Abstract

The long-run impact of export growth on the growth of the entire economy is a key issue for policymakers in emerging countries. There is a vast body of empirical research with respect to this issue, especially addressing the case of India, in which cointegration techniques as well as long-run Granger causality analysis are applied to exports and GDP series. However, results are inconclusive which can be attributed to differences in the choice of econometric approaches, the considered sample period and omitted variable biases. To address these issues, we apply both linear as well as non-parametric cointegration techniques for non-linear functional forms, we apply an innovative bootstrapping procedure to examine the robustness of results with respect to the selection of sample periods, and we include imports as third variable as imports may be the relevant variable with a causal link towards GDP instead of exports. We show that there is linear cointegration between exports and GDP which is likely to render the non-parametric cointegration test ineffective. Moreover, we obtain the result that the selection of the sample period is an important determinant for the inference whether there is cointegration or not. We find that evidence for the causality from exports to GDP is less robust than the causality from GDP to exports.

JEL: F43, O11, O53
Keywords: Economic Growth, Export-led Growth Hypothesis, Nonlinear Cointegration Test
1. Introduction

How to increase the Gross Domestic Product (GDP) and which economic variables can influence the behavior of economic growth is among the key research topics in economics. In the course of the past decades, international trade grew at unprecedented levels. There is a large body of literature that studies the relationship between international trade and output growth. Although the number of contributions is large, it is possible to identify a main hypothesis in this respect called the “exports-led growth (ELG) hypothesis”. This hypothesis reflects the causal link from exports to economic growth: the increase of export may lead to the accomplishment of a certain degree of economic development of the country. We therefore examine the validity of the export-led growth (ELG) hypothesis in this study. Dash (2009) suggests the following reasons for the validity of the ELG hypothesis: (1) comparative advantages brought by fostering specialization in exporting industries; (2) utilizing the optimum capacity of the plant size wherever possible in the economy as a whole and in the exporting industry as well as upstream and down-stream firms in particular; (3) reaping the getting benefits of economies of scale brought by new and (opening of) larger markets; (4) advantages brought from R&D expenses made in particular by export competing industries; and (5) a boost in economic growth particularly in developing countries brought by rapidly increasing exports through generation of adequate amounts of foreign exchange that allow for more imports of intermediate goods including advanced technology know-how that in turn raises capital formation. The empirical validity of the ELG hypothesis has important implications particularly for those economies in which policy-makers make decision on external and internal policies based on the exports performance of the countries. For example, exports expansion can contribute directly to the economic growth of an economy being a component of GDP. Apart from this, ELG policies can increase employment opportunities as well as real wage, provided that there is a high foreign demand related to the exportable goods of an economy.

In this study we consider the case of India due to several reasons. India is among those developing nations whose export sector has expanded more rapidly than the country’s real output, particularly in the post-reform period. During the pre-reform period India’s GDP growth rate was about 3.5% on average what is known as ‘Hindu Rate of Growth’ in the literature (see e.g. Rodrik and Subramanian, 2004). However, during the post-reform period it has increased significantly (during 2000-2013 it was 7% p.a.) and in 2010 it was double digit. Since 2002
Aviral Kumar Tiwari, Alexander Ludwig and Besma Hkiri (2014). Cointegration and causality between India’s exports and GDP: A sample period-robust testing framework, Economic Research (forthcoming)

India has maintained a growth rate of more than 5% except for 2013. The export sector experienced similar changes. In the pre-reform period and even in the early reform period (i.e. during 1993-2005) India’s export growth was not distinctly higher than its GDP growth. Yet, since 2002 it has accelerated rapidly (see Veeramani, 2007). In fact, in the post-reform period the actual growth of exports has been above the potential offered by the growth of world demand (Veeramani, 2007). The reason for such buoyant growth in India’s merchandise sector may be, among others, the persistent and sound domestic trade policies encompassing both bilateral and multilateral levels which have resulted in a surge in the export competitiveness in a wide range of sectors. According to the WTO release of March 2014, India’s trade to GDP ratio amounted to 51.2% during 2010-12 and in merchandise exports India was ranked 19th in 2012. The share of merchandise trade in relation to India’s GDP increased from 12.1 % in 1980 to 15.6% in 1993 and further to 42.1% in 2012. During the same periods, India’s exports of goods and services as a ratio of GDP, respectively, have been 6%, 10%, and 24%. India’s share in total world trade already grew to more than 1%. Thus, given the importance of India’s growth and trade and in the world market and that India has been consistently putting efforts to boost the exports sector in every five year plan of hers, we consider India as a special case to be studied.

