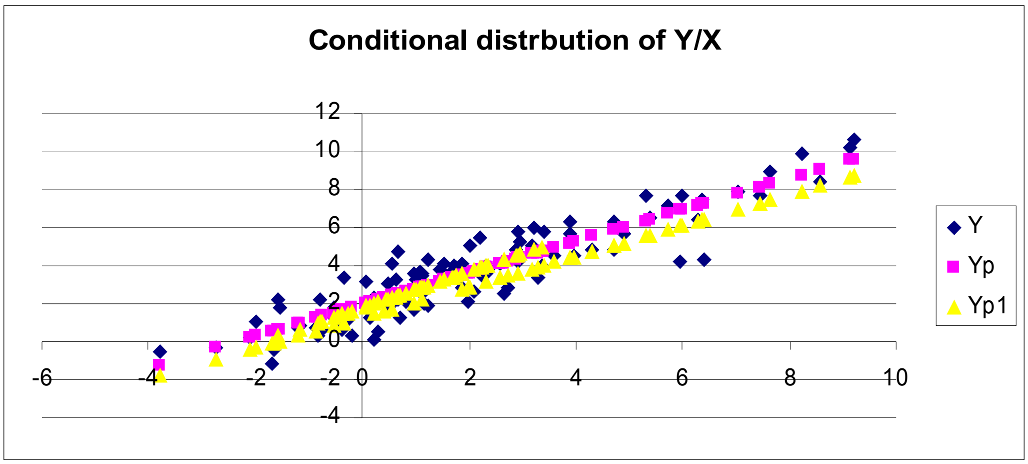
- Have some knowledge from history on intervention in a series
- Apply some statistical test(e.g. Chow Test) to verify that intervention
- If chronological intervention is supported by statistical tests then apply regression on two data sets separately.
- The stable conditional distribution will be probably the true causal relation
- If such interventions exist for both of the variables at a particular time period then we can not find causal direction by such tests.

