Trade, Investment and Growth: Nexus, Analysis and Prognosis

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Abstract

This paper looks at the patterns of causation between income, export, import, and investment growth for 25 developing countries. Our approach differs from previous efforts in a number of ways. First, we examine each country individually in order to allow for complete heterogeneity and properly account for the stochastic trending properties of the data. Second, we apply novel model selection techniques which are based on in-sample goodness-of-fit criteria and ex-ante predictive ability criteria to identify the *best* model for each country. Our approach allows us to shed new light on the incidence of causation and reverse causation between various economic variables which are commonly believed to *lead* economic growth, for example. Finally, we propose a rather novel device based on simple contingency tables which allows us to assess whether our models are capable of accurately predicting turning points in GDP growth. We find that countries with high trade exposure fare poorly in this dimension and posit that the GDP growth in such countries is best modelled using an index of global business cycle conditions, in addition to the above variables. Overall, we find that in around two thirds of the countries examined, growth is best explained by exports and/or imports. Further, and in contrast to previous findings of bi-directional causality, around 70% of the countries exhibit uni-directional causality.

JEL classification: F43, O47.
Keywords: Exports, Investment, Growth, Causality.

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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 was 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 of these schools of thought 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 ones 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), argued that there was a vicious circle present. Firms did not industrialize because there was no market for their goods and there was no market for their goods because income was low and income was 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. Hirschman's discussion of "*backward*" and "*forward*" linkages was an integral part of this analysis. Here, *linkages* refer to the effects of one investment on the profitability of subsequent investments at earlier and later stages of development. Investment by a firm can, through *forward* linkages, motivate investment by another firm which uses the first firm's output as an input. Similarly, through *backward* linkages, one firm's investment can motivate another firm, which provides inputs to the first firm, to invest. Instead of industrializing a large number of sectors, he argued that what was needed was the industrialization of the "leading" sectors. Then, through backward and forward linkages these sectors would spark the industrialization of 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 for example 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 as providing evidence that patterns of trade are important in driving R&D spillovers, since counter factual random trade patterns do even better in explaining the data than do 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, Saul 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!

Another influential set of ideas links trade policy and orientation with growth. However, because trade policy is multi-faceted there is no unique measure of openness, and indeed various different openness measures are loosely used to cover a host of different concepts, resulting in considerable confusion of terminology (see e.g. Krishna (1992)). Thus, it is not surprising 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. Krishna (1992) shows that such trade share measures are indices of vulnerability to terms of trade shocks, as they can be interpreted as the elasticity of indirect utility with respect to the terms of trade. One caveat of trade share measures is that they do not necessarily serve as an adequate measure of the strength of trade barriers: Small countries tend to have larger trade shares than large ones, *ceteris paribus*. In addition, indices of trade barriers are much harder to construct because of aggregation problems involved with forming an index number that reflects the extent of all tariff and non-tariff barriers, and which is comparable across countries (see Krishna (1992) for a discussion of the advantages and limitations of existing indices).

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.

One feature which many new trade theories have in common is that an increase in market size or in the availability of productive technology associated with imports can affect the returns to innovation, and hence lead to higher steady state growth rates. Thus, externalities associated with liberal trade policies are seen as leading to higher levels of GDP or 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 look for evidence that a neutral stand on trade and the domestic economy (one definition of greater openness) causes growth. Alternatively, one could argue that it is exposure to world conditions, and a correspondingly high ratio of trade to income that causes growth.

Finally, it should be noted that one set of ideas links investment with growth and with exports. An increase in exports will be correlated with growth because higher investment demand causes a rise in exports (see Rodrik (1995)). Similarly, Young (1994) argues that in contrast to export led growth, the success of the NICs could also be explained by policies that promoted investment in productive resources and human capital. According to this view, investment would be causally prior to GDP.

Of course, one could argue that all of the above is headed in the wrong direction and that in fact, everything causes everything else! Thus, one might argue that it is growth that causes exports or investment rather than the other way around! An obvious way to address this issue empirically is to look for evidence of causality. 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 Granger causality analysis to annual data on exports and GDP. Jung and Marshall (1987) find that only four of the thirty-seven countries in their dataset 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.[1] 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 six countries[2] 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.[3] 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. One of the reasons for her findings may be that her panel approach restricts the dimensions in which countries can differ from each other, as outlined later in more detail. In her defense, it is worth noting that econometric techniques for nonstationary panels have only recently become available as outlined in Sections 3 and 4. Based on cross-sections and panels of data for LDCs, Harrison finds that there is generally a positive association between growth and openness, although the strength of association is highly dependent on the particular measure of openness used. She also controls for other variables and finds that greater openness is associated with greater growth. However, her results are sensitive to whether sample averages, five year averages or annual data are used.[4] Thus, convincing dynamic empirical evidence on the link between trade and development remains elusive, although 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. In particular, empirical models consisting of GDP, investment, imports, and exports are examined. By directly including investment in our empirical models, we are able to select among theories which suggest that investment leads growth,

[1] However, 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.

[2] The Dominican Republic, Indonesia, Korea, Taiwan, and Thailand.

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

[4] Frankel, 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 does have a strong effect on growth.

and theories which are based on exports and imports, for example. In addition, 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 standard Granger causality tests do. Rather, we attempt to directly examine the predictive ability of the four variables for one another. Given that Granger causality tests can be viewed as tests of predictive ability, this approach of directly assessing marginal predictive content offers an alternative to previous approaches. A final feature of our model selection approach is that we take a two-pronged strategy to disentangling the relationships among our variables. First, we use a standard model selection tool based on the comparison of complexity based penalized likelihood criteria among competing empirical models. This method is based on in-sample estimation. Our second approach is somewhat more novel, and involves the simulation of a real-time policy setting environment. In particular, we mimic the information available to policy-makers in the day-to-day process of policy setting. This is done by creating sequences of real-time economic forecasts of our variables using increasing windows of observations and a variety of alternative empirical models. By selecting the "best" models based on this approach we are able to truly assess the predictive content of our variables, thereby gaining valuable new insight into the causal linkages among them. An important aspect of this two-pronged strategy for implementing our analysis is that we are able to show that our findings are by and large quite robust.

An assumption which is perhaps not unreasonable is that one of the leading reasons why the evidence to date has yielded such mixed results is that the empirical models examined are misspecified in some way. For example, given the likelihood that data examined in this area are generated by models which include nonstationary variables, an important candidate for model misspecification is the inadequacy of previous models to adequately account for cointegration. In order to address this issue, we ask the question: Are GDP, investment, imports, and exports linked in the long-run by the presence of common stochastic trends? If so, then how does this impact on the marginal predictive content of the various variables for one another?[5]

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

[5] Recent work by Ahmad and Harnhirun (1995) and Xu (1996) have begun to look at these issues.

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, by directly including investment in our empirical models we are able to select among theories which suggest that investment leads growth, and theories which are based on exports/imports.

In contrast to previous work, we find limited evidence of bi-directional causality between GDP, exports, imports, and investment. In addition, both of our model selection analyses indicate that the "best" models of growth in our sample of countries are usually characterized by uni-directional causality either from investment or from exports and/or imports to output, once stochastic trending properties of the data are correctly accounted for. Of equal interest is our finding that when a filter based on the ability of country specific models to correctly predict economic turning points is applied to our empirical models, nine out of twenty-five are found to be inadequate, or confused. While this is perhaps disturbing because we are left with little to guide us with regard to the avenues for growth in these nine countries, a number of surprising results emerge. First, of the sixteen remaining countries eleven are consistent with the hypothesis of trade led growth. Second, the nine countries which are confused are among the most exposed countries in our sample, when using the ratio of exports plus imports to output as a measure of trade exposure. One reason which may explain this finding is that these countries are heavily exposed to the global economy, and as such are highly subject to the vagaries of the global market. In order to address this possibility, we augment our original empirical models with two different indices of global market conditions. Interestingly, models which incorporate global market conditions are usually less confused, and the fall in confusion is larger the more exposed the country!

Thus, our contribution to the literature is twofold. On the methodological side, by adopting a model-selection approach, we believe that we contribute not only to the discussion of causality and growth in developing countries but also to the methodology of examining this and similar issues. Also, by using two alternative model selection procedures, one based on in-sample estimation, and one based on ex-ante prediction, we can assess the robustness of our findings. On the analytical side, we include imports and exports as well as investment in our analysis, propose a rather novel device based on simple contingency tables which allows us to assess whether our models are capable of accurately predicting turning points in GDP growth, and examine whether global market conditions indices might prove to be important additional variables in growth models for countries with high trade exposure rates.

The rest of the paper is organized as follows. Section 2 discusses our dataset, while Section 3 outlines the econometric methodology used. Our findings are gathered in Section 3, where we discuss the time series properties of the data, report our findings based on our model selection approach, introduce a filter which allows us to weed out countries for which our approach has little to say, and examine the importance of global market conditions indices in empirical models of growth. Section 4 contains concluding remarks.

