PRODUCTIVITY AND SAVING CHANNELS OF ECONOMIC GROWTH AS LATENT VARIABLES: AN APPLICATION OF CONFIRMATORY FACTOR ANALYSIS (*)

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Summary

When it comes to measure the sources of growth and draw economic policy conclusions, economists rely on growth accounting. According to this approach, per capita growth is explained by two sources: capital accumulation and total factor productivity. Our contention is that growth accounting suffers from serious pitfalls once we take into account that: (i) Total factor productivity and investment are not independent of each other, and (ii) Total factor productivity is badly measured. The result is that the sources of growth are directly unobservable, undermining any conclusion based on available measures.

To partially overcome these problems, we introduce a technique especially designed to deal with unobservable, or latent variables, called confirmatory factor analysis. We examine both the relationship between fourteen variables correlated to the growth rate and two latent variables: the "saving channel" and the "productivity channel", and the correlation between the latter.

(*) I'd like to thank Rod MacDonald (Department of Psychology, University of Illinois) and Doug Simpson, Yonghong Gao, and Amy Goodwin (Department of Statistics, University of Illinois), and Hadi Esfahani, Werner Baer, and Andres Almazan (Department of Economics, University of Illinois) for their invaluable help and support. I'm also indebted to Jose Luis Arrufat and other participants at the Conference on Growth and Technology in Tafi del Valle, Argentina, and seminar participants at the Universidad Nacional de La Plata, Argentina.

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Introduction

It is well-known that the rate of economic growth per capita can be decomposed into two sources: total factor productivity and capital per worker. For four decades, scholars have developed econometric and accounting methods to measure these sources. Recently, following the seminal contribution by Barro (1991), economists have attempted to explain economic growth in terms of a number of economic and institutional variables (for the current state of the debate around these growth regressions, see for instance Sala-i-Martin (1997)). A natural extension of these two approaches has been to run separate regressions of total factor productivity and the investment rate on the same set of variables explaining growth, looking for separate explanations for technological progress and capital accumulation.

Our claim is that this last procedure suffers from two drawbacks: first, technological progress is incorrectly measured by total factor productivity as calculated in growth accounting studies, and, second, both sources interact with each other in a complex fashion. Consequently, any attempt to know the channel (productivity or capital accumulation) through which each economic and institutional variable ultimately affects growth turns out to be sterile.

The change in total factor productivity is usually calculated as a residual, defined as the fraction of output growth that cannot be explained by the change in measurable productive factors. In some cases, the variation in productive inputs includes quality improvements. Primary difficulties are the specification of the output elasticity of the different inputs and the proper measurement of the quantity and quality components, which very often rely on bold assumptions (see Chen (1997) and Young (1995)). Referring to the second caveat, it is to be expected for a productivity change have an impact on capital accumulation. Furthermore, several theoretical models show that physical capital is complementary with human capital (see for example, Mankiw, Romer, and Weil (1992)) and with pure technological progress (see Romer (1986)).

Provided technological progress and capital accumulation are measured independently, a structural model would serve to deal with the endogeneity of both sources. But the appropriate measurement of the dependent variables is still a debatable matter. To illustrate the problem, suppose that there is a productivity increase, associated with the increase in a hypothetical variable *X*. Assuming away an eventual income effect, this shock is likely to stimulate investment. Since the productivity change is measured as a residual, the impact of investment on growth will be overestimated. Moreover, when running regressions of productivity change and investment on a set of predictors, the estimation might suggest that the variable X is correlated with investment and not with total factor productivity.

These considerations suggest that the sources of growth are essentially unobservable, in the sense that available measures become blurred once the interaction between them is taken into account. Policy prescriptions based on this framework are consequently to be less reliable; some recent examples are Young (1995), Krugman (1994), Klenow y Rodriguez-Clare (1997), and Easterly and Levine (1999).

The main contribution of this paper is the introduction of a statistical technique especially designed to deal with unobservable, or latent, variables. *Confirmatory factor analysis* is a branch of the more general *linear structural equation modeling*, whose primary goal is to explain correlations between many observed variables by means of relatively few underlying latent variables. Each observed variable is associated, via theoretical arguments, to one or more latent factors, the objective being to minimize the difference between the sample covariance matrix and the same covariance matrix expressed in terms of the parameters of the model. Although this method entails a departure from regression analysis, it can be shown that regression analysis is a particular case of linear structural equation modeling.

