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*We are grateful to Pat Colgate for providing us with some of the data, and to Jason Wong for assisting us with the compilation of other data series.

1. Introduction

The promotion of the export sector as a means of achieving aggregate growth is one of the most widely discussed strategies in the economic development literature. More specifically, it has been suggested by many authors that a growth in real exports *causes* a growth in real GNP or real GDP. For example, see Little *et al.* (1970), Bhagwati (1978) and Krueger (1978), among others.

The export-led growth (ELG) thesis has been popular in the context of both less developed countries (LDC's) and newly industrialised countries (NIC's). The ELG hypothesis has often been used as the basis for explaining the observed differences in the development patterns of such countries, and it has been tested empirically in a number of studies. The results of these studies are mixed, partly because of differences in the extent to which the data that have been used are actually relevant for testing the hypothesis of interest, but also because of a considerable variation in the degree of sophistication of the associated econometric analysis.

Recently, the ELG hypothesis has been the subject of considerable local discussion in New Zealand, as that economy struggles to emerge from a major recessionary phase of the business cycle. In this case, however, the validity of the ELG hypothesis appears to have been accepted without question by politicians and commentators alike. Accordingly, this paper tests the validity of the export-led growth argument in the context of the New Zealand economy. In doing so, we also illustrate (in a deliberately expository manner) how various recent developments in the analysis of economic time-series data, and other modern econometric techniques, can be used to test the ELG hypothesis in an appropriate way.

The plan of the paper is as follows. In the next section we discuss the economic motivation behind the ELG hypothesis, and summarise the related empirical evidence. Section 3 describes the econometric methodology that we use to test formally whether the rate of growth of real exports *causes* the rate of growth in real GDP in New Zealand, and Section 4 discusses the data that we use. The results that we obtain are given in Section 5, and the final section comprises some concluding remarks.

2. Theoretical and Empirical Background

Various arguments have been put forward in support of the notion that export growth may promote a subsequent growth in real output. For example, Jung and Marshall (1985) suggest the following possibilities. First, export growth may reflect a rise in the demand for the country's outputs, and this in turn will be realised in real GNP or GDP growth. Second, by raising the level of exports, additional foreign exchange will be generated, and this may facilitate the purchase of productive intermediate goods. Third, a growth in exports may lead to greater productive efficiency (perhaps through economies of scale or technical improvements as a result of contact with foreign competitors) and enhanced output.

On the other hand, arguments have also been made (*e.g.*, Prebisch (1950) and Bagchi (1982)) in support of the opposite viewpoint. Specifically, and drawing especially on the experience of certain Latin American countries, it has been argued that trade with the "North" may actually hinder the development of countries in the "South". Recently, Eswaran and Kotwal (1991) have provided a two-country two-sector model which explains why the success or failure of an ELG strategy may depend crucially on the type of good that is being traded. This suggests that in our own empirical analysis it may be important to disaggregate total real exports by commodity group, something that has not been fully addressed in other empirical studies of the ELG hypothesis.

Generally, the ELG hypothesis is expressed as a causal link between the *rates of growth* of real exports and real domestic output (*e.g.*, Kindleberger (1961), Kravis (1970) and Meier (1976)). Recently, Buffie (1992) has presented a formal justification for this interpretation of ELG in terms of a dynamic general equilibrium model of a small country in which an expansion of exports transmits a cyclical effect to the rest of the economy as a result of its impact on capital accumulation. (See, also, Eaton (1987).) It is worth noting that other forms of the ELG hypothesis have been suggested. For example, Voivodas (1973) uses a two-gap model as the basis for postulating a relationship between the *level* of real exports and real GNP *growth*. However, this departs from the thrust of the literature on this topic, and we do not pursue the possibility of causal relationships of this form in this paper.

The empirical evidence associated with the ELG hypothesis is very mixed, partly as a result of the different techniques and data that have been used, and partly because of a failure, in some cases, to distinguish between statistical *association* and statistical *causality*. Jung and Marshall (1985) provide a useful tabular summary of many of the earlier empirical studies. These varied in terms of their use of either time-series or cross-section data, but most were based on Ordinary Least Squares (OLS) regression. They also differed with respect to measuring either or both of the exports and output variables in terms of levels or growth rates. For example, Maizels (1968) used pooled time-series/cross-section data for nine countries over thirteen years and regressed the level of GNP on the level of (contemporaneous) exports. He found in favour of the ELG hypothesis. Feder (1983) came to the same conclusion by using pure cross-section data for thirty one countries, and OLS multiple regression of GDP growth on contemporaneous export growth (or export share) and other variables such as investment share and foreign investment share as other explanatory variables.

Early studies of this type effectively mistook the positive *associations* that were revealed by such basic regression analysis for evidence of *causality* between one variable and another. This was also true of the study of Michaely (1977), who measured the Spearman rank correlations between *per capita* GNP growth and the growth of export share for forty one countries. More recently, this important distinction has been more fully appreciated, and several studies have re-considered the ELG hypothesis by testing for Granger causality in a formal way. As a result, the validity of this hypothesis has been brought into question, contrary to the apparently strong earlier empirical support.

For example, Jung and Marshall (1985) applied Granger causality tests to data for thirty seven developing countries and found evidence of causality from exports growth to real output growth for only four of them. Chow (1987) considered eight NIC's and, using Sims' (1972) variant of testing for causality, found evidence of uni-directional causality from manufactured exports growth to manufactured output growth in only one country. He also found evidence of bi-directional causality in six countries; and no evidence of any such causal links in the other case. Hsiao (1987) analyzed data for four Asian NIC's and concluded that only in the case of Hong Kong is there evidence of causality, and then it is in the opposite direction to that suggested by the ELG hypothesis.

