Economic Modelling 28 (2011) 870–876

Contents lists available at ScienceDirect

Economic Modelling

journal homepage: www.elsevier.com/locate/ecmod

Testing for Granger causality in heterogeneous mixed panels

Furkan Emirmahmutoglu *, Nezir Kose

Department of Econometrics, Gazi University, Incitasi Sokagı No:4, 06500 Besevler, Ankara, Turkey

ARTICLE INFO

Article history:
Accepted 29 October 2010

Keywords:
Granger causality
Meta analysis
Mixed panels
Cross-sectional dependency

ABSTRACT

In this paper, we propose a simple Granger causality procedure based on Meta analysis in heterogeneous mixed panels. Firstly, we examine the finite sample properties of the causality test through Monte Carlo experiments for panels characterized by both cross-section independency and cross-section dependency. Then, we apply the procedure for investigating the export led growth hypothesis in a panel data of twenty OECD countries.

1. Introduction

Vector autoregressive (VAR) models have been used frequently to test Granger causality relationships between two subsets of variables. In the VAR framework, Granger causality test is based on null hypothesis which is formulated as zero restrictions on the coefficients of the lags of a subset of the variables. Wald test is standard tool for testing zero restrictions on the coefficients of VAR processes. If the variables in the VAR system are stationary, then Wald statistic has an asymptotically chi-square distribution with q degrees of freedom, where q is the number of restrictions under the null hypothesis. On the other hand, Park and Philips (1989), Sims et al. (1990) and Toda and Phillips (1993) have shown that the standard asymptotic theory is not applicable to hypothesis testing in level VAR model if the variables are integrated or cointegrated. Therefore, the usual Wald test statistics for Granger non-causality based on level VAR not only have non-standard asymptotic distribution, but depend on nuisance parameters in general if variables are non-stationary. In this circumstance, if variables are known to be non-stationary, but all integrated of order one and cointegrated with each other, then a VAR model in the first order differences of the variables can be estimated so that the standard asymptotic theory is valid for hypothesis testing in the VAR. Similarly, if variables in VAR are cointegrated, then one natural way to test Granger non-causality hypothesis is to employ Vector Error Correction Model (VECM). But, it is not known a priori whether variables are integrated, cointegrated or stationary in most applications; a pre-test needs to determine order of integration of variables before estimating the appropriate VAR model in which statistical inferences are conducted. However, Granger non-causality test may suffer from severe pre-test biases.

To overcome this problem, Toda and Yamamoto (1995) have proposed an alternative approach for testing coefficient restrictions of a level VAR model for integrated or cointegrated process. Their approach leads to Wald tests with standard asymptotic chi-square distribution. They recommend using a modified Wald (MWALD) test in a lag augmented VAR (LA-VAR) which has conventional asymptotic chi-square distribution when a VAR($p+d$max) is estimated, where p is lag order and $d$max is the maximal order of integration suspected to occur in the process. The only prior information needed for the LA-VAR approach is the maximum order of integration of the processes. In light of the fact that the pre-tests for a unit root and cointegrating rank are not required, the associated pre-test bias and size distortion can be avoided, at least, asymptotically (Yamada and Toda, 1998:59). Yamada and Toda (1998) show that the actual size of LA-VAR quickly approaches the (theoretical) asymptotic size as the sample size increases. However, the artificial lag augmentation may be quite costly in terms of size and power in finite samples.

Recently, some approaches examining causality relationships among variables in panels are available. The first approach determining dynamic relationships between variables in panel data is Holtz-Eakin et al. (1988). They have developed a method of estimating and testing Panel Vector Autoregression (PVAR) equations for homogeneous panels. They use Generalized Method of Moments (GMM) panel estimator developed by Arellano and Bond (1991). Hurlin (2008) proposes a simple test of Granger (1969) non-causality for heterogeneous panels with fixed coefficients. He allows that autoregressive parameters to differ across groups. However, contrary to Weinhold (1996) and Nair-Reichert and Weinhold (2001), parameters are fixed. Also, Hurlin (2008) assumes that lag orders on autoregressive coefficients and exogenous variable coefficients are the same for all cross-section units of the panel,

* Corresponding author. Tel.: +90 3122161306; fax: +90 3122132036.
E-mail address: emirfurkan@gmail.com (F. Emirmahmutoglu).

0264-9993/$ – see front matter © 2010 Elsevier B.V. All rights reserved.
doi:10.1016/j.econmod.2010.10.018

and the panel is balanced. The structure of their test is very similar to the unit root test proposed by Im et al. (2003) in heterogeneous panels. They propose a test statistic based on averaging standard individual Wald statistics of Granger non-causality tests. Under the cross-section independence assumption, they show that individual Wald statistics have an identical chi-squared distribution and average Wald statistic converge to a standard normal distribution when T and N tend sequentially to infinity. Finally, Konya (2006) suggests a different panel causality test which is based on Seemingly Unrelated Regressions (SUR) estimator proposed by Zellner (1962), and Wald test with country-specific bootstrap critical values. This test does not require pretesting for unit roots and cointegration apart from the lag structure. This is an important problem since the unit-root and the cointegration tests in general suffer from low power and different tests often lead to contradictory results.

The aim of this paper is to propose a new panel causality approach based on Meta analysis in heterogeneous mixed panels. The Meta analysis developed by Fisher (1932) is a statistical technique which has been planned to obtain a common result combining the results of a number of independent studies which test the same hypothesis. In recent years, the Meta analysis approach has been efficiently applied to non-stationary heterogeneous panels by many authors.[1] They conduct N separate time series tests and obtain the corresponding significant levels (p-values) of the test statistics. Then, combine the p-values of the N tests into a single panel test statistic. In this study, we extend LA-VAR approach via Meta analysis to test Granger causality between variables in heterogeneous mixed panels.

In this study, we have investigated the finite sample properties of the causality test based on Meta analysis via Monte Carlo experiments in heterogeneous mixed panels. Finally, we illustrate the panel causality test with LA-VAR approach in the presence of cross-sectional dependence to the issue of the link between export and economic growth in twenty OECD countries for the quarterly data between 1987 and 2006.