Empirical results in the literature regarding the validity of the ELG hypothesis are manifold, for which we provide a brief overview in the following. Dhawan and Biswal (1999) examined the ELG hypothesis for India using cointegration and a vector autoregressive (VAR) model covering the period 1961-93. They found that there is one long-run equilibrium relationship among three considered variables (real GDP, real exports and terms of trade), and the Granger-causality runs from the growth in GDP and terms of trade to the growth in exports. Ekanayake (1999) tested the ELG hypothesis for eight Asian developing countries using data for the period 1960-1997 employing cointegration and error-correction models and found evidence for cointegration between exports and GDP for India and bi-directional causality between export growth and economic growth. Kemal et al. (2002) found support for cointegration for India’s GDP and exports in the period 1960-1998 and for bidirectional long-run causality between these variables. On the other hand, covering the period 1980-2000, Chandra (2002) did not find cointegration relations between India’s real exports and real GDP. Love and Chandra (2005) tested the ELG

---


hypothesis for South Asian countries including India in the period 1950-1998 employing residual-based cointegration and error-correction models. They did not find evidence for cointegration between exports and GDP. Using linear cointegration as well as non-linear cointegration tests, Sharma and Panagiotidis (2005) examined the validity of the ELG hypothesis for India covering the period 1971–2001. They neither found significant evidence for cointegration nor for the ELG hypothesis.

Raju and Kurien (2005) employed cointegration and Granger-causality tests to test the ELG hypothesis in India covering the pre-reform period 1960-92. They found significant evidence of uni-directional causality running from exports to economic growth using Granger causality regressions based on stationary variables, with and without an error-correction term. Using data for India in the post-liberalization period 1992-2007, Dash (2009) found the existence of a long-run relationship between output and exports, and a unidirectional Granger-causality running from exports to GDP. Using data from 1950-2004 for India and employing Johansen’s cointegration and error correction model, Haldar (2009) found evidence for the ELG hypothesis. Pradhan (2010) tested the ELG hypothesis for India using the Engle-Granger residual-based and Johansen’s cointegration approach for the period 1970-2010. In both approaches the author finds support for cointegration and using the Engle-Granger residual-based error-correction approach the ELG hypothesis was supported. Mishra (2011) investigated the ELG hypothesis for India covering the period 1970-2009 and utilizing cointegration and vector error correction estimation. The author showed the existence of a long-run equilibrium relation between the variables but his tests rejected the validity of the ELG hypothesis.

Inconsistent results among studies are likely to be due to 1) the selection of the econometric approach, 2) the selection of differing data samples, 3) the omission of relevant variables such as imports which leads to omitted variable biases, or 4) even a combination of some of these points. This paper contributes to the literature as it tries to solve for these aspects. First, besides standard linear cointegration models, we apply non-linear cointegration techniques that do not require a specification of the functional form of the model equation. They can thus cover a wide range of (true but unknown) functional specifications between the variables. Second, we propose a bootstrapping approach to examine the robustness of test results with respect to the sample period considered. To the authors’ best knowledge, this approach is a first attempt to systematically analyze the effects of sample selection. Third, we expand on the conventional ELG hypothesis including a third variable (imports). There are a few numbers of studies that consider imports as a control variable. Failure to control for imports may lead to a spurious
relationship between exports and economic growth as export growth is usually associated with rapid import growth. Further, imports typically serve as important intermediary goods and may lead to significant technology progress (Tang, 2013). Consequently, when imports are not included the problem of omitted variables bias is likely to occur as the relationship found to happen between exports and economic growth may be between imports and economic growth.

The article is organized as follows. Section 2 describes the econometric methodology adopted in this work. Section 3 presents the empirical results and Section 4 concludes.

2. Methodology

In this section we provide the methodological background for the linear cointegration analysis (Section 2.1), the non-linear cointegration analysis (Section 2.2) and how we embed these approaches into a sample-period robust testing framework (Section 2.3).

