THE JAMES A. BAKER III INSTITUTE FOR PUBLIC POLICY
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SOCIAL CAPITAL, BARRIERS TO PRODUCTION AND CAPITAL SHARES;

IMPLICATIONS FOR THE IMPORTANCE OF PARAMETER HETEROGENEITY FROM A NONSTATIONARY PANEL APPROACH

BY

PETER PEDRONI, PHD

WILL CLAYTON NONRESIDENT SCHOLAR IN INTERNATIONAL ECONOMICS
JAMES A. BAKER III INSTITUTE FOR PUBLIC POLICY
RICE UNIVERSITY

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Peter Pedroni

Williams College
and the James A. Baker, III Institute for Public Policy

mailing address: Economics, Williams College
Williamstown, MA 01267

email: peter.pedroni@williams.edu

Technical Abstract: Recent advances in the growth literature have proposed that difficult to quantify concepts such as social capital may play an important role in explaining the degree of persistent income disparity that is observed among countries. Other recently explored possibilities include institutional mechanisms which generate barriers to aggregate production. An important limitation for empirical work in this area stems from the fact that it is difficult to distinguish sources of heterogeneity when direct observations are not available. In this study, we show how developments in the analysis of nonstationary panels can aid in this endeavor. In contrast to traditional dynamic panel data analysis, this approach focuses explicitly on low frequency behavior. Under relatively mild assumptions, the approach can be used to infer properties of aggregate production which are robust to the presence of large classes of unobserved features. In this framework we are able to estimate and test the distribution of production function parameters that would be required in order to generate conditional forecast convergence of per capita incomes even when some of the key factors required to explain growth are unobserved. The results indicate that in order to fully explain the observed persistence in the disparity of per capita incomes, the manner in which unobserved mechanisms influence production must go beyond merely accounting for differences in the trending behavior of aggregate productivity. Specifically, the results demonstrate that if such mechanisms are to be successful empirically, then they must also be able to account for cross country heterogeneity in steady state capital shares. This adds to a growing literature that provides support for models with multiple production regimes.

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Executive Summary

One of the challenging tasks facing economists is a more thorough understanding as to why the disparity in national per capita incomes has remained so large across the globe. Most importantly, evidence as to whether or not these disparities are tending to diminish over time is at best mixed. This is despite the fact that many standard economic theories tell us that in an increasingly interconnected global economy, we should expect to see per capita incomes converge, with poorer countries eventually catching up to wealthier countries.

Recently economists have conjectured that explanations for the apparent lack of convergence in per capita incomes internationally may lie in the differences among countries that have traditionally received less attention from the economics profession. These include international differences in social and political institutions, differences in social norms and the degree of social cohesion, differences in the levels of education and health care and differences in the degree of social and political openness to new ideas and new technologies. Collectively, these concepts have come to be termed social capital, human capital, and barriers to production. The challenge that these ideas present for economists is that they are notoriously difficult to quantify, let alone define precisely. This has made it relatively easy to conjecture about the roles that these factors play, but relatively difficult to provide convincing empirical evidence to confirm or deny these roles.

The inherent difficulty in providing convincing empirical evidence regarding these conjectures stems both from the lack of reliable data, and from the way in which existing empirical approaches have attempted to deal with this problem. In particular, conventional empirical approaches attempt to deal with the lack of data by searching for observable proxies for the missing data. The idea is that although the data of interest does not exist, other observed measures that reflect some aspect of the unobserved data can serve in its place. Unfortunately, given the imprecise and general nature of these concepts, most proxies of this type tend to be static measures that are already known to be strongly correlated with the degree of economic development. For example, a measure of political stability measured by the number of regime changes may proxy for the strength of social institutions, and of course will be strongly correlated with national per capita income. But is this correlation due to the fact that political stability created wealth, or because wealth created political stability, or more likely that there is a complex feedback between the two processes? Ideally, one would like a measure of political stability is well defined and varies substantially over time so that one can better sort out the nature of the causality that runs between the two processes. But since such measures observed over long periods of time are difficult to come by, it remains easy to produce numerous ideas about the nature of the relationship based on simple statistical correlations, and difficult to provide evidence that can distinguish among competing ideas.

The approach that is used in this study exploits a very different line of recently developed empirical tools, known as nonstationary panel data methods, that allow us to circumvent some of these difficulties by inferring indirectly the implications for unobserved factors on variables that are observed. The way in which these methods are able to accomplish this feat is by systematically looking for those instances in the data in which the signal obtained from known relationships among observed variables is an order of magnitude greater than the noise that stems from conventional obstacles, such as missing variables and reverse causality among the variables, which serve to distract from the relationship of interest. This type of relationship in which the signal is an order of magnitude greater than the noise, known formally as cointegration, is repeated often enough across individual countries of the data so that for the panel of countries as a whole it becomes possible to reliably infer properties about the nature of the typical relationships that tie together the variables over the long run, even when other key factors that govern the relationship are unobserved. While the approach is necessarily more subtle, it permits one to examine relationships that would otherwise not be possible.

Based on these newly developed techniques, one of the key findings put forth in this study is that the role of unobservable factors such as social capital is likely to be more subtle than many researchers have proposed. In particular, the results show that simple differences in the extent to which barriers to productivity exist, and simple differences in the extent to which unobserved factors such as social or human capital have been accumulated among countries, are not sufficient to explain the persistent differences in observed per capita incomes. Instead, the results point to the fact that in order to fully explain the observed differences in per capita incomes it is not simply the accumulation of these factors, but also the way the accumulation of these factors interact with production technologies that matters. Specifically, the empirical results from this study show that in order to fully account for the persistent differences in per capita incomes internationally, one must also explain international differences in the mix of labor and capital that is used in the production of aggregate output. Only once one accounts for the differences in the mix of labor and capital combined with the unobserved factors one can account for the cross county per capita income differences. This finding contradicts most traditional models of economic growth, which presume that the share of labor and capital in production is relatively similar across countries.

