A Structural Approach for Testing Causality

Zahid Asghar®

Quaid-i-Azam University, Islamabad

ABSTRACT

The ever present possibility of confounding factors creates difficulties in identifying causal effects on the basis of observational data. A large number of approaches to resolve this difficulty have been proposed; see Zaman (2010) for a recent survey. One involves using a "natural experiment," where nature acts like an experimenter in changing the setting of a key variable, allowing us to differentiate between 'treatment' and 'control' observations. This idea has been used by Hendry and Ericsson (1991), Hoover (2001), and Keane (2010) in rather complex settings. This paper presents an elementary version of this structural approach for detecting causality in the simplest possible setting. The structural method is able to detect contemporaneous causality. We illustrate the uses of this technique on a simulated data set, and also apply it to the export-led growth hypothesis for India and energy-growth data for Shanghai.

Key words: *Structural Causality, Granger Causality, Extra-statistical Information, Export led Growth*
JEL Classifications: C, C5, C59

1. INTRODUCTION

An econometric model can be used mechanically to summarize data, or to predict the future, by extrapolating from existing correlations within the data. A much deeper and more difficult problem arises if we wish to predict the results of interventions. This requires separating correlations from causation, which is simultaneously most important and most slippery particularly in observational studies. For example, we observe that education, life expectancy, and GNP per capita are all increasing together. Are all three driven by some unobserved factor X which causes growth, or is one of the factors the cause of the other two? Policy decisions hinge crucially on isolating the causal factors, and being able to differentiate these from mere correlations.

Though in the early part of the twentieth century causal analysis was a basic organizing principle in animating the development of econometrics, yet causal language is absent from our standard econometrics textbooks. Hoover (2004) in his article "Lost Causes," describes and explains how causality dropped out of economic discourse. Causality re-entered the scene after Granger introduced a notion of causality based on the predictability of one series by another. Though it is well known that Granger-Causality is not detecting causality (Madala and Kim, 2000:188-189; Hoover, 2001:150-155), yet various authors continue to rely on this technique and validate causality claims for time series data. There are many others who switch from association to causation while making interpreting their results. Granger himself

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® Zahid Asghar, Quaid-i-AzamUniversity, Islamabad, (email: g.zahid@gmail.com).
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never claimed this as a test of causality and warns that many authors have evolved somewhat unclear and incorrect form of his definition as they have not looked at the original papers. Pagan (1989) remarks about Granger causality that

> '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.'

Nevertheless, one positive aspect of Granger causality is that it reinvigorates the issue of causality in economics in the last couple of decades. Causality is now explicitly discussed in some econometrics books (e.g. Mostly Harmless Econometrics: An Empiricist's Companion by Joshua D. Angrist and Jörn-Steffen Pischke, 2009). Hoover (2001) "Causality in Macroeconomics" provides an in-depth analysis of causality in economics. After explaining the importance of causality in macroeconomics he surveys current approaches to causality, exogeneity and the Lucas critique. He also discusses the structural procedure for detecting causality by using extra-statistical information in an econometric model. This is the approach we adopt in the present paper.

For readers interested in techniques going beyond the discussion in this paper, Pearl (2009) is an important reference. Pearl uses Directed Acyclical Graphs (DAGs) to invoke asymmetries between cause and effect to uncover the causal relationships in contemporaneous time. Such causality is generally left uncovered in Granger causality. Pearl's approach is an attempt to infer causal relations from observational data. In addition, Zaman (2010) provides a useful survey of causality in econometric models. He points out various examples where simple regression results apparently show causal relations but when analyzed outside the range of conventional econometric techniques causal claims did not hold. Zaman (2010) seems in close agreement with Freedman (1991) who has advised us to use shoe leather – meaning real world information not easily reducible to numbers or statistics – to discover causal conclusions. In a nutshell, the basic idea is to look for events where nature played the role of the experimenter – structural changes occurred due to exogenous causes. Judging this exogeneity requires real world knowledge going outside the system under study. Evaluating the effects of such exogenous events can allow us to discern causal laws from observational data.