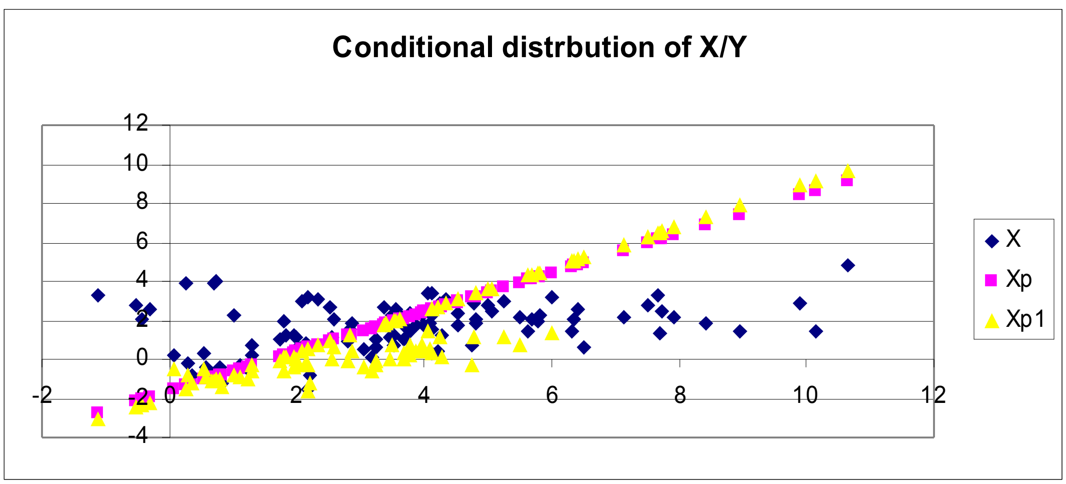
3 Example

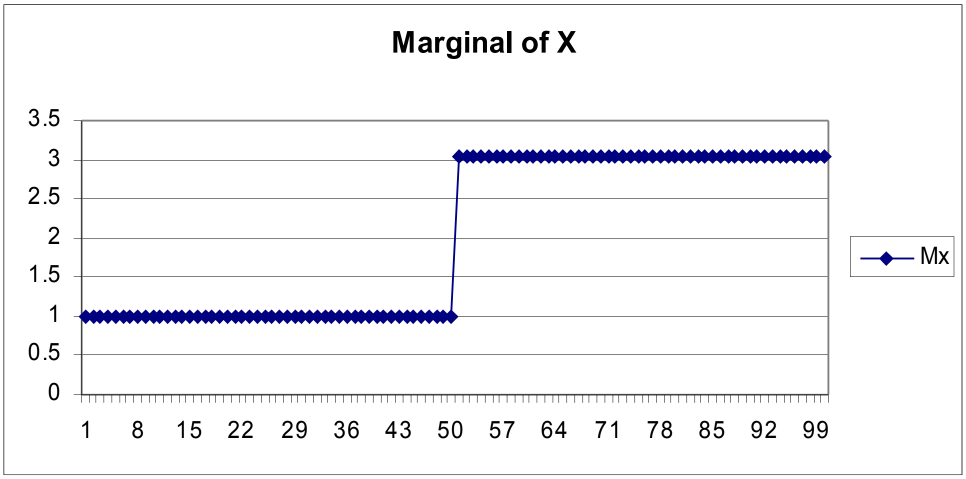
Now we are going to apply this above mentioned idea on a simulated series. Causality has been tested between two variables X and Y where

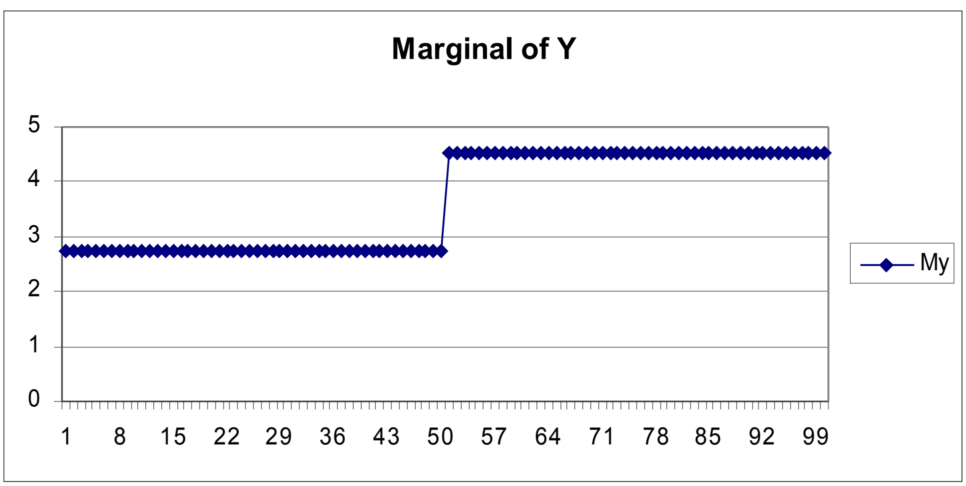
$X=1+e_i$ and $Y=2+0.8*X+e_{j,}$: both random errors are N(0,1) and covariance is zero between these two error terms. Now we have generated 100 observations on X and Y, and from this observed sample we can not make a decision that whether its X which is causing Y or vice versa. Nevertheless, if there is any structural change in any one of the variables and 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 $e_i \sim N(0,1)$ for i=1,2,…,50 and $X_{i+50}=1+e_{i+50}$ where $e_i \sim N(2,3)$. The four distributions namely f(X/Y), f(Y/X), f(X) and f(Y) are given as follows;









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 f(Y/X) remains stable. Both the maginal of X and Y are unstable .This as per our definition indicates that it is the X which is causing Y and not vice versa. So observationally X and Y are equivalent but extra statistical information could lead us to trace the causal pattern.

We are going to implement this idea of finding the direction of causality to the export led growth for the Indian data.

4 Causality Test for Export-Growth Data for India

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; Blasa 1978; Heller and Porter, 1978; Tyler, 1981; Feder(1983), suggested that export promotes overall economic growth. 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.[2]

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.[3]This increase in capital goods in turn boosts economic growth by raising the level of capital formation. 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.

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[2]

[3] Reizman, Summers, and Whiteman (1996)

Secondly, the growth of exports can increase productivity by offering larger economies of scale.

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, better forms of organizations, labor training , and knowledge about technology and intellectual markets .In short export growth has beneficial impact on output growth.[4]

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. 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 (Herzer et al(2006)).

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, and there is break point at 1990 in export series. This may be due to the fact that Indian Policy makers changed their policies of investment and opened its economy for foreign investment in early 1990s which might led export to grow and then ultimately economic growth. Although results of these policies materialized in

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

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 conditional 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.

In this paper we have used yearly data for India (1955-2002) on GDP, export, unit value of export, and GDP deflator from International Financial Statistics website ifs.apdi.net.

