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The Causal Relationship Between Imports and Economic Growth in the Nine Provinces of South Africa: Evidence from Panel Granger Causality Tests

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This paper examines the causal relationship between imports and growth in nine provinces of South Africa for the period 1996-2011, using panel causality analysis, which accounts for cross-section dependency and heterogeneity across regions. Our empirical results support unidirectional causality running from economic growth to imports for Gauteng, Mpumalanga, North West, and Western Cape; a bi-directional causality between imports and economic growth for KwaZulu-Natal; and no causality in any direction between economic growth and imports for the rest of provinces. This suggests that import liberalisation might not be an efficient strategy to improve provincial economic performance in South Africa. Indeed, provincial imports tend to increase in some provinces as economic growth improves.

1. Introduction

There seems to be a consensus among economists that trade openness is favourable to economic growth, with export serving as the primary channel[4]. Consequently, supportive empirical evidence mainly focuses

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[4] There are conflicting views about the relationship between export and economic growth. One strand of the literature is favourable to the export-led growth hypothesis while the other supports the growth-driven export model. The export-led growth hypothesis is derived from the comparative advantage theory which asserts that trade expansion results in more productive and efficient allocation of resources favourable to economic growth. On the other hand, the growth-driven export model emphasizes that increasing economic activity through human capital

on the export-growth nexus with less attention on the relationship between import and economic growth. However, various openness measures have different linkages with growth and hence different policy implications. In an attempt to complement the economic impact of trade, this study analyses the import-growth nexus in South Africa. Rodrik (2008) indicates that both import-substitution and export-oriented firms in South African face much greater competitive discipline with import penetration levels having increased significantly within manufacturing from around 20% on average before 1990 to around 28 percent in 2000s. Concomitantly, economic growth remains relatively low compared o its pre-1994 levels. Therefore, understanding the causal link between imports and economic growth is crucial from a policy perspective as trade openness represents an important strategy in the South African government's effort to improve the performance of the economy.

Theoretically, the relationship between imports and economic growth is quite complex. Imports are expected to improve the productive efficiency of domestic import-substituting firms through innovation and restructuration which, in turn, enhances the performance of the economy. However, this assumption may lead to different conclusions depending on the market structure and institutional factors. In the neoclassical model with perfect competition, import liberalization reduces factors usage in the short run and guarantees more productive, innovative and competitive industries in the long run; resulting in an upward shift of the supply curve of firms. Conversely, the model with imperfect competition predicts a fall in import-substituting domestic market as imports increase. The resulting decrease in investment trims down the productivity, causing a fall in economic performance. However, a certain level of monopoly which ensures excess profits may boost domestic firms' productivity through research and development (R&D) investment. Furthermore, as imports of capital and intermediate goods that cannot be produced locally increase, domestic firms tend to diversify and specialize, thus improving their productivity (Kim *et al.*, 2007). Endogenous growth models are also favourable to the import-led growth hypothesis and assert that imports are important source of

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and technology improvements stimulates export growth since producers need new foreign markets to absorb the subsequent increase in supply. Based on Bootstrap causality approach, Chang *et al*. (2013) provide the evidence that the heterogeneity in the provincial composition of exports play an important role in driving the export-growth relationship in South Africa.

economic growth through the transfer of technology from industrialized to developing countries. Accordingly, foreign R&D generally embodied in imported intermediate goods such as computers, machines and equipments is important for productivity growth which in term determines the economic growth.

Similarly, theoretical models have documented both positive and negative causalities from economic growth to imports. It is believed that a rise in economic activity stimulates imports through consumption. On the other hand, economic growth improves the productivity of the import-substituting firms, causing the domestic market to increase and hence the imports to fall. In light of this divergent state of the literature, the causality between imports and economic growth should be investigated empirically.

