Leveraging Growth Regressions for Country Analysis

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Abstract

This paper shows how growth regressions can be useful for analyzing a country's growth performance. Growth regressions describe changes in key macroeconomic variables that countries typically experience during their growth process. Such partial correlations facilitate comparative analysis, can usually be linked to policies, and can hence be informative from a policy perspective. Against this background, the paper introduces a new data set of growth correlates spanning more than 150 countries from 1970 to 2019. Additionally, it presents several econometric reference models and details their application for country-level growth analysis. Two distinct metrics highlight infrastructure and human capital as exhibiting the strongest correlations with growth.
Leveraging Growth Regressions for Country Analysis*

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1. Introduction

Economic growth continues to be a key driver of living conditions. It is the main driver of recent poverty reductions and shows a near one-to-one relationship with important welfare indicators for most countries (Dollar et al., 2015 and 2016; Crespo Cuaresma et al., 2022). It is hence not surprising that policymakers set ambitious growth targets, other societal challenges notwithstanding. Applied research can facilitate such growth agendas by providing insights into country-specific growth episodes.

Economists use several methods to investigate country-level growth performances. For example, filtering techniques allow separating cyclical shocks from long-term growth that is in line with an economy’s underlying potential (Hodrick and Prescott, 1981). Growth accounting decomposes growth into contributions from production factors, like capital and labor, and productivity growth (Hulten, 2010). Other decomposition techniques are widely used to investigate to what extent productivity improvements are due to structural change, e.g., workers moving to more productive sectors (Timmer and de Vries, 2009; McMillan et al., 2014) or firm dynamics (Brown et al., 2018; Diao et al., 2021). Most of those methods are part of a standard toolkit to analyze country-level growth performance and, for example, part of the World Bank growth diagnostics guidelines (CEM 2.0).

However, most of those country-specific methods leave critically important policy questions unanswered. Notably, the above-mentioned filtering and decomposition techniques rarely tell us anything about underlying policy drivers, let alone their relative importance. Moreover, studies of firm dynamics are mostly limited to the formal manufacturing sector. What happens in other parts of the economy usually remains unclear.

In this paper, we make the case that growth regressions can provide policy-relevant insights into a country’s growth performance, even if they only provide descriptive correlations. Such correlations tell what policy-relevant changes in key macroeconomic variables countries typically experience in their growth process. This allows for a quantitative assessment of how special or representative the policy mix of a country’s growth performance is. For example, if typical growth correlates can explain a country’s growth performance well, this suggests that key macroeconomic variables move in line with the experience of other growing economies. Even in this case, the policy mix of this country may still be unique (see the Ethiopia case study in Moller and Wacker, 2017). Conversely, if typical growth correlates cannot explain a country’s performance well, this can be insightful in its own way. Can we learn something new for growth theory from this country? Or has the country just had “good luck”? Obtaining quantitative assessments of successful policy mixes is particularly useful today as growth policies may face trade-offs with climate goals (Haberl et al., 2020; Wollburg et al., 2023).

To facilitate the application of growth regressions, our contribution makes them readily available. In this paper we present a novel comprehensive data set and reference models. Our dataset contains about 20 variables for approximately 150 countries between 1970 and 2019 in non-overlapping 5-year averages. It largely builds upon previous work of Araujo et al. (2016) and Beyer and Wacker (2023) and their methodology but adds several climate-relevant and demographic variables, including income inequality. Our data and codes for estimation and analysis are available through the GitHub repository KMWacker/growthdata and provide a rich open data source to researchers and economic policy analysts.

While our paper focuses on the application of growth regressions for country analysis, it seems

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1 For example, McMillan et al. (2014) suggest that undervaluation and labor market flexibility promote productivity-enhancing structural change. But devaluation may make capital accumulation more expensive, and deregulation may deter labor market participation. This factor-reducing effect and associated policy tradeoffs would not be accounted for.

2 We plan to regularly update and expand the data set and invite scholars and analysts to comment on the code and suggest improvements; either by contacting the corresponding author or by push requests on GitHub.
natural to ask for the most important correlates of growth across countries. To assess this issue, we provide standardized beta coefficients and a variance decomposition for our novel data set. Both reaffirm that economic growth is usually tightly related to infrastructure developments. The variable in our dataset that explains variation in income across countries the best is human capital. This may be surprising because education variables are often statistically insignificant in growth regressions. Our result suggests that this statistical insignificance, possibly driven by measurement problems, should not lead to a premature neglect of education from a growth-policy perspective.

The remainder of this paper is structured as follows: Section 2 gives an overview of what has happened in growth econometrics since its heyday in the early 1990s and highlights an increasing shift towards descriptive country analysis. In section 3, we provide a short introduction to growth regressions. Particularly, we discuss the neoclassical growth model, its dynamic implications, and parameter estimation. Section 4 discusses the variables included in our dataset. Specifically, we describe the construction and sources of those variables, and motivate their inclusion with reference to the previous literature. Section 5 presents and discusses our regression results, including a series of alternative estimation approaches and robustness checks. In Section 6, we illustrate how our model can be used to analyze country-specific growth patterns, using the period 2000-2009 in Bangladesh as an example, and discusses additional practical aspects, such as extending the analysis to more recent periods or dealing with poor predictive performance of the model for individual countries. Section 7 concludes the paper by discussing potential extensions and future developments and putting some key results into a broader perspective.

2. The Case for Growth Regressions for Comparative Analysis

Growth regressions experienced their heyday in the 1990s, starting with seminal contributions by Barro (1991), Mankiw, Romer, and Weil (1992), and Sachs and Warner (1997). Those contributions quickly led to econometric debates about the robustness of growth correlates (Levine and Renelt, 1992; and Sala-i-Martin, 1997) and regional peculiarities (Islam 1995). Over time, researchers increasingly discussed different estimation strategies (e.g., Hauk and Wacziarg, 2009; Bazzi and Clemens, 2013; Kraay, 2015) and econometric concepts such as model uncertainty (e.g., Fernández et al., 2001) and parameter heterogeneity (e.g., Feng et al., 2022) in application to growth regressions. This was facilitated by broad agreement on the theoretical framework (i.e., the neoclassical Solow model) and the availability of consistent macroeconomic data.

Most scholars meanwhile acknowledge challenges with respect to causal identification in growth regressions. Dollar et al. (2015), for example, treat estimates from growth regressions as “estimated partial correlations rather than causal effects”. From a statistical perspective, randomized control trials, regression discontinuity approaches, or natural experiments provide much cleaner identification strategies to infer causal effects of specific policies such as public education interventions, microfinance, tax policies, or the effects of infrastructure projects. But they are usually focused on one policy (or event) in one country, instead of a policy mix, and their external validity is frequently questioned.
Although growth regressions cannot substitute for causal identification of growth policies, they can still be useful for comparative country analysis. Early attempts to use growth regressions in a policy context originated from two companion studies at the World Bank for Latin America and Chile, respectively (Loayza et al., 2005; Gallego and Loayza, 2002). Although those studies still followed a causal interpretation, they used their estimated drivers of growth to gauge the relative importance of domestic policies compared to external factors, which highlighted the benefit of growth regressions for policy analysis. Moreover, they illustrated how those estimates can be used to assess the role of policy complementarities, an approach that was furthered by Chang et al. (2009).

Araujo et al. (2016) revived this policy-driven approach when they studied whether a period of catch-up growth in the early 2000s in Latin America and the Caribbean (LAC) was driven by ‘good policies’ or ‘good luck’ from high commodity prices. Other analyses built on Araujo et al (2016) to explore country- and region-specific growth episodes. For example, results from Haile and Moller (2018) pointed to the importance of financial deepening, macro policy, and infrastructure for previously poorly understood growth accelerations in the West African Economic and Monetary Union (WAEMU). Geiger et al. (2019) revealed that typical growth correlates explain the exceptional growth performance of Ghana up to 2010 but not afterwards. They interpret this as an abatement of structural improvements in the economy and an increasingly cyclical growth performance.7

Moller and Wacker (2017) illustrated how growth regressions can provide a solid underpinning for understanding a country’s macroeconomic policy mix. They confirmed that typical correlates of growth can explain Ethiopia’s decade-long growth acceleration after 2003. They then showed that what made Ethiopia exceptional was its outstanding performance in essential growth correlates, notably infrastructure, and its heterodox macroeconomic policy mix. Analyzing typical correlation patterns with a cluster analysis, they showed that Ethiopia benefitted from a unique combination of overvalued exchange rates and financial repression that facilitated infrastructure spending.

