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Exports and growth: Granger causality analysis on OECD countries with a panel data approach

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Abstract

This paper investigates the possibility of Granger causality between the logarithms of real exports and real GDP in twenty-four OECD countries from 1960 to 1997. A new panel data approach is applied which is based on SUR systems and Wald tests with country specific bootstrap critical values. Two different models are used. A bivariate (GDP–exports) model and a trivariate (GDP–exports–openness) model, both without and with a linear time trend. In each case the analysis focusses on direct, one-period-ahead causality between exports and GDP. 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.

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1. Introduction

Since the early 1960s policy makers and scholars alike, have shown great interest in the possible relationship between exports and economic growth. The motivation is clear. Should a country promote exports to speed up economic growth or should it primarily focus on economic growth, which in turn will generate exports?

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There are basically four propositions. According to the export-led growth (ELG) hypothesis, export activity leads economic growth. Trade theory provides several plausible explanations in favour of this idea. For example, export promotion directly encourages the production of goods for exports. This may lead to further specialisation in order to exploit economies of scale and the nation's comparative advantages. Moreover, increased exports may permit the imports of high quality products and technologies, which in turn may have a positive impact on technological change, labour productivity, capital efficiency and, eventually, on the nation's production. The second proposition, the growth-driven exports (GDE) hypothesis, postulates a reverse relationship. It is based on the idea that economic growth itself induces trade flows. It can also create comparative advantages in certain areas leading to further specialisation and facilitating exports. These two propositions do not exclude each other, so the third notion is a feedback relationship between exports and economic growth. Finally, it is also possible that there is no relationship, or just a simple contemporaneous, maybe spurious relationship, between these two variables.

There is a vast amount of empirical literature on this issue. The most recent and most comprehensive survey of this literature is due to Giles and Williams (2000) who reviewed more than one hundred and fifty export-growth applied papers published between 1963 and 1999. These papers fall into three groups. The first group of studies is based on cross-country rank correlation coefficients, the second applies cross-sectional regression analysis, and the third uses time series techniques on a country-by-country basis. Two thirds of the papers belong to this third group, and more than seventy of these are based on the concept of Granger causality and on various tests for it.

The present paper does not fit into any of these groups. Our purpose is to test for Granger causality between the logarithms of real exports and GDP in twenty-four OECD countries between 1960 and 1997. However, unlike single-country time series studies, we use a new panel data approach which is based on seemingly unrelated regressions (SUR) and Wald tests with country specific bootstrap critical values. This approach has two advantages. Firstly, it does not require joint hypotheses for all panel members, but allows for contemporaneous correlation across them, making it possible to exploit the extra information provided by the panel data setting. Secondly, apart from the lag structure, there is no need for pretesting.

Our focus is on bivariate systems. Yet, we consider a trivariate specification, as well. In this latter model the third variable is the logarithm of openness, defined as the proportion of the total real trade flows to GDP. However, this variable is treated as an auxiliary variable, so the analysis can handle only direct, one-period-ahead causality between exports and economic growth, disregarding the possibility of indirect causality at longer time horizons.

The rest of this paper unfolds as follows. Section 2 discusses the technical issues, including the data, the model, the estimation method and the test procedure. Section 3 presents the empirical results. The concluding remarks are in Section 4.

2. Technical issues

2.1. Data

The data set comprises annual measures on 24 OECD countries: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Greece, Iceland, Ireland, Italy, Japan, Republic of Korea,

¹ A similar approach is recommended by Breuer et al. (2001) and Enders (2004) for panel unit-root testing.

Luxembourg, Mexico, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, UK and USA. The variables are as follow: GDP (1995 \$US), exports of goods and services (1995 \$US) and openness (the proportion of the sum of exports and imports of goods and services in GDP).² The natural logarithms of these variables are denoted as LNGDP, LNEXP and LNOPEN. Our purpose is to test for Granger causality between LNGDP and LNEXP within a bivariate framework, but later we augment the information set with LNOPEN. The sample period is 1960–1997 for all countries.

2.2. Model

In a country-by-country analysis the possibility of Granger causality between LNGDP and LNEXP can be studied using the following bivariate finite-order vector autoregressive (VAR) model:

$$y_{i,t} = \alpha_{1,t} + \sum_{l=1}^{mly_i} \beta_{1,i,l} y_{i,t-l} + \sum_{l=1}^{mlx_i} \gamma_{1,i,l} x_{i,t-l} + \varepsilon_{1,i,t}$$

$$x_{i,t} = \alpha_{2,i} + \sum_{l=1}^{mly_i} \beta_{2,i,l} y_{i,t-l} + \sum_{l=1}^{mlx_i} \gamma_{2,i,l} x_{i,t-l} + \varepsilon_{2,i,t}$$
(1)

where index *i* refers to the country (i=1,...,N), *t* to the time period (t=1,...,T) and *l* to the lag. $\varepsilon_{1,i,t}$, $\varepsilon_{2,i,t}$ are supposed to be white-noise errors that may be correlated for a given country, but not across countries.³ Moreover, it is assumed that y_t and x_t are stationary or cointegrated so, depending on the time-series properties of the data, they might denote the level, the first difference or some higher difference of LNGDP and LNEXP, respectively.

With respect to this system, in country i there is one-way Granger causality running from X to Y if in the first equation not all $\gamma_{1,i}$'s are zero but in the second all $\beta_{2,i}$'s are zero, there is one-way Granger causality from Y to X if in the first equation all $\gamma_{1,i}$'s are zero but in the second not all $\beta_{2,i}$'s are zero, there is two-way Granger causality between Y and X if neither all $\beta_{2,i}$'s nor all $\gamma_{1,i}$'s are zero, and there is no Granger causality between Y and X if all $\beta_{2,i}$'s and $\gamma_{1,i}$'s are zero.

