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Export-led Growth: A Survey of the Empirical Literature and Some Noncausality Results Part 2[1]

Judith A. Giles and Cara L.Williams
University of Victoria

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Abstract

This paper continues the investigation of Giles and Williams (2000) on export-led growth (ELG). In the first part, we surveyed the empirical export-led growth literature; it was evident that Granger noncausality tests are commonly applied as a test for ELG. In this paper, we explore the sensitivity of the test for exclusions restrictions often used as the Granger noncauality test for ELG by reconsidering two applications: Oxley's (1993) study for Portugal and Henriques and Sadorsky's (1996) analysis for Canada. We focus on robustness to the method adopted to deal with nonstationarity, including the choice of deterministic trend degree. We show that different noncausality outcomes are easy to obtain, and consequently we recommend that readers interpret the empirical ELG literature with care. Our analysis also highlights the importance of examining the robustness of Granger noncauality test results to avoid spurious outcomes in applications.

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[1] Correspondence to: Judith A. Giles, Department of Economics, University of Victoria, PO Box 1700, Victoria, B.C., Canada, V8W 2Y2. Email: jgiles@uvic.ca; telephone: 250-721-8542. We are grateful to Les Oxley and Irene Henriques for providing us with their data sets, and we thank the referee, David Giles, Irene Henriques, Les Oxley, Nilanjana Roy, Perry Sadorsky and other seminar participants at the University of Victoria, Deakin University and the Reserve Bank of New Zealand for helpful comments. An earlier version of this paper was presented at the 1998 Canadian Economics Association Meeting. This research was supported by a grant from the Social Sciences and Humanities Research Council of Canada for the first author.

1. Introduction

Since 1985 (Gupta, 1985; Jung and Marshall, 1985) there has been considerable interest in testing for export-led growth (ELG) using the notion of Granger causality. The survey we provide in Giles and Williams (2000), hereafter denoted as GW, details over seventy such time series studies. While the usefulness of this concept to test the ELG hypothesis has been questioned, and the sensitivity of the causal outcome to certain characteristics of the modelling exercise (e.g., lag order, estimation period, information set) has been considered, there does not appear to have been an explicit examination of the sensitivity of the ELG causal outcome to the method adopted to deal with nonstationarity issues, including the choice of the deterministic trend degree. This is our aim.

There are various methods of examining for ELG using the Granger noncausality (GNC) concept; we detail several of these in GW. In this paper we limit attention to the common approach of formulating the GNC null hypothesis as a test of exact linear restrictions on the coefficients of a finite-order dynamic model, which may be a vector autoregressive (VAR) model in the levels data (hereafter denoted by VARL), a VAR model in the first-differenced data (hereafter denoted by VARD), or a vector error correction model (hereafter denoted by VECM). Other methods of detecting ELG include innovation accounting (e.g., forecast error variance decompositions and impulse response functions), Sims (1972, 1980) noncausality test, and an approach suggested by Geweke (1984). A consideration of these other techniques is beyond the scope of this paper, though our expectation is that they too would be similarly nonrobust. Our choice is based on the fact that over eight-five percent of the GNC export-led growth studies surveyed by GW use the hypothesis test we examine.

We examine robustness of GNC test outcomes to changes in the deterministic trend degree in the models and to the method used to handle nonstationarity concerns by reconsidering the data used by two export-led growth applications: Oxley's (1993) Portugal study and Henriques and Sadorsky's (1996) application for Canada. That we draw upon these should not be interpreted to imply our criticism of this work; on the contrary, both studies were quite rigorous in their investigations. They were chosen merely because the authors obligingly provided us with their data. It is our belief that the features we observe would result with any of the data sets in the literature. We carry out our analysis using two data sets so that we can assess whether the results are unduly sensitive to our choices. We consider Wald and likelihood ratio (LR) test statistics, as well as the F-variant of the Wald statistic adjusted for finite sample degrees of freedom; none of the studies in GW use a Lagrange Multiplier test statistic and as our aim is to replicate applied practice, we do not undertake testing with this statistic. We show that the GNC outcomes are sensitive to variations in the deterministic trend degree and to the nonstationarity method adopted.

The plan of this paper is as follows. In section 2 we provide the setup and information on testing for GNC. We also detail some potential concerns in section 2. Section 3 provides brief details about prior ELG studies for Canada and Portugal. This section also outlines the scope of our sensitivity study for these two countries and presents the results of our analysis. Section 4 concludes.

2. Testing for GNC

2.1. Background

The ELG causality studies base their notion of causality on that proposed by Granger (1963, 1969), which builds on earlier research by Weiner (1956). The premise is that causality is synonymous with predictability. The approach is atheoretical in the sense that no attempt is made to incorporate economic theory to impose any a priori restrictions upon the relationships between the variables of interest to the researcher. We say that y Granger-causes x if relevant past information allows us to predict x better than when past information except y is used.

More formally, let Ω_t be the information set containing relevant information available up to and including the time period t; let $x_t(1|\Omega_t)$ be the optimal (minimum mean squared error (MSE)) 1-step predictor of x_t at time t, based on the information in Ω_t; let $M_x(1|\Omega_t)$ denote the resulting 1-step forecast MSE. Then, y_t is said to Granger-cause x_t one-period ahead if, in the matrix sense, $M_x(1|\Omega_t) < M_x(1|\Omega_t \text{ excluding}\{y_t|s\leq t\})$, where Ω_t excluding $\{y_t|s\leq t\}$ is the set containing the relevant information except that pertaining to the past and present of y_t. We denote GNC from y_t to x_t as $y_t \not\rightarrow x_t$.

Given our task at hand, we limit attention to testing for GNC within a finite-order vector autoregressive model of order p in the levels of the variables, denoted as a VARL(p) model:

$$Z_t = \sum_{i=1}^{p} \Pi_i Z_{t-i} + u_t \qquad (1)$$

for a $K\times1$ time series Z_t $\{Z_t$: t=1,2,…,T$\}$ containing $z_{1,t}$ through $z_{K,t}$, where u_t is a ($K\times1$) vector white noise series and Π_i are $K\times K$ parameter matrices. The system (1) is initialized at t=-p+1, …, 0 and the initial values can be any random vectors including constants. As our study will involve cointegration analysis, we write (1) as a vector error correction model of order (p-1); we denote this representation as a VECM(p-1):

$$\Delta Z_t = \Pi Z_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta Z_{t-i} + u_t \qquad (2)$$

where Δ is the first-difference operator ($\Delta Z_t = Z_t - Z_{t-1}$), $\Pi = -\left(I_K - \sum_{i=1}^{p} \Pi_i\right)$ and $\Gamma_i = -\left(\sum_{j=i+1}^{p} \Pi_j\right)$ for i=1,2,…,p-1. We assume that all the roots of $\left|I_K - \sum_{i=1}^{p} \Pi_i w^i\right| = 0$ lie outside the complex unit circle except for possibly some unit roots. The matrix Π contains information on cointegrating relations between the K elements of Z_t. When $0<r<K$, there are r stationary relationships between the K variables; see Engle and Granger (1987) and Johansen (1995). Then, Π can be decomposed as $\Pi=\alpha\beta^T$, where α and β are $K\times r$ matrices of rank r, with the matrix β giving the r linear combinations $\beta^T Z_t$ that are stationary, and the matrix α contains the error correction or adjustment vectors that measure the response of the process Z_t to the disequilibirum error. When r=0 we have $\Pi=0$, there is noncointegration and (2) collapses to a VAR in first-differences, denoted by VARD(p-1). Finally, when r=K, the variables in Z_t are stationary. Given the nature of the data involved in our study, our focus is on $0\leq r<K$.

