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Cointegration and causality in international agricultural economics research

Hector O. Zapata[a,*], José M. Gil[b]

[a]Department of Agricultural Economics and Agrib., Louisiana State University, Baton Rouge, LA 70803, USA
[b]Servicio de Investigación Agroalimentaria, P.O. BOX 727, 50080, Zaragoza, Spain

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Abstract

A review of literature on applications of Granger causality to problems in international agricultural economics research is summarized. The review relates to cointegration theory, and it identifies the areas where recent econometric developments may be of value. Testing procedures are outlined, and a discussion is provided on questions such as non-stationarity and asymptotic distribution of non-causality tests, the relationship between cointegration and causation, the relative merits of various testing procedures, and concerns about testing bivariate causality in higher dimensional models. Finally, a recent econometric development is discussed and its future use in applied research is discussed.

1. Introduction

The recent developments in non-stationarity and cointegration theory have contributed to a better understanding of long-run and short-run dynamics in international economics and finance. Many applications in agricultural economics research have focused on the problem of testing Granger non-causality. Some of the most recent applications include the analysis of price linkages in international commodity markets (e.g. Mohanty et al., 1995), test whether factor price movements tend to influence the type of technological innovations which are developed and adopted – the 'induced innovation hypothesis' (e.g. Machado, 1995), analysis of, and testing for, spatial international market integration (e.g. Ardeni, 1989), and the study of causal relationships between agricultural productivity and exports in various countries (e.g. Arnade and Vasavada, 1995), among others.

Unquestionably, the application of recent developments in time series analysis in these works has contributed to a better understanding of the results and implications of econometric models of equilibrium behavior, particularly in what relates to non-causality testing. However, there appears to be a gap between the most recent developments in cointegration and Granger non-causality testing and their appropriate use in applied research. The purpose of this paper is to fill some of this gap.

The paper is structured as follows. The second section provides a summary of previous work in causality testing, highlighting testing procedures previously used; the third section presents the econometric meth-

*Corresponding author. Tel.: +1-504-388-2766; e-mail: xp2647@1suvm.sncc.1su.edu

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odology of testing Granger non-causality in the context of non-stationarity and cointegration; the fourth section is a discussion of questions applied researchers must often confront, emphasizing the main asymptotic and Monte Carlo results available to date.

2. Review of previous work

The works of Granger (1969) and Sims (1972) introduced and popularized the application of Granger non-causality tests to the problems in agricultural economics and in many other fields. The definition of causality has caused considerable controversy among researchers regarding its usefulness in identifying the direction of causation. As discussed by Granger (1980, 1988a, b), causality in mean is the one that has empirical relevance because of its forecasting content, that is, *if y(t) causes x(t), then x(t+1) is better forecast if the information in y(t) is used than if it is not used, where better means a smaller variance of forecast error, or the matrix equivalence of variance*. It is an idea that most empirical studies have been adopted.

In the early works, the approach used to test for non-causality (lead–lag relationships) was based on the study of bivariate relationships, say between advertising and aggregate consumption (Ashley et al., 1980), lead–lag relationships between cash and futures markets (Brorsen et al., 1984), price dynamics across market channels (Ward, 1982); and price variability versus trading volume (Garcia et al. (1986); among others). In these works, single equations or bivariate models were estimated, and F-type tests were applied to test for instantaneous, unidirectional or bidirectional causality (refer to Sarker (1995) for a recent survey). Most researchers recognized that some type of filtering was usually needed to either remove deterministic components in the series or to render the series stationary (Guilkey and Salemi (1982); Zapata et al. (1988); among others).