Similarly, Beyer and Wacker (2023) built on growth regressions to explain decades of solid growth in Bangladesh. By putting growth correlates into a comparative perspective, they showed that Bangladesh’s improvements in growth correlates between 1990 and 2004 were in the global top 5 percent for any 15-year period since 1970. Further comparing Bangladesh to other countries with periods of rapid improvements in key macroeconomic variables, they showed that Bangladesh does not show the typical pattern of mean-reversion in growth rates, which they attributed to outstanding macroeconomic stability.

This paper builds on the above-mentioned country studies from Latin America, Africa, and South Asia. Specifically, we provide a dataset that is comparable to the data employed in the above studies but can be freely accessed through the GitHub repository KMWacker/growthdata. We further discuss the methods that are needed for such country analysis on a more conceptual level.

6 In our view, growth regressions additionally provide a useful cross-check for causal identification approaches. E.g., if education and microfinance interventions improve incomes at the micro level, should we not also check for reasonable correlations of education and financial development with income at a highly aggregated macro level before rolling out large-scale programs?

7 Ghana’s debt default in 2022 suggests they had a point.
3. A Short Overview of Growth Regressions

In this section, we discuss the modern econometric foundation of the neoclassical growth model (Solow, 1956; Swan, 1956). To facilitate growth analysis, we particularly highlight how a change in income (i.e., growth) is related to levels of income in this model.

3.1 The Neoclassical Growth Model and Its Implications

The standard approach in the empirical growth literature is to model the logarithm of a country $c$’s per capita income level at period $t$, $\ln y_{ct}$, as a function of growth correlates, $x_{k,ct}$ ($k=1,...,K$), and the lagged income level, $\ln y_{c,t-1}$ (e.g., Araujo et al., 2016; Moller and Wacker, 2017; Brueckner and Lederman, 2018):

$$\ln y_{ct} = \theta \ln y_{c,t-1} + \beta_1 x_{1,ct} + \cdots + \beta_K x_{K,ct} + \delta_t + \alpha_c + \varepsilon_{ct}.$$  (1)

This equation includes an autoregressive term $\ln y_{c,t-1}$ (‘lagged dependent variable’) that determines the dynamics of the model (more on this below), country fixed effects $\alpha_c$, which account for (time-invariant) unobserved differences in income levels across countries, and period fixed effects $\delta_t$, which account for global shocks to income levels (e.g., during the global financial crisis).

To see why (1) is actually a “growth” model, one can calculate changes over time (‘first differencing’):

$$\Delta \ln y_{ct} = \theta \Delta \ln y_{c,t-1} + \beta_1 \Delta x_{1,ct} + \cdots + \beta_K \Delta x_{K,ct} + \Delta \delta_t + \Delta \varepsilon_{ct},$$  (2)

where $\Delta$ is the difference operator: $\Delta x_t = x_t - x_{t-1}$. Note that log-changes approximate percent changes such that equation (2) has percent growth rates on the left-hand side and is hence a ‘growth equation’. Country fixed effects are ‘differenced away’ in equation (2) since they are time-invariant. Importantly, the other central model parameters $\theta$, $\beta_1$, ..., $\beta_K$ are mathematically equivalent in equations (1) and (2). Because growth can be rather volatile over time (e.g., Easterly et al., 1993; Pritchett and Summers, 2015), estimation of the model in levels usually provides more reliable estimates of those parameters, which can then be applied to the analysis of growth in the first-difference equation (2).

Dynamic Implication of the Model

Equations (1) and (2) imply that a change in a growth correlate $x_k$ is associated with a permanent change of the income level but a temporary change of the growth rate. A change in $x_k$, $\Delta x_k$, in period $t$ and country $c$ will have a contemporaneous correlation $\beta_k$ with the growth rate of that country. Since this growth rate, $\Delta y_c$, will be the lagged growth rate in the next period $t+1$, the relationship shows some ‘autoregressive’ persistence $\theta$ over time. However, if $\theta<1$, which is usually the case, this association fades out over time. This is economically intuitive: if a country implements an infrastructure project today, it will boost growth and the income level. Some positive relationship with growth may still be present in the next period, but it will fade out over time. Because growth can be rather volatile over time (e.g., Easterly et al., 1993; Pritchett and Summers, 2015), estimation of the model in levels usually provides more reliable estimates of those parameters, which can then be applied to the analysis of growth in the first-difference equation (2).

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8 In practice, estimates of those parameters will differ between estimation with fixed effects (equation 1) or in first differences (equation 2), but they are asymptotically equal. This equivalence is used to estimate the “growth equation” in levels (equation 1), which usually provides more efficient results.

9 This differs from dynamic implications of endogenous growth models, where, for example, education and research or institutional changes can have a permanent effect on the growth rate (by speeding up technological progress).
that the short-run effect of a change in $x_k$ on income levels, $\partial \ln y_t/\partial x_k$, equals $\beta_k$, while the long-run effect is given as:

$$\frac{\partial \ln y_{t+1}}{\partial x_k} = \beta_k + \theta \beta_k + \theta^2 \beta_k + \theta^3 \beta_k + \cdots + \theta^j \beta_k \xrightarrow{j \to \infty} \frac{\beta_k}{1-\theta}.$$  

(3)

Section 6.7 provides an illustration of this dynamic relationship.

Convergence Implications

In the presence of country fixed effects, the lagged dependent variable governs a country’s convergence towards its own steady-state.\(^\text{10}\) It does not say anything about cross-country convergence. Conversely, in a cross-country regression setup with no country fixed effects, the coefficient $\theta$ governs “beta convergence” across countries. In such a cross-country context, $(\theta-1)<0$ implies that an economy with a lower initial income level grows faster than an economy with a higher initial income level. Patel et al. (2021) provide comprehensive evidence on such cross-country convergence patterns that can in principle also be analyzed with our dataset.

3.2 Estimation of the Parameters $\theta$ and $\beta$

It is common to estimate the parameters of the above growth model in the levels equation (1) and to include country and period fixed effects. More specifically, we apply a least-square dummy variable estimator to equation (1) for our baseline estimation. We also follow the convention to work with periods $t$ representing non-overlapping 5-year averages to smooth out cyclical variation in the data.\(^\text{11}\)

Least-square estimation will provide partial correlations, not causal effects of growth determinants. This is due to the presence of various sources of endogeneity, such as omitted variables, reverse causality, heterogeneity, or measurement error.\(^\text{12}\) For example, it is not clear to what extent infrastructure causes growth and to what extent a higher income level causes a higher level of infrastructure. The results of such least-square estimation are hence partial correlations, indicating the extent to which income levels and right-hand-side variables are correlated with each other. Or, in the context of equation (2): how much changes in variables $x$ are correlated with economic growth. As discussed above, such a descriptive exercise can still be useful from a policy perspective.

Online Appendix A.4 additionally provides results from System-GMM estimation and discusses the peculiar problems that come with this estimation approach, including weak identification and associated susceptibility to instrument specification choice. Accordingly, we consider those estimates too arbitrary to serve as a baseline and rather treat them as a crude cross-check. Additionally, we check for parameter heterogeneity across country groups in subsection 5.3.

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\(^{10}\) This can be seen after subtracting $\ln y_{c,t-1}$ from both sides of equation (1), which yields: $\Delta \ln y_{c,t} = (\theta - 1) \ln y_{c,t-1} + \beta x_{1,c,t} + \cdots + \beta x_{K,c,t} + \bar{\delta} + \alpha_c + \varepsilon_{c,t}$. A random shock $\varepsilon_{c,t}$ that is not driven by any fundamental growth correlates $x$ will impact $\ln y_{c,t}$ but since $(\theta-1)<0$, it will revert in the next period. The economy converges back towards its steady state, as the neoclassical Solow model implies.

\(^{11}\) Additionally, the conventional GMM moment condition of serially uncorrelated shocks is more likely to be ensured in 5-year averages than in annual data.

\(^{12}\) A particular case of endogeneity arises for the autoregressive coefficient of the lagged dependent variable, which is downward biased by construction in fixed effect models (“Nickell bias”). Since we are not particularly interested in this particular coefficient, we accept this bias in our baseline least squares estimation and note that it could be analytically corrected (Kiviet, 1995) and is addressed in our System-GMM estimates in Online Appendix A.4.
4. Variables and Data Sources

Our dataset has a panel structure (repeated observations for each country); ‘geo’ and ‘period’ are the variables that identify country and time, respectively. The former is an encoded variable: it ranges from 2 (Albania) to 208 (Zimbabwe) but STATA displays country names instead of numbers. Our dataset additionally contains a ‘country’ and ‘NAMES_STD’ variable\textsuperscript{13} and their ‘iso3’ code as a string variable. Additionally, ‘region_un’ classifies each country’s region, based on UN standards.