The plan of the paper is as follows. Section 2 sets out model specification. Section 3 presents the Monte Carlo evidence. We discuss an empirical application of Export–Growth relationship in Section 4. Finally, Section 5 concludes the paper.

2. Model specification

We consider heterogeneous panel VAR (k_i) model with p variables:

$$z_{i,t} = \mu_i + A_{i1} z_{i,t-1} + \ldots + A_{ik_i} z_{i,t-k_i} + u_{i,t} \quad i = 1,2,\ldots,N, \quad t = 1,2,\ldots,T \tag{1}$$

where the index i denotes individual cross-sectional units and the index t denotes time periods. μ_i is a p dimensional vector of fixed effects. $A_{i1},\ldots,A_{ik_i}$ are fixed $(p \times p)$ matrices of parameters that are allowed to vary across units. For each cross section unit $i = 1,2,\ldots,N$, $u_{i,t}$ is a column vector of p error terms. For all time periods, the vector $u_{i,t}$ is independently and identically distributed (i.i.d) across individual with $E(u_{i,t}) = 0$ and $V(u_{i,t}) = \Sigma_{u_i}$ is positive definite covariance matrices. The order k_i of the process is assumed to be known or it may be estimated by some model selection criterion (Lutkepohl, 2005). Also, the lag structure (k_i) may differ across cross-sectional units.

Wald tests are standard tools for testing restrictions on the coefficients of VAR systems. Let $\alpha_i = vec[\mu_i, A_{i1,\ldots,} A_{ik_i}]$ for $i = 1,\ldots, N$ be the vector of all VAR coefficients. Suppose that we are interested in testing q_i independent linear restrictions on cross-sectional unit i, in the case of Granger non-causality, the null hypothesis can be expressed as

$$H_0 : R_i \alpha_i = \underset{\sim}{0} \quad \text{for all } i \tag{2}$$

against the possibly heterogeneous alternatives,

$$H_1 : R_i \alpha_i \neq \underset{\sim}{0} \quad i = 1,\ldots,N_1; \quad R_i \alpha_i = \underset{\sim}{0} \quad i = N_1 + 1,\ldots,N \tag{3}$$

where R_i is a $(q_i \times p^2 k_i)$ matrix with rank q_i for each cross-sectional units and $\underset{\sim}{0}$ is a $(q_i \times 1)$ zeros vector. If z_{it} is partitioned in m and $(p–m)$ dimensional subvectors $x_{i,t}$ and $y_{i,t}$,

$$z_{i,t} = \left(x_{i,t}, y_{i,t}\right)' \text{ and } A_{ij} = \begin{bmatrix} A_{11,ij} & A_{12,ij} \\ A_{21,ij} & A_{22,ij} \end{bmatrix} \quad i = 1,2,\ldots,N, j = 1,2,\ldots,k_i$$

where A_{ij} are partitioned in accordance with the partitioning of $z_{i,t}$, then $y_{i,t}$ does not Granger cause $x_{i,t}$ if and only if the heterogeneous hypothesis $H_0 : A_{12,ij} = 0$ for $i = 1,2, \ldots,N, j = 1,2,\ldots,k_i$ is true.

Panel VAR (k_i) model (1) can be written in the following matrix notation for all individual units:

$$Z_i = B_i Q_i + U_i \quad \text{for } i = 1,2,\ldots,N \tag{4}$$

where for all $i = 1,\ldots,N$

$$\begin{aligned} Z_i &= (z_{i,1},\ldots,z_{i,t})(p \times T)\text{matrix} \\ B_i &= (\mu_i, A_{i1}\ldots,A_{ik_i})(p \times (pk_i + 1))\text{matrix} \\ Q_{i,t} &= \begin{bmatrix} 1 \\ z_{i,t} \\ \vdots \\ z_{i,t-k_i+1} \end{bmatrix} ((pk_i + 1) \times 1)\text{matrix} \\ Q_i &= \left(Q_{i,0},\ldots,Q_{i,T-1}\right)((pk_i + 1) \times T)\text{matrix and} \\ U_i &= \left(u_{i,1},\ldots,u_{i,T}\right)(p \times T)\text{matrix} \end{aligned}$$

Then the OLS estimator of the B_i for all individual units is:

$$\hat{B}_i = Z_i Q_i' \left(Q_i Q_i'\right)^{-1} \tag{5}$$

and $\hat{\alpha}_i = vec\left(\hat{B}_i\right)$. The asymptotic normal distribution of $\hat{\alpha}_i$ is followed as:

$$\sqrt{T}\left(\hat{\alpha}_i\right) \xrightarrow{d} N\left(0, \Gamma_i^{-1} \otimes \textstyle\sum_{u_i}\right) \quad \text{for } i = 1,2,\ldots,N \tag{6}$$

where $\Gamma_i = p \lim Q_i Q_i'/T$ and $\xrightarrow{d}$ denotes convergence in distribution.

The standard individual Wald statistics for testing H_0 is

$$W_i = T \hat{\alpha}_i' R_i' \left(R_i' \left(\left(Q_i' Q_i\right)^{-1} \otimes \hat{\Sigma}_{u_i}\right) R_i\right)^{-1} R_i \hat{\alpha}_i \quad \text{for } i = 1,2,\ldots,N \tag{7}$$

where $\hat{\Sigma}_{u_i}$ is consistent OLS estimator of Σ_{u_i}. The individual Wald statistics have an asymptotic chi-square distribution with q_i degrees of freedom if $\hat{\Sigma}_{u_i}$ is nonsingular. If variables in VAR process are stationary, OLS estimators and Wald statistics are valid. However, if variables contain unit roots, then Wald statistics based on OLS estimation of level VAR model have non-standard asymptotic distributions that may involve nuisance parameters (Sims et al., 1990). Therefore, Granger causality test is not valid for non-stationary variables. To avoid this problem, Toda and Yamamoto (1995) proposed a simple alternative approach for testing coefficient restrictions of a level VAR model. They used the LA-VAR approach to test restrictions on the parameters of the VAR(k) model. More

[1] See Maddala and Wu (1999) and Choi (2001) available in literature.

precisely, they propose to intentionally overfit the level VAR model by extra $d$max lags.