2.1. Linear Cointegration Analysis

Consider an \( n \)-dimensional time series \( y_t \) with possible time trend. A vector autoregressive process with \( p \) lags, VAR \((p)\), is defined by

\[
y_t = \omega_t + \eta_1 y_{t-1} + \ldots + \eta_p y_{t-p} + \xi_t \tag{1}
\]

where the error term, \( \xi_t \), is assumed to be Gaussian, \( \omega_t \) is an \( n \)-dimensional vector of constants and \( y_t \) is an integrated process of order \( 1 \), i.e. \( I(1) \). A vector error-correction representation for the VAR \((p)\) process could be written as follows:

\[
\Delta y_t = \omega_t + \Pi y_{t-1} + \eta_1^* \Delta y_{t-1} + \ldots + \eta_{p-1}^* y_{t-p+1} + \xi_t \tag{2}
\]

where \( \eta_j^* = -(I - \sum_{i=1}^{j} \eta_i) \) for \( j=1,\ldots,p-1 \) and \( \Pi = -(I - \sum_{i=1}^{p} \eta_i) \). The term \( \Pi y_{t-1} \) in equation (2) is referred to as the error-correction term. The coefficient matrix \( \Pi \) contains information about the long-run relationships between the variables. Three cases are of interest in relation to \( \Pi \). If rank \((\Pi) = n\), the matrix \( \Pi \) has full rank and \( y_t \) is stationary. The vector error-correction model (VECM) is not informative and \( y_t \) can be studied directly. If rank \((\Pi) = 0\), this implies that the matrix \( \Pi \) is a null matrix and \( y_t \) is not cointegrated. Then equation (2) corresponds to a traditional VAR model with differenced time series. Finally, if rank(\( \Pi \)) = \( r \in [1,n-1] \),
Johansen (1988) proposed likelihood ratio (LR) tests for the hypothesis of \( r \) cointegrating vectors. The cointegrating rank \( r \) can be tested using two statistics, the trace and the maximal eigenvalue statistics. However, Cheung and Lai (1993), among others, suggested that the trace test shows more robustness to both skewness and excess kurtosis in the residuals than the maximal eigenvalue test. Hence, we apply the trace statistic in this paper.

In the application of the Johansen (1988) tests for cointegration the limiting distribution depends on the deterministic function \( \omega_t \) in the dynamic model. We therefore use the Pantula principle (Johansen 1992, 1995) for an appropriate specification of the model.\(^2\) Applying the Pantula principle, both the correct rank order and the deterministic component are determined jointly. We can summarize the procedure related to the Pantula principle as follows. First of all, different specifications of the models are estimated and the results are presented from the most restrictive to the least restrictive alternative. The models employed are Model A which includes an intercept in the cointegration relation, Model B which allows deterministic trends in levels, and Model C which allows for trends in the cointegration space. Thereafter, the test procedure is to move through from the most restrictive model to the least (that is move from Model A to Model C) and compare the trace test statistic to its critical value at each stage. We stop this selection process at the first time when the null hypothesis is not rejected.

In the case cointegration vectors are found, we can examine long-run Granger causality by applying likelihood ratio tests on the error-correction terms in the VECM (cf. Johansen, 1988). If the speed of adjustment coefficient related to a variable is significant, this variable reacts on shocks to the equilibrium path of the system of variables in the long-run.

Linear cointegration tests are likely to lead to the rejection of cointegration in cases of nonlinearities in the relationships between variables. Economic and financial series may be characterized by nonlinearities that rise at times of structural breaks. According to Beak and Brock (1992), linear tests are merely sensitive to causality in the conditional mean, so these tests may not be appropriate to identify nonlinear effects on the conditional distribution (Ajmi et al. 2013). In this view, nonparametric approaches are interesting in order to detect nonlinear

\(^2\) In testing the ELG hypothesis, the Pantula principle for selecting an appropriate specification of the cointegration test was applied, among others, by Love and Chandra (2005), Dawson (2006) and Lim et al. (2010). Our elaborations on this test is adopted from Lim et al. (2010).
2.2. Non-linear cointegration analysis

Suppose a time series \( y_t \) is a function of another time series \( x_t \) of the following form:

\[
y_t = f(x_t) + \xi_t,
\]

(3)

where, \( y_t \sim I(1) \) and \( f(x_t) \sim I(1) \), and \( \xi_t \) represents stochastic disturbances.\(^3\) Linear cointegration tests are based on the assumption that \( f(x_t) \) is a linear function of \( x_t \). Breitung (2001) proposed a cointegration test based on rank transformations of the time series. The advantage of the rank test is that a sequence of ranks is invariant to monotone transformations of the data, i.e. if \( x_t \) is a random walk then the ranked series of \( x_t \) behaves like a random walk as well. Correspondingly, if two series are possibly nonlinearly cointegrated, the ranked series are cointegrated as well. Therefore, by the rank transformation one does not have to specify functional forms of the cointegrating relationship. The application of the rank test is based on a measure of the distance between the ranked series. If the test statistic assumes values smaller than the appropriate critical value, this result is evidence against the null hypothesis of no cointegration in favor of the alternative hypothesis of cointegration. In this case the variables move closely together over time and do not drift too far apart. Hence, such a test checks whether the ranked series move together over time towards a long-run cointegrating equilibrium that may be linear or nonlinear.