The ‘period’ variable indicates 5-year average periods, where period 1 encompasses the 1970-1974 data, while period 10 contains the 2015-2019 data. Note that the inclusion of those time-fixed effects accounts for all global factors that affect all countries equally (in proportionate terms, as the dependent variable is logged). They could reflect global commodity prices or the global interest rate environment, or global advances in technology.\textsuperscript{14}

4.1 Income Level

The dependent variable we aim to explain is $lrgdpna_{pc}$, the real (inflation-corrected) income level per capita, in logarithmic terms. The variable is based on PWT10.0 and constructed by dividing the series $rgdps$ by $pop$. The natural log is taken so that changes in the explanatory variables can be interpreted as percent changes in per capita income levels.

Although national income data are converted into (constant 2017) US$, note that this variable does not allow for proper comparison of welfare across countries because it does not account for differences in price levels across countries. If goods are half the price in one country compared to others, half the income level (in US$) is needed for the same consumption welfare. Such comparisons are facilitated through PPP adjustments, as in the PWT series $rgdps$ or $rgdpe$ (Feenstra et al., 2015), which are also contained in our data set. PPP adjustments, however, can cause short-term country-specific fluctuations in the PPP-income variable (Inklaar et al., 2022), which can distort analysis of country-specific growth contributions.

Our model and results based on $lrgdpna_{pc}$ still have a proper welfare interpretation because they control for cross-fixed effects and hence differences in price levels across countries. But for cross-country comparison of welfare levels or analyses without country fixed effects, we recommend the variables $lrgdpe_{pc}$ (or $lrgdpo_{pc}$), which are also contained in our data set.

4.2 Correlates of Growth

In table 1, we provide an overview of variables contained in our dataset and models. Variables are ordered by their availability: variables in the “small model” are widely available, hence allowing for a sample of approximately 1,500 observations (168 countries). The “small model” hence has the broadest coverage and should therefore provide most precise parameter estimates. However, it does not contain some potentially relevant variables that previous research has found to correlate with growth but which are only available for fewer countries. We hence include those additional variables in a separate “medium” and “large” model. For those models, the sample decreases to 967 (149 countries) and 635 observations (128 countries), respectively. The variables, their construction, and rationale for inclusion are discussed below the table. While the table focuses on variables we include in different model variants, the text also highlights alternative variables included in the data set, where available.

\textsuperscript{13} The NAMES_STD is a standardized country identification from STATA’s ‘kountry’ ado command.

\textsuperscript{14} Some of the mentioned factors may impact country groups differently (e.g., commodity prices for importers vs. exporters). It is possible to interact the period dummies with dummies for country groups (by region, income level, commodity dependence etc.) if one is interested in this aspect.
**Variables in the “Small Model” (Largest Availability)**

**Inflation** is measured as the log change of $v_c/q_c$ (household consumption at current national prices / household consumption at constant national 2017 prices) from the national account module of PWT10.0, which has larger availability than inflation data from WDI. We add 1 to this variable to avoid negative numbers and then take logs to obtain \( \text{linflation}_{na} \).\(^{15}\)

The **real exchange rate**, \( \text{ler} \), is calculated as the log of the GDP price level (at purchasing power parity) over the nominal exchange rate: \( \frac{pl_{gdpo}}{x} \), both taken from PWT10.0. Since \( x \) is measured as national currency/US$, an increase in \( \text{ler} \) reflects a real appreciation, which is expected to negatively affect output and growth through various channels (e.g., Rapetti, 2019; Levy-Yeyati et al., 2013). We also calculate (absolute) deviations of the real exchange rate from a HP-filtered trend, \( \text{mad}_{\text{ler} \_ \text{deviation}} \), which is included in the data set as alternative, but not included in our models.

**Trade openness** is conventionally captured as the sum of exports and imports over GDP. To account for higher trade shares of smaller countries and higher trade in times of higher demand from abroad, irrespective of trade policies, we calculate a \( \text{trade}_{resid} \) as the residual of a regression of exports and imports over GDP on log of exporter population and global GDP, which acts as demand shifter. We then take the log of that residual which first requires transformation to positive values. This is done as: \( \text{ltraderesid} = \ln(\text{trade}_{resid} - \min(\text{trade}_{resid}) + 0.01) \). All respective variables are taken from PWT10.0.

**Infrastructure** is captured by an index, as often is the case in the literature (surveyed in Välilä, 2020). We therefore combine information on phone lines, mobile phones, internet coverage, availability of secure internet connections, and access to electricity from WDI. Since they have different sample coverage, we use the most available series (phone lines) to predict missing values of the second-most available (mobile phones), use those to predict missing values in the next series, etc. Each of those five updated infrastructure series is then Pearson standardized (i.e., transformed to mean 0 and standard deviation 1). Their weights in the final infrastructure index are the number of available original observations at each year, divided by the total number of original observations from all five series in the same year.

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\(^{15}\) This shift transformation is consistent with the earlier approach in Araujo et al. (2016) and most common in the literature. We are aware of potential problems and that there are possible alternatives which researchers are free to explore using our data set. See also Karakaplan et al. (2020).
Table 1: Summary statistics

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<th>Source</th>
<th>Mean</th>
<th>SD</th>
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<td>0.09</td>
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<td>Log of real exchange rate</td>
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<td>Log trade openness (corrected for population and global GDP)</td>
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</tr>
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<td>lhc</td>
<td>Log of human capital index</td>
<td>PWT10.0</td>
<td>0.72</td>
<td>0.35</td>
<td>1,329</td>
</tr>
<tr>
<td>dgini</td>
<td>Change in the Gini coefficient of market incomes</td>
<td>SWIID</td>
<td>0.18</td>
<td>1.17</td>
<td>940</td>
</tr>
<tr>
<td><strong>Additional variables available in the data set</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>emprate</td>
<td>Employment-to-population rate</td>
<td>PWT10.0</td>
<td>0.39</td>
<td>0.09</td>
<td>1,491</td>
</tr>
<tr>
<td>agri_valadded</td>
<td>Agriculture, forestry, and fishing, value added (% of GDP)</td>
<td>WDI</td>
<td>15.29</td>
<td>13.77</td>
<td>1,299</td>
</tr>
<tr>
<td>remittances</td>
<td>Personal remittances, received (% of GDP)</td>
<td>WDI</td>
<td>3.66</td>
<td>10.31</td>
<td>1,196</td>
</tr>
</tbody>
</table>
To illustrate this weighting, consider a case where 150 original observations for log phone lines were available in 1970, and 50 observations were available for electricity. We attribute a weight 3/4 to the former and the latter gets a weight 1/4, while the remaining three infrastructure variables are not part of the composite index in 1970. This weighting reflects two aspects: statistical reliability and economic relevance. Fewer observations of a variable for a given year mean more predicted values for that variable, which are less reliable than the original observations. Statistically, one hence wants to attribute less weight to this ‘less reliable’ series. Fewer observations also reflect less relevance of the indicator. Secure internet connections or mobile phones were simply not available or not as important in the 1970s, their availability was hence not recorded in the data. This constitutes an economic reason for attributing less weight to series with fewer original observations.

Alternatively, our data also allows using those series individually (in logs), where \( \text{Iphone} \) has the largest coverage.

To include variables for financial crises, we rely on the database from Laeven and Valencia (2020), which have coverage until 2017. Our dataset contains dummy variables for individual years of banking, currency, or sovereign debt crises and a dummy variable, \( \text{dum\_fin\_crisis} \), if either of those crises is reported. Alternatively, the variable \( \text{fin\_crisis\_years} \) captures the number of years with some financial crisis during a 5-year period (with a maximum of 3).

Climate change can affect economic activity through various channels (see e.g., Acevedo et al., 2020). We take data from the World Bank’s Climate Change Knowledge portal on historical monthly temperatures by country and calculate their standard deviation over a 5-year period, \( \text{sd\_temperature} \). Alternatively, mean temperatures, \( \text{temperature\_celsius} \), are available in the data set as well. Both have shown to be negatively correlated with economic growth in the past (e.g., Burke et al., 2015; Kotz et al., 2021) but external validity about future causal impact of climate change is difficult to establish, due to non-linearities and the fact that countries are differently affected by global warming (e.g., Ortiz-Bobea et al., 2021).

Our dataset further includes the variables \( \text{disaster\_aff} \) and \( \text{disaster\_death} \), which capture the number of people affected by or deceased from natural disasters, respectively, per million inhabitants. The data come from the Emergency Events Database (EM-DAT). Since GDP does not take destruction into account and disasters are usually followed by reconstruction, which boosts GDP, the negative economic consequences of natural disasters are usually not captured in cross-country growth regressions. We therefore do not include those variables in our regression models.

To account for positive and negative shocks due to changes in international price levels, we include terms of trade changes, \( \text{dltot} \), calculated as changes in the log of the export price level relative to the import price level (\( \text{pl\_x/pl\_m} \)), both taken from PWT10.0.