The evidence *against* this hypothesis is augmented by the results of Kwan and Cotsomitis (1990) and Ahmad and Kwan (1991). The former authors consider data for China and find that any causality between exports growth and output growth is either bi-directional or absent, depending on the time-period chosen for the analysis. The latter authors examine the evidence for forty seven African countries. In their study, total and manufactured real export *levels* and either real *per capita* GDP or its rate of growth are used in the Granger causality tests. They conclude that there is no evidence in favour of the ELG hypothesis, and that there is *weak* support for causation running from economic growth to exports. Additional references to studies which focus on empirical tests of the ELG hypothesis are given by Jung and Marshall (1985) and Ahmad and Kwan (1991).

In summary, while several earlier investigations uncovered an *association* between export growth and aggregate economic growth for a range of countries, the subsequent evidence based on formal tests of Granger *causality* between these variables suggests very strongly that there may be less empirical support for the export-led growth hypothesis in its literal form than was previously assumed. However, even these later studies do not take account of certain recent developments in the analysis of time series data. In particular, the importance of testing for unit roots and possible cointegration between economic time-series has not been considered in the context of the problem under discussion here. Taking all of this into account, any reliance that is placed on the ELG theory for a particular country must be brought into question in the absence of strong affirmative empirical evidence, based on current econometric technology. This motivates our consideration of the New Zealand economy, where great hopes have been pinned on the ELG hypothesis, despite the current absence of any such affirmative evidence.

3. Econometric Methodology

3.1 Defining Causality

In defining "causality" we shall follow Granger (1969) : X "causes" Y if and only if Y(t) is predicted better by using the past history of X, together with the past history of Y itself, rather than by using just the past history in the Y variable. So, any formal econometric test of "causality" must be based on *time-series* data. In fact, several of the earlier studies that have been referred to above used *cross-section* data in the context of conventional OLS regression. This, in itself, indicates that the associated results may be of limited use in appraising the presence or otherwise of causality running from export growth to real growth in domestic output.

If X causes Y and Y does not cause X, we say that "uni-directional causality" exists from X to Y. If X does not cause Y and Y does not cause X, we say that either X and Y are statistically independent, or else they are contemporaneously related, but they are not related in any other way. Finally, if X causes Y and Y causes X, we say that there is bi-directional causality (or feedback) between these two variables.

Several tests of (Granger) causality have been proposed and used in numerous empirical economic studies, including ones which address the ELG issue. These tests are all based on the estimation of autoregressive or vector autoregressive (VAR) relationships involving X and Y, together with tests of the significance of (sub-) sets of lagged regressor variables. All of these tests have only (large sample) asymptotic justification. However, Guilkey and Salemi (1982) have examined the finite-sample properties of three of the most common such tests. These are the basic Granger test, as popularised by Sargent (1976); Sims' (1972) test, which introduces both leads and lags into the equations which form the basis of the analysis; and a modification of the latter, involving the inclusion of own lags to compensate for serial correlation of the error term, as suggested by Geweke *et al.* (1983). The results of Guilkey and Salemi (1982) support the use of the first of these testing procedures, and we shall follow this approach in the present study.

However, before detailing the exact form of the Granger/Sargent causality testing framework, some consideration has to be given to the possibility that the time-series data that we shall be using may be non-stationary. This is a likely situation, with several implications for our analysis. These can best be seen by considering two concepts associated with time series data - the "order of integration" of each series, and the possibility of "cointegration" between two (or more) of the series.

3.2 Modelling With Non-Stationary Time-Series

If a stochastic process is stationary then its probability distribution is the same at all points in time, and many of its characteristics can be inferred by looking at a histogram of observations from the process. In our case, these observations are temporally ordered - the process is a time-series. Standard methods of statistical inference are generally valid only if the data are stationary. While many economic time-series are *non-stationary*, most are "homogeneous non-stationary", which means that they can be reduced to stationary processes by differencing the data an appropriate number of times. A series which is stationary after being differenced "d" times is said (Granger (1981)) to be "integrated of order d", or I(d). So, an I(0) series is stationary, and it remains stationary if differenced further. Accordingly, such data can be used in either level or differenced form in a regression model. However, many economic time-series have been found to be I(1) or I(2), so it is immediately clear that care must be taken if such data are to be used in any sort of regression analysis, including those regressions which underlie tests for Granger causality, as described in the next sub-section.

It may seem that data which are I(d) should be differenced "d" times prior to being used in a regression model. While this is often the case, there is also an important exception to this. It is readily established that adding a series that is I(0) to one which is I(1) results in an I(1) series. Similarly (*e.g.*, Engle and Granger (1987)), a linear combination of two series which are each I(1) will *usually* produce another I(1) series. However, this need not be so. In particular, it is possible that there exists a linear combination of two I(1) series which is I(0). If such a combination exists then it is unique, and in this case the two original series are said to be "cointegrated" (Granger (1981), and Granger and Weiss (1983)).

There are several implications (*e.g.*, Granger (1983), Engle and Granger (1987)) of cointegration that will be important here. First, if two I(1) series are cointegrated then there is a tendency for them to move together in the long run. If there are shocks which drive them apart, then there are common characteristics which bring the series back together. Second, if X and Y are both I(1) and cointegrated, then there is either uni-directional or bi-directional (Granger) causality between X and Y. So, if we test for, and establish, cointegration between real exports growth and growth in real GDP (for example), then some evidence of causality (in at least one direction) should emerge from the Granger causality tests themselves. Of course, with a finite sample of data, the tests may not be sufficiently powerful to detect this, but in principle this provides a cross-check on the results from our subsequent analysis.