For the application of this technique to the study of economic growth, we will define the sources of growth using an economic rather than accounting conception, defining two channels: the "saving" channel and the "productivity" channel. In the end, the impossibility to quantify the "pure" technological progress and capital accumulation components of growth stems from the fact that the equilibrium investment rate is jointly determined by the variables behind both saving and investment behavior. However, it is needless to say that while investment is basically determined by the marginal productivity of capital, saving has to do with consumption smoothing. Making this distinction may help clarify the identification of the ultimate growth channels. In our setting, a variable will be related to growth through the "saving" channel if it affects directly the supply of savings, while it will be related to growth through the "productivity" channel if it affects directly or indirectly the productivity of the investment in physical or human capital, as well as the ability to create and/or adopt technology. Fourteen variables used in growth regressions will be studied in this light.

The foundations of the technique will be presented in the next section. Afterwards, the methodology will be applied to the problem at hand. Although the estimated coefficients should be read cautiously, the results appear to support this approach.

Section 1: Foundations of Confirmatory Factor Analysis

Factor analysis has an illustrious tradition in social and natural sciences that goes back to the turn of this century, with applications to psychology, sociology, geology, and medicine (see Harman (1967)). Factor analysis can be categorized into two classes: exploratory and confirmatory (for a detailed analysis, see McDonald (1985)). In exploratory factor analysis, there is no specific model relating observed and latent variables, the number of factors is not set in advance, and latent variables influence all observable variables, with underidentification being a common problem. In contrast, under confirmatory factor analysis, a model is constructed in advance, the number of latent variables is set by the analyst, and some coefficients are fixed to zero or other constant. Additionally, measurement errors may be allowed to correlate in this case, although identification requirements impose some inevitable constraints.

The centerpiece of confirmatory factor analysis is the *measurement model*, which specifies a structural model connecting latent variables to one or more observed variables. Formally, the measurement model takes the following matrix form:

$$\mathbf{X} = \Lambda_x \xi + \delta \qquad (1)$$

where **X** is a (q × 1) column vector of observed variables in deviation form; Λ_x is a (q × m) matrix of structural coefficients; ξ is a (m × 1) column vector of latent variables; δ is a (q × 1) column vector of measurement error terms associated with the observed variables; and q and m denote the number of observed variables and latent constructs, respectively. It is assumed that E(δ) = E(ξ) = E(ξ δ) = 0. Equation (1) establishes that although the underlying factors are not observable, there exist a number of observable indicators that are imperfect measures of those factors, and that these indicators can be expressed as linear functions of the latent variables plus an error term. Λ_x is the matrix of factor loadings, that is, the coefficients linking the latent to the observed variables.

The null hypothesis in confirmatory factor analysis is that Σ = Σ (θ), namely, the population covariance matrix of the observed variables Σ equals the covariance matrix written as a function of the free model parameters in θ, $\Sigma(\theta)$ (the implied covariance matrix, hereafter). In turn, $\Sigma(\theta)$ can be rewritten in terms of Equation (1) as:

$$
\begin{aligned}
\Sigma(\theta) &= E(XX') \\
&= E[(\Lambda_x \xi + \delta)(\xi' \Lambda'_x + \delta')] \\
&= \Lambda_x E(\xi\xi')\Lambda'_x + E(\delta\delta') \\
&= \Lambda_x \Phi \Lambda'_x + \Theta_\delta
\end{aligned}
\qquad (2)
$$

where Φ and Θ_δ are the correlation matrix of the latent variables and the measurement errors, respectively. The observed variables are correlated with each other because they all are associated with at least one latent variable. Once that information is extracted to transform the initial data set into the proper number of latent factors, there remains a measurement error, sometimes referred to as uniqueness, uncorrelated with none of the factors. The estimation procedure aims at finding the implied covariance matrix $\Sigma(\hat{\theta})$ as close as possible to S, the sample covariance matrix of the observed variables. The most popular fitting function for general structural equation models is the maximum likelihood function. The procedure iteratively searches the parameters that minimize (for a derivation, see Bollen (1989)):

$$F_{ML} = \log|\Sigma(\theta)| + tr(S\Sigma^{-1}(\theta)) - \log|S| - q \qquad (3)$$