We further include the log of government consumption as a share of GDP, \( \text{lkg} \), calculated as the log of \( \text{csh\_g} \) from PWT10.0, into our model. This variable is supposed to capture growth-reducing effects through either distortionary taxation (Afonso and Furceri, 2010), or public debt issuance. Note that the negative association with growth is motivated by the fact that we already control for the positive effects that government consumption may have on growth, e.g., through education or infrastructure spending. As our model describes long-run growth, it is also important not to conflate the short-term positive stimulus effect that increased government consumption can have during economic downturns. For similar reasons we also do not include fiscal deficit variables, which are highly cyclical and hence tend to smoothen out over 5-year averages.

Since growth volatility can negatively impact long-term growth (e.g., Ramey und Ramey, 1995; Hnatkovska and Loayza, 2005), our data set includes the standard deviation of annual growth rates over a 5-year period. This variable is endogenous by construction, which calls for more advanced

\[^{16}\text{Due to copyright restrictions concerning republishability, those data are not directly included in our dataset and need to be manually added; see lines 435ff of }0\_\text{WBPRWP\_datacr.do} \text{ in our GitHub directory.}\]
estimation approaches if one is interested in investigating this link. To somewhat mitigate this problem in our data, we lag growth rates by two years (e.g., the 5-year period 1990-1994 includes the standard deviation of growth rates between 1987-1988 and 1991-1992).

Our data further contains changes in the share of urban population, \textit{urbanpop}, from WDI. We include this variable in differences as we think that fast urbanization periods are correlated with growth spells. Our dataset further contains population density, \textit{pbdens}, from WDI.

\textit{Variables in the “Medium Model”}

To measure countries’ financial development, we use the log of domestic credit to the private sector as a percentage of GDP, \textit{lcredit}, taken from WDI. The literature on financial development and its relationship to growth has grown extensively over the last decades (e.g., Levine, 2005; Arcand et al., 2015) and various studies and data sets on more detailed aspects of the issue have appeared (e.g., Svirydzenka, 2016). Credit over GDP, however, has the clear advantage of wide availability across countries and over time and has been used by several seminal studies in the literature on finance and growth. Brunnermeier et al. (2021) also confirm that credit expansion is rather a sign of financial deepening than the prelude for financial busts.

Foreign direct investment acts as a proxy for the activity of multinational corporations (Casella et al., 2023). We take the inward FDI stock as a percentage of GDP from UNCTAD. Since no stock data are reported before 1980, we fill the missing decade of data with an interpolation from FDI flow data (as a percentage of gross fixed capital formation). The sample correlation of both variables is high, 0.87. The variable is logged and labeled \textit{lFDIstock_ip}.

For export diversification, we rely on the export diversification index of the IMF (Papageorgiou et al., 2015), which is a Theil index. A higher value hence indicates lower diversification. Since this index stops in 2014, we interpolate the missing years with the Herfindahl-Hirschmann Product Index from UNCTAD. The correlation between both series in the sample is high, 0.90. The variable is logged and labeled \textit{EDI_ipol}. Moreover, we take the square of the variable because a non-linear or U-shaped relationship is expected (see Imbs and Wacziarg, 2003, and Papageorgiou et al., 2015: Fig. 3).

Institutions are widely acknowledged as a key ultimate source of cross-country income differences (e.g., Acemoglu et al., 2001; 2005). However, their measurement problems have also been highlighted (e.g., Glaeser et al., 2004; Voight, 2013) and deep institutional aspects barely vary over time, which is the key dimension we use for identification of our model parameters (due to the presence of country fixed effects). Moreover, most common measures of institutional quality are not available for the whole sample we aim to investigate. Instead of using a fine measure of institutional quality, we hence rely on data about major \textit{episodes of political violence} from Systemicpeace.org., which has the advantages of wide coverage and considerable variation over time. In the regression models, we rely on \textit{actotal}, which aims to capture the magnitude of major events. Our dataset further contains a breakdown of this variable for interstate and societal violence (\textit{inttot} and \textit{civtot}), as well as a dummy variable, \textit{dum_mepv}, which equals 1 for any period that contains a major episode of political violence. Note that Systemicpeace.org data does not include data for 2019.\textsuperscript{17}

\textsuperscript{17} In future updates of the dataset, we plan to include data from the Varieties of Democracy Project to capture institutional quality.
Variables in the “Large Model”

For human capital (education) we rely on the log human capital index, \( lhc \), from PWT10.0, which linearly interpolates data on educational attainment from Barro and Lee (2013) and assumes a certain rate of return for primary, secondary, and tertiary education. Human capital is widely assumed to be a key driver of cross-country income differences (Mankiw et al., 1992; Glaseser et al., 2004; Hanushek and Woessmann, 2015) but problems in adequately measuring human capital across a wide range of countries have also been pointed out in the literature (e.g., Pritchett, 2001; Hanushek and Woessman, 2012).

To measure inequality, we take the Gini coefficient of market and disposable incomes, \( gini_mkt \) and \( gini_disp \), respectively, from the Standardized World Income Inequality Database (Solt, 2019). It should be noted that this data is severely over-imputed.\(^\text{18}\) Following the literature (e.g., Bruckner and Lederman, 2018; Scholl and Klasen; 2019), we do not log-transform this variable. As discussed in those studies, there are several approaches to address apparent endogeneity concerns for this variable and several arguments suggest various functional forms (changes vs. levels, quadratic and interaction terms; e.g., Gründler and Scheuermeyer, 2018; Blotevogel et al., 2022). We opt for changes in the Gini of market incomes, \( dgini \), in our regression models.

5. Reference Models and Results

5.1 Baseline Results from Least Squares Estimation

Table 2 contains the results of the fixed effect regression, as specified in equation (1), with the variables introduced above. The “small model” in column (1) captures fewer variables, which allows for a larger sample size (~1,500 observations from 168 countries). At each column of table 2, the model is sequentially extended, shrinking the sample accordingly.

The results in table 2 can be summarized as follows:

(i) First, the autoregressive parameter is in the expected range, hovering around 0.8. Note that this parameter is likely downward biased, as further discussed in section 5.4.

(ii) Second, a number of correlations is quite robust: infrastructure and trade are positively correlated with income per capita levels, financial crises, inflation, and inequality changes negatively. All those correlations are statistically different from 0 across all specifications (at conventional levels of significance).

(iii) Third, a number of correlations are in line with expectations and show reasonable standard errors but cannot be reliably distinguished from a 0-correlation in most models. This concerns the negative coefficient estimates for temperature variability, terms of trade changes, and growth volatility, as well as the positive parameter estimate for credit/GDP, FDI, human capital, and the non-linear U-shaped relationship with export concentration. The latter suggests that medium specialization (around the sample mean) is associated with the lowest income levels and growth strategies can either be successful through diversification (e.g., United States, Netherlands) or specialization in goods with outstanding comparative or factor advantage (e.g., Saudi Arabia, United Arab Emirates).

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\(^{18}\) For this reason, we plan to include data from pip.worldbank.org in future updates of the dataset instead.
Table 2: Main Regression Results