Third, in the case of I(1) series which are cointegrated, the Granger Representation Theorem tells us how to model the relationship between such variables in the form of a VAR model. This theorem shows that we can either construct the VAR in terms of the *levels* of the data; or else we can construct a long-run VAR in terms of the *first-differences* of the variables, but also include an "error correction" term in each equation to capture short-run dynamics. The latter term comprises the lagged residuals from an OLS regression of X on Y and an intercept (or *vice versa*). The latter regression is generally termed the "cointegrating regression", and the associated coefficients form the "cointegrating vector" which combines X and Y into an I(0) series. There are two interesting features to this theorem. It tells us that if we do the "obvious" thing and difference the I(1) data to make them stationary, then an extra term must be added to the equations of the VAR if the variables are cointegrated. It is *not* appropriate to omit this term. Also, if X and Y are cointegrated then we can legitimately construct a VAR model using non-stationary data! Indeed, it turns out that the application of OLS to the levels of the variables in this special case yields parameter estimates which are "super-consistent" (Stock (1987)) - they converge to the true values faster than the conventional rate of $T^{-1/2}$. All of these considerations are important for the way in which we will test for Granger causality between real exports growth and real GDP growth in New Zealand in this study.

3.3 Testing for Causality

The procedure that we adopt is as follows. Given the form of the ELG hypothesis that we wish to test, it is convenient to measure the variables in natural logarithms, so that their first differences are (continuously compounding) rates of growth. First, we test for the order of integration of each of the series being used. In particular, we use the t-statistic version of the Augmented Dickey-Fuller test for this purpose. Although alternative tests (such as the Phillips-Perron variant of the Dickey-Fuller test) have been proposed, our choice here reflects the fact that the available simulation evidence (*e.g.*, Campbell and Perron (1991 p.16)) suggests that these alternatives can exhibit severe size-distortion in finite samples. Complete details of the testing strategy that we adopt are best considered in the context of specific results, and so these are given in Section 5. If real exports and real GDP are *both* I(1), then we test for cointegration between them, using the Augmented Dickey-Fuller test. Otherwise, both variables are used in log-difference form in the equations of the VAR models given below, as is also the case if they are found *not* to be cointegrated. (It will be recalled that differencing an I(1) renders it stationary and differencing an I(0) series does not alter its stationarity.) On the other hand, if the two variables *are* found to be cointegrated, then the VAR equations below are augmented with the appropriate "error correction" terms prior to estimation and testing for Granger causality.

So, in any case, the variables in the VAR model, except for possible error correction terms, are in log-difference form. The standard way of then testing for Granger causality between the growth rates of X and Y is to estimate the following VAR model :

$$DLX_t = \alpha + \sum_{i=1}^{m} \beta_i DLX_{t-1} + \sum_{j=1}^{n} \gamma_i DLY_{t-j} + u_t \tag{1}$$

$$DLY_t = a + \sum_{i=1}^{q} b_i DLY_{t-i} + \sum_{j=1}^{r} c_j DLX_{t-j} + \upsilon_t \tag{2}$$

where $DLX_t = \log(X_t) - \log(X_{t-1})$, *etc.*, and u_t and v_t are zero-mean, serially uncorrelated, random disturbances. Estimation of equations (1) and (2) can be by OLS, or by joint maximum likelihood (ML) if the VAR model is treated as a system of "seemingly unrelated regression equations" (a SURE model). There may be gains in terms of asymptotic efficiency if full ML estimation is used, and it is well known (Srivastava and Giles (1987, pp. 17-18)) that the two estimators coincide if n = q and m = r, or if the contemporaneous error covariance matrix (Ω) is diagonal. So, we test for the diagonality of Ω using the standard asymptotic Likelihood Ratio (LR) and Breusch-Pagan Lagrange Multiplier (BP-LM) tests. We then test for Granger causality between X and Y in the context of single equation OLS estimation if the null hypothesis of a diagonal Ω cannot be rejected; and we proceed in the context of the two-equation system if this hypothesis *is* rejected. Again, it will be recalled that equations (1) and (2) will also include "error correction" terms if log(X) and log(Y) are each I(1) and cointegrated.

Given values for the lag lengths, m,n,q and r, we test to see if Y (Granger) causes X by testing the hypothesis $H_o : \gamma_1 = \gamma_2 = ... = \gamma_n = 0$ against the alternative H_a : not H_o. Similarly, we test if X (Granger) causes Y by testing the hypothesis $H_o' : c_1 = c_2 = ... = c_r = 0$ against the alternative H_a' : not H_o'. To do this under OLS estimation we form the usual "F-statistics" (F_1 and F_2 respectively) for testing the significance of a subset of regressors. It is well known that this is equivalent to constructing the Wald test of these zero restrictions on the coefficients. However, given the presence of lagged dependent variables in the equations, these statistics are *not* F-distributed under the null (*e.g.*, Sims (1980, p.17) and Evans and Savin (1982)), contrary to what is assumed in a number of studies of this type. Schmidt (1976, p.99) shows that the Wald statistics, nF_1 and rF_2, are asymptotically Chi Square with n and r degrees of freedom respectively. A simple logarithmic transformation converts Wald statistics into LR test statistics, which are also asymptotically Chi Square, and Sims (1980, p.17) suggests a modified version of the latter which involves a simple degrees of freedom correction. Under joint ML estimation, the Wald statistics for testing the same zero restrictions are again constructed, and they are also asymptotically Chi Square under the null hypotheses of "no causality". In this case, too, Sims suggests a modified LR statistic which adjusts for the number of coefficients relative to the number of equations in the model.

The application of these tests assumes that the lag lengths associated with the regressors in equations (1) and (2) are known. Of course, in practice this will not be the case, and the maximum lag lengths have to be determined empirically. Typically, this is a point that has not been treated well in many causality studies. In particular, some authors (*e.g.*, Jung and Marshall (1985), Chow (1987) and Hsiao (1987)) simply assign values to m,n,q and r *a priori*. Others add successive lags until further ones are "insignificant". Neither of these approaches is satisfactory. In both cases there is the risk of mis-specifying the lag length and invalidating the subsequent inferences, with the pre-test distortion of the sizes of the sequential significance tests being uncontrollable in the second case. The latter approach can be improved upon by assigning relatively large values for the maximum lag lengths, and sequentially *reducing* their values, testing for significance using the usual rules for size-control that are associated with testing "nested" hypotheses (*e.g.*, Mizon (1977)). However, there is still then the risk of beginning the search with a lag length that is too short.