The statistic we use to test for GNC depends on the value of r, and is obtained from one of four models: a VARL, an augmented VARL model, a VECM, or a VARD model; the augmented VARL is considered below. In each of these models, we need to specify the lag length p prior to calculating the GNC statistic; the selection of p is considered in sub-section 2.2. Irrespective of the model adopted, the GNC hypothesis can be written as follows. Let θ be an $m\times1$ vector of parameters and let R be a known nonstochastic $q\times m$ matrix with rank q. To test H_0: $R\theta=0$, a Wald statistic is

$$W=T\hat{\theta}^T R^T\{R\hat{V}[\hat{\theta}]R^T\}^{-1}R\hat{\theta} \qquad (3)$$

where $\hat{\theta}$ is a consistent estimator of θ, and $\hat{V}[\hat{\theta}]$ is a consistent estimator of the asymptotic variance-covariance matrix of $\sqrt{T}(\hat{\theta}-\theta)$. We assume $\hat{\theta}$ is the unconstrained least squares (LS) and maximum likelihood estimator (MLE) of θ. Given appropriate conditions, W is asymptotically distributed as a $\chi^2(q)$ variate under H_0. A LR statistic to test H_0 is

$$LR=2(l(\hat{\theta})-l(\bar{\theta})) \qquad (4)$$

where $l(\theta)$ is the log-likelihood function satisfying certain regularity conditions, and $\bar{\theta}$ is the constrained MLE of θ. This statistic, given appropriate conditions, is also asymptotically distributed as a $\chi^2(q)$ variate under H_0. It is well recognized that the asymptotic critical values may be inaccurate in finite samples, which leads some researchers to examine an F-type statistic to test H_0, assuming an F(q, df) approximate null distribution:

$$F=W/q \qquad (5)$$

where df is the appropriate denominator degrees of freedom.

Let $Z_t=\left(Z_{1t}^T, Z_{2t}^T, Z_{3t}^T\right)^T$ where Z_{st} is a $K_s\times 1$ vector for s=1,2,3 with $K=\sum_{s=1}^{3}K_s$. Also, with Π_i conformably partitioned, let $\Pi_{i,13}$ be the $K_1\times K_3$ top-right partition of Π_i. Suppose we wish to test for GNC from Z_{3t} to Z_{1t}. Then, in the VARL(p) model, given by (1), the null hypothesis of GNC is H_0^L: $P_{13}=0$ where $P_{13}=[\Pi_{1,13}, \Pi_{2,13},..., \Pi_{p,13}]$. This null hypothesis can be written in the form Rθ=0, so the Wald statistic from (1), denoted W_L, is then given by (3) where $\hat{\theta}$ is the estimator of θ=vec[Π_1, Π_2,...,Π_p] and R is a selector matrix such that Rθ=vec[P_{13}]. Correspondingly, we respectively denote the LR statistic and F statistic for examining H_0^L as LR_L and F_L. The statistic W_L is asymptotically distributed as a $\chi^2(K_1K_3p)$ variate under H_0^L when each series is either stationary or nonstationary with "sufficient" cointegration concerning the variables whose causal effects are under examination: Sims et al. (1990) and Toda and Phillips (1993, 1994). The condition for "sufficient" cointegration is difficult to test for and tends to be ignored in practical applications. When the data are nonstationary and noncointegrated, the statistic W_L has a nonstandard, but free of nuisance parameters, limiting distribution for a non-intercept or an intercept/time trend VARL model, and a nonstandard asymptotic null distribution involving nuisance parameters results for an intercept/ no time trend model. The statistic W_L has a nonstandard limiting distribution that may depend on nuisance parameters when the relevant nonstationary series are "insufficiently" cointegrated.

Within the framework of the error correction model (2), with Γ_j conformably partitioned with ΔZ_t, let $\Gamma_{j,13}$ be the $K_1 \times K_3$ top-right partition of Γ_j, j=1,..p-1. Then, the null hypothesis of GNC (between Z_{3t} and Z_{1t}) is H_0^{EC}: $G_{13}=0$ and $\alpha_1\beta_3^T=0$ where $G_{13}=[\Gamma_{1,13}, \Gamma_{2,13},..., \Gamma_{p-1,13}]$, α_1 contains the first K_1 rows of α, and β_3^T contains the last K_3 columns of β^T. We estimate system (2) by maximum likelihood as outlined in Johansen (1988) using the normalization suggested by Johansen (1988: 235). The Wald statistic from (2) with $\Pi=\alpha\beta^T$, denoted W_{EC}, is then given by (3) where $\hat{\theta}$ is the unconstrained estimator of $\theta=\text{vec}[\Gamma_1, \Gamma_2, ...,\Gamma_{p-1}, \alpha\beta^T]$ and R is a selector matrix such that $R\theta=\text{vec}[G_{13}, \alpha_1\beta_3^T]$. The sample value can be obtained using the transformations given in (for instance) Lütkepohl (1993). We likewise denote the LR statistic and F statistic of H_0^{EC} from (2) as LR_{EC} and F_{EC}.

The statistic W_{EC} is an asymptotic $\chi^2(K_1K_3p)$ variate under H_0^{EC} when $\text{rank}(\alpha_1)=K_1$ or $\text{rank}(\beta_3)=K_3$, with this null limiting distribution being maintained, provided that the definitions of the statistics are altered appropriately, whether or not the model has a constant term, or Z_t has a deterministic trend, and whether we take account of this when estimating the model. Nuisance parameters and nonstandard distributions result for the asymptotic null distribution when the rank conditions fail. Applied researchers rarely examine for the validity of these rank conditions, which implies that the GNC hypothesis may be examined using incorrect asymptotic distributions; Toda and Phillips (1994) provide some test suggestions.

When the variables in Z_t are integrated series of order one, but not cointegrated, we can examine the GNC hypothesis (between Z_{3t} and Z_{1t}) using the VARD(p-1) model, given by

$$\Delta Z_t = \sum_{i=1}^{p-1} \Gamma_i \Delta Z_{t-i} + u_t \tag{6}$$

In this first-differences model, the GNC null hypothesis is H_0^D: $G_{13}=0$ where G_{13} is as above so the

Wald statistic from (6), denoted W_D, is then given by (3) where $\hat{\theta}$ is the unconstrained estimator of θ=vec[Γ_1, Γ_2, ...,Γ_{p-1}] and R is a selector matrix such that Rθ=vec[G_{13}]. Corresponding LR and F statistics can also be obtained, denoted as LR_D and F_D respectively. The results of Toda and Phillips (1994, Proposition 1) ensure that W_D is asymptotically distributed as a $\chi^2(K_1K_2(p-1))$ variate under H_0^D. The reader should note that as the degrees of freedom of this test is different from that of the previous GNC tests we need to take care when interpreting the results.