2 Data

Annual data for 25 developing countries[6] reported on in *International Financial Statistics* (IFS) published by the International Monetary Fund are used. The period covered is 1961-1996. The series are GDP, y_t, gross fixed capital formation (our investment series), i_t, imports, m_t, and exports, x_t. In addition, the following series were used as proxies for global economic conditions (w_t): i) Real US GDP and ii) An Index of Industrial Production for 22 Industrialized Countries. All variables are in natural logs and in 1990 prices in the national currency. The consumer price indices (CPI) from the IFS were used to convert nominal values to real values (except for real US GDP in 1990 prices, which is taken directly from the IFS). Our summary variables (see Table 8) were constructed using these variables.

3 Econometric Methodology

One of the main drawbacks associated with the use of cross sections and panels within our context is that there are competing theories of growth. Moreover, one theory might be appropriate for one country, while a different theory could be appropriate for another country. Indeed, if the correctness of a theory is dependent on the country in question, then the simple use of pooled data from different countries may pose serious problems, and coefficient estimates associated with standard pooled regressions may be suspect. To illustrate, consider the case of panels of data. One advantage of panel data models is that by fixing some (or all) of the coefficients in a model *across* countries, one is able to estimate a model with more observations, and hence more degrees

[6]These countries are Bolivia, Chile, Colombia, Costa Rica, Egypt, El Salvador, Ghana, Greece, Guatemala, India, Israel, Jamaica, Kenya, Korea, Malaysia, Mauritius, Morocco, Pakistan, Panama, Peru, Portugal, Singapore, Sri Lanka, Thailand, Venezuela.

of freedom than if one were to estimate a separate time series model for each country. Of course, under *complete* heterogeneity (i.e. all parameters used in the specification of a growth model differ for each country in the panel), one needs to allow all coefficients in a panel data model to vary by country. If this is not done, then parameter estimates are not guaranteed to be consistent estimates of the parameters of interest in the model. However, allowing all coefficients in a panel data model to vary essentially reduces the degrees of freedom and the precision of econometric estimates to that associated with simple separate estimation of time series models.[7] Thus, as the evidence to date on growth models is so mixed, we make the assumption that models are heterogeneous, and estimate a separate time series model for each country.

In addition to allowing for the possibility that different theories describe growth in different countries, we examine each country individually in order to easily account for the stochastic trending properties of the data. This is important, as much of the empirical evidence gathered to date is based on the construction of causality tests. However, in these studies, the potential impact of long-run cointegrating restrictions (cointegration) among the variables is never accounted for, and standard F- or Wald-tests for causality are prone to severe upward size distortions when vector error correction (VEC) models are estimated using only differenced data, without accounting for cointegrating restrictions (see e.g. Swanson, Ozyildirim and Pisu (1996)). One of the reasons why this problem arises is that the moving average representation for a model with cointegrated regressors will not yield a finite order VAR representation. Put another way, testing bias arises in part because least squares becomes "confused" when potentially significant variables (the error-correction terms) are omitted from regression models. This "confusion" may account for the evidence discussed above that there is bi-directional causality between exports and GDP, for example. Thus, in order to assess the importance of heterogeneity across countries, and to examine the importance of the "nonstationary" characteristics of our data, we begin by specifying models of the form:

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

[7] In the above example, we are assuming for simplicity that the researcher is interested in constructing estimates of *all* coefficients in the growth models. If this were not so, then some coefficients could in certain cases be averaged, resulting in degrees of freedom gains. In addition, when testing for cointegration in panels, degrees of freedom gains may accrue by simply assuming that the rank of the cointegrating space is the same for each country, for example (see Holz-Eakon, Newey, and Rosen (1987) and Pedroni (1997,1998) for further discussion of this and related issues).

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.[8] The vector q_t is a vector of between two and five variables, with vector elements chosen from the set $\{y_t, x_t, m_t, i_t, w_t\}$ (see above for variable descriptions). In addition, $z_{i,t-1} = \hat{\alpha}' q_{t-1}$, i=1,...,$r$, is a vector of I(0) error-correction terms defined as in Engle and Granger (1987). For each country, r is the estimated rank of the cointegrating space, and is estimated using standard maximum likelihood procedures. The lag order of our models, say l, is chosen alternately using the SIC and the AIC. In all cases, the number of lags for each endogenous variable in the system is the same. It should perhaps be stressed that we are not imposing cointegration on our models, as an estimate of zero for r is allowable. In addition, we later report unit root test statistics which confirm that all of our undifferenced variables are consistently viewed as I(1) around a linear deterministic trend.

Our approach to assessing the relative usefulness of investment versus export driven growth theories is to implement two rather novel "causality tests". As we shall later see, the use of these "tests" not only enables us to unravel the problem of bi-directional Granger causality, but also signals an important form of misspecification in our models. The "tests" which we use in our analysis are based on a model selection approach to assessing the predictive (or causal) content of one group of variables for another. As such, they do not rely on classical testing theory, in the sense that the traditional approach of fixing the test size (given that the limiting size is known) and rejecting the null hypothesis at that size regardless of sample size is not adopted. Rather than focusing directly on testing zero coefficient restrictions, as is done with standard F- and Wald-tests, our approach is to measure the relative predictive accuracy of alternative econometric models. In particular, competing econometric models are specified. One of these contains the variable(s) whose causal effect is of interest, while the other one does not contain the variable(s). Then, noncausality can be directly tested by simply observing which model is selected as "best", according to some model selection criterion. As it has been known from the beginning that Granger causality tests are interpretable as tests of predictive ability, we design our model selection approach so that it provides an alternative to classical causality testing which addresses the key issue of predictive

[8] In passing, it 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 Terasvirta (1993), Kuan and Liu (1995) and the references contained therein).

ability. One desirable feature of the model selection approach is that the probability of selecting the truly best model approaches unity as the sample size increases, if the approach is properly designed. On the other hand, it can sometimes be difficult to assess the Type I error associated with testing the implicit assumption that the two models being considered perform equally well based on observed differences in realized model selection criteria. This defect is of the same order of magnitude as using a traditional test whose size is known only asymptotically. The two model selection approaches which we consider can be summarized as follows:

I. A Complexity Based Likelihood Criterion Approach

Granger, King, and White (1995) suggest that although standard hypothesis testing has a role to play in terms of testing individual economic theories, it is more difficult to justify using standard hypothesis tests for choosing between two competing models. One reason for their concern is that one model must be selected as the null, and this model is often the more parsimonious model. However, it is often difficult to distinguish between the two models (because of multicollinearity, near-identification, etc.), so that the null hypothesis may be unfairly favored. For example, it is far from clear that pre-test significance levels of 5% and 1%, say, are optimal, as pointed out by Fomby and Guilkey (1978) in the context of serial correlation tests. The use of model selection criteria neatly avoids related sticky issues associated with how to test theories and how to arbitrarily choose significance levels.

In a recent paper, Sin and White (1995) consider the use of penalized likelihood criteria for selecting models of dependent processes. In the context of strictly nested, overlapping or nonnested, linear or nonlinear, and correctly specified or misspecified models they provide sufficient conditions on the penalty to ensure that the model selected attains the lower average Kullback-Leibler Information Criterion, with probability (approaching) one. Two leading examples of criteria which fall within the class considered by Sin and White (1995) are the Akaike Information Criterion and the Schwarz Information Criterion. These are the two criteria which we will use below, and they are defined as:

(i) Akaike Information Criterion,

$$AIC = Tlog|\hat{\Sigma}| + 2f,$$

(ii) Schwarz Information Criterion,

$$SIC = Tlog|\hat{\Sigma}| + flog(T),$$

where f is the total number of parameters in the model and $\hat{\Sigma}$ is variance/covariance matrix of the residuals. If only one equation in (1) is being examined, then $|\hat{\Sigma}|$ is replaced by the residual sum of squares. From a practical perspective, the implementation of these criteria is extremely easy, as one need only estimate competing models with and without the variable(s) of interest using the entire dataset, construct SIC or AIC criteria based on these estimated models, and select as "best" the model which attains the lowest criterion value. If the best model contains the variable of interest, then that variable is said to be "causal" in the sense of marginal predictive ability. Swanson (1998) implements a version of the above procedure to assess the marginal predictive content of money for output, and finds that previous evidence of a lack of predictive ability may be due to the inability of F- and Wald-tests to appropriately account for model misspecification.

II. An Ex-Ante Predictive Ability Criterion Approach

Although AIC and SIC criteria are useful for examining statements of causality (see e.g. Swanson, Ozyildirim and Pisu (1996) for Monte Carlo and related evidence), note that they are calculated "in-sample" as are standard F- and Wald- tests. Thus, they provide only indirect finite sample evidence concerning the predictive usefulness of our variables for economic growth. Our second model selection approach involves simulating a real-time economic environment, thus enabling us to directly assess the relative predictive ability of our different variables. There are many papers which discuss predictive ability, model selection, and *ex ante* forecasting of this type. Some of these include Diebold and Mariano (1995), Swanson and White (1997a), and the references contained therein. For example, Diebold and Mariano (1995) conclude their paper by suggesting that versions of the ex-ante forecasting approach which we adopt here may be of interest as a model specification diagnostic, and to test both nested and nonnested hypotheses under nonstandard conditions.