An important issue in confirmatory factor analysis is the identification of the model. For a unique solution to exist for the structural parameters in Λ_x, ϕ, and Θ in terms of S, some restrictions must applied, otherwise the model would be underidentified. From Equation (2), there are [qm+(1/2)m(m+1)+(1/2)q(q+1)] parameters to be estimated, where each term corresponds to the number of parameters in the matrices Λ_x, ϕ, and Θ, respectively, while there are only (1/2)q(q+1) nonredundant elements in S. A necessary but not sufficient condition for identification is that the number of parameters estimated within the model should not exceed this upper bound. To satisfy this criterion, the correlation among the measurement errors is usually set to zero. However, the analyst must exert her judgement in imposing additional restrictions. In fact, more complex (less restrictive) models improve the traditional measures of fit, as the degrees of freedom decrease. In the extreme case of exact identification, $\Sigma(\hat{\theta}) = S$, and the fitting function in Equation (3) equals zero, meaning that a trivial, perfect fit has been accomplished. A thorough account of model evaluation will be provided along with the discussion of the results.

At this point, it is convenient to clarify the differences between the classic econometric regression and confirmatory factor analysis. As is clear from Equation (1), the measurement model can be viewed as a regression, with the particular feature that the regressors are not observed. As shown by Bollen (1989, chapter 4), as long as all the variables involved are observed, regression analysis is a special case of linear structural equation modeling, and can be solved with the methodology explained below. Instead of minimizing the difference between the observed and predicted values for individual observations, linear structural equation modeling emphasizes covariances rather than observations, with the residual equating the difference between the sample and the predicted covariances. More importantly, in regression analysis the regressors are perfect measures of the attributes they are supposed to represent, while this assumption does not hold in linear structural equation modeling.

In our particular case, the ideal regression would be one of per capita growth on the variation of total factor productivity and capital per capita. But since these regressors are not directly observed, a number of observed economic and institutional variables are included under the assumption that they jointly are perfect measures for the sources of growth, without further knowledge about the precise attribute (productivity or capital) they are supposed to be measuring. This creates an error-in-variable problem. Conversely, in our setting it is explicitly recognized that the observed variables are imperfectly associated with the underlying factors. The measurement model is precisely directed at extracting the maximum amount of information from the covariance matrix of the observed variables in order to construct the underlying, unobserved factors.

Section 2: Economic Growth and Confirmatory Factor Analysis

2.1 Productivity and Saving Channels

For our purposes, we will interpret the sources of growth in a rather unconventional way, consistent with the discussion carried in the Introduction. A variable will be related to growth through the "saving" channel if it affects directly the supply of savings, while it will be related to growth through the "productivity" channel if it affects directly or indirectly the productivity of the investment in physical or human capital, as well as the ability to create and/or adopt technology.

Growth regressions include a series of state and control variables. Although a large number of variables have been included in these studies, we will narrow down our attention to 14 of them: the initial GDP per capita, the average years of secondary schooling, the public expenditure on education as a share of GDP, the government consumption as a share of GDP, the black-market premium on foreign exchange, the dependency ratio, the life expectancy, the credit to the private sector as a share of GDP, the current account as a share of GDP, the sum of exports and imports as a share of GDP, the consolidated public sector surplus, the exports of primary goods as a share of total exports, the fuel and mineral exports as a share of total exports, and the index of rule of law. The variables are 10-year averages over the period 1965-1995, and the basic source is the World Bank's Economic Growth Database, in several cases updated to cover the period 1986-1995. The reason for excluding other variables is that most of them are highly correlated with at least one of the 14 variables included, turning the covariance matrix non positive-definite and suggesting that no further information is added. In what follows we will examine their likely effects on the saving and productivity dimensions of growth:

Initial GDP per capita: According to the Solow model, countries with low capital per worker (and consequently low GDP per capita) tend to have a higher return on capital, and grow faster, than countries with high initial levels of capital per capita. Previous growth regressions have shown that this convergence effect appears only after controlling for other effects, in what is referred to as conditional convergence. On the other hand, the smoothing-consumption motive might diminish desired saving, in regard of the predicted upward path in permanent income.

Average years of secondary education: A more educated population is capable to absorb and implement new technologies faster and more efficiently, having therefore a positive relationship to national productivity.

Public Expenditure on Education as a share of GDP: As the previous measure of education represents only years of schooling, this variable introduces an adjustment for quality. As for most variables, it must be said that this is an imperfect proxy to measure this particular feature, owing to the lack of any indication about the efficiency of that expenditure and the situation in the private school system. Furthermore, a high correlation between public expenditures on education and education attainment is likely to be observed.