As regards the estimation of (1), since for a given country the two equations contain the same predetermined, i.e. lagged exogenous and endogenous variables, the OLS estimators of the parameters are consistent and asymptotically efficient. This suggests that the 2N equations involved in the analysis can be estimated one-by-one, in any preferred order. For example, we can divide the equations into two groups, the first one consisting of the equations on Y and the

² The original trade figures extracted from the World Bank's *World Tables* are nominal exports and imports given in \$US, and index numbers (1995=100) calculated from real exports and imports in 1995 local currencies. In order to obtain real trade data in 1995 \$US, the index series have been multiplied by the 1995 trade figures given in 1995 \$US (million).

 $^{^3}$ $\epsilon_{1,i,t}$ and $\epsilon_{2,i,t}$ are correlated when there is feedback between *X* and *Y*, i.e. in the non-reduced form of (1), called structural VAR, y_t depends on x_t and/or x_t depends on y_t (Enders, 2004, pp. 264–266).

⁴ This definition implies causality for one period ahead. This concept has been generalised by Dufour and Renault (1998) to causality h periods ahead, and to causality up to horizon h, where h is a positive integer.

second of the equations on X. In other words, instead of the N VAR systems like (1), we can consider the following two sets of equations:

$$y_{1,t} = \alpha_{1,1} + \sum_{l=1}^{mly_1} \beta_{1,1,l} y_{1,t-l} + \sum_{l=1}^{mlx_1} \gamma_{1,1,l} x_{1,t-l} + \varepsilon_{1,1,t}$$

$$y_{2,t} = \alpha_{1,2} + \sum_{l=1}^{mly_1} \beta_{1,2,l} y_{2,t-l} + \sum_{l=1}^{mlx_1} \gamma_{1,2,l} x_{2,t-l} + \varepsilon_{1,2,t}$$

$$\vdots$$

$$y_{N,t} = \alpha_{1,N} + \sum_{l=1}^{mly_1} \beta_{1,N,l} y_{N,t-l} + \sum_{l=1}^{mlx_1} \gamma_{1,N,l} x_{N,t-l} + \varepsilon_{1,N,t}$$

$$(2)$$

and

$$x_{1,t} = \alpha_{2,1} + \sum_{l=1}^{mly_2} \beta_{2,1,l} y_{1,t-l} + \sum_{l=1}^{mlx_2} \gamma_{2,1,l} x_{1,t-l} + \varepsilon_{2,1,t}$$

$$x_{2,t} = \alpha_{2,2} + \sum_{l=1}^{mly_2} \beta_{2,2,l} y_{2,t-l} + \sum_{l=1}^{mlx_2} \gamma_{2,2,l} x_{2,t-l} + \varepsilon_{2,2,t}$$

$$\vdots$$

$$x_{N,t} = \alpha_{2,N} + \sum_{l=1}^{mly_2} \beta_{2,N,l} y_{N,t-l} + \sum_{l=1}^{mlx_2} \gamma_{2,N,l} x_{N,t-l} + \varepsilon_{2,N,t}$$

$$(3)$$

Compared to (1), this alternative specification has two distinctive features. Firstly, each equation in (2), and also in (3), has different predetermined variables. The only possible link among individual regressions is contemporaneous correlation within the systems.⁵ Hence, these sets of equations are not VAR but SUR systems. Secondly, since we shall use country specific bootstrap critical values, y_t and x_t are not supposed to be stationary, they denote the levels of LNGDP and LNEXP, irrespectively of the time-series properties of these variables.

With respect to these SUR systems, in country i there is one-way Granger causality running from X to Y if in (2) not all $\gamma_{1,i}$'s are zero but in (3) all $\beta_{2,i}$'s are zero, there is one-way Granger causality from Y to X if in (2) all $\gamma_{1,i}$'s are zero but in (3) not all $\beta_{2,i}$'s are zero, there is two-way Granger causality between Y and X if neither all $\beta_{2,i}$'s nor all $\gamma_{1,i}$'s are zero, and there is no Granger causality between Y and X if all $\beta_{2,i}$'s and $\gamma_{1,i}$'s are zero.

In order to include a third variable into our analysis, namely the logarithm of openness, we shall also consider the following augmented variants of (2) and (3)

$$y_{1,t} = \alpha_{1,1} + \sum_{l=1}^{mly_1} \beta_{1,1,l} y_{1,t-l} + \sum_{l=1}^{mlx_1} \gamma_{1,1,l} x_{1,t-l} + \sum_{l=1}^{mlz_1} \eta_{1,1,l} z_{1,t-l} + \varepsilon_{1,1,t}$$

$$y_{2,t} = \alpha_{1,2} + \sum_{l=1}^{mly_1} \beta_{1,2,l} y_{2,t-l} + \sum_{l=1}^{mlx_1} \gamma_{1,2,l} \gamma_{1,2,l} x_{2,t-l} + \sum_{l=1}^{mlz_1} \eta_{1,2,l} z_{2,t-l} + \varepsilon_{1,2,t}$$

$$\vdots$$

$$y_{N,t} = \alpha_{1,N} + \sum_{l=1}^{mly_1} \beta_{1,N,l} y_{N,t-l} + \sum_{l=1}^{mlx_1} \gamma_{1,N,l} x_{N,t-l} + \sum_{l=1}^{mlz_1} \eta_{1,N,l} z_{N,t-l} + \varepsilon_{1,N,t}$$

$$(4)$$

⁵ Due to the strong economic ties among the OECD countries, contemporaneous correlation is very likely in these systems.

