Asymmetric Panel Causality Tests with an Application to the Impact of Fiscal Policy on Economic Performance in Scandinavia

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Abstract

Tests for conducting asymmetric Granger causality within a panel system are introduced in this paper. It is shown how the cumulative sums of negative and positive shocks can be constructed to investigate whether the potential causal effects of these shocks are asymmetrical or not within a panel system. These tests can be based on asymptotic or bootstrap distributions. The tests are applied to assess the impact of contractionary as well as expansionary fiscal policy on the economic performance of the three Scandinavian countries. The results show that allowing for asymmetry in the panel causality testing has important repercussions for the underlying causal inference.

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1. Introduction

Since the dawn of humankind one of the most important and inspirational issues must have been to figure out what is the cause and what is the effect. It is a well-established fact that many philosophers have dedicated much of their thinking throughout the history to causality as a paradigm. Yet the issue of defining causality and above all how to measure it is a controversial issue. There is still no universally accepted definition of causality and there is no universally accepted approach of testing for causality.

In the time series analysis Granger causality is a well-known concept. Granger's (1969) approach is increasingly used in empirical research to determine the direction of causal interaction between the underlying variables measured across time. Since the pioneering work of Granger many additional papers have attempted to provide modified tests for Granger causality. This is especially the case since the unit root revolution. Granger (1986, 1988) and Engle and Granger (1987) initiated the idea of implementing tests for causality within an error correction model to take account for the effect of unit roots. Toda and Yamamoto (1995) provide a modified Wald test that can be used for casualty testing between integrated variables within a vector autoregressive, VAR, model. Hacker and Hatemi-J (2006) showed that the modified Wald test does not have the correct size if the underlying data set is not normally distributed and volatility is time-varying. The authors suggest a bootstrap corrected test for causality with leverage adjustments that perform well even in situations in which some desirable statistical assumption do not hold. It is also possible to conducted causal inference within in a panel system based on the contributions of among others Holtz-Eakin, Newey and Rosen (1988), Hurlin (2004a, b) and Westerlund (2007) among others.[1]

However, the theoretical papers on the Granger causality testing are implicitly based on the supposition that the causal impact of positive shocks is of the same absolute magnitude as the causal impact of negative shocks. In other words, no asymmetry is allowed in the causality testing. This supposition might be too restrictive since in the reality people react differently to negative shocks compared to the positive ones. This seems to be the case even in a potential situation in which the absolute magnitude of the

[1] The origin of panel data analysis is attributed to Herman Wold.

shock is the same. Allowing for potential asymmetry is also important for other reason such as the fact that many markets are characterized by the asymmetric information property as shown by the pioneer works of Akerlof (1970), Spence (1973) and Stiglitz (1974). Granger and Yoon (2002) have introduced the concept of hidden cointegration that allows for potential asymmetry in the steady state relationship between time series variables. Recently, Hatemi-J (2012) has suggested asymmetric causality tests for time series analysis. The main goal of this paper is to extend these causality tests into a panel framework. Conducting causality tests within a panel has several advantages compared to the traditional time series approach. Combining the time series and the cross sectional dimensions results in increased degrees of freedom, which is very useful especially when the time series dimension is rather short as it is the case for many economic variables for developing and emerging markets. Another advantage of panel data analysis is that it can result in more efficiency due to taking into account the cross sectional spillover effects that are neglected in pure time series data analysis. This is especially relevant nowadays given the fact that economies are increasingly interlinked across the borders due to the intensified globalization phenomenon. The asymmetric panel causality tests suggested in this paper are applied to assess the causal impact of fiscal policy on the economic performance in the Scandinavian economies. The results show that it matters for the causal inference whether the asymmetric property in the causality testing is taken into account or not.

We structure the rest of the paper as the following. Next section introduces asymmetric causality testing within a panel perspective. Section 3 provides an application. The final section offers the concluding points. An appendix that represents a Wald statistic for implementing the causality test is provided at the end of the paper.

