

Trade, Investment and Growth: Nexus, Analysis and Prognosis*

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Abstract

Patterns of causation between income, export, import, and investment growth for 39 developing countries are examined using model selection techniques which are based on ex-ante predictive ability criteria to identify the *best* predictive model for each country. In particular, we look at the incidence of causation and reverse causation between various economic variables which are commonly believed to *lead* economic growth and find that there is less reverse causation from income to these variables than previously thought. We also construct an index of global business cycle conditions, and find that models of countries with high trade exposure, growth rates, and investment rates tend to gain in predictive ability from the addition this variable.

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1 Introduction

In the post world war II decades, much attention has been directed to the problem of development. Why, it has been asked, did some countries develop and others, which looked quite similar, did not? In particular, what causes growth and what retards it? There are many schools of thought on this issue, and the ideology and analysis associated with these schools permeates the body of work known as development economics. In much of the literature, exports are seen as causing growth. One school of thought sees the stumbling block in attaining self sustaining growth as a lack of demand for one's products. In this area an influential set of ideas has come to be called the “*big push*” or “*balanced growth*” doctrine. Rosenstein-Rodan (1943), along with Nurkse (1953), Scitovsky (1954), and Fleming (1955), support an argument based on the presence of a “vicious circle”, where firms do not industrialize because there is no market for their goods, and there is no market for their goods because income is low, and income is low because firms did not industrialize. This kind of low level equilibrium, it was argued, could be broken by the simultaneous industrialization of a large part of the economy, and any failure to industrialize was essentially viewed as a coordination problem. Of course, exports, by breaking this circle of causation, could provide an important avenue for growth. The other “*unbalanced growth*” camp, led by Albert O. Hirschman (1958), while agreeing on the existence of a vicious circle, argued that industrialization of certain “*leading*” sectors would pull along the rest of the economy. Exports, especially in such leading sectors, could jump start the industrialization process.

Exports may be seen as causing growth for other reasons as well. One might believe that the stumbling block to growth is the lack of the technology needed to be competitive in the market, and if appropriate machinery needs to be imported, then exports of goods to pay for said imports will be required for growth. Thus, exports or foreign aid can fill in the “foreign exchange gap” that was perceived as an obstruction to growth (see e.g. McKinnon (1964)).

Exporting firms, especially multinationals, have also been seen as providing externalities by serving as conduits for the dissemination of world class technology to less dynamic domestically oriented firms. Coe and Helpman (1995), for example, argue that there are international R&D spillovers as foreign R&D has beneficial effects on domestic productivity, and that these are stronger the greater is trade. However, Keller (1998) demonstrates that there are problems with their interpretation of the data (they suggest that there is evidence that patterns of trade are important

in driving R&D spillovers), since counter factual random trade patterns are more closely linked to actual observation than are actual trade patterns.

Alternatively, it is argued that firms which export, learn from exporting. However, recent micro-level studies of the externality view seem to contradict this story. For example, based on examinations of plant level panel data, Clerides, Lach and Tybout (1998), Aw, Chen, and Roberts (1997), and Bernard and Jensen (1997) find that learning-by-exporting does not appear to have a strong impact on growth. Rather than learning-by-exporting, self-selection of high productivity firms into exporting sectors seems to be the main reason for the growth of exports. Thus, it is not export oriented firms which become productive; rather, it is productive firms which export!

Yet another strand of the literature uses endogenous growth models to link trade policy to growth. Ben-David and Loewy (1997), for example, ask whether free trade can have a permanent effect on output levels and growth rates. They emphasize the effects of knowledge spillovers which are due to increased trade, and find that these externalities can have an effect on income convergence and growth rates during transition, as well as in the long-run. Many new trade theories relate an increase in market size or in the availability of productive technology associated with imports to the returns to innovation, and hence to higher steady state growth rates. Thus, externalities associated with liberal trade policies are seen as leading to higher levels of GDP or higher growth (e.g. see Grossman and Helpman (1992) for a comprehensive discussion of a class of such models). In this context, one can argue that it is interference in the economy that prevents growth, and thus, one might look for evidence that a neutral stand on trade and the domestic economy (one definition of greater openness) causes growth.

However, conceptually well based indices of trade barriers are hard to construct. The only such index is the distance function based measure outlined in Anderson and Neary (1996)¹. Moreover, because trade policy is multi-faceted, no unique measure exists. Indeed, various different measures that have been suggested in the literature are loosely used to cover a host of different concepts

¹However, the index is based on a rather restrictive assumption: that of implicit separability of the difference in the revenue and expenditure functions of a country. It is not unreasonable to make this assumption separately for each of the two functions, but separability of the difference is hard to justify without additionally assuming that imported goods are not produced at home and exported goods are not consumed at home, as in this case, implicit separability of the two functions individually ensures implicit separability of their difference. It is also worth noting that their approach could be implemented without the assumption of implicit separability by using a computable general equilibrium model (see e.g. O'Rourke (1997), who also argues that their approach is misleading in practice).

and theories, resulting in considerable confusion of terminology. This point is argued forcefully by Krishna (1992), where the advantages and limitations of existing indices are discussed. Indeed, it turns out that different measures of “openness” are generally uncorrelated with each other, as shown by Pritchett (1996). Perhaps the most common measure for openness is the ratio of trade to national income. This ratio can be interpreted as an index of vulnerability to trade shocks as it equals the elasticity of indirect utility with respect to the terms of trade². However, trade share does not give a measure of the strength of trade barriers, as small countries tend to have larger trade shares than large ones, *ceteris paribus*. For all of these reasons, we do not use measures of openness or trade policy. Instead, we focus directly on exports and imports when evaluating different theories of growth.

Finally, it should be noted that investment has also been linked with growth and with exports. For example, one hypothesis holds that an increase in exports will be correlated with growth because higher investment demand causes a rise in exports (see e.g. Rodrik (1995)). Similarly, Young (1994) argues that in contrast to export led growth, the success of the NICs can also be explained by policies that promoted investment in productive resources and human capital. According to this

²Let there be n goods, of which the first m are exported and the remainder are imported, and assume that trade is balanced. Let $V(P^1, P^2, \dots, P^m, \dots, P^n, R(P^1, \dots, P^n, E))$ be the indirect utility function for the aggregate consumer who has homothetic preferences, where $R(P^1, \dots, P^n, E)$ represents the revenue function, and E is the factor endowment vector. Consider a terms of trade shock, θ , which affects the price of all imported goods. Then, the vulnerability index or index of exposure, denoted by ε , is the elasticity of indirect utility with respect to θ , evaluated at $\theta = 1$. Thus,

$$\begin{aligned}
\varepsilon &= \frac{\partial V(P^1, \dots, P^m, \theta P^{m+1}, \dots, \theta P^n, R(P^1, \dots, \theta P^n, E))}{\partial \theta} \frac{\theta}{V(\cdot)} \\
&= \left(\sum_{j=m+1}^n V_j(\cdot) P^j \right) \frac{\theta}{V(\cdot)} + V_{n+1} \left(\sum_{j=m+1}^n R_j(\cdot) P^j \right) \frac{\theta}{V(\cdot)} \\
&= \left(-V_{n+1} \left(\sum_{j=m+1}^n C_j(\cdot) P^j \right) + V_{n+1} \left(\sum_{j=m+1}^n X_j(\cdot) P^j \right) \right) \frac{\theta}{V(\cdot)} \\
&= \frac{V_{n+1}}{V(\cdot)} \sum_{j=m+1}^n P^j (X_j(\cdot) - C_j(\cdot)) \\
&= \frac{\sum_{j=m+1}^n P^j (X_j(\cdot) - C_j(\cdot))}{R(\cdot)} = 1/2(\text{Trade share}),
\end{aligned}$$

where the last equality follows from homotheticity, which in turn ensures that the indirect utility function is linear in income so that $\frac{V_{n+1}}{V(\cdot)} = \frac{1}{R(\cdot)}$.

view, investment would be causally prior to output growth.