Following Breitung (2001), we can define a ranked series as \( R(w_t) = \text{Rank of } w_t \) among \( (w_1, w_2, ..., w_T) \), where \( w = \{y, x\} \). Two consistent rank test statistics based on the differences between the sequences of ranks are defined as follows:

\[
B_1 = T^{-1} \sup_{1 \leq i \leq T} \left| d_i \right|,
\]

(4)

and

\[
B_2 = T^{-3} \sum_{t=1}^{T} d_i^2,
\]

(5)

\(^3\) This section is largely based on Chang et al. (2011).
where \( d_t = R(y_t) - R(x_t) \). These tests are only meaningful if \( R(y_t) \) and \( R(x_t) \) are both monotonically increasing or decreasing. Otherwise, if there is a cointegration relationship with negative slope parameter, the test would not reject the null of no cointegration (see the discussion in Liew et al., 2012). We check this assumption before applying the test in Section 3.2.

The above test statistics are developed under the assumption that the time series \( y_t \) and \( f(x_t) \) are mutually and serially uncorrelated random walks. To relax this assumption, Breitung (2001) suggests that the monotonic functions of \( x_t \) and \( y_t \) may converge with correlation coefficient \( \rho \). If the value of \( \rho \) is small, the test statistics contain the following corrections:

\[
B_1^* = \frac{\sup |d_t|}{T \hat{\sigma}_{\Delta d}},
\]

and

\[
B_2^* = \frac{\sum_{t=1}^{T} d_t^2}{T^3 \hat{\sigma}^2_{\Delta d}},
\]

where: \( \hat{\sigma}^2_{\Delta d} = T^{-2} \sum_{t=1}^{T} (d_t - d_{t-1})^2 \) is used to adjust for the possible correlation between the two series of interest. If \( |\rho| \) is close to 1, the test statistics \( B_1^{**} \) and \( B_2^{**} \) should be obtained as:

\[
B_1^{**} = \frac{B_1^*}{1 - 0.174(\rho^R_t)^2},
\]

and

\[
B_2^{**} = \frac{B_2^*}{1 - 0.462(\rho^R_t)^2},
\]

where: \( \rho^R_t \) is the correlation coefficient for differences of ranks as follows:
Aviral Kumar Tiwari, Alexander Ludwig and Besma Hkiri (2014). Cointegration and causality between India’s exports and GDP: A sample period-robust testing framework, Economic Research (forthcoming)

\[ \rho^R_t = \frac{\sum_{t=2}^T \Delta R_t(x_i) \Delta R_t(y_j)}{\sqrt{\left(\sum_{t=2}^T (\Delta R_t(x_i))^2\right) \left(\sum_{t=2}^T (\Delta R_t(y_j))^2\right)}}. \]

The asymptotic distribution of the test statistics \( B_{1*} \) and \( B_{2*} \) are the same as \( B_1^* \) and \( B_2^* \), respectively. The null hypothesis of no cointegration is rejected if the value of the test statistic is smaller than the critical value.

As shown by Breitung (2001), the rank test can also be generalized to test cointegration among \( k+1 \) variables \( y_t, x_{it},...,x_{kt} \), where it is assumed that \( R_t(y_t) \) and \( R_t(x_{jt}) \) for \( j = 1,...,k \) are monotonic functions. One may compute the following multivariate rank statistic:

\[ B_3[k] = T^{-3} \sum_{t=1}^T (\tilde{u}_t^R)^2 \]

with

\[ \tilde{u}_t^R = R(y_t) - \sum_{j=1}^k \tilde{b}_j R(x_{jt}) \]

in which \( \tilde{b}_1,...,\tilde{b}_k \) are the least squares estimates from a regression of \( R(y_t) \) on \( R(x_{it}),...,R(x_{kt}) \) and \( \tilde{u}_t^R \) are the estimated residuals.

While the bilateral rank tests are one-sided tests that are applicable to functions that are known to be either monotonically increasing or decreasing, multivariate rank tests are two-sided tests that are useful when it is unknown whether the functions are monotonically increasing or decreasing. Again, to integrate a possible correlation between the series, the statistics are modified as follows

\[ B_3^*[k] = B_3[k] / \hat{\sigma}_{\Delta \tilde{u}}^2 \]

where:

\[ \hat{\sigma}_{\Delta \tilde{u}}^2 = T^{-2} \sum_{t=2}^T (\tilde{u}_t^R - \tilde{u}_{t-1}^R)^2 \]
2.3. A sample period-robust testing framework

In order to address the issue of the sensitivity of test results to the selected time period, we perform a bootstrapping approach for the sample period. To our best knowledge, this approach has not been applied yet in other empirical work. Our extension to a sample period-robust framework consists of the following steps.