Our approach is to construct a sequence of real-time one-step ahead forecasts of a given variable of interest, say t_t, using (1). In order to properly simulate real-time responses of output to our other endogenous variables (and of our other endogenous variables to output), we begin by estimating all coefficients, the lag length, the cointegrating rank, and the cointegrating space of (1) based on a sample of length R, say, where $R < T$, and T is the entire sample size. A one-step ahead forecast of t_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 t_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 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 $ferr_t$ are the real-time forecast errors.[9] By forming competing models with and without a particular variable of interest we can assess causal directionality by simply picking the model with the lowest MSE value, say, and observing whether that model does or does not contain the variable of interest. In addition, Corradi, Swanson, and Olivetti (1998) show that the test proposed in Diebold and Mariano (1995) for assessing whether the MSEs from two different models are the same can be applied in the current context, and we can construct a probability value for the null hypothesis that nothing is gained by including the variable of interest (i.e. the absence of a causal linkage).

4 Empirical Findings

4.1 Stochastic Trending Properties of the Variables

We begin our empirical investigation by examining the basic time series properties of the data. The main reason for this is that the integration and cointegration properties of the data are critical in the subsequent analysis. For example, if cointegration is not accounted for, our regression models are misspecified and standard causality tests become invalid in principle. Some of the dangers involved with inference in this context are discussed above.

Tables 1 and 2 summarize our findings. In Table 1, we assess whether the variables in our dataset can be viewed as I(1) or I(0). This is done by forming Dickey-Fuller unit-root test statistics, which are reported in columns 3-6 of the table. The test statistics are based on regressions of the form

$$\Delta u_t = a + bt + cu_{t-1} + \sum_{i=1}^{p} d_i \Delta u_{t-i} + \nu_t, \tag{2}$$

[9] In 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 Swanson and White (1997b) for further discussion of these loss functions. Other loss functions besides MSE, MAD and MAPE are also available, but are not examined here. For a discussion of loss functions in economics, see Christoffersen and Diebold (1997), Weiss (1996), and the references contained therein.

where the lag order, p, is selected by examining the significance of estimates of d_i, i=1,...,p (see e.g. Ng and Perron (1995)), u_t is some variable of interest, and the test statistic is the standard t-statistic associated with the least squares estimate of c. The null hypothesis of the test is that the series in question in I(1). Rejections of this null hypothesis at 5% significance levels are reported in the table as starred entries. As is immediately apparent, almost all of our country specific series can be viewed as I(1) variables.

Given this property, it is important to assess whether the variables are also cointegrated. If country specific variables are cointegrated, then we must include so-called error-correction terms as additional variables in our econometric models in order to ensure correct specification. In order to determine whether cointegration might be an issue for individual countries, we first examine our entire panel of countries, using the test proposed by Pedroni (1997) which requires that the cointegrating rank in the different countries is the same. (Later, we individually test each country for cointegration.) Table 2 presents the results of bi-variate Dickey-Fuller and Phillips-Perron type cointegration tests (see Pedroni (1997,1998)) under the assumption of a positive deterministic trend in the data ($\delta_i > 0$) and under the assumption of constant no deterministic growth ($\delta_i = 0$). Starred entries correspond to bivariate combinations for which the null hypothesis of no cointegration is rejected at a 5% significance level. Clearly, and regardless of whether δ_i is zero, there is substantial evidence of cointegration among y_t, x_t, m_t, and i_t, at least based on panel evidence. Because of this evidence, we are particularly careful to test and correct for the consequences of cointegration in our country specific models.

4.2 Model Selection Evidence

4.2.1 Is Bi-Directional Causality An Issue?

One of our main goals in this paper is to provide new evidence with regard to the bi-directional causality problem in the empirical development literature. With this in mind, we turn first to a discussion of Tables 3-6, which contain a summary of our model selection analysis.[10]

[10] In order to keep the length of the paper managable, and because all of our findings are qualitatively similar, we report results based on the SIC version of our complexity based likelihood criterion approach, and on the MSE version of our ex-ante predictive ability criterion approach. In addition, the lag structure of all estimated models is based on the SIC. In almost all cases reported in this paper, the SIC picked one lag. Using only one lag corresponds to a loss of at most 4 or 5 degrees of freedom when estimating our final empirical models. This in turn allows us

Tables 3 and 4 contain findings based on our SIC model selection approach. In essence, this approach is based on constructing competing empirical models and "selecting" the "best" model by examining SIC criterion values (the lower the SIC value, the "better" the model). 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 of GDP growth for Panama is a model which includes lags of GDP growth as well as lags of investment growth. This suggests that growth in Panama is consistent with investment led growth theories. By examining only the bold faced entries in the table, a basic picture emerges. Growth in our twenty-five countries is best explained by models which include: exports and/or imports (17 countries), investment (6 countries), and a mixture of exports, imports, and investment (2 countries). At this stage, however, we have only discussed predictive (or causal) association from Δx_t, Δm_t, and Δi_t to Δy_t.

In order to tackle the issue of bi-directional causality, we must also consider reverse causation. For example, while Δi_t appears to cause Δy_t for Panama, we do not yet know whether the reverse also holds. For evidence on this, we turn to Table 4. In Table 4, the Δx_t, Δm_t, and Δi_t in our VEC model are individually specified with and without Δy_t. In each of the three vertical panels of entries in the table, boldfaced entries indicate that the preferred models do not contain lagged GDP growth. As an illustration, note that for Columbia we see that GDP growth does not cause investment, export, or import growth (as the smaller models which do not contain GDP growth are preferred to the larger models in all three panels). In addition, recall that in Table 3 we have evidence that the "best" model for GDP growth in Columbia contains imports. Since we now also know that imports are not caused by GDP, we have evidence of uni-directional causality from imports to GDP for Columbia. Note that the preferred model from Table 3 is given beside each country in Table 4. This is useful, as it allows us to directly assess whether bi-directional causality is a problem.

In particular, say that a preferred model for country *abc* from Table 3 contains x_t and m_t. Then, we need only look at the x_t and m_t panels in Table 4 for country *abc*, and if the panels

to obtain surprisingly precise estimates, even given the relatively small country specific samples which we examine. Complete empirical results are available upon request from the authors.

indicate a lack of predictive ability from GDP to the variables (i.e. in both panels the smaller model is preferred, or, equivalently, in both panels there are boldfaced entries for country *abc*), 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, 16 of 25 countries yield evidence of uni-directional causality, while 9 countries exhibit bi-directional causality, including: Bolivia, Chile, Ghana, Kenya, Korea, Mauritius, Panama, Portugal, and Venezuela. As we shall see below, 5 of these are contained in a group of 9 countries which should perhaps be "filtered" from our sample because of poor performance in predicting turning points in GDP growth (see Table 7), including Chile, Kenya, Korea, Panama, and Portugal. In light of this, a better summary statistic is that 12 of 16 (75%) countries (in our filtered sample) exhibit evidence of uni-directional causality.

This rather surprising new evidence of uni-directional causality among our sample countries may be attributed to a number of factors.[11] First, note that bracketed integer values in Table 3 denote the rank of the cointegrating space in our empirical models. In particular, entries other than zero (which are seen for around one third of our countries) signal the existence of cointegrating relations among the variables, and as our empirical models account for this cointegration at the estimation stage, we have avoided a form of misspecification which might lead to spurious causality findings.[12] Second, our models separately account for exports and imports, and also include investment. Previous studies which focussed on only exports (or openness measures) may have been misspecified in two ways: (i) Basing an analysis solely on exports or openness leads to model misspecification if investment is a relevant variable. As we have evidence of this for some countries, causality results, particularly those based on panels of data where all countries are merged together might become quite confused, leading to spurious results. (ii) As mentioned above, separately treating exports and imports avoids assumptions made in order to construct openness variables. Third, by focussing on model selection rather than in-sample based classical hypothesis testing we avoid sticky issues related to specification of a null model and what significance levels to use, for example. Rather, we simply choose the "best" empirical model, and determine which variables it includes. However, it

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

[12]When particular variables were omitted from (1) in order to form our menu of alternative models, these variables were also omitted from any possible cointegrating relations.

should be stressed that we do not explicitly address predictive ability using our approach (standard Granger causality tests suffer from the same shortcoming). Instead, we essentially focus on the "fit" of the competing models, as the SIC criterion is a complexity penalized likelihood criterion. This potential shortcoming of our approach based on the SIC is one of the driving forces behind our adoption of an alternative ex-ante predictive ability criterion approach.

