MILITARY SPENDING AND ECONOMIC GROWTH IN SOUTH AFRICA:
A CAUSAL ANALYSIS

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ABSTRACT

There are a number of studies which consider the relation between military spending and economic growth using Granger causality techniques rather than a well-defined economic model. Some studies have used samples of groups of countries, finding no consistent results. Other studies have focused on individual countries, which has the advantage of the researchers bringing to bear much more data than the cross country samples and a greater knowledge of the structure of the economy and the budget. This paper adds to the literature by providing an analysis of South African data, a particularly interesting case study given the considerable changes that have taken place in recent years. It is a developing country with a developed military sector and despite huge reductions in military expenditure still retains a relatively high military burden. In addition to analysing South African data using standard "pre-cointegration" Granger causality techniques, this paper employs modern vector autoregressive (VAR) methodology that utilises cointegration via Granger's representation theorem. This is an important improvement in the econometric analysis and indicates a significant negative impact of military spending on growth in South Africa, one that is not apparent when using the standard techniques.

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0. INTRODUCTION

There has been considerable debate over the economic effects of military spending on economic growth since the contribution by Benoit (1973, 1978) which suggested that military spending and development went hand in hand. This led to considerable research activity using econometric analysis, which improved upon the approach taken by Benoit, and has tended not to support Benoit's findings. Single equation and simultaneous equation models have been estimated and more recently there has been the application of techniques which investigate causal links. Studies have varied from extensive cross-country analyses, which failed to reach any consensus, to detailed case studies of individual countries. Dunne (1996) provides an extensive survey. This paper contributes to the debate in two ways. Firstly, it provides a further case study of a particularly interesting country, South Africa, and secondly it goes beyond the standard "Granger causality" econometric techniques used in previous econometric work.

South Africa provides a particularly useful case study because of the considerable changes that have taken place over the last thirty years, with both marked increases and decreases in military burden. The imposition of apartheid policies and the use of the military to defend white minority rule against internal and external threats led to increasing levels of military spending, and the establishment of a domestic arms industry. Since 1989 the two main sources of conflict in Southern Africa - the Cold War and apartheid - have disappeared. With the transition to democracy has come a process of demilitarisation, which included dramatic cuts in military spending. Despite the cuts, South Africa remains the continent's largest military spender in absolute terms, and in 1995 accounted for more than 70% of total military spending in Southern Africa.

Previous studies of the relationship between military spending and growth using Granger causality techniques have, in general, had one noticeable weakness. Although, they recognised the possibility of integration in the variables of interest, usually real output and share of military expenditure in GDP, they only specified the causal vector autoregression (VAR) model in first differences. Often completely ignoring any long-run relation (cointegration) amongst these two variables, which is incorporated in the levels of the time series. However, if cointegration exists among output and the military expenditure share, then this long-run information should be utilised and causality should be examined within the framework of the error correction representation of a VAR model (see Engle and Granger (1987), and Oxley (1993) for an application).

In this paper, we specifically examine Granger causality on the basis of existence of a cointegration relationship amongst real output and share of military expenditure in GDP for the South African data.
Section 1 provides some information on the South African economy and its military spending, followed by a brief survey of previous studies in section 2. Section 3 then investigates the properties of the South African military spending and output series and section 4 considers the causal links and cointegrating relationships between economic growth and military burden. Finally section 5 provided some conclusions.

1. THE SOUTH AFRICAN ECONOMY AND MILITARY SPENDING

South Africa is Africa's largest and most sophisticated economy. The country is richly endowed with national resources, and the economy was built up on the basis of mining and agriculture. However, in recent years, the secondary (i.e. manufacturing) and tertiary (e.g. transport, financial services) sectors have come to dominate the economy. The smooth trend in real output in Figure 1 hides a much more varied path of economic growth as Figure 2 shows. Real output growth has declined over the sample period with increasing volatility from the mid 1970’s when the military burden peaked.

{Figure 1, about here}
{Figure 2, about here}

The South African economy experienced its longest and most severe recession - since the depression of the 1930s- between 1989 and 1993. During this period GDP growth averaged less than 1% per annum in real terms, while GNP per capita declined every year in real terms. Employment and investment declined over this period and exports showed little positive growth, largely because of the continued presence of trade and financial sanctions. Inflation also remained stubbornly high during this period, averaging 13.6% per annum. Since 1993, however, the South African economy has experienced positive GDP growth for four consecutive years, Gross Domestic Fixed Investment recovered quite dramatically and exports also experienced positive growth, largely as a result of the lifting of trade sanctions, which accompanied the ending of apartheid. Inflation was brought under control and in 1996 inflation was 7.4%, the lowest rate since 1972. The only disappointing economic indicator since 1993 has been the trend in formal employment and the continued inequality and social unrest.

There have been wide variations in military spending in South Africa in the last 35 years, in absolute terms and as a share of GDP. As Figure 3 shows South Africa's military burden (military spending as a % of
GDP) was just over 1% in the early 1960s, but increased to over 3% by 1964 as a result of the start of the ANC’s armed struggle, and the imposition of the first UN arms embargo. During the next few years military spending declined from over 3% of GDP to around 2% in 1970 as the South African government was able to contain domestic political opposition.

{Figure 3, about here}

Military spending began to increase again in the early 1970s as a result of growing external and internal opposition to apartheid. From the early 1970s the South African Defence Force (SADF) was deployed in Namibia in support of the South African Police against infiltrations by the South West African People's Organisation (SWAPO), and in 1975 South Africa became involved in the Angolan civil war in support of UNITA. In 1977/78 military spending peaked at 5% of GDP, and over 18% of total government expenditure in response to internal unrest, the purchase of large amounts of weapons prior to the imposition of the mandatory UN arms embargo, and the government's implementation of "Total Strategy" to combat the "Total Onslaught" of communist expansionism in Southern Africa (see Cobbett (1989)). Military spending then declined quite dramatically between 1977/78 and 1980/81, but then began to increase again during the 1980s as a result of South Africa's increasing involvement in Angola, Namibia and Mozambique, and increasingly violent domestic opposition to apartheid. Military spending peaked again in 1989/90 at 4% of GDP and 13% of total government expenditure, and then declined quite dramatically after 1989. Indeed by 1996 South Africa's defence budget had been cut by more than 50% in real terms and as a share of GDP from 4% to less than 2% (Batchelor and Willett, 1998).