The use of the VARL, VECM, or VARD models to test for GNC presupposes knowledge of the nonstationarity characteristics of the data. Toda and Yamamoto (1995) and Dolado and Lütkepohl (1996) (hereafter denoted as TYDL) propose one method that does not require such information; we call this the augmented lags approach. Consider the augmented VARL model

$$Z_t = \sum_{i=1}^{p} \Pi_i Z_{t-i} + \sum_{i=1}^{d} \Pi_{p+i} Z_{t-p-i} + u_t \qquad (7)$$

where d is the highest order of integration for any element of Z_t and note that the elements of Π_{p+1},...,Π_{p+d} are zero under our assumptions. In this augmented levels model, the null hypothesis of GNC (between Z_{3t} and Z_{1t}) is H_0^{AL} : P_{13}=0 where P_{13} is as above so that H_0^L and H_0^{AL} test the same set of restrictions in the VARL and augmented VARL models, respectively. The Wald statistic from (7), denoted W_{AL}, is then given by (3) where $\hat{\theta}$ is the unconstrained estimator of θ=vec[Π_1, Π_2,...,Π_{p+d}] and R is a selector matrix such that Rθ=vec[P_{13}]. Correspondingly, we respectively denote the LR statistic and F statistic for examining H_0^{AL} as LR_{AL} and F_{AL}. The statistic W_{AL} is shown by TYDL to be asymptotically distributed as a $\chi^2(K_1K_3p)$ variate under H_0^{AL}, irrespective of the integration or cointegration properties of Z_t; the inclusion of the augmentation terms removes the covariance matrix singularity problem that can arise with nonstationarity. This approach is practically appealing, though not costless, as there are power and efficiency losses arising from the inclusion of redundant regressors in the model.

There are other methods available within the VAR framework to examine for GNC allowing for nonstationarity; e.g., the fully modified VAR (FM-VAR) procedures (e.g., Phillips, 1995 and

Quintos, 1998). We do not examine these other approaches here, as they were not used by the applied ELG studies outlined in GW. Further, note that the model in (1) or (2) assumes that the K time series do not have deterministic trends, and that the cointegrating relations $\beta^T Z_t$ have zero equilibrium values. This may not be realistic with economic data; we return to this issue in the next sub-section.

2.2 Potential issues when testing for GNC

Even within the relatively straightforward framework we examine, there are several sources of difficulties that may lead to nonrobustness of the GNC outcome. We briefly outline four issues below.

Definition of the information set: The definition of relevant information is problematic. This relates to both the issue of which variables to include, the level of temporal aggregation of the data, and estimation time period. The finding of GNC in an annual system need not imply GNC with higher frequency data. Likewise, employing seasonally adjusted variables may not produce the same causal outcome as using seasonally unadjusted variables.

Lag-order selection: Typically, the VAR lag order is unknown; researchers usually either arbitrarily assign a lag-order or they employ a databased method to estimate p. The choice of the lag length is important to avoid spurious causality (or spurious absence of causality). GW's survey suggests that common approaches include presetting the lag order and choosing p using a model selection criterion. The impact of always under-specifying or over-specifying the lag order on the size and power of the Wald statistic for GNC is evaluated with Monte Carlo experiments by Toda and Phillips (1994), Dolado and Lütkepohl (1996), and Zapata and Rambaldi (1997), while Giles and Mirza (1999) allow for the lag order to be selected by sequential testing methods and two information criterion: Schwarz's (1978) criterion (SC) and Akaike's (1969) Final Prediction Error (FPE) criterion. The findings of Giles and Mirza indicate some preference for the SC in lower dimensional systems, and the FPE in larger systems. Typically, the size distortions for the GNC Wald statistics when using databased lag order selection methods are not as serious as those found when p is always under- or over- specified, and over-specifying seems preferable to under-specifying.

Non-stationarity: We outlined in sub-section 2.1 the models and test statistics researchers commonly use to examine for GNC when there are nonstationarity concerns. When the data are stationary it is preferable to test H_0^L from the VARL(p) model (1) using W_L, LR_L or F_L. This approach is also applicable when Z_t is integrated (we assume at most I(1) data) and there is "sufficient" cointegration, though in this latter case, assuming knowledge of r, we could alternatively test H_0^{EC} from the VECM(p-1) using W_{EC}, LR_{EC} or F_{EC}. When Z_t is nonstationary and noncointegrated, one approach is to examine for GNC via the VARD(p-1) model, testing H_0^D using W_D, LR_D or F_D. Alternatively, we could ignore the cointegration issue, assume a value for the integration order of Z, and undertake the GNC test via H_0^{AL} using W_{AL}, LR_{AL} or F_{AL}.

A key ingredient to several of these approaches is knowledge of the cointegrating rank, r. This is rarely known a priori, which has led to a common practice of using prior cointegration tests to estimate r, so that (hopefully) appropriate conditions are met for valid χ^2 GNC inference, at least asymptotically. The particular pretest (PT) strategy differs with the choice of cointegration test; we schematically outline three such PT strategies in Figure 1. We consider the Engle-Granger Augmented Dickey-Fuller (EG-ADF) noncointegration test (Engle and Granger, 1987); the commonly called Johansen maximum likelihood test for the cointegrating rank, r, denoted by JJ (Johansen, 1988 and Ahn and Reinsel, 1990); and the McCabe et al. (1997) test for cointegration, denoted as MLS. The EG-ADF and JJ tests dominate applied practice, but given classical significance levels, we only reject in favour of cointegration for extreme samples. As our primary interest is usually with cointegration, rather than noncointegration, it may be preferable to have this outcome as the null hypothesis as is the case with the MLS test. Given space constraints, we do not outline the cointegration tests here; Giles and Mirza (1999) provide details for instance.

The first step of the sequential JJ PT procedure, based on the JJ cointegrating rank test, is to estimate the lag order from the VARL model, denoted $\hat{p}$. The cointegrating rank is then estimated, denoted as $\hat{r}$, within the K-dimensional VARL($\hat{p}$) model. There are two common statistics for testing for the value of r: the maximal eigenvalue statistic, denoted λ_{max}, and the trace statistic. Although the limiting null distributions of the test statistics do not depend on the lag length, the choice of p may result in the use of a misspecified model, and so the value used for p will affect finite sample inference on r. The final step in the JJ PT strategy, having determined $\hat{p}$ and $\hat{r}$, is to test for GNC using one of W_D, LR_D or F_D when $\hat{r}$=0, or to use W_{EC} , LR_{EC} or F_{EC} when 0<$\hat{r}$<K, or, when $\hat{r}$=K, to examine for GNC using W_L, LR_L or F_L.

