DYNAMIC ECONOMETRIC MODELS
Vol. 11 – Nicolaus Copernicus University – Toruń – 2011

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On the Interpretation of Causality in Granger's Sense

A b s t r a c t. The concept of causality formulated in 1969 by C.W.J. Granger is mostly popular in the econometric literature. The central assumption of the concept is the fact that the cause precedes the effect and can help in forecasting the effect. Years of application of Granger causality idea have resulted in many misunderstandings related with the interpretation of the empirical findings. The paper focuses on systematization of the definitions based on Granger concept and their proper interpretation.

K e y w o r d s: Granger causality, systematic causality, informational causality, nonlinear causality.

Introduction

The concept of causality formulated in 1969 by Clive Granger, based on earlier paper by Wiener (1956), is mostly popular in the econometric literature. The central assumption of the concept is the fact that the cause precedes the effect and can help in forecasting it. It is further assumed that the cause includes unique information of the effect, which is not available in any other way. The potential causes are chosen from all information connected with the effect.

The general definition of Granger's causality is formulated in the framework of conditional probability distribution. Let $F(Y \mid X)$ denote conditional distribution of *Y* given *X*, and Ω_t represents all information in the universe in time *t*. It is said that X_t does not cause Y_t if for all $k > 0$ the following relation is true:

$$F(Y_{t+k} \mid \Omega_t) = F(Y_{t+k} \mid \Omega_t \setminus X_t),$$

where: $\Omega_t \setminus X_t$ denotes all information in the universe except for those included in X_t. Otherwise X_t cause Y_t (Granger, Newbold, 1986). The above definition cannot be called operational for the reason of using the phrase 'all information in the universe' that cannot be identified in practice. Since 1969 several operational definitions have been formulated. They were the subject of statistical verification. The word 'causality' present in all these definitions is the source of misunderstanding.

In the paper the attention is focused on the operational definitions of causality in Granger's sense and their interpretation in the two contexts: philosophical as well as empirical.

1. Systematic Granger Causality

Modelling conditional mean of the endogenous variable *via* the econometric model means that we are looking for a systematic, repeatable relation which can be used, among others, in forecasting. We call Granger causality defined for linear representation of time series 'the systematic Granger causality' because it refers to such cases.

Operational definition of Granger causality, corresponding to systematic causality concept, is formulated for wide sense stationary time series and it is measured in terms of forecasting errors. It is assumed that autoregressive (or vector autoregressive) representation of the time series that constitutes 'all the information in the universe' can be used in forecasting. The direction of causality is the subject of testing. Granger causality tests were discussed widely in Osinska (2008) and will not be the subject of further analysis. The attention is concentrated at the definitions and their understanding.

We say that X_t Granger-cause Y_t if:

$$\sigma^2(Y_t \mid \Omega_t^{'}) < \sigma^2(Y_t \mid \Omega_t^{'} \setminus X_t^{'}), \qquad (1)$$

where $\sigma^2(Y_t \mid \Omega_t^{'})$ is the prediction error in the case where all information from the past are used and $\sigma^2(Y_t \mid \Omega_t^{'} \setminus X_t^{'})$ is the prediction error corresponding to the situation when X_t was excluded from the information set. Key function in the above definition is played by the information set Ω_t, because the results of testing for Granger causality strongly depend on it. Granger did not define explicitly Ω_t, leaving it to the researchers. If the variables included into the information set come directly from the economic theory then the definition, despite of its limitations, is closer to the meaning of the word 'causality'. If however, the information set is based on the data, we cannot expect finding out any unknown relations which will occur a new economic law in future. As Cartwright (2007) wrote 'no cause in - no cause out'. So we should not expect anything more than it comes out from the data.

