A review of the Granger-causality fallacy

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Abstract: Methods used to infer causal relations from data rather than knowledge of mechanisms are most helpful and exploited only if the theoretical background is insufficient or experimentation impossible. The review of literature shows that when an investigator has no prior knowledge of the researched phenomenon, no result of the Granger-causality test has any epistemic utility due to different possible interpretations. (1) Rejecting the null in one of the tests can be interpreted as either a true causal relation, opposite direction of the true causation, instant causality, time series cointegration, not frequent enough sampling, etc. (2) Bi-directional Granger causality can be read either as instant causality or common cause fallacy. (3) Non-rejection of both nulls possibly means either indirect or nonlinear causality, or no causal relation.

Keywords: Granger-causality, epistemology of causality, causality testing

Introduction

The aim of this paper is to prove the illegitimacy of usual interpretations of Granger-causality test results.

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What exactly is Granger-causality? The simplest definition was provided by the author (Granger, 1980: p. 334): 'A (time series) variable A causes B, if the probability of B conditional on its own past history and the past history of A (beside the set of the available information) does not equal the probability of B conditional on its own past history alone.'

Previously, the question what legitimate conclusions can be drawn from an application of Granger-causality when the scholar has no prior theoretical knowledge has never been considered. On the one hand, the existence of Granger-causality is usually tested when the theory on (eventually causal) mechanisms connecting the two time series is insufficient or does not exist. On the other hand, a review of the literature conducted below shows some serious pitfalls of the method. It is shown in the paper that in case of limited knowledge on the investigated phenomenon, one cannot judge whether the relation discovered by Granger-causality test is true or erroneous due to e. g. inappropriate sampling frequency, the existence of rational expectations, nonlinear causal relationship, time series cointegration etc. (cf. Conclusions).

Therefore, I attempt to answer the question what conclusions (if any) are justified in the case of each Granger-causality test results of the possible four. Although there are studies on some aspects of the method's fallaciousness, the findings are a novelty given the assumption that the researcher using Granger-causality tests does know neither a theory nor any additional statistics on the studied phenomenon.

First, the importance of a better understanding of the Granger-causality pitfalls is explained by its popularity and respectability. Second, Granger-causality definition and its philosophical sources are reviewed. The main part of the paper consists of an analysis of this phenomenon. The discussion is summed up in Conclusions, where I attempt to determine what conclusion(s) on causal relations between two investigated variables are justified given a certain test result.

Popularity of the Method

Studying Granger-causality testing continues to be expedient due to the growing popularity of both the fields of science where theoretical background is insufficient and the quantitative methods as such. Hoover (2006) states that Granger-causality is the most influential approach to causality in economics. Granger's (1969) method of inferring causal relationship between stochastic variables without any prior theoretical knowledge met with strong criticism, focused mostly on the difference between Granger-causality and the common sense understanding of the cause-effect relationship (Liu, Bahadori 2012). In addition, some researchers highlight several problematic aspects of methodology and empirical misapplications (e.g. Russo 2008). The growing popularity of a statistical method employed to infer causal relations from data (i. e. Granger-causality) makes it impossible to agree with LeRoy's statement that 'it is true that the topic of causality has been of passing interest to economists' (Le Roy 2004, p. 2).

Despite criticism, Granger-causality tests have been applied to over 45 thousand studies indexed by the world's most popular scholar papers search engine. (Jascó 2005). The growing popularity of Granger's method is shown in Graph 1. Granger-causality is now being applied not only to econometrics, but for example to neuroscience, epidemiology, financial analysis etc. The growing trend is more and more rapid, which is especially visible after the year 2002 when the number of one thousand papers per year was exceeded for the first time.