The EG-ADF PT procedure, assuming Z_t~I(1), begins with determination of the augmentation parameter, denoted v, which is needed to undertake the ADF test on the cointegrating regression residuals. There are many suggestions for assigning a value to v: Hall (1994) and Ng and Perron (1995), among others. The null hypothesis of noncointegration is then tested, from which we use either a VARD model when the outcome is noncointegration, or a VECM when cointegration is supported, with the residuals from the cointegrating regression forming the error correction term. The lag order is then estimated, denoted $\tilde{p}$, with the final task being to test for GNC, either using W_D, LR_D or F_D when the model is a VARD($\tilde{p}$-1), or using W_{EC}, LR_{EC} or F_{EC} for the VECM($\tilde{p}$-1).

The MLS PT strategy is identical to that just outlined for the EG-ADF PT method, except for the first stage, which involves estimating an appropriately specified autoregressive integrated moving average model to account for correlation patterns; specific details can be found in Giles and Mirza (1999). The estimator $\hat{s}$ is the autoregressive order for this auxiliary regression. The MLS statistic is then used to test for cointegration, from which we model the nonstationary data as either a VARD or a VECM, and proceed as for the EG-ADF PT approach.

The PT approach of testing for GNC dominates the applied ELG literature examined by GW; of the seventy four studies that employ some form of VAR model to explore for GNC between exports and economic growth, 10% adopt a VARL model; 30% use a VARD model without pretests for unit roots; 3% (two studies) apply some other filter to transform the data to stationarity; 54% use the PT approach (though no study examines for “sufficient” cointegration); while only four studies apply the TYDL augmented lags method. Those analyses that employ VARL models in the raw data may well suffer from spurious regression problems, as the series under study are typically believed to be nonstationary, which may result in invalid GNC testing. In a similar way, the VARD models are misspecified when there is indeed cointegration, as this model then omits the error correction term(s).

These preliminary test methods can also suffer problems; in particular, the method depends crucially on the ability of the prior tests to accurately determine the cointegrating rank. However, it is well known that typically applied nonstationarity tests suffer from size distortion and often have low power, which suggests that an appropriate model may often not be used for the GNC test. Giles and Mirza's (1999) Monte Carlo study, on the properties of GNC procedures, indicates that this pretesting route is often unsatisfactory. In many common types of situations the PT strategy leads to severe over-rejection of a noncausal null; i.e., pretesting for nonstationarity before the GNC test can often lead to wrong conclusions of causality. Their results also demonstrate that the method used to pretest for nonstationarity is crucial. In contrast, the simulations undertaken by Giles and Mirza (1999) suggest that the augmented lags approach of TYDL performs well across a wide range of data generating processes, including those that are mixed stationary-integrated or near-integrated systems.

Deterministic trends: This is an important question that is ignored by virtually all of the studies examined by GW[2]. What deterministic trends should be included? How should they be included? Does it matter in terms of GNC conclusions? Limiting our attention to at most linear deterministic components, there are several possible extensions to (1) and (2): e.g., Johansen (1995), Franses (1999) and Pesaran et al. (2000). A natural extension of the VARL(p) model (1) is:

$$(Z_t-\mu-\delta t) = \sum_{i=1}^{p} \Pi_i (Z_{t-i} - \mu - \delta(t-i)) + u_t \qquad (8)$$

where μ and δ are K-vectors of unknown coefficients. We can write (8) equivalently as

$$Z_t = \mu^* + \delta^* t + \sum_{i=1}^{p} \Pi_i Z_{t-i} + u_t \qquad (9)$$

where $\mu^*=(-\Pi\mu+\Pi^*\delta)$, $\delta^*=-\Pi\delta$, $\Pi^*=\sum_{j=1}^{p} j\Pi_j$, and Π is as defined previously; i.e., $\Pi=-\left(I_K - \sum_{i=1}^{p}\Pi_i\right)$.

We can also write (8) (and (9)) as a VECM(p-1)

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2 The exception is Marin (1992: 685) who tries four different specifications for each country - with and without an error correction (EC) term and, with and without a linear trend term. He concludes "...the specification matters for the causality test results. The inclusion of the error-correction terms and/or the time trend have changed the p-values and the F-statistics considerably in most cases, although the basic results do not depend on the specification."

$$\Delta Z_t = \Pi^*\delta + \Pi(Z_{t-1}-\mu-\delta t) + \sum_{i=1}^{p-1}\Gamma_i \Delta Z_{t-i} + u_t \qquad (10)$$

which, when rank(Π)=r so that $\Pi=\alpha\boldsymbol{\beta}^{\mathbf{T}}$**,** can be written as

$$\Delta Z_t = \Pi^*\delta + \alpha(\beta^T Z_{t-1}-\mu_0-\delta_0 t) + \sum_{i=1}^{p-1}\Gamma_i \Delta Z_{t-i} + u_t \qquad (11)$$

where $\mu_0 = \beta^T\mu$ and $\delta_0 = \beta^T\delta$. The vector $(\mu_0+\delta_0 t)$ can be regarded as the attractor for the stationary relationships $\beta^T Z_{t-1}$.

These models suggest that there are three practical cases to examine in practice. The first case, denoted as Case I, results when $\mu=\delta=0$, so that we consider models (1) and (2), which contain no deterministic components. This case corresponds to Case 0 in Osterwald-Lenum (1992), model $H_2(r)$ in Johansen (1995), and Case I in Pesaran et al. (2000) and MacKinnon et al. (1999). The second case of interest, denoted as Case II, results when $\delta=0$, which gives

$$Z_t = -\Pi\mu + \sum_{i=1}^{p}\Pi_i Z_{t-i} + u_t \qquad (12)$$

and

$$\Delta Z_t = \Pi(Z_{t-1}-\mu) + \sum_{i=1}^{p-1}\Gamma_i \Delta Z_{t-i} + u_t \qquad (13)$$

so that the intercept term is restricted. Specifically, when there are r cointegrating relationships, out of the K intercept terms in (12), r of the terms are unrestricted while the remaining (K-r) terms must satisfy prior restrictions. Moreover, the r cointegrating relationships have a nonzero attractor given by $\mu_0 = \beta^T\mu$. This Case II is denoted as Case 1^* in Osterwald-Lenum (1992), Model $H_1^*(r)$ in Johansen (1995), and Case II in Pesaran et al. (2000) and MacKinnon et al. (1999).

The final case, denoted by Case III, is as given in (9) and (10), and it is called Case 2^* in Osterwald-Lenum (1992), Model $H^*(r)$ in Johansen (1995), Model (13) in Franses (1999), and Case IV in Pesaran et al. (2000) and MacKinnon et al. (2000). Note that the linear trend coefficient in (9) is restricted as it depends on Π; e.g., it is zero when there is noncointegration. Other ways of incorporating deterministic trends are sometimes examined (e.g., Osterwald-Lenum, 1992; Johansen, 1995; Pesaran et al., 2000; MacKinnon et al., 1999), but they are not necessarily compatible with the underlying VARL model (8), and so perhaps implausible. It is feasible to extend (1) to allow for quadratic trends; we leave this for future research as our aim of illustrating the nonrobustness of GNC outcomes to the specification of deterministic trends can be achieved by examining Cases I, II and III.