While the number of performed tests is below 10,000:

1. Draw a random integer \( L \) from a uniform distribution over the interval \([L_{min}; T]\) where \( T \) is the total sample size
2. Draw a random integer \( S \) from a uniform distribution over the interval \([0; S_{max}]\)
3. If \( S + L \leq T \),
   - restrict the sample to the interval \((S; S + L]\)
   - perform the tests analogue to the entire sample
   - increase the number of performed tests by 1
4. Go back to 1.

In a final step, we calculate the share of test runs in which the null of the respective test has been rejected. Applying this procedure, we can examine the sensitivity of results towards sample selection. Note that the minimum sample length \( L_{min} \) should not be too low in order to keep a sufficiently high power of the test. Note also that this procedure guarantees that only observations from both ends of the original sample are neglected in each iteration.

3. Empirical Results

In this section, we describe the data under consideration (Section 3.1). We present results from the application of Johansen’s trace test (Section 3.2) and the rank-based cointegration test by Breitung (Section 3.3). For both cases, we also report results of the bootstrap-based sensitivity
3.1. Data: descriptive statistics and unit root tests

We use annual data for exports, imports and GDP for India from the International Monetary Fund’s *International Financial Statistics (IFS)*. Observations range from 1950 to 2012 yielding a sample size of $T = 63$. We present descriptive statistics for the data in Table 1 in the appendix.

Prior to testing for a long-run cointegration relationship between the time series, it is necessary to establish that time series have the same order of integration. To test for the order of integration we apply the linear unit root tests proposed by Dickey and Fuller (1979) and Phillips and Perron (1988) as well as the non-parametric unit root test proposed by Breitung (2002) that also works well in connection with non-linear data generating processes. We found that variables are integrated of order one. This unique order of integration of the variables allows us to proceed for the analysis of cointegration.

3.2. Linear cointegration analysis

Table 1 presents the results of the linear cointegration test. According to the Pantula principle we start with the most restrictive model (rank 0 at Model A) and compare the trace test statistic with the critical value at a 5% level of significance. If the model is rejected, we continue to Model B with the rank kept fixed. This procedure is continued till the null is accepted for the first time. As can be seen from Table 1, the null is accepted for the first time when using Model B and testing for the null of rank 1 (in the bivariate model) and rank 2 (in the trivariate model), respectively. Hence, using Model B we obtain a reduced rank for the parameter matrix $\Pi$. Model B includes an unrestricted constant in equation (2) which represents deterministic trends in the levels of both series. Considering the deterministic trends in all series

---

4 For space considerations, the results from the unit root analysis of the variables are not presented but they are available by the authors upon request. Most of the computations and simulations are done in gretl. All codes are available from the authors upon request for gretl and R or alternatively one can access codes from the first author’s website at: http://aviralkumartiwari.weebly.com/.
Aviral Kumar Tiwari, Alexander Ludwig and Besma Hkiri (2014). Cointegration and causality between India’s exports and GDP: A sample period-robust testing framework, Economic Research (forthcoming)

visualized in Figure 1 in the appendix, the selection of Model B is plausible. We therefore proceed on the basis of this model parameterization.

From the linear cointegration analysis we conclude that the trace test performed on the bivariate model for GDP and exports and the trivariate model for GDP, exports and the control variable imports strongly rejects the null hypothesis of a rank equal to 0 (no-cointegration between variables) and accepts the hypothesis of cointegration between GDP, exports and imports. Hence, GDP and exports share a cointegrating relation, which is robust to the inclusion of imports as a third variable in the model.

<table>
<thead>
<tr>
<th>Hypothesized cointegration rank</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Case 1: Ln(GDP) and Ln(Exports)</td>
<td>VAR Lag Order Selection Criteria : SIC (Lag 1)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>R=0</td>
<td>129.06 [0.0000]</td>
<td>34.01 [0.0000]</td>
<td>49.146 [0.0000]</td>
</tr>
<tr>
<td>R=1</td>
<td>8.2989 [0.0733]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Case 2: Ln(GDP), Ln(Exports), and Ln(Imports)</td>
<td>VAR Lag Order Selection Criteria : SIC (Lag 1)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>R=0</td>
<td>151.46 [0.0000]</td>
<td>55.357 [0.0000]</td>
<td>71.457 [0.0000]</td>
</tr>
<tr>
<td>R=1</td>
<td>26.12 [0.0058]</td>
<td>17.364 [0.0242]</td>
<td>32.834 [0.0046]</td>
</tr>
<tr>
<td>R=2</td>
<td>9.5039 [0.0423]</td>
<td><strong>1.3087 [0.2526]</strong></td>
<td>-</td>
</tr>
</tbody>
</table>

Note: (1) Figures in parenthesis are the p-values of the respective test statistics.