Understanding the patterns of causation between growth in output, exports, imports, and investment is thus very important for development policy. For example, if exports cause output changes, and causality does not run the other way, then export promoting policies look good. However, if causality runs both ways, or if exports do not enter into some sort of “preferred” model, then export promoting policies look less inviting.³ One obvious way to address this issue empirically is to look for evidence on patterns of causality, and this is the approach taken in this paper. Unfortunately, the evidence which has been uncovered to date has been mixed.

Most of the previous time series research in this area is based on the application of in-sample Granger causality tests to annual data on exports and GDP. Jung and Marshall (1987) find that only four of the thirty-seven countries in their data set show evidence of a causal linkage from export growth to output growth. Hsiao’s (1987) causality tests indicate no causal relationship between exports and output in either direction for Korea, Singapore, and Taiwan.⁴ Bahmani-Oskooee et al. (1991) address the issue of optimally selecting the lag structures for empirical models used to explore causality, and find that for five countries⁵ out of twenty in their sample, export growth is causally prior to output growth. Taking a different tack, Chow (1987) asks whether export growth promotes industrialization as proxied by growth in the manufacturing industries in eight NICs.⁶ He finds bi-directional causality for six of these countries, causality from export growth to manufacturing growth for Mexico, and no causal relationship in either direction for Argentina.

In a novel paper which estimates panel data models with fixed effects, Harrison (1996) finds evidence of bi-directional Granger causality between openness and growth, and concludes that the issue of causality remains unresolved. Based on cross-sections and panels of data for LDCs, Harrison also finds: (i) that there is generally a positive association between growth and openness, even after: (i) controlling for other variables; (ii) applying various different measures of openness; and using

³Another example of reverse causality is discussed in Carroll and Weil (1994), where it is suggested that there may be reverse causation between output and savings, and hence investment (as investment tends to track savings - see e.g. Feldstein and Horioka(1980)).

⁴However, using the Sims (1972) version of Granger (1969) causality tests, he finds bi-directional causality, except for Hong Kong which exhibits causality only from output to exports.

⁵The Dominican Republic, Indonesia, Korea, Taiwan, and Thailand.

⁶The countries used in his study are Argentina, Brazil, Hong Kong, Israel, Korea, Mexico, Singapore, and Taiwan. Sample sizes range from 20 to 24 years.

sample averages, five year averages, and annual data.⁷ In summary, while great strides have clearly been made in the empirical analysis of growth, the frequent findings of bi-directional causality suggest that convincing dynamic empirical evidence on the link between trade and development remains elusive, even though economic policy-makers in general regard openness to trade as an integral part of successful development strategies.

In this paper, a model selection approach is employed to examine the marginal predictive content of trade variables and investment for GDP, and vice versa. The paper has two main components. In the first component we focus on which models are chosen by the data and on whether there is bi-directional causality or not. In particular, we begin our analysis by noting that different countries do indeed seem to warrant different models (i.e. the “best” model for one country can differ from the “best” model for another country). This is done by estimating panel data models with fixed effects, where it is noted that coefficient estimates and significance levels vary substantially depending upon which countries are included in the panels. For example, in one set of regressions, countries are partitioned by growth of per capita GDP into high (above 50th percentile) and low (below 50th percentile) average growth groups. In the low average growth group, investment does not enter significantly into the model. In the high average growth group, the marginal contribution of investment to GDP is three times as high as for the low group, and enters significantly into the model. Because of findings of this type, we adopt the approach of first choosing the best model for each individual country via a model selection approach based on predictive ability, and subsequently looking for evidence of bi-directional causality. Our findings suggest that bi-directional causality is much less prevalent than suggested by earlier work.

In the second component of this paper, we argue that previous work may also have omitted an important variable, namely the economic state of a countries’ trading partners. This is represented by the effective external economic conditions (EEEC) index which is the weighted average growth rate of the real *GDPs* of trading partners (measured at constant prices), where effective export shares are used as weights. We argue that if this index is important, then including it in our models should result in greater predictive ability, particularly for more open countries. We show that this does indeed appear to be the case.

⁷Frankel, Romer, and Cyrus (1996) tackle the problem of endogeneity in cross sections. In particular, they correct for the endogeneity of trade using an instrumental variables approach, and find that openness has a strong effect on growth.

The model selection approach which we use contrasts with the techniques used in previous papers, in the sense that it does not rely on classical hypothesis testing as when standard Granger (1969) causality t- and F-tests are used. Rather, we attempt to directly examine the predictive ability of the variables for one another. This approach is consistent with Granger's (1980) comments on causality testing, where he notes that causality tests should be formed by comparing the predictive ability of competing models.⁸ Another feature of our approach is that instead of attempting to use various different measures of trade policy, we focus on two of the basic targets of development strategy, namely exports and imports. We take this approach because previous causality tests based on the use of trade shares as a measure of openness suffer from the implicit assumption that the coefficients on exports and imports are constrained to be the same. Instead, we ask how important each individual variable is for predicting the behavior of GDP over time. In addition, we directly include investment in our empirical models, enabling us to select among a wider class of theories, including those that suggest investment leads growth, and those that are based on exports and imports. Our findings based on predictive ability suggest that linear models of GDP growth have predictive ability over and above that provided by "strawman" (or benchmark) random walk models for virtually all countries examined, and that there is essentially an equal mix of "preferred" models that include investment, and "preferred" models that include trade variables.

The rest of the paper is organized as follows. Section 2 discusses our data set, while Section 3 outlines the econometric methodology used. Our empirical findings are gathered in Section 4. Section 5 contains concluding remarks.

2 Data

Annual data for 39 developing countries are used (see Table 1 for a list of countries). These data are reported in the International Monetary Fund publication entitled *International Financial Statistics* (IFS). The period covered is 1951-1998 (for numerous countries) to 1970-1997 for Malaysia (see Table 1 for a complete listing of sample sizes). The series which we examine include: the growth rate of real *GDP* (deflated using the *GDP* deflator), called y_t ; the rate of growth in gross fixed

⁸Ashley, Granger, and Schmalensee (1980) and Chao, Corradi, and Swanson (2001) contain further discussion on the use of causality tests in empirical economics.

capital formation (our investment series), called i_t ; the growth rate of imports, called m_t ; and the growth rate of exports, called x_t . In addition, we compute an effective external economic conditions (EEEC) index for each country, as the weighted average growth rate of the real GDP of the countries' primary trading partners, where effective export shares are used as weights (all figures used in the calculation are in real GDP deflated units). This can be motivated as follows.

Consider an Armington model, where each country makes one good and imports other countries' goods. Treat the prices of other countries' goods and their incomes as exogenous. The utility level at home, u_i , and price of its good, p_i , are treated as endogenous. Assume there are no tariffs. Using the dual approach, the system is given by the following where E is the rest of the worlds' demand for good i or the exports of country i . As usual, $e(P, u)$ and $r(p, V)$ denote the expenditure and revenue functions of the economy:

$$\begin{aligned} e(p_i, p_{-i}, u_i) &= r(p_i, V_i) \\ e_{p_i}(p_i, p_{-i}, u_i) + E &= r_{p_i}(p_i, V_i), \end{aligned}$$

where the first equation gives u_i and the second gives p_i in equilibrium. Totally differentiating this and allowing only E to change will give $\begin{bmatrix} dp_i \\ du_i \end{bmatrix} = A \begin{bmatrix} dE \\ 0 \end{bmatrix}$. Assume that $E = \sum_{j \neq i} m_j Y_j$ where m is the marginal propensity to consume and Y is income. Hence,

$$dp_i = \alpha dE = \alpha \sum_{j \neq i} m_j Y_j \hat{Y}_j.$$

Thus,

$$\frac{dr}{r} = \hat{Y}_i = \frac{r_{p_i}}{r} dp_i = r_{p_i} \alpha \frac{E}{r} \sum_{j \neq i} \frac{m_j Y_j}{E} \hat{Y}_j = \beta_i \sum_{j \neq i} s_{ji} \hat{Y}_j,$$

where s_{ji} is the share of j in i 's exports which motivates our use of export shares as weights in constructing the *EEEC* index.