3. Sensitivity analysis for Canada and Portugal

Our discussion in the previous section, and that associated with some empirical research in GW, suggests that the GNC test results are sensitive to the estimation period, the adopted lag selection method, the economic growth and export growth definitions used, the choice of auxiliary variables in the VAR analysis, the method used to deal with issues arising from potential nonstationarity, including whether any allowance is made for deterministic trends. Our aim in this section is to undertake a small sensitivity study of the GNC test outcomes in the ELG case. We limit our attention to examining the impact on the GNC result of the method used to account for nonstationarity issues, including the choice of deterministic trends. Others have illustrated that noncausality test results are sensitive to the functional form structure of the estimating equations, the specified lag structure, the approach used to obtain white-noise errors, and to variable misspecification: e.g., Feige and Pearce (1979), Jacob et al. (1979), Roberts and Nord (1985), Sephton (1989). Accordingly, we limit our attention to only one sample period for each country, one lag selection method (Akaike's (1973) Information Criterion, denoted by AIC), and to the information sets examined by the original authors.

We address this part of our study by reconsidering the data used by Oxley (1993) for Portugal and Henriques and Sadorsky (1996) for Canada. The authors of these studies kindly provided us with their data, and it is this that led to our choice, rather than the studies themselves. It is our firm belief that we would observe similar sensitivities if we had used other data. The analysis for Portugal is based on a bivariate GNC test, while that for Canada involves an auxiliary variable, as well as the usual variables representing overall economic activity and export performance; for the Canadian case we take the opportunity to present results based on a bivariate and trivariate model. As our aim is to examine robustness issues, we do not discuss the trade policies and relevant economic issues for the countries, though we recognize the merits of this for a detailed individual country application.

3.1 Canadian study

3.1.1 Previous Canadian GNC ELG papers

GW provides information on nine studies that have estimated VAR/VECM models to examine for Canadian ELG using the GNC tests we have outlined: Afxentiou and Serletis (1991), Serletis (1992), Arnade and Vasavada (1995), Jin and Yu (1995), Bodman (1996), Henriques and Sadorsky (1996), Pomponio (1996), Riezman et al. (1996) and Yamada (1998). Table 1 provides a summary. Given our aims, we do not discuss these papers in detail; it is clear that the lag selection methods, time periods, definitions of "relevant" information set, the forms of the "preferred" model (e.g., VARL, VECM, VARD), the methods adopted to arrive at this "preferred" model, the assumed deterministic trends differ widely, and given these variations in setups, it is extremely difficult to distinctly pinpoint reasons for the different GNC outcomes for these Canadian studies. We make two observations at this stage: first, several of the studies introduce deterministic trends in their models in ways that are not consistent with those discussed in sub-section 2.2; second, several authors directly impose noncointegration by using VARD models, which could be misspecified by ignoring potential Granger-causality from any long run relationships.

3.1.2 Focus for Canada

We use the full annual data set of Henriques and Sadorsky (1996), which covers the period 1877 to 1991; we are aware that there are likely structural breaks present that we are ignoring. The data are real GDP and real exports, with real imports being included as an auxiliary variable; natural logarithms of the data are examined so that first differences are growth variables. We use the AIC, calculated from the VARL model, to determine lag lengths, allowing for up to a maximum of 8 lags. We first illustrate in the next sub-section that modifying the testing method can alter the GNC conclusion. We then show in sub-section 3.1.4 that the choice of deterministic trends also impacts on the GNC outcome by comparing the GNC results for Cases I, II and III.

3.1.3 Canada: method matters

We restrict our attention to pretests for cointegration. We recognize that unit root tests are typically undertaken as well, but their impact is well researched in the literature. To limit scope we assume that the data series in their log-levels are integrated of order one, which is a reasonable assumption from prior research. We focus on the three cointegration PT strategies we outlined in sub-section 2.2, and we present results using the λ_{max} statistic for the JJ PT method. We use a general to specific testing strategy to choose the augmentation terms for the EG-ADF PT method, and we follow the approach outlined by McCabe et al. (1997) and Leybourne and McCabe (1999) to consistently estimate the necessary autoregressive order for the auxiliary regression for the MLS PT method. For this part of our study, we examine Case II; i.e.; we assume that there is a restricted constant in the VARL representation that results in a non-zero attractor for any cointegrating relationships. This implies that Z_t consists of (3-r) I(1) variables and r level stationary variables when the cointegrating rank is r. For the trivariate model, we present results for the JJ PT approach that does not test for "sufficient" cointegration and for the Toda and Phillips (1993, 1994) method, which includes an additional pretest for sufficient cointegration; we denote the latter asTP PT. We follow the recommendation of Toda and Phillips (1994) and use their strategy P1[3]. Testing for "sufficient" cointegration is unnecessary in a bivariate model. We compare these pretesting methods with the TYDL augmented lags approach, adding one additional lag given our assumption of I(1) variables. The AIC lag order is four for both the bivariate and trivariate models. Table 2 summarizes the bivariate and trivariate results for testing for ELG and GLE, with the reported numbers being p-values for the GNC statistics assuming a limiting χ^2 null distribution for the W and LR statistics, and an appropriate central-F distribution for the F statistics.

The GNC outcomes, for this application, do not change when we add the auxiliary variable to the information set, nor do they alter with the choice of test statistic. The TYDL augmented lag method suggests noncausality in both directions, while the residual based PT methods (EG-ADF PT and MLS PT) support GLE, but not ELG; this latter result occurs even though the two methods

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[3]Suppose we wish to test that z_{3t} noncauses z_{1t}. Let $\hat{r}$ be the estimated cointegrating rank, α_1 be the first row of α and is of dimension $\hat{r}$, β_3 be the last row of β and let the relevant Γ parameters for the causal test be $\gamma_1 ... \gamma_{p-1}$. The strategy P1 of Toda and Phillips (1993) is to test H_1: $\alpha_1=0$ via a Wald test statistic, which is asymptotically $\chi^2(\hat{r})$ under the null. If H_1 is rejected, we then test H_2: $\gamma_1=...=\gamma_{p-1}=0$ & $\alpha_1\beta_3=0$ via a Wald test statistic, which is asymptotically $\chi^2(p)$ under the null; otherwise we test H_3: $\gamma_1=\ldots=\gamma_{p-1}=0$ via a Wald test statistic, which is asymptotically $\chi^2(p-1)$ under the null.

arrive at different cointegration conclusions. In contrast, the JJ PT approach suggests support for bidirectional causality. Simply by changing the method of dealing with nonstationarity, we observe GNC, GLE, and bidirectional Granger-causality.