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>small model</th>
<th>medium model</th>
<th>large model</th>
</tr>
</thead>
<tbody>
<tr>
<td>lagdependent</td>
<td>0.798***</td>
<td>0.802***</td>
<td>0.738***</td>
</tr>
<tr>
<td></td>
<td>(0.0242)</td>
<td>(0.0285)</td>
<td>(0.0359)</td>
</tr>
<tr>
<td>linflation_na</td>
<td>-0.227***</td>
<td>-0.109*</td>
<td>-0.128***</td>
</tr>
<tr>
<td></td>
<td>(0.0425)</td>
<td>(0.0604)</td>
<td>(0.0326)</td>
</tr>
<tr>
<td>ltraderesid</td>
<td>0.0818***</td>
<td>0.121***</td>
<td>0.117***</td>
</tr>
<tr>
<td></td>
<td>(0.0262)</td>
<td>(0.0454)</td>
<td>(0.0322)</td>
</tr>
<tr>
<td>infra_index</td>
<td>0.0813***</td>
<td>0.0719***</td>
<td>0.1000***</td>
</tr>
<tr>
<td></td>
<td>(0.0160)</td>
<td>(0.0208)</td>
<td>(0.0205)</td>
</tr>
<tr>
<td>dum_fincrisis</td>
<td>-0.0483***</td>
<td>-0.0389**</td>
<td>-0.0274***</td>
</tr>
<tr>
<td></td>
<td>(0.00894)</td>
<td>(0.0104)</td>
<td>(0.00833)</td>
</tr>
<tr>
<td>sd_temperature</td>
<td>-0.0237</td>
<td>-0.0473*</td>
<td>-0.0337</td>
</tr>
<tr>
<td></td>
<td>(0.0199)</td>
<td>(0.0266)</td>
<td>(0.0263)</td>
</tr>
<tr>
<td>dltot</td>
<td>-0.0266</td>
<td>-0.0459</td>
<td>-0.0448</td>
</tr>
<tr>
<td></td>
<td>(0.0399)</td>
<td>(0.0444)</td>
<td>(0.0446)</td>
</tr>
<tr>
<td>lkg</td>
<td>-0.0468***</td>
<td>-0.00898</td>
<td>0.0280</td>
</tr>
<tr>
<td></td>
<td>(0.0184)</td>
<td>(0.0207)</td>
<td>(0.0213)</td>
</tr>
<tr>
<td>sd_growth</td>
<td>-0.622***</td>
<td>-0.156</td>
<td>-0.261</td>
</tr>
<tr>
<td></td>
<td>(0.236)</td>
<td>(0.256)</td>
<td>(0.280)</td>
</tr>
<tr>
<td>durbanpop</td>
<td>0.0103***</td>
<td>0.0100*</td>
<td>-0.00789</td>
</tr>
<tr>
<td></td>
<td>(0.00395)</td>
<td>(0.00551)</td>
<td>(0.00535)</td>
</tr>
<tr>
<td>lcredit</td>
<td>0.0151</td>
<td>0.0162</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00988)</td>
<td>(0.0147)</td>
<td></td>
</tr>
<tr>
<td>IFDIstock_ipol</td>
<td>0.0132**</td>
<td>0.0122</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00621)</td>
<td>(0.0123)</td>
<td></td>
</tr>
<tr>
<td>lEDI_ipol</td>
<td>-0.268*</td>
<td>-0.299**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.154)</td>
<td>(0.149)</td>
<td></td>
</tr>
<tr>
<td>lEDI_ipol_sq</td>
<td>0.127*</td>
<td>0.138**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0665)</td>
<td>(0.0653)</td>
<td></td>
</tr>
<tr>
<td>actotal</td>
<td>-0.0137**</td>
<td>-0.0186***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00668)</td>
<td>(0.00447)</td>
<td></td>
</tr>
<tr>
<td>lhc</td>
<td></td>
<td>0.150</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.0912)</td>
<td></td>
</tr>
<tr>
<td>dgini</td>
<td></td>
<td>-0.0110**</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.00530)</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>1.924***</td>
<td>2.033***</td>
<td>2.629***</td>
</tr>
<tr>
<td></td>
<td>(0.202)</td>
<td>(0.252)</td>
<td>(0.308)</td>
</tr>
<tr>
<td>Observations</td>
<td>1,507</td>
<td>967</td>
<td>635</td>
</tr>
<tr>
<td>R-squared (within)</td>
<td>0.897</td>
<td>0.894</td>
<td>0.923</td>
</tr>
<tr>
<td>No. countries</td>
<td>168</td>
<td>149</td>
<td>128</td>
</tr>
<tr>
<td>Estimation</td>
<td>FE</td>
<td>FE</td>
<td>FE</td>
</tr>
<tr>
<td>Period FEs</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Cluster robust standard errors in parentheses,
*** p<0.01, ** p<0.05, * p<0.1
The positive parameter estimate for the real exchange rate is rather surprising: an increase in this variable reflects a real appreciation, which is expected to be negatively correlated with output and growth through various channels. Although our parameter estimate is statistically indistinguishable from 0 in column (1), the positive correlation is significant in all other three specifications and raises doubt about the conventional wisdom that devaluations will boost growth (see Rodrik 2008 and comments by Henry and Woodford 2008, Gopinath et al. 2020, Krugman and Taylor 1978). Possibly, the positive association reflects a Balassa-Samuelson effect or that a real appreciation of the home currency may improve access to foreign inputs and capital goods.

We are not as confident about the estimated parameters for government consumption and changes in the share of urban population. Those estimates change across specifications and partly show large standard errors compared to individual point estimates. Nevertheless, those variables may matter for certain country groups (which may be less present in the smaller samples) and/or show some degree of non-linearity that makes estimates susceptible to sample variations.

In what follows, we focus on the medium and large models, because the small model (1) excludes several potentially policy-relevant variables and, reassuringly, estimated coefficients are very similar across specifications in any case – none of the coefficient signs changes, except for the change in urban population, which turns negative and insignificant in the large model.

5.2 What Variables Correlate Strongest with Growth across Countries?

Since the regression coefficients show how much a one-unit change in explanatory variables is associated with changes in the income per capita level, their economic relevance is difficult to compare. For example, the coefficient estimate for infrastructure is lower than for inflation. But how can we compare the two? A look at the summary statistics in table 1 suggests that the former varies more than the latter and is hence more likely to matter more for income changes.

Standardizing beta coefficients by the standard deviation of explanatory variables takes those differences in measurement units and variability into account. Such standardized beta coefficients can be interpreted like correlation coefficients (ranging from -1 to 1, with 0 indicating no correlation between the explanatory and the dependent variable). They are reported in Online Appendix A.2, table A.2 for the medium and large models (corresponding to columns (2) and (3) in table 2). Neglecting the lagged dependent variable (which is not of policy relevance), one can observe that standardized beta coefficients are largest for infrastructure, trade diversification, and the real exchange rate.

Another way to assess economic relevance of the different variables is a variance decomposition that investigates the relative contribution of each variable to an overall model fit statistic, in our case the $R^2$ squared. This method, called dominance analysis (Grömping, 2007), estimates $2^K$ sub-models of regression equations (where $K$ is the number of parameters/variables; 65,535 and 262,143 regressions, respectively, for our medium and large model) and calculates the weighted average marginal contribution of each variable to the explained variance across all those models. When looking at the resulting standardized dominance statistics, we find human capital, infrastructure, FDI, and credit/GDP to explain variation in income well.

Both approaches to gauge the economic relevance of variables can differ because dominance analysis assesses the goodness of a variable to explain variation of income within the sample and not across countries. The variance decomposition method, on the other hand, is based on the idea that a variable is important if it explains a significant portion of the income variance within the sample.
takes various sub-models into account. Standardized beta coefficients, in contrast, gauge the potential importance of a variable in one model with all variables included. FDI and credit are examples of variables that show strong dominance but rather low standardized beta coefficients. This may be the case because they are both standardized by GDP, increasing the co-variability with the dependent variable without necessarily having a high partial correlation with the latter.

**Figure 1: Measures of economic relevance**

![Figure 1: Measures of economic relevance](image)

Note: The figure shows standardized beta coefficients (vertical axis) and standardized dominance statistics (horizontal axis) for the large model. Red indicates a negative coefficient estimate. Light color indicates that the estimate is not statistically different from 0 on a 10% significance level. For export diversification (EDI), which enters with a linear and quadratic term, (absolute) beta coefficients of both terms are averaged and treated as a “set” in the dominance statistic.

Figure 1 plots the standardized beta coefficients on the vertical axis and the standardized dominance statistic on the horizontal axis. They are based on the large model, with qualitatively similar results of the medium model in the online appendix (Figure A.1). A number of observations are worth discussing.

(i) The overall correlation between both measures is rather modest (0.36 for the large model; 0.64 for the medium model), reflecting the fact that both statistical measures capture different aspects of economic relevance.

(ii) Infrastructure shows high economic relevance in both dimensions. This confirms findings in the recent literature that highlight the importance of infrastructure for growth and productivity.
(iii) Interestingly, the strongest dominance is attributed to human capital. This appears conflicting with the conclusion from several growth regressions that stress the statistical insignificance of this variable, which also cannot be distinguished from a 0-correlation in our regression. But statistical insignificance can be the result of poor measurement of that variable, which has been pointed out in the literature (Pritchett 2001; Hanushek et al. 2017) and should not be confused with economic irrelevance (that dominance criteria aim to measure). More sophisticated measurement approaches usually confirm the importance of human capital for growth (e.g., Hanushek and Woessmann 2012; Maloney and Valencia Caicedo, 2022). In line with the potential problem of measurement error (which biases estimated coefficients towards 0), the standardized beta coefficient suggests a more modest economic relevance than the dominance statistics. This may also reflect that human capital is usually quite persistent and shows little variability over time, which lowers the standardized beta coefficients by construction (see previous footnote).

(iv) To a lesser extent, FDI and credit/GDP provide a good fit for income per capita levels in the sample but only show modest partial correlations with the latter (which cannot be distinguished from 0 in a statistical sense, except for FDI in the medium model, see Online Appendix A.2).

(v) Conversely, trade diversification,21 the exchange rate, political violence, trade openness, and inflation show relevant partial correlations with income but are attributed a low dominance. In the medium model (see Online Appendix A.2), the partial correlation further increases for trade openness and financial crises but declines for the exchange rate.