A country's primary trading partners are assumed to be a fixed list of countries such that for any given year a minimum of 80% of a country's exports are sent to the members of the list. Effective export shares are calculated for each country's list of trading partners on an annual basis as a straight percentage of the aggregate exports to all members of the list.⁹ Our final *EEEC* index, e_t ,

⁹For the majority of countries in our sample, export data are available for the entire sample period. However, the following countries are exceptions to this rule, as data were missing for exports in a number of years: Dominican Republic (1957), Ecuador (1958-1959), Haiti (1957-1958), Iran (1951-1963, 1969-1980), Korea (1951-1954),

is defined to be the export share weighted growth rate of real GDP of a countries' primary trading partners.

All growth rates were constructed using the natural logs of the raw data in 1990 prices. In addition, all measures given in Table 8 are constructed from the above variables.

3 Empirical Methodology

Since standard F- or Wald-tests for causality are prone to severe upward size distortions if unit roots and/or cointegration are not properly accounted for when specifying empirical models (see e.g. Swanson, Ozyildirim and Pisu (2001)), the first step in our empirical approach involves the examination of the stochastic trending properties of our variables. This is done by carrying out unit root and cointegration tests on individual country data. The models estimated in this part of the analysis are of the form

$$\Delta u_t = a + bt + cu_{t-1} + \sum_{i=1}^p d_i \Delta u_{t-i} + \nu_t, \quad (1)$$

for unit root testing, where the lag order, p , is selected by examining the significance of estimates of d_i , $i=1,\dots,p$ (see e.g. Ng and Perron (1995)), u_t is the variable of interest (selected from the set of regressors defined below as q_t , and the test statistic is the standard t-statistic associated with the least squares estimate of c . For cointegration tests, we estimate so called “vector error correction” models of the form:

Malaysia (1951-1967), Mauritius (1967), Paraguay (1951-1956), Saudi Arabia (1951-1963), Singapore (1951-1959, 1961, 1964-1967), Thailand (1951-1955), and Venezuela (1971). For these years with missing observations, exports were extrapolated linearly using the two surrounding observations. When insufficient observations were available for this extrapolation, exports of the first (last) available year were fixed and used to construct the effective export shares. Note in addition that for a small number of observations across countries and sample periods, some countries' fixed list of trading partners constituted less than 80% of a countries' total exports. Finally, note that the EEEC index was also constructed using GDP and export data deflated using CPI data and GDP and export data expressed in U.S. PPP adjusted dollars, with PPP weights obtained from the Penn World Table. As all calculations led to similar results when the EEEC index was included, we focus our subsequent discussion only on the EEEC index constructed based on real GDP deflated using the GDP deflator.

$$\Delta q_t = \beta_0 + \tau(t) + B(L)\Delta q_{t-1} + \sum_{i=1}^r \beta_i z_{i,t-1} + \epsilon_t, \quad (2)$$

where ϵ_t is a vector of innovations, $\tau(t)$ is a polynomial function of time ($\tau(t)=0$ or $\tau(t) = \gamma_1 t$), and $B(L)$ is a matrix polynomial in the lag operator L .¹⁰ The vector Δq_t is a vector of between two and five variables, with elements chosen from the set $\{y_t, x_t, m_t, i_t, e_t\}$ (see above for variable descriptions). In addition, $z_{i,t-1} = \hat{\alpha}' q_{t-1}$, $i=1,\dots,r$, is a vector of “error-correction” terms defined as in Engle and Granger (1987). For each country, r is the rank of the cointegrating space, and is estimated using standard maximum likelihood procedures. The lag order of our models, say l , is chosen using the Schwarz Information Criterion (SIC) discussed below.

Given knowledge of the stochastic trending properties of our data, our next objective is to assess the relative usefulness of investment versus export driven growth theories. We do this by first estimating a number of fixed effect panel data regression models, and examining the magnitudes and significance levels of estimated coefficients in these models. Thereafter, we consider individual countries, and form real-time predictions of Δq_t using models with GDP and investment, models with GDP, investment, exports, and imports, etc. This in turn enables us to directly assess the relative predictive ability of models with and without investment, imports, and exports.¹¹ In particular, we begin by estimating all coefficients, the lag length, the cointegrating rank, and the cointegrating space of equation (2) based on a sample of length R , say, where $R < T$, and T is the sample size. A one-step ahead forecast of Δq_t for period $R + 1$ is then constructed. At this point, we augment our sample with one new observation, re-estimate all coefficients, the lag length, and the cointegrating rank, and form a second real-time one-step ahead forecast of Δq_t for period $R + 2$. This process is continued until the entire sample of T observations is exhausted, and we are left with a sequence of P one-step ahead forecasts, where $T = R + P$. A sequence of real-time

¹⁰It is worth mentioning that the linear and fixed parameter vector autoregression methodology which we adopt is subject to a variety of reservations. For example, time varying parameter and other sorts of nonlinear models are receiving increasing attention in the literature (see e.g. Granger and Teräsvirta (1993), and the references contained therein), and may be relevant for some of the countries in our sample which have experienced periods of different economic regimes.

¹¹A small number of papers which discuss predictive ability, model selection, and *ex ante* forecasting of the variety considered here include Amato and Swanson (2001), Diebold and Mariano (1995), Swanson and White (1997a), Swanson (1998), and the references contained therein.

forecast errors is then constructed by subtracting the real-time forecasts from actual realizations of the variable of interest. These forecast errors are used to construct the *Mean Square Forecast Error* - $MSE = \sum_{t=R+1}^T \hat{ferr}_t^2 / P$, where P is the number of real-time forecasts made, and \hat{ferr}_t are the real-time forecast errors.¹² By forming competing models with and without a particular variable of interest (say investment) we can assess causal directionality by simply picking the model with the lowest MSE value, say, and observing whether or not this model contains the variable of interest. In addition, we can apply the test proposed in Diebold and Mariano (1995) and discussed in McCracken (1999) and Swanson and White (1997a,b) for assessing whether the MSE s from two different models are the same (i.e. we can construct a probability value for the null hypothesis that nothing is gained by including the variable of interest – the absence of a causal linkage).

4 Empirical Findings

4.1 Stochastic Trending Properties of the Variables

Table 1 summarizes our findings based on the examination of Dickey-Fuller unit-root test statistics which test the null hypothesis that a variable is nonstationary against the alternative that it is stationary. Rejections of the null hypothesis at a 5% significance level are noted in the table by the placement of a star next to the associated statistic value. As is immediately apparent, almost all of our country specific series can be viewed as difference stationary in logs, thereby providing support for our use of growth rates of the variables, and also suggesting that it is important to assess whether the variables are cointegrated. If country specific variables are cointegrated, then we must include so-called error-correction terms (the z_t in equation (1)) as additional variables in our regression models in order to ensure correct specification. Along these lines, we estimated two parallel sets of regressions in all of our subsequent analysis. One set included cointegrating relations when they were relevant based on the application of standard cointegration tests. The second set involved re-estimating all models under the assumption that there was no cointegration. It turned

¹²In addition to the MSE , the forecast errors are used to construct *Mean Absolute Forecast Error Deviation (MAD)* and *Mean Absolute Forecast Percentage Error (MAPE)* criteria. Results based on these criteria are similar to those reported below for MSE , and are available upon request. See Weiss (1996), Christoffersen and Diebold (1997), and Swanson and White (1997b) for further discussion of these and other loss functions that are useful for selecting among competing prediction models.

out that although cointegration is often important, our empirical findings based on models with and without cointegration do not change, and hence in the sequel we report and discuss results based only on models in which the cointegrating rank, r , in equation (1) is assumed to be zero. Complete tabulated results are available from the authors upon request.