Do imports result in or from economic growth? Only few studies have attempted to address this question; most of the existing evidence focusing on the determinants of imports demand. The selected exception includes Awokuse (2007), Kim *et al.* (2007), Uǧur (2008), Rahman Shahabaz (2011) and Islam *et al*. (2012). Awokuse (2007) uses a cointegration approach with Granger causality test to show a unidirectional causality between trade liberalization (including import variable) and economic growth for transition economies. Similar result is reported by Kim *et al.* (2007) who find the evidence of import-led productivity growth for Korea using a Vector Correction Model (VCM). By decomposing Turkey imports in different categories, Uǧur (2008) shows that the direction of the causality between import and growth depends on the type of goods. Particularly, a bidirectional causality is reported between GDP and investment goods imports as well as raw materials imports while there is a unidirectional relationship between GDP and other goods imports including consumption. Rahman and Shahbaz (2011) use the Autoregressive Distriburted Lag (ADRL) model with the Granger causality test and find a bidirectional causal effect between GDP growth and imports in Pakistan. Based on the same methodology, Islam *et al*. (2012) investigate the import-growth nexus in 62 countries and find that the direction of the causality depends on the level of income. High income countries which included South Africa as well were found to support the import-led growth hypothesis, whereas low income countries exhibit a bidirectional causality between the two variables. Being at the national levels, these studies however, fail to capture heterogeneity as well as spatial effect across regions which could result in potential bias in the estimates.

The aim of this paper is therefore to re-investigate the causal relationship between imports and economic growth in nine provinces of South Africa over the period of 1996-2011. Besides each province specific factors, it is rational to expect a particular shock to one province to spillover onto other provinces provided their high level of integration. This suggests that provinces are not only heterogeneous but also cross-dependent. Unlike previous studies, we apply panel causality approach which addresses the issue of cross-sectional dependency and heterogeneity across regions. Ignoring cross-section dependency leads to substantial bias and size distortions (Pesearan, 2006), implying that testing for the cross-section dependence is a crucial step in a panel data analysis.

As an open economy, South Africa exhibits imports dependency on various types of goods such as final consumption, capital and intermediate goods. Considering socio-economic imbalances across provinces, the degree of imports liberalisation is likely to vary from one province to another, resulting in different causality between provincial imports and growth. The initial inspection of the data seems to corroborate this hypothesis as provincial trends in imports and GDP plotted in Figure 1 display different patterns across provinces. We also observe a relatively high volatility in provincial imports compared to GDP, possibly suggesting a variation in trade policy orientation and productivity performance across provinces. Empirical results could not reject this hypothesis. Specifically, we find that the direction of the causality between imports and economic growth varies across provinces; most of them being unfavourable to the causal relationship in any direction between the two variables. While KwaZulu-Natal is favourable to a bi-directional causality between economic growth and imports, a unidirectional causality running from economic growth to imports is reported in four provinces, namely, Gauteng, Mpumalanga, North West and Western Cape. This suggests that import liberalisation might not be an efficient strategy to improve provincial economic performance in South Africa. Indeed, provincial imports tend to increase in some provinces as economic growth improves. The rest of the paper proceeds as follow: Section 2 presents the methodology, section 3 discusses the empirical results and section 4 concludes.

2. Methodology and data

2.1. Preliminary Analysis

One important issue in a panel causality analysis is to take into account possible cross-section dependence across regions. This is because high degree of economic and financial integrations makes a region to be sensitive to the economic shocks in other region with a country. Cross-sectional dependency may play important role in detecting causal linkages of housing activity for South Africa.

The second issue to decide before carrying out causality test is to find out whether the slope coefficients are treated as homogenous and heterogeneous to impose causality restrictions on the estimated parameters. As pointed out by Granger (2003), the causality from one variable to another variable by imposing the joint restriction for the panel is the strong null hypothesis Furthermore, as Breitung (2005) contends the homogeneity assumption for the parameters is not able to capture heterogeneity due to region specific characteristics. In the housing activity and economic growth nexus – as in many economic relationships – while there may be a significant relationship in some regions, vice versa may also be true in some other regions.

Given the above consideration before we conduct tests for causality, we start with testing for cross-sectional dependency, followed by slope homogeneity across regions. Then, we decide to which panel causality method should be employed to appropriately determine the direction of causality between housing activity and economic growth in nine provinces of South Africa countries. In what follows, we outline the essentials of econometric methods used in this study.