In section 2 we discuss the procedure for testing structural causality in the simplest possible setting. Then we illustrate by applying this procedure to 3 examples. Section 3 studies an artificial example with simulated data to illustrate the mechanics of the structural approach. In section 4, we apply the approach to a real world data set studying the causal relation between exports and growth in India. Our results provide some support for the export led growth hypothesis. Section 5 studies the relation between energy and growth for Shanghai. Here our approach leads to suggests that causal directions cannot be determined because of lack of structural change. The final section provides concluding remarks.

2. METHOD FOR DETECTING STRUCTURAL CAUSALITY

We will now explain the basis of the method for detecting structural causality. Let (X,Y) be a sequence of observations with *i.i.d.* distribution $N(\boldsymbol{\mu},\boldsymbol{\Sigma})$. Such a sequence of observations can be generated in three different ways:

Method 1: Let (V,W) be *i.i.d.* $N(0,\mathbf{I}_2)$. Since $\mathbf{\Sigma}$ is a 2 x 2 positive definite matrix, it is possible to decompose it as $\mathbf{\Sigma}=\mathbf{UU}'$. We can generate ($X$,$Y$) from ($V$,$W$) via the linear transformation:

$$\begin{pmatrix}\mathbf{X}\\ \mathbf{Y}\end{pmatrix} = \mu + \mathbf{U}\begin{pmatrix}\mathbf{V}\\ \mathbf{W}\end{pmatrix}$$

Then X, Y will be jointly normal according to the prescribed distribution. If this is how the world generates this data, then X, Y are jointly caused by hidden variables V and W. Neither variable causes the other.

Method 2: Generate X from its marginal distribution $X\sim N(\boldsymbol{\mu}_1,\mathbf{\Sigma}_{11})$. Generate Y from its conditional distribution $Y|X\sim N(\boldsymbol{\mu}_2+\mathbf{\Sigma}_{21}\mathbf{\Sigma}_{22}^{-1}(\mathbf{X}-\boldsymbol{\mu}_1),\mathbf{\Sigma}_{11}-\mathbf{\Sigma}_{12}\mathbf{\Sigma}_{22}^{-1}\mathbf{\Sigma}_{21})$. This can also be written as a regression model

$$Y = a + bY + \varepsilon$$

If this is how the real world generates (X,Y) then X is the cause of Y and changes in X will lead to changes in Y but not the other way around.

Method 3: Generate Y from its marginal and X from its conditional. In this case, Y is the cause of X.

All three methods will lead to data with exactly the same distribution, so all three are observationally equivalent. This shows why it is difficult to evaluate causality from observational data. Suppose, however, that structural change takes place. The mean and variance of the marginal distribution of X change. Now the three models will behave differently. In the first model, the relation between X and (V,W) must change since mean and variance of X has changed. So the equation $\mathbf{X}=\mathbf{U}_{11}\mathbf{V}+\mathbf{U}_{12}\mathbf{W}$ will change in parameters $\mathbf{U}_{11}$, $\mathbf{U}_{12}$. In the second model, the parameters of the distribution of X will change, but there will be no change in the regression model which describes the conditional distribution of Y given X. In the third model, first suppose that the structural change does not affect the marginal distribution of Y. Then a relationship of the type

$$X = c + dY + \varpi$$

cannot remain stable, but must shift to accommodate the shift in the distribution of X. So estimates of this relationship will show structural change. Even if the structural shift affects the distribution of Y, such shifts would also typically create instability in the conditional distribution of X given Y. Thus looking at which of the two conditional distributions remains stable can give us a clue about the direction of causality between X and Y *if there are structural shifts*. An interesting corollary of this argument is that it is impossible to detect causality if there are no structural shifts – both causal directions, as well as simultaneous determination – are observationally equivalent.