Other, better, options are available. For example, Ahmad and Kwan (1991) use Akaike's Information Criterion (AIC) to determine the optimal lag lengths, but their approach is unnecessarily restrictive as they impose the constraints $m=n$ and $q=r$. We follow the approach of Hsiao (1979, 1981), and more recently Bahmani-Oskooee and Sohrabian (1992), to determine the optimal maximum lag lengths in equations (1) and (2). One advantage of their approach is that, as a by-product, it offers a direct cross-check on the outcome of the causality tests. Along with the results of the cointegration tests, this may be especially helpful in applications involving relatively short time-series, where appeals to the asymptotic validity of the various tests may not be very convincing.

The values of m and n in equation (1), say, have been chosen by minimising Akaike's Final Prediction Error (FPE) in a two-step fashion. First, we set $n=0$ and vary m to find the value $m=m^*$ which minimizes

$$FPE(m) = [(T+k)/(T-k)][SSR(m)/T]. \tag{3}$$

Here T is the sample size; $k = (m+1)$ if log(X) and log(Y) are *not* cointegrated, and $k = (m+2)$ if they *are* cointegrated (and an error correction term is added to the equation); and SSR(m) is the sum of the squared residuals. Then, with $m=m^*$ in equation (1), we vary n to find the value $n=n^*$ so as to minimize $FPE(m^*,n)$, where now $k = m^*+n+1$ (or $k =$

$m^{*}+n+2$ in the cointegrated case). If $FPE(m^{*},n^{*}) < FPE(m^{*})$, then this suggests that Y Granger-causes X. Noting that log(FPE) differs from AIC only by a term of order at most T^{-2} (*e.g.*, Judge *et al.* (1985, p.245)), it is clear that asymptotically this search procedure is identical to one based on Akaike's Information Criterion, but following the same type of two-step approach. This highlights the distinction between our search and the more limited one adopted by Ahmad and Kwan (1991).

The methodology that has been described in this section is applied in this paper to time-series data for New Zealand relating to real GDP and total real exports. Various disaggregated components of exports are also considered, in order to investigate the possibility that only certain export sub-sectors may be involved in causal relationships with aggregate economic activity. This is an important novel feature of our study. The details of our data set are now described.

4. The Data

The data that are used in this study comprise annual time-series for the period 1963 to 1991 inclusive. While it would be feasible to undertake our analysis with quarterly data, our use of annual time-series circumvents several potential disadvantages with the former option. In particular, we keep the use of unofficial data to a bare minimum. The unofficial GDP figures which are referred to below are used only for timing adjustments, and we avoid possible inadequacies which may be associated with the detailed quarterly estimates. Second, we avoid some important (and not fully resolved) issues with respect to testing for unit roots and cointegration in seasonal economic time-series data, and the associated consequences for estimation of models using such data. Simply "seasonally adjusting" the data and then proceeding with the conventional unit root and cointegration tests is not appropriate. Recent developments in this area are discussed by Osborn *et al.* (1988) and Hylleberg *et al.* (1990), for example.

Although New Zealand's external trade statistics are currently recorded monthly, historically they have been compiled on a year-ended-30th June basis, and this convention has been adopted here. This poses a difficulty with respect to real GDP data as until very recently the annual national accounts related to a fiscal year ending on 31st March in New Zealand and official quarterly national accounts are not compiled. To circumvent this problem unofficial real quarterly GDP data were obtained from the New Zealand Institute of Economic Research. This enabled us to construct real (1982/1983) GDP on a June-year basis to match the available exports data.

Disaggregation of the real exports data by type of goods also presents some difficulties. Not surprisingly, the definitions of the major export categories has changed several times over the sample period. By limiting our sample to begin in 1963 we were able to adjust and link the data provided by the New Zealand Department of Statistics in their *Key Statistics* and *Overseas Trade* publications. Accordingly, seven categories of f.o.b. exports are distinguished in the following analysis. Re-exports are excluded, as are commodities and transactions n.e.c.. The latter have been apportioned over the following seven categories (with 1987 percentages as the weights) to preserve the recorded value of total exports. The figures in parentheses refer to the harmonisation system classification chapters used in the compilation of these data since January 1988 :

1. Live animals, meat and edible meat offal (01-02).
2. Fish, crustacea, dairy produce and other animal produce (03-05).
3. Vegetables, fruit, prepared foodstuffs, beverages and tobacco (06-24).
4. Minerals, chemicals, plastic materials and their products (25-40).
5. Manufactures and goods classified by material, excluding metals (41-71).
6. Metals and articles of metal (72-83).
7. Other exports (84-98).