2.1.1. Testing cross-section dependence

To test for cross-sectional dependency, the Lagrange multiplier (LM hereafter) test of Breusch and Pagan (1980) has been extensively used in empirical studies. The procedure to compute the LM test requires the estimation of the following panel data model:

$$y_{it} = \alpha_i + \beta_i' x_{it} + u_{it} \quad \text{for} \quad i = 1, 2, ..., N; \quad t = 1, 2, ..., T \qquad (1)$$

where *i* is the cross section dimension, *t* is the time dimension, x_{it} is $k \times 1$ vector of explanatory variables, α_i and β_i are respectively the individual intercepts and slope coefficients that are allowed to vary across states. In the LM test, the null hypothesis of no-cross section dependence- $H_0 : Cov(u_{it}, u_{jt}) = 0$ for all t *and* $i \neq j$ - is tested against the alternative hypothesis of cross-section dependence $H_1 : Cov(u_{it}, u_{jt}) \neq 0$, for at least one pair of $i \neq j$. In order to test the null hypothesis, Breusch and Pagan (1980) developed the LM test as:

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

where $\hat{\rho}_{ij}$ is the sample estimate of the pair-wise correlation of the residuals from Ordinary Least Squares (OLS) estimation of equation (1) for each *i*. Under the null hypothesis, the LM statistic has asymptotic chi-square with $N(N-1)/2$ degrees of freedom. It is important to note that the LM test is valid for N relatively small and T sufficiently large.

However, the CD test is subject to decreasing power in certain situations that the population average pair-wise correlations are zero, although the underlying individual population pair-wise correlations are non-zero (Pesaran *et al*., 2008). Furthermore, in stationary dynamic panel data models the CD test fails to reject the null hypothesis when the factor loadings have zero mean in the cross-sectional dimension. In order to deal with these problems, Pesaran *et al*. (2008) proposes a bias-adjusted test which is a modified version of the LM test by using the exact mean and variance of the LM statistic. The bias-adjusted LM test is:

$$LM_{adj} = \sqrt{\left(\frac{2T}{N(N-1)}\right)} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij} \frac{(T-k)\hat{\rho}_{ij}^2 - \mu_{Tij}}{\sqrt{v_{Tij}^2}} \qquad (3)$$

where μ_{Tij} and v_{Tij}^2 are respectively the exact mean and variance of $(T-k)\hat{\rho}_{ij}^2$, that are provided in Pesaran *et al*. (2008, p.108). Under the null hypothesis with first T→∞ and then N→∞, LM_{adj} test is asymptotically distributed as standard normal.

2.1.2. Testing slope homogeneity

Second issue in a panel data analysis is to decide whether or not the slope coefficients are homogenous. The causality from one variable to another variable by imposing the joint restriction for whole panel is the strong null hypothesis (Granger, 2003). Moreover, the homogeneity assumption for the parameters is not able to capture heterogeneity due to region specific characteristics (Breitung, 2005).

The most familiar way to test the null hypothesis of slope homogeneity- $H_0: \beta_i = \beta$ for all *i*- against the hypothesis of heterogeneity- $H_1: \beta_i \neq \beta_j$ for a non-zero fraction of pair-wise slopes for $i \neq j$- is to apply the standard *F* test. The *F* test is valid for cases where the cross section dimension (N) is relatively small and the time dimension (T) of panel is large; the explanatory variables are strictly exogenous; and the error variances are homoscedastic. By relaxing homoscedasticity assumption in the *F* test, Swamy (1970) developed the slope homogeneity test on the dispersion of individual slope estimates from a suitable pooled estimator. However, both the *F* and Swamy (1970)'s test require panel data models where *N* is small relative to *T* [24]. Pesaran and Yamagata (2008) proposed a standardized version of Swamy (1970)'s test (the so-called $\tilde{\Delta}$ test) for testing slope homogeneity in large panels. The $\tilde{\Delta}$ test is valid as $(N,T) \to \infty$ without any restrictions on the relative expansion rates of N and T when the error terms are normally distributed. In the $\tilde{\Delta}$ test approach, first step is to compute the following modified version of the Swamy (1970)'s test:

$$\tilde{S} = \sum_{i=1}^{N} \left(\hat{\beta}_i - \tilde{\beta}_{WFE}\right)' \frac{x_i' M_\tau x_i}{\tilde{\sigma}_i^2} \left(\hat{\beta}_i - \tilde{\beta}_{WFE}\right) \tag{4}$$

where $\hat{\beta}_i$ is the pooled OLS estimator, $\tilde{\beta}_{WFE}$ is the weighted fixed effect pooled estimator, M_τ is an identity matrix, the $\tilde{\sigma}_i^2$ is the estimator of σ_i^2.[5] Then the standardized dispersion statistic is developed as:

[5] In order to save space, we refer to Pesaran and Yamagata (2008) for the details of estimators and for Swamy (1970)'s test.

$$\tilde{\Delta} = \sqrt{N}\left(\frac{N^{-1}\tilde{S}-k}{\sqrt{2k}}\right) \tag{5}$$

Under the null hypothesis with the condition of $(N,T)\rightarrow\infty$ so long as $\sqrt{N}/T\rightarrow\infty$ and the error terms are normally distributed, the $\tilde{\Delta}$ test has asymptotic standard normal distribution. The small sample properties of $\tilde{\Delta}$ test can be improved under the normally distributed errors by using the following bias adjusted version:

$$\tilde{\Delta}_{adj} = \sqrt{N}\left(\frac{N^{-1}\tilde{S}-E(\tilde{z}_{it})}{\sqrt{\operatorname{var}(\tilde{z}_{it})}}\right) \tag{6}$$

where the mean $E(\tilde{z}_{it})=k$ and the variance $\operatorname{var}(\tilde{z}_{it})=2k(T-k-1)/T+1$.

2.2. Panel Causality Test

Once the existence of cross-section dependency and heterogeneity across South Africa is ascertained, we apply a panel causality method that should account for these dynamics. The bootstrap panel causality approach proposed by Kónya (2006) is able to account for both cross-section dependence and region-specific heterogeneity. This approach is based on Seemingly Unrelated Regression (SUR) estimation of the set of equations and the Wald tests with individual specific region bootstrap critical values. Since region-specific bootstrap critical values are used, the variables in the system do not need to be stationary, implying that the variables are used in level form irrespectively of their unit root and cointegration properties. Thereby, the bootstrap panel causality approach does not require any pre-testing for panel unit root and cointegration analyses. Besides, by imposing region specific restrictions, we can also identify which and how many states exist in the Granger causal relationship.

The system to be estimated in the bootstrap panel causality approach can be written as:

$$\begin{aligned}
y_{1,t} &= \alpha_{1,1} + \sum_{i=1}^{ly_1} \beta_{1,1,i} y_{1,t-i} + \sum_{i=1}^{lx_1} \delta_{1,1,i} x_{1,t-i} + \varepsilon_{1,1,t} \\
y_{2,t} &= \alpha_{1,2} + \sum_{i=1}^{ly_1} \beta_{1,2,i} y_{2,t-i} + \sum_{i=1}^{lx_1} \delta_{1,2,i} x_{2,t-i} + \varepsilon_{1,2,t} \\
&\vdots \\
y_{N,t} &= \alpha_{1,N} + \sum_{i=1}^{ly_1} \beta_{1,N,i} y_{N,t-i} + \sum_{i=1}^{lx_1} \delta_{1,N,i} x_{1,N,t-i} + \varepsilon_{1,N,t}
\end{aligned} \tag{7}$$

and

$$\begin{aligned}
x_{1,t} &= \alpha_{2,1} + \sum_{i=1}^{ly_2} \beta_{2,1,i} y_{1,t-i} + \sum_{i=1}^{lx_2} \delta_{2,1,i} x_{1,t-i} + \varepsilon_{2,1,t} \\
x_{2,t} &= \alpha_{2,2} + \sum_{i=1}^{ly_2} \beta_{2,2,i} y_{2,t-i} + \sum_{i=1}^{lx_2} \delta_{2,2,i} x_{2,t-i} + \varepsilon_{2,2,t} \\
&\vdots \\
x_{N,t} &= \alpha_{2,N} + \sum_{i=1}^{ly_2} \beta_{2,N,i} y_{N,t-i} + \sum_{i=1}^{lx_2} \delta_{2,N,i} x_{N,t-i} + \varepsilon_{2,N,t}
\end{aligned} \tag{8}$$

where y denotes real income, x refers to imports, l is the lag length. Since each equation in this system has different predetermined variables while the error terms might be contemporaneously correlated (i.e. cross-sectional dependency), these sets of equations are the SUR system.