and

$$x_{1,t} = \alpha_{2,1} + \sum_{l=1}^{mly_2} \beta_{2,1,l} y_{1,t-l} + \sum_{l=1}^{mlx_2} \gamma_{2,1,l} x_{1,t-l} + \sum_{l=1}^{mlz_2} \eta_{2,1,l} z_{1,t-l} + \varepsilon_{2,1,t}$$

$$x_{2,t} = \alpha_{2,2} + \sum_{l=1}^{mly_2} \beta_{2,2,l} y_{2,t-l} + \sum_{l=1}^{mlx_2} \gamma_{2,2,l} x_{2,t-l} + \sum_{l=1}^{mlz_2} \eta_{2,2,l} z_{2,t-l} + \varepsilon_{2,2,t}$$

$$\vdots$$

$$x_{N,t} = \alpha_{2,N} + \sum_{l=1}^{mly_2} \beta_{2,N,t} y_{N,t-l} + \sum_{l=1}^{mlx_2} \gamma_{2,N,l} x_{N,t-l} + \sum_{l=1}^{mlz_2} \eta_{2,N,l} z_{N,t-l} + \varepsilon_{2,N,t}$$

$$(5)$$

where $z_{i,t-l}$ ($l=1, ..., mlz_i$) denote the lagged values of LNOPEN. However, in these trivariate systems our focus will remain on the bivariate, one-period-ahead relationship between LNGDP and LNEXP, so we shall not study the possibility of causality at longer horizons, nor the possibility of two variables jointly causing the third one. In other words, LNOPEN is treated as an auxiliary variable, it will not be directly involved in the Granger causality analysis.

In the rest of this chapter we discuss how to estimate the (2) and (3) bivariate systems and how to test for Granger causality within these systems. Nevertheless, both procedures apply to the (4) and (5) trivariate systems as well.

2.3. Estimation method

The appropriate method to estimate (2) and (3) depends on the properties of the error terms. If there is no contemporaneous correlation across countries, then each equation is a classical regression. Consequently, the equations can be estimated one-by-one with OLS and the OLS estimators of the parameters are the best linear unbiased estimators. On the other hand, in the presence of contemporaneous correlation across countries the OLS estimators are not efficient because they fail to utilise this extra information. In order to obtain more efficient estimators, the equations in (2), and also in (3), must be stacked and the two stacked equations can be estimated individually with the feasible generalised least squares or maximum likelihood methods. In this study we use the SUR estimator proposed by Zellner (1962).

Prior to estimation, we have to specify the number of lags. This is a crucial step because the causality test results may depend critically on the lag structure. In general, both too few and too many lags may cause problems. Too few lags mean that some important variables are omitted from the model and this specification error will usually cause bias in the retained regression coefficients, leading to incorrect conclusions. On the other hand, too many lags waste observations and this specification error will usually increase the standard errors of the estimated coefficients, making the results less precise.

Unfortunately, there is no simple rule to decide on the maximal lag, though there are formal model specification criteria to rely on. Ideally, the lag structure is allowed to vary across countries, variables and equation systems. However, for a relatively large panel like ours, this would increase the computational burden substantially. For this reason in each system we allow different maximal lags for *Y* and *X*, but do not allow them to vary across countries. This means that altogether there are four maximal lag parameters. Assuming that their range is 1–4, we estimate (2) and (3) for each

⁶ The stacked forms of (2) and (3) are shown in the Appendix.

⁷ The estimations were performed by the SUR routine of TSP4.5.

possible pair of mly_1 , mlx_1 and mly_2 , mlx_2 , respectively, and choose the combinations which minimize the Akaike Information Criterion (AIC) and Schwartz Criterion (SC) defined as:

$$AIC_k = \ln|\mathbf{W}| + \frac{2N^2q}{T} \tag{6}$$

and

$$SC_k = \ln|\mathbf{W}| + \frac{N^2 q}{T} \ln(T) \tag{7}$$

where **W** is the estimated residual covariance matrix, N is the number of equations, q is the number of coefficients per equation and T is the sample size, all in system k=1, 2. Occasionally, these two criteria select different lag lengths.

The SUR estimators are more efficient than the OLS estimators only if there is contemporaneous correlation in the system. Therefore, it is of interest to test whether the variance—covariance matrix of the errors is diagonal. For a given k, the null and alternative hypothesis are as follows:

 H_0 : $Cov(\varepsilon_{k,i,t}, \varepsilon_{k,j,t}) = 0$

 H_A : $Cov(\varepsilon_{k,i,t}, \varepsilon_{k,j,t}) \neq 0$ for at least one pair of $i \neq j$.

Table 1 Granger causality tests, bivariate models without trend

Country	Test. Stat.	Bootstrap critical values		
		1%	5%	10%
Australia	14.0354	46.3559	23.9342	16.5506
Austria	2.2599	62.8019	33.1471	22.4611
Belgium	49.9296**	84.3959	44.9849	31.5651
Canada	8.7767	56.7728	31.1144	21.2145
Denmark	47.5470***	46.7049	25.5098	17.5914
Finland	117.0711***	81.7748	46.7888	32.6505
France	1.1604	81.3904	47.5087	33.3071
Greece	1.6566	70.3146	36.0907	25.5742
Iceland	59.3819**	70.8289	36.5695	25.4032
Ireland	4.6040	59.3401	31.0093	20.6354
Italy	41.6957**	66.9769	36.2394	25.3153
Japan	0.5740	101.7512	57.9946	41.2662
Korea Rep.	14.7746	45.0959	26.4705	18.4592
Luxembourg	0.5566	83.2505	46.4273	32.5585
Mexico	0.0003	45.3087	22.5652	15.2157
Netherlands	1.5367	65.0687	35.2122	24.1087
New Zealand	18.2058*	47.7755	26.3025	17.9973
Norway	15.2294	77.0165	39.3330	27.1631
Portugal	12.9984	68.1022	38.3697	26.5469
Spain	34.1144**	39.5807	21.8654	14.7806
Sweden	52.4326**	57.3112	29.8017	20.2532
Switzerland	22.8821	65.4215	33.9300	23.4155
UK	1.6239	66.4740	38.2939	26.3185
USA	2.1799	68.6377	36.8282	25.5935

Note: ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

If H₀ is true there is no payoff to SUR. Assuming normality, Breusch and Pagan (1980), BP in brief, suggested the following Lagrange multiplier test statistic:

$$\lambda = T \sum_{i=2}^{N} \sum_{j=1}^{i-1} r_{ij}^{2} \tag{8}$$

where r_{ij} is the estimated correlation coefficient between $\varepsilon_{k,i,t}$ and $\varepsilon_{k,j,t}$ (for a given k and $i \neq j$) from individual OLS regressions. Under H₀, this statistic has an asymptotic chi-square distribution with N(N-1)/2 degrees of freedom (Greene, 2003, p. 350).