The simulation experiments undertaken by Giles and Mirza (1999) show that the PT approaches often overreject a valid GNC null hypothesis, while the TYDL approach is typically more consistent at obtaining the correct conclusion. We may be observing these features here. Irrespective of reason, the results reported in Table 2 show the sensitivity of GNC outcomes to the method used to handle nonstationarity concerns.

3.1.4 Canada: deterministic trends

In this section we illustrate the impact of the choice of deterministic trends on the GNC outcome. We limit our attention to the JJ PT and TP PT approaches, and to the augmented lags method of TYDL, which remains valid with deterministic trend terms. We present results for Cases I, II and III, which we outlined in sub-section 2.2, reporting results for Wald statistics only, as the previous sub-section suggests that the GNC outcomes are not sensitive to the statistic adopted. The AIC is again applied to select the lag order from the VARL model augmented by appropriate deterministic components. The optimal lag orders did not change from that determined for Case II in the previous sub-section.

Table 3 provides the estimated asymptotic p-values for the λ_{max} tests for cointegrating rank for both the bivariate and trivariate models. Irrespective of the choice of deterministic components, there is strong support for one cointegrating vector in the bivariate case. In the trivariate case, there is support for two cointegrating vectors with Cases I and II, but for only one stationary relationship with Case III; the choice of deterministic terms is important. The p-values for the resulting Wald GNC tests, assuming a limiting χ^2 null distribution, are presented in Table 4; the TYDL method provides no support for Granger-causality, irrespective of information set or deterministic trends, while the PT approaches result in outcomes that vary with information set and deterministic trends. Specifically, the bivariate model suggests bidirectional Granger-causality for Case I and II, but only GLE with Case III. In contrast, we find GNC for Case III with the trivariate model, GLE with Case I and bidirectional Granger-causality with Case II. Altering the information set and the deterministic trends impacts on the GNC test outcome.

3.2 Portuguese study

3.2.1 Previous Portuguese GNC ELG papers

GW details six papers that have examined for ELG via GNC tests for Portugal: Jung and Marshall (1985), Hutchison and Singh (1992), Dodaro (1993), Oxley (1993), Sharma and Dhakal (1994) and Riezman et al. (1996). Table 5 provides a summary. Due to space constraints, we do not discuss these papers, though as with the Canadian studies, it is evident that the lag selection methods, time periods, definitions of "relevant" information set, the forms of the "preferred" model, the methods adopted to arrive at this "preferred" model, and the assumed deterministic trends differ widely. We again note that several of the studies introduce deterministic trends in ways that are not consistent with the models presented in sub-section 2.2, and that several authors directly use VARD models, which may be misspecified by omiting long run relationships.

3.2.2 Focus for Portugal

We use Oxley's (1993) annual data on real exports and real GDP, which covers 1865 to 1991. We employ the full bivariate data set and transform each series into natural logarithms. The effects of structural breaks on the procedures are left for future work. We use the AIC, calculated from the VARL model, to determine lag lengths, allowing for up to a maximum of 8 lags. This results in a VARL(5) for Case II, which we use to show that the GNC outcome varies with the method adopted to deal with nonstationarity issues; see sub-section 3.2.3. We do not use the TP approach here, as cointegration in a bivariate system is sufficient. We follow in sub-section 3.2.4 with a comparison of the GNC outcomes for Cases I, II and III.

3.2.3 Portugal: method matters

We examine Case II and the methods we detailed in sub-section 2.2: TYDL, JJ PT, MLS PT and EG-ADF PT. As with our Canadian analysis, we assume that the log-levels data are integrated of order one. Table 6 summarizes the results for testing for ELG and GLE, with the reported numbers being p-values for the GNC statistics, assuming a limiting χ^2 null distribution for the W and LR statistics, and an appropriate central-F distribution for the F statistics.

We observe that the GNC results do not vary with the choice of test statistic, and that the four methods we present each support GLE, while the JJ PT approach is the only method that suggests bidirectional causality. Interestingly, the MLS PT indicates noncointegration while the EG-ADF PT and JJ PT both suggest the existence of a cointegrating relationship; nevertheless, the MLS and EG-ADF PT procedures still reached the same causality conclusions.

3.2.4 Portugal: deterministic trends

As for our Canadian study, we limit attention here to the JJ PT and TYDL methods, reporting results only for the Wald statistics. Estimated asymptotic p-values for the λ_{max} cointegrating rank test are reported in Table 7 for Cases I, II and III; there is support for cointegration, with some uncertainty with Case III. We use the opportunty to illustrate the impact of this uncertainty on the GNC test outcome by examining Case III with a DVAR(4) and a VECM(4). The asymptotic p-values for the observed Wald GNC test statistics are given in Table 8. Regardless of method and case, the results suggest that there is GLE, but there is mixed evidence for bidirectional causality. The TYDL augmented lags method suggests some support for bidirectional causality when there are no deterministic terms in the model, which may be spurious ELG arising from the omission of relevant deterministic components, as inclusion of the latter eliminates support for this outcome. The VECM models advocate bidirectional causality for Cases I, II and III (when $\hat{r}=1$), but not for Case III when $\hat{r}=0$; this illustrates the potential nonrobustness of the GNC outcome to the specification of the cointegrating rank and the importance of accurate determination of that rank when a pretest based approach is adopted. The conflicting outcomes from the TYDL and JJ PT approaches could be due to either the JJ PT approach overrejecting GNC or the TYDL method showing power deficiency. Both are possibilities here. Irrespective of reason, our Portugal example illustrates the sensitivity of GNC test results to nonstationarity methods, including specification of the deterministic trends.

4. Concluding Remarks

In this paper we have studied the sensitivity of Granger noncausality test outcomes for examining for causation between exports and overall economic activity to the method adopted for dealing with nonstationarity issues, including assumed deterministic trends. Our study has shown the nonrobustness of GNC test results, which is discouraging, as it implies that it is relatively easy to obtain different results. Our study demonstrates that applied researchers need to exercise care when using GNC tests to avoid spurious outcomes.

How can applied researchers proceed when they wish to use GNC tests to examine for ELG, given that GNC outcomes are sensitive to the deterministic trend assumptions and the specification of the cointegrating rank (when applicable)? We offer the following thoughts. Although our study suggested that the TYDL method, which does not require specification of the cointegrating rank, seemed relatively robust to the deterministic trend degree, we believe it would still be wise to attend to this issue. One way to proceed is to adopt a general-to-specific testing strategy to determine the deterministic trend degree, while an alternative approach is to use an information criterion to simultaneously determine the lag order and the trend terms.