This variation in both military spending and economic growth makes South Africa a particularly good case study for investigating any links between the two. Given the nature of the South African economy the result of the analysis may well be suggestive of the likely relations in other developing countries. Ascertaining whether there is any relation between military spending and economic development is extremely important for government policy as it allows an understanding of likely responses of the economy to declining military spending and informs the design of any policies of conversion.

2. THE PREVIOUS LITERATURE

Following the work of Benoit (1973, 1978) which suggested that there was a positive relation between military spending and development there has been considerable debate over the links between
military spending and development. After the comprehensive critique provided by Ball (1983) a large number of econometric work attempted to overcome the deficiencies of the applied analysis in Benoit. There have been studies using single equation analyses, simultaneous equation systems and large macro-econometric models, all developed from a variety of theoretical positions. Studies have been applied to different cross sectional samples of countries, time series for individual countries and pooled time series and cross sectional data. No consensus has been developed but the most common findings are that military spending has no significant impact, or a negative impact, on economic growth (Dunne, 1997 provides an extensive survey).

One important part of the single equation work has been the recent application of ‘causality tests’ to the data to see if there is any effect of military spending on growth and vice versa. Joerding (1986) considered two measures of military spending and growth for 57 LDCs for the period 1962-77 and found no evidence that military spending causes growth, while Chowdhury (1991) studying 73 LDCs and Kusi (1994) 77 LDCs found no common result. The findings that there was no general result sparked a number of more detailed case studies. Kinsella (1990) studied the causal relationship between defence spending and various economic variables (including output) of the USA and concluded that there was no substantial relationship between defence spending and output. Looney (1991) analysed India and Pakistan and found a positive effect of military spending on growth for Pakistan but a negative one for India. Chen (1993) analysed China and found no evidence of a causal link, while Hasan (1994) found a positive effect of military spending on growth when reworking Chen’s data with VAR methods. Madden and Haslehurst (1995) find no causal relationship between military spending and growth. Finally, Kollias and Makrydakis (1999) examine Greek data and find out that there is no causal relationship between military expenditure and economic growth.

Over time the techniques available for analysing causality have been developed and refined, and this is reflected in the literature. In the early stages of the Granger causality approach, time series were assumed to be covariance stationary and, therefore, VAR models were specified using time series in levels (possibly after linear de-trending). However, it has been discovered that many individual economic time series have at least one unit root, or in other words, they are integrated (of order one), or they need (first order) differencing to achieve stationarity. Integrated time series of order one, denoted I(1), accumulate all past errors and for this reason their variance is proportional to time. An I(1) time series becomes stationary only after first order differencing.
This meant that an immediate reaction for "proper" Granger causality testing is to specify VAR models in first differences. However, this approach will suffer from serious drawbacks if the involved time series are integrated individually, but also cointegrate. Two or more integrated time series are said to cointegrate if a particular linear combination of all the involved series is integrated of order lower than the order of integration of individual time series. In the case of I(1) time series, cointegration implies that there is a linear combination involving all the time series which is I(0), i.e. covariance stationary. According to the analysis of Engle and Granger (1987): the so-called Granger's representation theorem, the best VAR model in the presence of cointegration is what is called a vector error correction model (VECM). That is a VAR model in first differences which incorporates the long-run information, as captured by the (first order) lag of the cointegrated linear combination (long-run error), or a consistent estimator of this error. (The mathematical details are beyond the scope of this paper.) Furthermore, if a set of integrated time series do cointegrate, short-run Granger causality effects should be examined via the VECM, and the VAR model in (first) differences which ignores this valuable long-run information is misspecified. Any causal orderings established, or any failures to specify causal relationships using a VAR in (first) differences should be treated with caution. The problem we face when we use the VAR model in (first) differences instead of the correct VECM is a standard omitted variables problem. Omitting the error correction term increases the corresponding regression variance and, therefore, it biases all $F$-type-, LR-, and LM-tests downwards, not allowing them to reject the no-causality null, even if it is incorrect.

Some of these issues have been raised in the context of arms race modelling. Kinsella and Chung (1998) employ VEC models to examine the arms race between the US and the Soviet Union, while Kollias and Makrydakis (1997) have employed cointegration techniques to analyse the Greek-Turkish arms race and Ward and Rajmaira (1992) the US-USSR one. There has, however, been little recognition of the issues in the literature on the economic effects of military spending, despite the increasing recognition of the need to consider more detailed case studies with time series data (Dunne, 1996). Before moving on to analyse the South African data, we need to outline the techniques used in more detail and to discuss how they need to be developed.

3. INTEGRATION PROPERTIES OF SOUTH-AFRICAN TIME SERIES
As mentioned, previous studies, such as Chowdhury (1991) and Madden and Haslehurst (1995), have examined existence of causal relationship between real output growth and the share of military expenditure in GDP using VAR models in first differences. There is no unique pattern from these studies for the direction of causality for different countries. The most common findings were that there is no Granger-causality from military spending to output growth, or if there was such causality the overall impact was negative. However, as we have already mentioned, one should establish both integration and cointegration properties of the involved time series before any robust inference about causality is drawn. In particular, the order of integration of each time series should be established, and if there are some integrated time series, appropriate tests for cointegration should be undertaken to specify the correct dynamic model (either VAR in differences or VECM). We have already discussed that using a misspecified dynamic model may lead to incorrect inference about causal effects, and this criticism may apply to some previous studies in the literature, since they ignore the possibility that integrated time series may cointegrate.