This approach for testing causality requires investigation of the underlying economic mechanism not only on theoretical grounds but also in historical prospective. We need to find shifts in distributions which are due to exogenous causes. This requires extra statistical information such as shift in government policies, minutes of the Central Bank's monetary policy etc. From this historical information, it may be possible to infer that the intervention was not caused by the variable under study. In such cases, the intervention is like the treatment effect created by an experimenter. Hoover (2001) mentions that this intervention should be traced in historical perspective and then statistical tests should also be carried out to validate 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.

If the time of intervention in one variable is being determined, then further analysis, by considering conditional and marginal distributions of the variable, is possible. The mechanism to find causal direction proceeds as follows:

- 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 cannot find causal direction by such tests.

3. ILLUSTRATIVE EXAMPLE: SIMULATED DATA

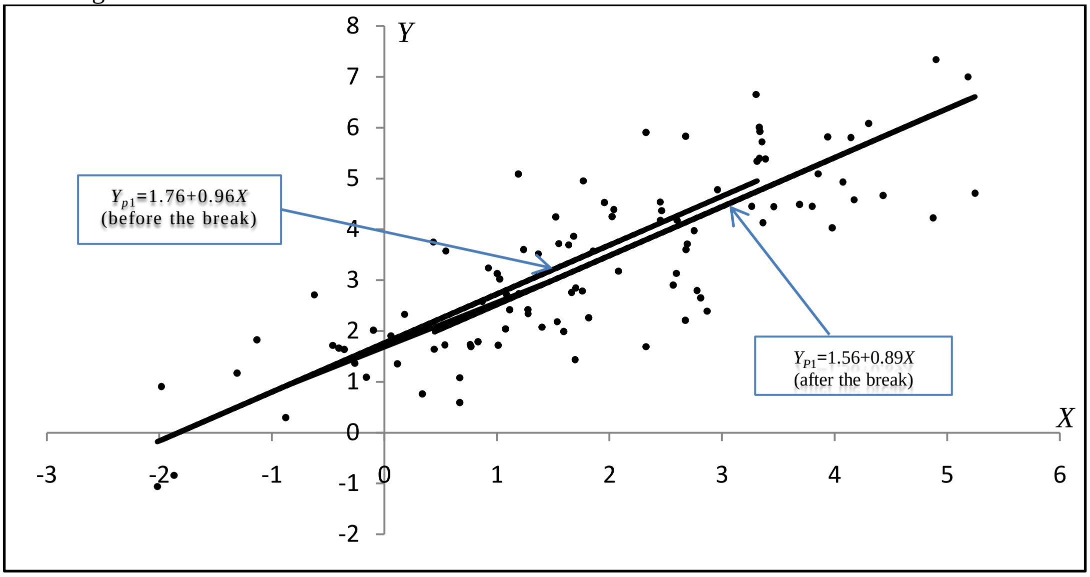
Now we apply the concept of section 2 on a simulated series. Causality has been tested between two variables X and Y where X_i=1+e_i and Y_i=2+0.8$*X_i$+ϵ_i. Both random errors e_i and ϵ_i are N(0,1) and covariance is zero between these two error terms. Now we have generated 100 observations on X and Y, and from this observed sample we cannot make a decision whether X is causing Y or vice versa. This is because, as we have argued in the previous section, the causal model above is observationally equivalent to one in which (X,Y) are bivariate normal and jointly simultaneously determined. It is also observationally equivalent to one in which Y is determined first, and then X is drawn from the conditional distribution of $X|Y$, making X causally dependent on Y. However, if there is any structural change in any one of the variables, it may be possible to determine causality. Of the two conditional distributions, the one which reflects the true causal relationship would remain stable, while the other one would display shifting parameters.

To observe the behavior of these probability distributions we have changed the values of second half of the X variable, X_i=1+e_i where e_i ~N(0,1) and X_{i+50}=3+e_{i+50} where e_{i+50}~N(0,1) for i=1,2,…,50.