Government Consumption as a share of GDP: Other things equal, it is expected that government consumption (net of defense and education outlays) be less efficient than private expenditure, reducing as a result average productivity. Crowding-out and tax distortions may be part of the argument.

Black-Market Premium on Foreign Exchange: This is a proxy for market distortions that might signal an inefficient allocation of resources -that adversely affects productivity-, and the existence of macroeconomic risk -that increases the risk-adjusted required rate of return on new investments and discourages some of them-.

Dependency Ratio: The demographic profile of population has been identified as a powerful explanatory variable of saving behavior (see Edwards (1995)). In particular, the higher the dependency ratio (the population under 15 years old and above 65 over total population), the lower the saving rate, in accord to the life cycle hypothesis.

Life Expectancy: This is an indicator of health standards in a country, and hence it is likely to foster productivity in human and physical capital.

Credit to the Private Sector as a ratio of GDP: Financial development improves the allocation of saving, reduces deadweight costs of transaction, and mitigates liquidation risk often attached to high productivity projects. However, some recent contributions (see Japelli and Pagano (1994)) emphasize that, by relaxing previous borrowing constraints, the size of the financial system may reduce the saving rate.

Current Account: Foreign savings may be a substitute for domestic savings, lowering the national saving rate.

Exports plus Imports as a share of GDP: More open economies are thought to have better access to technology developed worldwide. Moreover, external competition fosters the search for efficiency gains and alleviates rent-seeking activities. In sum, productivity growth is favored by external openness.

Consolidated Public Sector Surplus: According to the Ricardian Equivalence, fiscal imbalances should have no impact on national saving rates. Nevertheless, the empirical consensus is that this hypothesis fails in practice. The contention therefore is that public deficits curtail the saving rate, while surpluses increase it.

Exports of Primary Goods as a ratio of Total Exports: An economy relatively dependent on the primary sector may experience slower productivity growth vis-a-vis a more industrialized one.

Exports of Fuel and Minerals as a share of Total Exports: The existence of rich mineral deposits and oil fields may be detrimental to national saving.

Rule of Law: This proxies for the security of property rights and the enforcement of contracts. This is a major issue at the time of undertaking investments in both human and physical capital.

Based on these theoretical points, our measurement model is:

$$
\begin{bmatrix} GDP \\ SYR \\ GEE \\ GOV \\ BMP \\ DEPR \\ LIFE \\ CRED \\ CA \\ XM \\ SURP \\ XPR \\ XFM \\ LAW \end{bmatrix} = \begin{bmatrix} \lambda_{11} & \lambda_{12} \\ \lambda_{21} & 0 \\ \lambda_{31} & 0 \\ \lambda_{41} & 0 \\ \lambda_{51} & 0 \\ 0 & \lambda_{62} \\ \lambda_{71} & 0 \\ \lambda_{81} & \lambda_{82} \\ 0 & \lambda_{92} \\ \lambda_{10,2} & 0 \\ 0 & \lambda_{11,2} \\ \lambda_{12,1} & 0 \\ 0 & \lambda_{13,2} \\ \lambda_{14,1} & 0 \end{bmatrix} \times \begin{bmatrix} \xi_1 \\ \xi_2 \end{bmatrix} + \begin{bmatrix} \delta_1 \\ \delta_2 \\ \delta_3 \\ \delta_4 \\ \delta_5 \\ \delta_6 \\ \delta_7 \\ \delta_8 \\ \delta_9 \\ \delta_{10} \\ \delta_{11} \\ \delta_{12} \\ \delta_{13} \\ \delta_{14} \end{bmatrix}
$$

where λ_{ij} represent the factor loadings to be estimated within the model. The first column on Λ_x corresponds to the productivity channel and the second one to the saving channel.

2.2 Results

The sample consists of 10-year averages for 138 countries over the period 1965-1995.[1] The estimation was conducted with the LISREL program (version 8.20, 1998) originally developed by Joreskog and Sorbom in 1986. The following table displays the estimated measurement model:

[1] As customary in this literature, missing values were replaced by the sample mean of each variable.