Matters are further complicated when a method for testing for Granger noncausality is adopted that requires specification of the cointegrating rank. This is a preferable route, but accurate determination of the cointegrating rank is needed, and this seems difficult, especially given that currently applied procedures are sensitive to the deterministic trend degree and lag order, typically specified prior to the cointegration pretest. One possible alternative is to simultaneously determine the cointegrating rank, the lag order and the trend degree, which could be readily achieved using an information criterion. Let $P=K(r+(p-1)K+d)$ be the number of fitted parameters for the VECM, where r denotes the cointegrating rank, d denotes the trend degree, p the VARL lag order, and K the system's dimension. Then, for example, the AIC and SC can be formed as $AIC(p,r,d)=\log|\omega|+2P/T$ and $SC(p,r,d)=\log|\omega|+P\log(T)/T$ respectively, where T is the sample size and ω an appropriate estimate of the error covariance matrix. Phillips (1996) proposes a Bayesian model determination criterion, the posterior information criterion (PIC), explicitly for this problem. Specifically, Phillips' PIC is given by $PIC(p,r,d)=\log|\omega|+\log(\phi)/T$, where the penalty factor ϕ is a function of the dimension of the model and the observed data. An alternative possibility is to undertake hypothesis tests for the presence of the deterministic trend terms; see, e.g., Johansen (1995) and Pesaran et al. (2000). It remains for future research to explore the finite sample properties of GNC tests when such approaches are adopted.

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Table 1 Canadian GNC Studies

Authors	Data	Method and Model[a]	Auxiliary Variables	Result
Afxentiou & Serletis (1991)	annual, 1950:85; logs, real GNP, real exports.	PT strategy using Phillips & Perron (1988) test; noncointegrated so VARD; Case I; F_D; SC for lags.		GLE
Serletis (1992)	annual, 1870:1985; 1870:1944; 1945:85; logs, real GDP, real exports.	PT strategy using Phillips & Ouliaris (1990) test; noncointegrated so VARD with unrestricted constant; F_D; SC for lags.	Real imports.	ELG for 1870:1944; 1870:1985. NC for 1945:85.
Arnade & Vasavada (1995)	annual, 1961:87; real agricultural output, real agricultural exports.	JJ PT strategy; noncointegrated so VARD; Case II; F_D; lags preset to 3.	Unit export value.	NC
Jin & Yu (1995)	qtrly, seas. adj. 1960(1):87(4); logs; real GDP, real exports.	VARD with constant; F_D; FPE for lags.		GLE
Bodman (1996)	qtrly, seas. adj. 1960(1):95(4); logs; real manuf. output per employee; real total output per employee; real exports of manuf. goods; real exports.	JJ PT strategy; cointegrated;VECM with unrestricted constant; zero mean for cointegrating relationship; F_{EC}; lags by SC & LR.		ELG & BD for manuf. exports & manuf. labor productivity.
Henriques & Sadorsky (1996)	annual, 1877:1945; 1877:1991; 1946:91; logs, real GDP, real exports.	JJ PT strategy; unrestricted constant; zero mean for cointegrating relationship; cointegrated; VARL with unrestricted constant; F_L; SC, HQ & AIC for lags.	Terms of trade (export unit value/import unit value)	ELG
Riezman et al. (1996)	annual, 1950:90; GDP & export growth in real international dollars.	VARD with no deterministic trends; F_D; lags not specified.	Real import growth.	NC
Pomponio (1996)	annual, 1965:85; nominal manuf. output & exports.	VARD or VARL depending on cointegration outcome (not reported for individual countries); Case I; F_D or F_L; lags preset to 2.	Investment.	ELG
Yamada (1998)	qtrly, seas. adj. 1960(1):87(4); logs; real GDP output per employee, real exports. Only tested for ELG.	TYDL augmented lags method with constant; W_{AL}; AIC for lags.	Terms of trade; real GDP of OECD countries.	ELG

a. SC denotes Schwarz's (1978) criterion; HQ denotes Hannan and Quinn's (1979) criterion; FPE denotes Akaike's (1969) Final Prediction Error criterion; AIC denotes Akaike's (1973) Information Criterion; ELG denotes export-led growth; GLE denotes growth-led exports; BD denotes bidirectional Granger causality; NC denotes GNC in both directions.

Table 2 Canada: GNC p-values (Case II)

GNC Statistic	GNC Hypothesis – Bivariate		GNC Statistic	GNC Hypothesis – Trivariate	
	exp $\nrightarrow$ gdp	gdp $\nrightarrow$ exp		exp $\nrightarrow$ gdp	gdp $\nrightarrow$ exp
TYDL - W_{AL} (a)	0.659	0.283	TYDL - W_{AL} (a)	0.614	0.169
TYDL - LR_{AL} (a)	0.664	0.294	TYDL - LR_{AL} (a)	0.619	0.181
TYDL - F_{AL} (a)	0.660	0.290	TYDL - F_{AL} (a)	0.615	0.179
JJ PT – W_{EC} (b)	<0.001	<0.001	TP PT – W_{EC} (e)	0.005	<0.001
JJ PT – LR_{EC} (b)	0.035	0.005	TP PT – LR_{EC} (e)	0.054	0.001
JJ PT – F_{EC} (b)	<0.001	<0.001	TP PT – F_{EC} (e)	0.009	<0.001
MLS PT – W_D (c)	0.534	0.044	JJ PT – W_{EC} (f)	0.005	<0.001
MLS PT – LR_D (c)	0.538	0.049	JJ PT – LR_{EC} (f)	0.054	0.001
MLS PT – F_D (c)	0.537	0.049	JJ PT – F_{EC} (f)	0.009	<0.001
EG ADF PT – W_{EC} (d)	0.713	0.001	MLS PT – W_D (g)	0.420	0.036
EG ADF PT – LR_{EC} (d)	0.717	0.001	MLS PT – LR_D (g)	0.425	0.042
EG ADF PT – F_{EC} (d)	0.714	0.001	MLS PT – F_D (g)	0.424	0.042
			EG ADF PT – W_{EC} (h)	0.691	<0.001
			EG ADF PT – LR_{EC} (h)	0.695	0.001
			EG ADF PT – F_{EC} (h)	0.691	0.001

a. One additional lag is included in the system based on our prior belief that the variables are integrated of order one.
b. The sample values of the λ_{max} statistic are 19.156 and 10.758 for testing H_{01}: r=0 vs. H_{a1}: r=1 and H_{02}: r=1 vs. H_{a2}: r=2, respectively. Estimated asymptotic p-values are 0.001 and 0.270 respectively (MacKinnon et al., 1999). We reject H_{01} and support H_{02}, which suggests one cointegrating vector; GNC testing is then undertaken using a VECM(3).
c. The observed value of the test statistic is 0.704, which can be compared to a 10% critical value of approximately 0.097 (McCabe et al., 1997), so we reject the null and support noncointegration. Consequently, a VARD(3) model, with no deterministic terms, is used to test for GNC.
d. Eight augmentation terms are included as chosen via general to specific testing. The observed test statistic value of -3.846 has an estimated p-value of 0.015 (MacKinnon, 1994). A VECM(3) is then used to test for GNC, with the error correction term formed from the residuals from the static cointegrating regression.
e. Our estimate of r is 2. For both GNC hypotheses, we reject H_1, given in footnote 3, so that the p-value reported in the table is from testing H_2.
f. The sample values of the λ_{max} statistic for testing H_{01}: r=0 vs. H_{a1}: r=1, H_{02}: r=1 vs. H_{a2}: r=2 and H_{03}: r=2 vs. H_{a3}: r=3 are 24.381, 16.240 and 12.395 with estimated asymptotic p-values of 0.0004, 0.044 and 0.616 respectively (MacKinnon et al., 1999). These results suggest two cointegrating vectors in the VECM(3).
g. The observed value of the test statistic is 0.594, which we compare to an approximate 10% critical value of 0.081 (McCabe et al., 1997). Consequently, a VARD(3) model, with no deterministic terms, is used to test for GNC.
h. Eight augmentation terms (from a general to specific testing strategy) are included. The observed value of the test statistic is -3.749, which has an estimated p-value of 0.020 using MacKinnon (1994). The GNC tests are undertaken via a VECM(3), with the residuals from the static cointegrating regression as the error correction term.