Furthermore, the formula (1) turns our attention to the understanding of causal relations in terms of forecasting. This is not satisfactory from the philosophical point of view but very practical. Forecasting ability is definitely one of the desired characteristics of causal relation, and when we are able to identify the cause and its effect we expect that the cause (or rather set of causes) will result in the occurrence of a given effect. But causality in Granger's sense cannot be identified as the relation determining that the cause is able to induce the effect. It is obvious that in the case when economic theory states that there is the causal relation between two variables, say, the magnitude of money supply and the inflation rate, testing for causality in Granger's sense will confirm that statement. In many cases however the theory says nothing and the researchers are looking for any relation confirmed by the data. A good example of such an investigation is testing for Granger causality between variables characterizing financial markets, for example indices of two or more stock exchanges. The question arises then what we should expect using Granger causality tests.

First of all let us turn the attention to the case when Granger causality can be thought as an idea of finding causal relations using structural econometric models. This was explained by LeRoy (2004).

Assume simple structural econometric model of the form:

$$y_{1t} = a_{12} y_{2t} + b_{11} y_{1t-1} + b_{12} y_{2t-1} + \varepsilon_{1t}, \tag{2}$$

$$y_{2t} = a_{21} y_{1t} + b_{21} y_{1t-1} + b_{22} y_{2t-1} + \varepsilon_{2t}, \tag{3}$$

where the explanatory variables (on the RHS of each equation) are not correlated with the residuals. The model is not identified and lagged values of variables are earlier than those observed in time *t*. The condition $a_{12} = 0$ defines conditional causality of the form $y_{1t} \Rightarrow y_{2t} \mid y_{1t-1}, y_{2t-1}$ (LeRoy, 2004). This condition cannot be tested directly because observable implications for it do not exist.

On the other hand, Granger causality is defined for reduced form of the model:

$$y_{1t} = c_{11} y_{1t-1} + c_{12} y_{2t-1} + u_{1t}, \tag{4}$$

$$y_{2t} = c_{21} y_{1t-1} + c_{22} y_{2t-1} + u_{2t}, \tag{5}$$

where: $c_{12} = (b_{12} + a_{12} b_{22})/(1 - a_{12} a_{21})$. We say that y_{2t} does not Granger cause y_{1t}, if $c_{12} = 0$. This condition is neither necessary nor sufficient for conditional causality $y_{1t} \Rightarrow y_{2t} \mid y_{1t-1}, y_{2t-1}$. That is why Granger causality does not allow stating what is prior: y_{1t} or y_{2t}. Only if $b_{12} = 0$ and $b_{22} \neq 0$, $c_{12} = 0$ is equal to $a_{12} = 0$ and then Granger causality is equivalent to the condition $y_{1t} \Rightarrow y_{2t} \mid y_{1t-1}, y_{2t-1}$. Such a case can occur very rarely in practice.

Respecting the explanation given above, one may ask whether the structural econometric model is able to state causal relation between variables. The answer we often put is 'no'. To say 'yes' we need some additional information of interventions (Hoover, 2001).

Granger causality concept was the subject of criticism in econometric literature (Basmann, 1988; Zellner, 1988 and LeRoy, 2004). On the other hand the explosion of causality tests based on Granger's idea shows great support for this concept (see for example: Caporale, Pittis, Spagnolo, 2002; Geweke 1984; Hsiao, 1979; Pierce, Haugh, 1977)).

The main objection is that in Granger's definition no stress is put to the role of the economic theory. Granger did not also take into account the definition of causality formulated by Feigl. Feigl understood causality as forecasting according to a law or a set of laws that joins prediction with the theory (Basmann, 1988; Zellner, 1979). Hoover (2001), in his classification of different concepts of causality in econometrics, includes causality in Granger's sense to the process approach, defined as the inference based on the data. This puts Granger in line with the continuators of Hume's philosophy who rejected any metaphysics and indicated observation as the main source of scientific finding.

Important limits of Granger causality were indicated by Zellner (1979). He argues, among others, that minimum prediction error cannot be used as a criterion of causal relation because the prediction error can be reduced using many techniques, not necessarily by including causes into the model.