To be more specific, the results imply that, regardless of the accumulated stock of capital, countries that have used higher proportions of labor relative to capital in aggregate production have on average performed more poorly over the post-war period in terms of per capita income growth. Furthermore the mix that favors higher use of overall capital relative to labor in aggregate production is associated with countries that have accumulated more social capital. This points to the relatively subtle but essential role that missing factors such as social capital play in promoting a more growth-favoring mix of labor and capital in aggregate economic production. Specifically, it demonstrates that it is not simply the accumulation of social and human capital that matter, but rather it is essential to consider how the presence of these factors impact the mix of capital and labor that is used in national aggregate production.

There are many ways in which we could imagine such a mechanism operating. To give one such example, the absence of strong social norms and institutions, such as ownership protections, or the successful rule of law in general, may create conditions under which individuals are less likely to risk the use of private capital and thus indirectly promote the under-use of capital relative to labor domestically. Another equally plausible example might occur when low levels of human capital investment in the form of education and health care protection, and low levels of social capital investment in the form of social safety nets induce populations to promote legislation that favors less efficient labor intensive means of production. But of these examples illustrate scenarios in which the production mix becomes shifted away from what might be technologically best suited to facilitate long term economic growth given the country's resources. Taken at face value, the implications of such results are clear for policymakers faced with managing public goods resources: when it comes to investing in various forms of social and human capital, such as political and legal institutions, health care and education, it is not enough to simply ask "how much", since the "how" can be just as essential when considering how these will interact with economic production.

Following the introductory section, the paper is divided into two primary sections. The first of these describes the empirical strategy that is used in the paper, and relates this to traditional interpretations of economic growth models. The second of these presents and interprets the results of the study. Following these two primary sections, a final section offers concluding remarks. The tables and figures that are referred to throughout the paper are collected in the appendix.

I. Introduction

Much of the empirical growth literature has been devoted to trying to explain the enormous disparity of per capita incomes that is observed around the world. It is often noted that the wealthiest economies have a level of per capita income that is well over 30 times greater than that of the poorest economies. Another often noted feature is that these disparities appear to be very persistent over time, and it is difficult to discern under what conditions we might anticipate that these differences are likely to expand or diminish. A full explanation for this disparity and its apparent persistence has eluded economists despite an enormous amount of research devoted to the topic.

Nonetheless, several important themes have emerged in recent years which have brought us closer to understanding this phenomenon. For example, economists have long noticed that variations in the share of physical investment resources that are devoted to production cannot alone explain the disparities that are observed in per capita output. This has lead many to conjecture that certain forms of intangible capital, most notably human capital in the form of education, may play an important role in the explanation. Early empirical work by authors such as Mankiw, Romer and Weil (1992) demonstrated that accounting for levels of education goes a long way toward explaining the observed cross sectional variations in per capita income. More recently, researchers have asked whether human capital alone may not be enough to explain the disparity, and have looked toward more pervasive forms of intangible capital for explanations, such as what some have termed “social capital”. Although researchers differ on the precise meaning or intent, predominantly the concept has come to refer to intangible forms of capital such as social and political institutions, or even the presence of social norms and morals. The basic idea is that by fostering the productivity of more conventional categories of productive inputs, these relatively difficult to quantify notions of capital may help to explain why variations in measured inputs alone do not appear to be sufficient to explain the persistent long run differences in per capita incomes that are observed across countries. Examples of recent empirical research in this area include Hall and Jones (1999) and Temple and Johnson (1998).

Another line of research which shares similar overtones in some regards has attempted to explain more directly the reasons why different countries do not appear to use the best available aggregate production technologies. This line of research, exemplified in recent years by the works of Parente and Prescott (1994, 1999) emphasizes the importance of barriers to efficient production. Similar to the literature on social capital, this literature appeals to country specific institutional and political economic reasons to explain why traditional forms of intangible capital such as the level of education are not sufficient to explain the observed disparity in per capita incomes. The idea is that institutional and political factors can create incentives for firms not to employ the most efficient means of production technology. A central implication of this line of research is that despite a common set of globally available production technologies, country specific barriers to the adoption of new technologies lead to a situation in which total factor productivity may in effect grow at different rates across countries, depending on the nature and strength of such barriers. This line of research helps to focus attention on the fact that it is the different rate of absorption of new technologies that may help to explain why the variation in measured inputs alone cannot explain the persistent dispersion of per capita incomes across countries.

At a basic level, each of these approaches rely on the argument that certain intangible or unobserved factors may help to explain the apparent inability of variations in observed factors to explain the disparity in observed per capita incomes in a manner consistent with the basic neoclassical model with shared production technologies. Another important tradition in the literature takes a somewhat different approach, and seeks to explain observed differences in per capita income relative to observed inputs by attempting to understand why the process of economic development may lead to effectively different aggregate production functions, depending on the level of development experienced by the country. Early examples of this line of research include among others the work of Aziardis and Drazen (1990), which emphasizes the possibilities of threshold externalities associated with the level of human capital present, and the works of Durlauf (1993) and Murphy, Schleifer and Vishney (1989) which emphasize how coordination failures can produce the possibility of multiple steady states associated with different aggregate production parameterizations of factor shares. A central implication of this line of research is that a single log linear specification implied by common aggregate production technologies may not be sufficient to characterize the steady state evolution of per capita income in terms of factor inputs.