In the bootstrap panel causality approach, there are alternative causal linkages for each province in the system that (i) there is one-way Granger causality from x to y if not all $\delta_{1,i}$ are zero, but all $\beta_{2,i}$ are zero, (ii) there is one-way Granger causality running from y to x if all $\delta_{1,i}$ are zero, but not all $\beta_{2,i}$ are zero, (iii) there is two-way Granger causality between x and y if neither $\delta_{1,i}$ nor $\beta_{2,i}$ are zero, and finally (iv) there is no Granger causality in any direction between x and y if all $\delta_{1,i}$ and $\beta_{2,i}$ are zero. Details about the Bootstrap procedure see Appendix.

The annual data used in this study covers the period from 1996 to 2011 for nine provinces of South Africa. The variables include real GDP and real imports. Real GDP is measured in constant 2005 Rand and comes from the Statistic South Africa (SSA). Nominal imports are obtained from the RSA Provincial Trade Indicators (Quantec). We use the consumer price index (CPI) drawn from the International Monetary

Fund database to obtain the real imports. Tables 1 and 2 show the summary statistics of real GDP and real imports for nine provinces, respectively. Based on Tables 1 and 2, we find that Gauteng and Northern Cape have the highest and lowest mean real GDP of R517 billions and R33.1 billions, respectively, and Gauteng and North West have the highest and lowest mean real imports of R2 billions and R12.8 millions, respectively. With the exception of real imports for Limpopo, the remaining series are approximately normal as the Jarque Bera test could not reject the null of normality for eight provinces.

3. Empirical findings

Before we test for causality we first test for both cross-sectional dependency and region-specific heterogeneity as we believe that these nine provinces in South Africa are highly integrated in their economic relations. To investigate the existence of cross-section dependence we carried out four different tests (*LM*, CD_{lm},CD, LM_{adj}). Secondly, as ndicated by Kónya (2006), the selection of optimal lag structure is of importance because the causality test results may depend critically on the lag structure. In determining lag structure we follow Kónya (2006)'s approach that maximal lags are allowed to differ across variables, but to be same across equations. We estimate the system for each possible pair of ly_1, lx_1, ly_2 and lx_2 respectively by assuming from *1* to *4* lags and then choose the combinations which minimize the Schwarz Bayesian Criterion.

Tests for cross-sectional dependency and heterogeneity are presented in Table 3. As can be seen from Table 3, it is clear that the null hypothesis of no cross-sectional dependency and slope heterogeneity across the countries is strongly rejected at the conventional levels of significance. This finding implies that a shock that occurred in one of these provinces countries seems to be transmitted to other provinces. Furthermore, the rejection of slope homogeneity implies that the panel causality analysis by imposing homogeneity restriction on the variable of interest results in misleading inferences.[6] In this respect, the panel causality analysis based on estimating a panel vector autoregression and/or panel vector error correction model by means of generalized method of moments and

[6] Though $\tilde{\Delta}_{adj}$ fails to reject the null hypothesis of slope homogeneity, both $\tilde{\Delta}$ and $\tilde{S}$ reject the null hypothesis of slope homogeneity.

of pooled ordinary least square estimator is not appropriate approach in detecting causal linkages between housing activity and economic growth in nine provinces of South Africa.

The establishment of the existence of cross-sectional dependency and heterogeneity across nine provinces suggests the suitability of the bootstrap panel causality approach. Results of the bootstrap causality tests are presented in Tables 4 and 5. Our empirical results support unidirectional causality running from economic growth to imports for Gauteng, Mpumalanga, North West, and Western Cape; a bi-directional causality between imports and economic growth for KwaZulu-Natal; and no causality in any direction between economic growth and imports for the rest of provinces. In KwaZulu-Natal, there was a bidirectional causality between imports and economic growth thus supporting the feedback hypothesis where imports and GDP serve as complements to each other. The policy implication of our finding is that reduced imports may lead to adverse effects on economic growth in KwaZulu-Natal.

These findings appear to corroborate the hypothesis that import-growth nexus is mainly driven by the heterogeneity in the geographical composition of import goods. Consistent with Uğur (2008), provinces whose imports mostly depend on consumption goods exhibit a unidirectional causality running from growth to imports. This is particularly the case for Gauteng, Western Cape and Mpumalanga where socio-economic advantages favour imports of consumption goods. Gauteng and Western Cape are the leading provinces in term of economic development while Mpumalanga has great potential for fast growth; manufacturing and mining being its major sources of income. On the other hand, provinces with diversified economy tend to exhibit a bidirectional causality between imports and growth. KwaZulu-Natal is an illustration. It is the second largest contributor to South Africa’s GDP and its economy depends on various activities including tourism, agriculture and manufacturing. Finally, neither imports nor economic growth is sensitive to each other in rural provinces, namely Northern Cape, Eastern Cape and Limpopo. This may suggest that the level of the development matters for the import-growth relationship.