Table 1: Category Exports as % of Total Exports, and Total Exports as % of GDP

June Year Total	Cat. 1 as % of Total Exports	Cat. 2 as % of Total Exports	Cat. 3 as % of Total Exports	Cat. 4 as % of Total Exports	Cat. 5 as % of Total Exports	Cat. 6 as % of Total Exports	Cat. 7 as % of Total Exports	Total Exports as % of GDP
1963	30.0	29.0	2.1	1.6	37.0	0.1	0.2	19.1
1964	28.0	28.8	2.4	1.9	38.5	0.1	0.3	19.3
1965	29.0	31.7	2.6	3.2	32.8	0.2	0.4	17.6
1966	26.3	30.8	2.7	4.0	35.5	0.2	0.5	17.5
1967	27.7	34.4	3.3	4.0	29.6	0.4	0.7	16.9
1968	29.7	32.1	3.1	4.0	29.3	0.6	1.2	18.5
1969	29.1	28.6	3.0	4.1	32.8	0.7	1.8	20.0
1970	29.7	28.0	4.1	4.5	30.5	1.0	2.2	20.0
1971	30.1	28.1	4.0	5.2	29.2	1.0	2.4	19.3
1972	29.8	26.0	3.3	4.3	31.7	2.3	2.6	19.7
1973	25.8	21.5	3.1	2.3	42.1	3.2	2.0	22.7
1974	24.3	24.3	3.4	2.9	37.7	4.7	2.7	19.2
1975	29.7	22.5	5.1	3.6	30.2	4.4	4.4	16.4
1976	27.8	22.0	5.7	3.7	32.6	4.2	4.0	19.2
1977	25.5	23.4	5.3	3.4	34.1	4.6	3.7	22.3
1978	24.9	22.0	5.5	4.2	33.8	4.9	4.7	22.1
1979	25.7	20.2	5.2	3.9	34.2	5.9	4.9	23.2
1980	21.5	22.6	4.9	4.7	36.4	5.2	4.6	24.3
1981	24.5	21.9	5.2	5.2	32.1	5.4	5.6	24.1
1982	24.5	22.6	5.5	5.2	30.5	5.6	6.1	22.5
1983	26.4	23.1	5.8	5.4	27.8	6.2	5.3	24.3
1984	22.4	22.9	8.2	5.1	27.6	7.6	6.2	24.2
1985	20.8	21.4	10.3	5.5	26.3	7.5	8.1	25.8
1986	18.9	23.2	11.5	6.8	26.2	7.2	6.2	25.7
1987	21.8	24.1	11.3	5.2	26.3	6.2	5.1	27.8
1988	20.9	23.6	12.4	4.9	25.9	6.3	6.0	28.0
1989	21.8	22.8	10.9	5.5	25.2	7.1	6.7	28.3
1990	18.7	21.7	11.7	7.8	25.0	8.0	7.1	26.3
1991	18.6	22.2	12.0	9.9	21.8	8.3	7.2	29.5

Data for these variables are available in nominal terms, and these were then converted to real 1962/1963 values by using the following separate deflators for each category:

1. Meat export price index.
2. Dairy products export price index.
3. Food and beverages export price index.
4. Aluminium export price index.
5. Non-food manufactured goods export price index.
6. Non-fuel crude materials export price index.
7. Total exports price index.

It is impossible to get a perfect match between the classifications of nominal exports and of the exports prices, but these choices are considered to be quite adequate. Certainly, they are superior to the choices that have been necessary in some other related studies. (For example, Jung and Marshall (1985) had to use the consumers' price index to deflate exports for some of the countries in their analysis.) The total real exports series is also used in the tests of the ELG hypothesis. Table 1 summarises some of the key characteristics of our data in terms of (real) export shares, and the ratio of real total exports to real GDP. The latter ratio has grown markedly over the sample period, so the ELG hypothesis warrants investigation in the New Zealand context.

5. Results

All of our empirical results have been obtained with the SHAZAM package (White *et al.* (1990)). The first stage of our analysis involves testing the various time-series for their orders of integration, using the Augmented Dickey-Fuller (ADF) test. The optimal "order of augmentation" (p) was determined separately at each stage (*i.e.*, for each possible order of integration), and for each possible combination of the drift/trend version of the Dickey-Fuller (DF) regression, by examining the autocorrelation and partial autocorrelation functions for the residuals from the DF regressions to ensure that the associated errors were approximately white noise. Other approaches for choosing p have been suggested in the literature (*e.g.*, Campbell and Perron (1991) and Hall (1990)). Although it is widely recognised that the choice of p can have an important effect on the subsequent tests, there is no clearly preferred basis for this choice. Our approach addresses the heart of the matter - the purpose of "augmenting" the Dickey-Fuller regression is to achieve white noise errors. When the order of augmentation is zero, the ADF test collapses to the basic DF test.

The DF regressions were considered with and without drift (intercept) and trend terms included. The sequential procedure suggested by Dolado *et al.* (1990), and described below, was used to test for the order of integration. A 10% significance level was used throughout to ensure that the individual tests have reasonable power. It should be noted that when the DF regression includes a *significant* trend and/or drift, the usual ADF (or DF) statistic is asymptotically standard normal, rather than following the non-standard asymptotic distribution for which critical values are tabulated by Fuller (1976, p.373), Dickey and Fuller (1981, p.1063) and Guilkey and Schmidt (1989), for example.

Briefly, the testing strategy is as follows. We begin with the following DF regression for the time-series Y_t, having previously determined the optimal order of augmentation, "p":

$$\Delta Y_t = \alpha + \beta t + \gamma Y_{t-1} + \sum_{j=1}^{p} \beta_j \Delta Y_{t-j} + \epsilon_t \tag{4}$$

We test $H_o : \gamma = 0$ vs. $H_a : \gamma < 0$, using the DF critical value. If H_o is rejected we conclude that Y_t is I(0) and stop testing. If H_o is *not* rejected we test the significance of the trend term under the null. If the trend is significant we test H_o again using the standard normal critical value. (Some authors (*e.g.*, Muscatelli and Hurn (1992) and Hylleberg and Mizon (1989)) argue that the DF critical value, or an alternative value (*e.g.*, Goerlich (1992)), should be used at this stage as the normal approximation may not be valid in finite samples. Although we follow Dolado *et al.* (1990) on this point, we use a 1% test size in recognition of these concerns.) If the trend term is *not* significant under the null we re-formulate (4) without the trend:

$$\Delta Y_t = \alpha + \gamma Y_{t-1} + \sum_{j=1}^{p} \beta_j \Delta y_{t-j} + \epsilon_t. \tag{5}$$

Using this equation we determine the appropriate value of p and then test H_o using the appropriate DF critical value. If H_o is rejected we conclude that the series is I(0) and stop testing. If H_o is *not* rejected we test the significance of the drift term under the null. If the drift is significant we test H_o again using the standard normal critical value. If the drift is *not* significant under the null we re-formulate (5) without the intercept :

$$\Delta Y_t = \gamma Y_{t-1} + \sum_{j=1}^{P} \beta_j \Delta Y_{t-j} + e_t. \tag{6}$$

Finally, we determine p again and then test H_o using the appropriate DF critical value. A rejection of H_o implies that Y_t is I(0), while non-rejection implies that it is integrated of order one or higher. In the latter case we then difference Y_t and repeat the whole procedure to determine if the series is I(1) or I(2), *etc.*

The results of this sequential testing, which appear in Table 2, suggest that the logarithm of real GDP (GDPR), the logarithm of total real exports (TOTAL), and the logarithms of real exports in categories 1,2,3,4,and 5 (CAT1, CAT2, CAT3, CAT4 and CAT5) are I(1); while the logarithms of the other individual exports categories are I(0). As an additional exercise, we also formulated a Divisia real exports index. It was also found to be I(1). All of the following analysis was replicated with this series in place of simple aggregative total exports, and none of the conclusions were altered. Accordingly, these results are omitted to conserve space. The next step is to test for (pairwise) cointegration between GDP and each of the exports categories which are I(1).