Many researchers, including Bernard and Jones (1996), Durlauf and Johnson (1995), Caselli, Esquivel and Lefort (1996), Lee, Pesaran and Smith (1997, 1998) and Masanjala and Papageorgiou (2004) have noted that, empirically, capital factors shares appear to vary considerably across countries. For example Durlauf and Johnson (1995) employ a regression tree analysis to show that a cross sectional regression of the Summers and Heston data appears to provide support for several distinct regimes in which aggregate production functions vary among countries according to their level of development. As Durlauf and Johnson (1995) point out, however, a cross sectional based approach is inherently limited in its ability to deal with omitted variables such as social capital, which are difficult to quantify. The reason for this is straightforward. In a conventional cross sectional based approach, omitted variables that are important for conditioning may induce apparent differences in the slope coefficients of the linear regression fit. As we will see, the nonstationary panel approach employed in this study will permit us to examine the distribution of key slope coefficients across countries which will be invariant to a broad class of such omitted variables. Consequently, the approach taken in this paper provides an alternative that helps to provide evidence that is more robust to omitted variables than traditional cross sectional based methods and therein complements the growing literature that finds evidence for the importance of parameter heterogeneity and the need to consider specifications beyond the common linear production function. It also allows us to examine in more detail the sample distribution of corresponding production function parameters even among subgroups of relatively similar countries. Most importantly, rather than simply asking whether parameter estimates are heterogeneous, the approach we take allows us to ask whether the apparent heterogeneity is likely to be an essential part of the explanation for persistent per capita income disparities in the context of the neoclassical model, or whether unobserved factors are sufficient to explain the observed disparities.

Methodologically, it is important to distinguish a panel approach that exploits the nonstationary features of the data from more traditional static and dynamic panel approaches. For example, while Durlauf and Johnson (1995) conclude that a panel approach may be required in order to more fully investigate the nature of the cross country variations in these coefficients, Durlauf and Quah (1999) point out that conventional panel approaches also have important limitations in that they may inadvertently tend to uncover high frequency relationships rather than the long run low frequency relationships that are of interest for the growth literature. The reason for this is also straightforward. In conventional panels which involve stationary variables, the fixed effects tend to absorb those features of the sample which evolve at relatively low frequencies, leaving the regressors to explain the higher frequency relationships.

By contrast, the nonstationary approach that we employ explicitly estimates the long run low frequency relationships among the variables, despite the presence of fixed effects. The approach also allows us to address many of the other issues that have been important for empirical work in the growth literature. For example, our approach allows us to relax many important exogeneity assumptions, and also allows us to relax the assumption that countries stay relatively close to their steady state positions at all points in time. For these reasons, we believe that recent developments in nonstationary panel techniques offer considerable promise in further helping us to distinguish among empirical relationships which can aid researchers to better pinpoint fruitful directions for the development of growth theory. In this study, we demonstrate how such nonstationary panel techniques can be used to investigate the distribution of coefficients which reflect key structural parameters of the production function in a way that accounts for the possibility of intangible social capital, barriers to production and multiple regimes in explaining persistent per capita income disparities across countries.[1] Furthermore, we do so in a framework which permits us to link this directly to a notion of conditional convergence, as we will see. The results of this study add to a growing empirical literature that points to the importance of relaxing the traditional assumption of a common linear production function, and argues that an appeal to unobserved factors alone is unlikely to suffice as a substitute for heterogeneity of the production function.

The remainder of the paper is organized as follows. In the next section we discuss our general empirical strategy and the interpretation of our approach relative to a neoclassical growth model. In section III we discuss the details of our econometric techniques and interpret the results. Section IV offers some concluding remarks.

II. The Empirical Specification

It is important to recognize that by using a nonstationary panel approach we are implicitly assuming that the pattern of low frequency variations observed over time across a group of countries can aid us in understanding the nature of the cross sectional dispersion of per capita incomes. The basic reasoning that connects our empirical approach to the issue is relatively straightforward. The Solow growth model tells us that in the long run steady state, permanent changes in the savings rate will be associated with permanent changes to the level of per capita income and that the relationship is determined by the capital share parameters of the Cobb-Douglas production function. Since the share of investment is our best measure for savings rates, this tells us that if the pattern of time series variations is going to be informative about this relationship, then we should search for instances in which permanent variations in the investment share have occurred. These permanent changes in investment shares may be due to changes in tastes, changes in government policy, or any number of reasons which may differ from case to case. What is important is simply that such permanent variations in investment shares are present so that we have the potential to observe any permanent co-movements that have been observed in per capita income.

One practical way to model these permanent variations in investment shares empirically when they occur is to treat them as changes to the expected long run values, so that the series for investment shares mimics a unit root process, which is non mean reverting. Clearly, it does not make sense to think of this as a global property of

[1] For recent reviews of the nonstationary panel literature, see Breitung and Pesaran (2006) and Pedroni and Urbain (2006).

investment shares, since ultimately investments shares must be bounded by the resources available to an economy. Rather, we prefer to think of this simply as a feature which describes the local behavior of the series within sample, and thus has implications for the properties of the estimators that are constructed from these samples. Indeed, Jones (1995) points out that for many countries, with the notable exception of the U.S., the series for investment shares appear to be consistent with such unit root behavior within sample. We also find this to be the case for many countries, though certainly not all countries, and as we explain below, we use this as a criteria for selecting countries from within the Summers and Heston (1991) panel which are most likely to be informative for the questions we ask.

The important point in our interpretation of this feature of the data is that there is nothing which necessarily indicates that investment shares *must* behave as a unit root process. The feature depends on what has determined tastes, government policy and so forth in the post war period, which we anticipate to be relatively country specific and sample specific. For some countries, these factors have been relatively stable and have lead investment shares in turn to be relatively stable. Other countries have had experiences that have lead to relatively frequent revisions in the expected long run investment share, which leads us to observe investment share series with permanent movements that can be well-approximated by a unit root process. Since the neoclassical model in conjunction with our econometric technique tells us that these permanent changes to investment shares can help us to uncover the parameters of the production function when they are associated with permanent changes in output, our empirical strategy is to look for instances in which this pattern has occurred in the Summers and Heston panel.