The variables we have used are real export and real GDP. Y is used for real GDP which is obtained as the ratio of GDP to GDP deflator and X (real export) is obtained as the ratio of export value of goods and services to unit value of export. Both Y and X variable are measured at annual frequency and are in log form.

Results for these data ranges and plots of these ranges are given below.

Unit Root Test results by ADF test indicate that both the variables are nonstationary at level and stationary at the first difference.

Table 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 represents 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.

Chow Breakpoint Test

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

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)
		(0.0.017) (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 the DY and DX.

By observing fig 1.1-1.4 it seems that three distributions breakdown and only one remains stable, which implies f(Y/X) is the stable relation and X is causing Y and not vice versa.

Following are the 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.

Marginal of X :   X1F is for the whole data set, X2F is the for the data set 1955−1989

X3F is for the data set 1990−2002

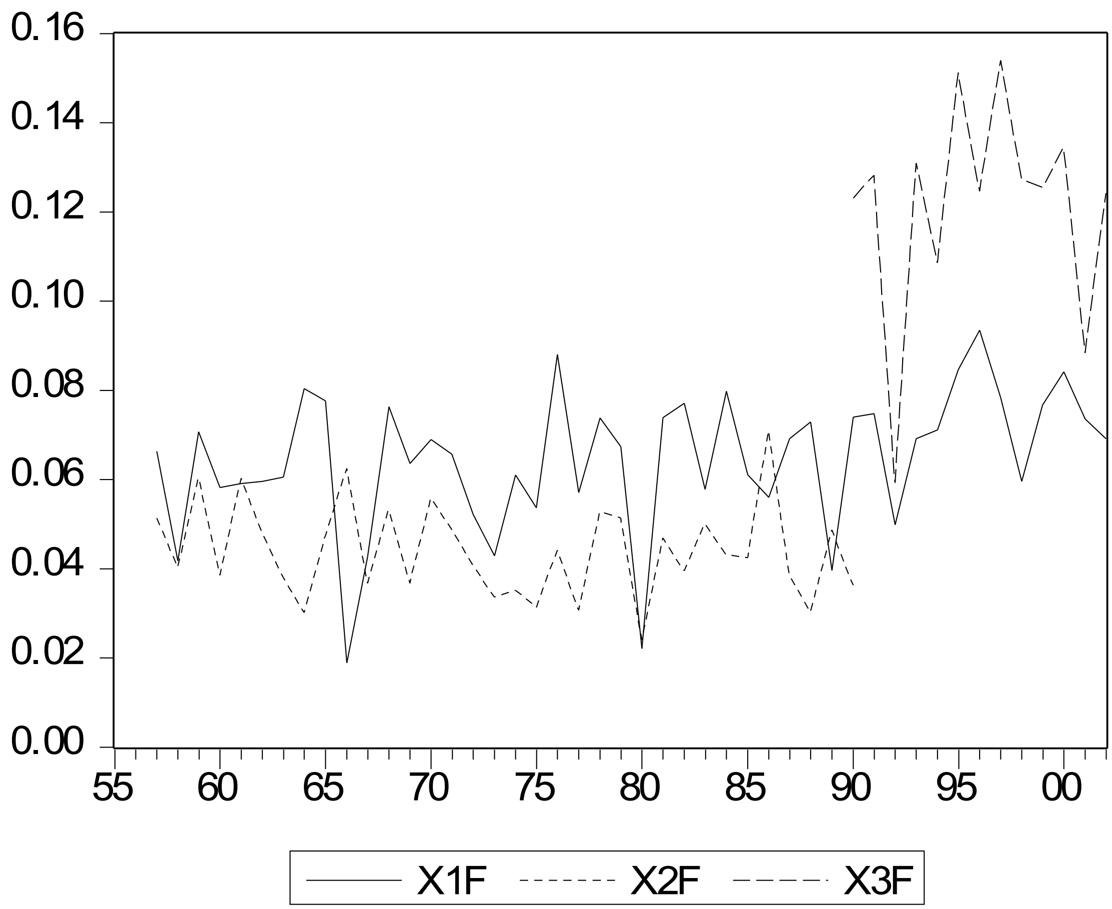


Fig1.1

Conditional of Y   : Y1F is conditional distribution for the whole range

Y2F for range 1955−1989, Y3F for the range 1990−2002

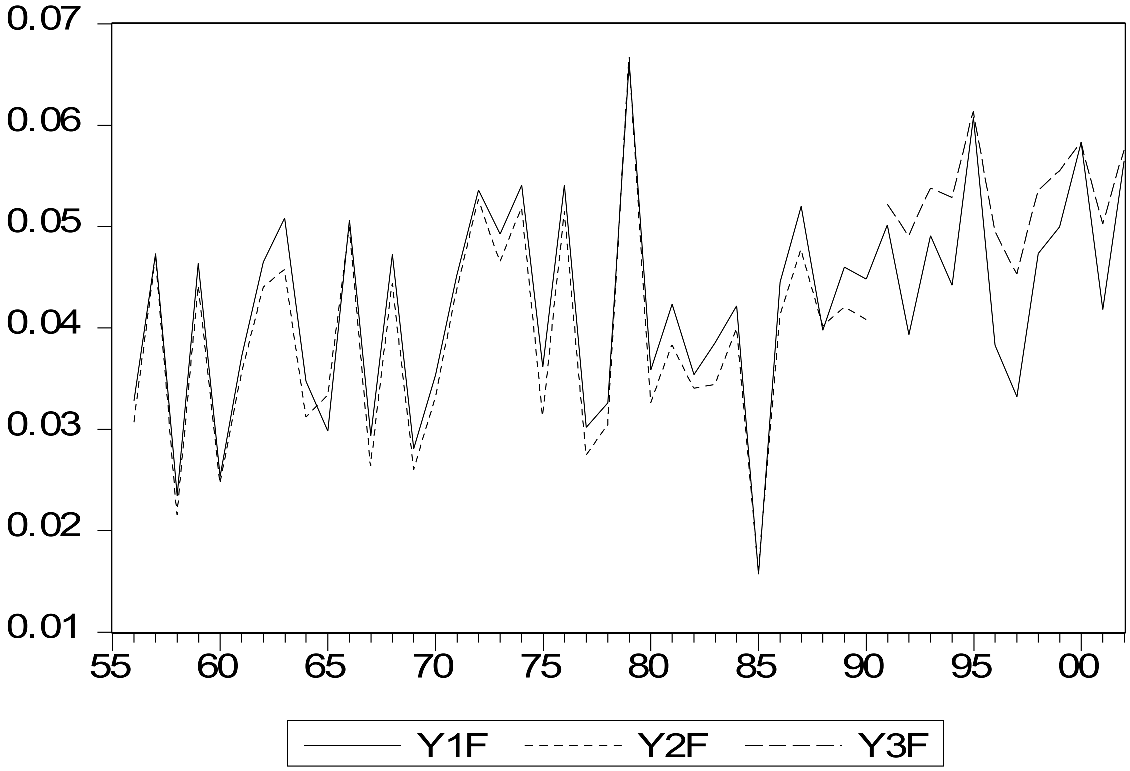
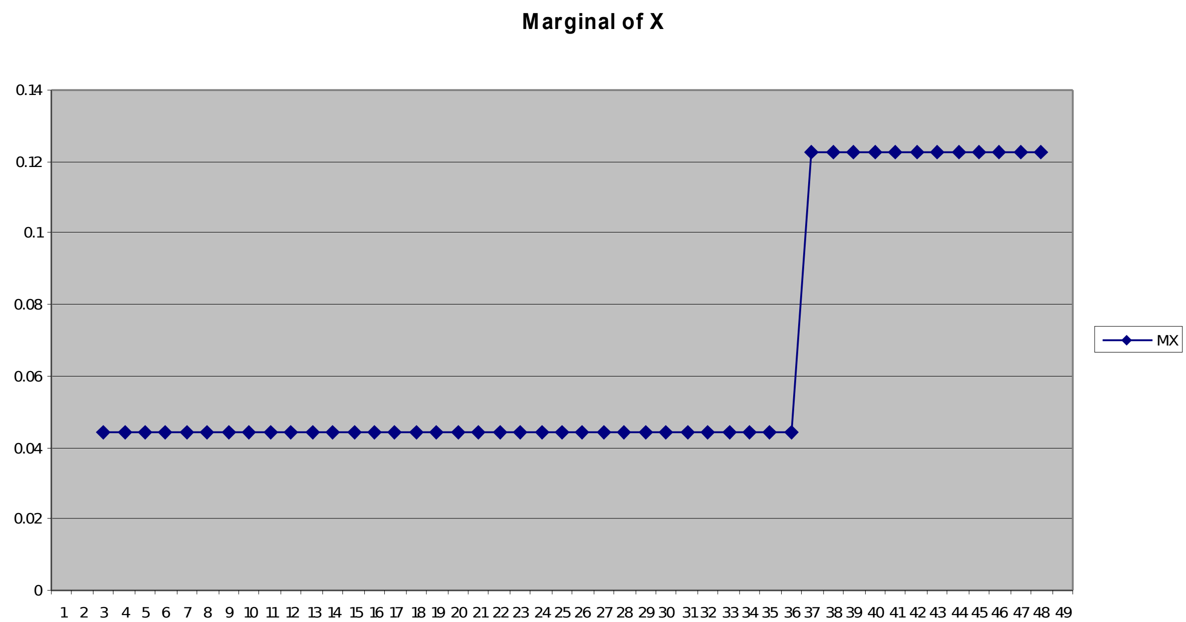