To establish the order of integration of an observed time series, we employ unit root tests developed by Dickey and Fuller (1979), DF for short. We employ two variants of these tests, one with an intercept and one with an intercept and linear trend. For a time series, \( x_t \), say, the first class of tests is based on the autoregression

\[
\Delta x_t = \mu_0 + \gamma_0 x_{t-1} + \sum_{i=1}^k \gamma_i \Delta x_{t-i} + \eta_t, \tag{1}
\]

and the unit-root null hypothesis is \( H_0 : \gamma_0 = 0 \). The intercept-trend class is based on the autoregression:

\[
\Delta x_t = \mu_0 + \mu_t + \gamma_0 x_{t-1} + \sum_{i=1}^k \gamma_i \Delta x_{t-i} + \eta_t, \tag{2}
\]

where both an intercept and linear trend are added in the model; the unit root null remains the same (\( H_0 : \gamma_0 = 0 \)), however, the critical values are different. The additional lagged differences of the series are employed to “whiten” the error of the auxiliary autoregressions. When the auxiliary autoregressions contain lagged differences, DF tests are called augmented DF tests; hence the acronym ADF test arises. The maximum lag order, \( k \), may be selected using an information criterion. Notice that there may be conflict in the choice of optimal model from various criteria.

\{Table 1, about here\}

The notation we follow in this paper is as follows: \( y_t \) stands for the logarithm of South African GDP in constant 1985 prices, and \( sm_t \) stands for the share of military expenditure in GDP of South Africa. In
addition, \( d(77 - 94) \), is a dummy variable, which takes value 1 for the embargo years, that is 1977 - 1994 (both inclusive). Both South African level series in this paper extend from 1961 to 1995.

The results of (A)DF tests for the logarithm of output and the share of military expenditure in output are presented in Table 1. The first panel of Table 1 presents (A)DF tests for \( y_t \) and \( sm_t \), using an intercept in the auxiliary autoregressions (equation 1). The second panel of this table presents (A)DF tests for the same variables using intercept and trend in the auxiliary autoregression (equation 2). For the logarithm of the real GDP, \( y_t \), Dickey Fuller (DF) and augmented Dickey Fuller (ADF) tests with an intercept suggest that \( y_t \) is non-integrated, I(0), that is they verify the absence of a unit root. All (three) information criteria employed, AIC, SBC and HQC, select an autoregression with no lagged differences, the corresponding t-ratio being -4.2377 (exact 5 % critical value -2.9591), which clearly rejects the unit root null for the logarithm of South African output. However, this conclusion is altered if we use an auxiliary autoregression with intercept and linear trend, see the first part of the second panel of Table 1. There is strong evidence in favour of integration for \( y_t \) and this variable appears to be I(1). Conflicting inference about a unit root, as it is the case for the logarithm of South African output, has to be resolved by other means. In our further analysis, we will treat \( y_t \) as integrated of order, I(1), that is we are going to rely on the (A)DF tests with intercept and trend. This is because \( y_t \) appears to be trending, see Figure 1, or, in other words, it appears to have "drift", which will be linear trend under a unit root. For this reason, equation 2, containing linear trend, provides a robust result for the presence of a unit root, while equation 1 does not. Furthermore, to justify our decision of treating \( y_t \) as I(1), we examine integration property of real output growth, \( \Delta y_t \). The results (not reported here) indicate that the differenced series (\( \Delta y_t \)) is non-integrated, I(0), and this has two implications. First, there is no second unit root in \( y_t \). Secondly, from the definition of difference stationarity, a time series contains a unit root (i.e. it is difference stationary) if its own first difference is stationary. Notice that this is a necessary condition only. For example, the first difference of an I(0) time series is also I(0), although such an over-differenced series contains a moving average unit root. Therefore, a necessary and sufficient condition for \( y_t \) to have one unit root is that \( \Delta y_t \) is I(0) and that \( \Delta y_t \) has no moving average unit root. It is true that the South African output growth, \( \Delta y_t \), is I(0) by usual (A)DF tests, and, in addition, there is no sign of a moving average unit root in the moving average part of \( \Delta y_t \). We are confident that the logarithm of South African output is an integrated process of order one, I(1). Finally, we test for a unit root in the share of military expenditure in GDP, \( sm_t \). From Table 1, there is no evidence against the presence of
a unit root in this series, and we confidently treat $sm_t$ as integrated of order one, I(1).

In view of the findings that both $y_t$ and $sm_t$ are integrated time series (or "random walks"), one realises that standard Granger causality techniques are not applicable in this case, since they are designed for stationary time series only. To overcome this problem, most previous studies suggest to specify a VAR model in the first differences of these series, $\Delta y_t$ and $\Delta sm_t$ respectively. However, such a solution implies that output, $y_t$, and share of military expenditure in output, $sm_t$, are completely independent in the long-run. This may not be the case and output and the share of military expenditure in output may move together in an unknown long-run equilibrium relationship. Thus, although output and military burden may move persistently and erratically when viewed individually, this may not be the case if the two series are examined together. Output and military burden may trend together, i.e. they may have a common stochastic trend. In this case, we say that output and military burden cointegrate, i.e. there is a constant $\lambda$ such that $y_t - \lambda sm_t$ is a weakly stationary (I(0)) time series. There are various testing procedures that can detect cointegration between a set of time series. In our case this will give us an estimate of $\lambda$ as well. Furthermore, if the two series do cointegrate, a VAR model in first differences will be misspecified, and Granger causality inference from this misspecified VAR will be unreliable.

Since both (the logarithm of) real GDP in 1985 prices, $y_t$, and the share of military expenditure in GDP, $sm_t$, are integrated of order one, I(1), it is of great interest to know whether there is a long-run (cointegration) relationship amongst these variables. As we have already discussed and will explain later, short-term causality between output growth, $\Delta y_t$, and changes in the share of military expenditure in GDP, $\Delta sm_t$, is affected by the presence of a long-run relationship between $y_t$ and $sm_t$. If these series cointegrate, a VAR model in first differences ignores the long-run information and is misspecified. A model which incorporates both short-run and long-run dynamics is required and this model is the (vector) error correction model.