Since the reason permanent changes to investment shares are particularly informative is because the Solow model tells us that these should in turn be associated with permanent changes to the level of per capita income, this tells us that we should expect to find cointegrating relationships between per capita incomes and investment shares in those instances. Furthermore, when the level of per capita effective human capital or other intangible capital inputs are relatively stable across countries, or evolve relatively smoothly over the long run, then these features will be absorbed into the fixed effects or heterogeneous deterministic trends for our panel specification, depending on the case. In such cases, the steady state relationship between per capita income and investment shares characterized by the cointegrating relationship traces out the implied curvature of the production function for each country as determined by the capital share parameters of the tangible and intangible capital inputs.

Consequently, the key empirical reduced form equation that we will investigate takes the form

$$\ln y_{it} = c_i + g_i t + \beta_i \ln(I/Y)_{it} + \mu_{it} \tag{1}$$

where $\ln y_{it}$ represents log per capita income over time periods $t = 1,...,T$ and countries $i = 1,...,N$. Likewise $\ln(I/Y)_{it}$ represents the log of investment shares over the same time periods and countries, while c_i represents the country specific fixed effects, and $g_i t$ represent potentially heterogeneous country specific deterministic trends. Much of our empirical analysis revolves around examining conditions under which the residuals of this equation, μ_{it}, are, or are not, covariance stationary for various groups of countries. For example, our econometric approach will allow us to ask under certain conditions whether the inclusion of unobserved factors or barriers to production alone are likely to be able to explain the persistent dispersion of per capita incomes. More to the point, the econometric approach will also allow us to ask whether heterogeneity of the production function share parameters are also likely to be necessary in order to explain the persistent dispersion of per capita incomes even after accounting for unobserved factors and barriers to production. In this way our approach has the potential to uncover structural characteristics of the production function which under a broad class of behaviors are robust to the presence of unmeasured intangible capital inputs and mechanisms such as barriers to production that may lead to differential rates of adoption of technological growth. The approach is also robust to the violation of a number of strong assumptions that have typically been made in the literature, including the assumption that regressors and omitted initial conditions are exogenous, and that countries lie close to their steady state positions at all points in time. Also, in contrast to conventional dynamic panel techniques, we do not require transitional dynamics to be similar among countries.

Conceptually, the reason we are able to accomplish this is because the conditions under which the residuals μ_{it} are stationary with zero mean provides us with an appealing framework for relating the various possible unobserved mechanisms that may explain per capita income disparities in a way that maps naturally into a well defined notion of conditional convergence that is appropriate for the nonstationary panel setting. Specifically, because the residuals of the cointegrating relationship are stationary mean zero processes, this implies that any differences among the residuals are temporary. This corresponds closely to Bernard and Durlauf's (1996) concept of time-series forecast convergence, except that we are applying the idea here to the residuals of a steady state relationship rather than raw per capita income data. In this way, the definition becomes appropriate for conditional convergence in a nonstationary panel in that the cointegrating relationship picks out those features upon which it is necessary to condition in order for per capita outputs to be conditionally convergent in the sense that any remaining differences are only transitory.

In this context, an important distinction in the cointegrated panel specification relative to conventional cross sectional based specifications is the treatment and interpretation of unobserved mechanisms that potentially explain per capita income dispersion across countries. In the cross sectional framework it is imperative to find direct quantifiable variables that can proxy for unobserved mechanisms. In the nonstationary panel framework, the combination of the extra dimension and the long run properties of the cointegrating relationship provide us with an alternative approach. In this framework statistical proxies such as the fixed effects and heterogeneous trend components can serve to capture a broad class of these unobserved mechanisms. By capturing the role of such mechanisms in these deterministic terms, we are able to study the distribution of the structural parameters of the production function in a way that is robust to the presence of these features.

From cross sectional studies we know that the estimated value of the slope coefficient from a reduced form regression analogous to (1) maps into the structural share parameters of the aggregate production function, and it is relatively intuitive to see that any omitted factors that are constant over time or evolve smoothly over time will be absorbed into the country specific deterministics c_i and $g_i t$. It is worth noting, however, that the specific structural interpretation given to the deterministics and even the slope coefficients will vary depending on the nature of the unobserved factors. Our primary econometric tests to determine whether production function heterogeneity is essential even after accounting for unobserved factors will not depend on the specific structural interpretation of the estimated coefficients. However, as a byproduct of these tests, it will also be interesting to obtain estimates for the cross country distribution of the structural parameters. For this we will need to see more specifically how the reduced form coefficients relate to the structural parameters. Thus, it is worthwhile to examine the relationship between the reduced form equation (1) and the augmented Solow model in a panel setting.

To see the details of this, recall that the typical augmented Solow model analysis specifies an aggregate Cobb-Douglas production function such as

$$Y_{it} = K_{it}^{\alpha_i} X_{it}^{\varphi_i} (E_{it} L_{it})^{1-\alpha_i-\varphi_i} \tag{2}$$

In the typical treatment of the augmented Solow model the share parameters α_i, φ_i are taken to be common across countries $i = 1,...N$. However, we do not impose this condition since it is one of the features that we wish to study. The variable X_{it} is an intangible capital input such as human capital, and E_{it} is the labor augmenting level of productivity. Labor and productivity evolve as

(3) $$L_{it+1} = (1+n_i)L_{it} \quad , \qquad E_{it+1} = (1+g_i)E_{it}$$

where n_i and g_i are the exogenous growth rates of labor and labor augmenting technology. Likewise, physical capital grows according to the accumulation equation

(4) $$K_{it+1} = I_{it} + (1-\delta_i)K_{it} \ , \quad I_{it} = S_i Y_{it}$$

where δ_i is the constant rate of capital depreciation, and I_{it} is the rate of physical capital investment determined in the Solow model as a share of output given by the savings rate S_i. Again, it is worth noting that although the typical treatment of the Solow model imposes homogeneity of the parameters g_i and δ_i, we do not.