Before turning to our discussion of ex-ante prediction, it is worth noting that the random walk with drift alternative (given as the first column of entries in Table 3) obtains a lower SIC (and is hence preferred) for 10 of 25 countries. This is rather surprising, and might be taken as evidence that causality does not run in either direction for these 10 countries. However, based on the following two additional observations, it should become clear that this would not be the correct conclusion to draw. First, we shall see when we examine our ex-ante predictive ability results in the next subsection that the random walk with drift (RW w/d) model outpredicts all of our growth models for only 7 of 25 countries based on a MSE measure of predictive ability (see Table 5). Of these 7 countries, 2 have MSE values which are actually the same up to two decimal places for the RW w/d model and our MSE-"best" model, and 4 are "filtered" from our sample because of poor performance in predicting turning points (see Table 7). Thus, there is actually very little evidence based on predictive ability that any country's GDP growth is best explained using a RW w/d model. Second, it is not obvious whether a good policy model should be required to "beat" a random walk alternative in our context. One reason for this is that empirical evidence based on ex-ante prediction suggests that VAR models in differences are not always outperformed by VEC models (see e.g. Hoffman and Rasche (1996) and Lin and Tsay (1996)). Thus, if a hypothetical VAR in differences is based on a VAR(1) in levels, say, then one equation of the analogous VEC model could take the form:

$$\Delta p1_t = \alpha_1 + \alpha_2 z_{t-1} + \nu_t,$$

say, where z_{t-1} is an error-correction term which is constructed by forming a stationary linear combination of the original variables in the VAR model, $p1_t$ is the target variable (say GDP growth), and ν_t is an error term. But in this context, if z_{t-1} is not useful for prediction, then a random walk model will perform just as well (i.e. set $\alpha_2 = 0$) as a model with z_{t-1} in it. This is so, even if the above equation represents the truth! Thus, even if z_{t-1} contains a potential causal variable, say $p2_t$, one might be misled into believing that $p2_t$ is not causal for $\Delta p1_t$ if one only notes that the random walk model performs just as well (from a predictive standpoint) as the model which contains z_{t-1}.

4.2.2 Is There Real-Time Predictability?

As discussed in the previous subsection, the use of a real-time experiment to pick growth models which are truly "best" from a predictive standpoint may shed further light on the issues of causality and model selection in the current context. This is the approach which we take in our ex-ante predictive ability experiments.

Our main findings based on ex-ante predictive ability model selection using a 15 year ex-ante simulation period (1982-1996) are gathered in Tables 5 and 6. The tables are organized in similar fashion to Tables 3 and 4, except that predictive MSE values rather than SIC values are reported, with lower MSE values corresponding to "better" models. In addition, models which outperform the random walk model based on the version of the Diebold and Mariano (1995) test for predictive ability proposed by Corradi and Swanson (1998) are superscipted with $*$, based on a significance level of 25%. We use a 25% significance level because the appropriate significance level is not obvious in our context, as discussed above. Note that in numerous cases, the "best" model (in boldface font) outperforms the random walk with drift model based on Diebold-Mariano tests. In addition, and as discussed above, only 3 countries prefer the random walk with drift model when "point" MSE estimates are compared.

Following the approach of the previous subsection, Table 5 can be summarized by noting that growth is best explained by models which include: exports and/or imports (14 countries), investment (8 countries), and a mixture of exports, imports, and investment (3 countries). In addition, 16 of 25 countries yield evidence of uni-directional causality, while 9 countries exhibit bi-directional causality, including: Bolivia, Columbia, Egypt, Greece, Kenya, Pakistan, Peru, Portugal, and Singapore. Thus, we have some evidence that the findings based on our first model selection approach are robust. As we shall see below, 3 of these are contained in the group of 9 countries which are "filtered" because of poor predictive performance, including Kenya, Portugal, and Singapore. In light of this, and corresponding to the results reported based on our SIC approach, a better summary statistic is that 10 of 16 (63%) countries (in our filtered sample) exhibit evidence of uni-directional causality.

As mentioned above, the current approach can be viewed as a truly real-time policy simulation.

In light of this, the results based on ex-ante prediction might be more reliable than our results based on the SIC approach. However, there still appear to be a number of questions which merit additional attention. First: Why is it that there seems to be a roughly equal split between countries for which investment led growth makes sense, and countries for which export and import led growth makes sense? Second: What is to be made of the countries for which a mixture of all of our variables appear to be important? Third: Why do some countries exhibit bi-directional causality? By next focussing our attention on the third question, we hope to provide information which may be useful for answering the first two questions.

4.2.3 Can Our Models Predict Turning Points?

In order to shed light on the questions raised above, we consider a third model selection approach to examining the data. In particular, we conduct a real-time simulation to assess the ability of country specific empirical models to accurately predict turning points in GDP growth. This approach is directly analogous to our ex-ante predictive ability approach, except that we now focus on the "confusion" of our models based on 15 year simulation period. By assessing the "confusion" of our models we attempt to answer the question: Are our models able to accurately predict business cycle (as measured by GDP growth) turning points? If the answer to this question is yes, we have further evidence of the robustness of our prior findings. If the answer is no, then our ex-ante predictive ability results are cast into doubt, and we are left with a new puzzle to solve[13].

Table 7 contains our findings based on confusion rates. The confusion rates which we report are the proportion of times for which our models correctly predict the direction of change in Δy_t based on the sequence of 1-step ahead real-time forecasts constructed as discussed above. The reported confusion rates can be constructed by forming what are called confusion matrices in Swanson and White (1995). A hypothetical confusion matrix is:

$$\begin{array}{llcc} & & \multicolumn{2}{c}{\textit{actual}} \\ & & \textit{up} & \textit{down} \\ \textit{predicted} & \textit{up} & 8 & 7 \\ & \textit{down} & 6 & 5 \end{array}$$

The columns in the matrix correspond to actual GDP growth rate moves, up or down, and the rows correspond to predicted moves. In this way, the diagonal cells correspond to correct directional predictions, the off-diagonal cells correspond to incorrect predictions, and the confusion rate is the

[13]Note that while mean squared errors are hard to compare across countries, confusion rates are not.

sum of off-diagonal elements divided by the sum of all elements. Because the confusion matrix is simply a 2x2 contingency table, the hypothesis that a given model is of no value in predicting turning points can be expressed as a hypothesis of independence between the actual and predicted directions, and in our context can be tested using a standard χ^2-test of independence (see e.g. Pesaran and Timmerman (1994)). In columns 3 through 9 of the table, confusion rates superscripted with a $*$ signify those models for which the null hypothesis of no predictive ability is rejected at a 95% level of confidence. Thus, for the model of GDP growth for Bolivia which contains y_t and i_t we have a confusion rate of 0.29, suggesting that we incorrectly predict the direction of change in GDP growth 29% of the time, and this value is superscripted, suggesting that this predictive performance is not due to chance.

One important feature of this approach is that it allows us to isolate countries for which all of our models are "confused". In order to operationalize our examination of the "confusion" of models, we shall make the assumption that models which are confused 40% of the time or more are sufficiently poor at prediction that these models should not be entertained as potential "best" models based on our previous model selection approaches. Thus, we use the confusion rate as a type of filter to separate out essentially "nonsense" models from those which are useful. Interestingly, it turns out that there are 9 countries for which all of our models appear to be "confused", including: Chile, Israel, Jamaica, Kenya, Korea, Malaysia, Panama, Portugal, and Singapore. (Note that these are the 9 countries alluded to in the previous two subsections.) One of the reasons why these countries may be so confused is that their respective models are all misspecified, possibly due to missing variables. This possibility is discussed in the next section.

If we remove the 9 filtered countries from our sample, hence restricting our attention to countries where the "best" model predicts adequately well, we may be able to formulate a clearer picture of growth dynamics for the remaining countries. As discussed above, based on the SIC, we end up with a 75% incidence of uni-directional causality, while based on ex-ante prediction, we end up with a 63% incidence of uni-directional causality. In addition, based on the SIC, growth in our remaining countries is best explained by models which include: exports and/or imports (13 countries) and investment (3 countries). Interestingly, there are no countries remaining for which models based on a mixture of exports, imports, and investment are preferred. Correspondingly, based on ex-ante prediction, growth is best explained by models which include: exports and/or imports (10 countries), investment (4 countries), and a mixture of exports, imports, and investment

(2 countries). Combining these findings, we see that growth is best explained solely by exports and/or imports for around two thirds of the countries. Thus, the roughly equal split between countries consistent with investment led versus export and import led growth no longer characterizes our sample of data. In addition, note that the incidence of countries for which mixtures of trade and investment variables is preferred drops off dramatically when the 9 confused models are removed. Finally, and as discussed in the previous sections, the incidence of bi-directional causality decreases when the 9 confused countries are filtered out of the sample. Clearly, then, model confusion offers at least a partial answer to all three of the questions posed at the end of the previous section.

Even though our filtering approach appears useful, the question of why 9 countries are confused remains open. Some light can be shed on this issue by examining the overall summary statistics reported for the 25 countries in Table 8. Note that the highlighted countries are the ones which are confused, and all of the confused countries fall within the group of 12 countries with the highest trade to GDP ratios! Recall that the trade to GDP index can be interpreted as a vulnerability index as in Krishna (1992). This suggests that high trade exposure makes a country vulnerable to world market conditions, which in turn suggests that one reason why 9 of our models are confused is that there is an important omitted variable, say world GDP. Thus, we have a plausible explanation for the poor predictive performance of 9 of our countries, namely model misspecification in the form of an omitted world market conditions or global business cycle conditions variable, say. In the next section we proxy global business cycle conditions, and assess whether our 9 confused models can be improved by the inclusion of such proxies.