In the past decade, the application of Granger non-causality tests have regained popularity with the introduction of cointegration analysis formally introduced in Engle and Granger (1987). The idea of cointegration suggests that if $x(t)$ and $y(t)$ are both integrated of order 1 (denoted as I(1)), without trends in means, so that their changes are both I(0) and with zero means, then it is possible that there will exist a constant such that a linear combination of $x(t)$ and $y(t)$, say $x(t) - \beta y(t) = z(t)$, is I(0). Thus, cointegration is concerned with the long-run and equilibrium (Granger, 1988a). An important consequence of cointegration is given by the Granger representation theorem which basically says that when two or more variables are cointegrated, they can be modeled in error-correction form, where the changes are the dependent variables, and the lagged changes and the error-correction term (ECT) $z(t)$ are the independent variables. The link between cointegration and causation becomes explicit in the error-correction model (ECM) where there are two sources of causation, through the ECT or through the lagged changes. As pointed out by Granger (1988a), classical time series modelling techniques based on some form of ARMA models, which do not incorporate the effect of the ECT, would be misspecified. The consequence of this being that some forecastibility from one variable to the other is ignored. Therefore, past causality research based on classical procedures, when the series are cointegrated, missed some of the forecastibility and hence reached incorrect conclusions about non-causality in mean.

Recent work on causality with cointegrated series has used ECMs of the Engle–Granger-type. Typically these applications are based on bivariate models where the coefficient β uniquely defines one cointegrating relation between $x(t)$ and $y(t)$. When this is the case, either for bivariate or multivariate ECMs, a classical Wald statistic can be used to test for non-causality, where the distribution follows a standard χ^2 with degrees of freedom equal to the number of restrictions. Application of standard causality tests to non-stationary processes in general is not appropriate because their distribution is often non-standard and involves nuisance parameters (Toda and Phillips, 1993). In the context of bivariate cointegration, Lütkepohl and Reimers (1992) present the distribution of the Wald statistic using a maximum likelihood approach proposed by Johansen and Juselius (1990). The approach consists in estimating a ECM and then retransforming it to a vector autoregression (VAR) in levels to which linear restrictions are applied. The distribution of the statistic for the general case (p variables) is discussed in Toda and Phillips (1993).

Although these developments in cointegration and causation solved important inference problems, other questions appeared. One of these relates to estimation efficiency gains that can be obtained by imposing the cointegrating constraints under both the null and alternative hypotheses (Mosconi and Giannini (1992)). Another question, closely related to the previous one, deals with the 'degree of cointegration.' Lütkepohl (1993a) and Toda and Phillips (1993) indicate that there needs to be sufficient cointegration to guarantee the distribution of the Wald test to a standard χ^2. The answer to these first two questions requires a rather complex analysis in the framework of the model proposed by Johansen and Juselius. Toda and Yamamoto (1995) and Dolado and Lütkepohl (1996), however, have introduced simpler procedures to deal with questions of estimation and inference in multivariate ECMs. Monte Carlo evidence on the relative merits of these approaches in small and large samples are presented in Mosconi and Giannini (1992) and in Zapata and Rambaldi (1997).

In what follows, a review of literature is presented, in a somewhat condensed form, of causality works in the agricultural economics and applied economics literature to highlight the models and methods previously used in testing for non-causality. In this review, we emphasize the developments over the past few years because an extensive review of previous works is presented in Sarker (1995).

Several recent applications of the causality concept to problems in international agricultural economics research include tests of the export led growth hypothesis, the induced innovation hypothesis, price dynamics, market integration, and linkages between the macroeconomy and agriculture. These application, for the most part, used various Walt-type tests (or MSE tests) for testing non-causality. We discuss some of these applications with the intent of highlighting the somewhat varied nature of non-stationarity and cointegration properties that characterize many of the economic time series data that are frequently used in this type of research. It is also fair to point out that many of the empirical applications were completed before some of the recent developments in non-stationarity and cointegration were published.