When the model is augmented with an endogenous intangible capital such as human or social capital, then this is often taken to evolve as

(5) $$X_{it+1} = I_{it}^{x} + (1-\delta_i^{x})X_{it} \ , \quad I_{it}^{x} = S_i^{x} Y_{it}$$

where δ_i^x is the rate of depreciation of the intangible capital stock, and the rate of investment in this stock is determined by a constant fraction of output S_i^x, both of which are permitted to vary across countries in our specification. The model can then be solved for the steady state value of log per capita income, $\ln y_{it} \equiv \ln Y_{it} - \ln L_{it}$, in terms of log investment shares, $\ln(I/Y)_{it} = \ln S_i$, which gives

(6) $$\ln y_{it} = \ln e_{io} + \varphi_i(1-\alpha_i)^{-1}\ln x_{it}^{*} - \alpha_i(1-\alpha_i)^{-1}\ln(n_i + g_i + \delta_i) + g_i\, t + \alpha_i(1-\alpha_i)^{-1}\ln(I/Y)_{it}$$

as an approximation when the values of g_i and δ_i are relatively small. Here e_{io} is the initial condition for labor augmenting technology, and $\ln x_{it}^{*} \equiv \ln X_{it} - \ln E_{it} - \ln L_{it}$ is the steady state value of the intangible capital stock in log per capita efficiency units. Alternatively, note that the steady state relationship can also be expressed in terms of the rate of savings, S_i^x, for the intangible capital stock, so that

$$\ln y_{it} = \ln e_{io} + \varphi_i(1-\alpha_i-\varphi_i)^{-1}\ln S_i^x - (\alpha_i+\varphi_i)(1-\alpha_i-\varphi_i)^{-1}\ln(n_i+g_i+\delta_i) + g_i t + \alpha_i(1-\alpha_i-\varphi_i)^{-1}\ln(I/Y)_{it} \tag{7}$$

Given that we want a general treatment that does not presume what constitute the unobservable factors X_{it}, it is worth considering how the reduced form equation (1) can best be interpreted depending on the nature of X_{it}. Specifically, this will depend on how the unmeasured intangible capital stocks are accumulated. In particular, we can think of two distinct categories for such unmeasured capital inputs. Broadly speaking, we can think of one such class of unmeasured intangible capital input as being similar to the way human capital is typically modeled in that the accumulation of human capital is accomplished at the expense of some fraction of income. We can think of another possible class of unmeasured intangible capital as differing from this to the extent that the accumulation of such capital stocks tends to be accomplished more generally by means other than at the expense of some fraction of measured income. This is not to say that the accumulation of this intangible capital stock is exogenous or independent of income, or that it occurs without effort or sacrifice. Rather, the key distinguishing feature of this second class of intangible capital is that it does not specifically require a fraction of income to be set aside. This may be typical of many, though not necessarily all, forms of social capital. For example, we might think of the development of trust or property rights, or common social values to be examples of this type of intangible capital stock, which evolve gradually over long periods of time and enhance the productivity of other measured inputs, but do not necessarily require a fraction of measured income to be set aside in order to be accumulated. Most likely, the accumulation of these forms of social capital require effort in the form of investment, but perhaps these efforts are at the expense of personal resources that are not a part of aggregate measured income.

The reason it is important to bear in mind the distinction between these two different types of intangible capital assets is because they affect the structural interpretation of the parameters of the panel specification that is given in terms of measured aggregate per capita income and investment shares of tangible physical capital. Consider first the type of intangible capital input that is akin to the social capital that we have described as being accumulated without the need to set aside a fraction of measured income. In this case, the most suitable way to describe the role of this omitted factor input is likely to be in terms of the steady state relationship given by equation (6). In comparing equation (6) with the reduced form specification (1), we see that this form relates the omitted intangible capital input in terms of its steady state stock value, measured in per log capita efficiency units, $\ln x_{it}^*$. In this case, we might think of the fixed effects, c_i, as picking up the effect of this unmeasured capital stock under certain scenarios. For example, if the level of such capital measured in efficiency units is relatively stable over the length of the sample for any one country, then it will only impact the level of per capita income after we have conditioned upon the measured physical capital investment shares, $\ln(I/Y)_{it}$, and any country specific trend growth rates, $g_i t$. This is likely to be the case for certain types of broad social capital which evolve only very slowly. If the long run value is relatively constant for any one country, we can think of simply dropping the t index, from the steady state specification, so that this could be represented simply as $\ln x_{it} = \ln\tilde{z}_i^*$ for some unknown country specific value $\ln\tilde{z}_i^*$. In this case, these country specific values will be absorbed into the fixed effects along with other relatively constant country specific factors, so that $c_i = \ln e_{io} + \varphi_i(1-\alpha_i)^{-1}\ln\tilde{z}_i^* - \alpha_i(1-\alpha_i)^{-1}\ln(n_i + g_i + \delta_i)$. In this sense, the unmeasured capital stock behaves no differently than the population growth rate, n_i, which, even though it may be time varying, is relatively stable and only impacts the country specific intercept of the log linear steady state relationship. In fact, more generally the conditions under which this category of unmeasured capital stock will be accounted for in the panel regression is even broader, and does not require that it be constant for the duration of the sample. Rather, we simply require for this category of unmeasured capital that the value is stationary around its trend values. Provided that this capital stock evolves relatively smoothly, even if it does change over the sample, it will be absorbed into a combination of the fixed effects and country specific trend terms $g_i t$. If all unmeasured intangible capital were of this form, then the reduced form specification could be interpreted in terms of equation (6), in which case the slope coefficient for the measured share of physical capital investment would be a function solely of the production function share parameter for physical capital, such that $\beta_i = \alpha_i(1-\alpha_i)^{-1}$.