4.3 Global Business Cycle Conditions and Growth

In this section we conduct a preliminary investigation of the impact of two different global business cycle conditions proxies on our countries' growth prospects. In particular, we focus on the 9 confused countries discussed above. However, it should be noted that as each country has different geographical characteristics and trading patterns, it is unlikely that any one index is appropriate for all countries. One may wish to construct something like a trade weighted Partner GDP index for each country. For example, if Singapore trades mostly with Australia and Malaysia, then conditions in these countries would have a greater impact on Singapore's growth prospects than those in a country it has little trade with. However, the precise weights are not easy to defend. To illustrate the problem associated with defining weights, consider that trade weights seem natural, but clearly the elasticity of trade with respect to growth can differ across countries, and common shocks can affect all countries, thus casting into doubt the use of simple trade weights. Nevertheless, in order to provide initial evidence on the matter, we examine the usefulness of U.S. GDP and an index of industrial production based on 22 leading industrialized economies as potential proxies for global market conditions. In Figure 1, we report the lowest confusion rates based on our usual tableau of alternative models, but with and without adding our proxy for global market conditions given by U.S. GDP. Results based on the other proxy are qualitatively similar, and are available upon request. Note that when the change in the confusion rate is plotted against the trade exposure of the country a clear positive correlation is apparent. Countries with a high exposure tend to become less confused when models are augmented by our global market conditions index. This suggests that there may be an omitted variable problem that has been unaccounted for in work to date, and suggests an interesting direction for future work.

5 Conclusions

We have used a model selection approach based on ex-ante predictive ability and in-sample goodness of fit measures to examine the patterns of causation between income, export, import, and investment growth for 25 developing countries. We offer the following conclusions. First, many of the variables used are found to be I(1), with cointegrating restrictions. We suggest that taking these restrictions into account when modelling growth avoids potentially spurious findings with respect to causality. 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. Third, we find strong new evidence of uni-directional causality, particularly based on measures of real-time predictive ability, although it must be stressed that we avoid the use of standard Granger causality tests, as our model selection approach essentially equates Granger causality with marginal predictive ability. Finally, we propose a rather novel device based on simple contingency tables which allows us to assess whether our models are capable of accurately predicting turning points in GDP growth. Based on findings associated with the use of this device, we posit that the GDP growth in countries with high trade exposure is better modelled by including an index of global business cycle conditions, in addition to the above variables. We provide evidence supporting this hypothesis by modelling growth in a group of countries with high levels of trade exposure.

6 References

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Table 1: Integration Test Results[1]

Country	Nobs	y_t	i_t	m_t	x_t
Bolivia	35	-2.65(1)	-2.63(1)	-2.45(1)	-2.49(1)
Chile	36	-1.06(2)	-1.15(2)	-1.15(1)	-0.93(2)
Colombia	36	-5.57(3)*	-3.12(0)	-2.83(1)	-3.09(0)
Costa Rica	36	-2.99(1)	-2.81(1)	-2.82(1)	-3.09(1)
Egypt	36	-2.42(1)	-3.87(3)*	-3.20(1)	-2.72(1)
El Salvador	36	-3.01(1)	-3.11(1)	-2.84(1)	-2.20(0)
Ghana	32	-3.20(3)	-2.94(0)	-2.74(0)	-2.46(0)
Greece	36	-2.67(1)	-2.92(0)	-2.86(1)	-2.13(1)
Guatemala	36	-2.28(1)	-3.10(1)	-2.49(1)	-2.20(1)
India	34	-2.42(1)	-2.55(1)	-3.23(1)	-2.68(1)
Israel	36	-3.24(3)	-3.29(3)	-3.06(3)	-3.07(3)
Jamaica	34	0.58(2)	1.52(2)	0.02(2)	-0.11(2)
Kenya	33	-3.37(1)	-3.23(3)	-1.93(0)	-1.90(0)
Korea	31	-1.17(1)	-1.35(1)	-1.70(1)	-1.56(1)
Malaysia	36	-2.32(1)	-2.94(1)	-2.73(0)	-2.66(0)
Mauritius	34	-2.08(1)	-2.54(1)	-2.34(1)	-1.95(0)
Morocco	36	-2.95(3)	-1.67(1)	-2.06(1)	-3.50(0)
Pakistan	36	-3.63(1)*	-4.03(1)*	-2.92(1)	-2.84(0)
Panama	36	-1.25(1)	-2.83(1)	-1.40(0)	-1.43(0)
Peru	36	-1.54(2)	-1.60(2)	-1.62(2)	-1.58(2)
Portugal	36	-2.13(2)	-1.85(3)	-2.05(3)	-2.02(1)
Singapore	36	-2.35(1)	-1.97(1)	-1.63(1)	-1.20(0)
Sri Lanka	36	-3.27(1)	-2.90(1)	-3.71(1)*	-3.89(0)*
Thailand	35	-2.80(1)	-3.77(3)*	-3.32(1)	-3.30(1)
Venezuela	36	3.22(0)	1.86(1)	1.83(0)	1.29(0)

[1] Notes: Nobs is the number of annual observations. All other numerical entries 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,...,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: Panel Cointegration Test Results[1]

LHS Variable	RHS Variable	Trend	ρ-stat	pp-stat	adf-stat
y_t	i_t	$\delta_i > 0$	-77.01*	-15.45	-17.72*
		$\delta_i = 0$	-48.46*	-11.81	-11.40
	m_t	$\delta_i > 0$	-103.7*	-19.26*	-21.12*
		$\delta_i = 0$	-54.93*	-12.72*	-12.75*
	x_t	$\delta_i > 0$	-80.05*	-16.15*	-18.76*
		$\delta_i = 0$	-60.48*	-13.20*	-14.26*
i_t	y_t	$\delta_i > 0$	80.15*	-15.89	-18.42*
		$\delta_i = 0$	-62.33*	-13.95*	-14.60*
	m_t	$\delta_i > 0$	-82.14*	-17.83*	-20.47*
		$\delta_i = 0$	-74.68*	-16.11*	-17.38*
	x_t	$\delta_i > 0$	-65.87	-14.50	-15.67
		$\delta_i = 0$	-70.96*	-14.73*	-15.80*
m_t	y_t	$\delta_i > 0$	-105.1*	-19.39*	-21.32*
		$\delta_i = 0$	-58.72*	-13.48*	-13.97*
	i_t	$\delta_i > 0$	-83.48*	-17.93*	-21.44*
		$\delta_i = 0$	-69.35*	-15.61*	-17.18*
	x_t	$\delta_i > 0$	-110.8*	-21.13*	-25.75*
		$\delta_i = 0$	-91.34*	-17.94*	-20.74*
x_t	y_t	$\delta_i > 0$	-87.34*	-16.74*	-17.85*
		$\delta_i = 0$	-67.77*	-14.39*	-15.48*
	i_t	$\delta_i > 0$	-63.20	-14.22	-14.74
		$\delta_i = 0$	-63.80*	-13.95*	-14.87*
	m_t	$\delta_i > 0$	-107.3*	-20.81*	-24.71*
		$\delta_i = 0$	-98.54*	-19.27*	-21.82*

[1] Notes: Reported (pairwise) cointegration test statistics are based on a panel regression of the form $x_{it} = \alpha_i + \delta_i t + \beta_i y_{it} + e_{it}$, where i indices the number of countries, t indices the number of years in the panel, $(\alpha_i + \delta_i t)$ is a country specific intercept term, and the e_{it} are residuals. Critical values, as well as the precise form of the cointegration test statistics for the three reported panel versions of Dickey-Fuller (adf-stat) and Phillips-Perron (ρ-stat and pp-stat) type cointegration tests are given in Pedroni (1997,1998). * denotes rejection of the null hypothesis of no cointegration at the 5% level of significance.

Table 3: **Model Selection Results Based on a Penalized Likelihood Approach**[1]