The causal relationship between agricultural productivity and exports, a test of the export led growth (ELG) hypothesis, for selected Asian and Latin American countries was studied by Arnade and Vasavada (1995). The data were annual series on exports, productivity, output and terms of trade for the 1961–1987 period. Tests of unit roots revealed that most of the series were I(1), but there were instances when some series were I(0) at either the 5- or 10-percent level. For the I(1) cases, a four variable model was specified and estimated via maximum likelihood methods. The findings suggested that for most cases there was cointegration, with the number of cointegrating relations being less than the number of variables. The paper mentions the work of Toda and Phillips (1993) for the conditions needed to ascertain good asymptotic properties of the causality tests and also cautions that the causality test statistics used should be viewed as the best available approximation to the true statistics. From the methodology on causality tests, it appears that an ECM of the Engle–Granger-type was estimated for the cases when cointegration was found. The results of 33 country's analysis were mixed, finding that for five countries exports caused productivity, and for three countries, productivity caused exports.

A similar application of the ELG hypothesis to Malaysia is found in Ghatak et al. (1997). The Malaysian aggregated data used were annual real GDP, non-export real GDP and real exports for the period 1955–1990. Bivariate models for the GDP and exports variables were estimated using the Engle–Yoo three-step estimator. The findings suggested causality from exports to real and non-export real GDP using a combination of t-test (on the error-correction term) and F-test on the lagged differences of the causal variable. Disaggregated real export data (manufacturing, fuel and non-fuel primary products) for the period 1966–1990 were also used to identify the separate effect on each of real GDP and non-export real GDP. Since there were more than two variables in the model, the paper used the maximum likelihood method of Johansen and Juselius (1990) to identify the number of cointegrating relations. The findings suggested a unique cointegrating relation for real GDP and disaggregated exports, and two cointegrating vectors for the non-export real GDP versus disaggregated exports model. The paper proposed to identify an economically meaningful cointegrating relation as means of solving the problems associated with multiple cointegrating relations in causality testing. Once this was achieved, the three-step estimator of Engle et al. (1991) was used to reestimate the ECM. The resulting

t-tests on the error-correction term suggested long-run causality from some non-traditional exports (non-fuel primary exports) on real GDP and non-export real GDP. The paper did not discuss the implications of this testing approach on the validity of the causality results, neither it justified the use of this testing strategy in a manner consistent with the Toda and Phillips (1993) approach (see Lee et al. (1996), for example, on the application of this approach).

Another application of interest in international agricultural economics research is that of testing the hypothesis that factor price movements tend to influence the type of technological innovations which are developed and adopted (e.g. Machado (1995)), that is, the Induced Innovation Hypothesis (IIH). This is an application that leads very naturally to the use of cointegration theory because there may be long lags in the effect of factor prices on technical change biases. Briefly, cointegration between the factor shares and the exogenous variables in a translog cost system is assumed to imply long-run neutrality of technical change. Therefore, if cointegration is not found then technical change can be considered to be a biased process. Using aggregate U.S. agriculture data for the period of 1948–1983, Machado found mixed unit roots in the factor share variables, thus leading to the conclusion that neutrality is rejected. The paper does not, however, explore dynamics in the Granger causal sense, or the implications of mixed integration for dynamic modeling of the IIH.

Applications of non-stationarity and cointegration methods have also been undertaken to study dynamic agricultural price relationships and market integration. For instance, Hudson et al. (1996) reports an evaluation of future and spot cotton price relationships in the Southwest region of the US using cointegration methods. The econometric procedures in this paper used a variant of the Granger causality test based on the traditional single equation approach of estimating restricted and unrestricted equations but applied to an error-correction model of the Engle–Granger-type. Consistent with other literature on this subject, the paper finds that cash producer price and the futures price were not cointegrated in 2 of the 4 years studied. Another example of the study of price dynamics relates to the linkages between the macroeconomy and agriculture. Bradshaw and Orden (1990) examined the impact of the real agricultural trade-weighted exchange rate on forecasts of real cash prices and export sale volumes of wheat, corn and soybeans in bivariate models. The procedure used to test Granger non-causality was a test of differences in forecast MSE between univariate and bivariate models. The results supported Granger causality from the exchange rate to export sales, but the evidence for causality from the exchange rate to prices was mixed. Considerable new empirical evidence exits on the cointegrated macroeconomic–agricultural linkages in the short and the long run (e.g. In and Mount (1994)); the results support unit roots in most series and strong long-run relationships. For instance, in terms of the interaction between prices and demand or supply variables in each sector, significant feedback effects were found from commodity demand to prices, from financial asset demand to prices, and from input demand to factor prices. These results imply endogeneity in price variables. These previous works could be usefully expanded to a closer examination of causal relationships in a system's framework using MLE methods which impose the cointegration and causality restrictions in both the short and the long run. Further, future research could begin to address questions related to mixed order of integration and non-causality tests of macroeconomic–agricultural linkages.