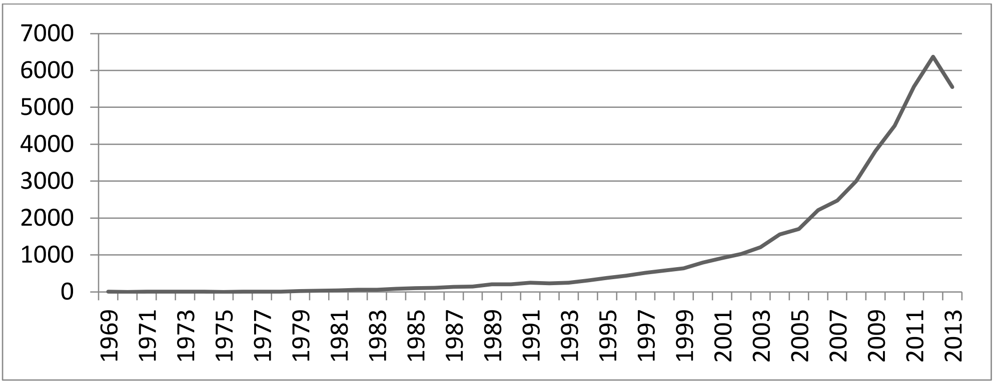

Figure 1: The number of papers with 'Granger-causality' as one of the keywords. Source: Own calculations based on data delivered by Google Scholar.

The growing popularity of statistical studies and fields of research benefiting from the use of Granger-causality (i.e. where experimentation is not possible) is supposed to explain why this method has been becoming more and more popular. On the other hand, Bressler and Seth (2011) point out that, nowadays, the use of statistical causality tests is easier due to the popularity of computer software packages containing such tools.

Granger's ideas on causality

Although philosophers have been interested in causality since the beginning of philosophy itself (Beebee et al. 2009, p. 21), its definitions are still not widely accepted (Granger 1980). Present plurality of viewpoints was summed up well by Nancy Cartwright (2006) - not the actress who was Bart Simpson's voice but a philosopher of science – *Each author of any definition argues that his definition is informative*. Then, it is all too clear that at the outset of the dispute the goal of economics should be highlighted. Ever since it came to be as a field of scientific research, understanding the economic phenomena as a cause-effect process has been its objective, which can be demonstrated by the title of Smith's book (1776) that is directly connected to causal inquiries. Other classical economists dealing with the philosophy of causation are Ricardo and Mill (Chu et al. 2004).

Despite the existent tradition among economists, Granger's source of inspiration to create a method of statistical testing whether causal dependency between two time series exists or not, was Hume (1739), who maintained that the human mind was incapable of recognizing causal relationships (cf. Hoover 2001). Hume argued in favour of reductionism: an observer can perceive only one event. It implies that the relationship between the cause and the effect, which connects two moments of temporal continuum, is impossible to be recognized. Consequently, Hume's point of view is that a phenomenon can be called 'causal' if it meets the following requirements: (Granger 2012)

(1) Cause precedes effect in time.
(2) Cause includes information about the effect that is not available in a wide group of other variables.

The first quantifiable definition of causation was formulated by Wiener (1956, p. 127) who too took into account the following axiom, 'For two simultaneously measured signals, if we can predict the first signal better by using the past information from the second one than by using the information without it, then we call the second signal causal to the first one.'

Axioms

Granger's definition of causation is based on three assumptions: (Granger 1980)

(1) The past and the present may cause the future, but the future cannot cause the past.

(2) Ω_n(all the knowledge available in the Universe on t)contains no redundant information, so that if some variable Z_n is functionally related to one or more other variables, in a deterministic fashion, then Z_n should be excluded from Ω_n.

(3) All causal relationships remain constant in direction throughout time.

In the Award Ceremony Speech delivered on the occasion of being granted The Sveriges Riskbank Prize in Economic Sciences in Memory of Alfred Nobel, Granger admitted that the first two axioms were inspired by Hume's ideas on causation (Dufour and Taamouti 2010). Axiom number three was added in order to make a distinction between a random correlation and causation, which is known to be the most popular 'sin' of statisticians (Stern 2011). Granger (1980) justifies this assumption by an example of a model containing three time series (number of patients accepted into hospital on day t; number of patients leaving hospital on day t; number of ice-cream portions sold in the considered city on day t) and claims that the only constant over time dependencies can be suspected to be causal. Although the temporal correlation between the number of patients leaving the hospital and the number of ice-cream portions sold may be observed, these two variables are not structurally related and their relationship is probably insignificant if sufficiently long time series are taken into account.