Having defined the limits of Granger causality concept let's take a glance at its advantages:

1. The definition is operational and allows for testing such important aspects of causal relations as: time sequence of variables, asymmetry of relationships and forecasting ability in the sample and out of the sample.
2. The definition resulted in many statistical tests, developed for different classes of data.
3. The definition was extended for causality in conditional variance as well as causality in risk and nonlinear causality. This allows finding out many relationships of different nature present in the observable economic reality.
4. The information set included into the model is chosen by the researcher. This is a chance for combing of data analysis with a certain theory and developing an individual approach to a specific problem.
5. It is easy to be used in practice.

Granger's definition and its modifications, as well as the tests based on that concept should be used with care and interpreted only in the domain they are specified for. We cannot interpret any relation confirmed by Granger causality test as 'causal' in the broad philosophical sense. Analyzing the data without any theoretical background one cannot avoid spurious causality or symptomatic causality resulting from the presence of the third variable not included into the information set. If, however a certain theory is tested using Granger causality tests it can be stated that it is accepted or rejected by the data in the sense of asymmetry and forecasting ability. The question whether it ensures repeatability in future cannot be answer directly because it depends on the economic policy in a given country, which – in normal conditions - changes from one economic regime to another.

It should be stated that attempts at formulating operational definition of causality are not very popular because it is very difficult to do (Cartwright, 2007). For that reason Granger's definition, although far from excellence, is so much important. There are some further implications that can be applied jointly with forecasting ability like the analysis of interventions (Hoover, 2001), thick causality (Cartwright, 2007) or modular concept (Pearl, 2000) but none of these concepts can be thought of as universal.

At first Granger causality concept was formulated for stationary time series possessing autoregressive representations. Further, it was developed for cointegrated time series (Granger, 1981; Toda, Yamamoto, 1995) and, what is very important, Granger causality considered in the sample and out of the sample that allows determining whether Granger cause in the sample is still able to help predicting the effect out of the sample (Ashey, Granger, Schmalensee, 1980; Chao, Corradi, Swanson, 2001). All the mentioned concepts refer to the direct causality in Granger's sense such as $X_t \rightarrow Y_{t+1}$. In the recent years Dufour and Renault (1998) turned their attention to the indirect causality concept, based on the definition given by Hsiao (1979). It is not the subject of further analysis here because Hsiao definition of causality can be decomposed into Granger understanding of causality in the terms of forecasting.

2. Informational Granger Causality

In the previous part the attention was concentrated on causality in mean based on linear systems. However Granger causality can be also considered in terms of causality in conditional variance, and the related concept of causality in risk. We will call it 'the informational Granger causality' because it is related mainly with financial markets where relations between different stocks, portfolios or derivatives are usually the subject of influence of the information affecting both: the cause and the effect.

Cheung and Ng (1996), basing on Granger's definition have proposed the following formulation for causality in variance. Let X_t and Y_t denote stochastic processes which are covariance stationary and $\Omega_t = \{X_{t-j}, Y_{t-j}; j > 0\}$ is a set of all information from the past, available at time t and $\Omega_t \setminus X_t$ is the corresponding information set excluding X_t.

It can be said that X_t Granger does not cause Y_t in variance, if:

$$E\left\{\left(Y_t - \mu_{Y_t}\right)^2 \mid \Omega_t \setminus X_t\right\} = E\left\{\left(Y_t - \mu_{Y_t}\right)^2 \mid \Omega_t\right\}, \tag{6}$$

where: μ_{Y_t} is a conditional mean of Y_t, assuming the information set $\Omega_t \setminus X_t$.