Model Country	RW w/d	y_t,i_t,m_t,x_t	y_t,i_t	y_t,m_t,x_t	y_t,i_t,x_t	y_t,i_t,m_t	y_t,x_t	y_t,m_t
Bolivia	147.5	127.0(0)	157.7(0)	**123.5**(0)	133.5(0)	126.6(0)	134.4(0)	125.3(0)
Chile	75.94	84.86(0)	82.35(0)	81.85(0)	85.72(0)	81.66(0)	83.28(0)	**78.72**(0)
Colombia	-35.43	-30.12(1)	-33.20(1)	-33.50(1)	-29.65(1)	-32.82(1)	-33.77(1)	**-36.92**(0)
Costa Rica	1.910	-1.530(0)	6.480(0)	-4.680(0)	-4.890(0)	3.090(0)	**-7.050**(0)	-0.070(0)
Egypt	-46.92	-46.38(1)	**-52.31**(1)	-45.12(1)	-49.19(1)	-49.73(1)	-42.43(1)	-45.27(0)
El Salvador	-45.97	-40.46(0)	-43.55(0)	-43.50(0)	-42.79(0)	-40.01(0)	**-44.69**(0)	-42.51(0)
Ghana	44.63	53.74(1)	48.83(1)	50.32(1)	51.83(1)	53.37(1)	49.76(1)	**47.34**(0)
Greece	-51.94	-53.92(2)	-46.66(2)	-56.47(2)	-47.87(2)	-57.04(2)	-49.77(2)	**-59.42**(0)
Guatemala	-5.100	-9.130(0)	-4.790(0)	-12.22(0)	-12.63(0)	-4.780(0)	**-14.52**(0)	-8.290(0)
India	-43.42	-34.38(0)	-39.87(0)	-36.49(0)	-36.63(0)	-37.88(0)	-39.15(0)	**-39.98**(0)
Israel	66.76	80.56(0)	74.81(0)	77.70(0)	77.12(0)	77.28(0)	**74.17**(0)	75.25(0)
Jamaica	1.410	7.010(0)	**0.380**(0)	4.010(0)	3.800(0)	3.850(0)	1.980(0)	1.450(0)
Kenya	-37.97	-35.11(0)	**-41.85**(0)	-32.07(0)	-38.56(0)	-38.40(0)	-33.97(0)	-34.12(0)
Korea	-45.46	**-63.92**(1)	-60.59(1)	-54.58(1)	-61.96(1)	-63.16(1)	-47.03(1)	-57.43(0)
Malaysia	-43.17	-33.20(0)	-38.12(0)	-36.49(0)	-36.33(0)	-36.49(0)	**-39.89**(0)	-38.53(0)
Mauritius	-12.86	-13.25(2)	**-20.39**(2)	-6.690(2)	-11.79(2)	-18.85(2)	-8.860(2)	-7.700(0)
Morocco	-37.28	-31.01(0)	-32.09(0)	-32.92(0)	-28.98(0)	-33.81(0)	-31.87(0)	**-36.43**(0)
Pakistan	-51.43	-47.11(0)	-49.50(0)	-49.69(0)	-50.35(0)	-46.37(0)	**-52.46**(0)	-46.46(0)
Panama	-56.06	-53.46(1)	**-56.87**(1)	-55.41(1)	-52.35(1)	-50.28(1)	-53.64(1)	-52.30(0)
Peru	136.5	151.1(1)	146.9(1)	147.7(1)	149.2(1)	149.5(1)	**145.7**(1)	145.9(0)
Portugal	-56.54	-47.50(2)	-53.55(2)	-49.38(2)	-49.99(2)	**-55.59**(2)	-52.90(2)	-52.85(0)
Singapore	-48.54	-37.59(0)	-43.42(0)	-41.15(0)	-39.87(0)	-40.27(0)	-43.34(0)	**-43.73**(0)
Sri Lanka	-30.93	-27.76(1)	**-33.37**(1)	-28.88(1)	-31.26(1)	-29.97(1)	-30.18(1)	-28.55(0)
Thailand	-45.97	-40.14(0)	-41.93(0)	-40.57(0)	-41.96(0)	-42.14(0)	**-44.08**(0)	-41.11(0)
Venezuela	22.01	22.26(1)	20.99(1)	**19.60**(1)	22.90(1)	23.88(1)	19.62(1)	22.26(0)

[1] **Notes:** Entries are Schwarz Information Criterion (SIC) values. Thus, when examining alternative models for a given country, the model associated with the smallest SIC value is preferred. All entries are based on the y_t equation of a fitted vector error-correction (VEC) or vector autoregression (VAR) in differences model, so that only lags of explanatory variables are used to explain GDP growth. In this way, all models correspond to alternative GDP growth specifications. y_t is GDP, i_t is investment, m_t is imports, and x_t is exports. Estimated co-integration ranks of the systems, based on 5% significance level trace test statistics, are reported in parentheses next to each model selection criterion entry. If $1 < r < 4$, the models are estimated with cointegrating restrictions included, while if $r = 0$, standard autoregressions in differences are estimated. In each row, the bold entry denotes the model which has the lowest SIC among the six candidate models. Lag selection for the VEC and VAR models is based on use of the SIC.

Table 4: Penalized Likelihood Approach Bi-directional Causality Results[1]

Country	Lags Included −− > *Preferred Model*	Equation for i_t: y_t,i_t,m_t,x_t	Equation for i_t: i_t,m_t,x_t	Equation for m_t: y_t,i_t,m_t,x_t	Equation for m_t: i_t,m_t,x_t	Equation for x_t: y_t,i_t,m_t,x_t	Equation for x_t: i_t,m_t,x_t
Bolivia	y_t, m_t, x_t	118.2(0)′	132.2(0)	122.0(0)′	134.7(0)	123.4(0)′	135.1(0)
Chile	y_t, m_t	87.22(0)	**84.53**(0)	86.71(0)′	87.75(0)	96.79(0)′	97.35(0)
Colombia	y_t, m_t	10.98(1)	**9.900**(1)	-17.17(1)	**-17.82**(1)	1.860(0)	**-0.870**(0)
Costa Rica	y_t, x_t	19.26(0)	**16.33**(0)	1.630(0)	**-1.910**(0)	33.55(0)	**30.89**(0)
Egypt	y_t, i_t	16.84(1)	**13.84**(1)	0.130(1)	**-1.330**(1)	21.29(0)	**19.95**(0)
El Salvador	y_t, x_t	-1.160(0)	**-2.770**(0)	-0.200(0)	**-2.690**(0)	13.30(0)	**9.780**(0)
Ghana	y_t, m_t	70.87(1)	**69.79**(1)	60.58(1)′	61.39(1)	64.82(0)	**64.60**(0)
Greece	y_t, m_t	-45.10(2)′	-34.02(2)	-9.370(2)	**-13.67**(2)	-26.73(0)	**-28.42**(0)
Guatemala	y_t, x_t	17.62(0)	**14.65**(0)	3.950(0)	**0.410**(0)	23.26(0)	**20.66**(0)
India	y_t, m_t	12.37(0)	**8.970**(0)	-50.54(0)	**-53.47**(0)	-11.02(0)	**-14.51**(0)
Israel	y_t, x_t	81.02(0)	**79.50**(0)	78.26(0)	**75.04**(0)	83.58(0)	**81.38**(0)
Jamaica	y_t, i_t	32.29(0)	**31.24**(0)	34.40(0)	**31.85**(0)	38.83(0)	**38.62**(0)
Kenya	y_t, i_t	9.990(0)′	11.50(0)	-27.94(0)	**-28.74**(0)	8.920(0)′	15.21(0)
Korea	y_t, i_t, m_t, x_t	-16.23(1)′	-15.19(1)	-32.17(1)′	-31.23(1)	-9.840(0)	**-12.79**(0)
Malaysia	y_t, x_t	0.340(0)	**-3.030**(0)	-11.65(0)	**-15.04**(0)	1.220(0)	**-0.940**(0)
Mauritius	y_t, i_t	1.93(2)′	2.21(2)	5.320(2)′	5.370(2)	13.71(0)	**10.32**(0)
Morocco	y_t, m_t	1.790(0)	**-1.75**(0)	-8.850(0)	**-12.39**(0)	1.320(0)	**-1.700**(0)
Pakistan	y_t, x_t	19.01(0)′	20.50(0)	-34.97(0)′	-33.48(0)	23.80(0)	**23.09**(0)
Panama	y_t, i_t	26.16(1)′	27.28(1)	40.87(1)	**39.27**(1)	24.46(0)′	28.76(0)
Peru	y_t, x_t	146.6(1)	**143.1**(1)	146.1(1)	**142.5**(1)	151.5(0)	**147.9**(0)
Portugal	y_t, i_t, m_t	-23.51(2)′	-12.92(2)	-26.96(2)	**-28.78**(2)	-15.60(0)′	-13.69(0)
Singapore	y_t, m_t	1.520(0)	**-0.33**(0)	-16.41(0)	**-17.88**(0)	6.600(0)	**5.790**(0)
Sri Lanka	y_t, i_t	7.020(1)	**3.07**(1)	7.670(1)	**6.410**(1)	3.420(0)	**2.980**(0)
Thailand	y_t, x_t	-3.220(0)	**-6.53**(0)	-21.78(0)	**-25.30**(0)	-8.190(0)	**-10.97**(0)
Venezuela	y_t, m_t, x_t	35.71(1)	**31.74**(1)	16.61(1)′	**16.61**(1)	63.12(0)′	66.86(0)

[1] **Notes:** See notes to Table 3. The remaining three equations (*Equation for* i_t, m_t, and x_t) from the VEC and VAR models in differences reported on in Table 3 are examined both with and without lags of GDP growth. In each panel, a smaller SIC criterion value picks the "better" model. Thus, for Bolivia, the m_t (imports) equation achieves a lower criterion value (122.0) when lags of GDP growth (y_t) are included as additional expalantory variables. This suggests that there is predictive ability of y_t for i_t, in the Granger causal sense. The second column of the table reports the "best" model for explaining GDP growth based on the results reported in Table 3. To illustrate, note that for Bolivia, GDP growth is best expalined by lags of GDP, import, and export growth. Since import growth is also explained by GDP growth, we have evidence of bi-directional causality for Bolivia. Entries in boldface within each panel denote smaller models (without lags of GDP growth) which are selected in pairwise comparison with the associated bigger model (which includes lags of GDP growth), while entries with a ′ indicate predictive ability in the other direction (e.g. from GDP growth to investment growth).