More generally, however, we can expect that other forms of intangible capital exist which do not necessarily follow this behavior, and which require that a fraction of measured income be dedicated in order to accumulate the stock. Most notably human capital has conventionally been modeled in this way, and presumably there may be some forms of unmeasured social capital that also better fit this description. In this case, the accumulation equation (4) applies, and the long run values for the stocks, $\ln x_{it}^*$, of this capital type need not necessarily be stationary around trend even when measured in log per capita efficiency units. The reason for this stems from the fact that the accumulation of this type of capital depends on a fraction of measured income, which in turn depends on the rate of measured physical investment shares. In this case, the more appropriate steady state specification for per capita incomes is in the form of equation (7), which specifies the relationship in terms of the rate of savings, $\ln S_i^x$, of the intangible capital, rather than the stock value. The important point to notice is that in this case the interpretation of both the intercept and the slope coefficient changes in the panel specification. If all unmeasured intangible capital stocks were in this form, then the fixed effects, c_i, absorb the country specific rate of savings for the intangible capital stock such that $c_i = \ln e_{io} + \varphi_i(1-\alpha_i-\varphi_i)^{-1}\ln S_i^x - (\alpha_i+\varphi_i)(1-\alpha_i-\varphi_i)^{-1}\ln(n_i+g_i+\delta_i)$, and in this case the slope coefficient for the measured share of physical capital investment would be a function of both the physical capital and intangible capital share parameters such that $\beta_i = \alpha_i(1-\alpha_i-\varphi_i)^{-1}$.

In the most general case, we might expect that some of both types of categories are likely to make up the stock of unmeasured intangible capital stocks. In this case, we can think of a more finely specified production function that includes both types of intangible capital, one of which requires a fraction of measured income in order to accumulate and another which does not. Now the fixed effects absorb the impacts that both of these types of intangible capital inputs have on the level of per capita income after conditioning on measured physical capital investment shares and any country specific trend growth rates, $g_i t$. But the slope coefficient on measured physical capital investment shares still depends only on production function share parameters of the capital stock types which are accumulated by using a fraction of measured income, such as human capital and possibly some components of social capital. The key point in this discussion is that the cointegrated panel specification is sufficiently general to handle a number of different possibilities regarding the nature of the unmeasured intangible capital stock, but we must take care to interpret the meaning of the slope coefficients accordingly. Similarly, the inclusion of the heterogeneous deterministic trend terms permits the panel specification to be sufficiently general to accommodate mechanisms that might explain the cross country dispersion of per capita incomes in terms of differing rates of productivity. For example, if country specific barriers to the adoption of global technologies impact the level of productivity, then this will be absorbed into the fixed effects, c_i. More generally, if such barriers impact the rate of technological adaptation, then this will be absorbed into the country specific trend rates $g_i t$. This is as important distinction relative to conventional dynamic panel approaches. As Durlauf and Quah (1999) point out, conventional dynamic panel approaches tend to inadvertently estimate higher frequency short run relationships among the variables, while relegating the long run relationships to the fixed effects. This does not occur in our nonstationary panel data setting, which explicitly extracts the long run relationship among the variables in the form of the cointegrating vectors which include the slope coefficients.

III. Estimation and Testing

In this section we describe the details of the estimation and testing procedures that we employ for the nonstationary panel specification, which allows us to investigate the distribution of parameters across countries. As we argued in the previous section, the first step in our empirical strategy is to look for instances in which we have observed permanent or at least highly persistent changes in rates of investment that can be approximated locally within the sample as a unit root process. In doing so, our presumption is that the events that lead to unit root behavior of the investment shares is relatively pervasive in the data, but that it need not be present in all countries.

Thus, we have selected from the Summers and Heston data a panel of countries for which the investment share series are likely to be consistent with this feature. In practice, this means that for the 51 countries of the Summers and Heston panel for which the full span of data is available from 1950 to 1992 for investment shares and per capita output,[2] we eliminate from our core sample any countries for which the investment share series does not pass a simple ADF unit root test. This sample section procedure initially results in the selection of a total of 31 countries. By setting aside the other countries, we have in effect eliminated those countries for which the investment series is unlikely to be informative about the relationship in which we are interested. This has the effect of dramatically increasing the signal to noise ratio in the sample with which we are working. Of course, our sample selection procedure is based on a test which takes the null hypothesis to be a unit root, and one might argue that rather than dropping those countries for which the unit root null is rejected, we should drop the countries for which stationarity is rejected. In fact, we also compute results for the standard KPSS stationarity test applied to the individual country series and the panel as a whole, and we also conduct our subsequent analysis for the subset of 23 countries for which this stronger criteria applies and find similar results. However, our general view is that in light of the relatively weak power of either of these tests for any series which spans only 43 years of data, it would be excessive to demand that we strictly reject stationarity. Rather, we simply wish to set aside those countries for which the evidence appears to run contrary to the presumption that permanent changes to the savings rate have occurred that are consistent with a unit root process, with the recognition that while this still leaves important sources of noise in the sample, it has substantially reduced its prevalence.

Furthermore, to support the idea that the inclusion of this number of countries in our sample is not due simply to lack of power in the individual country ADF test, we also compute the panel based tests of Im, Pesaran and

[2] Specifically, we use the Laspeyres real GDP.series, RGDPL, and the corresponding investment shares.