Our overall reading of those results is that: (i) they confirm the potentially important role of infrastructure for growth, which the recent literature has emphasized, (ii) typically insignificant parameter estimates of human capital in growth regressions shall not lead to the conclusion that education does not matter, and (iii) export diversification may potentially play a large role that should be investigated in further research.

Note that this cross-country perspective on economic relevance does not mean that those variables are also most likely growth correlates in individual countries. For example, the partial correlation between major episodes of political violence and income levels may be large but there may not be much variability of such events across the whole sample. For a conflict-affected country, only a country-specific growth analysis, as outlined in section 6, will reveal its importance.

5.3 How Stable Are Parameters across Country Groups?

A policy-relevant concern with growth regressions is that parameters are not identical across country groups. Regional heterogeneities were extensively discussed in the context of the “Africa dummy” in growth regressions (see, e.g., Easterly and Levine 1997; Sachs and Warner 1997). Furthermore, it is also plausible that growth correlates are systematically different across country groups with different income levels.

In country-specific analysis, we therefore advise to statistically test if parameters of the country under investigation are systematically different, or if parameters for a reasonably similar peer group are systematically different from the overall sample. Such a peer group could consist of countries with similar geographic or socio-economic features. Empirically, such tests can be implemented with simple interaction of country- or group-specific dummy variables with the relevant model variables. Examples for such group-specific interactions in regression commands (for income and regional groups) are provided in the code that is available in the GitHub repository KMWacker/growthdata accompanying this paper. Parameter estimates that are significantly different

21 Because EDI consists of the linear and squared term, we take the average of both (absolute) coefficients for the display of the standardized beta coefficient and group them together as a so-called “set” in the dominance analysis.
should then be applied to the quantitative assessment.

To assess how likely systematic differences in parameters across country groups are, we estimate the ‘small’ model separately by income and regional group. Note that this drastically limits the number of observations by regression and, accordingly, leads to a higher standard error of parameter estimates. For this reason, we also limit this exercise to the ‘small’ model, where most observations are available. Sample sizes drop to approximately 500 observations by income group and to as little as 296 observations by regional group (in the case of Europe). Figures 2 and 3 plot the parameter estimates and their 95% confidence intervals for income and regional groups, respectively.

**Figure 2: Parameter heterogeneity across income groups**

Note: Reported parameters are partial correlation coefficients, not standardized beta coefficients.

A key message from this exercise is that country group heterogeneities do not turn key results upside down but that there are heterogeneities across groups that are mostly in line with economic reasoning. For example, growth volatility seems most negatively associated with growth in low-income countries, which have the least macroeconomic options to cushion themselves against shocks. Inflation does not seem to correlate with growth in high-income countries, consistent with the idea that such a relationship only prevails at higher inflation rates, which are rarely observed in high-income countries during the sample period. There also seems no relationship between infrastructure and growth in high-income countries, possibly reflecting that existing gaps are modest and marginal.

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22 For the income classification, we classify each country into low, middle, and high income depending whether they fall into the lowest, middle, or highest third of the income distribution in a given period. This implies that countries can switch classification over time. For the regional classification, we follow STATA’s ‘kountry’ ado UN classification into 4 regions.
returns hence lower than in lower-income countries. On the other hand, it is interesting to see the most negative and positive parameter estimates for inflation and infrastructure for Europe in the regional breakdown of Figure 3. Taken together, this suggests that the applied regional classification is probably too broad. Finally, it is worth highlighting that temperature volatility negatively correlates with growth mostly in low-income countries, which often heavily rely on agriculture.

Taken together, our results suggest that using growth regressions for country-specific analysis should actively test for parameter heterogeneity. In case significant parameter heterogeneity is found for the country (group) of interest, it remains to be seen whether it also translates into quantitatively relevant differences in country-specific growth correlates in the sense of section 6.1.

**Figure 3: Parameter heterogeneity across regional groups**

Note: Reported parameters are partial correlation coefficients, not standardized beta coefficients.
5.4 Additional Robustness Checks and Analysis

We report additional robustness checks and analysis in an Online Appendix, available in the GitHub repository KMWacker/growthdata. Online Appendix A.3, for example, checks for influential outliers and provides estimation results without those observations and checks for changes in parameters or model performance over time. Online Appendix A.4 provides results from System-GMM estimation which is a possibility to use internal instruments (i.e., lags and leads of potentially endogenous variables) for parameter identification. This possibility, however, comes with the well-known downside that results can be susceptible to instrument choice. It is now standard to restrict the instrument set to avoid instrument proliferation (Roodman, 2009) but this does not resolve (or even aggravate) problems of weak identification. Kraay (2015) provides a discussion of this problem and some solutions, which are not very promising for the large set of variables we consider. Given that problems of ordinary least square regressions and associated fixed effects are much better-understood, we consider them more appropriate for our baseline. The most relevant difference that our System-GMM crosscheck provides to this baseline is that the correlation between income p.c. and temperature variability becomes positive in the System-GMM results. Moreover, the coefficient for the lagged dependent variable, $\theta$, is estimated to be larger under System-GMM, which is expected due to the “Nickell bias” in fixed effects estimation of dynamic models. On average, across all three main models considered (small, medium, large), this difference is about 15%. In other words, the System-GMM results suggest stronger persistence effects.

6. Practical Aspects for Country-Specific Growth Analysis

This section illustrates in more detail how typical country-specific growth analysis is conducted in studies covering a wide range of different countries and regions such as Araujo et al. (2016) for Latin America and the Caribbean, Moller and Wacker (2017) for Ethiopia, Haile and Moller (2018) for the West African Economic and Monetary Union, Geiger et al. (2019) for Ghana, or Beyer and Wacker (2023) for Bangladesh.

6.1 Analyzing Country-Specific Growth Correlates: An Illustration

Recall equation (2) from section 3:

$$\Delta \ln y_{ct} = \theta \Delta \ln y_{c,t-1} + \beta_1 \Delta x_{1,ct} + \cdots + \beta_k \Delta x_{k,ct} + \Delta \delta_t + \Delta \epsilon_{ct},$$

which can now be parameterized with the results from the previous section to analyze country-specific growth performances. Specifically, we have obtained the relevant parameter estimates $\beta$, $\theta$, and $\delta$ in section 5 (although the latter were not displayed in table 2). We illustrate this procedure based on the small model (1) in table 2 for the case of Bangladesh between period 7 (2000-2004 averages) and period 8 (2005-2009 averages), when growth was above 4% p.a. Table 3 first reproduces the parameter estimates from table 2 in column (1). As equation (2) highlights, those need to be multiplied with changes in the explanatory $x$ variables. Column (4) contains those variable changes between period 7 and 8. For example, the inflation variable $\text{inflation_na}$ increased from 0.035 in period 7 to 0.101 in period 8 – a difference of 0.066, which gets multiplied with the

23 The implication of this difference in persistence for the short-run and long-run parameter estimates of other variables is not clear and can go both ways. See Keele and Kelly (2005) for an instructive discussion.
parameter in column (1) to obtain the growth contribution of -1.49% in column (5). This result reflects the idea that increases in the inflation rate are usually negatively correlated with growth. Repeating this exercise for the other x variables as well adds up to a growth contribution of 2.96%. Note that we are looking at 5-year intervals, so all growth rates shall be divided by 5 to approximate annualized values.