Granger builds the following General Definition upon the above assumptions:

Y_n causes X_{n+1} iff:

$$P(X_{n+1} \in A|'\Omega_n) \neq P(X_{n+1} \in A|'\Omega_n - Y_n) \qquad \text{for some A}$$

$X_t; Y_t$- variables suspected to be causally connected

$'\Omega_t$ - all the knowledge available in the Universe on t

A direct application of the above definition is impossible due to the degree-of-freedom problem implied by the finiteness of real-world time series and the requirement of considering all available knowledge. Taking into account the applicability of the definition to empirical research, it is essential to have an operational definition of causality. The aim of such a definition is to allow inference about cause-effect relationships from observational studies. In order to make his definition applicable, Granger (1969) redefined $'\Omega_n$ to be understood as a dataset which contains all useful information. In accordance with the above definition, variable Y causes variable X if Y contains additional, original information that is helpful in predicting the second variable.

One year after Granger's paper on inferring causal relations from statistical data, Suppes (1970, p. 15) develops a Probabilistic Theory of Causation. One of its improvements consisted in *prima facie* causality: '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.'

$$P(B|A) > P(B)$$

Inspired by this idea, Granger (1980) uses *prima facie* causality for a time series analysis which allowed him to build a quantifiable definition. Variable Y *prima facie* causes variable X, if:

$$P(X_{n+1} \in A|X, Y) \neq P(X_{n+1} \in A|X) \qquad \text{for some A}$$

X; Y – history of time series: X; Y

X_{n+1} – the value of X on t+1

Some critics of Granger-causality focus on pointing out the differences between the common-sense understanding of causality and the method in question. Granger (1980) defends his idea with the following argument: Common words, such as 'apple' and 'fear', are used and understood in the same way by most people. Similarly, when you start a lecture, you can define what is meant by 'variance' or 'cos x' in order to be understood. Moreover, Granger argues, by defining 'x^3' in a way that is usually designated by 'cos x' you will not gain popularity among students, but this is not a logical mistake. Accepting these arguments implies that considering whether Granger-causality tests are informative and valuable for economics and science is much more important than comparing Granger's idea with what 'causation' means.

Granger-causality test application and fallacy

In spite of the ever-growing popularity in empirical research, the findings of Granger-causality tests may lead to erroneous results. In hitherto available literature on statistical tests of causality scarcely any attention is devoted to informativity of Granger-causality tests in cases where the investigator has no additional knowledge about the researched phenomenon. Therefore, analysing every area of fallacy of the method seems important to understand whether a scholar applying the Granger causality test to stochastic time series can draw any accurate conclusions.

Methodology

Many statistical tests are developed to find Granger-causality dependencies. The most popular include Granger direct test (Granger 1969) and Sims test (Sims 1972). Causal relationship is detected when some equation parameters are statistically significant. Geweke (et al. 1984) proves deductively that the power of eight different tests they considered is different, i.e. they reject the null-hypothesis with different frequencies. The same results were obtained by the Monte Carlo method by Nelson et al. (1982) and Geweke et al. (1984). Conway et al. (1984, p. 2) summed up these results with the following statement: 'one could easily produce conflicting conclusions by employing a battery of causality tests on the same data sets'.

Therefore, it is possible to apply two Granger-causality tests to the same data set and obtain different outcomes: one confirming the null and the other rejecting it. These findings are not intuitive and, in addition, contradict axiom three of Granger's definition, which states that causality is constant in time.

In addition, the researcher must arbitrarily choose a number of lags taken into consideration to estimate regression coefficients. Ashrafulla et al. (2012) point out background knowledge as useful in making this choice. Another solution consists in using autocorrelation functions (ACF) or Akaike Information Criterion (AIC) (Liu and Bahadori 2012).

Arbitrariness of this decision may lead investigators using the same Granger-causality test to different conclusions. Such a difference in findings was observed by Slaugh (1981) who compared papers on money-income causality. (Conway et al. 1984)

In addition, the result confirming the null may be obtained even though there is a causal, nonlinear relation. The most popular tests (e. g. General Granger-causality Test, Sims Test and Modified Sims Test), were developed to test the existence of (only) linear dependencies. Therefore, some asymmetry in tests' behaviour can be observed. The null rejection means there is a (linear) Granger-causality. On the other hand, non-rejection of the null is interpreted as evidence for lack of causality, even though a nonlinear relation may occur.