2.4. Testing for Granger causality

We consider all countries simultaneously so as to allow for contemporaneous correlation across countries, and test for Granger causality from X to Y in (2) and from Y to X in (3) performing Wald tests with country specific bootstrap critical values.

Bootstrapping is basically a re-sampling method. The main issue is how to generate and use the bootstrap samples. For the sake of simplicity, we focus on testing causality from X to Y in (2). A similar procedure is applied for causality from Y to X in (3). The procedure is as follows.

Table 2 Granger causality tests, bivariate models with trend

Country	Test. Stat.	Bootstrap critical values		
		1%	5%	10%
Australia	4.9274	44.9502	23.7773	15.8615
Austria	2.0903	46.0760	25.5603	17.7136
Belgium	40.7549**	67.2100	36.0454	25.9321
Canada	1.9880	50.4355	28.1825	19.0841
Denmark	1.9171	47.9771	25.7858	17.7085
Finland	95.9589***	67.3755	39.5021	28.0329
France	2.5671	58.9602	32.9669	23.3843
Greece	5.6056	55.7208	29.3109	19.5535
Iceland	48.1102**	52.1462	28.5711	19.6107
Ireland	24.0476**	38.9385	18.9367	12.6405
Italy	26.7408*	61.0029	32.8487	23.0069
Japan	0.5573	63.7872	34.6542	23.3168
Korea Rep.	11.2901	48.9211	26.4227	18.0600
Luxembourg	2.5827	45.5638	23.2729	15.7491
Mexico	3.9819	57.4964	30.9360	20.8873
Netherlands	0.9676	46.8398	25.2731	17.5979
New Zealand	1.0328	61.6849	31.9327	21.6903
Norway	1.2722	66.2453	33.2371	22.9609
Portugal	6.2695	59.1283	31.7518	21.7676
Spain	19.2891	58.0146	29.9086	20.4672
Sweden	54.5221**	75.0285	41.9063	28.8297
Switzerland	5.5612	52.6466	27.0917	18.5265
UK	1.0506	61.3449	33.3542	23.0641
USA	8.8579	83.5405	45.1425	30.6277

Note: ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Step 1: Estimate (2) under the null hypothesis that there is no causality from X to Y (i.e. imposing the $\gamma_{1,i,l}=0$ restriction for all i and l) and obtain the residuals

$$e_{\mathrm{H}_0,i,t} = y_{i,t} - \hat{\alpha}_{1,i} - \sum_{l=1}^{mly_1} \hat{\beta}_{1,i,l} y_{i,t-l}$$
 for $i = 1, \dots, N$ and $t = 1, \dots, T$.

From these residuals develop the $N \times T$ [$e_{H_0,i,t}$] matrix.

- Step 2: Re-sample these residuals. In order to preserve the contemporaneous cross-correlation structure of the error terms in (2), do not the draw the residuals for each country one-by-one, but rather randomly select a full column from the $[e_{\mathrm{H}_0,i,t}]$ matrix at a time. Denote the selected bootstrap residuals as $e_{H_0,i,t}^*$, where $t=1,\ldots,T^*$ and T^* can be greater than T.
- Step 3: Generate a bootstrap sample of Y assuming again that it is not caused by X, i.e. using the following formula:

$$y_{i,t}^* = \hat{\alpha}_{1,i} + \sum_{l=1}^{mly_1} \hat{\beta}_{1,i,l} y_{i,t-1}^* + e_{H_0,i,t}^*, \qquad t = 1, \dots, T^*$$
(9)

Step 4: Substitute $y_{i,t}^*$ for $y_{i,t}$, estimate (2) without imposing any parameter restrictions on it, and for each country perform the Wald test implied by the no-causality null hypothesis.

Table 3
Granger causality tests, trivariate models without trend

Country	Test. Stat.	Bootstrap critical values		
		1%	5%	10%
Australia	20.1310	70.8388	38.9654	27.1498
Austria	4.4312	56.8711	29.3511	19.7442
Belgium	8.3532	44.4521	25.0899	17.5941
Canada	50.3255**	77.6141	44.1090	31.5578
Denmark	24.8830**	40.3318	21.3206	14.9248
Finland	64.4543***	38.9966	20.4078	14.0350
France	0.3142	61.1686	32.1122	21.7349
Greece	4.0504	50.2856	26.4782	17.4576
Iceland	56.2137**	65.4543	34.9303	24.3757
Ireland	2.4428	31.6640	16.1893	11.0039
Italy	176.5551***	65.5361	35.4477	23.2992
Japan	7.7595	36.6456	19.4813	13.2128
Korea Rep.	15.4466	77.4050	40.9225	28.6700
Luxembourg	0.0460	61.6956	34.1923	23.6342
Mexico	0.2332	36.3429	19.5024	13.1556
Netherlands	2.9943	49.4201	29.0913	19.5493
New Zealand	0.1760	44.9626	23.6473	16.4965
Norway	2.8951	32.9314	17.2651	11.9219
Portugal	22.2611	75.1086	41.2025	28.3773
Spain	15.0647*	33.3295	18.3991	12.7532
Sweden	55.2470***	39.4812	20.9282	14.6339
Switzerland	4.0053	47.6054	25.8869	17.4781
UK	0.9630	54.2225	31.5985	22.4790
USA	1.0979	68.9215	36.3892	24.2719

Note: ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Step 5: Develop the empirical distributions of the Wald test statistics repeating steps 2–4 many times, and specify the bootstrap critical values by selecting the appropriate percentiles of these sampling distributions.