Some recent papers have studied the question of market integration in various countries (e.g. Ravallion, 1986; Ardeni, 1989; Goodwin, 1992; and Zanias, 1993). Considerable attention has been given in these works to the distinction between short-run versus long-run market integration, and to the effect of expectations formation and adjustment costs. The most recent applications in this inquiry have adopted the maximum likelihood method of Johansen and Juselius (1990) to suggest that the existence of cointegration is necessary for market integration. In the application of this approach to multiple series, however, little consideration has been given to tests of exclusion from the cointegrating space, Granger non-causality and weak exogeneity (e.g. Boccaletti and Moro, 1990) and its implications for the role certain markets (or countries) play in the exchange of information and/or its meaning for market integration. In fact, none of the recent developments have been used to address questions of sufficient cointegration, efficiency, and mixed integration.

3. Testing Granger non-causality

3.1. The Model

The basic VAR model for $\boldsymbol{p}$ variables and $\boldsymbol{k}$ ***lags*** with Gaussian errors is given by

$$\Phi(LZ_t)\begin{bmatrix}\Phi_{11}(L) & \Phi_{12}(L)\\ \Phi_{21}(L) & \Phi_{22}(L)\end{bmatrix}\begin{bmatrix}Z_{1t}\\ Z_{2t}\end{bmatrix}=e_t \qquad t=1,\ldots,T \tag{1}$$

where $e_1,\ldots, e_T$ are i.i.d. $N\sim(0,\Sigma)$, and the maximum lag in $\Phi(L)$ is k, Z_{1t} consists of p_1 variables and Z_{2t} of p_2 variables. Omitting deterministic components for simplicity, the error-correction form of this model can be expressed as (e.g. Zapata and Rambaldi, 1997):

$$\Delta Z_t = \Gamma_1\Delta Z_{t-1} + \ldots + \Gamma_{k-1}\Delta Z_{t-k+1} - \Pi Z_{t-k} + e_t \tag{2}$$

where $\Gamma_i = -(I_p - \Phi_1 - \ldots - \Phi_i)$, $i=1,\ldots, k-1$, and $\Pi = I_p - \Phi_1 - \ldots \Phi_k$,which using compact matrix notation reduces to

$$Z_0 = \Gamma Z_1 + \Pi Z_k + E \tag{3}$$

with Z_0 a $p \times T$ matrix of observations on first differences of Z, Z_1 contains lagged differences, Z_k is the kth lag of Z_t, Γ is a $(p \times (k-1)p)$ matrix of the stacked Γ_is, and E is the $p \times T$ matrix of disturbances for the p equations in the system.

The usual cointegration condition is that the rank of Π equals $r<p$ which in hypothesis form is given by

$$H_C(r) : \Pi = \alpha\beta' \tag{4}$$

where α and β are $p \times r$ matrices, and r is the number of cointegrating relations $\beta' Z_t$. This restriction also provides some insight into the causality implications of cointegration because causality can occur through the cointegrating relations $\beta' Z_t$ or by conditioning on α such that a row of α equating to zero essentially excludes 'long-run causality' in that equation.