The effects of time series transformation

Least Squares Method, used to estimate the parameters of equation in most of Granger-causality tests, requires some conditions to be met to get reliable results. If nonlinearity occurs, data must be linearized. Logarithm transformation is one of the standard econometric methods of data pre-processing in this case. In spite of its widespread use, Roberts and Nord (1985), analysing data on nominal income, earnings and money supply, observed that the functional form of the model influences the findings of Granger-causality tests. On the one hand, causal relation is observed between raw time series. On the other hand, logarithmized data does not reject the null hypothesis. Despite these findings, Brassler and Seth (2010) admitted that linearization is a good approximation for Granger-causality testing in neuroscience.

Non-stationary data poses another problem in applying econometric methods to empirical time series. If a variable is driven by a stochastic trend, its value averages for different periods differ significantly. In this case, calculating the first difference is recommended:

$$X'_t = X_t - X_{t-1}$$

The above procedure improves the quality of a model but at the same time influences Granger causality tests' findings. The two models of causality between GDP and power consumption in South Korea (one based on cointegrated data and error-correction models) show contradictory results (Glasure and Lee 1998). A strong, bidirectional causal relation is detected in the second case. The first model shows no significant relation. In addition, the findings of Glasure and Lee differ from the conclusions of Yu and Choi (1985). A possible explanation is the use of differentiated data, but the researchers indicated a different period of the study (Glasure and Lee 1998).

Lee (et al. 2002) supposed that Granger-causality tests are not objective in the case of cointegrated time series and pointed out that the findings can be biased, so that they more often reject the null. Further discussion and conclusions of different Granger-causality tests can be found in Hacker and Abdulnasser (2006). However, these facts are not widely known by econometricians. For example, Osińska (2008, pp. 75) advises to apply the Granger-causality tests to nonstationary and cointegrated time series when they can be transformed by adding determinist components (e. g. trend, seasonality) or mathematical transformation.

ARIMA (Autoregressive Integrated Moving Average) models are another, more sophisticated method developed to deal with non-stationarity and seasonality. Shortly after Granger-causality had been defined, scientists thought nonlinear transformations (e. g. logarithm transformation) do not influence causality tests (Conway 1984). Further research contradicted this. Feige and Pearce (1976) tested dependencies between GDP growth, money supply and inflation. Schwert (1979) analysed data on innovativeness transformed by the ARIMA model in three different ways. He concludes that the null hypothesis is rejected too rarely by causality tests. A contradictory result was obtained by Lee et al. (2002). The Monte Carlo simulation showed that the null is rejected too often between two independent ARIMA (1,1,0) processes. These findings and the common-sense view that mathematical transformations should not influence the direction of a causal relation made Schwert (1979, p. 82) write, '[...] semantic distinction between 'causality' and 'incremental predictability' should be emphasized.'

Sampling frequency and causality

Economic time series are usually published at time intervals. Quarterly sampled observations modelled by VAR (vector autoregressive model) are equivalent to monthly VARMA, where the MA (i. e. moving average) period is 3. Taking into consideration previously discussed results, temporal aggregation appears to influence Granger-causality tests.

Causal relation was tested between money and income in three cases differently aggregated over time by McRorie and Chamber (2005) who concluded that economic processes, if sampled too rarely, would show bi-directional Granger-causality, even though the real, one-way causal relation exists and can be detected. The scholars emphasized that finding bi-directional causality is not a sufficient condition to conclude that the real relation is identical.

The same conclusions were drawn by Harvey and Stock (1989) who tested Granger-causality in a continuous time model of money-income. Granger-causality test does not reject the null in such a case. On the other hand, temporally aggregated (i.e. quarterly sampled) time series show a significant causal relation. Causality detection depends on the time interval used in modelling in the case of flow variables. In addition, the above conclusion can be true in the case of stock variables (Harvey and Stock 1989). These results were corroborated by Renault et al. (1998) who tested causality between the Swiss Franc and the Deutsche Mark in models with continuous and discrete time.

Rational expectations and cause-effect relationship

Human behaviour based on appropriate predictions can make scholars misconstrue Granger-causality tests. The term 'rational expectations' means that better predictions are impossible unless someone possesses better information. In other words, someone who makes predictions does not make a systematic mistake. For example, if companies were able to predict inflation (I) rationally (in the above meaning) and make purchases whose amount depends on future rise of prices and storage cost, then the expected causal relation would have the opposite direction to the flow of time:

$$I_{t+1} \xrightarrow[Granger-causes]{} X_t$$

This result would contradict axiom one of Granger's definition (cf. 3.1. Axioms, above), which states that the future cannot cause the past. Is it possible that (anticipated) future values of one variable cause the present values of the other? The researchers' opinions are divided. Noble (1982) found statistically significant causal relationship between the unemployment rate and aggregate nominal spending. These findings contradict theoretical expectations that aggregate spending is supposed to cause unemployment (Nelson 1981), which suggests that the rational expectations hypothesis is true and may enable discovery of erroneous Granger-causality relations.