2. Asymmetric Panel Causality Testing

The well-known Granger causality concept is based on the idea of investigating whether the past values of one variable significantly improve the forecast of another variable or not. This is usually formulated as a null hypothesis in terms of zero restrictions imposed on the underlying parameters within an autoregressive model. If the null is rejected it is interpreted as evidence supporting the existence of Granger causality. Testing for asymmetric causality is based on a similar approach except for one main difference that the causal impact of positive shocks could be different than the causal impact of negative shocks. Thus, it is necessary to construct these shocks, which can be achieved by using the cumulative sums of the underlying shocks.[2] More specifically, assume that we are interested in testing for causality between variables x_1 and x_2 within a panel system. Assume also that each variable is integrated of the first degree as presented, with the corresponding solution obtained by the recursive method, in the following:

$$x_{i1,t} = x_{i1,t-1} + e_{i1,t} = x_{i1,0} + \sum_{j=1}^{t} e_{i1,j}$$

$$x_{i2,t} = x_{i2,t-1} + e_{i2,t} = x_{i2,0} + \sum_{j=1}^{t} e_{i2,j}$$

For i=1, …, n. Where n is the size of the cross sectional dimension and e is the white noise error term. The shocks can be identified as $e_{i1,t}^{+} := max(e_{i1,t}, 0)$, $e_{i2,t}^{+} := max(e_{i2,t}, 0)$, $e_{i1,t}^{-} := min(e_{i1,t}, 0)$ and $e_{i2,t}^{-} := min(e_{i2,t}, 0)$. Based on these definitions we can construct the cumulative sums of the shocks as

$$x_{i1,t}^{+} = x_{i1,0}^{+} + e_{i1,t}^{+} = x_{i1,0} + \sum_{j=1}^{t} e_{i1,j}^{+}$$

$$x_{i2,t}^{+} = x_{i2,0}^{+} + e_{i2,t}^{+} = x_{i2,0} + \sum_{j=1}^{t} e_{i2,j}^{+}$$

$$x_{i1,t}^{-} = x_{i1,0}^{-} + e_{i1,t}^{-} = x_{i1,0} + \sum_{j=1}^{t} e_{i1,j}^{-}$$

$$x_{i2,t}^{-} = x_{i2,0}^{-} + e_{i2,t}^{-} = x_{i2,0} + \sum_{j=1}^{t} e_{i2,j}^{-}$$

[2] The original idea of constructing cumulative sums is attributed to Granger and Yoon (2002)

The panel causality test can be conducted within a vector autoregressive seemingly unrelated regression model of order k, VAR-SUR(k), to allow for the possibility that the error terms across the cross sectional units might be contemporaneously dependent.[3] Assume that we are interested in the causal impact between cumulative positive shocks of the underlying variables, i.e., the vector $\left(x_{i1,t}^{+}, x_{i2,t}^{+}\right)$. Then, the following VAR-SUR(k) model can be estimated:

$$\begin{bmatrix} x_{i1,t}^{+} \\ x_{i2,t}^{+} \end{bmatrix} = \begin{bmatrix} \beta_{i0} \\ \gamma_{i0} \end{bmatrix} + \begin{bmatrix} \sum_{r=1}^{k} \beta_{i1,r} & \sum_{r=1}^{k} \beta_{i2,r} \\ \sum_{r=1}^{k} \gamma_{i1,r} & \sum_{r=1}^{k} \gamma_{i2,r} \end{bmatrix} \times \begin{bmatrix} x_{i1,t-r}^{+} \\ x_{i2,t-r}^{+} \end{bmatrix} + \begin{bmatrix} \varepsilon_{i1}^{+} \\ \varepsilon_{i2}^{+} \end{bmatrix} \tag{1}$$

The lag order k can be selected by minimizing an information criterion. The null hypothesis that $x_{i2,t}^{+}$ does not Granger cause $x_{i1,t}^{+}$ for the cross sectional unit i in the panel is defined as

$H_0: \beta_{i2,r} = 0, \forall\, r$. Where $r = 1, \ldots, k$.

This null hypothesis can be tested by using a Wald test, which is described in the appendix. It is also operational to conduct causality tests between negative components, i.e., $\left(x_{i1,t}^{-}, x_{i2,t}^{-}\right)$, in a similar way. Moreover, other combinations are potentially possible, i.e., using the vector $\left(x_{i1,t}^{-}, x_{i2,t}^{+}\right)$ or $\left(x_{i1,t}^{+}, x_{i2,t}^{-}\right)$. The cumulative sums of the shocks for each cross sectional unit are constructed by using an algorithm written in Gauss, which is available on request.