Two forms of "cointegrating regressions" are suggested:

$$Y_t = \alpha + \beta X_t + \phi t + z_t \tag{7}$$

or

$$Y_t = \alpha + \beta X_t + z_t. \tag{8}$$

Table 2: ADF Tests for Order of Integration

Variable	H_0: I(1) *vs* H_A: I(0)			Variable	H_0: I(2) *vs* H_A: I(1)		
	p^+	t-statistic	Order of Integration		p^+	t-statistic	Order of Integration
GDPR	4	-2.27[c]	not I(0)	GDPR	0	-4.52[a]	I(1)
CAT1	2	-2.25[c]	not I(0)	CAT1	2	-5.96[a]	I(1)
CAT2	2	2.67[d]	not I(0)	CAT2	0	-5.69[a]	I(1)
CAT3	4	0.20[c]	not I(0)	CAT3	6	-4.54[a]	I(1)
CAT4	0	-1.17[c]	not I(0)	CAT4	0	-3.39[a]	I(1)
CAT5	2	1.45[d]	not I(0)	CAT5	2	-3.87[b]	I(1)
CAT6	1	-3.08[b]	I(0)	CAT6	not	applicable	
CAT7	3	-3.81[a]	I(0)	CAT7	not	applicable	
TOTAL	5	-1.14[c]	not I(0)	TOTAL	5	-3.08[b]	I(1)

\+ This is the p-value used in the model from which the t-statistic is obtained.

a Reject H_0: $\gamma = 0$ in model (4); t-statistic compared with DF critical value.

b Cannot reject H_0: $\gamma = 0$ and H_0: $\gamma = \beta = 0$ in (4). Reject H_0: $\gamma = 0$ in (5); t-statistic compared with DF critical value.

c Cannot reject H_0: $\gamma = 0$ and H_0: $\gamma = \beta = 0$ in (4). Cannot reject H_0: $\gamma = 0$ in (5), reject H_0: $\gamma = \alpha = 0$ in (5); t-statistic compared with standard normal critical value.

d Cannot reject H_0: $\gamma = 0$ and H_0: $\gamma = \beta = 0$ in (4). Cannot reject H_0: $\gamma = 0$ and H_0: $\gamma = \alpha = 0$ in (5). Cannot reject H_0: $\gamma = 0$ in (6); t-statistic compared with DF critical value.

The results suggest that the trend term (t) is statistically significant, but we have considered both (7) and (8) and have used the ADF test to ascertain whether z_t is non-stationary. This test is based on the OLS residuals, $\hat{z}_t$, from the cointegrating regression, (7) or (8), as follows:

$$\Delta\hat{z}_t = \gamma\hat{z}_{t-1} + \sum_{j=1}^{p}\beta_j\Delta\hat{z}_{t-j} + \epsilon_t. \tag{9}$$

The "cointegrating regression Augmented Dickey-Fuller" (CRADF) test then considers H_o: $\gamma = 0$ *vs.* H_a: $\gamma < 0$. If this hypothesis is rejected then X_t and Y_t are inferred to be cointegrated. The ADF critical values here are different from those used when testing for the order of integration as residuals rather than true errors appear in (9). Moreover, the critical values now also depend on p, which we have chosen by the method outlined at the beginning of this section. As OLS is "super-consistent" in the cointegrating regressions, asymptotically it is irrelevant whether these regressions are normalised on Y or X. In finite samples the normalisation may matter, and we have considered both possibilities. The results of our CRADF tests appear in Table 3, where we see that the only cointegration appears to be between the logarithm of real GDP and each of the logarithms of real exports in categories 1 and 5.

From Granger's Representation Theorem, then, there is evidence of bi-directional or uni-directional causality between *the (log-) level* of real output and *the (log-) level* of each of the "live animals and meat" and "manufactured goods" real exports groups. Only in the case of these cointegrated variables can this result be analyzed more carefully, using Granger causality tests, to determine the direction(s) of the causality in terms of the *(log-) levels* of the data. As the GDP series is I(1), it must be first-differenced prior to being used as the dependent variable in any regression, except in these special cases where it is cointegrated with the regressor(s).

However, the results of Tables 2 and 3 determine the forms of the VAR models that should be used as the basis for the Granger causality tests relating to the growth rates (*log*-differences) of the series. Specifically, except when testing for causality with the cointegrated pairs of variables, we formulate the VAR's as in equations (1) and (2). In the case of the cointegrated pairs, those equations are simply augmented with an error correction term. As noted earlier, this is just the lagged residual vector from a (cointegrating) regression of the *(log-) level* of GDPR on an intercept and the *(log-) level* of CAT1 or CAT5 in the case of equation (1), say, and the

Table 3: Cointegrating Regression ADF Test

Dependent Variable	Explanatory Variable	Time trend included in cointegrating regression		Time trend excluded from cointegrating regression		Cointegrated
		p	t-statistic	p	t-statistic	
GDPR CAT1	CAT1 GDPR	0 2	-2.64 -4.65*	2 2	-4.71* -5.25*	Yes
GDPR CAT2	CAT2 GDPR	0 0	-2.56 -3.30	0 0	-2.11 -1.83	No
GDPR CAT3	CAT3 GDPR	0 2	-1.75 -2.89	4 4	-0.92 -0.27	No
GDPR CAT4	CAT4 GDPR	0 0	-2.23 -3.12	0 0	-1.42 -1.30	No
GDPR CAT5	CAT5 GDPR	1 1	-2.65 -4.51*	1 1	-4.60* -4.74*	Yes
GDPR TOTAL	TOTAL GDPR	0 3	-1.89 -3.23	0 0	-3.15* -2.80	No

* indicates reject the non-stationarity of the residual terms (the variables are cointegrated) at the 10% significance level.

lagged residual vector from the converse regression in the case of equation (2). In addition, bearing in mind equation (8) above, we considered formulating the error correction terms as the lagged residuals from cointegrating regressions which included a linear trend. The latter results are given in parentheses in Tables 4 to 6, and none of our conclusions are affected by this choice.