4.2 Panel Data Regression Results

Although we are primarily concerned with the examination of alternative models of growth based on individual country data, for completeness we include the results of a number of panel data regressions with GDP growth as dependent variable. These results are gathered in Table 2. A number of clear findings emerge. First, the significance and magnitude of the coefficients associated with investment, imports, and exports sometimes depend on which countries are modelled. For example, Models 3 and 4 report results when countries are partitioned into those with average growth rates of per capita GDP below the 50th percentile and those above the 50th percentile. Notice that the magnitude of investment as a determinant of GDP growth is 3 times as great for countries above the 50th percentile. Also, the coefficient on investment is significantly different from zero at a 95% level of confidence for countries above the 50th percentile (i.e. the t-statistic in brackets is approximately 1.96), while this is clearly not true for countries below the 50th percentile. In Models 5 and 6, we see that exports are much more important in GDP growth regressions involving countries with GDP growth rates below the mean panel GDP growth rate than in those with GDP growth rates above the panel mean. Similarly, the external economic conditions index is significant in countries with higher GDP growth rates while it is not in countries with lower growth rates. Thus, the relative magnitude and significance of our different trade variables appears to depend somewhat on which country is examined. This suggests that analysis at the individual country level may provide useful information for uncovering the determinants of growth. Second, notice that the signs on the different trade variables are consistent across different models; exports enter positively and imports negatively. This result is useful, as it serves as a type of “robustness check” of our linear regression models. Third, notice in Models 9 and 10 that the external economic conditions index is highly significant in countries where it is found to provide useful predictive information (see below), as might be expected. Finally, notice that the goodness of fit of the models (as measured by \bar{R}^2) depends on how the countries are partitioned, and that values are usually around 0.10.

4.3 Out-of-Sample Predictive Ability and Bi-Directional Causality

Our main findings based on ex-ante predictive ability model selection using a 15 year prediction period (the ex-ante period is the most recently available 15 year period for each country) are gathered in Tables 3 and 4.¹³ In these tables, predictive *MSE* values are reported, with lower *MSE* values corresponding to “better” models. In particular, Table 3 takes GDP growth as the target variable, and estimates numerous versions of the GDP growth equation in (1). The variables listed in the first row of the table are the explanatory variables (all lagged) used in the growth equation. Focussing on the second through eighth columns of numerical entries in the table, note that the “best” model for each country is given in boldface font. Thus, for example, the preferred model for Panamanian GDP growth is a model which includes lags of GDP growth as well as lags of investment, imports, and exports. This suggests that growth in Panama is consistent with investment *and* trade led growth. By examining only the bold faced entries (associated with our “best” models), a basic picture emerges. Growth is best explained by models which include: exports and/or imports (20 countries), investment (13 countries), and a mixture of exports, imports, and investment (6 countries). Thus, whether investment and imports/exports is important appears to depend to a large extent on country specific characteristics; a finding which is consistent with the results of our analysis of panel data regression models.

In Table 3, when our preferred model outperforms the strawman random walk model, the associated *MSE* entry is superscripted with *, based on a significance level of 5%. Similarly, when the random walk with drift model outperforms the preferred model for any given country, the random walk *MSE* value is superscripted with a *. It is noteworthy that the random walk model significantly outpredicts our preferred model for only 4 of 39 countries. Additionally, our preferred model significantly outpredicts the random walk model for 23 of 39 countries¹⁴. This finding is contrary to the frequent finding in the empirical macroeconomic literature that there is little to choose between random walk models and more heavily parameterized models when comparing predictive ability (see e.g. Stock and Watson (1999)).

¹³The lag structure of all estimated prediction models is chosen by using the SIC. In almost all cases reported in this paper, the SIC picked one lag. We thus use only one lag in all models, corresponding to a loss of at most 4 degrees of freedom when estimating our final empirical models, and thereby allowing us to obtain surprisingly precise coefficient estimates, even given the relatively small country specific samples which we examine.

¹⁴The preferred model for South Africa also outperforms the random walk model, but at a 10% level of significance.

In order to tackle the issue of bi-directional causality, we must consider reverse causation, which is done in Table 4. The first column of the table lists the countries and the second column lists the preferred model based on Table 3. For example, while i_t appears to cause y_t for Jamaica as the preferred model is y_t, i_t in Table 3, we do not yet know whether the reverse also holds; that is, whether y_t causes i_t . In Table 4, results from regressions which contain each of i_t, m_t and x_t as dependent variable are presented. In addition, models of these variables both with and without lags of y_t are reported. In each of the three vertical panels (corresponding to each of the 3 dependent variables) of entries in the table, primed entries indicate that the preferred models do contain lagged GDP growth. As an illustration, note that for Jamaica, *GDP* growth causes investment, and also causes exports (as the smaller models which do not contain *GDP* growth are preferred to the larger models only in the second panel). Since the “best” model for *GDP* growth in Jamaica contains investment (Table 3) and *GDP* also causes investment (Table 4), we have evidence of bi-directional causality from investment to *GDP*. Note that in general, only the variables in the preferred model for a country need to be looked at. If these panels indicate a lack of predictive ability from GDP to the variables (i.e. in both panels the smaller model is preferred) then we have evidence of uni-directional causality. By examining each country in this fashion, we may summarize our evidence of bi-directional causality. In particular, note that 27 of 39 countries yield evidence of uni-directional causality, while 12 countries exhibit bi-directional causality, including: Bolivia, Chile, Costa Rica, Cyprus, El Salvador, Greece, Jamaica, Korea, Panama, Philippines, Thailand, and Uruguay. We take this as rather surprising new evidence of uni-directional causality among our sample countries, which is in large part due to the out-of-sample form of causality tests that we apply.¹⁵

4.4 Global Business Cycle Conditions and Growth

In this section we suggest that there is possibly an omitted variable in our above analysis. We argue that countries, especially those which trade a great deal, and so have large trade to *GDP* shares, are particularly vulnerable to changes in global economic conditions. This macro economic linkage between countries needs to be accounted for. If important, and not accounted for, it could result in spurious findings of causal linkages. For example, if macro economic conditions in the economies of trading partners of a particular country improve, the trading partners may increase their imports,

¹⁵We view our evidence as surprising given that there is almost no evidence of uni-directional causality in the literature to date, as discussed above.

hence leading to increased exports and thus increased GDP in the country of interest. This in turn will show up as a strong causal linkage from export growth to GDP growth, given that the health of the economies of the trading partners are not accounted for in our models. However, the conclusion of a direct causal linkage between export growth and GDP growth would be inappropriate. For this reason, we add the *EEEC* index, e_t , to the list of variables considered. Continuing our earlier discussion of the *EEEC* index, it is worth noting that our use of trade weights is intuitively justified by noting, for example, that if Singapore trades mostly with Australia and Malaysia, then conditions in these countries would have a greater impact on Singapore's growth prospects than conditions in a country that it has little trade with.¹⁶ Given the above arguments, we hypothesize that the inclusion of the *EEEC* index in our models should result in greater predictive ability, particularly for more open countries.

Empirical evidence on the usefulness of our e_t variable is presented in Table 5. By comparing preferred models in this table with preferred models in Table 3, we see that including e_t results in a “best” MSE reduction in 12 countries, including Bolivia, Chile, Colombia, Costa Rica, El Salvador, Ghana, Guatemala, Mexico, Portugal, South Africa, Syria, and Trinidad and Tobago. Note that in all of these cases, the other variables included in the preferred model are the same as those appearing in the preferred model in Table 3. It is also interesting to note that of the 9 countries in our sample which might be characterized as being in the Latin America region, 7 are among the above group of 12, including: Bolivia, Chile, Colombia, Costa Rica, El Salvador, Guatemala, and Mexico. Indeed, only Panama and Honduras do not appear in this list. These findings are analogous to our in-sample based panel data regression findings reported in Table 2, where it was found that e_t is significant in a panel of the 12 countries listed above, but is insignificant when a panel of the remaining 29 countries is used (i.e. see Models 9 and 10 in Table 2). Thus, we have evidence of the usefulness of e_t in growth models for *some* of the countries in our study.¹⁷

In order to shed additional light on these findings, we also ranked countries according to a variety of criteria including export share, trade share, investment share, and per capita GDP .