To test the hypothesis (2), we consider estimating a level VAR ($k_i + d\max_i$) in heterogeneous mixed panels:

$$z_{i,t} = \mu_i + A_{i1} z_{i,t-1} + \ldots + A_{ik} z_{i,t-k_i} + \sum_{l=k_i+1}^{k_i+d\max_i} A_{il} z_{i,t-l} + u_{i,t} \quad i = 1,2,\ldots,N, \; t = 1,2,\ldots,T \tag{8}$$

Note that the parameter restrictions (2) do not involve A_{il}'s, so the hypothesis (2) can be tested using a standard Wald statistics. Under the null hypothesis (2), the individual Wald statistics have an asymptotic chi-square distribution with q_i degrees of freedom even if variables are non-stationary but integrated at order not greater than $d\max_i$.

We use Fisher test statistic proposed by Fisher (1932) in order to test the Granger non-causality hypothesis in heterogeneous panels. Fisher (1932) considered combining several significant levels (p-values) identical but independent tests. If the test statistics are continues, p-values p_i ($i = 1, \ldots, N$) are independent uniform (0,1) variables. In this case, Fisher test statistic (λ) is written as follows:

$$\boxed{\lambda = -2\sum_{i=1}^{N} ln(p_i) \quad i = 1,2,\ldots,N} \tag{9}$$

where p_i is the p-value corresponding to the Wald statistic of the i-th individual cross-section. This test statistic has a chi-square distribution with $2N$ degrees of freedom. The test is valid only if N is fixed as $T \to \infty$.

However, the limit distribution of the Fisher test statistic is no longer valid in the presence of cross correlations among the cross-sectional units. As a way to deal with such inferential difficulty in panels with cross correlations, we use the bootstrap methodology to Granger causality test for cross-sectional dependent panels. To accommodate for contemporaneous correlation in panels, we obtain empirical distribution of the test statistic using the following bootstrap method.

We consider the level VAR model with $k_i + d\max_i$ lags in heterogeneous mixed panels:

$$\boxed{x_{i,t} = \mu_i^x + \sum_{j=1}^{k_i+d\max_i} A_{11,ij} x_{i,t-j} + \sum_{j=1}^{k_i+d\max_i} A_{12,ij} y_{i,t-j} + u_{i,t}^x} \tag{10}$$

$$y_{i,t} = \mu_i^y + \sum_{j=1}^{k_i+d\max_i} A_{21,ij} x_{i,t-j} + \sum_{j=1}^{k_i+d\max_i} A_{22,ij} y_{i,t-j} + u_{i,t}^y \tag{11}$$

where $d\max_i$ is maximal order of integration suspected to occur in the system for each i. In simplicity, we focus on testing causality from x to y in Eq. (11). A similar procedure is applied for causality from y to x in Eq. (10). The steps of our bootstrap procedure proceed as follows.[2]

Step 1: Firstly, in order to determine maximal order of integration of variables in the system for each cross-section unit, we use the traditional unit root tests as Dickey and Fuller (1981). We then estimate the regression (11) by OLS for each individual and select the lag orders k_i's via Schwarz information criteria (SBC) or Akaike information criteria (AIC) by starting $k_i = 8$ and applying a top to down strategy.

Step 2: By using k_i and $d\max_i$ from step 1, we re-estimate Eq. (11) by OLS under the non-causality hypothesis ($A_{21,i1} = \ldots = A_{21,ik_i} = 0$) and obtain the residuals for each individual.

$$\hat{u}_{i,t}^y = y_{i,t} - \hat{\mu}_i^y - \sum_{j=k_i+1}^{k_i+d\max_i} \hat{A}_{21,ij} x_{i,t-j} - \sum_{j=1}^{k_i+d\max_i} \hat{A}_{22,ij} y_{i,t-j} \tag{12}$$

Step 3: Stine (1987) suggests that residuals have to be centered with

$$\tilde{u}_t = \hat{u}_t - (T-k-l-2)^{-1} \sum_{t=k+l+2}^{T} \hat{u}_t \tag{13}$$

where $\hat{u}_t = \left(\hat{u}_{1t}, \hat{u}_{2t}, \ldots, \hat{u}_{Nt}\right)'$, $k = \max(k_i)$ and $l = \max(d\max_i)$. Furthermore, we develop the $[\tilde{u}_{i,t}]_{N \times T}$ from these residuals. We select randomly a full column with replacement from the matrix at a time to preserve the cross covariance structure of the errors. We denote the bootstrap residuals as $\tilde{u}_{i,t}^*$ where $t = 1,2,\ldots,T$.

Step 4: We generate the bootstrap sample of y under the null hypothesis:

$$y_{i,t}^* = \hat{\mu}_i^y + \sum_{j=k_i+1}^{k_i+d\max_i} \hat{A}_{21,ij} x_{i,t-j} + \sum_{j=1}^{k_i+d\max_i} \hat{A}_{22,ij} y_{i,t-j}^* + \tilde{u}_{i,t}^* \tag{14}$$

where $\hat{\mu}_i^y, \hat{A}_{21,ij}$ and $\hat{A}_{22,ij}$ are the estimations from Step 2.

Step 5: Substitute $y_{i,t}^*$ for $y_{i,t}$, estimate (Eq. (11)) without imposing any parameter restrictions on it and then the individual Wald statistics are calculated to test non-causality null hypothesis separately for each individual. Using these individual Wald statistics have an asymptotic chi-square distribution with k_i degrees of freedom, we compute individual p-values. Then, the Fisher test statistic given Eq. (9) is obtained.

We generate the bootstrap empirical distribution of the Fisher test statistics repeating steps 3–5 many times and specify the bootstrap critical values by selecting the appropriate percentiles of these sampling distributions.

3. Monte Carlo experiments

3.1. Design of the data generating process (DGP)

In this section, we perform Monte Carlo experiments to examine finite sample properties of the causality test based on Meta analysis in heterogeneous mixed panels. In these experiments, we consider four different cases. The following data generating processes (DGP) are employed in these cases.