4. Wald tests

Wald tests are perhaps the most popular tests used to test Granger non-causality in VARs. These tests have the virtue of being simple to implement and, under certain conditions, converge to a χ^2 distribution. Several estimation approaches have been proposed in the cointegration literature which follow the same structure as the Wald test for non-cauality in VARs. Two popular approaches are: (a) Wald test on a levels VAR obtained by a transformation of the MLE (e.g. Lütkepohl, 1993a); and (b) Wald test on Augmented VAR, procedure which has been independently introduced by Toda and Yamamoto (1995) and Dolado and Lütkepohl (1996). This second test is based on the estimation of a VAR in levels with lag order equal to the 'true' plus d, where d is the degree of integration.

5. Wald test from ECM

Let $z_t' = [x_t' y_t']$ so that in Eq. (1) we can represent the hypothesis that x_t does not Granger-cause y_t as (Lütkepohl (1993b), p. 378):

$$H_o : \Phi_{12,i} = 0 \qquad \textit{for} \qquad i = 1,2,\ldots,k \tag{5}$$

where Φ_{12} is the coefficient matrix on x_t in the y_t equations. In a bivariate system, for instance, $\Phi_{12,i}$ is the 1×1 coefficient on x_t in the y_t variable. Similarly, y_t does not Granger-cause x_t if and only if the corresponding $\Phi_{12,i}$ coefficients equal zero. Let $\phi = \text{vec}[\Phi_1,\ldots,\Phi_k]$ be the vector of all VAR coefficients. The hypothesis in Eq. (5) can be written as $H_o : \boldsymbol{R}\phi = 0$ against $H_1 : \boldsymbol{R}\phi \neq 0$ for a suitable chosen matrix $\boldsymbol{R}$; and the corresponding Wald statistics $W = T\phi'\boldsymbol{R}'(\boldsymbol{R}\Sigma_\phi\boldsymbol{R}')^{-1}\boldsymbol{R}\phi$ where $\boldsymbol{R}$ is $N \times p^2k$, N is the rank of $\boldsymbol{R}$ and Σ_ϕ is the variance–covariance of ϕ. W has a χ^2 distribution with N degrees of freedom under H_o if there is sufficient cointegration in the sense that if we are interested in whether the p_2 elements of x_t are 'not causing' the p_1 elements of y_t, then for W to converge in distribution to a χ^2 the dimension of the cointegrating space β for x_t or the dimension of the speed of adjustment space α corresponding to y_t must meet full rank conditions, which can be tested using MLE.

6. Augmented VAR: Wald test

The procedure in this approach consists in estimating a VAR$(k + d_{\max})$ where $d_{\max}$ is the maximum order of integration in the process. After such a model has been estimated by multivariate least squares, the first k coefficient matrices are selected (a VAR(k) is chosen) to test non-causality. From here onwards, the estimation of the Wald statistic is the same as the estimation in a levels VAR. Note that in this approach knowledge about cointegration is not used and that testing for unit roots, although not needed either, ensures the adding of extra lags. Toda and Yamamoto (1995) prove that the Wald test for restrictions on the parameters of a VAR(k) has an asymptotic χ^2 distribution when a VAR($k + d_{\max}$) is estimated (see also Dolado and Lütkepohl (1996)).

7. The Likelihood ratio test

The LR test for non-causality when there is cointegration is the one proposed by Mosconi and Giannini (1992). The ECM is estimated via MLE (Johansen and Juselius, 1990), but the testing procedure is somewhat more complicated because cointegration and non-causality imply restrictions on the number of cointegration relations, and on the long- and short-run parameters.