Various techniques for testing for cointegration are now available. Residual based tests for cointegration examine whether the residual $y_t - \hat{\lambda} sm_t$ contains one unit root. If this residual has no unit root, then $y_t$ and $sm_t$ cointegrate. We test for cointegration between $y_t$ and $sm_t$ by using Johansen’s (1988) cointegration method. It has been shown in the literature that Johansen's procedure is quite robust to identify the number of cointegration vectors in a vector of integrated time series. Since $y_t$ and $sm_t$ are very different in nature, see Figure 1 and 3, we allow for a restricted intercept in the mean of both variables. The details of
this approach can be found in Pesaran and Pesaran (1997, p. 430, Case II).

Table 2 presents various maximum eigenvalue LR tests for the rank of the corresponding long-run impact matrix in a VAR(1) model for the \([y_t, sm_t]’\) vector with an intercept. If this matrix is of lower than full rank, then there is cointegration. (If the rank of this matrix equals the number of time series (rows in the VAR), then the VAR is stationary.) Tests for the rank of the long-run impact matrix, \(r\), to be equal to 0 (no cointegration), 1 (one distinct cointegrating vector), etc are presented. (In our case, we have two variables only, so a rank of 2 will imply a stationary representation for the series involved.)

Rejection of the null \(r = 0\), in favour of the alternative \(r = 1\), implies the existence of (at least) one cointegrating vector, and so on. Rejection of \(r = 1\), in favour of \(r = 2\) establishes the existence of (at least two) distinct cointegrating vectors (for our two-dimensional system, this would imply a stationary VAR). The evidence for South Africa, using both available tests, is that there is one cointegrating vector (indicating a long-run relationship) between \(y_t\) and \(sm_t\). This is because the null hypothesis, \(r = 0\), is rejected in favour of \(r = 1\), while the null hypothesis \(r = 1\) is not rejected. (In general, if the rank of the long-run impact matrix is one, then there is one cointegrating vector. If the rank is two there two cointegrating vectors, and so on.) Furthermore, statistical evidence, not reported in this paper, based on a VAR(2) model, arrives at the same conclusion, that there exists one cointegrating vector (indicating a long-run relationship) between \(y_t\) and \(sm_t\). As we have already mentioned, and shall explain later on, existence of a long-run (cointegration) relationship between \(y_t\) and \(sm_t\) may create problems in the examination of short-run causality, especially if this long-run information is neglected. Current literature on causal analysis of military expenditure on growth tends to rely on the short-run information (that is a VAR in first differences) and completely ignores existence of any long-run behaviour of the underlying level series. This means that a VAR for \(\Delta y_t\) and \(\Delta sm_t\) will be misspecified since \(y_t\) and \(sm_t\), cointegrated. To avoid misspecification, the VAR model in first differences should be augmented by an error correction term that takes into account the long-run behaviour of the levels series. Since this error correction term is unknown, an estimate of this error needs to be provided.

Finally, we consider the effect of the 1977 - 1994 embargo on growth and military burden. Table 3 presents a regression of real output growth on a constant and a dummy variable \(d(77-94)\), that takes the value of one in the embargo years and zero otherwise. There is a negative growth effect for these years, and the average growth rate of 4.7 % per year drops by 3.1 % to an average of 1.6 % for the embargo years.
The pattern is not followed by changes in the military expenditure to GDP ratio, as the corresponding column of Table 3 verifies. In view of the effect of the embargo on growth, we may need to re-specify any VAR models by adding the embargo dummy variable \( d(77 - 94) \), to capture regime shifts.

4. CAUSALITY AND COINTEGRATION

Granger causality (see Granger (1969)) and the consequent testing procedures developed subsequently constitute a concept designed to characterise any causal direction from one or more stationary variables to another stationary variable. For stationary time series, no distinction is made between the short- and the long-run. More specifically, for two stationary, I(0) in present terminology, variables, \( z_t \) and \( x_t \), standard Granger causality testing is based on the model

\[
z_t = \mathbf{d}' \mathbf{\mu}_1 + \sum_{i=1}^{k} \alpha_i z_{t-i} + \sum_{j=1}^{l} \beta_j x_{t-j} + \eta_{1t}
\]

(3)

where \( \mathbf{d} \) is a vector of exogenous variables and/or deterministic components and the orders \( k \) and \( l \) are to be selected by employing some information criterion. If, on the other hand, the null hypothesis \( H_0: \beta_1 = \beta_2 = \ldots = \beta_l = 0 \) is not rejected, then \( x_t \) does not Granger-cause \( z_t \). That is, rejection of \( H_0: \beta_1 = \beta_2 = \ldots = \beta_l = 0 \) implies Granger causality from \( x_t \) to \( z_t \). Similarly, using the model

\[
x_t = \mathbf{d}' \mathbf{\mu}_2 + \sum_{i=1}^{m} \gamma_i x_{t-i} + \sum_{j=1}^{n} \delta_j z_{t-j} + \eta_{2t}
\]

(4)

we may examine Granger causality from \( z_t \) to \( x_t \) by testing the null \( H_0: \delta_1 = \delta_2 = \ldots = \delta_n = 0 \). Rejection of the last null hypothesis implies Granger causality from \( z_t \) to \( x_t \).