Estimation of the Measurement Model

Variable	*Latent Variable* **Productivity**	**Saving**
Initial GDP per capita	3.88 (9.44)	-0.86 (-2.05)
Years of Secondary Schooling	5.75 (17.91)	--
Public Expenditure on Education (% of GDP)	0.07 (7.94)	--
Public Consumption Expenditure (% of GDP)	-0.33 (-8.32)	--
Black Market Premium	-1.43 (-5.54)	--
Dependency Ratio	--	-0.36 (-9.21)
Life Expectancy	0.94 (19.83)	--
Credit to the Private Sector (% of GDP)	1.53 (8.30)	-0.22 (-1.14)
Current Account (% of GDP)	--	0.23 (3.83)
Total Exports plus Imports (% of GDP)	0.88 (4.05)	--
Fiscal Surplus (% of GDP)	--	0.04 (1.87)
Primary Exports (% of GDP)	-1.54 (11.71)	--
Oil and Mineral Exports (% of GDP)	--	-0.53 (-3.11)
Rule of Law Index	0.10 (14.89)	--

**T-Statistics in parenthesis.*

Results are strongly supportive of our hypotheses, both in sign and statistical significance. Note however that the absolute value of the coefficients lack any meaningful interest because, first, the factors are unobservable and, second, standard deviations were rescaled to facilitate the numerical search procedure on which the estimation is based. In fact, no quantitative conclusions should be extracted from the estimation. Also, in view of the restrictions imposed on the error covariance matrix, coefficients must be interpreted with caution, although this caveat will be relaxed later on.

Schooling, public expenditure on education, life expectancy, financial development, trade openness, and rule of law are found to be highly associated with productivity in a positive fashion, whereas the black-market premium and primary exports over total appear to be negatively associated with this factor. As for saving, negative coefficients appear on initial GDP per capita, dependency ratio, fuel and mineral exports, and financial development (although this one is not statistical significant), while positive ones load on the current account and fiscal balances (in this last case, slightly above 5% significance). The coefficient for productivity on initial GDP is positive, supporting the convergence hypothesis once we take into account that standard growth regressions have the form

$$y_{i,t} - y_{i,t-1} = (\delta - 1) y_{i,t-1} + \lambda' x_{i,t} + \varepsilon_{i,t} \qquad i = 1, \ldots, N \text{ and } t = 1, \ldots, T$$

or

$$y_{i,t} = \delta y_{i,t-1} + \lambda' x_{i,t} + \varepsilon_{i,t} \tag{4}$$

where i stands for each of the N cross-section units, t represents each of the T time-series units, y stands for the log of real GDP, δ is a scalar, λ' is a $k \times 1$ vector of coefficients, x is a $1 \times k$ vector of other explanatory variables, and $\varepsilon_{i,t}$ is an error term.

Since there is theoretical background to expect a positive association between the productivity and saving channels, its correlation was estimated within the model, yielding a value of 0.77 (t-statistic 9.74). This correlation lends support to the claim that countries with high saving rates also have high productivity growth (for a confronting view in the case of the East Asian countries, see Krugman (1994)). We return to this point in the next section.

A number of overall goodness-of-fit have been developed to evaluate this type of model (see Joreskog and Sorbom (1993) and Bollen (1989)), and we will discuss them next. As usual, the most straightforward, and often the most valuable, tool is scrutinizing the individual parameter estimates. In the light of the previous results, we can be confident about the adequacy of the proposed structure.

To reinforce this impression, some overall measures will be assessed. One popular indicator is the Goodness-of-Fit Index (GFI) and the Adjusted Goodness-of-Fit Index (AGFI). There are defined as:

$$AGFI = 1 - \frac{Tr[\Sigma(\hat{\theta}) - S]^2}{Tr[S]^2}$$

$$\begin{aligned} AGFI &= 1 - \left(\frac{c}{df_h}\right)\frac{Tr[\Sigma(\hat{\theta}) - S]^2}{Tr[S]^2} \\ &= 1 - \left(\frac{c}{df_h}\right)(1 - GFI) \end{aligned}$$

where *Tr* stands for trace, c is the number of nonredundant variances and covariances of observed variables, r is the number of parameters to be estimated within the model, and df_h = c-r are the degrees of freedom of the hypothesized model. In the present case, c=105, r=31, and df_h=74. It is easy to see the resemblance that these measures bear with the R-squared and adjusted R-squared in regression analysis. These indices should fall between 0 and 1, with larger values indicating a better data-model fit. The AGFI penalizes more complex models (with more parameters to be estimated) increasing the index as the degrees of freedom increase. For our model, the GFI and the AGFI equal 0.84 and 0.78, respectively, suggesting an acceptable fit.