There are a few remarks to be made. In this study the common sample size for all countries is T=38 and the maximal lags are allowed to vary between 1 and 4, inclusively. In *Steps 2* and 3, depending on the lag structure, we draw at least $T^*=68$ bootstrap residuals and generate the same number of bootstrap $y_{i,t}^*$ values for each country. To commence the recursive algorithm defined by (7) the first 2-5 $y_{i,t}^*$ values are set to zero and, to minimize the effect of this initialization onto the results, in *Step 4* the Wald tests are performed over only the last 34-37 values. In *Step 5*, the bootstrap distribution of each test statistic is derived from 10,000 replications.

3. Empirical results

Apart from the lag structure, we have used eight different specifications: the (2), (3) bivariate and the (4), (5) trivariate systems, both without and with a linear time trend. The time trend is a proxy variable that might substitute for some variables that are missing from the original specifications. In the trivariate models, for the sake of simplicity, we assumed that $mlz_1 = mlx_1$ in (4) and that $mlz_2 = mly_2$ in (5).

Table 4
Granger causality tests, trivariate models with trend

Country	Test. Stat.	Bootstrap critical values		
		1%	5%	10%
Australia	20.6420*	47.9166	24.5841	17.1082
Austria	2.0723	52.7526	26.6879	18.3595
Belgium	8.3174	42.8557	23.3806	16.1799
Canada	46.5293**	59.1462	33.8297	23.8910
Denmark	2.9905	42.6331	23.5976	16.2990
Finland	81.9133***	38.1726	21.2960	15.2674
France	1.6366	51.4130	28.7956	19.5556
Greece	5.7806	37.3312	19.1748	13.2258
Iceland	35.2216***	33.8635	17.9201	12.3765
Ireland	10.8147	38.4173	20.1125	13.5368
Italy	138.2330***	51.1509	27.7067	18.2875
Japan	4.7571	51.1845	26.0837	17.9016
Korea Rep.	8.2592	52.6153	28.5190	19.2131
Luxembourg	0.0360	27.1431	15.3509	10.3613
Mexico	2.3028	31.4106	16.7033	11.3480
Netherlands	28.3924**	50.5739	26.9187	18.5134
New Zealand	0.0653	53.1587	26.6861	17.8886
Norway	0.9634	52.0038	27.9259	18.8886
Portugal	12.6993	60.8617	31.6792	21.3500
Spain	8.1976	42.3827	23.1044	15.4865
Sweden	77.7667***	47.0224	25.3123	16.8852
Switzerland	3.9464	44.6977	23.5394	16.0739
UK	0.6244	57.7400	30.4047	20.7797
USA	5.1053	56.3187	30.7782	21.4997

Note: ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Table 5
Granger causality tests, bivariate models without trend

Country	Test.	Bootstrap critical values		
	Stat.	1%	5%	10%
Australia	0.8819	98.3000	57.7863	42.1248
Austria	15.9799	115.7287	70.3122	52.0452
Belgium	0.4013	111.7765	67.3121	49.5530
Canada	0.6753	113.3162	72.0254	53.1896
Denmark	1.4953	62.6198	33.6888	22.5928
Finland	6.3672	128.6086	76.5622	55.1843
France	37.4613	96.8379	57.5567	41.7498
Greece	27.7548	96.8532	54.7762	40.4995
Iceland	4.6933	93.1382	54.0679	39.2226
Ireland	2.1777	109.7144	66.1653	48.9091
Italy	0.1459	93.6821	54.3334	39.3522
Japan	45.8411*	106.3809	59.6395	44.2198
Korea Rep.	0.0682	91.3334	49.9548	35.9302
Luxembourg	0.1002	67.3298	39.6455	26.9615
Mexico	14.7100	75.7252	44.7650	32.7233
Netherlands	17.6714	123.3528	74.2962	53.8880
New Zealand	2.3334	92.6045	51.6368	36.1042
Norway	0.2159	75.7752	41.5942	28.4166
Portugal	0.7087	89.8361	54.3521	39.6245
Spain	0.2952	85.9868	46.3169	32.1964
Sweden	27.3850	100.7840	58.3013	42.1561
Switzerland	12.9077	94.1938	53.3470	37.3508
UK	4.1126	74.4471	39.4244	27.9551
USA	2.7763	53.6381	29.1731	20.4057

Note: ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

H₀: LNGDP does not cause LNEXP.

In each case the analysis consisted of three stages. We started with SUR for all possible pairs of maximal lags, and selected mly_1 , mly_2 , mlx_1 and mlx_2 by minimizing the (6) and (7) model selection criteria. Interestingly, AIC and SC always took their smallest values at a single lag for each variable. Overall, the bivariate systems without time trend generated the lowest, and the trivariate systems with time trend generated the highest AIC and SC values. Yet, since the correct specification might change from country to country, we kept all eight options alive. Then, we performed the BP test. In all eight cases we could reject the null hypothesis of no contemporaneous correlation within the system even at the half percent significance level, justifying the application of SUR. Finally, we tested for Granger causality with Wald tests and country specific bootstrap critical values from LNEXP to LNGDP in (2) and (4), and from LNGDP to LNEXP in (3) and (5). Since our main interest is in testing for causality, only these latter results are reported in this paper.