However, if \( z_t \) and \( x_t \) are integrated I(1) variables and there is one cointegrated long-run equilibrium relationship (vector), short-run Granger causality should be examined by equations similar to (1) and (2), where \( z_t \) and \( x_t \) are replaced by their first differences \( \Delta z_t \) and \( \Delta x_t \), respectively, provided that the (long-run) error correction term (ECT) has been added to both equations lagged once. This ECT can be the estimated residual from a levels regression of \( z_t \) on \( x_t \) lagged once, see Engle and Granger (1987) for the theory, and Oxley (1993) for an empirical exposition. Alternatively, one can use Johansen’s (1988) procedure to estimate the long-run coefficients and produce a long-run ECT. In practise, arbitrary long-run coefficients have also been used to produce an estimate of the unknown long-run ECT.
In this case, the relevant models are

\[ \Delta z_t = d_1' \mu_1 + \sum_{i=1}^k \alpha_i \Delta z_{t-i} + \sum_{j=1}^l \beta_j \Delta x_{t-j} + \Theta_1 ECT_{t-1} + \eta_t, \]  

(5)

\[ \Delta x_t = d_2' \mu_2 + \sum_{i=1}^m \gamma_i \Delta x_{t-i} + \sum_{j=1}^n \delta_j \Delta z_{t-j} + \Theta_2 ECT_{t-1} + \eta_t, \]  

(6)

where \( ECT_{t-1} \) is either the lagged residual from the levels regression of \( z_t \) on \( x_t \), or a Johansen-type error correction term, or any arbitrarily constructed series (usually utilising postulates of economic theory) that describes the long-run equilibrium between the level variables. Indeed, (5) and (6) arise from Granger’s representation theorem (see Engle and Granger (1987)) for a set of two cointegrated variables.

In the literature on the causal analysis of military spending on growth, see for example Chowdhury (1991) and Madden and Haslehurst (1995), none of the above causality testing models is undertaken. Indeed, researchers in the field, having realised that the level series, \( y_t \) and \( sm_t \) in this case, are integrated (by suitable unit root testing) do not apply causality testing via levels models like (3) and (4), nor do they apply models (5) and (6). Indeed, they often just ignore the possibility of cointegration between the level variables and specify testing models in first differences. This amounts to employing misspecified versions of (5) and (6) without the error correction term \( ECT_{t-1} \) present, and this is likely to cause incorrect inference.

Considering the South African data and following the approach of ignoring cointegration, we estimated the following VAR(2) model in first differences:

\[ \Delta y_t = \mu_1 + \alpha_1 \Delta y_{t-1} + \alpha_2 \Delta y_{t-2} + \beta_1 \Delta sm_{t-1} + \beta_2 \Delta sm_{t-2} + \eta_t, \]  

(7)

\[ \Delta sm_t = \mu_2 + \gamma_1 \Delta sm_{t-1} + \gamma_2 \Delta sm_{t-2} + \delta_1 \Delta y_{t-1} + \delta_2 \Delta y_{t-2} + \eta_2, \]  

(8)

\{Table 4, about here\}

In view of our findings about cointegration between \( y_t \) and \( sm_t \), (7) and (8) constitute a misspecified VAR model in first differences. This is because no long-run information is utilised via an error correcting term. The long-run relationship between \( y_t \) and \( sm_t \) is ignored by this model.

Focusing upon the short-run effect of military burden on output growth, we report estimates and diagnostics for equation (7) in Table 4. Both \( \beta_1 \) and \( \beta_2 \) are not significant and the null hypothesis \( H_0: \beta_1 = 0 \beta_2 = 0 \) cannot be rejected. The relevant \( \chi^2 \) LM statistic is 0.48406 [0.785], while the \( \chi^2 \) LR statistic is 0.48776 [0.784], and the exact finite sample F-test is 0.20735 [0.814]. (In square brackets, we report p-values of the corresponding test when compared to the relevant asymptotic or exact critical value. If this p-value is less than 0.05 we reject the corresponding null hypothesis at 5% significance level.
and if this p-value is less than 0.10 we reject the corresponding null hypothesis at 10 \% significance level, and so on.) So there is no causality from military expenditure to growth according to all these statistics. For equation (8), the null \( H_0: \delta_1 = 0 \delta_2 = 0 \) is also not rejected by all three statistics: the \( \chi^2 \) LM statistic is 1.3580 [0.507], the \( \chi^2 \) LR is 1.3876 [0.500], and the F-test is 0.59829 [0.557]. Hence, there is no short-run causality from output growth to military expenditure either. However, the previous conclusions may be altered if cointegration is taken into account. We know that (7) and (8) constitute a misspecified VAR model, and we need to correct this VAR model in first differences, by taking into account the long-run information, to have robust inference about any short-run Granger causality between output growth and changes in military burden. For this purpose, we estimate

\[
y_t = \kappa + \lambda \cdot sm_t + \epsilon_t, \tag{9}
\]

and the estimated residual, \( \hat{\epsilon}_{t-1} \), is to added in both (7) and (8) to capture all long run effects. It serves as an estimate of the error correction term. Other estimates for ECT can be employed with asymptotically equivalent results. Thus, we consider the following vector error correction model:

\[
\Delta y_t = \mu_1 + \alpha_1 \Delta y_{t-1} + \alpha_2 \Delta y_{t-2} + \beta_1 \Delta sm_{t-1} + \beta_2 \Delta sm_{t-2} + \theta_1 \hat{\epsilon}_{t-1} + \eta_t, \tag{10}
\]

\[
\Delta sm_t = \mu_2 + \gamma_1 \Delta sm_{t-1} + \gamma_2 \Delta sm_{t-2} + \delta_1 \Delta y_{t-1} + \delta_2 \Delta y_{t-2} + \theta_2 \hat{\epsilon}_{t-1} + \eta_t, \tag{11}
\]

To justify the significance of employing \( \hat{\epsilon}_{t-1} \) in (10) and (11) respectively, the corresponding t-ratios should not be compared to the standard \( t \) critical values for a given sample, or to 2 in absolute value asymptotically, but rather to some other unknown exact finite sample critical value. To overcome this problem, a (conservative) rule of thumb, which has been employed in this situation, is to compare the t-ratio of \( \theta_1 \) and \( \theta_2 \) to 3 (three) in absolute value. Non-rejection of \( \theta_1 = 0 \), say, has some econometric significance. It means that the corresponding variable (in this case \( y_t \)) is exogenous. Similarly, non-rejection of \( \theta_2 = 0 \) implies that the corresponding variable (\( sm_t \) in this case) is exogenous.