Case 1: If $x_{i,t}$ and $y_{i,t}$ are $I(0)$, then the following DGP are used:

$$\begin{bmatrix} y_{i,t} \\ x_{i,t} \end{bmatrix} = \begin{bmatrix} \alpha_i \\ \theta_i \end{bmatrix} + \begin{bmatrix} \phi_i & 0 \\ \beta_i & \rho_i \end{bmatrix} \begin{bmatrix} y_{i,t-1} \\ x_{i,t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{i,t}^y \\ \varepsilon_{i,t}^x \end{bmatrix} \quad i = 1,2,\ldots,n_1 \tag{15}$$

Case 2: If $x_{i,t}$ is $I(0)$ and $y_{i,t}$ is $I(1)$, we then consider the following DGP:

$$\begin{bmatrix} \Delta y_{i,t} \\ x_{i,t} \end{bmatrix} = \begin{bmatrix} \alpha_i \\ \theta_i \end{bmatrix} + \begin{bmatrix} \phi_i & 0 \\ \beta_i & \rho_i \end{bmatrix} \begin{bmatrix} \Delta y_{i,t-1} \\ x_{i,t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{i,t}^y \\ \varepsilon_{i,t}^x \end{bmatrix} \quad i = 1,2,\ldots,n_2 \tag{16}$$

Case 3: If $x_{i,t}$ and $y_{i,t}$ are $I(1)$ but non-cointegrated, then DGP is given as the following:

$$\begin{bmatrix} \Delta y_{i,t} \\ \Delta x_{i,t} \end{bmatrix} = \begin{bmatrix} \phi_i & \gamma_i \\ T^{-1/2}\beta_i & \rho_i \end{bmatrix} \begin{bmatrix} \Delta y_{i,t-1} \\ \Delta x_{i,t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{i,t}^y \\ \varepsilon_{i,t}^x \end{bmatrix} \quad i = 1,2,\ldots,n_3 \tag{17}$$

[2] For similar bootstrap approaches, see Konya (2006) and Ucar and Omay (2009).

Case 4: If $x_{i,t}$ and $y_{i,t}$ are $I(1)$ and cointegrated, then we adopt bivariate VAR(2) cointegrated process used by Dolado and Lutkepohl (1996) in panel data context. In this VAR(2) process, the following Vector Error Correction Model (VECM) can be written.

$$\begin{bmatrix}\Delta y_{i,t}\\ \Delta x_{i,t}\end{bmatrix}=\begin{bmatrix}-\lambda_i & \lambda_i\\ 0 & 0\end{bmatrix}\begin{bmatrix}y_{i,t-1}\\ x_{i,t-1}\end{bmatrix}+\begin{bmatrix}\phi_i & \gamma_i\\ T^{-1/2}\beta_i & \rho_i\end{bmatrix}\begin{bmatrix}\Delta y_{i,t-1}\\ \Delta x_{i,t-1}\end{bmatrix}+\begin{bmatrix}\varepsilon^y_{i,t}\\ \varepsilon^x_{i,t}\end{bmatrix}\quad i=1,2,\ldots,n_4 \tag{18}$$

where the process has cointegration rank $r=1$ if $\lambda_i\neq 0$ and $r=0$ if $\lambda_i=0$ for each i in the VECM. Long-run coefficients λ_i in VECM are randomly generated from U(−1.2,−0.8) for each i where U denotes the uniform distribution.

In all DGP, the coefficients φ_i and γ_is are drawn according to U(0.5,0.9) for each i. The other coefficient ρ_is are randomly generated form U(−0.5,0.5) for all i. Under the non-causality hypothesis, $\beta_i=0$ for each i, while β_is are drawn from U(0,2) for all i under the alternative hypothesis. In all of the experiments, individual residuals $(\varepsilon^y_{it},\varepsilon^x_{it})$ are drawn in i.i.d. normal distribution with zero means and heterogeneous variances σ_i^2. Heterogeneous variances σ_i^2 are generated according to U(0.5,1.5). All of the parameters values are fixed throughout replications and initial values are set equal to zero. Furthermore, the differencing operator is expressed by Δ.

3.2. Simulation results

In this section, we conduct Monte Carlo experiments to investigate the finite sample performance of LA-VAR approach for panels characterized by both cross-section independency and cross-section dependency. In all the experiments, under the non-causality hypothesis, $\beta_i=0$ for all i in each case, while under the alternative, β_i is different from zero for all i. The simulations are performed for all combinations of $N\in\{15, 25, 50\}$ and $T\in\{50, 100, 150, 200, 300\}$. In addition, we use 2000 replications to compute empirical size and power of the LA-VAR approach based on Meta analysis in mixed panels under the cross-section independency assumption. On the other hand, for cross-section dependency, each simulation run is carried out with 1000 replications, each of which uses bootstrap critical values computed from 500 bootstrap replications. The nominal size for the simulation results was set at %5.

All the Monte Carlo results are presented in Tables 1–4. In these tables, n_1, n_2, n_3 and n_4 show the number of individuals belonging to the appropriate DGP within all individuals. For example, n_3 denotes the number of individuals which are generated as DGP (Eq. (17)). Monte Carlo experiments are repeated for n's different values. Thus, it will be useful to investigate how the causality test performs in mixed panels involving individuals which have different time series characteristics.

The simulation results for the empirical size and power of LA-VAR approach under the cross-section independency are reported in Tables 1 and 2. Generally, LA-VAR approach seems to have a good empirical size for large T in mixed panels. In addition to these results, becoming large N leads to the size distortion for small values of T. But, as $T\rightarrow\infty$, it does not seem to suffer from this problem even for all values of N. In terms of empirical power, it tends to be more powerful even when N and T are small.

Tables 3 and 4 provide Monte Carlo results for finite sample performance of the bootstrap method proposed in the Section 2 under the cross-section dependency assumption. In general, LA-VAR approach suffers from serious size distortion for small T. This problem is particularly serious if T is small as $N\rightarrow\infty$. On the contrary, the empirical size is converging at the 5% nominal size when fixed N as $T\rightarrow\infty$. We turn to finite sample power of the LA-VAR approach under the cross-section dependency. Generally, it seems that LA-VAR approach performs satisfactory for whole values of T and N.

4. Examining the export-led growth hypothesis for OECD countries

The ideas that export growth are a major determinant of output growth; the "export-led growth hypothesis" has considerable appeal to many countries. One reason lies in the fact that the export sector generates considerable economic activity and creates a good number of jobs and income.