¹⁶Recall also our earlier discussion motivating the construction of this index.

¹⁷The fact that e_t is useful in the “best” models for 12 countries is rather strong evidence in support of using this variable. The reason for this is that *ex ante* prediction is a very difficult yardstick with which to measure the usefulness of new variables. Were we instead to use in-sample t-statistics, for example, we would find that e_t is useful in many more than 12 countries. The reasons for this are explained in Chao, Corradi and Swanson (2001).

These summary measures are gathered in Table 6. In this table, the 12 countries which have preferred models that include e_t are superscripted with a *. Note that starred entries tend to be dispersed rather uniformly across different ranking of the countries according to the 4 different measures reported in the table. This might be taken as evidence that countries are not necessarily vulnerable to changes in global economic conditions.

Another predictive ability criterion which is commonly used to assess the predictive ability of competing models is the “confusion rate”. The confusion rate measures the percentage of times that the direction of change in a variable is incorrectly predicted. For example, if our first prediction is that *GDP* growth will increase, and, ex-post, growth does actually increase, then we have correctly predicted the direction of change in growth. We calculated confusion rates for each of our countries when prediction models were alternatively constructed both with and without e_t .¹⁸ At least 5 of the top 10 countries in terms of trade share, export share, and per capita income were less confused when e_t was added to their preferred models. Thus, we have some evidence that e_t tends to be included for more open countries, as expected. Clearly, other measures of global economic conditions can be entertained in analyses such as ours. As such, our findings in this regard should be viewed as preliminary. However, policy makers’ concern with what happens in the economies of their country’s trading partners appears warranted. In particular, although we do not explicitly quantify linkages across trading partners, it does appear to be the case that global conditions variables should not be overlooked when constructing models of economic growth for the purpose of assessing testable implications of the various theories of growth discussed above.

5 Conclusions

We have used a model selection approach based on ex-ante predictive ability to examine the patterns of causation between income, export, import, and investment growth for 39 developing countries. We offer the following conclusions. First, many of the variables used are found to be I(1), with cointegrating restrictions. Taking these restrictions into account when modelling growth avoids

¹⁸Note that the forecasting exercise was precisely the same as that carried out when we calculated *MSE*, so that the only difference is our summary measure of predictive ability. Tabulated figures based on the “confusion rate” model selection criterion which are analogous to Tables 3 and 5 are available upon request, but are omitted here for the sake of brevity.

potentially spurious findings with respect to causality. In our analysis, however, cointegration does not impact upon our conclusions, and indeed adds little to the predictive content of our models. For this reason, all of our reported findings are based on vector autoregressions in growth rates. Second, we find that separately including exports, imports, and investment is useful as growth in some countries appears to be led by investment, while for other countries, growth is driven primarily by trade. This finding is supported via analysis of the out-of-sample predictive accuracy of competing models as well as via examination of fitted in-sample panel regression models. Third, we find new evidence of uni-directional causality, and suggest that the reason for this is our use of predictive ability as a measure of causation. Finally, we posit that GDP growth is better modelled by including an index of global business cycle conditions, in addition to the above variables. Evidence suggests that this is indeed the case, as 12 of our countries have “preferred” growth models which include our global business cycle conditions index, 7 of these being members of our 9 country sample from Central America.

6 References

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Table 1: Integration Test Results¹

Country	Sample	y_t	i_t	m_t	x_t	e_t
Bolivia	1960-1998	-1.480(1)	-0.288 (0)	-1.102 (2)	-2.129 (1)	-0.441 (0)
Chile	1960-1997	2.016(0)	0.962 (2)	-0.944 (0)	-0.640 (2)	-0.124 (0)
Colombia	1968-1996	-1.696(3)	0.050 (3)	-0.414 (0)	-1.390 (0)	-1.014 (0)
Costa Rica	1960-1997	-2.264(1)	-2.462 (0)	-1.608 (0)	-1.123 (0)	-2.425 (0)
Cyprus	1960-1996	-1.085(0)	-2.401 (2)	-2.243 (2)	-1.922 (2)	-1.801 (0)
Dominican Republic	1962-1997	-2.058(0)	-1.768 (0)	-0.205 (2)	-0.961 (0)	-1.084 (0)
Ecuador	1965-1996	-3.806(0)*	-3.175 (0)	-2.874 (0)	-2.965 (0)	-0.539 (0)
El Salvador	1951-1998	-1.455(1)	-2.086 (0)	-1.549 (0)	-1.694 (0)	-0.369 (0)
Ghana	1955-1997	0.189(0)	-0.231 (0)	-0.626 (0)	-2.241 (1)	-1.539 (0)
Greece	1951-1994	-4.670(0)*	-3.303 (0)	-2.529 (0)	-1.501 (0)	-0.819 (0)
Guatemala	1951-1998	-1.925(1)	-1.529 (1)	-1.383 (0)	-1.446 (0)	-0.924 (0)
Haiti	1966-1997	-2.778(0)	-2.697 (0)	-2.658 (0)	-1.648 (0)	-1.249 (2)
Honduras	1951-1998	-1.031(0)	-0.265 (0)	-0.238 (2)	-0.591 (0)	-1.474 (0)
India	1960-1995	1.797(0)	1.185 (0)	0.741 (0)	0.948 (0)	-0.523 (0)
Iran	1964-1997	-2.705(1)	-2.709 (1)	-2.835 (1)	-1.615 (0)	-1.659 (0)
Israel	1968-1998	-2.213(0)	-1.725 (0)	-4.387 (0)*	-3.820 (0)*	0.140 (0)
Jamaica	1960-1996	-2.116(1)	-1.437 (0)	-1.328 (0)	-1.513 (0)	-2.240 (0)
Kenya	1967-1997	-2.624(2)	-1.535 (0)	-1.113 (0)	-1.560 (0)	-0.771 (0)
Korea	1953-1997	0.684(0)	-1.011 (0)	-1.169 (2)	-3.993 (0)*	-4.118 (2)*
Malaysia	1970-1997	1.188(0)	0.006 (1)	0.770 (0)	0.781 (0)	1.139 (0)
Mauritius	1960-1996	0.952(0)	-0.970 (2)	-0.343 (3)	-0.549 (2)	-1.223 (0)
Mexico	1951-1997	-3.423(0)	-1.915 (0)	1.525 (3)	1.103 (2)	-0.506 (0)
Morocco	1964-1997	-2.184(1)	-2.623 (3)	-1.609 (0)	-0.161 (0)	-1.926 (0)
Myanmar	1970-1998	-0.682(0)	-2.931 (1)	-2.026 (3)	-0.909 (2)	-0.047 (0)
Pakistan	1960-1998	0.943(0)	-0.406 (1)	-0.479 (0)	-0.334 (0)	-0.616 (0)
Panama	1951-1997	-2.490(3)	-1.474 (0)	-0.670 (3)	-0.642 (0)	-1.182 (0)
Paraguay	1962-1997	-1.926(1)	-1.453 (1)	-0.598 (0)	-0.969 (0)	0.130 (0)
Peru	1951-1997	-1.727(1)	-1.616 (1)	-1.894 (0)	-2.314 (0)	0.175 (0)
Philippines	1951-1998	-1.629(1)	-1.875 (1)	-0.334 (0)	-0.065 (0)	0.583 (0)
Portugal	1966-1997	-1.988(0)	-2.064 (2)	-2.008 (0)	-1.118 (2)	-0.841 (0)
Saudi Arabia	1968-1997	-2.865(0)	-2.568 (0)	-2.864 (0)	-2.641 (1)	0.609 (0)
Singapore	1960-1997	-2.548(1)	-2.757 (3)	-1.770 (0)	-1.070 (0)	-0.783 (3)
South Africa	1951-1998	-3.014(1)	-2.004 (2)	-1.064 (0)	-1.392 (0)	0.723 (0)
Sri Lanka	1965-1997	1.512(0)	-0.311 (0)	-1.073 (0)	-1.075 (0)	1.683 (2)
Syria	1963-1997	-1.732(0)	-2.199 (0)	-1.824 (0)	-0.634 (0)	-3.509 (0)
Thailand	1951-1997	0.033(1)	-0.913 (2)	0.755 (0)	1.544 (0)	0.857 (0)
Trinidad & Tobago	1966-1996	-2.199(1)	-1.854 (0)	-2.550 (0)	-2.590 (1)	-0.901 (0)
Uruguay	1955-1998	0.687(2)	-1.972 (1)	-0.643 (0)	-1.202 (0)	-0.913 (0)
Venezuela	1957-1998	-3.173(0)	-2.710 (1)	-2.061 (0)	-2.081 (0)	-1.266 (0)