Now we analyze the behavior of the two regressions through simulated data using models 2 and 3.

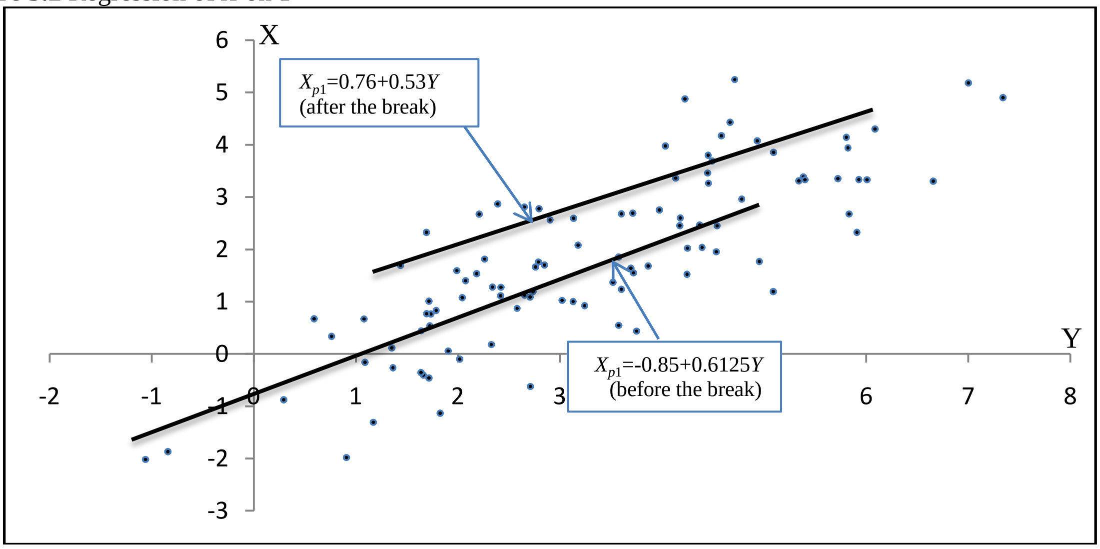
Figure 3.1 shows the regression of Y on X for the full sample, before and after the intervention. The two regressions before and after the interventions shows no significant differences. Figure 3.2 shows the regression of X on Y for the full sample, before and after the intervention. We observe significant shift in the two regressions before and after the intervention. The stability of the regression of Y on X, together with the structural change in X suggests that the causal direction is from X to Y. Lack of stability in the other direction shows that the reverse causality does not hold.

Figure 3.1 Regression of *Y* on *X*



Notes: Y_{p1} is the regression equation of *Y* on *X* before and after the break

Figure 3.2 Regression of *X* on *Y*



Notes: X_{p1} is the regression equation of *X* on *Y* before and after the break

4. STRUCTURAL 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.

Many arguments have been put forth to support export led growth (ELG) hypothesis theoretically. From a demand side perspective, it is assumed that sustained demand growth in a small domestic economy cannot be maintained permanently since domestic demand exhausts very soon. Export markets, on the other hand, 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. Many other arguments have been given in support of ELG. At the same time, opponents have put forth many counter-arguments. For example, increase in real GDP could lead to realization of economies of scale and cost reduction that could, in turn, boost exports. An attempt to resolve this controversy has been made using empirical work. There are several studies which investigate whether strong association between export and economic growth can be translated into causal relationship or vice versa. Since Granger causality (GC) is the most commonly tools used for studying causal direction between export and economic growth for time series data, we provide a discussion and comparison.