The alternative hypothesis is that of cointegration given in Eq. (4). The Granger non-causality (G) restrictions imply:

$$H_{\mathrm{G}}(r) : B'\Gamma V = 0, B'\Pi A = 0 \quad (6)$$

where Γ and Π are the parameters of model (3), and

$$B = \begin{bmatrix} 0 \\ I_{p_2} \end{bmatrix}, \ A = \begin{bmatrix} I_{p_1} \\ 0 \end{bmatrix}, \ V = I_{(k-1)} \otimes A \quad (7)$$

and B is $p \times p_2$, A is $p \times p_1$ and V is $p(k-1) \times p_1(k-1)$, Ip_i $(i = 1{,}2)$ is an identity matrix of order p_i and $B'A = 0$. Cointegration and Granger non-causality (denoted by the subscript GC) imply the combination of the hypotheses in Eqs. (4) and (6). This new hypothesis is written as:

$$H_{\mathrm{GC}}(r) : B'\Gamma V = 0, B'\Pi A = 0, \Pi = \alpha\beta' \quad (8)$$

which is also referred to by MG as $H_{\mathrm{GC}}(r, r_1, r_2)$. Denoting the values of the likelihood functions under Eqs. (4) and (9) as $\mathrm{L}_{\max} H_{\mathrm{C}}(r)$ and $\mathrm{L}_{\max} H_{\mathrm{GC}}(r, r_1, r_2)$, respectively, the LR test can be used to estimate a likelihood ratio test given by

$$-2\ln\frac{L_{\max}[H_{\mathrm{GC}}(r, r_1, r_2)]}{L_{\max}[H_{\mathrm{C}}(r)]}, \quad (9)$$

which is asymptotically χ^2 distributed with $q_{\mathrm{GC}}(r, r_1, r_2) = p\,r - p_1\,r_1 - p_2\,r_2 - r_1\,r_2$ degrees of freedom (Toda and Phillips, 1993; Mosconi and Giannini, 1992; Zapata and Rambaldi, 1997). The restrictions implied by non-causality are extremely important for empirical works aimed at testing hypotheses suggested by international trade theories (e.g. testing technological gap). If there is cointegration, the restrictions must be tested on the short- and long-run coefficients.

8. Discussion

These recent developments in testing for non-causality with cointegration raise questions regarding the validity of results generated from traditional testing procedures. It appears, based on recent applications of this concept, that some discussion is needed to addresses-specific methodological issues related to non-stationarity, cointegration and non-causality tests.

8.1. *Non-stationarity and asymptotic distribution of non-causality tests*

One result from the recent developments is that Wald tests of non-causality between subsets of variables may not have the classical distributions commonly adopted in applied work. In general, the limit theory of these tests involves nuisance parameters and non-standard distributions (Toda and Phillips, 1993). Thus, the use of the F-type tests in levels or first differences is in general not recommended.