To examine the robustness of our results with respect to sample period selection, we apply the procedure described in Section 2.3. We set the minimum sample length $I_{\text{min}} = 40$ as smaller sample sizes are likely to lead to a low power of the trace test statistic. Further, we set the maximal start observation $S_{\text{max}} = 15$ as larger values would lead to a large share of irregular combinations with the minimum sample length, i.e. cases when their sum is larger than the original sample size $T = 63$. Table 2 shows that at the 5% level in more than 70% of all drawn sample periods the application of the trace test leads to the inference that there is a reduced rank of matrix $\Pi$ in equation (2) and hence cointegration. Thus, our finding that there is linear...
cointegration in the entire sample period is supported by the majority of randomly drawn sub-
samples. This result is robust to the inclusion of imports as a third variable. However, in about
30% of all cases, the empirical researcher would not obtain the result that there is a cointegration
relationship. The selection of the sample period thus influences the test results.

Note that the power of the trace test is likely to be smaller in each iteration of this
robustness check than for the original sample as the drawn sample sizes are maximally as large
as the original sample size. If the power of the test were always as large as in the case of the
original sample size, one could expect even larger shares of cases with cointegration. We hence
conclude that the result for a linear cointegration relationship is achieved with most of the
sample periods considered and is hence robust.

Table 2: Rank distribution from bootstrap-based sensitivity analysis (linear cointegration test)

<table>
<thead>
<tr>
<th>Level</th>
<th>1%</th>
<th>5%</th>
<th>10%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Case 1: Ln(GDP) and Ln(Exports)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cases with rank 0</td>
<td>31.7%</td>
<td>24.6%</td>
<td>20.3%</td>
</tr>
<tr>
<td>Cases with rank 1</td>
<td><strong>68.3%</strong></td>
<td><strong>73.1%</strong></td>
<td><strong>72.4%</strong></td>
</tr>
<tr>
<td>Cases with rank 2</td>
<td>0.0%</td>
<td>2.4%</td>
<td>7.3%</td>
</tr>
<tr>
<td>Case 2: Ln(GDP), Ln(Exports), and Ln(Imports)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cases with rank 0</td>
<td>37.7%</td>
<td>25.7%</td>
<td>19.8%</td>
</tr>
<tr>
<td>Cases with rank 1</td>
<td><strong>61.9%</strong></td>
<td><strong>36.5%</strong></td>
<td><strong>14.2%</strong></td>
</tr>
<tr>
<td>Cases with rank 2</td>
<td>0.5%</td>
<td>36.4%</td>
<td>54.5%</td>
</tr>
<tr>
<td>Cases with rank 3</td>
<td>0.0%</td>
<td>1.4%</td>
<td>11.5%</td>
</tr>
</tbody>
</table>
3.3. Non-linear cointegration analysis

We now apply the rank-based cointegration test of Breitung (2001). With respect to this test, Liew et al. (2012) point out that it can only be reasonably applied if there is a positive relationship between the series considered. In the case of cointegration with a negative cointegration parameter, the rank differences would still be high as both series move in different directions and hence the tests would reject cointegration with negative cointegration parameters. In this case a variable transformation would be required. As the variables in all bivariate models move in the same direction over time (see Figure 1), such a transformation is not needed in our case. Moreover, Breitung recommends to not apply this test to series that follow deterministic time trends and to de-trend the series first (see the discussion in Liew et al., 2012). In accordance with his clarification, we also apply the rank tests to detrended series and compare results below.

We present results of our analysis for the bivariate and trivariate cases in Table 3. Critical values are computed from 10,000 simulations of linearly (detrended) independent random walk sequences with $T = 63$ observations as in our sample. The corresponding critical values are similar to those obtained by Breitung (2001) and Liew et al. (2012). Table 3 shows that the test results do not change qualitatively using detrended data. The null hypothesis of no cointegration between the economic variables considered can be rejected by the bivariate rank test statistics $B_1^*, B_2^*, B_1^{**}$ and $B_2^{**}$ at conventional significant levels. The last column contains the correlation coefficient calculated from differences of ranks in order to adjust the bivariate test statistics for correlation.