Strictly speaking, GC is not comparable with the method under discussion. GC relies on timing and the possibility of predicting one series from lagged values of the other for decisions about causality. The examples of sections 2 and 3 have contemporaneous causality – lagged values of X and Y contain no information about future values. In such cases, GC would not detect any causality, while the structural method would work, as illustrated. The structural method can detect timing effects. To match the GC methodology, we could look at the regression of Y on lagged values of X as well as the regression of X on lagged values of Y. If one of these regressions captures a causal effect, its coefficients will remain stable through a period of structural change. Of course, if there is no structural change, then both regressions will remain stable, and the structural method will be unable to detect causal effects. An example of this type is given in section 5.

For the sake of comparison with the structural technique, we illustrate the use of GC on Indian data for exports and growth. Our primary conclusion is the extreme sensitivity of the GC results to choice of sample period, as well as the specification of lag order. We have used yearly data for India (1955-2002) on GDP, export, unit value of export and imports, and GDP deflator from International Financial Statistics (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 the unit value of export. All the data are annual and variables are used in natural log form.

For India, Table 4.1 and 4.2 present the GC results by Toda and Yamamoto (1995, TY) procedure for two different sample ranges. The basic idea of TY approach is to artificially augment the correct order of the VAR model by maximal order of integration, say d_{max}. Once we indentify and estimate a VAR model with ($d_{max}+k$) order, we apply the standard Wald test, exclude the coefficients of last lagged vector d_{max}, on the remaining k parameters to find out whether X GC Y or vice versa. To represent the GDP-export model in the VAR system TY version of GC test has the following form.

$$Y_t = \alpha_0 + \sum_{i=1}^{n} \alpha_{1i} X_{t-i} + \sum_{i=n+1}^{d_{\max}} \alpha_{2i} X_{t-i} + \sum_{j=1}^{m} \phi_{1j} Y_{t-j} + \sum_{j=m+1}^{d_{\max}} \phi_{2j} Y_{t-j} + \varepsilon_{t1} \tag{4.1}$$

$$X_t = \delta_0 + \sum_{i=1}^{k} \delta_{1i} X_{t-i} + \sum_{i=k+1}^{d_{\max}} \delta_{2i} X_{t-i} + \sum_{j=1}^{l} \varphi_{1j} Y_{t-j} + \sum_{j=l+1}^{d_{\max}} \varphi_{2j} Y_{t-j} + \varepsilon_{t2} \tag{4.2}$$

Where X_t log of real export and Y_t is the log of real GDP. The initial lag length n, m, k and l are chosen using AIC and SC criterion. Where ε_{t1} and ε_{t2} are the error terms.

From Eq (4.1), GC from X_t (export) to Y_t (GDP) implies $\alpha_{1i} \neq 0\ \forall i$; Similarly in Eq (4.2) Y_t (GDP) Granger cause X_t (export), if $\varphi_{1j} \neq 0\ \forall j$.

TY proves that Wald statistic used converges in distribution to a χ^2, no matter whether the process is stationary or non-stationary and whether it is cointegrated or not. Export seems to cause economic growth both at lag length (2,2) and (3,3) at 5% level of significance in Table

4.2 but in Table 4.1 it is not significant at 5%. AIC and SC are used for lag length selection but the two criteria provide different lag lengths.

Our results based on GC test for the case of India are given in Table 4.1:

Causal Direction	Lag Length	*p*-value	AIC	SC
$X \Rightarrow Y$	(2,2)	0.0547	-4.23	-4.03
$X \Rightarrow Y$	(2,3)	0.1346	-4.24	-3.99
$X \Rightarrow Y$	(2,4)	0.3361	-4.17	-3.88
$X \Rightarrow Y$	(3,3)	0.097	-4.2662	-3.98
$X \Rightarrow Y$	(1,3)	0.1049	-4.2661	-4.06

Table 4.1 Results for India 1955-2002.