Further development, made by Hong (2001), corresponding directly with the above definition concerns causality in risk. Granger causality in risk is defined as follows. Let $\{Y_{1t}, Y_{2t}\}$ is a bivariate not necessarily stationary stochastic time series. Let $A_{it} = A_{lt}\left(I_{l(t-1)}\right)$ l = 1,2 be the Value at Risk (VaR) at level $\alpha \in (0;1)$ for Y_{lt} predicted using the information set $I_{l(t-1)} = \{Y_{l(t-1)}, Y_{l(t-2)} \ldots\}$ available at time $t-1$. A_{lt} satisfies $P\left(Y_{lt} < A_{lt} \mid I_{l,(t-1)}\right) = \alpha$. In the case of Granger non-causality the null hypothesis takes the form:

$$H_0: \quad P\left(Y_{1t} < A_{1t} \mid I_{1,(t-1)}\right) = P\left(Y_{1t} < A_{1t} \mid I_{t-1}\right) \text{ almost surely} \tag{7}$$

where $I_{t-1} = \left\{I_{1(t-1)}, I_{2(t-1)} \ldots\right\}$,

with the alternative

$$H_1: \quad P\left(Y_{1t} < A_{1t} \mid I_{1,(t-1)}\right) \neq P\left(Y_{1t} < A_{1t} \mid I_{t-1}\right). \tag{8}$$

Comparing the above definition with the original one we may state that it concentrates only on the violations of value at risk computed for a given portfolio represented by Y_{1t}. So we interpret it as if information about the second portfolio represented by Y_{2t} could help change the probability of breaking the VaR. The definition captures the general characteristics of Granger causality concept. It can be extended for other risk measures, belonging to the class of coherent risk measures (Artzner, Delbaen, Eber, Heath, 1998).

As it was mentioned above, the concept of Granger causality was often criticized because it depreciates the philosophical nature of causal relation. On the other hand it is widely known and popular in econometric literature. In fact Granger's definition is related with predictability of one variable using previous values of another one. Such an approach takes into consideration only one of many characteristics of causal relation, however in practice it is often the unique possibility of measuring interdependencies between variables. It is particularly important when causality in conditional variance is considered. The number of factors that cause the volatility of financial returns is enormous. Furthermore, they change in time and occur only in some periods such as they cannot be observed systematically. Their nature is also very much complicated, starting from fundamental causes coming from company itself, through causes located in the macroeconomic surroundings, ending at those of social and psychological nature. However the results they cause are very important, observable and spread all over the world. Very similar situation takes place in the case of Granger causality in risk, where specified risk measures are applied. The causes, which evoke the failure of the risk measures are rarely of systematic nature. So if such a raise in risk occurs at one market it is very likely to be moved to another one. It is due to the risk-transferring procedure realized by many market participants including banks. Avoiding the risk by closing positions and moving financial capital from one market to another are the main characteristics of contemporary markets. It changes the liquidity preference in the markets that cannot be avoided without the intervention. Such a situation is called the contagion phenomenon (Allen, Gale, 2000).

3. Nonlinear Granger Causality

Nonlinear Granger causality is analyzed separately since it may consider other aspects of Granger causality that the ones discussed above. Baek and Brock (1992) formulated the general definition of Granger causality for nonlinear case. It is expressed in terms of the correlation integral that is a measure of local spatial correlation of time series which belong to a specified space. Formally, for a multivariate random vector W, the associated correlation integral $C_W(\varepsilon)$ is the probability of finding two independent realizations of the vector at a distance smaller (or equal) than ε, i.e.

$$C_W(\varepsilon) = P\{\|\mathrm{W}_1 - \mathrm{W}_2\| \le \varepsilon\} = \int\int I\left(\|s_1 - s_2\| \le \varepsilon\right) f_W(s_1) f_W(s_2) ds_2 ds_1, \quad (9)$$

where: $\mathrm{W}_1, \mathrm{W}_2$ are independent realizations of W, the integrals are taken over the sample of W, $\|\ \|$ is the supremum norm and I() is the indicator function, which is equal to one if its argument is true, and is zero otherwise.

Denote the *m*-length lead vector (*m*-history) of Y_t by $Y_t^m = (Y_t, Y_{t+1}, ..., Y_{t+m-1})$ and the *p*-length and *q*-length lag vectors of X_t and Y_t, respectively by $X_{t-p}^p = (X_{t-p}, X_{t-p+1}, ..., X_{t-1})$ and $Y_{t-q}^q = (Y_{t-q}, Y_{t-q+1}, ..., Y_{t-1})$.