¹ Notes: All data are annual, are logarithms, and are not differenced prior to carrying out the integration tests. (Elsewhere in the paper, y_t , i_t , m_t , x_t , and e_t denote growth rates.) Entries in columns 3-7 are Augmented Dickey-Fuller test statistics based on regressions of the form $\Delta u_t = a + bt + cu_{t-1} + \sum_{i=1}^p d_i \Delta u_{t-i} + \nu_t$, where the lag order, p , is selected by examining the significance of estimates of d_i , $i=1,\dots,p$ (see e.g. Ng and Perron (1995)), u_t is the variable of interest, and the test statistic is the standard t-statistic associated with the least squares estimate of c . Entries with a * denote rejection of the null hypothesis that the series is I(1) at a 5% significance level. The entries in parentheses indicate the optimal number of chosen lags.

Table 2: Fixed Effect Panel Data Regression Model Results¹
The Dependent Variable in All Models Is y_t

Regression Coefficients						DW
y_{t-1}	i_{t-1}	m_{t-1}	x_{t-1}	e_{t-1}	\bar{R}^2	
<i>Model 1: All countries; without external economic conditions index</i>						
0.1619 (4.8936)	0.0231 (2.0650)	-0.0121 (-1.0613)	0.0204 (2.1511)	-	0.1076	2.0201
<i>Model 2: All countries; with external economic conditions index</i>						
0.1507 (4.5293)	0.0234 (2.0991)	-0.0113 (-0.9910)	0.0190 (2.0070)	0.1134 (2.6534)	0.1115	2.0181
<i>Model 3: Countries with average growth rate of per capita GDP below 50th percentile</i>						
0.2825 (6.4275)	0.0114 (0.8227)	-0.0100 (-0.7460)	0.0148 (1.3836)	0.1623 (2.4800)	0.1182	2.0554
<i>Model 4: Countries with average growth rate of per capita GDP above 50th percentile</i>						
0.0446 (0.8802)	0.0345 (1.9489)	-0.0139 (-0.7122)	0.0252 (1.4718)	0.1020 (1.7581)	0.0877	1.9847
<i>Model 5: Countries with mean GDP growth below mean GDP growth of all countries</i>						
0.3018 (6.7157)	0.0202 (1.4574)	-0.0164 (-1.2148)	0.0275 (2.4679)	0.0962 (1.5079)	0.1394	2.0904
<i>Model 6: Countries with mean GDP growth above mean GDP growth of all countries</i>						
0.0477 (0.9721)	0.0254 (1.4352)	-0.0164 (-0.8407)	0.0111 (0.6900)	0.1375 (2.3934)	0.0396	1.9676
<i>Model 7: Countries with mean investment growth below mean investment growth of all countries</i>						
0.2888 (6.8412)	0.0257 (2.1507)	-0.0332 (-2.7681)	0.0171 (1.6781)	0.0836 (1.6886)	0.1403	2.0443
<i>Model 8: Countries with mean investment growth above mean investment growth of all countries</i>						
0.0710 (1.3560)	0.0219 (1.1038)	0.0093 (0.4471)	0.0214 (1.2852)	0.1385 (1.9901)	0.0562	2.0083
<i>Model 9: Countries where inclusion of e_t growth results in increased GDP predictability</i>						
0.1882 (3.2651)	0.0238 (1.3592)	-0.0314 (-1.7712)	0.0459 (2.9722)	0.2850 (3.4121)	0.1215	2.0898
<i>Model 10: Countries where inclusion of e_t growth does not result in increased GDP predictability</i>						
0.1416 (3.4470)	0.0232 (1.6329)	-0.0052 (-0.3610)	0.0105 (0.8836)	0.0695 (1.3806)	0.1065	1.9920

¹ **Notes:** Reported regression coefficients (and bracketed t-statistics) are based on least squares estimation of fixed effects unbalanced panel data models. All models are estimated using the growth rates of all variables, and all regressors are lagged one period, relative to the dependent variable. Thus, the panel data models are the panel versions of the vector autoregression equations in GDP growth reported on in Tables 2 and 4. Individual country intercept estimates are not reported, and are available upon request from the authors. DW statistics are Durbin-Watson test statistics for the presence of first order serial correlation. Sample lengths for each country are given in Table 1.

Table 3: Model Selection Results Based on a Predictive Ability Approach¹
without Effective External Economic Conditions Index
All Models are Vector Autoregressions

Model Country	RW w/d	y_t, i_t, m_t, x_t	y_t, m_t, x_t	y_t, i_t, m_t	y_t, i_t, x_t	y_t, i_t	y_t, m_t	y_t, x_t
Bolivia	11.54	7.68	7.18	7.14	6.78	6.12*	6.97	6.81
Chile	57.13	53.39	50.83	46.62	46.42	40.92*	44.21	46.11
Colombia	19.54	4.68	5.51	3.46	4.40	3.37	3.13*	3.81
CostaRic	20.17	19.56	15.93	16.59	18.89	19.17	15.35	17.95
Cyprus	47.70	62.31	60.67	43.48	43.91	35.40	44.02	19.41*
Dominica	26.82	16.57	14.20	15.61	18.81	14.06*	15.12	17.41
Ecuador	20.39	23.21	21.23	23.56	22.00	23.19	21.55	19.86
ElSalvad	21.26	23.52	22.88	18.26	23.35	18.01	17.98	22.72
Ghana	21.01	21.22	17.61	27.56	25.72	24.43	16.97	22.61
Greece	10.12*	17.72	17.69	16.89	17.52	16.27	16.67	17.32
Guatemal	11.71	8.57	7.74	7.41	8.45	7.16	6.41*	7.43
Haiti	23.21*	43.87	36.54	38.75	36.59	35.06	33.13	34.92
Honduras	14.50	8.71	8.12	8.45	8.25	7.86	7.96	7.20*
India	33.95	18.15	15.81	11.53	17.55	11.26	11.24*	14.04
Iran	90.65*	195.42	229.27	132.01	159.56	107.45	153.21	147.77
Israel	35.77*	122.13	130.87	62.95	116.38	50.77	37.65	137.29
Jamaica	11.08	10.78	13.31	9.82	10.18	9.49	10.42	11.73
Kenya	20.98	7.48	6.02	7.24	7.03	6.76	5.57*	5.81
Korea	64.38	9.60	9.30	8.68	9.32	8.84	8.61*	9.27
Malaysia	56.59	14.30	10.74	11.83	10.89	9.00	11.53	8.25*
Mauritiu	43.16	20.04	21.04	17.40	20.31	17.51	16.72*	24.92
Mexico	25.82	25.37	24.07	22.48	23.99	21.05	21.87	22.83
Morocco	37.75	22.79	21.67	21.27	20.64	20.22*	20.86	24.49
Myanmar	32.82	38.86	43.96	32.85	36.93	32.92	40.78	43.60
Pakistan	29.53	4.09	3.97*	4.50	4.85	4.86	4.58	4.93
Panama	53.84	35.16*	38.31	37.74	38.96	38.18	37.66	38.54
Paraguay	27.52	13.14	12.34	11.39	12.43	10.27*	10.94	12.08
Peru	49.28	52.66	52.89	52.07	51.35	50.59	52.72	50.71
Philippi	21.16	14.69*	16.98	15.06	15.86	15.76	16.89	17.01
Portugal	13.36	13.74	12.96	13.34	17.51	12.26	7.31	5.69*
SaudiAra	30.77	43.64	51.91	38.56	41.67	39.40	44.50	45.60
Singapor	64.78	7.77	7.61	8.07	7.77	7.47*	7.84	7.55
SouthAfr	8.89	7.54	7.25	6.69	9.28	7.83	6.52	8.71
SriLank	25.32	3.61	3.81	2.91	3.57	2.75*	3.12	3.55
Syria	52.97	51.69	44.77	37.46	57.36	41.85	35.78*	53.52
Thailand	56.25	6.21	6.30	6.67	6.04*	7.10	6.54	7.08
Trinidad	25.27	28.38	27.94	28.50	24.83	24.12	26.33	24.94
Uruguay	25.65	18.66	18.68	18.53	18.91	18.67	18.43*	18.53
Venezuel	21.03	24.43	26.08	30.14	23.33	28.24	28.55	25.20