4. Conclusions

This study applied the bootstrap panel Granger causality approach to test the causal link between imports and economic growth using data from the nine provinces of South Africa over the period of 1996-2011. Our empirical results support unidirectional causality running from economic growth to imports for Gauteng, Mpumalanga, North West, and Western Cape and a bi-directional causality between imports and economic growth for KwaZulu-Natal. However, a neutrality hypothesis was found for the rest of provinces indicating neither imports nor economic growth is sensitive to each other in these two provinces.

Our findings provide important policy implications in South Africa. Firstly, import liberalisation might not be an efficient strategy to improve provincial economic performance in South Africa. Indeed, provincial imports tend to increase in some provinces as economic growth improves. Secondly, national level- based studies hide important differences in import-growth nexus among provinces, resulting in misleading inference. For instance, the import-led growth evidence established by Islam *et al.* (2012) for South Africa implies that imports could be beneficial for economic growth. However, this policy implication is likely to result in adverse effects in all provinces except in KwaZulu-Natal where there is a dual causality between the two variables.

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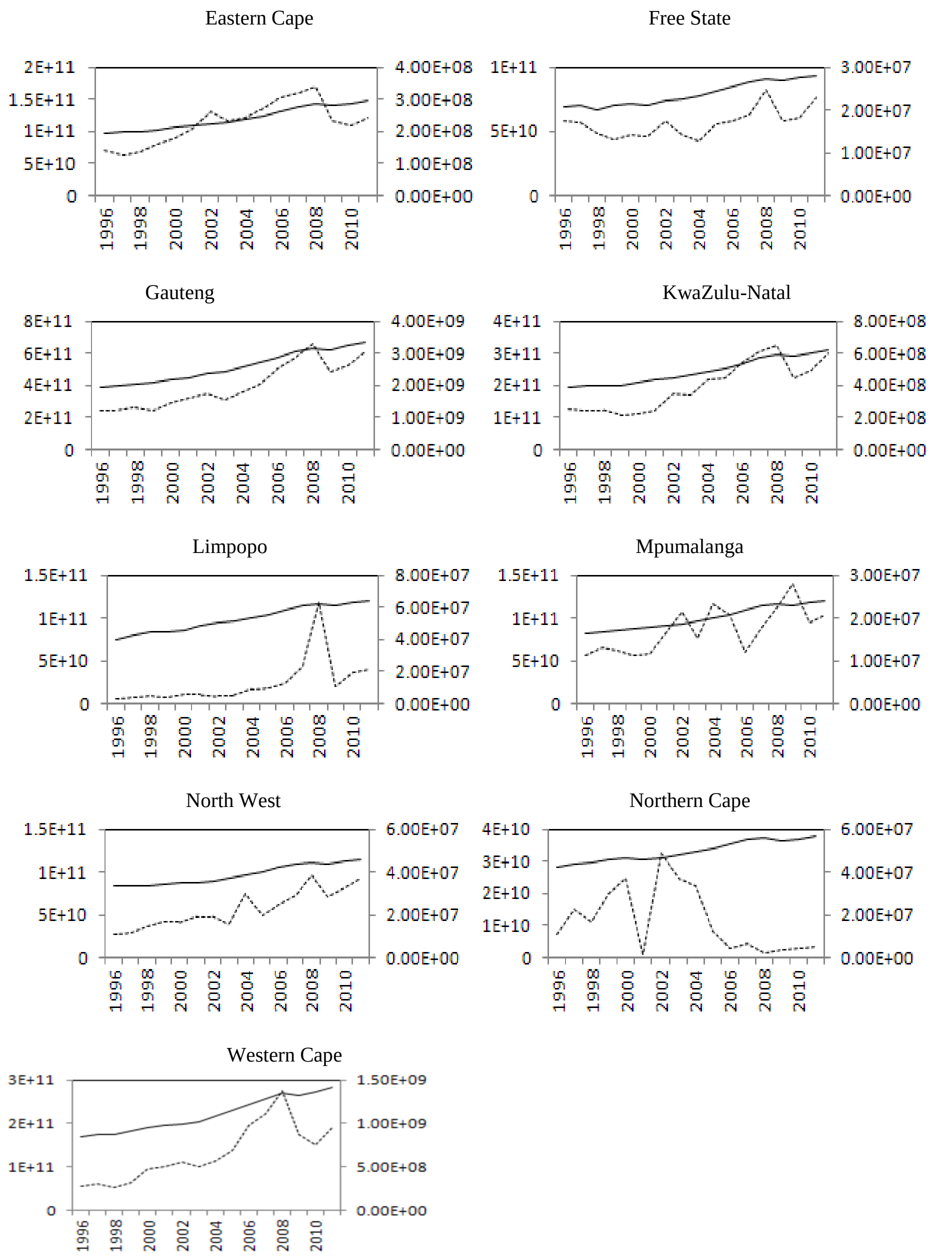
Figure 1: Real Imports and Real GDP across provinces