Another set of fit measures are the Normed and Nonnormed Fit Indices (NFI and NNFI). They compare the hypothesized model with more restrictive baseline models (rather than with no model at all, as in the GFI and AGFI). Since most models are nested within less restricted models, the hypothesized model can be compared to a very restricted, *independence model*, and with the least restricted, just-identified, *saturated model*. Under the independence model, no latent variable is presumed to underlie the observed variables, the measurement errors in Θ_δ are set to zero, and the observed variables are specified to be independent (Φ is specified to be a free but diagonal matrix). In the other extreme, the saturated model includes as many free parameters as there are variances and covariances of observed variables, leaving no degrees of freedom. To construct this index, another concept must be introduced. Under the null hypothesis $H_0{:}\Sigma=\Sigma(\theta)$ and the assumption of multivariate normality, the minimum value of the fitting function times (n-1), where n is the sample size, is distributed asymptotically as a χ^2-distribution with (c-r) degrees of freedom:

$$\chi^2 = (n-1)F[S, \Sigma(\hat{\theta})]$$

Using this notion, the NFI and the NNFI are defined as:

$$NFI = \frac{\chi_i^2 - \chi_h^2}{\chi_i^2} = \frac{F_i - F_h}{F_i}$$

$$NNFI = \frac{(\chi_i^2 / df_i) - (\chi_h^2 / df_h)}{(\chi_i^2 / df_i) - 1} = \frac{(F_i / df_i) - (F_h / df_h)}{(F_i / df_i) - (1/(n-1))}$$

where *i* stand for the independence model and *h* for the hypothesized one. For our application, the NFI and the NNFI reach reasonable levels of 0.75 and 0.69, respectively.

Yet another class of fit indices is comprised of various "parsimony-based" measures. Each parameter freed removes a model-induced constraint on the matrix S and therefore necessarily improves the fit between the data (represented by S) and the model (represented by $\Sigma(\theta)$). Taking this into account, the goodness-of-fit of overidentified models is downward-biased. To overcome this bias, two measures -in the spirit of the AGFI and the NNFI- are available: the Parsimony Goodness-of-Fit Index (PGFI) and the Parsimony Normed Fit Index (PNFI), which are given by:

$$PGFI = \frac{df_h}{df_n} GFI$$

$$PNFI = \frac{df_h}{df_i} NFI$$

where df_h denotes the degrees of freedom associated with the hypothesized model, df_n=c are the degrees of freedom when no model has been specified, and df_i are the degrees of freedom for the independence baseline model. With df_h=74, df_n=c= 105, and df_i =91, both the PGFI and the PNFI equal 0.59 in our model. These values are relatively high for this class of models, indicating that the overidentifying restrictions are appropriate.

2.3 Robustness and Sensitivity Checks

Several tests were run to put the robustness of the previous results under inspection. The first one consisted in running the model using 5-year averages instead of 10-year averages. The results were similar to the previous ones, with the exception that the loading on credit turned significantly positive on the saving channel, and the coefficients of initial GDP on both factors became statistically insignificant.[2]

Employing 5-year averages also allows us to observe eventual policy changes at higher frequencies, which might enrich the analysis through more detailed dynamic specifications. For example, a given variable may have a contemporaneous negative effect on growth, but a positive effect on future growth. For our set of variables, this may be pertinent when assessing the role of public expenditure on education and the trade variables. The contemporaneous impact of public expenditure on education may be detrimental owing to the fact that resources are being detracted from productive activities without an immediate benefit. As the young generation accumulating human capital becomes productive, those expenditures begin paying off with a lag. As for trade, it is likely that more open economies, or those more biased toward industrialized exports, tend to grow faster. But opening the economy and forcing the comparative advantage towards a more industrialized pattern may be a costly and painful process, which might be harmful to growth in its initial stages. Consequently, a lag between the implementation of such policies and the growth benefits is prone to be observed. Bearing this in mind, the model was re-specified with lagged values of public expenditure on education, trade openness, primary, and oil and mineral exports as a share of total exports. The estimation,

[2] The loading of GDP on productivity turned back to be highly significant once the loading on the saving channel was set to zero.

once again, did not change in any significant way with respect to the ones without lagged values.[3]