These results show that minor changes in specification can lead to different outcomes for the GC test. Similarly, if we change the sample to eliminate the last four years, we get the following results in Table 4.2:

Causal Direction	Lag Length	*p*-value	AIC	SC
$X \Rightarrow Y$	(2,2)	0.0317	-4.187	-3.9806
$X \Rightarrow Y$	(2,3)	0.0653	-4.201	-3.9504
$X \Rightarrow Y$	(3,3)	0.0437	-4.2390	-3.9465

Table 4.2 Results for India 1955-1998.

This shows the sensitivity of the GC test to minor changes in (model) specification. From these results it is hard to come to any definite conclusion about causality from the GC test. This is also reflected in the literature, in which different authors come to different conclusions. For example Love and Chandra (2004) find bi-directional causality between real export and real income for India, export led growth for Pakistan, and non-causality for Sri Lanka. Love and Chandra (2005) find export led growth causality for India and no relationship between export and economic growth for Pakistan and Sri Lanka. They have used the same statistical procedure in both of these papers.

We now illustrate the use structural causality approach to determine the direction of causality. If we investigate the two observed series 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. For export data we think opening of Indian economy for foreign investment in early 1990s and hence economic growth. Although results of these policies might have materialized in mid 1990s and onward, but due to data constraint we have applied Chow structural breakpoint test at 1990 (Table 4.2) and find that there is structural change. Therefore, we split data into two parts, i.e., 1955-1989 and 1990-2002.

	Test statistic		5% critical value	
Variables	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

Table 4.3 ADF test India (1955-2002).
Notes: 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.

ADF test results (Table 4.3) indicate that both GDP and export series are non-stationary at level and stationary at first difference, so we have used series in first difference form.

The Chow test confirms the existence of a structural break at 1990. Now we will examine the stability of the two regressions that is of *Y* on *X* and that of *X* on *Y*.

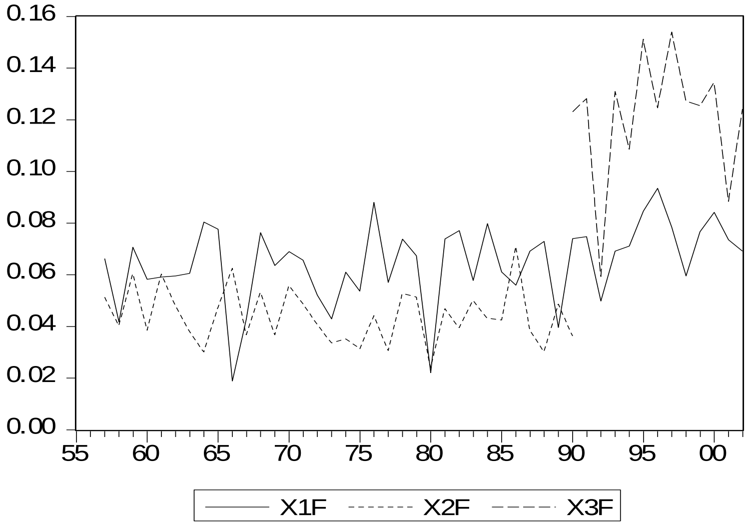
	Year		
	1990	1979	1965
Export	0.018	0.274	0.3751
GDP	0.089	0.498	0.769

Table 4.4 Chow Breakpoint Test.

Distributions	Year	Results
GDP Conditional	1955-2002	DY=0.483$DY(-1)$+ 0.2039$DX(-1)$
		(0.115) (0.056)
	1955-1989	DY=0.410$DY(-1)$+0.2189$DX(-1)$
		(0.0778) (0.1426)
	1990-2002	DY=0.7083$DY(-1)$+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=0.700$DY(-1)$ −0.0001$DX(-1)$
		(0.318657) (0.174)
	1990-2002	DX=2.4148$DY(-1)$−0.1126$DX(-1)$
		(0.7665) (0.3172)