Again, focusing upon the causality from military expenditure to output growth, Table 4 reports estimates and diagnostic tests for equation (10). It is clear that the equation now has a better fit and that the coefficient \( \theta_1 \) is significant, even if we compare its t-ratio to 3. Testing the direction of causality by testing the null hypothesis \( H_0: \beta_1 = 0 \beta_2 = 0 \) results in a LM \( \chi^2 \) statistic of 5.7337 [0.057], a LR \( \chi^2 \) statistic of 6.3184 [0.042], and an exact finite sample F-test of 2.8378 [0.077]. Hence, the LR test rejects the no-causality null hypothesis at 5 \% significance asymptotically, while the other two criteria do so at the 10 \%
significance level only. From the LR test statistic, based on the model with the long-run dynamics incorporated, we have some evidence (although asymptotic) of a negative effect of military expenditure on output growth at 5% significance level. From equation (11), for the null $H_0: \delta_1 = 0, \delta_2 = 0$, the corresponding $\chi^2$ LM statistic is 3.9909 [0.136], the LR $\chi^2$ statistic is 4.2626 [0.119], and the exact finite sample F-test is 1.8523 [0.177]. None of these tests reject the no-causality null hypothesis at even the 10% significance level. There is no evidence of output growth affecting military expenditure either positively or negatively.

From Table 4, reporting results and diagnostic tests for equation (10), there is no indication of misspecification. However, as we have already examined in Table 3, there is a growth slowdown in South Africa during the embargo years. This information should be utilized to examine direction of short-run Granger causality. We take into account the effect of the 1977-1994 embargo on growth and military burden. For this, we re-specify the previous VECM(2) model by adding the embargo dummy variable $d(77-94)$. This gives the following model:

$$\Delta y_t = \mu_1 + \alpha_1 \Delta y_{t-1} + \alpha_2 \Delta y_{t-2} + \beta_1 \Delta sm_{t-1} + \beta_2 \Delta sm_{t-2} + \theta_1 \hat{\epsilon}_{t-1} + \lambda_1 d(77-94), + \eta_{1t} \tag{12}$$

$$\Delta sm_t = \mu_2 + \gamma_1 \Delta sm_{t-1} + \gamma_2 \Delta sm_{t-2} + \delta_1 \Delta y_{t-1} + \delta_2 \Delta y_{t-2} + \theta_2 \hat{\epsilon}_{t-1} + \lambda_2 d(77-94), + \eta_{2t} \tag{13}$$

Table 4 reports estimates and diagnostic tests for equation (12). We see that $\lambda_1$ is significant and negative. Focusing on causality tests, we see that both the LM ($\chi^2$, 6.5674 [0.037]) and LR ($\chi^2$, 7.3505 [0.025]) tests reject the no-causality null hypothesis, $H_0: \beta_1 = 0, \beta_2 = 0$, at the 5% significance level asymptotically, while the exact finite sample F-test (F(2, 25), 3.2278 [0.057]) marginally does not reject the no-causality null hypothesis at the 5% significance level, its p-value being 0.057. However, at 10% significance level this test strongly rejects the no-causality null. Causality tests for (13), i.e. the null hypothesis $H_0: \delta_1 = 0, \delta_2 = 0$, do not reject the no-causality null hypothesis, not even asymptotically. The LM test is 1.7993 [0.407], the LR test is 1.8518 [0.396], and the F-test is 0.74471 [0.485]. There is no significant causal direction from changes in military burden to output growth.

Here, as is the case with many econometric studies, a finite sample is employed to draw inference, but asymptotic results have to be used, because the underlying exact distributions are not available. In such cases one has to be very cautious when interpreting such results, as they are only valid asymptotically. However, it should also be noticed that in such cases a sample of 50 is as small as 30. For this reason, we have not relied on asymptotic results solely. For example, when we justified the inclusion of the error correction term, we used a critical value for the t-ratio of 3 (as Monte Carlo studies suggest). Furthermore,
the finite sample critical values of Granger causality tests are not greatly affected by the inclusion of the error correction term and, given that our sample is small, we can securely rely on exact inference (using the F-tests) at a 10% significance level. Finally, we rely on a well founded and robust statistical methodology and, therefore, our results have similar properties.

Overall, for South Africa, there does seem to be some causality from changes in military expenditure share to output growth and the effect is a negative one. It is, however, only apparent when the standard test we have developed to allow for cointegration is used. It will be of interest to examine some of the previous cross country studies in the light of this finding.

5. CONCLUSIONS

This paper has provided an analysis of the relation between military spending and growth in South African data and has found evidence of a significant negative impact of military burden on the growth of output over the period 1964-96. This was achieved using a development of the standard Granger causality tests within the vector autoregression (VAR) framework. While the standard techniques suggest no significant relationship, the inclusion of long run information by taking cointegration into account provides a significant result. This is an important finding, both for the development of the literature, because it shows the importance of using the VAR approach to investigating such bivariate relationships, and for policy purposes, as it shows that the military burden of the apartheid regime did have a bad effect on the economy. The present cuts in military spending should then benefit the economy. This does not mean that achieving a “peace dividend” is simply a matter of cutting military spending, as there are bound to be short run adjustment costs. These will need to be dealt with by some form of conversion policy if the opportunity that is available to use the resources of the military sector to develop a stronger economy is not to be wasted (Batchelor and Dunne, 1998).
REFERENCES


**APPENDIX**

**Figure 1.** South-African GDP in 1985 Prices, Logarithmic Scale

**Figure 2.** South-African Real Output Growth (Fraction)

**Figure 3.** South-African Share of Military Expenditure in GDP (Fraction)
Table 1
Unit root tests for level variables: $y_t$ and $sm_t$, Intercept only
31 observations from 1965 to 1995