Table 5: Model Selection Results Based on a Predictive Ability Approach[1]

Model Country	RW w/d	y_t,i_t,m_t,x_t	y_t,i_t	y_t,m_t,x_t	y_t,i_t,x_t	y_t,i_t,m_t	y_t,x_t	y_t,m_t
Bolivia	600.6	18.21(0.6)	16.45(0.1)	15.99(1.0)	15.06(0.5)	18.94(0.1)	**13.36**(0.4)	16.00(0.2)
Chile	2.466	22.22(1.4)	7.955(0.5)	17.34(0.7)	21.06(1.4)	7.374(0.5)	19.49(1.0)	**4.804**(0.0)
Colombia	0.247	0.570(1.3)	**0.248**(0.9)	0.292(0.5)	0.516(0.7)	0.315(1.1)	0.381(0.3)	0.326(0.0)
Costa Rica	5.913	8.527(1.6)	10.01(0.0)	8.567(0.7)	9.270(0.8)	9.212(0.8)	**8.088**(0.4)	8.802(0.0)
Egypt	0.591	0.569(0.9)*	**0.342**(0.5)*	0.633(0.9)*	0.405(0.0)*	0.403(0.0)*	0.540(0.0)*	0.594(0.7)
El Salvador	1.062	1.182(1.3)	1.341(0.5)	**1.068**(0.5)	1.167(0.5)	1.383(0.8)	1.079(0.0)	1.325(0.1)
Ghana	27.04	0.274(1.5)	**0.206**(0.1)*	0.234(0.7)*	0.319(0.7)*	0.251(0.7)*	0.233(0.3)*	0.263(0.5)*
Greece	0.909	0.648(1.7)*	1.165(0.0)	0.651(1.5)	0.749(1.0)*	0.812(0.9)*	0.704(0.7)	**0.513**(0.5)*
Guatemala	5.358	**2.923**(1.7)*	4.506(0.3)*	3.956(0.7)*	3.056(0.9)*	4.557(1.2)*	3.691(0.7)*	4.279(0.5)*
India	0.367	0.473(1.1)	0.310(0.0)	0.339(0.1)	0.331(0.1)	0.290(0.0)	0.261(0.0)*	**0.243**(0.0)
Israel	40.24	0.589(0.2)	**0.485**(0.0)	0.668(0.2)	0.668(0.2)	0.678(0.1)	0.505(0.1)	0.687(0.1)
Jamaica	4.986	7.922(0.3)	5.886(0.1)	7.313(0.3)	6.883(0.3)	5.855(0.1)	6.475(0.3)	**5.664**(0.3)
Kenya	1.422	1.492(0.7)	**1.176**(0.3)*	1.411(0.0)	1.326(0.0)*	1.331(0.9)*	1.407(0.1)	1.354(0.1)
Korea	0.583	0.607(1.5)	0.604(0.5)	0.954(0.2)	**0.491**(0.5)	0.585(0.9)	0.737(0.0)	0.660(0.0)
Malaysia	0.539	1.743(0.5)	0.853(1.0)	0.764(0.0)	1.104(0.7)	1.431(1.0)	0.687(0.1)	**0.634**(0.0)
Mauritius	0.352	1.356(2.5)	0.612(0.0)	0.273(0.9)	0.837(2.0)	0.749(0.3)	0.309(0.0)	**0.205**(0.0)
Morocco	1.146	0.804(0.7)	0.586(0.9)*	0.599(0.6)*	0.614(0.4)*	0.559(0.3)*	0.698(0.1)*	**0.493**(0.0)*
Pakistan	0.307	0.275(0.4)*	0.267(0.0)*	0.229(0.0)*	0.233(0.1)*	0.263(0.0)*	**0.194**(0.3)*	0.226(0.0)*
Panama	0.623	0.031(0.5)	**0.006**(0.3)	0.029(1.1)	0.032(0.9)	0.009(0.5)	0.029(0.3)	0.011(0.3)
Peru	349.8	**4.973**(1.3)	5.743(0.3)	6.184(1.1)	5.132(1.1)	5.971(0.4)	6.027(0.4)	5.961(0.3)
Portugal	0.536	0.945(1.9)	**0.605**(0.6)	0.888(1.4)	0.821(1.1)	0.905(1.6)	0.749(0.7)	0.753(0.7)
Singapore	0.423	0.883(0.5)	0.479(0.2)	0.606(0.0)	0.422(0.4)	0.492(0.0)	**0.365**(0.0)	0.474(0.0)
Sri Lanka	1.891	2.703(0.9)	**1.154**(0.0)*	2.621(0.9)*	1.313(0.0)*	2.534(0.0)*	1.523(0.0)*	2.537(0.0)*
Thailand	0.269	0.403(0.0)	0.351(0.0)	0.169(0.0)	0.358(0.0)	0.419(0.0)	**0.145**(0.0)	0.160(0.0)
Venezuela	8.799	0.104(1.3)	0.108(0.1)	**0.082**(1.5)	0.086(0.9)	0.114(0.4)	0.092(0.0)	0.109(0.1)

[1] **Notes:** See notes to Table 3. Reported entries are Mean Squared Forecast Errors (MSE) multiplied by 100 (see above). The MSEs are based on GDP growth equations from VEC and VAR models which are used to construct a sequence of 1-step ahead forecasts for the period 1982-1996. Model specifications, including lag structures, cointegrating spaces, 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 w/d model at a 25% level of significance using the Diebold-Mariano test statistic discussed above. The high MSE values for Bolivia, Isreal, and Peru in the RW w/d case may be attributed to potential data problems (e.g. because of hyperinflationary periods), as noted in the IFS data description.

Table 6: Predictive Ability Approach Bi-directional Causality Results[1]

Country	Lags Included $-->$ *Preferred Model*	Equation for i_t		Equation for m_t		Equation for x_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	i_t,m_t,x_t
Bolivia	y_t, x_t	17.53(0.6)′	18.86(0.6)	15.82(0.6)′	17.25(0.6)	17.71(0.6)*	18.09(0.6)
Chile	y_t, m_t	34.93(1.4)′	35.13(0.4)*	14.00(1.4)	**12.12**(0.4)	34.70(1.4)	**33.46**(0.4)*
Colombia	y_t, i_t	1.602(1.3)′	1.626(0.2)	1.964(1.3)′	2.674(0.2)	3.120(1.3)	**2.349**(0.2)*
Costa Rica	y_t, x_t	7.462(1.6)	**4.161**(1.1)*	10.396(1.6)	**4.759**(1.1)*	19.71(1.6)	**11.91**(1.1)
Egypt	y_t, i_t	2.171(0.9)′	2.371(0.1)	2.760(0.9)	**2.574**(0.1)*	3.153(0.9)′	3.177(0.1)
El Salvador	y_t, m_t, x_t	3.809(1.3)	**3.546**(0.6)	4.146(1.3)	**4.085**(0.6)*	7.231(1.3)	**5.486**(0.6)*
Ghana	y_t, i_t	0.311(1.5)	**0.222**(1.1)*	0.777(1.5)	**0.564**(1.1)*	0.577(1.5)	**0.482**(1.1)
Greece	y_t, m_t	3.571(1.7)	**2.038**(1.0)	0.817(1.7)′	0.887(1.0)*	0.906(1.7)′	1.382(1.0)
Guatemala	y_t, i_t, m_t, x_t	4.638(1.7)	**3.480**(0.8)	9.690(1.7)	**5.953**(0.8)*	8.387(1.7)	**7.356**(0.8)*
India	y_t, m_t	0.308(1.1)	**0.295**(0.1)	1.863(1.1)	**0.668**(0.1)*	1.084(1.1)′	1.088(0.1)
Israel	y_t, i_t	0.583(0.2)	**0.480**(0.0)*	0.618(0.2)	**0.543**(0.0)*	0.690(0.2)	**0.598**(0.0)*
Jamaica	y_t, m_t	13.186(0.3)	**9.481**(0.1)*	15.11(0.3)	**11.07**(0.1)*	18.89(0.3)	**14.52**(0.1)*
Kenya	y_t, i_t	1.410(0.7)′	1.572(0.9)	5.183(0.7)	**4.213**(0.9)	5.777(0.7)′	5.966(0.9)
Korea	y_t, i_t, x_t	1.446(1.5)	**0.980**(0.6)*	1.542(1.5)	**1.249**(0.6)	3.109(1.5)	**2.973**(0.6)
Malaysia	y_t, m_t	2.787(0.5)	**2.361**(0.6)*	4.035(0.5)	**3.804**(0.6)	3.924(0.5)	**3.785**(0.6)
Mauritius	y_t, m_t	3.237(2.5)	**2.734**(1.0)	2.650(2.5)	**2.031**(1.0)*	3.237(2.5)	**2.944**(1.0)*
Morocco	y_t, m_t	2.937(0.7)	**1.945**(0.3)*	3.425(0.7)	**2.360**(0.3)*	1.711(0.7)′	1.721(0.3)
Pakistan	y_t, x_t	0.346(0.4)′	0.507(0.1)	1.655(0.4)′	2.013(0.1)	1.350(0.4)*	1.600(0.1)*
Panama	y_t, i_t	0.174(0.5)	**0.126**(0.0)	0.316(0.5)	**0.041**(0.0)	0.324(0.5)	**0.033**(0.0)
Peru	y_t, i_t, m_t, x_t	4.744(1.3)′	5.133(1.0)	4.483(1.3)′	5.037(1.0)	5.193(1.3)′	5.614(1.0)
Portugal	y_t, i_t	1.243(1.9)′	1.644(1.0)	1.423(1.9)	**1.212(**1.0)*	2.217(1.9)	**1.447**(1.0)*
Singapore	y_t, x_t	1.537(0.5)′	1.576(1.5)	2.595(0.5)′	2.603(1.5)*	2.343(0.5)′	2.552(1.5)
Sri Lanka	y_t, i_t	3.511(0.9)	**1.468**(0.0)*	5.893(0.9)	**1.045**(0.0)*	5.439(0.9)	**2.907**(0.0)*
Thailand	y_t, x_t	1.085(0.0)	**1.007**(0.0)*	2.122(0.0)	**1.770**(0.0)*	0.967(0.0)	**0.569**(0.0)*
Venezuela	y_t, m_t, x_t	0.120(1.3)	**0.109**(0.3)	0.250(1.3)	**0.212**(0.3)*	0.305(1.3)	**0.305**(0.3)

[1] **Notes:** See notes to Table 4 and Table 5.