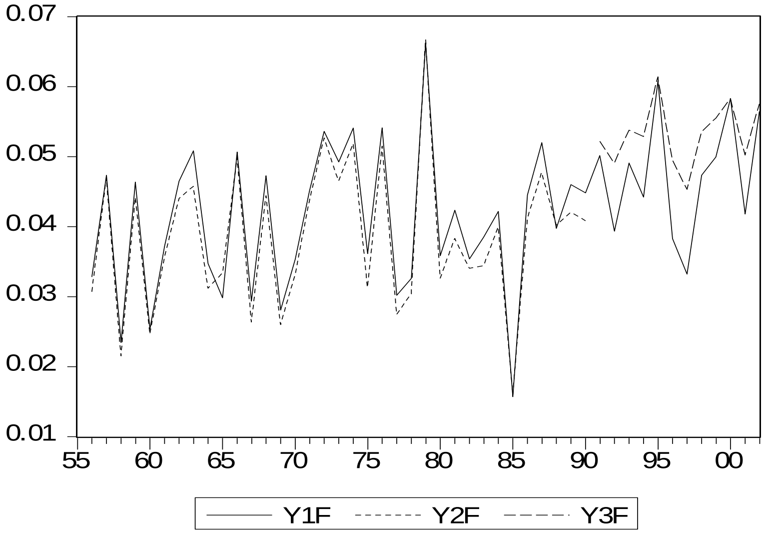
Table 4.5 Characterization of the two Regressions.
Notes: where *DY* is the first difference of the real GDP, *DX* is the first difference of the real export. *DY*(−1) and *DX*(−1) denote the first lag of the *DY* and *DX*.

Figure 4.3 Fitted values of *DX* on *DY*(-1) and *DX*(-1).



Notes: X1F is for the complete sample, X2F is the for the sample period 1955−1989, X3F is for the sample period 1990−2002

Figure 4.4 Fitted Values of *DX* on *DY*(-1) and *DX*(-1)



Notes: Y1F is for the full sample, Y2F for sample period 1955−1989 and Y3F for the sample period 1990−2002.

Figure 4.3 and 4.4 are fitted values of the regressions from six equations in Table 4.5.

We observe from Figure 4.3 and 4.4 that regression of *DX* on *DY*(-1) and *DX*(-1) (corresponding to f(*Y/X*) is stable before and after the break point detected by Chow test, where as regression of *DY* on *DX*(-1) and *DY*(-1) is unstable before and after the break point). Our results indicate that causal direction is from export to economic growth. Nevertheless, these results should be taken with care as there are many possible misspecifications which have not been tested for.

5. STRUCTURAL CAUSALITY ANALYSES FOR ENERGY GROWTH DATA OF SHANGHAI

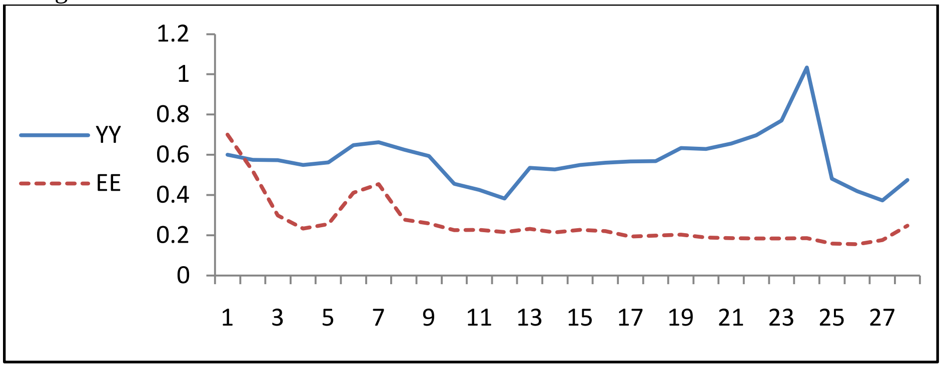
In this section, we try to apply the structural method to the Energy Growth data for Shanghai. We start with the standard GC analysis, both to serve as a benchmark, and for the sake of comparison. We start by replicating the results of Wolde-Rufael (2004) paper. Our results match with those of the results reported in the original paper. These results are reported in the first column of Table 5.6. As in the previous case studied, Column 2 of Table 5.6 shows that GC results are sensitive with respect to sample range.