The test statistic $B_3^*$, which was obtained from a regression of rank series onto each other, supports the significance of contagion in the bivariate model as well. However, including the detrended rank series related to the third variable, imports, the rejection of the null of no cointegration is a borderline case as the value of the test statistic is only slightly lower than the critical value. This causes doubt on the presence of non-linear cointegration relations as examined by the Breitung (2001) rank-based test. One should hence test the sensitivity of the results with respect to the sample selection, which we can achieve by the procedure outlined in Section 2.3.

---

After de-trending of the original series, assuming a linear cointegration relationship would lead to positive cointegration parameters such that the rank problem mentioned before does not occur for detrended series either.
Table 4 presents the results of the robustness check based on randomly drawn sub-periods. As we suspected, the selection of the sub-period does not have any influence on the results for non-linear cointegration in the case without de-trending. This result does not come as a surprise since both raw series contain a positive deterministic trend which greatly influences the behavior of the rank series. The rank series inherit the trends of the raw series such that the series of rank differences attains low values, which in turn leads to the inference in favor of cointegration. For this reason, Breitung recommended to not apply his test to trending series.

The results of the sensitivity analysis with regard to detrended data show a different picture (see the lower half of Table 4). At the 5% (10%) level, only in 4% (10%) of all randomly drawn sub-samples, the test shows cointegration. For the case that includes imports as a third variable, the ratio of sub-samples yielding cointegration is even smaller. We hence conclude that the results for non-linear cointegration, which are only reliable in the case of detrended data as argued before, are not robust with respect to the sample period selection.
Although the non-linear cointegration approach is more general as it covers the issue of non-linear functional relationships between variables, our results show that this flexibility comes at the cost of a smaller power of the test with respect to linear cointegration relationships. In the present case, we found evidence for linear cointegration between exports and GDP that is robust with respect to the selection of sample periods and to the integration of imports as a third variable. Using a non-linear cointegration technique in such a setup, it seems that the generality of the non-linear approach leads to a loss in precision (power) of the test.

3.4. **Granger-causality tests**

Based on the result that there is strong support for a linear cointegration relationship between exports and output, we now examine the significance of the error-correction term in all equations (lines) of the VECM. Its significance shows that the respective variable reacts on shocks to the equilibrium between the variables in order to equalize the deviation from the equilibrium in the long-run. The coefficient assigned to the error-correction term describes the intensity of the reaction on shocks and is therefore also called the speed of adjustment coefficient. Table 5 shows that in both cases, with and without imports as a third variable, both exports and GDP show significant reactions on shocks. The \( p \)-values of likelihood ratio tests on the significance of speed of adjustment coefficients are below 1%. In other words, if exports (GDP) move away from the joint equilibrium path, GDP (exports) reacts accordingly in order to reach again the equilibrium path. Based on the whole sample period, we thus find evidence for the export-led growth hypothesis as well as for its reversal, the growth-led export (GLE) hypothesis.
Table 5 also shows that imports are not relevant for the examination of these hypotheses. Imports do not play a significant role in the cointegration vector (p-value > 10%). Although its speed of adjustment coefficient is relatively large (0.1253), its p-value lies above the 10% level. This is likely to explain the small differences in the results of the linear cointegration robustness checks between cases 1 and 2 reported in Table 2.

### Table 5: Coefficients of VECM (whole sample)

<table>
<thead>
<tr>
<th>Case</th>
<th>Cointegration vector</th>
<th>Speed of adjustment coefficients</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Exports</td>
<td>GDP</td>
</tr>
<tr>
<td>Ln(GDP) &amp; Ln(Exports)</td>
<td>1.0000</td>
<td>-1.3859 [0.0000]</td>
</tr>
<tr>
<td>Ln(GDP), Ln(Exports) &amp; Ln(Imports)</td>
<td>1.0000</td>
<td>-0.8537 [0.0000]</td>
</tr>
</tbody>
</table>

Note: The table contains parameter values of the VECM and p-values of likelihood ratio tests of the significance of the coefficients (according to Johansen, 1991).

Lastly, we provide results of the sensitivity analysis regarding the sample period in Table 6. For the bivariate model, we found that in each case when there is cointegration there is also long-run causality from GDP to exports. There are considerably less cases for the causality from exports to GDP, which means that the result supporting the ELG hypothesis is hardly robust with respect to the sample period considered. For the trivariate model including imports, the differences in the ratios become even larger. This shows that the selection of the sample period is an important determinant on the test inference with regard to the ELG hypothesis but it seems to be of less influence when investigation the GLE hypothesis.