Table 7: Turning Point Predictive Ability Results[1]

Model Country	RW w/d	y_t,i_t,m_t,x_t	y_t,i_t	y_t,m_t,x_t	y_t,i_t,x_t	y_t,i_t,m_t	y_t,x_t	y_t,m_t
Bolivia	0.36	0.43(0.6)	**0.29**(0.1)*	0.43(1.0)	0.50(0.5)	0.36(0.1)*	0.57(0.4)	0.36(0.2)*
Chile	0.50	0.64(1.4)	**0.50**(0.5)	0.64(0.7)	0.64(1.4)	**0.50**(0.5)	**0.50**(1.0)	0.64(0.0)
Colombia	0.57	0.50(1.3)	0.43(0.9)	0.43(0.5)	0.43(0.7)	**0.36**(1.1)*	0.43(0.3)	**0.36**(0.0)*
Costa Rica	0.64	0.43(1.6)	0.29(0.0)*	0.57(0.7)	0.50(0.8)	0.29(0.8)*	0.29(0.4)*	**0.21**(0.0)*
Egypt	0.57	**0.29**(0.9)*	0.36(0.5)*	0.36(0.9)*	**0.29**(0.0)*	0.36(0.0)*	0.43(0.0)	0.43(0.7)
El Salvador	0.64	0.50(1.3)	0.43(0.5)	0.50(0.5)	**0.36**(0.5)*	0.57(0.8)	**0.36**(0.0)*	0.57(0.1)
Ghana	0.64	0.43(1.5)	**0.29**(0.1)*	0.57(0.7)	0.50(0.7)	0.71(0.7)	0.43(0.3)	0.50(0.5)
Greece	0.64	**0.29**(1.7)*	0.57(0.0)	0.43(1.5)	0.50(1.0)	0.36(0.9)*	0.57(0.7)	0.36(0.5)*
Guatemala	0.57	0.21(1.7)*	**0.14**(0.3)*	0.21(0.7)*	0.21(0.9)*	0.21(1.2)*	0.29(0.7)*	0.21(0.5)*
India	0.43	0.43(1.1)	0.50(0.0)	**0.36**(0.1)*	0.50(0.1)	0.50(0.0)	0.43(0.0)	0.43(0.0)
Israel	0.71	**0.57**(0.2)	**0.57**(0.0)	**0.57**(0.2)	**0.57**(0.2)	**0.57**(0.1)	**0.57**(0.1)	**0.57**(0.1)
Jamaica	0.50	0.71(0.3)	0.64(0.1)	0.57(0.3)	0.64(0.3)	0.64(0.1)	**0.50**(0.3)	0.57(0.3)
Kenya	0.50	0.64(0.7)	0.50(0.3)	0.57(0.0)	0.50(0.0)	**0.43**(0.9)	**0.43**(0.1)	0.64(0.1)
Korea	0.36	0.71(1.5)	0.57(0.5)	0.57(0.2)	0.57(0.5)	0.64(0.9)	**0.50**(0.0)	0.57(0.0)
Malaysia	0.43	0.64(0.5)	**0.43**(1.0)	0.57(0.0)	0.57(0.7)	0.57(1.0)	0.50(0.1)	0.57(0.0)
Mauritius	0.43	0.57(2.5)	0.43(0.0)	0.50(0.9)	0.50(2.0)	0.50(0.3)	0.50(0.0)	**0.36**(0.0)*
Morocco	0.79	0.29(0.7)*	**0.07**(0.9)*	0.29(0.6)*	0.14(0.4)*	0.21(0.3)*	0.21(0.1)*	0.21(0.0)*
Pakistan	0.57	**0.21**(0.4)*	0.36(0.0)*	**0.21**(0.0)*	0.29(0.1)*	0.36(0.0)*	**0.21**(0.3)*	0.36(0.0)*
Panama	0.64	**0.43**(0.5)	0.50(0.3)	0.64(1.1)	0.50(0.9)	0.50(0.5)	0.50(0.3)	**0.43**(0.3)
Peru	0.50	0.43(1.3)	0.43(0.3)	0.50(1.1)	0.43(1.1)	**0.36**(0.4)*	0.64(0.4)	**0.36**(0.3)*
Portugal	0.57	0.71(1.9)	0.64(0.6)	0.64(1.4)	0.64(1.1)	0.57(1.6)	0.71(0.7)	**0.43**(0.7)
Singapore	0.79	0.57(0.5)	0.50(0.2)	0.50(0.0)	0.50(0.4)	**0.43**(0.0)	**0.43**(0.0)	**0.43**(0.0)
Sri Lanka	0.50	0.64(0.9)	**0.36**(0.0)*	0.57(0.9)	0.57(0.0)	0.50(0.0)	0.50(0.0)	0.43(0.0)
Thailand	0.64	**0.29**(0.0)*	0.43(0.0)	0.36(0.0)*	0.36(0.0)*	**0.29**(0.0)*	0.36(0.0)*	**0.29**(0.0)*
Venezuela	0.64	0.43(1.3)	0.43(0.1)	**0.36**(1.5)*	**0.36**(0.9)*	0.43(0.4)	**0.36**(0.0)*	0.43(0.1)

[1] **Notes:** See notes to Table 5. Entries in the table are "confusion rates". These rates are defined to be the proportion of times for which a given model correctly predicts the direction of change in Δy_t based on the sequence of 1-step ahead real-time forecasts constructed as discussed above. Results are analogous to those reported based on MSE predictive ability, except that rather than MSEs, the "confusion" of the models based on a 15 year simulation period is now assessed. By assessing the "confusion" of the models we attempt to answer the question: Are the models able to accurately predict business cycle (as measured by GDP growth) turning points? If the answer to this question is yes, we have further evidence of the robustness of our prior findings. If the answer is no, then the previous ex-ante predictive ability results are cast into doubt. For those models with confusion rates below 0.40, χ^2 tests of independence are run, and rejections based on a 5% significance level are reported. The null hypothesis of the test is that there is no dependence between forecast and actual turning points.

Table 8: 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 $\dot{y}_t$	
India	0.061	India	0.135	Ghana	0.104	**Panama**	0.088
Pakistan	0.118	Colombia	0.290	Guatemala	0.139	**Malaysia**	0.112
Colombia	0.147	Pakistan	0.295	Bolivia	0.149	**Singapore**	0.124
Greece	0.156	Peru	0.339	El Salvador	0.151	Morocco	0.136
Ghana	0.164	Ghana	0.359	Pakistan	0.163	Thailand	0.154
Peru	0.166	Guatemala	0.392	Colombia	0.171	India	0.180
Guatemala	0.179	Greece	0.400	**Chile**	0.172	Guatemala	0.190
Egypt	0.197	Bolivia	0.460	Peru	0.181	Pakistan	0.198
Morocco	0.206	Morocco	0.474	India	0.182	El Salvador	0.198
Chile	0.221	Egypt	0.481	Morocco	0.197	Sri Lanka	0.199
Bolivia	0.224	Thailand	0.516	**Kenya**	0.198	Mauritius	0.200
Thailand	0.240	Venezuela	0.520	Sri Lanka	0.205	**Kenya**	0.202
Portugal	0.243	El Salvador	0.558	Costa Rica	0.205	Egypt	0.222
El Salvador	0.249	**Portugal**	0.587	**Panama**	0.211	Greece	0.268
Sri Lanka	0.282	**Kenya**	0.603	Egypt	0.216	**Portugal**	0.269
Kenya	0.288	**Korea**	0.606	Greece	0.218	**Korea**	0.286
Korea	0.288	Sri Lanka	0.638	Venezuela	0.218	Costa Rica	0.287
Venezuela	0.291	**Chile**	0.664	**Jamaica**	0.226	Venezuela	0.295
Costa Rica	0.319	Costa Rica	0.688	Mauritius	0.227	**Jamaica**	0.307
Israel	0.333	**Israel**	0.850	**Israel**	0.239	Colombia	0.386
Jamaica	0.436	**Jamaica**	0.928	**Portugal**	0.252	Ghana	0.533
Mauritius	0.539	Mauritius	1.111	**Malaysia**	0.264	**Israel**	0.681
Malaysia	0.580	**Malaysia**	1.145	Thailand	0.274	**Chile**	0.825
Panama	0.617	**Panama**	1.236	**Korea**	0.294	Bolivia	0.870
Singapore	1.207	**Singapore**	2.704	**Singapore**	0.331	Peru	1.224

[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 GDP per capita in constant dollars.