¹ **Notes:** Reported entries are Mean Squared Forecast Errors (MSE) multiplied by 10000. The MSEs are based on GDP growth equations from VAR models which are used to construct a sequence of 1-step ahead forecasts for the last 20 years of the sample period (see Table 1). Model specifications, including lag structures and parameters are re-estimated before each new forecast is constructed, as discussed above. In each row, the bold entry denotes the model which has the lowest MSE among the seven candidate models, and hence indicates the model (and associated explanatory variables) which yield the “best” predictive ability. Entries with a * denote models which outperform the RW with drift model (the first column of numerical entries) at a 5% level of significance using the Diebold-Mariano (1995) test statistic. Critical values for the test are taken from McCracken (1999), assuming that $\pi = 1/2$, where $P/R - > \pi$, P is the out-of-sample period, and R is the in-sample period. See Chao, Corradi, and Swanson (2001) for further details.

Table 4: Predictive Ability Approach Bi-directional Causality Results¹

Country	Lags Included --> <i>Preferred Model</i>	Equation for i_t		Equation for m_t		Equation for x_t	
		y_{t,i_t}	y_{t,i_t,m_t,x_t}	i_{t,m_t,x_t}	y_{t,i_t,m_t,x_t}	i_{t,m_t,x_t}	y_{t,i_t,m_t,x_t}
Bolivia	y_{t,i_t}	2.86'	2.91	19.46	17.04	16.11	15.62
Chile	y_{t,i_t}	2.56'	4.11	1.61'	2.58	1.47	1.33
Colombia	y_{t,m_t}	1.32	1.25	2.18	1.98	3.45	3.06
CostaRic	y_{t,m_t}	1.59'	2.22	1.61'	1.92	2.64	2.46
Cyprus	y_{t,x_t}	3.58	3.58	1.64	1.60	1.75'	1.88
Dominica	y_{t,i_t}	2.62	2.57	5.93'	6.47	7.52'	8.26
Ecuador	y_{t,x_t}	2.09'	2.11	1.70'	1.74	3.85	3.25
ElSalvad	y_{t,m_t}	2.77	2.44	2.12'	2.17	2.80'	3.08
Ghana	y_{t,m_t}	6.78	5.82	12.63	11.70	10.38	9.85
Greece	y_{t,i_t}	1.10'	1.39	0.53'	0.58	1.50	1.30
Guatema	y_{t,m_t}	4.26	2.76	5.28	4.27	2.33	2.09
Haiti	y_{t,m_t}	17.41	16.69	19.89	17.95	16.72	16.28
Honduras	y_{t,x_t}	2.50	2.39	1.28	1.20	1.16	0.97
India	y_{t,m_t}	0.36	0.36	1.50	1.25	1.87	1.40
Iran	y_{t,i_t}	8.58	6.03	10.16	9.27	26.42	24.36
Israel	y_{t,m_t}	3.88	3.84	3.28	3.13	2.03	1.97
Jamaica	y_{t,i_t}	3.40'	3.68	1.83	1.71	2.05'	2.15
Kenya	y_{t,m_t}	1.68	1.53	3.15	2.52	2.19	1.99
Korea	y_{t,m_t}	0.58	0.51	0.35'	0.41	2.12'	2.27
Malaysia	y_{t,x_t}	1.29	1.17	1.57	1.00	1.19	0.74
Mauritius	y_{t,m_t}	2.21	1.94	0.92	0.75	1.55	1.09
Mexico	y_{t,i_t}	3.17	2.93	2.39	2.00	2.51	2.36
Morocco	y_{t,i_t}	2.01	1.74	2.18	1.69	0.78	0.71
Myanmar	y_{t,i_t,m_t}	7.51	5.04	26.69	6.60	6.37	3.85
Pakistan	y_{t,m_t,x_t}	0.28'	0.30	1.02	1.01	1.30	1.28
Panama	y_{t,i_t,m_t,x_t}	9.01'	10.14	5.83	5.61	6.00'	6.03
Paraguay	y_{t,i_t}	1.39	1.29	3.22	3.10	7.49	7.29
Peru	y_{t,i_t}	4.31	4.23	1.87'	2.62	4.99	4.38
Philippi	y_{t,i_t,m_t,x_t}	2.55'	3.28	1.46'	1.55	1.11'	1.14
Portugal	y_{t,x_t}	1.03'	1.05	1.17'	1.24	1.33	1.31
SaudiAra	y_{t,i_t,m_t}	9.59	4.17	4.84	3.56	2.91	1.99
Singapor	y_{t,i_t}	0.71	0.68	0.79	0.72	0.92	0.89
SouthAfr	y_{t,m_t}	0.45'	0.51	1.55	1.43	1.05	0.98
SriLank	y_{t,i_t}	2.44	2.40	1.48	1.40	0.91'	1.07
Syria	y_{t,m_t}	6.79	6.26	5.84	4.89	3.85'	4.14
Thailand	y_{t,i_t,x_t}	0.63'	0.64	1.14'	1.23	0.79'	1.04
Trinidad	y_{t,i_t}	5.85	4.68	3.31	3.09	1.95	1.78
Uruguay	y_{t,m_t}	1.44'	1.84	0.81'	0.82	1.33	2.02
Venezuel	y_{t,i_t,x_t}	5.11	4.86	7.51	7.30	5.09	4.77

¹ **Notes:** See notes to Table 3. The remaining three equations (i.e. the equations for i_t , m_t , and x_t) from the VAR models in growth rates reported on in Table 3 are examined both with and without lags of GDP growth. In each panel, a smaller MSE criterion value picks the “better” model. The second column of the table reports the “best” model for explaining GDP growth based on the results reported in Table 3. Entries with a ' in the first column of each panel indicate predictive ability from GDP to the variable of interest, which is indicative of potential bi-directional Granger causality. All non-prime entries in the first column in each panel indicate that the smaller model without GDP is preferred, negating the possibility of bi-directional Granger causality. Thus, for Bolivia, the i_t (investment) equation achieves a lower criterion value (2.62) when lags of GDP growth (y_t) are included as additional explanatory variables. This can be taken as evidence that there is causation from y_t to i_t , in Granger sense. In addition, as Bolivian GDP growth is best explained by lags of GDP and investment growth (see column 2, where the “preferred” model from Table 2 is given), we have evidence of bi-directional causality in this case for Bolivia.