The optimal lag lengths for the variables in the VAR models, found by Hsiao's method, are given in Table 4. Also reported there are the associated FPE(m^*) and FPE(m^*,n^*) values. Using a "model selection" approach, rather than a formal testing procedure, and recalling the discussion in Section 3, these values suggest that there is bi-directional causality between the growth rates in real output and in real exports of meat/live animals. There is also evidence of Granger causality from the growth rate in real exports of metals to the growth rate in real output; and reverse causality from the latter variable to the growth rate in real exports of manufactured goods. Interestingly, two of these three cases involve cointegrated data, implying Granger causality in at least one direction in terms of the *log-levels* of the variables.

Table 5 shows the results of the formal Granger causality tests, these being tests of the joint significance of the lagged values of the non-dependent variables in equations of the form (1) and (2). As can be seen, the only evidence of causality here is from the growth rate in real exports of metals to the growth rate in real output. In the case of the results relating to models which include error correction terms, we also checked the estimated coefficients of these terms as a cross-check on the outcome of the cointegration tests - if the variables are cointegrated then a significant negative coefficient is expected, and this was obtained in the appropriate cases.

The possibility of estimating equations (1) and (2) as a joint SURE model is considered in Table 6. There we see that only in the case of real exports of mineral/chemicals/plastics do the LR and BP-LM tests reject the hypothesis of a diagonal contemporaneous error covariance matrix. When the system is estimated by joint Maximum Likelihood in this case, we find evidence of uni-directional causality from this category of exports growth to real output growth.

Table 4: Selection of Lag Lengths Using FPE

Dependent Variable	Independent Variable	m*	n*	FPE(m*)	FPE(m*,n*)
GDPR	CAT1**	1	2	6.62×10^{-4}	6.30×10^{-4}
		(1)	(1)	(7.06×10^{-4})	(7.59×10^{-4})
CAT1	GDPR**	4	4	6.72×10^{-3}	6.22×10^{-3}
		(4)	(2)	(6.23×10^{-3})	(6.31×10^{-3})
GDPR	CAT2	1	2	7.60×10^{-4}	8.26×10^{-4}
CAT2	GDPR	2	1	7.66×10^{-3}	7.89×10^{-3}
GDPR	CAT3	1	1	7.60×10^{-4}	8.13×10^{-4}
CAT3	GDPR	4	1	15.50×10^{-4}	17.10×10^{-3}
GDPR	CAT4	1	5	7.60×10^{-4}	8.17×10^{-4}
CAT4	GDPR	2	2	26.80×10^{-3}	30.30×10^{-3}
GDPR	CAT5	1	1	6.66×10^{-4}	6.98×10^{-4}
		(5)	(1)	(7.12×10^{-3})	(7.49×10^{-4})
CAT5	GDPR**	4	1	17.14×10^{-3})	16.26×10^{-3})
		(4)	(1)	(17.30×10^{-3})	(16.88×10^{-3})
GDPR	CAT6**	1	6	7.60×10^{-4}	6.46×10^{-4}
CAT6	GDPR	1	2	5.07×10^{-3}	5.34×10^{-3}
GDPR	CAT7	1	1	7.60×10^{-4}	8.05×10^{-4}
CAT7	GDPR	6	1	31.29×10^{-3}	34.69×10^{-3}
GDPR	TOTAL	1	3	7.60×10^{-4}	8.04×10^{-4}
TOTAL	GDPR	2	1	4.78×10^{-3}	4.84×10^{-3}

** Causality implied by comparison of FPE(m*) and FPE(m*,n*).

m* denotes maximum lag on dependent variable; n* denotes maximum lag on independent variable.

Figures in parentheses relate to cases where the error correction term is generated from a cointegrating regression which includes a time-trend.

Table 5: Causality Tests Based on OLS Estimation

Dependent Variable	Independent Variable	d.f.	Wald Test	Sims' LR Test
GDPR	CAT1	2	4.145	4.142
		(1)	(0.058)	(0.068)
CAT1	GDPR	4	8.055	8.122
		(2)	(2.942)	(4.051)
GDPR	CAT2	2	1.536	1.613
CAT2	GDPR	1	0.213	0.230
GDPR	CAT3	1	0.187	0.194
CAT3	GDPR	1	0.073	0.087
GDPR	CAT4	5	8.111	8.556
CAT4	GDPR	2	4.467	4.438
GDPR	CAT5	1	0.647	0.664
		(1)	(0.723)	(1.083)
CAT5	GDPR	1	2.601	2.934
		(1)	(2.049)	(2.731)
GDPR	CAT6	6	17.879**	16.505*
CAT6	GDPR	2	3.550	3.587
GDPR	CAT7	1	0.430	0.443
CAT7	GDPR	1	0.050	0.069
GDPR	TOTAL	3	3.792	3.976
TOTAL	GDPR	1	1.712	1.792

* Significant at the 5% level.

** Significant at the 1% level.

d.f. = χ^2 degrees of freedom for both Wald and LR tests.

Figures in parentheses relate to cases where the error correction term is generated from a cointegrating regression which includes a time-trend.

