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Granger Causality for Multivariate Time Series in Agriculture

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SUMMARY

Granger causality is a statistical concept of causality that is based on prediction. According to Granger causality, if "x Granger causes y", then past values of x should contain information that helps predict y above and beyond the information contained in past values of y alone. Its mathematical formulation is based on linear regression modeling of stochastic processes.

INTRODUCTION

A statistical approach proposed by Granger to infer cause and effect relationship between two or more time series is known as Granger causality. Granger causality is based on the simple logic that effect cannot precede cause. It is important to note that the statement "x Granger causes *y"* does not imply that *y* is the effect or the result of *x.* Granger causality measures precedence and information content but does not by itself indicate causality in the more common use of the term. It is a way to investigate causality between two variables in a time series. The method is a probabilistic account of causality.it uses empirical data sets to find patterns of Correlation. Causality is closely related to the idea of cause-and-effect, although it isn't exactly the same. A variable X is causal to variable Y if X is the cause of Y *or* Y is the cause of X.

Testing Granger Causality:

The simplest test is to estimate the regression which is based used for causality testing such as Sim's Causality test, Hasiao Causality Test etc.)

$$\boldsymbol{Y_t = \alpha_0 + \sum_{i=1}^{l} \alpha_i\, y_{t-i} + \sum_{j=1}^{l} \beta_j\, x_{t-j} + \varepsilon_t}$$

$$\boldsymbol{x_t = \omega + \sum_{i=1}^{l} \gamma_i\, y_{t-i} + \sum_{j=1}^{l} \theta_j\, x_{t-j} + \varepsilon_t}$$

If all the coefficients of x in first regression equation of y, i.e. β_i for i = 1......l are significant that the null hypothesis that x does not cause y.
However, the significance of the coefficient cannot be evaluated based on usual t-statistic.
Procedure of testing the models is used.

(i) Estimate the model without including lagged values of variable x. Suppose the R_2 from this estimate is R_1^2. (ii) Now estimate the model including lagged values of variable x.

Suppose, the R^2 from this estimate is R_2^2 (iii) F-ratio for improvement in the model is worked out as follows:

$$\mathbf{F} = \frac{(R_2^2 - R_1^2)/k^*}{(1-R_2^2)/(n-k)}$$

Where k* are the number of lag orders l of variable x, k is the total number of the parameters estimated and n is the number of observations. The null hypothesis of non-causality is rejected if F-statistic is greater than its critical value at k* and (n-k) degree of freedom.
Similarly from the second equation above, we can test the null hypothesis that '*y* does not cause *x'*. If only one of the two variables causes the second variable but the second variable does not cause the first variable it is called one-way causality. If both the variables cause each other it is called the feedback causality.

Example of the Usage of Granger Test:

Is it GDP that "causes" the money supply *M* (GDP → *M*)? Or is it the money supply *M* that causes GDP (*M* →GDP)? (Where the arrow points to the direction of causality). The Granger causality test assumes that the information relevant to the prediction of the respective variables, GDP and *M*, is contained solely in the time series data on these variables.

The test involves estimating the following pair of regressions:

$$\text{GDP}_t = \sum_{i=1}^{n} \alpha_i M_{t-i} + \sum_{j=1}^{n} \beta_j \text{GDP}_{t-j} + u_{1t}$$

$$M_t = \sum_{i=1}^{n} \lambda_i M_{t-i} + \sum_{j=1}^{n} \delta_j \text{GDP}_{t-j} + u_{2t}$$

Where it is assumed that the disturbances $u1t$ and $u2t$ are uncorrelated. In passing, note that, since we have two variables, we are dealing with bilateral causality. In the chapters on time series econometrics, we will extend this to multivariable causality through the technique of vector autoregression (VAR).

Equation (1) postulates that current GDP is related to past values of itself as well as that of *M*, and Eq. (2) postulates a similar behavior for *M*. Note that these regressions can be cast in growth forms, GDP ˙ and *M* , where a dot over a variable indicates its growth rate.

Test Procedure for Granger Causality Test:

The steps involved in implementing the Granger causality test are as follows. We illustrate these steps with the GDP-money example given in Eq. (1).

1. Regress current GDP on all lagged GDP terms and other variables, if any, but *do not* include the lagged *M* variables in this regression. This is the restricted regression. From this regression obtain the restricted residual sum of squares, RSS*R*.
2. Now run the regression including the lagged *M* terms. This is the unrestricted regression. From this regression obtain the unrestricted residual sum of squares, RSSUR.
3. The null hypothesis is $H0$: $\alpha i = 0$, $i = 1, 2, \ldots, n$, that is, lagged *M* terms do not belong in the regression.
4. To test this hypothesis, we apply the *F* test given by Eq. (3), namely,

$$F = \frac{(RSS_R - RSS_{UR})/m}{RSS_{UR}/(n-k)}$$

Which follows the *F* distribution with *m* and (*n* - *k*) df. In the present case *m* is equal to the number of lagged *M* terms and *k* is the number of parameters estimated in the unrestricted regression.

5. If the computed *F* value exceeds the critical *F* value at the chosen level of significance, we reject the null hypothesis, in which case the lagged *M* terms belong in the regression. This is another way of saying that *M* causes GDP.
6. Steps 1 to 5 can be repeated to test the model (2), that is, whether GDP causes *M*.

Before we illustrate the Granger causality test, there are several things that need to be noted:
1. It is assumed that the two variables, GDP and M, are stationary. Sometimes taking the first differences of the variables makes them stationary, if they are not already stationary in the level form.
2. The number of lagged terms to be introduced in the causality tests is an important practical question. But it should be added that the direction of causality may depend critically on the number of lagged terms included.
3. We have assumed that the error terms entering the causality test are uncorrelated.
4. Since our interest is in testing for causality, one need not present the estimated coefficients of models (1) and (2) explicitly (to save space); just the results of the *F* test given in Eq. (3) will suffice.

5. To obtain the result.

CONCLUSION

Granger causality methods are used to analyse the flow of information between time series. Granger causality estimates can be either severely biased or of high variance, even if estimated correctly, Granger causality estimates alone are not interpretable without examining the component behaviours of the system model. Granger causality mainly used in the field of econometric time series analysis.

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