8.2. *The relationship between cointegration and causation*

It is well understood that if there is cointegration then there exists causation in at least one direction. However, in high dimensional models (more than two variables), a careful examination of the cointegrating space must be conducted and 'sufficient cointegration' identified (e.g. Lütkepohl, 1993a; Toda and Phillips, 1993). It is possible that the classical tests may not converge to a standard χ^2. This is of particular importance to works related to the export-led growth hypothesis (e.g. Arnade and Vasavada, 1995; Ghatak et al., 1997) where a three- or four-variable model may be estimated. Toda and Phillips (1993) provide theoretical and practical guidelines regarding knowledge about unit roots and cointegration needed to determine the appropriate limit theory for non-causality tests. The conditions needed to ascertain standard χ^2 distribution of the Wald-type tests can perhaps be better illustrated by means of the ELG hypothesis discussed in the review of previous work. Suppose a three-variable model of y_1 = exports, y_2 = terms of trade, and y_3 = productivity is estimated, and assume that each series is I(1) and that there is one cointegrating relation involving all three variables. A test of the hypothesis that productivity does not cause exports (y_3 does not cause y_1) results in a Wald test that is asymptotically χ^2 because y_3 contains only one variable (of dimension 1), the rank of the cointegrating matrix for y_3 is also 1, and thus, the condition for sufficient cointegration holds. Consider, however, the same model but changing the test to the terms of trade and productivity do not cause exports (y_2 and y_3 do not cause y_1). In this instance, the dimension of the 'non-causal' vector is 2, but the rank of the cointegrating submatrix for y_2 and y_3 is 1, which is less than 2, and thus, failing the condition for sufficient cointegration. The main result is that the limiting distribution of the Walt test of non-causality is non-standard (even when there is one cointegrating relation between y_2 and y_3). This results does not appear to have made its way into much of the empirical work with more than two variables in the study areas reviewed in the previous section. Clearly, if this condition fails, then the usual Wald-type tests used in previous works have a limiting non-standard distribution. One feasible approach in these cases is the sequential testing procedure introduced by Toda and Phillips (1993). The approach of Mosconi and Giannini (1992) is also a candidate, particularly for the cases when small samples (less than 100 observations) are used. Other procedures that may work well in bigger samples (100 observations or more) are those of Toda and Yamamoto (1995); Phillips (1995); Dolado and Lütkepohl (1996); Quintos (1997). Note that the latter procedures are less restrictive in terms of the assumptions required for convergence to standard distributions, and that they are much easier to implement. It must also be pointed out that there exists other approaches to causality testing in high dimensional models that are less popular in the empirical literature. One of these is the approach to testing non-causality between a pair of variables introduced by Lütkepohl (1993b) who proposes testing zero restrictions on the coefficients of impulse response functions rather than on the model coefficients corresponding to non-causality between the two variables of interest.

8.3. *Efficiency gains, lags and sample size*

Mosconi and Giannini (1992) introduced the LR procedure as means of generating gains in estimation efficiency; their Monte Carlo experiment and the experiment by Zapata and Rambaldi (1997) suggest that for samples under 100 observations, the LR test works better than the other tests. Typical applications of the IIH or ELG hypotheses, for instance, use samples of size 50 or less; in these cases, therefore, these Monte Carlo results suggest that the use of the LR procedure is the preferred choice. Another important finding is that with small samples it is useful to remain parsimonious. The Monte Carlo results in Zapata and Rambaldi (1997) point to a reduction in power (and size) of the tests when over fitting occurs. The usual result that in large samples over fitting is better than under fitting holds true here also. However, the Monte Carlo work in the above two studies signal to a judgmental evaluation of alternative selection criteria in model selection.

It must be pointed out, however, that the power and size results in these experiments leave much uncertainty regarding the usefulness of these testing procedures when samples are very small (less than 50 observations). The Wald and modified Wald procedures have a considerable power and size loss, particularly for samples of size 25. The LR test, however, has good power and size properties even at 50 observations, but requires close scrutiny of model specification at 25 observations. Thus, it appears that having at least 50 observations, and using the LR test, is recommended for testing causality under cointegration. For samples of size 100, power and size seem comparable for all three testing procedures. However, we must await for the development of an optimality criterion that captures the trade off between size and power.

8.4. *New econometric developments*

Phillips (1995) has introduced a 'fully modified VAR' approach that allows for the existence of I(0) and I(1) series. In brief, the approach is a unified procedure for the estimation of VARs without pretesting the order of integration and rank conditions of long-run matrices. Previous work on the IIH and ELG hypotheses have found some variables to be I(0) and some to be I(1). Cointegration between two such variables is not possible, and thus, the hypothesis of neutral technical change in the IIH is rejected. In higher dimensional models, however, cointegration is possible under mixed integration; thus, the use of the FMVAR approach may shed light on the implications of mixed integration for causality relationships that may have been previously ignored. Quintos (1997) has discovered that an approach that combines the FMVAR with that of Toda–Yamamoto is a viable alternative to the ML approach for non-iid errors and when moving average terms are present in the error structure; the procedure yields a Wald test for Granger non-causality that is χ^2 distributed regardless of whether or not unit roots are included in the null. The finding is useful in that it allows for non-standard error structures that are often reported in practice but that are usually assumed away in most standard tests.

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