3.1. Causality from LNEXP to LNGDP

The Granger causality test results for the null hypothesis *LNEXP does not cause LNGDP* are shown in Tables 1–4. Notice that the bootstrap critical values are substantially higher than the chi-square critical values usually applied with the Wald test, and that they vary considerably from

⁸ On request, all the details are available to interested readers.

Table 6
Granger causality tests, bivariate models with trend

Country	Test. Stat.	Bootstrap critical values		
		1%	5%	10%
Australia	0.3307	43.3755	23.0001	15.5643
Austria	35.4676*	86.4247	47.1006	33.8906
Belgium	0.0002	57.5291	30.8494	21.3749
Canada	4.3071	46.3592	26.4467	18.8979
Denmark	13.9720	43.4269	23.0596	15.9555
Finland	46.3945**	67.3102	35.7893	24.8318
France	56.6527**	81.3019	47.7234	33.8019
Greece	61.6615**	63.3730	34.3919	23.9783
Iceland	0.1003	48.8035	26.7032	18.1656
Ireland	0.9425	54.0794	28.3393	18.8245
Italy	0.6928	51.0959	26.7375	18.1925
Japan	33.6077*	79.7445	43.8029	30.9001
Korea Rep.	9.5427	51.9153	28.0543	19.0599
Luxembourg	0.4512	68.6783	39.2664	27.0169
Mexico	0.4909	68.3765	34.8457	24.0258
Netherlands	14.5229	90.0013	52.2619	37.5673
New Zealand	0.0131	53.3064	28.2870	19.8061
Norway	10.6962	38.4943	20.3301	13.4083
Portugal	16.0039*	37.8578	19.6813	13.5150
Spain	1.2708	68.2161	37.3349	26.1451
Sweden	40.7920*	86.3040	48.1827	33.1017
Switzerland	2.9082	61.6371	34.8936	24.4103
UK	2.4230	52.3366	28.7249	19.8541
USA	4.6243	34.1554	23.3234	16.0332

Note: ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

H₀: LNGDP does not cause LNEXP.

country to country and from table to table. Yet, for 16 out of the 24 countries the tests are robust in the sense that they lead to the same conclusion regardless of the specification. Namely, at the 10% significance level there is not sufficient evidence against the null hypothesis in the case of Austria, France, Greece, Japan, Korea, Luxembourg, Mexico, Norway, Portugal, Switzerland, the UK and the USA, while it can be rejected in the case of Finland, Iceland, Italy and Sweden.

As for the remaining 8 countries (Australia, Belgium, Canada, Denmark, Ireland, the Netherlands, New Zealand and Spain), the test results are contradictory and without further analysis it is not possible to decide which specification to prefer. Although the overall AIC, SC measures supported the bivariate systems without the time trend, this specification is not necessarily best for every country. For this reason, we have also calculated the following single-equation versions of (6) and (7):

$$AIC_i = \ln(\hat{\sigma}_{i,i}^2) + \frac{2q}{T} \tag{10}$$

and

$$SC_i = \ln(\hat{\sigma}_{i,i}^2) + q \frac{\ln T}{T} \tag{11}$$

⁹ The chi-square critical values for one degree of freedom, i.e. for Wald tests with a single restriction, are 6.6349 (1%), 3.8415 (5%) and 2.7055 (10%).

where i refers to the country (i=1,2,...,N) and $\hat{\sigma}_{i,i}^2$ is the variance of the residuals from the ith equation, i.e. the (i,i)th element of the estimated residual covariance matrix, **W**. These criteria select the bivariate model without time trend for Australia, Belgium, Denmark, New Zealand and Spain, the bivariate model with time trend for Ireland, the trivariate model without time trend for Australia and Canada, and the trivariate model with a time trend for the Netherlands. Consequently, we reject the null hypothesis in the case of Belgium, Canada, Denmark, Ireland, the Netherlands, New Zealand and Spain, but maintain it for Australia.

In summary, there is evidence of exports Granger-causing growth at the 5% or lower significance level in Belgium, Canada, Denmark, Finland, Iceland, Ireland, Italy, the Netherlands, Spain and Sweden, and at the 10% level in New Zealand.

3.2. Causality from LNGDP to LNEXP

The Granger causality test results for the null hypothesis *LNGDP does not cause LNEXP* are shown in Tables 5–8. This time, the test results are unambiguous for 13 out of the 24 countries. There is not sufficient evidence against the null hypotheses, not even at the 10% significance level, in the case of Australia, Belgium, Iceland, Ireland, Italy, Korea, Luxembourg, New Zealand, Spain, Switzerland, the UK and the USA, but it can be rejected for Japan.

Table 7
Granger causality tests, trivariate models without trend

Country	Test. Stat.	Bootstrap critical values		
		1%	5%	10%
Australia	18.4669	92.9481	55.4531	40.2989
Austria	18.4063	81.9743	46.7939	33.3903
Belgium	11.3644	37.5814	20.6099	14.2706
Canada	0.5803	94.1784	55.9398	41.5133
Denmark	3.0132	39.2341	20.2542	13.9073
Finland	1.5883	33.6595	18.2407	12.6130
France	57.9532***	50.5674	29.0961	20.8293
Greece	50.1496**	60.4609	31.6846	22.1718
Iceland	5.3795	57.0858	30.6256	21.3012
Ireland	0.1711	34.5615	18.3770	12.3687
Italy	0.3993	30.4559	16.0901	10.8139
Japan	37.3399***	37.1087	21.5716	14.7479
Korea Rep.	1.9969	48.2031	27.0832	18.9960
Luxembourg	1.7402	42.1811	22.9960	15.4688
Mexico	16.5632*	35.0900	20.0979	13.7748
Netherlands	19.5892	69.9783	39.3454	27.5250
New Zealand	1.6898	69.4404	39.0297	27.5560
Norway	0.3292	62.0416	36.5409	25.9934
Portugal	0.4846	41.9566	21.8595	14.9851
Spain	0.2214	40.4031	20.9357	14.2798
Sweden	20.8996*	37.4208	21.1919	14.4703
Switzerland	0.1063	61.4697	34.6876	24.7604
UK	4.7013	47.1445	25.9812	17.8356
USA	0.8040	27.6822	15.2195	10.2969

Note: ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively. H_0 : LNGDP does not cause LNEXP.