Shin (2003). This allows us to test the null hypothesis that all members of the panel have a unit root versus the alternative that some fraction are stationary. The results, which are reported in table I, are unable to reject the hypothesis that all countries have a unit root, despite the fact that this test is known to have high power in panels of this dimensionality. On the other hand, as expected, we note that conversely, a panel test for the null of stationarity does reject the hypothesis that all countries are stationary against the null that a fraction contain unit roots.[3]

According to the Solow model, these permanent changes in investment shares should be associated with permanent changes in per capita income, which should be reflected as a cointegrating relationship between the two variables. Consequently, we will want to check for this condition as well in selecting our sample. One could imagine first testing each of the individual per capita GDP series, and then testing for cointegration. But establishing a unit root for per capita income is redundant once we establish a unit root for investment shares individually and cointegration between the two. Therefore, since we are more directly concerned with the cointegrating relationship, we base the second step of the sample selection procedure on the cointegration test between the two variables. Again, given the low power of the individual tests, to be consistent with the way in which we based the decision for the unit root tests on investment shares, here we will want to eliminate any countries for which we can reject the null of cointegration on an individual basis. For this, we used the Shin (1994) residual based test for the null of cointegration, which is analogous to the KPSS test for univariate series. Since our interpretation of the steady state regression allows for the possibility of country specific deterministic trends and intercepts, we included these in the tests. This procedure lead us to reject an additional 2 countries from the sample, namely Thailand and Uruguay. This leaves us with a total of 29 countries, 14 of which are OECD countries and 15 of which are non OECD countries.

Finally, to support the idea that again the inclusion of this number of countries in our sample is not due simply to lack of power in the individual country tests, we also computed a panel test for the null of cointegration by constructing a group mean panel test analogous to the one that we used for the KPSS based group mean panel test

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[3] We computed this panel test for the null of stationarity by constructing a group mean test based on the averaged Kwiatkowski *et al* (1992), KPSS, test values standardized by appropriate correction terms for the expected value and standard deviation of the nuisance parameter free limit distribution of the KPSS statistic. Specifically, let x_i be the KPSS test value for the series of country i. Let $u = \lim_{T\to\infty} E[KPSS_i]$ and $v^2 = \lim_{T\to\infty} E[KPSS_i]^2$ be the mean and variance of the limit distribution of the KPSS test under the null hypothesis, and let $\bar{x} = N^{-1}\sum_{i=1}^{N} x_i$ be the group mean value for x_i. Then the panel statistic $v^{-1}\sqrt{N}(\bar{x} - u) => N(0,1)$ is distributed normally under the null hypothesis that all series are stationary, and is a right tailed test that diverges to positive infinity under the alternative. We simulated u and v^2 using 20,000 i.i.d. draws from an i.i.d. distribution to construct $KPSS_i$ under the null. We also note that such a group mean test for stationarity was developed in Hadri (2000).

for stationarity.[4] The only difference is in the value of the adjustment terms used to construct the panel statistic, since these must be based on the estimated residuals of a cointegrating regression under the null.[5] The test confirms that null of cointegration is also not rejected. Likewise, we also computed individual tests for the null of no cointegration, as well as group mean panel tests for the null of no cointegration using the tests from Pedroni (1999, 2004a), which are also reported in table I. For unit root and cointegration tests that involve per capita output, we have allowed for a deterministic trend and intercept, whereas for unit root tests involving only investment shares we did not include a deterministic trend, but have allowed for heterogeneous fixed effects in the intercepts. The panel tests for per capita income are unable to reject the unit root null hypothesis, but strongly reject the stationary null hypothesis. These findings for per capita income are consistent with numerous other studies, including Canning and Pedroni (1999), Cheung and Lai (1992), Lee, Pesaran and Smith (1997) and Pedroni (1998).[6]

Note that for each of the group mean unit root and cointegration tests reported in table I, we report results for the raw data as well as for data that has been demeaned with respect to cross sectional dimension for each time period, which serves to extract common time effects from the data. In this way, the cross sectionally demeaned results can be interpreted as accounting for certain forms of cross sectional dependency that may be present in the data. An important criterion for this approach to be effective in eliminating or reducing cross sectional dependency is that the form of the dependency is such that it is driven by a single common source, and that individual countries respond in a similar fashion. In many cases this may be a fairly reasonable way to model the dependency. For

[4] We could narrow the sample further by requiring that countries also individually reject the reverse null, namely the null of no cointegration, but again, given the weak power of the individual tests, we do not want to be excessive in eliminating countries from the sample. Nevertheless, we did also experiment with this even narrower subset for parameter distribution testing procedures and did not find any substantial differences in the results. Tables summarizing all individual country unit root and cointegration test results are available upon request from the author.

[5] Specifically, in this case we constructed the $KPSS_i$ test from the estimated residuals of a regression $y_t = c + gt + bx_t + u_t$ and simulated the values u and v^2 based on the residuals from 20,000 such regressions where x_{it} and y_{it} were drawn as independent random walks.

[6] Evans (1998) also conducts panel tests for the unit root null for per capita incomes and is unable to reject the null for the raw series, but finds a rejection when the time means are subtracted, while we do not. We anticipate that this stems in part from the difference in our samples, since we specifically sought out those countries for which investment shares behave as a unit root process, which in turn implies that per capita outputs can be expected to follow a unit root process, even relative to the sample mean. Other differences stem from the fact that we have used the Im, Pesaran and Shin (2003) test, which allows for greater flexibility under the alternative hypothesis. The fact that we also allow for the presence of country specific trend terms is also significant, particularly since this substantially reduces the small sample power of such panel unit root tests. However, the B-trace and J-trace tests from Pedroni and Vogelsang (2005), which retain high power in small samples confirm the results.

example, if the data are in part driven by common global business cycles, or even a common stochastic trend, then the extraction of common time effects can serve to capture this effect. However, in other cases the dependency may be more general, in that countries respond in a heterogeneous fashion, or that there are multiple dependencies, or that there are idiosyncratic dynamic feedback effects between individual pairs of countries.