Baek and Brock proposed the following definition of Granger nonlinear causality:

X_t does not nonlinearly Granger cause Y_t if

$$\begin{aligned} &P\left\{\left\|Y_t^m - Y_s^m\right\| < \varepsilon \mid \left\|X_{t-p}^p - X_{s-p}^p\right\| < \varepsilon, \left\|Y_{t-q}^q - Y_{s-q}^q\right\| < \varepsilon\right\} = \\ &= P\left\{\left\|Y_t^m - Y_s^m\right\| < \varepsilon \mid \left\|Y_{t-q}^q - Y_{s-q}^q\right\| < \varepsilon\right\}. \end{aligned} \quad (10)$$

where $\|\ \|$ is the supremum-norm distance.

The definition says that, given ε, p lags of X_t does not incrementally help predict next period's value of Y_t, given *q* lags of Y_t. It seems to be clear why the event 'X_{t-p}^p is close to X_{s-p}^p' may help incrementally predict Y_t close to

Y_s, in case when $Y_t = f(X_{t-p}^p, Y_{t-q}^q)$ for some deterministic and continuous function *f*. While $Y_t = g(X_{t-p}^p, Y_{t-q}^q)$, where g is a stochastic function, the definition is motivated by a hope that at least part of the deterministic relation is present, especially when the conditional variance of Y_t, given X_{t-p}^p, Y_{t-q}^q is smaller than the unconditional variance of Y_t. It is worth noting that the definition is based on the assumptions concerning the choice of ε, the lags number p and q as well as the forecasting horizon m.

Note that from the definition of conditional probability

$$P\left\{\left\|Y_t^m - Y_s^m\right\| < \varepsilon \mid \left\|Y_{t-q}^q - Y_{s-q}^q\right\| < \varepsilon\right\} = \frac{P\left\{\left\|Y_t^m - Y_s^m\right\| < \varepsilon, \left\|Y_{t-q}^q - Y_{s-q}^q\right\| < \varepsilon\right\}}{P\left\{\left\|Y_{t-q}^q - Y_{s-q}^q\right\| < \varepsilon\right\}}. \quad (11)$$

Moreover, since the supremum norm implies that

$$P\left\{\left\|Y_t^m - Y_s^m\right\| < \varepsilon, \left\|Y_{t-q}^q - Y_{s-q}^q\right\| < \varepsilon\right\} = P\left\{\left\|Y_{t-q}^{m+q} - Y_{s-q}^{m+q}\right\| < \varepsilon\right\}, \quad (12)$$

the identity

$$P\left\{\left\|Y_t^m - Y_s^m\right\| < \varepsilon, \left\|Y_{t-q}^q - Y_{s-q}^q\right\| < \varepsilon\right\} = \frac{P\left\{\left\|Y_{t-q}^{m+q} - Y_{s-q}^{m+q}\right\| < \varepsilon\right\}}{P\left\{\left\|Y_{t-q}^q - Y_{s-q}^q\right\| < \varepsilon\right\}}, \quad (13)$$

is satisfied. By analogy

$$P\left\{\left\|Y_t^m - Y_s^m\right\| < \varepsilon \mid \left\|X_{t-p}^p - X_{s-p}^p\right\| < \varepsilon, \left\|Y_{t-q}^q - Y_{s-q}^q\right\| < \varepsilon\right\} =$$
$$= \frac{P\left\{\left\|Y_{t-q}^{m+q} - Y_{s-q}^{m+q}\right\| < \varepsilon, \left\|X_{t-p}^p - X_{s-p}^p\right\| < \varepsilon\right\}}{P\left\{\left\|Y_{t-q}^q - Y_{s-q}^q\right\| < \varepsilon, \left\|X_{t-p}^p - X_{s-p}^p\right\| < \varepsilon\right\}}, \quad (14)$$

thus the null hypothesis of Granger nonlinear noncausality given by (10) may be expressed as follows:

$$\frac{C1(m+q, p, \varepsilon)}{C2(q, p, \varepsilon)} = \frac{C3(m+q, \varepsilon)}{C4(q, \varepsilon)}, \quad (15)$$

where:

$$C1(m+q, p, \varepsilon) = P\left(\left\|Y_{t-q}^{m+q} - Y_{s-q}^{m+q}\right\| < \varepsilon, \left\|X_{t-p}^p - X_{s-p}^p\right\| < \varepsilon\right),$$

$$C2(q, p, \varepsilon) = P\left(\left\|Y_{t-q}^q - Y_{s-q}^q\right\| < \varepsilon, \left\|X_{t-p}^p - X_{s-p}^p\right\| < \varepsilon\right),$$

$$C3(m+q, \varepsilon) = P\left(\left\|Y_{t-q}^{m+q} - Y_{s-q}^{m+q}\right\| < \varepsilon\right) \text{ and}$$

$$C4(q,\varepsilon) = P\left(\left\|Y_{t-q}^{q} - Y_{s-q}^{q}\right\| < \varepsilon\right)$$

In practice, nonlinear causality is tested above the linear one, so first of all the linear relation should be excluded, for example by estimating a bivariate stationary VAR model. The tests are usually carried out on the residuals of the linear model. The same indication can be applied for causality in variance. If the source of nonlinearity is known and can be modeled, for example by GARCH models, it should also be filtered out to show whether other possible source of nonlinear Granger causality can be found.

Conclusions

In the paper we discussed the concept of Granger causality and its main developments present in the econometric literature. It should be emphasized that the concept refers to predictability as the one of the characteristics of causal relation. That is why it is too narrow to satisfy all the important attributes of philosophical nature of causal relations. On the other hand it is very practical and popular in economic as well as econometric applications. The user of Granger causality concept and the tests based on this background should bear in mind their limitations and not to expect finding out any unlikely relations between economic variables. From Granger definition it comes out only such characteristics of causal relation like: sequence in time, asymmetry of the cause and the effect and forecasting ability. However it can be analyzed in very many aspects: in the conditional mean and in the conditional variance, in linear and in nonlinear framework, in the short and in the long run as well as in the sample and out of the sample,. This variety of applications gives a possibility of wide empirical analyses which should be put in a theoretical framework if we want to consider them as causal in a broader philosophical sense.

In the paper the types of Granger causality were classified. We discriminated: systematic Granger causality, informational Granger causality as well as nonlinear Granger causality. The first one refers to linear causality in conditional mean, the second one corresponds to two related concepts of causality: i.e. causality in variance as well as causality in risk and the last one defines the relation which can happen over the two mentioned earlier.

Although Granger causality has many disadvantages from the philosophical point of view its usefulness can be compared with the Vector Autoregression model defined by C. Sims in 1980 who won the Nobel prize in 2011. The VAR model was thought of as atheoretical remedy for disadvantages of traditional, structural econometric models. In fact it became structural, among others, because of testing for Granger causality. That example shows that even a very narrow tool can be used in solving much more complicated and sophisticated theoretical problems. In the same sense proper use of Granger causality can be a method of verification of the economic theory and possibly the source of some new empirical facts.

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O interpretacji przyczynowości w sensie Grangera

Z a r y s t r e ś c i. Koncepcja przyczynowości sformułowana w 1969 roku przez C.W.J. Grangera jest najbardziej popularna w literaturze ekonometrycznej. Centralnym założeniem tej koncepcji jest fakt, że przyczyna poprzedza skutek i jest pomocna w prognozowaniu skutku w przyszłości. Lata stosowania koncepcji przyczynowości w sensie Grangera zaowocowały wieloma nieporozumieniami związanymi z interpretacją wyników empirycznych. Artykuł dotyczy systematyzacji definicji przyczynowości w sensie Grangera i ich właściwej interpretacji.

S ł o w a k l u c z o w e: przyczynowość w sensie Grangera, przyczynowość systematyczna, przyczynowość informacyjna, przyczynowość w zależnościach nieliniowych.