<table>
<thead>
<tr>
<th></th>
<th>Test</th>
<th>LL</th>
<th>AIC</th>
<th>SBC</th>
<th>HQC</th>
</tr>
</thead>
<tbody>
<tr>
<td>$y_t$</td>
<td>DF</td>
<td>-4.2377</td>
<td>77.6444</td>
<td>75.6444</td>
<td>74.2104</td>
</tr>
<tr>
<td></td>
<td>ADF(1)</td>
<td>-2.9953</td>
<td>77.7416</td>
<td>74.7416</td>
<td>72.5906</td>
</tr>
<tr>
<td></td>
<td>ADF(2)</td>
<td>-3.5535</td>
<td>79.3869</td>
<td>75.3869</td>
<td>72.5189</td>
</tr>
<tr>
<td></td>
<td>ADF(3)</td>
<td>-3.6845</td>
<td>80.3510</td>
<td>75.3510</td>
<td>71.7661</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Test</th>
<th>LL</th>
<th>AIC</th>
<th>SBC</th>
<th>HQC</th>
</tr>
</thead>
<tbody>
<tr>
<td>$sm_t$</td>
<td>DF</td>
<td>-1.2355</td>
<td>127.6517</td>
<td>125.6517</td>
<td>124.2177</td>
</tr>
<tr>
<td></td>
<td>ADF(1)</td>
<td>-1.7829</td>
<td>129.7014</td>
<td>126.7014</td>
<td>124.5504</td>
</tr>
<tr>
<td></td>
<td>ADF(2)</td>
<td>-2.2676</td>
<td>130.9329</td>
<td>126.9329</td>
<td>124.0649</td>
</tr>
<tr>
<td></td>
<td>ADF(3)</td>
<td>-1.5510</td>
<td>131.8772</td>
<td>126.8772</td>
<td>123.2922</td>
</tr>
</tbody>
</table>

95% critical value for the augmented Dickey-Fuller statistic = -2.9591

Unit root tests for level variables: $y_t$ and $sm_t$, Intercept and Linear Trend

<table>
<thead>
<tr>
<th></th>
<th>Test</th>
<th>LL</th>
<th>AIC</th>
<th>SBC</th>
<th>HQC</th>
</tr>
</thead>
<tbody>
<tr>
<td>$y_t$</td>
<td>DF</td>
<td>-1.7712</td>
<td>77.8603</td>
<td>74.8603</td>
<td>72.7094</td>
</tr>
<tr>
<td></td>
<td>ADF(1)</td>
<td>-1.7431</td>
<td>78.0441</td>
<td>74.0441</td>
<td>71.1761</td>
</tr>
<tr>
<td></td>
<td>ADF(2)</td>
<td>-1.7219</td>
<td>79.4362</td>
<td>74.4362</td>
<td>70.8512</td>
</tr>
<tr>
<td></td>
<td>ADF(3)</td>
<td>-1.7408</td>
<td>80.3608</td>
<td>74.3608</td>
<td>70.0589</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Test</th>
<th>LL</th>
<th>AIC</th>
<th>SBC</th>
<th>HQC</th>
</tr>
</thead>
<tbody>
<tr>
<td>$sm_t$</td>
<td>DF</td>
<td>-1.0555</td>
<td>127.7425</td>
<td>124.7425</td>
<td>122.5915</td>
</tr>
<tr>
<td></td>
<td>ADF(1)</td>
<td>-1.7221</td>
<td>129.7370</td>
<td>125.7370</td>
<td>122.8690</td>
</tr>
<tr>
<td></td>
<td>ADF(2)</td>
<td>-2.4214</td>
<td>131.4296</td>
<td>126.4296</td>
<td>122.8447</td>
</tr>
<tr>
<td></td>
<td>ADF(3)</td>
<td>-1.3923</td>
<td>131.9494</td>
<td>125.9494</td>
<td>121.6474</td>
</tr>
</tbody>
</table>

95% critical value for the augmented Dickey-Fuller statistic = -3.5615

LL = Maximized log-likelihood    AIC = Akaike Information Criterion
SBC = Schwarz Bayesian Criterion    HQC = Hannan-Quinn Criterion
Table 2
Cointegration with restricted intercepts and no trends in the VAR
34 observations from 1962 to 1995. Order of VAR = 1
List of variables included in the cointegrating vector:
\( y_t, \quad s_{mt}, \quad \text{Intercept} \)

List of eigenvalues in descending order:
.78317    .11937    0.00

<table>
<thead>
<tr>
<th>Null</th>
<th>Alternative</th>
<th>Statistic</th>
<th>95% CV</th>
<th>90% CV</th>
</tr>
</thead>
<tbody>
<tr>
<td>( r = 0 )</td>
<td>( r = 1 )</td>
<td>51.9742</td>
<td>15.8700</td>
<td>13.8100</td>
</tr>
<tr>
<td>( r \leq 1 )</td>
<td>( r = 2 )</td>
<td>4.3218</td>
<td>9.1600</td>
<td>7.5300</td>
</tr>
</tbody>
</table>

Cointegration LR Test Based on Trace of the Stochastic Matrix

<table>
<thead>
<tr>
<th>Null</th>
<th>Alternative</th>
<th>Statistic</th>
<th>95% CV</th>
<th>90% CV</th>
</tr>
</thead>
<tbody>
<tr>
<td>( r = 0 )</td>
<td>( r = 1 )</td>
<td>56.2960</td>
<td>20.1800</td>
<td>17.8800</td>
</tr>
<tr>
<td>( r \leq 1 )</td>
<td>( r = 2 )</td>
<td>4.3218</td>
<td>9.1600</td>
<td>7.5300</td>
</tr>
</tbody>
</table>

Table 3
Dependent variable \( \Delta y_t \), Dependent variable is \( \Delta s_{mt} \)