0.07
0.06
0.05
0.04
0.03
0.02
0.01
55
60
65
70
75
80
85
90
95
00
Y1F
Y2F
Y3F

Fig.1.2

Marginal of X and Y are as follows



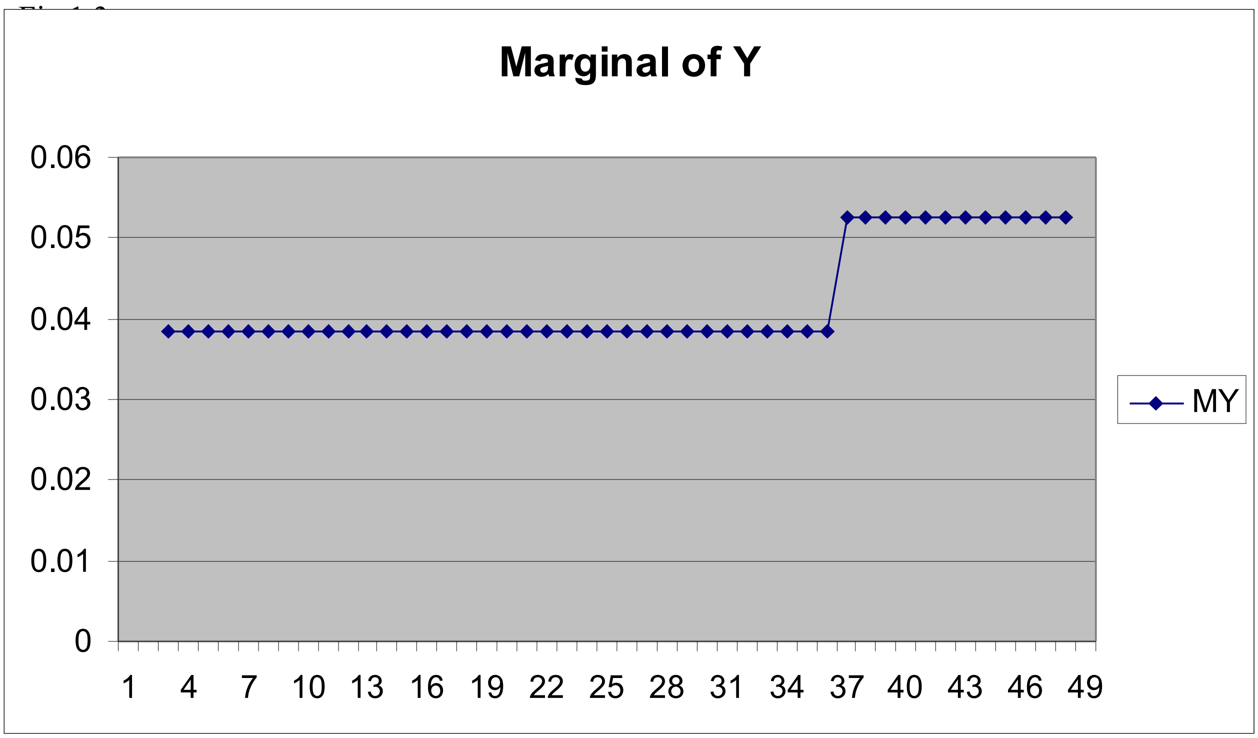


Fig 1.4

We have incorporated all the sources of information i-e historical, statistical, theoretical etc for evaluating the model. Introduction of this extra statistical information (historical events) helps to introduce asymmetry in the relationship, which in turn helps to determine causal direction. We conclude that real export is a cause of economic growth and export expansion has beneficial impact on GDP for India. Therefore, 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.

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