There exist enormous empirical studies that explore the link as well as direction of causation between exports and economic growth. The empirical studies published between the period of 1963 and 1999 were summarized with conclusions by Giles and Williams (2000). However, it seems that the overall conclusions are mixed and contradictory. Some studies support the existence of a causal relationship between exports and economic growth, while others fail to support it.

The empirical approaches examining relationships between export and growth can be categorized into three groups. These are cross-country, time series and panel data approaches. Within the cross-country approach, exports and growth performance have been examined both through Spearman rank correlation and through the use of ordinary least squares (OLS). In both sets of studies, exports and growth have been generally found to be important factors in determining each other.

Potential problems with the cross-country methods are well documented in this literature. A number of previous studies (e.g. Michaely, 1977; Balassa, 1978; Feder, 1982), using cross-sectional data, are based on the implicit assumption that countries share common characteristics. This may not be true, due to the fact that countries differ not only in their institutional, political, and economic structure but also in their reactions to external shocks. Thus, the estimates from cross-sectional regressions are potentially misleading because they do not take into account country-specific characteristics (Hatemi and Irandoust, 2000:356).

The studies in the second group apply various time series techniques to test the export–growth relationships. These techniques are as follows: regression models (OLS, two stages least square (2SLS)

Table 1
Empirical size of LA-VAR approach under the cross-section independency.

		T				
$n_1-n_2-n_3-n_4$	N	50	100	150	200	300
4–4–4–3	15	0.096	0.071	0.065	0.056	0.058
1–3–.4–7		0.099	0.067	0.065	0.048	0.060
2–4–6–3		0.108	0.066	0.070	0.055	0.053
3–5–6–1		0.099	0.079	0.068	0.055	0.056
15–0–0–0		0.079	0.061	0.054	0.050	0.052
0–15–0–0		0.101	0.062	0.058	0.055	0.052
0–0–15–0		0.119	0.075	0.070	0.064	0.059
0–0–0–15		0.068	0.067	0.055	0.040	0.053
6–6–6–7	25	0.102	0.081	0.063	0.068	0.056
3–8–9–5		0.107	0.082	0.068	0.065	0.055
4–7–7–7		0.099	0.077	0.060	0.064	0.061
2–7–10–6		0.108	0.078	0.061	0.067	0.061
25–0–0–0		0.081	0.065	0.057	0.065	0.053
0–25–0–0		0.089	0.076	0.060	0.058	0.058
0–0–25–0		0.131	0.086	0.080	0.076	0.069
0–0–0–25		0.065	0.057	0.065	0.051	0.057
12–12–13–13	50	0.121	0.083	0.064	0.065	0.067
8–16–18–8		0.128	0.089	0.062	0.066	0.066
6–12–20–12		0.128	0.092	0.069	0.066	0.070
2–7–21–20		0.140	0.089	0.065	0.069	0.069
50–0–0–0		0.080	0.067	0.054	0.059	0.059
0–50–0–0		0.108	0.069	0.061	0.060	0.059
0–0–50–0		0.194	0.103	0.089	0.082	0.063
0–0–0–50		0.087	0.069	0.054	0.056	0.048

Table 2
Empirical power of LA-VAR approach under the cross-section independency.

$n_1-n_2-n_3-n_4$	N	T 50	100	150	200	300
4–4–4–3	15	1.000	1.000	1.000	1.000	1.000
1–3–.4–7		1.000	1.000	1.000	1.000	1.000
2–4–6–3		1.000	1.000	1.000	1.000	1.000
3–5–6–1		1.000	1.000	1.000	1.000	1.000
15–0–0–0		1.000	1.000	1.000	1.000	1.000
0–15–0–0		1.000	1.000	1.000	1.000	1.000
0–0–15–0		0.983	0.987	0.992	0.995	0.995
0–0–0–15		0.924	0.950	0.961	0.978	0.976
6–6–6–7	25	1.000	1.000	1.000	1.000	1.000
3–8–9–5		1.000	1.000	1.000	1.000	1.000
4–7–7–7		1.000	1.000	1.000	1.000	1.000
2–7–10–6		1.000	1.000	1.000	1.000	1.000
25–0–0–0		1.000	1.000	1.000	1.000	1.000
0–25–0–0		1.000	1.000	1.000	1.000	1.000
0–0–25–0		1.000	1.000	1.000	1.000	1.000
0–0–0–25		0.995	0.999	1.000	1.000	1.000
12–12–13–13	50	1.000	1.000	1.000	1.000	1.000
8–16–18–8		1.000	1.000	1.000	1.000	1.000
6–12–20–12		1.000	1.000	1.000	1.000	1.000
2–7–21–20		1.000	1.000	1.000	1.000	1.000
50–0–0–0		1.000	1.000	1.000	1.000	1.000
0–50–0–0		1.000	1.000	1.000	1.000	1.000
0–0–50–0		1.000	1.000	1.000	1.000	1.000
0–0–0–50		1.000	1.000	1.000	1.000	1.000

and three stage least square (3SLS)) that do not take into consideration dynamic effects; causality analysis; cointegration tests and exogeneity. In recent years, among time series studies, many researchers have directed studies on the export–growth relationship towards the use of the Granger non-causality testing procedure. To explore casual link between exports and output in these studies, Granger causality tests are performed on the corresponding first differenced VAR model, VECM and Toda-Yamamoto or Dolado-Lutkepohl augmented VAR model in levels.

In recent years, there are some studies that have employed panel data techniques to examine export–growth relationship. These studies are detailed in Table 7. Bahmani-Oskooe et al. (2005) and Parida and Sahoo (2007) apply Pedroni's panel cointegration test to establish the long-run relationship between exports and output. On the other hand, Konya (2006) proposed a new panel data approach based on SUR systems and Wald tests with country-specific bootstrap critical values. His study examines the possibility of Granger causality between real exports and real GDP in 24 OECD countries.

In this section, we have investigated Granger causality between export and growth variables in 20 OECD countries. The data set comprises quarterly data on real gross domestic product (GDP) as proxy of output variables and real exports (EXP) for a period from 1987 to 2006 for all countries. All the data were obtained from the International Financial Statistics published by the International Monetary Funds. Real GDP series given in national currency were constructed by deflating corresponding nominal GDP series by the GDP deflators. On the other hand, real export values were expressed in US constant dollars and nominal exports series were deflated by the consumer price index series of the United States. For all real series, the base year is 2000. Furthermore, all data are measured in logarithms.