<table>
<thead>
<tr>
<th>Constant</th>
<th>0.047</th>
<th>0.002</th>
</tr>
</thead>
<tbody>
<tr>
<td>( (8.277) )</td>
<td>( (1.494) )</td>
<td></td>
</tr>
</tbody>
</table>

\( d(77 - 94)_t \)

<table>
<thead>
<tr>
<th>(-0.031)</th>
<th>(-0.003)</th>
</tr>
</thead>
<tbody>
<tr>
<td>( (-3.991) )</td>
<td>( (-1.755) )</td>
</tr>
</tbody>
</table>

\( R^2 = 0.332 \) \( R^2 = 0.088 \)

\( SE = 0.023 \) \( SE = 0.005 \)

\( DW = 1.430 \) \( DW = 1.786 \)

Diagnostic tests

Serial Correlation, LM
\( \chi^2_1 = 2.604 \) [0.107] \( \chi^2_1 = 0.132 \) [0.716]
F(1,31) = 2.572 [0.119] F(1,31) = 121 [0.730]

Normality
\( \chi^2_2 = 1.203 \) [0.548] \( \chi^2_2 = 1.227 \) [0.541]

Heteroskedasticity
\( \chi^2_1 = 2.827 \) [0.093] \( \chi^2_1 = 1.467 \) [0.226]
F(1,32) = 2.901 [0.098] F(1,32) = 1.443 [0.238]
Table 4

<table>
<thead>
<tr>
<th>Dependent variable is $\Delta y_t$</th>
<th>Equation 7</th>
<th>Equation 10</th>
<th>Equation 12</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta y_{t-1}$</td>
<td>0.453</td>
<td>0.226</td>
<td>0.092</td>
</tr>
<tr>
<td></td>
<td>(2.415)</td>
<td>(1.278)</td>
<td>(0.533)</td>
</tr>
<tr>
<td>$\Delta y_{t-2}$</td>
<td>0.060</td>
<td>-0.164</td>
<td>-0.318</td>
</tr>
<tr>
<td></td>
<td>(0.316)</td>
<td>(-0.925)</td>
<td>(-1.816)</td>
</tr>
<tr>
<td>$\Delta sm_{t-1}$</td>
<td>-0.375</td>
<td>-1.062</td>
<td>-1.186</td>
</tr>
<tr>
<td></td>
<td>(-0.386)</td>
<td>(-1.229)</td>
<td>(-1.489)</td>
</tr>
<tr>
<td>$\Delta sm_{t-2}$</td>
<td>-0.428</td>
<td>-1.899</td>
<td>-1.763</td>
</tr>
<tr>
<td></td>
<td>(-0.458)</td>
<td>(-2.049)</td>
<td>(-2.063)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.013</td>
<td>0.028</td>
<td>0.050</td>
</tr>
<tr>
<td></td>
<td>(1.866)</td>
<td>(3.662)</td>
<td>(4.339)</td>
</tr>
<tr>
<td>$\hat{e}_{t-1}$</td>
<td>-0.082</td>
<td>-0.079</td>
<td>-0.023</td>
</tr>
<tr>
<td></td>
<td>(-3.215)</td>
<td>(-3.338)</td>
<td>(-2.384)</td>
</tr>
<tr>
<td>$d(77-94)_t$</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

(t-ratios in parentheses underneath coefficient value)

$$
R^2 = 0.248 \quad R^2 = 0.462 \quad R^2 = 0.562 \\
SE = 0.025 \quad SE = 0.021 \quad SE = 0.020 \\
DW = 2.015 \quad DW = 1.974 \quad DW = 1.991
$$

Diagnostic tests

<table>
<thead>
<tr>
<th>Serial Correlation, LM</th>
<th>$\chi^2_1 = 0.765 [0.382]$</th>
<th>$\chi^2_1 = 0.746 [0.388]$</th>
<th>$\chi^2_1 = 0.157 [0.692]$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>F(1,26) = 0.636 [0.432]</td>
<td>F(1,25) = 0.597 [0.447]</td>
<td>F(1,24) = 0.118 [0.734]</td>
</tr>
<tr>
<td>Ramsey’s RESET</td>
<td>$\chi^2_1 = 2.033 [0.154]$</td>
<td>$\chi^2_1 = 0.126 [0.723]$</td>
<td>$\chi^2_1 = 0.645 [0.422]$</td>
</tr>
<tr>
<td></td>
<td>F(1,26) = 1.764 [0.196]</td>
<td>F(1,25) = 0.099 [0.756]</td>
<td>F(1,24) = 0.494 [0.489]</td>
</tr>
<tr>
<td>Normality</td>
<td>$\chi^2_2 = 1.015 [0.602]$</td>
<td>$\chi^2_2 = 0.630 [0.730]$</td>
<td>$\chi^2_2 = 0.343 [0.842]$</td>
</tr>
<tr>
<td>Heteroskedasticity</td>
<td>$\chi^2_1 = 0.122 [0.727]$</td>
<td>$\chi^2_1 = 2.335 [0.126]$</td>
<td>$\chi^2_1 = 0.713 [0.398]$</td>
</tr>
<tr>
<td></td>
<td>F(1,30) = 0.115 [0.737]</td>
<td>F(1,30) = 2.362 [0.135]</td>
<td>F(1,30) = 0.684 [0.415]</td>
</tr>
</tbody>
</table>

Causality tests

| LM                     | $\chi^2_2 = 0.484 [0.785]$ | $\chi^2_2 = 5.734 [0.057]$ | $\chi^2_2 = 6.567 [0.037]$ |
| LR                     | $\chi^2_2 = 0.488 [0.784]$ | $\chi^2_2 = 6.318 [0.042]$ | $\chi^2_2 = 7.351 [0.025]$ |
| F                      | F(2,27) = 0.207 [0.814]     | F(2,26) = 2.838 [0.077]     | F(2,25) = 3.228 [0.057]     |