### Table 6: Ratios of cases with long-run causality (conditioned on presence of cointegration)

<table>
<thead>
<tr>
<th>Level</th>
<th>1%</th>
<th>5%</th>
<th>10%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Case 1: Ln(GDP) and Ln(Exports)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>GDP --&gt; Export</td>
<td>68.3%</td>
<td>73.1%</td>
<td>72.4%</td>
</tr>
<tr>
<td>Export --&gt; GDP</td>
<td>11.9%</td>
<td>41.6%</td>
<td>53.5%</td>
</tr>
<tr>
<td>Case 2: Ln(GDP), Ln(Exports), and Ln(Imports)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>GDP --&gt; Export</td>
<td>36.9%</td>
<td>72.1%</td>
<td>67.3%</td>
</tr>
</tbody>
</table>
4. Conclusions

To access the long-run relationship between exports and India’s GDP we employed both linear as well as non-parametric cointegration techniques for non-linear functional forms. Further, the validity and reliability of results is examined by including imports as third variable (in order to address omitted variables bias) and by applying an innovative bootstrapping procedure (in order to address the robustness of results with respect to the selection of sample periods). Finally, a VECM-based Granger-causality test is used to examine the long-run Granger-causal relationships between the variables of interest.

We find the existence of linear long-run relationship between India’s exports and GDP and this finding is robust to the inclusion of imports as a third variable in the model as well as to the selection of sample periods. The presence of a robust linear cointegration relationship seems to render the non-parametric cointegration test ineffective as it is designed to have power against a broad range of functional relationships between the variables under consideration. Applying VECM-based long-run Granger-causality tests, we find that both exports and GDP react significantly on shocks. In other words, we find evidence of bidirectional Granger-causal relationships indicating the validity of both ELG and GLE (growth-led exports) hypothesis. However, results from a robustness check with respect to the sample period selection shows considerably less cases supporting the ELG hypothesis vis-à-vis GLE hypothesis in bivariate model. The differences between the evidence of ELG and GLE hypotheses become even larger with inclusion of imports as a third variable. This questions the reliability and validity of the findings for ELG hypothesis for India in the literature. Our findings show that the export promotion strategy in particular and the ongoing trade reforms in general are not sufficient to push India’s overall economic growth in the long-run.

Acknowledgment: The authors are grateful to an anonymous referee his/her constructive comments and suggestions on an earlier draft of the manuscript without which the paper would have remained flawed and incomplete. The authors are solely responsible for any remaining errors.
Aviral Kumar Tiwari, Alexander Ludwig and Besma Hkiri (2014). Cointegration and causality between India’s exports and GDP: A sample period-robust testing framework, Economic Research (forthcoming)

References


Aviral Kumar Tiwari, Alexander Ludwig and Besma Hkiri (2014). Cointegration and causality between India’s exports and GDP: A sample period-robust testing framework, Economic Research (forthcoming)


Aviral Kumar Tiwari, Alexander Ludwig and Besma Hkiri (2014). Cointegration and causality between India’s exports and GDP: A sample period-robust testing framework, Economic Research (forthcoming)


Appendix

Figure 1: Graphical plot of the variables

Table 7: Descriptive statistics of the variables

<table>
<thead>
<tr>
<th></th>
<th>Ln(Exports)</th>
<th>Ln(GDP)</th>
<th>Ln(Imports)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>5.046189</td>
<td>7.596484</td>
<td>5.236806</td>
</tr>
<tr>
<td>Median</td>
<td>4.630448</td>
<td>7.376258</td>
<td>4.99782</td>
</tr>
<tr>
<td>Maximum</td>
<td>10.08069</td>
<td>11.51498</td>
<td>10.36096</td>
</tr>
<tr>
<td>Minimum</td>
<td>1.856298</td>
<td>4.540098</td>
<td>1.871802</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>2.658084</td>
<td>2.188703</td>
<td>2.621527</td>
</tr>
<tr>
<td>Skewness</td>
<td>0.395080</td>
<td>0.202296</td>
<td>0.413623</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>1.797705</td>
<td>1.716594</td>
<td>1.858543</td>
</tr>
<tr>
<td>Jarque-Bera</td>
<td>5.4334</td>
<td>4.753419</td>
<td>5.216558</td>
</tr>
<tr>
<td>p-value</td>
<td>0.066093</td>
<td>0.092856</td>
<td>0.073661</td>
</tr>
<tr>
<td>Observations</td>
<td>63</td>
<td>63</td>
<td>63</td>
</tr>
</tbody>
</table>