The first step is to investigate the integrated properties of the series for all countries. Hence, Table 5 reports the Augmented Dickey Fuller (ADF) tests on the levels, first differences and second differences of the series. In consequence of the ADF test, maximum order of integration in the VAR system is determined as 1 for the other OECD countries excluding Finland.

The second step is to perform LA-VAR approach in mixed panels to test the hypothesis that there is a relationship between exports and the growth of the variables of output. The results of LA-VAR approach are given in Table 6. In this table, k_i is the number of appropriate lag orders in level VAR systems for i_th country. The results in Table 6 suggest that both null hypothesis of “Granger no causality form exports to growth” and “Granger no causality form growth to exports” cannot be rejected even at the 10% significance level for 13 OECD countries. On the other hand, there is strong evidence against null hypothesis “Granger no causality from growth to exports” at the 5% level of significance for Germany, Korea and United States, and at the 10% level for Australia and Norway, while in case of Japan the export-led hypothesis is supported at 5% significance levels. As for Turkey, we found strong empirical support for two-way Granger causality between exports and growth variables.

Table 3
Empirical size of LA-VAR approach under the cross-section dependency.

$n_1-n_2-n_3-n_4$	N	T 50	100	150	200	300
4–4–4–3	15	0.034	0.056	0.048	0.054	0.074
1–3–.4–7		0.028	0.041	0.050	0.058	0.092
2–4–6–3		0.045	0.048	0.050	0.049	0.074
3–5–6–1		0.034	0.055	0.048	0.046	0.048
15–0–0–0		0.052	0.053	0.042	0.048	0.050
0–15–0–0		0.055	0.052	0.042	0.046	0.051
0–0–15–0		0.048	0.052	0.047	0.053	0.054
0–0–0–15		0.013	0.024	0.027	0.024	0.044
6–6–6–7	25	0.037	0.059	0.056	0.065	0.081
3–8–9–5		0.030	0.062	0.060	0.062	0.067
4–7–7–7		0.029	0.058	0.053	0.055	0.075
2–7–10–6		0.036	0.059	0.066	0.069	0.073
25–0–0–0		0.048	0.053	0.057	0.054	0.047
0–25–0–0		0.053	0.066	0.058	0.055	0.050
0–0–25–0		0.069	0.076	0.067	0.067	0.053
0–0–0–25		0.008	0.020	0.030	0.019	0.037
12–12–13–13	50	0.023	0.034	0.053	0.063	0.085
8–16–18–8		0.030	0.035	0.050	0.057	0.073
6–12–20–12		0.034	0.040	0.051	0.062	0.077
2–7–21–20		0.026	0.035	0.045	0.065	0.094
50–0–0–0		0.042	0.045	0.049	0.062	0.064
0–50–0–0		0.046	0.051	0.053	0.050	0.064
0–0–50–0		0.080	0.068	0.065	0.056	0.065
0–0–0–50		0.007	0.011	0.014	0.011	0.022

Table 4
Empirical power of LA-VAR approach under the cross-section dependency.

$n_1-n_2-n_3-n_4$	N	T 50	100	150	200	300
4–4–4–3	15	1.000	1.000	1.000	1.000	1.000
1–3–.4–7		1.000	1.000	1.000	1.000	1.000
2–4–6–3		1.000	1.000	1.000	1.000	1.000
3–5–6–1		1.000	1.000	1.000	1.000	1.000
15–0–0–0		1.000	1.000	1.000	1.000	1.000
0–15–0–0		1.000	1.000	1.000	1.000	1.000
0–0–15–0		1.000	1.000	1.000	1.000	1.000
0–0–0–15		0.819	0.978	0.996	0.981	1.000
6–6–6–7	25	1.000	1.000	1.000	1.000	1.000
3–8–9–5		1.000	1.000	1.000	1.000	1.000
4–7–7–7		1.000	1.000	1.000	1.000	1.000
2–7–10–6		1.000	1.000	1.000	1.000	1.000
25–0–0–0		1.000	1.000	1.000	1.000	1.000
0–25–0–0		1.000	1.000	1.000	1.000	1.000
0–0–25–0		1.000	1.000	1.000	1.000	1.000
0–0–0–25		0.993	1.000	1.000	1.000	1.000
12–12–13–13	50	1.000	1.000	1.000	1.000	1.000
8–16–18–8		1.000	1.000	1.000	1.000	1.000
6–12–20–12		1.000	1.000	1.000	1.000	1.000
2–7–21–20		1.000	1.000	1.000	1.000	1.000
50–0–0–0		1.000	1.000	1.000	1.000	1.000
0–50–0–0		1.000	1.000	1.000	1.000	1.000
0–0–50–0		1.000	1.000	1.000	1.000	1.000
0–0–0–50		1.000	1.000	1.000	1.000	1.000

Table 5
ADF test results (with intercept)[a].

Country	EXP		GDP			$d\max_i$
	Levels	First differences	Levels	First differences	Second differences	
Austria	0.889	0.000[b]	0.047[b]	–	–	1
Australia	0.936	0.000[b]	0.994	0.000[b]	–	1
Canada	0.823	0.000[b]	0.995	0.000[b]	–	1
Denmark	0.669	0.000[b]	0.995	0.000[b]	–	1
Finland	0.792	0.000[b]	0.966	0.313	0.000[b]	2
France	0.483	0.000[b]	0.797	0.000[b]	–	1
Germany	0.933	0.000[b]	0.112	0.000[b]	–	1
Italy	0.489	0.000[b]	0.536	0.000[b]	–	1
Japan	0.637	0.000[b]	0.006[b]	–	–	1
Korea	0.861	0.000[b]	0.439	0.003[b]	–	1
Mexico	0.732	0.000[b]	0.917	0.000[b]	–	1
Netherlands	0.909	0.000[b]	0.737	0.000[b]	–	1
New Zealand	0.707	0.000[b]	0.998	0.000[b]	–	1
Norway	0.752	0.000[b]	0.962	0.000[b]	–	1
Portugal	0.277	0.000[b]	0.361	0.000[b]	–	1
Spain	0.616	0.000[b]	0.963	0.000[b]	–	1
Sweden	0.788	0.000[b]	0.997	0.005[b]	–	1
Turkey	0.997	0.000[b]	0.933	0.000[b]	–	1
United Kingdom	0.351	0.000[b]	0.998	0.000[b]	–	1
United States	0.116	0.000[b]	0.955	0.002[b]	–	1

[a] The values presented in Table are MacKinnon (1996) one-sided p-values.
[b] Rejects the null hypothesis of unit root at%5 significance level.