The rational expectation hypothesis was tested in order to defend the traditional view on causality, e. g. by Noble (1981). The findings contradicted the hypothesis, but it can be claimed that there are methodological weaknesses in the research. First, the survey data comes from the Survey Research Center at the University of Michigan despite the fact that the question about price level expectations was changed a few times during the research. Second, the frequency of the survey differed, too. Third, respondents were not asked to state the predicted change in price level but to answer if it was more likely to rise/fall or stay the same. The predicted level of inflation was estimated on the grounds of arbitrarily assigned number values to answers, e.g.: 'prices will be only a little higher' was understood as a 2% growth of the price level.

This methodology may lead to misleading conclusions. In addition, rational expectations may be supported in the same way as an efficient market hypothesis. It is enough for EMH to be true when only a few market participants will be right in their predictions, provided they have appropriate funds to influence the economy.

If the rational expectation hypothesis is true, it will make Granger-causality tests' findings contradictory to the real direction of causal relation.

Common cause and indirect causality

Misunderstanding causal relations between variables in the model can be a result of the previously discussed Granger-causality testing methods or an incorrect specification of the model. Granger-causality and other methods of inferring causality from data are exploited when the scholar does not possess theoretical knowledge about the phenomenon's mechanism. Insufficient knowledge may lead to a misspecified model, i.e. Granger causality tested between inappropriate time series. There are two such cases, common-cause fallacy and indirect causality.

The existence of a third variable, which causes both time series among which Granger-causality is tested, is known to be the most common reason for spurious causality (Chu et al. 2004). Common cause fallacy is illustrated with Figure 2:

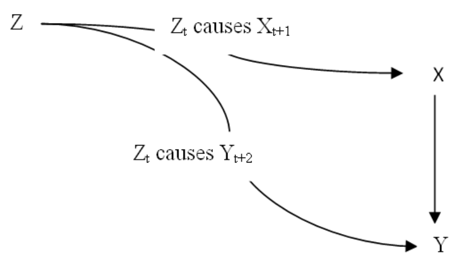

Figure 2: Common-cause fallacy.
Source: Author

A good example of such difficulties in the epistemology of causality is the example described by Woodward (2007): a scholar researching dependency between the type of school and exam scores, and does not consider the real determinant (i.e. parental income), will be likely to erroneously conclude that the choice of private education leads to better results.

Glymour and Sprites (1988) pointed out that there are econometric tests used to discover the existence of the so-called latent variables. However, their use in Granger-causality testing seems difficult or even impossible in the case of testing *prima facie* Granger-causality due to the lack of a typical econometric model.

Common cause fallacy should be suspected when Granger-causality tests indicate bi-directional Granger-causality:

$$X \rightarrow Y$$

$$Y \rightarrow X$$

Testing Granger-causality between two time series determined by a third one, generated with the Monte Carlo method, indicated that detecting bi-directional causality is more likely than one-directional causality (Sims 1977). Unfortunately, these findings are not known to all researchers making use of the method. In some cases, Granger causality test results that show a bi-directional dependency are misinterpreted. (e.g. Madrak-Grochowska and Żurek 2011)

Indirect causality is another situation when the researcher deals with a hidden variable. In contrast to the previously discussed common cause fallacy, that makes detecting spurious causality more likely; indirect causality may lead to type II error. Even though there are Granger-causality tests generalized to more than one period (e. g. Dufour and Taamouti 2010), the standard tests show only dependencies present within one period ahead, i.e. in both cases:

$$X_t \to Y_{t+2}$$

$$X_t \to Z_{t+1} \to Y_{t+2}$$

When causality is lagged more than one period or it is a case of indirect causality, standard Granger-causality tests do not reject the null, even though causal dependency occurs. Defenders of the method argue that the only cause-effect relationship that exists is between X and Z as well as Z and Y, which, in this case, is not a good point. Taking into account manipulationist's account of causality and considering a thought experiment - value added tax rate (X) causes demand (Z) which causes GDP (Y) (cf. the equation above) it is justified to say that the tax rate (X) causes GDP (Y).