Table 3: Calculation of growth contributions for Bangladesh in Period 8

<table>
<thead>
<tr>
<th></th>
<th>(1) parameter</th>
<th>(2) period 7 2000-04</th>
<th>(3) period 8 2005-09</th>
<th>(4) Difference (3)-(2)</th>
<th>(5) growth contribution: (1) x (4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inflation (linflation_na)</td>
<td>-0.227</td>
<td>0.035</td>
<td>0.101</td>
<td>0.066</td>
<td>-1.49%</td>
</tr>
<tr>
<td>Real exchange rate (lrer)</td>
<td>0.003</td>
<td>-5.521</td>
<td>-5.532</td>
<td>-0.011</td>
<td>0.00%</td>
</tr>
<tr>
<td>Trade openness (ltraderesid)</td>
<td>0.082</td>
<td>0.292</td>
<td>0.283</td>
<td>-0.009</td>
<td>-0.07%</td>
</tr>
<tr>
<td>Infrastructure (infra_index)</td>
<td>0.081</td>
<td>-0.191</td>
<td>0.154</td>
<td>0.345</td>
<td>2.81%</td>
</tr>
<tr>
<td>Financial crisis (dum_fincrisis)</td>
<td>-0.048</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.00%</td>
</tr>
<tr>
<td>Climate change (sd_temperature)</td>
<td>-0.024</td>
<td>3.556</td>
<td>3.400</td>
<td>-0.156</td>
<td>0.37%</td>
</tr>
<tr>
<td>Terms of trade changes (dltot)</td>
<td>-0.027</td>
<td>0.015</td>
<td>0.028</td>
<td>0.014</td>
<td>-0.04%</td>
</tr>
<tr>
<td>Government consumption (lkg)</td>
<td>-0.047</td>
<td>-2.657</td>
<td>-2.754</td>
<td>-0.097</td>
<td>0.45%</td>
</tr>
<tr>
<td>Growth volatility (sd_growth)</td>
<td>-0.622</td>
<td>0.005</td>
<td>0.008</td>
<td>0.003</td>
<td>-0.20%</td>
</tr>
<tr>
<td>Change in urban pop. (durbanpop)</td>
<td>0.010</td>
<td>2.354</td>
<td>3.451</td>
<td>1.097</td>
<td>1.13%</td>
</tr>
<tr>
<td><strong>SUBTOTAL</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td><strong>2.96%</strong></td>
</tr>
<tr>
<td>+ persistence</td>
<td>0.798</td>
<td>(growth period 6-7)</td>
<td>0.159</td>
<td>12.71%</td>
<td></td>
</tr>
<tr>
<td>+ period dummy</td>
<td>(=1)</td>
<td>-0.037</td>
<td>0.011</td>
<td>0.047</td>
<td>4.71%</td>
</tr>
</tbody>
</table>

**SUM (growth rate over 5 year period as predicted by model)**  **20.39%**

**ANNUALIZED growth rate (=sum divided by 5)**  **4.08%**
For the persistence term $\theta \Delta \ln y_{c,t-1}$, we need to multiply the autoregressive coefficient 0.798 with the growth rate from the previous period, where $\text{rgdps na pc}$ increased from 7.447 (in period 6) to 7.606 (in period 7), a (log) difference of 0.159, giving us a growth contribution of 12.7%. While this number appears large (2.5% when annualized), remember that this term is supposed to echo the contribution from all changes in past growth correlates and we are looking at the end of a very dynamic period in Bangladesh.  

For the component $\Delta \delta_t$, we simply calculate the change in the period dummies (which were not displayed in table 2), which gives us a growth contribution of 4.7%, so that all growth contributions add up to 20.4%, or 4.1% p.a. The difference to the actual growth rate of 4.4% (calculated as the change in $\text{rgdps na pc}$ divided by 5) reflects the residual $\Delta \epsilon_t$, which is not explained by the model. Figure 4 summarizes the main elements of this decomposition graphically.

In this example, the model performs well in explaining a country’s growth performance and we can conclude that infrastructure and urbanization were important contributors to growth, while inflation exerted a considerable drag. The case of Bangladesh is studied in more detail in Beyer and Wacker (2023) using the same data set but a slightly different selection of variables (and associated differences in the sample coverage).

**Figure 4: Growth contributions for Bangladesh (period 8, annualized)**

![Graph showing the contributions to growth for Bangladesh](image)

Notes: Figure 4 graphically depicts the contributions calculated in Table 3 in annualized terms. “Contemporaneous changes in growth correlates” corresponds to “subtotal” in Table 3. The difference between the actual growth rate (4.4%) and the sum of individual components (4.3%) is due to rounding.

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24 An alternative option is to use the predicted (instead of the actual) growth rate from the previous period. This option is slightly more difficult to implement because we need to predict growth and need to find a solution for how to do this for the first period. But it has the ability to capture changes in potential growth correlates that have not fully materialized in a given period. For example, a government may have implemented a large infrastructure project in 2004. Because this is the last year of period 7 (2000-2004), the growth benefits of this project may not have fully materialized in the actual growth rate for period 7 but would be captured in predicted growth (which uses infrastructure improvements as explanatory variable).
We finally recommend to cross-check country-specific decompositions with various model specifications (such as our small, medium, and large model), estimation techniques (GMM and alternative estimators) and sample heterogeneities (see section 5.3). The latter two aspects would simply mean using different parameters in column (1) of Table 3, the former would additionally involve altering the variables in the lines of Table 3.

6.2 Persistence Component: Problems and Alternatives

Our example of Bangladesh also suggests that the role of “persistence” is quite large in period 8. It is generally meaningful that the model captures past changes in growth correlates (see also section 3). An infrastructure project constructed in period 7, for example, is still likely to have an impact in period 8. And Bangladesh saw major improvements in typical growth correlates in periods 5 to 7 (Beyer and Wacker, 2023). Yet, there are several problems for the purpose of policy analysis.

A first problem is that large persistence (which results from high growth rates in previous periods) often masks the role of contemporary changes in growth correlates. Individual contemporaneous growth correlates would simply not be visible in Figure 4. We therefore recommend breaking this block down in a separate graph, possibly using a grouping of variables (see section 6.5 and Figure 3 in Beyer and Wacker, 2023).

A second problem is that the persistence component contains potential information about past changes in growth correlates and associated policies. In the above example, the model implies that contemporaneous changes in growth correlates will affect growth in period 9 by 0.6% x 0.8 (the persistence parameter) = 0.5%. Likewise, we can go back in time (e.g., to periods 5 to 7) and calculate how changes in growth correlates in previous periods would translate into growth in period 8, according to the model. It may be meaningful to perform such a calculation and split the persistence component in Figure 4 into a part that is explained by changes in growth correlates over the last periods, and the remaining “other persistence” (see Figure 2 in Beyer and Wacker, 2023). This helps to assess how much of the persistence term is backed by recent changes in typical growth correlates. It further gives the persistence term a more policy-relevant and less mechanical interpretation.

A third and related problem is that we used actually observed growth from the previous period to calculate the contribution of persistence. While this is the technically correct approach, it can be misleading if changes in growth correlates did not fully materialize in actually observed growth in the past. For example, an infrastructure project may have been realized in 2004. Since this is the final year of period 7, it may not be adequately reflected in the actual growth rate of that period and hence have little impact in subsequent periods via dynamic persistence effects. For another example, consider a temporary one-time shock that nullifies actual growth in a period despite many improvements in actual growth correlates taking place. Those improvements should have long-lasting persistence effects but due to a 0 observed growth rate, no persistence effects will be present.

Formally, we can use equation (3) to decompose the term \( \theta \Delta \ln y_{c,t-1} \) in equation (2) into:

\[
\theta \Delta \ln y_{c,t-1} = \sum_{j=1}^{J} \theta_j \sum_k \Delta x_{kt-t-j} + \nu_{t-1},
\]

where \( \nu \) is “other persistence”, and the first term sums persistence from past periods \( t-j \) over \( J \) periods. E.g., if we set \( J=1 \), we have \( \theta \sum_k \Delta x_{kt-1} \) as persistence explained by changes in growth correlates from period \( t-1 \). In the above example of considering periods 5 to 7 for period \( t=8 \), we would have \( J=3 \). Note that the lag depth \( J \) is limited in practice and that the first and second terms can go in opposite directions.

For another example, consider a temporary one-time shock that nullifies actual growth in a period despite many improvements in actual growth correlates taking place. Those improvements should have long-lasting persistence effects but due to a 0 observed growth rate, no persistence effects will be present.
We therefore suggest to alternatively consider the use of predicted growth rates in the persistence term. Based on equation (2), and suppressing the country subscript $c$, we can define predicted growth as:

$$\Delta \ln y_t = \theta \Delta \ln y_{t-1} + \beta_1 \Delta x_{1,t} + \cdots + \beta_k \Delta x_{k,t}, \quad (4)$$

such that any changes in $x$ will be reflected in this predicted growth rate and hence in subsequent persistence terms. Note that the presence of a lagged predicted growth rate in equation (4) requires some approximation (e.g., with actual growth) in the starting period.

6.3 What If the Model Does Not Predict Actual Growth Rates Well?

In the above example for Bangladesh, our model explained actual growth in the 2005-2009 period very well: the residual of 0.27 percentage points (=4.35% - 4.08%) is less than 10% of the actual growth rate. More generally, discrepancies of 1/3 are not exceptional, and they can easily amount to 1/2 in some cases. Such large residuals may result from various sources that may be informative in its own and require country-specific expert knowledge and additional analysis and tools to detect the underlying reasons of such deviations.

One possibility is that the model is not adequate for the country under consideration. For example, small-island states, resource-abundant economies, or transition countries feature specific peculiarities that may not be adequately captured by the model – either because relevant model variables are missing, or because the growth correlation with existing model variables is different for those countries. In the former case, extending the model with those relevant variables can be considered. In the latter case, one can investigate parameter heterogeneity for country groups.

Another possibility is that national GDP numbers are inflated – due to GDP rebasing or creative national accounting – or otherwise mismeasured. Comparing GDP data to alternative proxies of economic activity (e.g., nightlight) can be informative to substantiate this possibility.