Table 6
Results of Granger causality test.

Country	k_i	Export-led hypothesis		Growth-led hypothesis	
		W_i	p_i	W_i	p_i
Austria	3	0.953	0.813	1.662	0.645
Australia	1	0.759	0.384	3.262	0.071***
Canada	1	0.335	0.563	0.340	0.560
Denmark	1	1.699	0.192	0.066	0.797
Finland	1	0.004	0.953	1.727	0.189
France	1	0.651	0.420	1.691	0.193
Germany	1	1.901	0.168	7.943	0.005*
Italy	1	0.182	0.670	2.152	0.142
Japan	1	6.376	0.012**	0.754	0.385
Korea	5	6.055	0.301	21.659	0.001*
Mexico	1	0.263	0.608	0.196	0.658
Netherlands	1	0.021	0.884	0.689	0.407
New Zealand	1	0.368	0.544	0.955	0.328
Norway	2	4.258	0.119	4.866	0.088***
Portugal	1	0.126	0.723	0.061	0.805
Spain	1	0.003	0.957	0.350	0.554
Sweden	1	0.297	0.586	2.713	0.100
Turkey	3	13.971	0.003*	9.363	0.025**
United Kingdom	2	2.157	0.340	2.571	0.277
United States	1	0.951	0.329	4.444	0.035**
Calculated Fisher Test Statistic (λ)		48.85		78.31	

Lag orders k_i are selected by minimizing the Schwarz Bayesian criteria.
* Indicate significance at the 1% level.
** Indicate significance at the 5% level.
*** Indicate at the 10% level.

Fisher test statistic value combining the p-values of countries to assess an overall hypothesis for 20 OECD countries is given the last row of Table 6. This yields a test statistic distributed as χ^2_{2N} under the cross-section independency assumption. However, the limit distribution of the Fisher test statistic is not longer valid in the presence of cross-section dependency. Hence, we use Lagrange Multiplier (LM) test proposed by Breusch and Pagan (1980) in order to discover the presence of cross-section dependency in the data. LM statistics is valid for $T \to \infty$ with N fixed and defined as

$$LM = T \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij}^2 \tag{19}$$

where $\hat{\rho}_{ij}$ is the sample estimate of the pair-wise correlation of the residuals

$$\hat{\rho}_{ij} = \frac{\sum_{t=1}^{T} \hat{u}_{it}\hat{u}_{jt}}{\left(\sum_{t=1}^{T} \hat{u}_{it}^2\right)^{1/2} \left(\sum_{t=1}^{T} \hat{u}_{jt}^2\right)^{1/2}} \tag{20}$$

and $\hat{u}_{it}$ is the estimate of u_{it} in Eq. (10) or Eq. (11). LM statistic is asymptotically distributed as chi-squared with $N(N-1)/2$ degrees of freedom (Croissant and Millo, 2008: 28). According to the result of the LM test, we find that the LM statistic is 471.56. The LM test statistic is high and significant. Hence, there seems to find evidence of cross-section dependence on the data.

Lastly, in the case of cross-section dependency in mixed panels, we apply the bootstrap method to generate the empirical distributions of Fisher test. The bootstrap distribution of Fisher test statistics is derived from 10,000 replications. Bootstrap critical values are obtained at the 1, 5 and 10% levels based on these empirical distributions. For the 20 OECD countries, these critical values are 68.51, 58.88 and 54.43 at the 1%, 5% and 10% significance levels respectively for export-led hypothesis. Similarly, they are 69.15, 59.43 and 54.73 at the 1%, 5% and 10% significance levels respectively for testing growth led hypothesis. Notice that the bootstrap critical values are substantially higher than the asymptotic chi-square critical values applied with the Fisher test. When bootstrap critical values are used, our empirical findings indicate that the causal link between real exports and real GDP growth is one way from EXP to GDP for 20 OECD countries.

5. Conclusions

In this paper, we have proposed a simple procedure for Granger causality test with LA-VAR approach of Toda and Yamamoto (1995) in heterogonous mixed panels by using Meta analysis. The finite sample properties of the causality test based on Meta analysis in mixed panels are examined via Monte Carlo experiments for panels characterized by both cross-section independency and cross-section dependency. In each Monte Carlo experiment, we have considered four different DGPs in mixed panels involving $I(0)$, $I(1)$, cointegrated and non-cointegrated series.

The simulation results for the power of LA-VAR approach under both the cross-section independency and the cross-section dependency indicate that it is very powerful even if N and T are small. On the other hand, LA-VAR approach seems to have a good empirical size for large T in mixed panels under the cross-section independency. The empirical size is converging at the 5% nominal size when fixed N as $T \to \infty$. However, becoming large N leads to the size distortion for small values of T. According to Monte Carlo results for finite sample performance of the bootstrap method under the cross-section dependency assumption, LA-VAR approach affects from serious size distortion for small values of T. Especially, it emerges as a serious problem if T is small as $N \to \infty$. But, the empirical size corrects as $T \to \infty$, and it converges at the 5% nominal size.

Finally, we present an application for the linkage between export and economic growth employing the Granger causality test by using LA-VAR approach for a balanced panel of twenty OECD countries covering 1987:1-2006:4 in the context of the export-led growth hypothesis. According to the LM test result proposed by Breusch and Pagan (1980), the test strongly rejects the null hypothesis no cross-sectional dependence at least at the 1% significance level. Therefore, we have applied the bootstrap method to generate the empirical distributions of Fisher test. When bootstrap critical values are used, our empirical findings indicate that the causal link between real exports and real GDP growth is one way from export to growth for 20 OECD countries.

Table 7
Panel data studies of export–growth.

