SIMULATION EVIDENCE ON GRANGER CAUSALITY IN PRESENCE OF A CONFOUNDING VARIABLE

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Abstract

This paper provides simulation evidence on Granger causality between two variables when they are jointly caused by a third variable. Four Data Generating Processes (DGP_s) are considered for testing causality by Granger method and two DGP_s for testing causality by Toda and Yamamoto (1995) procedure. Our simulation involve three variables but causality has been tested only between two variable and the third variable (the real cause) has been ignored to show that its association which matters in these causality tests. Nevertheless, if we know that there are only two variables in economic dynamics and the true model is known then these causality tests work fine and for this we have carried out bootstrap simulation.

JEL codes:

Key words: Granger Causality, Toda and Yamamoto Procedure, Monte Carlo Simulation, Causation and Association, Bootstrap Simulation

1. Introduction

It has been established fact that there is strong correlation between variables (Export, Money, Energy, Investment etc) and economic growth. Many investigate whether this association can be translated into causal relationship. This has been an area of research where there is strong controversy. Many researchers have used Granger Causality to determine the direction of causation among these variables. Despite the fact that Granger definition which is based on a criterion of predictability is not in agreement with other definitions of causality, yet testing Granger causality in the time series

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econometrics has been very common since Granger introduced this concept in 1969. According to him a variable X_t is said to cause Y_t if the former helps to improve the forecast of the latter.

Several tests for detecting Granger causality have later on been developed. These tests are; Granger causality test, MWALD tests by Toda and Yamamoto (1995), Error Correction Model etc. Granger causality is used if the underlying series data are stationary. Toda and Yamamoto (1995) propose a method that is used to estimate unrestricted VAR whose order is k+d, where k is the true order and d is the highest degree of integration in the system. If the underlying time series data are non-stationary and cointegrated then the method used for testing causality is Engle and Granger error correction mechanism.

Previously some simulation experiments have been carried out to find the performance of different causality tests. Zapata and Rambaldi (1997) use the Monte Carlo simulation to check the performance of three tests for Granger non causality. These include two Wald tests, using VAR at level and vector error correction model and a likelihood ratio test proposed by Mosconi and Giannini (1992). Zapata and Rambaldi use six data generation processes, which include four bivariate and two trivariate models. Their Monte Carlo evidence show that likelihood ratio test perform better than Wald tests.

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

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

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

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

No one has tested Granger causality in the presence of a confounding variable which is often the case in economic theory that two variables seems cause of each other but the hidden variable is the true cause which derives both variables. For example Granger(1988) has presented a theorem that two variables X and Y are independent (r_{xy} =0) if only this pair is considered but X/Z and Y/Z need not be independent i.e. there exist a third variable which is correlated with both X and Y and due to this variable X and Y becomes correlated. If we put r_{xy} =0 in the partial correlation coefficient formula

$$r_{xy.z} = \frac{r_{xy} - r_{xz} r_{yz}}{\sqrt{(1 - r_{xz}^2)(1 - r_{yz}^2)}}$$

then $r_{xy.z}$ becomes

$$r_{xy.z} = \frac{-r_{xz} r_{yz}}{\sqrt{(1-r_{xz}^2)(1-r_{yz}^2)}}$$

and $r_{xy.z}$ becomes zero only if either r_{xz} =0 or r_{yz} =0. It means that if Z is affecting both X and Y, which are independent, then there could exist a relationship between X and Y due to the confounding variable Z unless one of r_{xz} , r_{yz} is zero.

We have conducted Monte Carlo simulation experiments where we have introduced a third variable which is mainly the cause of the other two variables.

First objective of this paper is to show that Granger causality indicates causation when actually there is simply association between two variables due to a third variable. Second objective is to test the performance of Granger Causality tests at different lag lengths, sample sizes etc under the presence of a confounding variable. Thirdly we have carried out bootstrap simulation to test the power of Granger causality when it is assumed that the researcher knows the true model. The contribution of this study is that it's the first time that simulation experiment has been conducted by considering a confounding variable in mind. Moreover, if the two variables under study are known and the true model is also known (which is normally not the case in at least observational studies) then bootstrapping suggest that Granger causality is a powerful tool for detecting the direction of causality. As mentioned above in all the previous studies performance of different methods has been judged when one variable is really cause of the other. This study will serve as a guide to those who misuse Granger causality as a test of causality without understanding in its proper context .In this regard Granger (1980) himself warned "However, it should be said that some of the recent writers on this topic, because they have not looked at the original papers, have evolved somewhat unclear and incorrect forms of this definition". Basically Granger emphasized on putting extra statistical information so that asymmetry can be introduced but majority of the economists have started using Granger causality equation blindly in the hope that significance of the results is sufficient to show causal relationship among the variables.