Conclusions

Presented arguments demonstrate that Granger causality does not meet the requirements of an investigator who uses this method due to epistemic reasons (i.e. in order to discover what variable is the cause and what is the effect) and does not possess prior knowledge on the phenomenon considered. Methods used to infer causal relations from data rather than knowledge of mechanisms are helpful and exploited only if the theoretical background is insufficient. Therefore, the usage of Granger-causality method is to be reconsidered due to its limitations.

The analysis of what justified information is given by specific Granger-causality test results, and the indication of reasons for misinterpretation when a scholar does not possess any additional knowledge about the mechanisms connecting two time series, are shown in Table 1.

An investigator who applies the Granger-causality test can get three different results reject the null in one of the tests (i.e. find a one-directional causal relation), reject the null hypothesis of the two tests (i.e. get a bi-directional Granger-causality) or do not reject the null hypothesis. Taking into account the deficiencies of the method, none of these results justifies implications of causality that are usually drawn from the test's outcome.

In the first instance, the null is rejected in one of the tests, i e. the common interpretation suggests the existence of unidirectional causal relationships between two time series. In accordance with previous argumentation, this result can mean:

(1) The Granger causality test is true; namely, sentence 'X Granger-causes Y' is true.
(2) The direction of the causal relation is opposite due to rational expectations. Economic actors' behaviour makes the scholar observe reversed dependency (Noble 1982).
(3) If sampling is not frequent enough, one of the null rejections can mean there is an instant causality (McRorie and Chamber 2005).
(4) Rejecting the null may occur due to time series non-linearity (Roberts and Nord 1985), time series cointegration (Lee et al. 2002), not frequent enough sampling (Harvey and Stock 1989) or common cause fallacy (Chu et al. 2004).

In the second instance, bi-directional Granger-causality is discovered, which possibly means:

(1) There is an instant Granger-causality between the time series.
(2) X and Y are determined by a third variable (Sims 1977).

The third instance, i. e. non-rejection of the null hypothesis in both tests, usually interpreted as a sign of no Granger-causality, can have several implications, too:

(1) There can be nonlinear Granger-causality between time series. Another reason would be indirect causality (Dufour and Taamouti 2010).

(2) Instant causality may be the case if the time series are non-stationary (Glasure and Lee 1998).

(3) There is no causal relation between X and Y.

It is true that some of the above causes of Granger-causality misinterpretation can be eliminated or, at least, detected (e. g.: time series cointegration, data nonlinearity). However, other factors are beyond the cognitive abilities of a scholar using Granger's method. For example, it is impossible to judge whether constant-time causal dependency would be the same or contradictory unless you have access to such data, which is rarely possible in economic research.

In defense of his method, Granger (1988, p. 200) wrote: 'Possible causation is not considered for any arbitrarily selected group of variables, but only for variables for which the researcher has some prior belief that causation is, in some sense, likely.' The discussion presented above confirms and expands this view. Drawing conclusions whether a causal relation exists between investigated time series and about its direction is possible only if theoretical knowledge of mechanisms connecting the time series is accessible.

Table 1: What makes the conclusions drawn from Granger-causality test results erroneous?

Real dependency / The test's result	$X \rightarrow Y$	$Y \rightarrow X$	$X \leftrightarrow Y$	$X \emptyset Y$
$X \rightarrow Y$	• the correct result	• rational expectations (Noble 1982)	• not frequent enough sampling (McRorie and Chamber 2005)	• spurious causality due to data nonlinearity (Roberts and Nord 1985); • cointegrated time series (Lee et al. 2002) • not frequent enough sampling (Harvey and Stock 1989) • common cause fallacy (Chu et al. 2004)
$X \leftrightarrow Y$			• the correct result	• common cause fallacy (Sims 1977)
$X \emptyset Y$	• nonlinear causal relationship • indirect causality fallacy (Dufour and Taamouti 2010)	• nonlinear causal relationship • indirect causality fallacy (Dufourandi Taamouti 2010)	• time series' nonstationarity (Glasoure and Lee 1998)	• the correct result

Legend: →- causes/Granger-causes; ↔- instant causality/bidirectional Granger-causality; ∅- no causal relation/test does not reject the null
Source: Author

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