Table 5: Model Selection Results Based on a Predictive Ability Approach¹
with Effective External Economic Conditions Index
All Models are Vector Autoregressions

Model Country	RW w/d	y_t, i_t, m_t, x_t, e_t	y_t, m_t, x_t, e_t	y_t, i_t, m_t, e_t	y_t, i_t, x_t, e_t	y_t, i_t, e_t	y_t, m_t, e_t	y_t, x_t, e_t
Bolivia	11.54	6.50	6.27	6.20	6.24	5.81*	6.10	6.54
Chile	57.13	41.13	39.76	36.03	37.59	33.19*	34.76	43.10
Colombia	19.54	5.40	6.25	3.39	4.97	3.14	3.03*	5.40
CostaRic	20.17	17.98	14.67*	16.10	18.49	19.99	15.25	17.34
Cyprus	47.70	68.31	64.51	46.19	57.56	37.13	45.10	20.64*
Dominica	26.82	18.96	18.71	18.93	20.52	15.67*	20.84	19.26
Ecuador	20.39	30.71	21.79	24.15	22.82	24.00	21.76	20.59
ElSalvad	21.26	23.44	22.43	18.22	23.03	17.74	17.56	22.28
Ghana	21.01	24.32	17.93	29.29	28.23	25.31	16.78	22.55
Greece	10.12*	18.22	18.20	17.32	18.23	16.83	17.23	17.70
Guatemal	11.71	7.71	7.05	6.68	7.65	6.57	5.84*	6.78
Haiti	23.21*	44.81	37.24	40.41	37.61	36.49	34.05	35.58
Honduras	14.50	10.31	9.68	9.85	9.83	9.22	9.34	8.98*
India	33.95	21.10	16.83	13.57	20.72	12.58	12.56*	15.22
Iran	90.65*	218.68	232.45	136.01	195.34	115.01	155.99	167.74
Israel	35.77*	134.70	135.62	71.62	138.14	51.67	46.36	165.54
Jamaica	11.08	15.84	19.89	14.64	16.16	11.46	16.16	18.91
Kenya	20.98	7.70	13.06	9.35	9.82	9.27	7.04*	8.08
Korea	64.38	9.79	9.40	8.71	9.42	8.90	8.62*	9.35
Malaysia	56.59	15.41	11.44	12.68	11.88	10.70	12.43	9.89*
Mauritiu	43.16	23.22	24.18	20.38	23.20	20.36	19.87*	26.79
Mexico	25.82	23.90	22.85	21.81	22.87	20.34	21.07	21.79
Morocco	37.75	27.70	22.28	22.82	25.60	23.95	21.42*	24.75
Myanmar	32.82	38.37	39.36	33.54	37.49	33.40	39.46	38.47
Pakistan	29.53	4.53	4.37*	5.06	5.18	5.28	5.07	5.18
Panama	53.84	35.48*	38.35	38.28	40.02	39.01	37.72	39.03
Paraguay	27.52	13.02	12.22	11.18	12.31	10.59*	10.70	11.80
Peru	49.28	53.26	53.32	52.56	51.81	50.95	52.89	51.04
Philippi	21.16	14.70*	17.04	15.03	15.84	15.76	16.94	17.05
Portugal	13.36	11.53	10.69	10.32	14.85	9.59	5.68	4.19*
SaudiAra	30.77	44.15	52.42	40.27	43.04	40.41	46.52	50.36
Singapor	64.78	8.21	7.73	8.31	7.98	7.79	7.82	7.54*
SouthAfr	8.89	7.34	7.02	6.51	8.90	7.56	6.34*	8.34
SriLank	25.32	4.46	4.59	3.49	3.86	2.75*	3.97	3.76
Syria	52.97	49.78	43.26	37.84	56.10	41.79	35.40*	52.70
Thailand	56.25	6.70	6.60	6.96	6.48*	7.31	6.78	7.14
Trinidad	25.27	24.41	24.95	24.72	21.86	21.27	23.77	21.62
Uruguay	25.65	19.50	19.29	19.35	18.99	18.73	19.07	18.67*
Venezuel	21.03	27.02	28.28	31.86	25.30	30.20	30.33	27.35

¹ Notes: See notes to Table 3.

Table 6: Various Rankings of Countries According To Macroeconomic Criteria ¹

	$\left(\frac{x_t}{y_t}\right)$	$\left(\frac{x_t+m_t}{y_t}\right)$	$\left(\frac{i_t}{y_t}\right)$	Av per Capita \dot{y}_t
1.25	Singapore†	2.78	Singapore†	0.064
0.57	Malaysia	1.12	Panama	Singapore†
0.56	Panama	1.10	Malaysia	0.058
0.55	Saudi Arabia	1.07	Mauritius†	Korea
0.52	Mauritius†	0.97	Trinidad & Tobago*†	0.045
0.51	Trinidad & Tobago*†	0.91	Cyprus	Portugal*†
0.41	Jamaica†	0.88	Jamaica†	Cyprus
0.41	Cyprus	0.87	Saudi Arabia	0.042
0.30	Costa Rica*†	0.78	Israel†	Greece
0.30	Venezuela	0.65	Costa Rica*†	0.041
0.30	Honduras	0.64	Sri Lanka	Malaysia
0.29	Sri Lanka	0.62	Honduras	Thailand
0.29	Israel†	0.60	Kenya	0.038
0.29	Kenya	0.55	Portugal*†	Greece
0.29	South Africa*	0.54	South Africa*	0.037
0.25	Dominican Republic	0.54	Dominican Republic	Israel†
0.24	El Salvador*†	0.53	El Salvador*†	0.038
0.23	Thailand	0.53	Venezuela	Myanmar†
0.23	Portugal*†	0.50	Thailand	Mexico*†
0.22	Ecuador	0.49	Syria*	0.024
0.21	Korea	0.48	Morocco	Pakistan
0.21	Philippines	0.47	Korea	0.024
0.21	Morocco	0.45	Haiti	Panama
0.20	Syria*	0.45	Philippines	0.024
0.20	Bolivia*	0.45	Ecuador	Morocco
0.20	Chile*†	0.43	Bolivia*	0.020
0.20	Iran	0.42	Paraguay	0.020
0.19	Ghana*†	0.42	Ghana*†	Colombia*
0.19	Paraguay	0.40	Chile*†	Jamaica†
0.19	Haiti	0.37	Greece	0.020
0.18	Peru†	0.37	Peru†	0.020
0.17	Uruguay	0.37	Guatemala*	Ecuador
0.17	Guatemala*	0.36	Iran	0.019
0.15	Colombia*	0.35	Uruguay	Saudi Arabia
0.14	Greece	0.29	Pakistan	0.019
0.14	Mexico*†	0.29	Colombia*	0.017
0.12	Pakistan	0.28	Mexico*†	0.016
0.09	Myanmar†	0.19	Myanmar†	0.016
0.06	India	0.14	India	Mauritius†
				Chile*†
				Paraguay
				Iran
				South Africa*
				El Salvador*†
				Guatemala*
				Honduras
				Venezuela
				Kenya
				Uruguay
				Peru†
				Bolivia*
				Peru†
				Bolivia*
				Peru†
				Bolivia*
				Ghana*†
				Haiti

¹ **Notes:** All measures are constructed from the dataset used above, and are sample averages based on the entire observation period. Av per Capita \dot{y}_t is the average growth rate of real per capita GDP in constant dollars. Countries superscripted with a * have preferred models which benefit from the addition of e_t based on our MSE predictive ability approach, and countries superscripted with a † have preferred models which benefit from the addition of e_t based on the examination of confusion rates (see above for further discussion).