We have carried out simulation experiment for detecting causality for four Data Generating Processes (DGP_s) by imposing the condition of stationarity. For non-stationary but cointegrated variables we have carried out Toda and Yamamoto (1995) procedure to determine the direction of causality. These simulation designs and methodology will be explained in the next section. In the final section results of simulation are reported.

2 Tests for causality testing and Monte-Carlo designs

2.1 Granger Causality test (1969)

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

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

$$Y_t = \alpha_0 + \sum_{i=1}^{k} \alpha_i Y_{t-i} + \sum_{j=1}^{k} \beta_j X_{t-j} + u_t \quad (2.1)$$

$$X_t = \alpha_0 + \sum_{i=1}^{k} \alpha_i Y_{t-i} + \sum_{j=1}^{k} \beta_j X_{t-j} + e_t \quad (2.2)$$

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

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

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

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

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

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

It is to be noted that Granger test is based on assumption that the variables 'X' and 'Y' are stationary and u_t *and* e_t are uncorrelated. So in all above equations we assume that the variables are stationary at levels and u_t *and* e_t are uncorrelated.

2.2 Toda and Yamamoto method (1995)

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

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

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

$$Y_t = \alpha_0 + \sum_{i=1}^{k} \delta_{1i} Y_{t-i} + \sum_{j=k+1}^{d_{\max}} \alpha_{1j} Y_{t-j} + \sum_{j=1}^{k} \theta_{1j} X_{t-j} + \sum_{j=k+1}^{d_{\max}} \beta_{1j} X_{t-j} + w_{1t} \quad (2.3)$$

$$X_t = \alpha_1 + \sum_{i=1}^{k} \delta_{2i} Y_{t-i} + \sum_{j=k+1}^{d_{\max}} \alpha_{2j} Y_{t-j} + \sum_{j=1}^{k} \theta_{2j} X_{t-j} + \sum_{j=k+1}^{d_{\max}} \beta_{2j} X_{t-j} + w_{2t} \quad (2.4)$$

where the error terms w_{1t} *and* w_{2t} across the different equations and within equation are uncorrelated, d_{max} is the maximum order of integration. The lag length in above three equations can be determined by using Akaike Information Criterion (AIC) and Schwarz Bayesian criterion (SBC).In equation (2.3) 'X' granger causes 'Y' provided that $\theta_{1j} \neq 0 \; \forall_j$. We can test the following null hypothesis in equation (2.3) and (2.4) by using modified Wald statistic:

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

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

3 Monte Carlo Experiments and the Results

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

We have defined the GDP as follows

$X_t = \Pi_1 X_{t-1} + \Pi_2 X_{t-2} + \epsilon_t$ X is a (3 x 1) column vector,
Π_i is a square matrix(3x3) and ϵ is a vector of order 3 x 1.
ϵ_{it} are generated independently from normal distribution with mean 0 and standard deviation 0 .

Initial values of all the three variables are zeros.

DGP 1

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

DGP 2

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

DGP 3

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

DGP 4

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

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

DGP 5

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

DGP 6

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

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

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

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

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

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

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

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

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

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

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

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

All this is sufficient to show that these causality tests which are based on prediction do not detect causal relation until and unless all the confounders are under control which is probably possible only in experimental studies and not in observational studies. There is still a long way to go to work on this topic of causality which is bread and butter of empirical economics. Freedman (1999) “Indeed, casual inference requires a lot of skill, intelligence and hard work. Natural variation needs to be identified. Data must be collected. Confounders need to be considered. Alternative explanations have to be tested.” Theory must support to find true causes and one must go deeper into the problem rather statistical analysis.

4. Bootstrap simulation

For bootstrap simulation we have picked two variables data of Wolde-Rufael (2004). The two variables are GDP and coal data of shanghai and if it is assumed that they are related as follows:

$Y_t = \alpha_0 + \sum_{i=1}^{k} \alpha_i Y_{t-i} + \sum_{j=1}^{k} \beta_j X_{t-j} + u_t$ Where Y and X are GDP and coal respectively. Lags are set at three. We have done bootstrapping by resampling regression residuals by having sample sizes of 1000, 5000 and 10,000. Our results indicate that Granger causality detects this causality 90.7%, 90.28% and 90.16% for 1000, 5000 and 10000 repetition respectively. Obviously magnitude of the parameters of X will matter but one may say that in presence of two variables when model is known Granger causality is a useful device. All this bootstrap has been done using Microsoft Excel. This provides evidence that if true model is known and all the relevant variables are included then one may test causality by using Granger methodology.

Table 1 MC simulation result

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

	X→Y	0.05	0.05	0.05	0.05	0.06	0.06
	Lag=3						
	Y→X	0.05	0.07	0.08	0.08	0.12	0.22
	X→Y	0.05	0.05	0.05	0.05	0.05	0.07

Table 2 MC Simulation for DGP 5 and 6

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

Table 3 Correlation between X and Y T=30

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

Table 4 Correlation between X and Y T=60

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

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