VAR:

Granger Causality:

1. Thus, the lack of a Granger-causal relationship from one group of variables to

the remaining variables cannot necessarily be interpreted as lack of a cause

and effect relationship. It must be remembered that a VAR or MA representation

characterizes the joint distribution of sets of random variables. In order

to derive cause and effect relationships from it, usually requires further assumptions

regarding the relationship between the variables involved

1. So far it has been assumed that the information set contains the variables

or groups of variables only for which we want to analyze the causal links.

**Often we are interested in the causal links between two variables in a higher**

**dimensional system. In other words, we are interested in analyzing Grangercausality**

**in a framework where the information set contains more than just the**

**variables of direct interest**. In the bivariate framework when the information

set is limited to the two variables of interest, it was seen that if the 1-step

ahead forecasts of one variable cannot be improved by using the information

in the other variable, the same holds for all h-step forecasts, h = 1, 2, . . . .

**This result does not hold anymore if the information set contains additional**

variables, as pointed out by L¨utkepohl

1. In other words, if yt is 1-step noncausal for zt, it may

still be h-step causal for h > 1. Consequently, it makes sense to define more

refined concepts of causality which refer explicitly to the forecast horizon. For

instance, yt may be called h-step noncausal for zt (yt→ (h)zt) for h = 1, 2, ...,

if the j-step ahead forecasts of zt cannot be improved for j ≤ h by taking into

account the information in past and present yt. Now the original concept of

Granger-causality corresponds to infinite-step causality.

1. In addition to these extensions related to increasing the information set, there are also other problems which may make it difficult to interpret Granger causal relations even in a bivariate setting. Let us discuss some of them in terms of an inflation/interest rate system. For example, it may make a difference whether the information set contains monthly, quarterly or annual data. If a quarterly system is considered and no causality is found from the interest rate to inflation it does not follow that a corresponding monthly interest rate has no impact on the monthly inflation rate. In other words, the interest rate may Granger-cause inflation in a monthly system even if it does not in a quarterly system.
2. Furthermore, **putting seasonally adjusted variables in the information set is not the same as using unadjusted variables.** Consequently, if Granger-causality is found for the seasonally adjusted variables, it is still possible that in the actual seasonal system the interest rate is not Granger-causal for inflation. Similar comments apply in the presence of measurement errors.
3. Still, causality analyses are useful tools in practice if these critical points are kept in mind. **At the very least, a Granger-causality analysis tells the analyst whether a set of variables contains useful information for improving the predictions of another set of variables.**

**Impulse Response Analysis:**

1. We have seen that Granger-causality **may not tell us the complete story** about the interactions between the variables of a system.

In applied work, it **is often of interest to know the response of one variable to**

**an impulse in another variable in a system that involves a number of further**

**variables as well**.

1. **Of course, if there is a reaction of one variable to an impulse in another variable we may call the latter causal for the former.** In this subsection, we will study **this type of causality** by **tracing out the effect of an exogenous shock or innovation** in one of the variables on some or all of the other variables.