Table 8
Granger causality tests, trivariate models with trend

Country	Test. Stat.	Bootstrap critical values		
		1%	5%	10%
Australia	1.1421	35.3809	18.3251	12.6579
Austria	27.9341*	53.6904	29.9627	20.6628
Belgium	14.5016	52.6378	26.8427	18.0250
Canada	24.3781**	42.5754	23.1491	15.8331
Denmark	18.3794*	48.6563	24.9390	17.3463
Finland	9.3529	29.5567	17.0451	11.4237
France	57.4876***	40.5761	22.8344	16.1348
Greece	54.7808***	42.7186	23.6121	15.9743
Iceland	0.0426	33.3752	17.6697	11.9799
Ireland	0.0810	37.3879	19.0692	13.0853
Italy	0.9626	45.7625	23.6018	16.2401
Japan	17.3196*	43.4852	22.9667	15.4694
Korea Rep.	6.8006	45.4066	23.5793	15.9233
Luxembourg	4.5059	54.1428	28.4616	19.7105
Mexico	4.3484	38.2491	19.5170	13.3698
Netherlands	52.8830**	58.8734	34.0082	23.5373
New Zealand	3.8092	51.4202	26.0709	18.0444
Norway	23.8289***	23.0985	12.4356	8.2334
Portugal	13.9020*	26.8409	14.3682	10.0393
Spain	0.0037	38.2585	19.7929	13.3334
Sweden	35.0152***	31.6064	17.9438	11.9494
Switzerland	0.0474	62.7892	36.0616	25.3582
UK	3.1047	46.5452	25.2914	17.4810
USA	3.1096	41.8270	22.8301	15.6436

Note: ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

H₀: LNGDP does not cause LNEXP.

In the other 11 cases the (10) and (11) statistics suggest the bivariate model without time trend for Sweden, the bivariate model with time trend for Austria, Denmark, Finland, Portugal and Sweden, the trivariate model without time trend for France, Greece and Mexico, and the trivariate model with time trend for Canada, France, the Netherlands and Norway. Therefore, we reject the null hypothesis in the case of Austria, Canada, Finland, France, Greece, Mexico, the Netherlands, Norway and Portugal, but maintain it for Denmark. As for Sweden, the two models selected by AIC and SC lead to contradictory outcomes.

In summary, there is evidence of growth Granger-causing exports at the 5% or lower significance level in Canada, Finland, France, Greece, the Netherlands, Norway, and at the 6–10% level in Austria, Japan, Mexico and Portugal.

4. Concluding remarks

This paper studies the possibility of Granger causality between the logarithms of real exports and real GDP in 24 OECD countries from 1960 to 1997. A new panel-data approach has been applied which is based on SUR systems and Wald tests with country specific bootstrap critical values. This approach has two advantages. On the one hand, it does not assume that the panel is homogeneous, so it is possible to test for Granger-causality on each individual panel member separately. However, since contemporaneous correlation is allowed across countries, it makes

possible to exploit the extra information provided by the panel data setting. On the other hand, this approach does not require pretesting for unit roots and cointegration, though it still requires the specification of the lag structure. This is an important feature since the unit-root and cointegration tests in general suffer from low power, and different tests often lead to contradictory outcomes.

Two different models have been used. A bivariate (*GDP–exports*) model and a trivariate (*GDP–exports–openness*) model, both without and with a linear time trend. In each case the analysis focussed on direct, one-period-ahead causality between exports and GDP. All things considered, our 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 between these variables.

Finally, it is important to mention that Granger causality between exports and GDP does not necessarily mean that the ELG or GDE hypothesis is valid. The signs of the regression coefficients involved in the causality tests are also crucial since the ELG and GDE hypotheses imply *positive* effects. Hence, in (2) and (4) the $\gamma_{1,i,1}$ parameters, while in (3) and (5) the $\beta_{2,i,1}$ parameters are expected to be positive (i=1,...,N). Indeed, the estimates of $\gamma_{1,i,1}$ in the preferred specifications are positive in all those cases when causality is detected from exports to GDP, with the exception of the Netherlands. However, in four out of the nine cases when causality is detected from GDP to exports, namely Canada, Finland, Norway and Portugal, the estimates of $\beta_{2,i,1}$ are negative.

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Appendix A

For the *i*th panel member (2) and (3) can be written in matrix form as

$$\mathbf{Y}_{i} = \alpha_{1,i} \mathbf{I} + \mathbf{Y}_{1,i}^{*} \boldsymbol{\beta}_{1,i} + \mathbf{X}_{1,i}^{*} + \boldsymbol{\gamma}_{1,i} + \boldsymbol{\varepsilon}_{1,i}$$
(2*)

and

$$\mathbf{X}_{i} = \alpha_{2,i}\mathbf{I} + \mathbf{Y}_{2,i}^{*}\boldsymbol{\beta}_{2,i} + \mathbf{X}_{2,i}^{*}\boldsymbol{\gamma}_{2,i} + \boldsymbol{\varepsilon}_{2,i}$$

$$(3*)$$

where \mathbf{t} is a $T \times 1$ vector of ones, \mathbf{Y}_i and \mathbf{X}_i are $T \times 1$ vectors of the observed values of Y and X, $\mathbf{Y}_{1,i}^*$, $\mathbf{X}_{1,i}^*$, $\mathbf{Y}_{2,i}^*$ and $\mathbf{X}_{2,i}^*$ are $T \times mly_1$, $T \times mly_2$ and $T \times mlx_2$ matrices of lagged Y and X values, $\varepsilon_{1,i}$ and $\varepsilon_{2,i}$ are $T \times 1$ vectors of the values of the error variables, $\alpha_{1,i}$ and $\alpha_{2,i}$ are the intercept terms, and $\boldsymbol{\beta}_{1,i}$, $\boldsymbol{\gamma}_{1,i}$, $\boldsymbol{\beta}_{2,i}$ and $\boldsymbol{\gamma}_{2,i}$ are $mly_1 \times 1$, $mlx_1 \times 1$, $mly_2 \times 1$ and $mlx_2 \times 1$ vectors of the slope coefficients, all for country i.