Authors	Methods	Country	Period	Conclusions
Bahmani-Oskooe et al. (2005)	Pedroni's Panel cointegration test	61 developing countries	1960–1999 annual data	Cointegration receives support in a model which export is the dependent variable.
Konya (2006)	Panel causality test based on SUR systems	24 OECD countries	1960–1997 annual data	The results indicate one-way causality from exports to GDP in Belgium, Denmark, Iceland, Ireland, Italy, New Zealand, Spain and Sweden. One-way causality from GDP to exports in Austria, France, Greece, Japan, Mexico, Norway and Portugal, two-way causality between exports and growth in Canada, Finland and the Netherlands, while in the case of Australia, Korea, Luxembourg, Switzerland, the UK and the USA there is no evidence of causality in either direction.
Fruoka (2007)	1. Pooled ordinary least squares 2. One-way fixed/random effects 3. Two-way fixed/random effects	Five ASEAN nations (Malaysia, Indonesia, the Philippines, Singapore and Thailand)	1985–2002 annual data	Empirical results show that the one-way fixed effects analysis is the best model among different models. As the one-way fixed effects model shows, there has been a significant positive relationship between exports and economic growth in the five ASEAN nations.
Parida and Sahoo (2007)	Pedroni's panel cointegration test	Four South Asian countries (India, Pakistan, Bangladesh and Sri Lanka)	1980–2002 annual data	The study finds long-run equilibrium relationship between GDP (and non-export GDP) and exports along with other variables supporting export-led growth hypothesis.

References

Arellano, M., Bond, S., 1991. Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. The Review of Economic Studies 58 (2), 277–297.

Bahmani-Oskooe, M., Economidou, C., Goswami, G.G., 2005. Export-led growth hypothesis revisited: a panel cointegration approach. Scientific Journal of Administrative Development 3, 40–55.

Balassa, B., 1978. Exports and economic growth: further evidence. Journal of Development Economics 5 (2), 181–189.

Breusch, T.S., Pagan, A.R., 1980. The Lagrange Multiplier test and its application to model specifications in econometrics. Review of Economic Studies 47, 239–253.

Choi, I., 2001. Unit root test for panel data. Journal of International Money and Banking 20, 249–272.

Croissant, Y., Millo, G., 2008. Panel data econometrics in R: the plm package. Journal of Statistical Software 27 (2), 1–43.

Dickey, D.A., Fuller, W.A., 1981. Likelihood Ratio Statistics for Autoregressive Time Series with a Unit Root. Econometrica 49, 1057–1079.

Dolado, J.J., Lutkepohl, H., 1996. Making Wald tests work for cointegrated VAR systems. Econometrics Reviews 15, 369–386.

Feder, G., 1982. On exports and economic growth. Journal of Development Economics 12, 59–73.

Fisher, R.A., 1932. Statistical Methods for Research Workers, 4th edition. Oliver and Boyd, Edinburgh.

Fruoka, F., 2007. Panel data analysis of export-led growth hypothesis in ASEAN. Munich Personal RePEc Archive Working Paper No: 5830.

Giles, J.A., Williams, C.L., 2000. Export-led growth: a survey of the empirical literature and some non-causality results, part 1. The Journal of International Trade and Economic Development 9 (3), 261–337.

Granger, C.W.J., 1969. Investigating causal relations by econometric models: cross spectral methods. Econometrica 37, 424–438.

Hatemi, J.A., Irandoust, M., 2000. Time-series evidence for Balassa's export-led growth hypothesis. The Journal of International Trade and Economic Development 9 (3), 355–365.

Holtz-Eakin, D., Newey, W., Rosen, S., 1988. Estimating vector autoregression with panel data. Econometrica 56, 1371–1395.

Hurlin, C., 2008. Testing for Granger non-causality in heterogeneous panels. Working Papers halshs-00224434, version 1.

Im, K.S., Pesaran, M.H., Shin, Y., 2003. Test for unit roots in heterogeneous panels. Journal of Econometrics 115, 53–74.

Konya, L., 2006. Exports and growth: Granger causality analysis on OECD countries with a panel data approach. Economic Modeling 23, 978–992.

Lutkepohl, H., 2005. New Introduction to Multiple Time Series Analysis. Springer.

MacKinnon, J.G., 1996. Numerical distribution functions for unit root and cointegration tests. Journal of Applied Econometrics 11, 601–618.

Maddala, G.S., Wu, S., 1999. A comparative study of unit root tests with panel data and a new simple test. Oxford Bulletin of Economics and Statistics 61, 631–652.

Michaely, M., 1977. Exports and growth: an empirical investigation. Journal of Development Economics 4 (1), 149–153.

Nair-Reichert, U., Weinhold, D., 2001. Causality tests for cross-country panels: a new look at FDI and economic growth in developing countries. Oxford Bulletin of Economics and Statistics 63, 153–171.

Parida, P.C., Sahoo, P., 2007. Export-led growth in South Asia: a panel cointegration analysis. International Economic Journal 21 (2), 155–175.

Park, J.Y., Philips, P.C.B., 1989. Statistical inference in regressions with integrated process: part 2. Econometric Theory 5, 95–132.

Sims, C.A., Stock, J.H., Watson, M.W., 1990. Inference in linear time series models with some unit roots. Econometrica 58, 113–144.

Stine, R.A., 1987. Estimating properties of autoregressive forecasts. Journal of the American Statistical Association 82, 1072–1078.

Toda, H.Y., Phillips, P.C.B., 1993. Vector autoregression and causality. Econometrica 59, 229–255.

Toda, H.Y., Yamamoto, T., 1995. Statistical inference in vector autoregressions with possibly integrated processes. Journal of Econometrics 66, 225–250.

Ucar, N., Omay, T., 2009. Testing for unit root in nonlinear heterogeneous panels. Economics Letters 104, 5–8.

Weinhold, D., 1996. Investment, growth and causality testing in panels. Economie et Prevision 126, 163–175.

Yamada, H., Toda, H.Y., 1998. Inference in possibly integrated vector autoregressive models: some finite sample evidence. Journal of Econometrics 86, 55–95.

Zellner, A., 1962. An efficient method of estimating seemingly unrelated regressions and tests for aggregation bias. Journal of the American Statistical Association 57, 348–368.