Table 6: Tests Relating to Joint ML Estimation

Export Category	Diagonality Tests BP-LM	LR	Causality Tests Exports → GDP Wald	LR	GDP → Exports Wald	LR
1	1.581 (2.093)	2.144 (2.719)	n.a. (n.a.)	n.a. (n.a.)	n.a. (n.a.)	n.a. (n.a.)
2	0.121	0.121	n.a.	n.a.	n.a.	n.a.
3	2.532	2.847	n.a.	n.a.	n.a.	n.a.
4	5.494*	8.731**	11.403*	9.794	3.273	2.227
5	0.641 (2.497)	0.765 (4.188*)	n.a. (0.409)	n.a. (0.178)	n.a. (1.906)	n.a. (1.758)
6	2.431	3.026	n.a.	n.a.	n.a.	n.a.
7	0.034	0.050	n.a.	n.a.	n.a.	n.a.
TOTAL	0.326	0.338	n.a.	n.a.	n.a.	n.a.

* Significant at the 5% level.

** Significant at the 1% level.

The BP-LM and LR tests for diagonality of the error covariance matrix are both asymptotically $\chi^2(1)$.

The Wald and LR tests for causality Exports → GDP are asymptotically $\chi^2(5)$, while those for causality GDP → Exports are asymptotically $\chi^2(2)$.

Figures in parentheses relate to cases where the error correction term is generated from a cointegrating regression which includes a time-trend.

Table 7: Results based on (Log-) Levels Data

Dependent Variable	GDPR	CAT1	GDPR	CAT5
Independent Variable	CAT1**	GDPR	CAT5**	GDPR
m*	1	4	1	4
n*	1	2	2	2
FPE(m*)	6.17×10^{-4}	6.20×10^{-3}	6.17×10^{-4}	15.90×10^{-3}
FPE(m*,n*)	6.02×10^{-4}	6.69×10^{-3}	5.89×10^{-4}	17.00×10^{-3}
Wald Test	2.532	4.049	3.102^{+}	3.917
Sims' LR Test	2.509	4.056	3.043^{+}	3.935
d.f.	1	2	1	2
BP-LM	0.346		0.186	
LR	0.449		0.198	

$^{+}$ Significant at the 10% level.

** Causality implied by comparison of FPE(m*) and FPE(m*,n*) values.

d.f. $= \chi^2$ degrees of freedom for both Wald and Sims' LR tests.

BP-LM and LR tests are both asymptotically $\chi^2(1)$.

Finally, let us return to the earlier evidence of cointegration between real GDP and each of the first and fifth exports categories. Table 7 provides results which are designed to check the implication of such cointegration, namely that causality in at least one direction should exist between the *(log-) levels* of these pairs of variables. In fact the evidence is mixed. The FPE results suggest uni-directional causality from exports (log-) levels to the (log-) level of GDP in both cases, and there is weak support (at the 10% significance level) for this on the basis of the Wald and LR tests in the case of "manufactured goods" exports. However, such support is not found in the case of the "live animals and meat" exports category. Although this conflicts mildly with the earlier cointegration result, this is undoubtedly attributable to the fact that the various tests have only (large sample) asymptotic justification, and they should be applied cautiously with samples as small as ours.

6. Conclusions

The hypothesis that the *rate of growth* in real exports is a causal determinant of the *rate of growth* in real GDP is a central theme in the trade and development literature. However, when tested empirically this hypothesis has met with varying support historically. Early attempts to test such causality confused this notion with that of "statistical association". Indeed, several such studies used data which were inappropriate to the task. Consequently, the early "evidence" in support of export-led growth was in fact spurious. This has been clarified in more recent studies, for various countries, where formal tests for Granger causality have been performed, and virtually no evidence of export-led growth has been found.

However, even these studies need re-consideration. For example, as we have shown in this paper, recent developments in the analysis of economic time-series data need to be taken into account when testing for causality. Specifically, unless the orders of integration of the series, and any possible cointegration between them, are taken into account, the testing framework (and the results that are obtained) may be distorted. Further, almost without exception, other such studies have focused on *aggregate* real exports. As is clear from our results, this may mask important underlying differences between different export categories. In particular, even if there is evidence of export-led growth relating to certain groups of goods, this may not be reflected at the aggregate level, and a spurious conclusion may be drawn if disaggregated data are not considered.

In this study we have found that, in the case of the New Zealand economy, there is mixed evidence in support of the export-led growth hypothesis. Specifically, while we reject the hypothesis at the aggregate level, there is some support for it in the case of certain export groups. This is summarised in Table 8, where the notation "$X \rightarrow G$" denotes uni-directional Granger causality from exports rate of growth to GDP rate of growth, *etc*. That table also summarises the evidence relating to causality between the *levels* of exports and GDP in the two cases where the data were found to be cointegrated.

Two important conclusions may be drawn from this table. First, the presumption that the rate of growth in real exports necessarily causes the rate of growth in real GDP cannot be sustained *per se*. In the New Zealand context, such causality has not held historically at the aggregate level, though there is evidence in its favour if attention focuses on exports of minerals, chemicals and plastic materials; exports of metal and metal products; and (to a lesser degree) exports of live animals and meat. Second, turning to export and GDP *levels*, rather than growth rates, there is clearly causality from real exports of manufactured goods, and of meat and live animals, to real GDP. The time series characteristics of the data preclude an equivalent analysis of the other exports categories.

Table 8: Summary of Causality Results

Export Category		Growth Rates		(Log-) Levels	
		FPE	χ^2 Tests	FPE	χ^2 Tests
1.	Live Animals, Meat, etc.	$X \leftrightarrow G$		$X \rightarrow G$	
4.	Minerals, Chemicals, Plastics.		$X \rightarrow G$		
5.	Manufactured Goods.	$X \leftarrow G$		$X \rightarrow G$	$X \rightarrow G$
6.	Metals, etc.	$X \rightarrow G$	$X \rightarrow G$		

Note: "X" denotes real exports; "G" denotes real GDP.
No entry signifies no causality detected.

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(Continued on next page)

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