Table 3 Canada: Estimated asymptotic p-values for λ_{max} cointegrating rank tests[a]

Case	Bivariate		Trivariate			Conclusion	
	r=0 vs. r=1	r=1 vs. r=2	r=0 vs. r=1	r=1 vs. r=2	r=2 vs. r=3	Bivariate $\hat{r}$	Trivariate $\hat{r}$
I	<0.001	0.995	<0.001	0.006	0.999	1	2
II	0.001	0.270	<0.001	0.044	0.616	1	2
III	0.049	0.875	<0.001	0.221	0.990	1	1

a. The estimated asymptotic p-values are generated from the Fortran code provided by MacKinnon et al. (1999).

Table 4 Canada: TYDL, JJ PT and TP PT Wald GNC p-values

Case	TYDL				JJ PT				TP PT	
	BIVARIATE		TRIVARIATE		BIVARIATE		TRIVARIATE		TRIVARIATE	
	exp $\nrightarrow$ gdp	gdp $\nrightarrow$ exp	exp $\nrightarrow$ gdp	gdp $\nrightarrow$ exp	exp $\nrightarrow$ gdp	gdp $\nrightarrow$ exp	exp $\nrightarrow$ gdp	gdp $\nrightarrow$ exp	exp $\nrightarrow$ gdp	gdp $\nrightarrow$ exp
I	0.682	0.356	0.604	0.198	<0.001	0.006	0.657	0.012	0.657[a]	0.012[a]
II	0.659	0.283	0.614	0.169	<0.001	<0.001	0.005	<0.001	0.005[a]	<0.001[a]
III	0.607	0.341	0.567	0.208	0.425	0.002	0.519	0.240	0.593[b]	0.255[b]

a. Reject H_1. P-values are for testing H_2.
b. Do not reject H_1. P-values are for testing H_3.

Table 5 Portuguese GNC Studies

Authors	Data	Method and Model[a]	Auxiliary Variables	Result
Jung & Marshall (1985)	annual, 1953:80; logs, real GNP, real exports.	VARD with constant; F_D; lags preset to 3.		NC
Hutchison & Singh (1992)	annual,1956:82; logs, real GDP, real non-export GDP, real exports.	VARD with no deterministic trends; F_D; lags preset to 2.	Real investment.	NC
Dodaro (1993)	annual, 1967:86; logs, real GDP, real exports.	VARD with constant; F_D; lags preset to 2.		NC
Oxley (1993)	annual, 1865:91; logs, real GDP, real exports.	JJ PT strategy; cointegrated; VECM with unrestricted constant; zero mean for cointegrating relationship; W_{EC}; lags by FPE.		GLE
Sharma & Dhakal (1994)	annual, 1960:87; logs, real GDP, real exports.	VARD with constant; F_D; lags by FPE.	Population, real world output, real exchange rate, real gross fixed capital formation.	BD
Riezman et al. (1996)	annual, 1950:90; GDP & export growth in real international dollars.	VARD with no deterministic trends; F_D; lags not specified.	Real import growth.	NC from bivariate model; GLE from trivariate model.

a. SC denotes Schwarz's (1978) criterion; HQ denotes Hannan and Quinn's (1979) criterion; FPE denotes Akaike's (1969) Final Prediction Error criterion; AIC denotes Akaike's (1973) Information Criterion; ELG denotes export-led growth; GLE denotes growth-led exports; BD denotes bidirectional Granger causality; NC denotes GNC in both directions.

Table 6 Portugal: GNC p-values (Case II)

GNC Statistic	GNC Hypothesis – Bivariate Model	
	exp $\not\rightarrow$ gdp	gdp $\not\rightarrow$ exp
TYDL - W_{AL} (a)	0.191	0.002
TYDL - LR_{AL} (a)	0.206	0.004
TYDL - F_{AL} (a)	0.201	0.004
JJ PT – W_{EC} (b)	<0.001	<0.001
JJ PT – LR_{EC} (b)	0.012	0.002
JJ PT – F_{EC} (b)	0.003	<0.001
MLS PT – W_D (c)	0.356	0.002
MLS PT – LR_D (c)	0.366	0.003
MLS PT – F_D (c)	0.362	0.003
EG ADF PT – W_{EC} (d)	0.192	0.002
EG ADF PT – LR_{EC} (d)	0.207	0.005
EG ADF PT – F_{EC} (d)	0.202	0.005

a. One additional lag is included in the system.

b. The λ_{max} statistic sample values for testing H_{01}: r=0 vs. H_{a1}: r=1 and H_{02}: r=1 vs. H_{a2}: r=2 are 19.325 and 9.676, with estimated asymptotic p-values of 0.001 and 0.365, respectively (MacKinnon et al., 1999). This cointegration is incorporated in a VECM(4) for the GNC tests.

c. The observed value of the test statistic is 0.779 compared to a 10% critical value of approximately 0.097 (McCabe et al., 1997); we reject the null and support noncointegration. The GNC tests are undertaken using a DVAR(4) model, with no constant term as this is restricted to zero with the noncointegration outcome.

d. General to specific testing indicated the need for five augmentation terms. The observed test statistic value of -3.302 suggests cointegration when compared with an estimated p-value of 0.062 from MacKinnon (1994). We then tested for GNC using a VECM(4) with the error correction term formed from the residuals from the static cointegrating regression.

Table 7 Portugal: Estimated asymptotic p-values for λ_{max} cointegrating rank tests[a]

Case	Bivariate		Conclusion
	r=0 vs. r=1	r=1 vs. r=2	$\hat{r}$
I	<0.001	1.000	1
II	0.001	0.365	1
III	0.104	0.834	0 or 1

a. Asymptotic p-values are generated from the Fortran code provided by MacKinnon et al. (1999).

Table 8 Portugal: TYDL and JJ PT Wald GNC p-values

GNC Hypothesis	TYDL			JJ PT			
	Case I	Case II	Case III	Case I	Case II	Case III	
						$\hat{r}=0$	$\hat{r}=1$
exp $\nrightarrow$ gdp	0.095	0.191	0.181	0.008	0.001	0.144	0.011
gdp $\nrightarrow$ exp	0.002	0.002	0.003	0.002	<0.001	0.001	0.005

Figure 1. Schematic outline of pretest strategies