Yet another experiment is to make use of the *modification indices*. For each fixed parameter in the model, a modification index can be constructed measuring how much the χ^2-statistic is expected to decrease if this particular parameter is set free and the model is reestimated.[4] None of the parameters in Λ_x will be relaxed, for two reasons: first, there is no theoretical interpretation to back up the relaxation of any of the fixed parameters, and second, none of these variables would improve the χ^2-statistic by more than 3%, which by the way shows that the model is correctly specified.[5]

In contrast, several elements of the matrix Θ_δ display high modification indices, and this is an indication that they should be estimated within the model. Thus, we have freed the correlation between the measurement errors of: initial GDP with the current account, with primary exports, and with fuel and mineral exports; government consumption with government expenditure in education, and with fiscal surplus; primary exports with credit to the private sector; and primary exports with fuel and mineral exports. With this less restrictive model, all the factor loadings were virtually unchanged, providing an additional robustness check for the earlier outcome. However, the overall goodness-of-fit improved substantially. These are the new values: GFI=0.92, AGFI=0.87, NFI=0.86, NNFI=0.85, PGFI=0.59, and PNFI=0.64.

The last exercise is the construction of factor scores. Although the factors are inherently unobservable, they can be estimated from the observable variables.[6] A popular

[3] Actually, this does not come as a surprise since most country characteristics are highly stable across time. Easterly et al. (1993) find that cross-decade correlations of these variables range from 0.6 to 0.9. On the other hand, growth rates are more unstable, with cross-decade correlation of 0.1 to 0.3. As a result, shocks rather than policy and other country variables explain growth variability.

[4] The use of modification indices constitutes a controversial issue in factor analysis. The main debate revolves around the use of a statistical tool as opposed to a more substantial theory to improve the overall goodness-of-fit. See Steiger (1990) and other papers in the April 1990 issue of *Multivariate Behavioral Research* for a discussion on model evaluation and modification. The controversy bears some resemblance with the use of stepwise regression techniques in econometric analysis.

[5] It must be recognized that growth and saving theories are incomplete and under continuous revision. The hypotheses followed here are widely accepted, though. It is possible to find theoretical, yet not consensual, justification to free some other loadings. In general, when additional loadings were freed, changes in the original coefficients were important, but the overall goodness-of-fit did not improve. A possible interpretation is that these additional variables are redundant, which is likely to inflate the variance of the other estimated coefficients.

[6] It is important to stress that the factor score estimate is not equal to the latent factor itself. This indeterminacy is due to the fact that there are more latent variables and measurement errors (m + q) than

method is to make a least-squares prediction. Recalling Equation (1), the best prediction in a least-squares sense is:

$$\hat{\xi} = \hat{\phi}\hat{\Lambda}_x \hat{\Sigma}^{-1} x \quad (5)$$

This expression offers a quantitative, yet imperfect, measure of the latent factors. The interest here is to corroborate whether these estimated factors, or factor scores, have a positive correlation with GDP per capita (see Equation (4)). We have used 10-year averages. A correlation table follows:

Correlations (p-value in parenthesis)

	GDP per capita	*Productivity Factor*	*Saving Factor*
GDP per capita	1.000		
Productivity Factor	0.859 (0.000)	1.000	
Saving Factor	0.753 (0.000)	0.923 (0.000)	1.000

As expected, the correlation of both factors with GDP per capita is significantly positive. Also interesting is that the correlation between factors is very high, ratifying once more that countries with high productivity growth have also high saving accumulation.

observed variables (q). A similar case would occur when trying to quantify the independent variables in a multivariate regression using only information about the dependent variable and the estimated regression coefficients: as long as measurement errors are not zero, the estimated independent variables would not equal the actual ones.

Conclusions

The goal of this paper was to overcome some drawbacks in the empirical analysis linking the sources of economic growth (productivity and capital accumulation) and a series of economic and institutional variables. Previous work is misleading in the sense that technological progress is incorrectly measured by total factor productivity as calculated in growth accounting studies, and that both sources interact with each other.

Once these phenomena are taken into account, it is clear that the sources of growth are unobservable. To deal with this problem, we proposed the use of confirmatory factor analysis. This technique allowed us to associate different variables to the two underlying latent factors. We built an empirical model, defining two factors or channels (productivity and saving) and determining the a priori link between them and fourteen economic variables usually employed in growth regressions. Although the coefficients should be interpreted with caution, the estimation seems to support the theoretical model.

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