Notes: Real GDP (solid line, scale on the left axis), real imports (dotted line, scale on the right axis).

Table 1: Summary Statistics of Real GDP

Province	**Mean**	**Max.**	**Min.**	**Std. Dev.**	**Skew[a].**	**Kurt[b].**	**J.-B[c].**
Eastern Cape	1.20E+11	1.49E+11	9.81E+10	1.80E+10	0.272	1.571	0.708
Free State	7.92E+10	9.40E+10	6.73E+10	9.58E+09	0.284	1.479	0.794
Gauteng	5.17E+11	6.72E+11	3.89E+11	9.78E+10	0.208	1.570	0.626
KwaZulu-Natal	2.45E+11	3.13E+11	1.92E+11	4.23E+10	0.245	1.568	0.673
Limpopo	9.92E+10	1.21E+11	7.47E+10	1.51E+10	-0.042	1.615	0.484
Mpumalanga	1.00E+11	1.21E+11	8.13E+10	1.36E+10	0.149	1.523	0.604
North West	9.72E+10	1.15E+11	8.44E+10	1.17E+10	0.283	1.429	0.830
Northern Cape	3.31E+10	3.80E+10	2.80E+10	3.33E+09	0.109	1.572	0.541
Western Cape	2.20E+11	2.83E+11	1.70E+11	3.94E+10	0.255	1.547	0.701

Note: 1. The sample period is from 1996 to 2011
2. a, b, c refer to Skewness, Kurtosis and Jarque Bera statistics, respectively.

Table 2: Summary Statistics of Real Imports

Province	**Mean**	**Max.**	**Min.**	**Std. Dev.**	**Skew[a].**	**Kurt[b].**	**J.-B[c].**
Eastern Cape	2.26E+08	3.38E+08	1.26E+08	6.48E+07	0.284	2.045	0.230
Free State	1.70E+07	2.46E+07	1.29E+07	3271329	0.865	3.261	2.012
Gauteng	2.00E+09	3.32E+09	1.20E+09	7.07E+08	0.487	1.870	0.951
KwaZulu-Natal	3.97E+08	6.50E+08	2.14E+08	1.54E+08	0.273	1.649	0.655
Limpopo	1.29E+07	6.28E+07	3198303	1.47E+07	2.542	9.095	**26.52*** **
Mpumalanga	1.74E+07	2.80E+07	1.13E+07	5167183	0.388	2.092	0.607
North West	2.28E+07	3.89E+07	1.07E+07	8880199	0.409	1.945	0.724
Northern Cape	1.74E+07	4.91E+07	1530053	1.55E+07	0.672	2.062	1.424
Western Cape	6.56E+08	1.37E+09	2.65E+08	3.01E+08	0.634	2.492	1.138

Note: 1. The sample period is from 1996 to 2011
2. a, b, c refer to Skewness, Kurtosis and Jarque Bera statistics, respectively.