3. An Application

The method suggested in this paper is applied to investigate whether expansionary fiscal policy can promote economic growth in the three Scandinavian countries, i.e., Denmark, Norway and Sweden. These countries, with their common cultural and language origins as well as close current political and social bonds, have demonstrated remarkable

[3] The VAR model was introduced by Sims (1980) and the SUR model was developed by Zellner (1962).

economic performance even during the recent financial crisis. These counties are also known for their active fiscal policies, which offer a unique case to investigate whether the conducted fiscal policy has been successful in achieving its pronounced goal of enhanced economic performance. It is especially interesting to find out whether asymmetric structure within this context is a relevant issue or not. Thus, the investigation of the causal impact of contractionary fiscal policy is also an integral part of the analysis. The data is collected from the statistical bureau of each country. The sample covers the period 1993Q1-2010Q4. The variables in the model are the Gross Domestic Product (GDP) and the total government expenditure. Both variables are expressed at constant prices. Prior to causality testing, penal unit root tests were conducted. The results, not reported, showed that there is a unit root in each panel. Thus, an unrestricted lag needs to be included in the panel in order to account for the impact of the panel unit root on the distribution of the underlying test.

The results of panel causality tests are presented in Table 1. The symmetric causality test results show that the null hypothesis that the government spending is not Granger causing output cannot be rejected for any of the three countries in the panel. Conversely, the asymmetric panel causality tests show that the null hypothesis that positive shocks in the government expenditure does not cause positive shocks in the output can be rejected in the case of Denmark. The estimated parameter is, however, negative in this case. This means that conducting expansionary fiscal policy can harmful to the economic growth in Denmark. In the case of Sweden the null hypothesis that negative shocks in the government spending do not cause negative shocks in the output can be rejected. The estimated parameter is positive which means that contractionary fiscal policy can be harmful in Sweden. In the case of Norway none of the hypothesis can be rejected.

Table 1: The Results of Symmetric and Non-asymmetric Panel Causality Tests.

COUNTERY	NULL HYOTHESIS	P-Value	Significant Causal Parameter
Denmark	$S \quad \neq> Y$	0.8549	
	$S^- \neq> Y^-$	0.0432	-0.3387
	$S^+ \neq> Y^+$	0.4826	
Norway	$S \quad \neq> Y$	0.2530	
	$S^- \neq> Y^-$	0.6817	
	$S^+ \neq> Y^+$	0.3801	
Sweden	$S \quad \neq> Y$	0.8292	
	$S^- \neq> Y^-$	0.8126	
	$S^+ \neq> Y^+$	0.0370	0.1647

1. The denotation $S \neq> Y$ means that government spending does not Granger cause GDP.
2. The estimated causal parameter is 0.249 and 0.437 for positive and negative shocks respectively.
3. The lag order in the model is one. An extra unrestricted lag was also included in the VAR-SUR model in order to account for the impact of a panel unit root, based on the work by Toda and Yamamoto (1995).

4. Concluding Points

It is a well-established fact that markets with asymmetric information exist. It is also widely agreed that economic agents react differently to a negative shock than a positive one even in a case in which the absolute magnitude of the shock is the same. Hence allowing for asymmetry when tests for causality are conducted is a relevant issue. This paper suggests an approach for implementing asymmetric causality tests within a panel perspective. It shows how cumulative sums for positive and negative shocks can be constructed for this purpose. The method suggested in this paper is expected to improve on the causal inference in empirical analysis by providing more channels of information. The investigator can find out, by applying this method, whether the causal impact of positive shocks is different than the causal impact of negative shocks within a panel system. In case asymmetric impacts are found, it is also possible to measure these impacts by estimating the underlying causal parameters for both positive and negative shocks. These parameters will offer the possibility to see how serious the impact of the asymmetric property is on the causal interaction between the variables of interest.

An application to the impact of the fiscal policy on economic performance in the three Scandinavian countries is provided. The results indicate that asymmetry matters for the causal inference. Standard symmetric causality test show that government spending is not causing output for any of the three countries in the panel. However, asymmetric panel causality testing reveals that expansionary fiscal policy has negative impact on economic performance in Denmark, while contractionary fiscal policy does not have any causal impact. In Sweden, contractionary fiscal policy is harmful for economic growth but expansionary policy does not have any impact. In the case of Norway, neither expansionary nor contractionary fiscal policy has any causal impact on the economic performance. All in all, it seems that the impressive economic performance in these Scandinavian countries is not a consequence of the implemented fiscal policy. However, only the future applications of the asymmetric tests can reveal whether the results are general or not.