Results of Causality from 1952-1999 (at lag length 4)		
Source	1952-1999 (lag4)	1965-1999 (Lag4)
$KK \Rightarrow YY$	0.0019	0.730152
$TE \Rightarrow YY$	0.0032	0.919491
$EE \Rightarrow YY$	0.0018	0.899251

Table 5.6 Granger causality results by the TY Procedure.
Notes: *CC, EE, KK, TE* and *YY* are the logs of coal, electricity, coke, total energy consumption and real GDP, respectively. The numbers in the table are the *p*-values.

We see that GC gives ambiguous and conflicting results regarding the relation between energy and growth in Shanghai. We shall try to apply the test for structural causality. We expected to find structural change due to the Oil Crisis in the early 70's. However, a graph of the data shows no apparent structural change. Similarly, statistical testing also fails to reveal any significant breakpoints. A rolling Chow test, which is the most powerful as recommended by Andrews (1993) – Andrews calls it the sup *F* test, gives no evidence of structural change in either of the two regressions. Results of Rolling Chow test are plotted in Figure 5.5. We don't find any structural break if we follow the rule of thumb that value greater than 5 show structural change for the Chow statistics.

Figure 5.5 Rolling Chow Statistics



This is surprising given the steep rise in energy prices following the Oil crisis in 1970's. This means that the structural approach is not applicable to this data set. Nevertheless, to match our results with GC we report results for the regression of *Y* on *X* and *X* on *Y* in Table 5.2 and we find both are stable.

Distributions	Year	Results
GDP Conditional	1952-1999	DY=0.348$DY(-1)$ -0.036467$DE(-1)$
		(0.274) (0.266)
	1952-1965	DY=0.313$DY(-1)$-0.0886DE−1)
		(0.571) (0.568)
	1966-1999	DY=0.336$DY(-1)$+0.257 $DE(-1)$
		(0.284) (0.326)
Export Conditional	1952-1999	DE=0.376 $DY(-1)$+0.1096 $DE(-1)$
		(0.244) (0.252)
	1952-1965	DE=0.476 $DY(-1)$+0.0001 $DE(-1)$
		(0.554) (0.552)
	1990-2002	DE=0.044$DY(-1)$+0.588$DE(-1)$
		(0.219) (0.240)

Table 5.7 Characterization of the two Regressions.
Notes: where *DY* is the first difference of the GDP, *DE* is the first difference of the Electricity, $DY(-1)$ and $DE(-1)$ Denote the first lag of the *DY* and *DE*.

This seems to match the GC results in terms of saying that both causal directions are compatible with the data. This situation illustrates a methodological comment of Hendry, relating to the widespread breakdown of econometric models following the 70's oil crisis. He stated that when there is no structural change, all models (good or bad) perform equally well. When structural change occurs than correlations based on causal relationships will persist, while accidental correlations will break down.

6. CONCLUSION

The basic essence of this procedure is to trace some structural change, i.e., a change which helps in determining the procedure of data generating process. Otherwise it is impossible to detect causality by looking at the data so long as there is no structural change. To determine the causal direction we find that it is important to determine the point of structural intervention both from historical and institutional knowledge in the variables under study. If statistical tests support historically detected intervention in the variable(s) then it might be possible to find the causal ordering which is consistent with data. This approach does not reject alternative approaches to causality (Granger causality or Graph theoretic approach) rather it uses additional information to resolve the issue of causality. This approach seems quite promising and requires that every problem should be resolved by using evidence obtained from different sources rather inferring causation by using statistical tools alone. We have described this procedure for two variable cases but this can easily be extended to multiple variable regression models.

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