A third possibility is that growth dynamics during periods of large residuals are driven by cyclical factors. Neoclassical growth models focus on the role of fundamental long-run growth correlates, as opposed to cyclical factors. The next subsection will give an example of such cyclical deviations.

6.4 Crises and Growth Underperformance

The example of Ghana in Geiger et al. (2019) is instructive to see how deviations between model and actually observed growth rates reflect cyclical effects and can be used to assess potential growth vulnerabilities. Their model only predicts a growth rate of 1.1% for the early-2010s but actual growth was almost 10%. As is noted in their paper, actual growth mainly reflected cyclical factors (oil discoveries, commodity prices, loose fiscal stance) and was not sufficiently backed up by relevant long-run growth correlates that feature in the model. This can be a warning sign for growth to run out of steam – as actually happened in the case of Ghana, which defaulted on its external debt in 2023. Using filtering techniques that separate growth into a trend and cyclical component can be useful to detect such cyclical deviations from trend. Moreover, it could be a warning sign for vulnerabilities to build up if developments in credit/GDP are unusually large, particularly if paired with large government consumption and foreign financing (e.g., fast increases in FDI or other capital inflows, or an increasing current account deficit).

A separate case concerns longer-lasting periods when growth considerably underperforms in a country, with growth rates hovering around or below 0. On top of the steps suggested under 6.3, one could look at levels of main growth correlates (see 5.2) in comparison to faster-growing but structurally similar peer countries and check if the country is considerably falling back in a typical growth correlate. Moreover, one could investigate in which period actual growth started to
significantly underperform relative to predicted growth and check for economic policy changes during this period.

6.5 Grouping of Variables

With an increasing number of explanatory variables in the model, it becomes increasingly difficult to display the results in an easy-to-access fashion for several periods. The studies cited at the beginning of this section hence aggregate those variables into different groups. In the above illustration for Bangladesh, for example, one could group the growth contributions of inflation, the real exchange rate, financial crises, government consumption, and growth volatility into a “macro stabilization” category. Grouping choices will depend on the question or hypothesis one is interested in. For example, Araujo et al. (2016) were particularly interested in whether the solid growth performance in most Latin American and Caribbean countries in the early 2000s was due to good policies or a favorable external environment, which motivated their variable grouping into structural policies, stabilization policies, and external conditions.

6.6 Extending the Model to More Recent Periods

Our data set ends with period 10, covering the years 2015-2019. If one wants to analyze a more recent period for an individual country, one does not necessarily need to update the whole data set (although we plan for regular updates in the GitHub repository). Remember that country-specific growth analysis is performed with changes of variables. One can hence rely on the parameter estimates from models like those in table 2 and apply them also to more recent changes in variables, even if they are not fully consistent with the level variables in the model. For example, one may not be able to re-calculate the full infrastructure index in our dataset for more recent periods. But one could alternatively create a similar index for the country under investigation with available variables that resembles the index in the dataset for the pre-2019 periods as good as possible and then take changes beyond 2019 for country-specific growth analysis.

6.7 Creation of Growth Scenarios and Benchmarking

A likely question that arises in a policy context is: what growth could a country expect if a certain explanatory variable changes? Recall that the model is not suited to provide an estimate of causal effects for such a scenario, but rather a thought experiment along the lines: what income changes did countries usually experience during periods when x changed, holding several other aspects constant?

Usually, benchmarking to an aspirational peer country provides a meaningful magnitude for a potential improvement in a growth correlate. For example, column (3) of Table 3 shows that the infrastructure index for Bangladesh stands at 0.154 in period 8. From the data set in the GitHub repository, we can further infer that the infrastructure index in Indonesia stood at 0.655 in the same period. What growth did countries usually observe when they closed the remaining gap of 0.5 units? For simplicity, we assume that the closure of the whole gap happens in one period. The model then implies an associated increase in income per capita levels of \( \Delta \xi \beta = 0.5 \times 0.08 = 4.1\% \) in the short run and \( \Delta \xi \beta / (1 - \theta) = 0.04 / (1 - 0.8) = 20.2\% \) in the long run.

Such benchmarking exercises can help prioritize broad areas of reform because they combine partial growth correlations (captured in the parameters \( \beta \)) with magnitudes of gaps in typical growth correlates \( \xi \). In other words, section 5.2 highlights how important \( \beta \) possibly is across countries, but

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27 This is a possible but very ambitious improvement. The average (median) change in the infra index per period over all sample observations is 0.12 (0.16). The 95th (99th) percentile change is 0.43 (0.63).
country-specific benchmarking relative to peer countries additionally adds information about existing gaps in variable scope for policy prioritization. Assuming that improvements are easiest in variables where gaps are large, such benchmarking may help identify areas with the “biggest bang for the buck”. Araujo et al. (2016: pp. 58-66) provide an instructive example of such a benchmarking exercise.

It is finally instructive to display the dynamics of such an exercise. Assuming that we observe a 0.5-unit improvement of the infrastructure index in period 8, we can expect the above-mentioned growth improvement of 4.1 percentage points in period 8. Since this magnitude refers to the whole 5-year period 8, it would imply a 0.8 percentage point increase of the annual growth rate during this period. Given that we looked at a tremendous increase in the variable that arguably shows the highest partial correlation with growth in the sense of section 5.2, this highlights how difficult it is to achieve large increases of the growth rate through improvements in structural correlates of growth over a policy-relevant time horizon.

Via the persistence term $\theta$, the infrastructure improvement in period 8 translates into income growth of $4.1\% \cdot 0.8 = 3.2\%$ in period 9, to $3.2\% \cdot 0.8 = 4.1\% \cdot 0.8^2 = 2.6\%$ in period 10, etc. This decaying dynamic is presented in Figure 5. Extending the periods until infinity and adding all bars up lead to the limit of a $4.1\%/(1-0.8) = 20.2\%$ improvement in income per capita in the long run. This highlights the nature of exponential growth: while the 0.8 percentage point increase of the annual growth rate we derived above may seem small from a short-run perspective, it adds up to a substantial income increase above 20% over time.

**Figure 5: Income increase associated with a 0.5-unit raise of infrastructure**

Note: Figure 5 displays the percentage point increase in income per period that is associated with a one-time 0.5-unit increase in the infrastructure index in period 8, according to the model. Note that this predicted income change refers to a 5-year period and is not (additional) growth per annum.
7. Conclusion

We have illustrated how growth regressions can be a useful tool for country-specific policy analysis of growth patterns. Economists performing such analysis will find the data and models presented in our paper a useful reference and can further tailor those to their specific needs (e.g., by exploring further heterogeneities, applying different estimators or model averaging, adding or updating variables). Our reference data can additionally be used by researchers and analysts to explore certain growth-relevant aspects in more detail (e.g., looking at threshold relations or other non-linearities for variables like inflation).

Future research could further improve policy modeling with growth regressions. One apparent angle is to reconsider the dynamic implications of the econometric neoclassical growth model, which assumes that persistence is uniform across countries and variables. Country heterogeneities could easily be addressed with recent advances in the grouped heterogeneity panel econometrics literature (e.g., Bester and Hansen, 2016; Muris and Wacker, 2022). But it may also be necessary to consider alternative dynamic modeling strategies that account for the plausibility that improvements in infrastructure, for example, have more persistent correlations with growth than certain macroeconomic stabilization policies like taming inflation. Another angle worth exploring is to develop metrics that can plausibly compare the relative importance of different policy packages. For example, economists are often curious about the extent to which domestic policies or a favorable external environment can explain a country’s growth episode. Explicit modeling of such relative importance appears futile. Researchers may rather consider using clustering techniques to separate common time-varying shocks in groups of reasonably similar countries (which can then be interpreted as external factors) from variation in growth that is explained by domestic policy variables.

Since our analysis is mostly descriptive and aims to facilitate country-specific growth analysis, future work could also further the identification of peer and reference groups in growth patterns. Moller and Wacker (2017) provide an example by using a cluster analysis to reveal the uniqueness of Ethiopia’s macroeconomic policy mix. The benchmarking of Bangladesh to other top performers in terms of changes in growth correlates in Beyer and Wacker (2023) is another example that could be furthered with more elaborate statistical techniques.

Finally, more research will be needed to better integrate climate aspects into conventional empirical growth models. This includes an integrated assessment of climate vs. growth impacts of different policies, as well as more elaborate modeling of the relationship between climate change and growth. Our dataset can be a fruitful resource for such research.

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28 In most empirical specifications, the list of “domestic” variables will be more extensive than the set of variables capturing the external environment (see, e.g., Araujo et al., 2016). This will give more explanatory power to the former. It is also not straightforward how to best account for the fact that different countries respond differently to changes in “external” variables.
References


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