References

Akerlof G., (1970) The market for lemons: Quality Uncertainty and the Market Mechanism, *Quarterly Journal of Economics*, 84, 485-500.

Engle R. and Granger C. W. J., (1987) Co-Integration and Error Correction: Representation, Estimation, and Testing, *Econometrica*, 55, 251-276

Granger, C. W. J., (1969) Investigating Causal Relations by Econometric Models and Cross-spectral Methods, *Econometrica,* 37, 424-439.

Granger, C. W. J., (1988) Causality, cointegration, and control, *Journal of Economic Dynamics and Control*, 12, 551-559.

Granger, C.W., Yoon, G. (2002) Hidden Cointegration. Department of Economics Working Paper. University of California. San Diego.

Hacker R. S. and Hatemi-J A. (2006) Tests for causality between integrated variables using asymptotic and bootstrap distributions: theory and application. *Applied Economics*, 38(13), 1489-1500.

Hatemi-J, A., (2012) Asymmetric Causality Tests with an Application, *Empirical Economics*, 43(1), pages 447-456.

Holtz-Eakin, D., Newey, W., and Rosen, H. (1988) Estimating Vector Autoregressions with Panel Data, *Econometrica*, 56, 1371-95.

Hurlin, C. (2004a) Testing Granger Causality in Heterogeneous Panel Data Models with Fixed Coefficients, Miméo, University Orléans.

Hurlin, C. (2004b) A Note on Causality Tests in Panel Data Models with Random Coefficients, Miméo, University Orléans.

Sims C., (1980) Macroeconomics and Reality, *Econometrica*, 48, 1-48.

Spence M. (1973) Job Market Signalling, *Quarterly Journal of Economics*, 87, 355-374.

Stiglitz J. (1974) Incentives and Risk Sharing in Sharecropping, *Review of Economic Studies*, 41, 219-255.

Toda, H. Y., and Yamamoto, T., (1995) Statistical Inference in Vector Autoregressions with Possibly Integrated Processes, *Journal of Econometrics,* 66, 225-250.

Westerlund J. (2007) Testing for Error Correction in Panel Data. *Oxford Bulletin of Economics and Statistics*, 69, 709-748.

Zellner A (1962) An Efficient Method of Estimating Seemingly Unrelated Regressions and Tests for Aggregation Bias, *Journal of the American Statistical Association*, 348-368.

Appendix

By making use of some denotations, it is possible to express the panel data model (1) as the following:

$$\begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix} = \begin{bmatrix} Z_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & Z_n \end{bmatrix} \times \begin{bmatrix} \beta_1 \\ \vdots \\ \beta_n \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \vdots \\ \varepsilon_n \end{bmatrix} = Z\beta + \varepsilon$$

Where n is representing the size of the cross sectional dimension. The $n \times n$ variance and covariance matrix of the disturbance is defined as

$$\Sigma = \begin{bmatrix} \sigma_{11} & \cdots & \sigma_{1n} \\ \vdots & \ddots & \vdots \\ \sigma_{n1} & \cdots & \sigma_{nn} \end{bmatrix}$$

The generalized least squares estimator is

$$\hat{\beta} = [Z'(\Sigma^{-1} \otimes I)Z]^{-1} Z'(\Sigma^{-1} \otimes I)y$$

Where $\otimes$ is the Kronecker product operator and I is an identity matrix. The null hypothesis of no panel Granger causality in this setting can be expressed as

$H_0: R\hat{\beta} = 0,$

where R is an indicator matrix consisting of one and zero elements. The following Wald test can be used to test the null hypothesis:

$$Wald = (R\hat{\beta})' \left[R\widehat{Var}(\hat{\beta})R'\right]^{-1} (R\hat{\beta})$$

Where $\widehat{Var}(\hat{\beta})$ is the estimated variance and covariance matrix of the parameters. If the assumption of normality holds, this test is asymptotically distributed as chi-sqr with degrees of freedom equal to the number of restrictions. If the assumption of normality does not hold, however, the bootstrap technique developed by Hacker and Hatemi-J (2006) can be utilized.