Stacking the equations for all i (i=1,...,N), the two sets of equations can be written as

$$\mathbf{Y} = \mathbf{\alpha}_1 + \mathbf{Y}_1^* \boldsymbol{\beta}_1 + \mathbf{X}_1^* \boldsymbol{\gamma}_1 + \boldsymbol{\varepsilon}_1 \tag{2**}$$

and

$$\mathbf{X} = \mathbf{\alpha}_2 + \mathbf{Y}_2^* \mathbf{\beta}_2 + \mathbf{X}_2^* \mathbf{\gamma}_2 + \mathbf{\varepsilon}_2 \tag{3**}$$

where

$$\mathbf{Y} = \begin{bmatrix} \mathbf{Y}_1 \\ \mathbf{Y}_2 \\ \vdots \\ \mathbf{Y}_N \end{bmatrix}, \mathbf{X} = \begin{bmatrix} \mathbf{X}_1 \\ \mathbf{X}_2 \\ \vdots \\ \mathbf{X}_N \end{bmatrix}, \boldsymbol{\alpha}_1 = \begin{bmatrix} \alpha_{1,1} \boldsymbol{\iota} \\ \alpha_{1,2} \boldsymbol{\iota} \\ \vdots \\ \alpha_{1,N} \boldsymbol{\iota} \end{bmatrix}, \boldsymbol{\alpha}_2 = \begin{bmatrix} \alpha_{2,1} \boldsymbol{\iota} \\ \alpha_{2,2} \boldsymbol{\iota} \\ \vdots \\ \alpha_{2,N} \boldsymbol{\iota} \end{bmatrix}, \boldsymbol{\varepsilon}_1 = \begin{bmatrix} \boldsymbol{\varepsilon}_{1,1} \\ \boldsymbol{\varepsilon}_{1,2} \\ \vdots \\ \boldsymbol{\varepsilon}_{1,N} \end{bmatrix}, \boldsymbol{\varepsilon}_2 = \begin{bmatrix} \boldsymbol{\varepsilon}_{2,1} \\ \boldsymbol{\varepsilon}_{2,2} \\ \vdots \\ \boldsymbol{\varepsilon}_{2,N} \end{bmatrix}$$

are $NT \times 1$ vectors,

$$\mathbf{Y}_{1}^{*} = \begin{bmatrix} \mathbf{Y}_{1,1}^{*} & \mathbf{0} & \dots & \mathbf{0} \\ \mathbf{0} & \mathbf{Y}_{1,2}^{*} & \dots & \mathbf{0} \\ \vdots & \vdots & \vdots & \vdots \\ \mathbf{0} & \mathbf{0} & \dots & \mathbf{Y}_{1,N}^{*} \end{bmatrix}, \mathbf{X}_{1}^{*} = \begin{bmatrix} \mathbf{X}_{1,1}^{*} & \mathbf{0} & \dots & \mathbf{0} \\ \mathbf{0} & \mathbf{X}_{1,2}^{*} & \dots & \mathbf{0} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \mathbf{0} & \mathbf{0} & \dots & \mathbf{X}_{1,N}^{*} \end{bmatrix}$$
$$\mathbf{Y}_{2}^{*} = \begin{bmatrix} \mathbf{Y}_{2,1}^{*} & \mathbf{0} & \dots & \mathbf{0} \\ \mathbf{0} & \mathbf{Y}_{2,2}^{*} & \dots & \mathbf{0} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \mathbf{0} & \mathbf{0} & \dots & \mathbf{Y}_{2,N}^{*} \end{bmatrix}, \mathbf{X}_{2}^{*} = \begin{bmatrix} \mathbf{X}_{2,1}^{*} & \mathbf{0} & \dots & \mathbf{0} \\ \mathbf{0} & \mathbf{X}_{2,2}^{*} & \dots & \mathbf{0} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \mathbf{0} & \mathbf{0} & \dots & \mathbf{X}_{2,N}^{*} \end{bmatrix}$$

are $NT \times Nmly_1$, $NT \times Nmlx_1$, $NT \times Nmly_2$ and $NT \times Nmlx_2$ matrices, and

$$oldsymbol{eta}_1 = egin{bmatrix} oldsymbol{eta}_{1,1} \ oldsymbol{eta}_{1,2} \ oldsymbol{eta}_{1,N} \end{bmatrix}, oldsymbol{\gamma}_1 = egin{bmatrix} oldsymbol{\gamma}_{1,1} \ oldsymbol{\gamma}_{1,2} \ oldsymbol{eta}_{2,N} \end{bmatrix}, oldsymbol{eta}_2 = egin{bmatrix} oldsymbol{eta}_{2,2} \ oldsymbol{eta}_{2,N} \ oldsymbol{eta}_{2,N} \end{bmatrix}, oldsymbol{\gamma}_2 = egin{bmatrix} oldsymbol{\gamma}_{2,1} \ oldsymbol{\gamma}_{2,2} \ oldsymbol{eta}_{2,N} \end{bmatrix}$$

are $N mly_1 \times 1$, $N mlx_1 \times 1$, $N mly_2 \times 1$ and $N mlx_2 \times 1$ vectors.

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