Table 3: Cross-sectional Dependence and Homogeneous Tests

Test			
LM	223.052***		
CD_{LM}	22.044***		
CD	13.793***		
LM_{adj}	21.507***		
Swamy's Test	40.099***		
$\tilde{\Delta}$	7.33***		
$\tilde{\Delta}_{adj}$	0.525		

Note: *** indicates significance at the 0.01. LM Tests test the null hypothesis of no cross province dependency against the alternative of cross province dependency. Swamy's Tests test the null hypothesis of homogeneity against the alternative of heterogeneity. In both cases, the null hypothesis is rejected as the statistics are significant.

Table 4: Granger causality test running from Imports to GDP

	Wald Statistics	**Bootstrap Critical Value**		
		10%	5%	1%
Eastern Cape	2.635	31.268	50.313	121.272
Free State	0.497	40.288	62.970	156.381
Gauteng	9.413	33.716	56.972	141.894
KwaZulu-Natal	50.538**	29.609	47.337	109.283
Limpopo	3.988	39.877	63.831	153.235
Mpumalanga	3.589	33.884	54.724	140.618
North West	16.168	27.261	41.071	87.062
Northern Cape	0.324	44.243	71.297	170.314
Western Cape	2.714	21.566	36.539	98.221

Note: 1. ** indicates significance at the 0.05 level. The entries refer to the statistics of the null hypothesis testing that Imports do not Granger cause GDP against the alternative that Imports do Granger cause GDP. The null hypothesis is rejected in KwaZulu-Natal as the corresponding statistic is significant.

2. Bootstrap critical values are obtained from 10,000 replications.

Table 5: Granger causality test running from GDP to Imports

	Wald Statistics	**Bootstrap Critical Value**		
		10%	5%	1%
Eastern Cape	1.560	19.159	30.133	63.971
Free State	0.774	12.153	19.141	37.858
Gauteng	16.515**	6.983	10.789	22.083
KwaZulu-Natal	15.497*	14.257	21.618	44.590
Limpopo	7.435	19.338	29.955	62.909
Mpumalanga	118.549***	9.768	14.632	30.186
North West	40.995**	20.902	31.752	61.427
Northern Cape	6.869	7.778	11.834	25.481
Western Cape	22.926**	12.198	18.167	39.042

Note: 1. ***, ** and * indicate significance at the 0.01, 0.05 and 0.1 levels, respectively. The entries refer to the statistics of the null hypothesis testing that GDP does not Granger cause Imports against the alternative that GDP does Granger cause Imports. The null hypothesis is rejected in Gauteng, KwaZulu-Natal, Mpumalanga, North West and Western Cape as the corresponding statistics are significant.

2. Bootstrap critical values are obtained from 10,000 replications.

Appendix

The appropriate method to estimate (7) and (8) 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 utilize this extra information. In order to obtain more efficient estimators, the equations in (7), and also in (8), must be stacked and the two stacked equations can be estimated individually with the feasible generalized 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.

Following the Konya (2006), the Bootstrapping procedure is as follows:
Step 1: Estimate (7) under the null hypothesis that there is no causality from X to Y (i.e. imposing the $\delta_{1,i,l} = 0$ restriction for all i and l) and obtain the residuals

$$eH0_{i;t} = y_{i,t} - \hat{\alpha}_{1,i} - \sum_{i=1}^{ly_1} \beta_{1,1,i} y_{i,t-1} \quad \text{for i=1,2,...N and t=1,2,...T.}$$

From these residuals develop $NxT[eH0_{i,t}]$ matrix.

Step 2: Re-sample these residuals. In order to preserve the contemporaneous cross-correlation structure of the error terms in (7), do not the draw the residuals for each country one-by-one, but rather randomly select a full column from the $[eH0_{i,t}]$ matrix at a time.

Denote the selected bootstrap residuals as $e^{*}H0_{i,t}$, where t=1, 2,…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:

$$y^{*}_{i,t} = \hat{\alpha}_{1,i} + \sum_{i=1}^{ly1} \hat{\beta}_{1,i,l} y^{*}_{i,t-1} + e^{*}H0_{i,t} \quad \text{t=1, 2,…T*}$$

Step 4: Substitute $y^{*}_{i,t}$ for $y_{i,t}$, estimate (7) without imposing any parameter restrictions on it, and for each country perform the Wald test implied by the no-causality null hypothesis.

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. In Step 5, the bootstrap distribution of each test statistic is derived from 10,000 replications.

A similar procedure is applied for causality from Y to X in equation (8).