To accommodate some of these more general forms of dependency, we also implemented tests that are designed to be robust to these more general forms. One of these is the group mean cross sectionally augmented ADF (CADF) panel unit root test proposed by Pesaran (2006a). The idea behind this approach is to include estimates of the time effects and the lag differences of the time effects directly in the individual country ADF regressions that are used to constructing the group mean statistic. A key difference as compared to the approach based on simply extracting time from the data is that the individual countries are permitted to respond to the common time effect in a heterogeneous fashion, as reflected by the country specific coefficients on the time effects. In this way, the time effects can serve to proxy for a single unobserved common factor that may be driving the data.

The other two tests that are implemented to check robustness with respect to cross sectional dependency are the ones proposed in Pedroni and Vogelsang (2005). The idea behind this approach is to model the panel as a large N-dimensional system and construct a non-parametric unit root test that is invariant to the presence of general cross sectional dependencies of unknown form, including multiple common factors and idiosyncratic dynamic feedback effects between individual pairs of countries. Another feature of these tests that is particularly important for our application is that it retains high power to distinguish the unit root null against highly persistent but stationary processes even in the presence of country specific deterministic trends, which is generally not the case with other panel unit root tests. The tests are also attractive in that they can accommodate heterogeneous country specific dynamics without the need to choose lag truncations as with ADF based tests, or to choose bandwidth as with conventional semi-parametric based tests. One such test, which we refer to as the B-trace test, is constructed as the trace of a multi-variate version of the ratio of an untruncated Bartlett kernel estimator and the standard variance estimator. The other test, which we refer to as the J-trace test, is constructed as a the trace of a multi-variate version of the traditional time series unit root J-test. The results for the B-trace and J-trace tests, as well as the Pesaran CADF test, are reported in the last row of table I. In all cases, these tests confirm the results of the other panel unit root tests in that they are unable to reject the null hypothesis of a unit root in all members of the panel.

The next step in our empirical strategy is to estimate the coefficients of the cointegrated panel corresponding to the reduced form equation (1). The basic framework which we use is based on the group mean fully modified OLS procedures for cointegrated panels studied in detail in Pedroni (2001, 2000). However, as a robustness check, we also compare estimates using the common correlated effects mean group estimator developed in Pesaran (2006b) and recently extended in Kapetanios, Pesaran and Yamagata (2006) to the case with nonstationary common factors. Following our initial discussion of the estimation of the parameters of the reduced form equation, we will then discuss the various approaches that we use to test the degree of heterogeneity required in order to explain the persistence of per capita income differences across countries.

The fully modified OLS (FMOLS) approach exploits the fact that under cointegration the asymptotic bias that occurs when the regressors are endogenous is a second order bias, and the differences in the regressors can serve as an instrument for this bias. Nuisance parameters associated with the dynamics are eliminated from the limiting distribution using nonparametric kernel estimates. The associated t-statistics constructed for individual countries are then distributed as standard normal. The group mean FMOLS estimator and test is then constructed from the sample averages of the individual member FMOLS estimators and test statistics, and thus allows for full endogeneity of the regressors as well as heterogeneity of the dynamics among countries. The estimator is superconsistent under cointegration, and is robust to the omission of variables that do not form part of the cointegrating relationship.

Pedroni (2000) also studies the small sample properties of the group mean FMOLS estimators and shows that, in contrast to pooled versions of the test, the group mean version has very small finite sample biases and the size distortion of associated t-tests are very small even in relatively short panels. Thus, even though the FMOLS estimates and tests for any one country based on only 43 years of data may not be very accurate, as the number of countries increases, the estimates become increasingly reliable. In short, even though we need to use caution when interpreting the estimators and tests for the data of any one individual country, estimates and standard errors regarding properties of the distribution become viable as the cross section dimension increases. Intuitively, even though the long run signals contained in 43 years of data may be relatively weak for any one country, as the signal pattern is repeated over a number of countries, the signal is amplified sufficiently to be observed and tested.

In table II we report the individual country FMOLS estimates for our sample and in table III we report the panel group mean estimates for various subgroupings of the sample. Our intuition is borne out by these results. The FMOLS group mean estimator for the panel as a whole, as well as various subgroupings provide credible estimates for the slope parameters as well as the average mean and average trend values. For example, for our sample of 29 countries, we find the estimated group mean trend growth rate to be 2.4%, and the group mean slope estimate to be 0.37, which implies a capital share parameter value $\alpha = 0.27$ with a standard error of 0.01. The group mean point estimates are superconsistent under cointegration, and converge at rate $T\sqrt{N}$, which permits us to obtain much more accurate estimates than would be possible with conventional methods. Furthermore, the point estimates for the group mean values are reasonable despite the fact that our panel regression does not include direct proxies for the intangible factors, and despite the fact that the regressors are endogenous. This is due to the fact that the group mean estimation is robust to endogeneity of the regressors, and the fact that for the cointegrated panel specification the effects of the unobserved factors are captured by the deterministic fixed effects and heterogeneous trends, so that the slope coefficient becomes a superconsistent and unbiased estimate which depends only on the structural parameters of the underlying production functions. These values are in stark contrast to the results from cross section regressions, which tend to produce unreasonably large estimates for the share parameters when intangible factors are not directly included in the regression.[7] We also report analogous group mean values in table III for the case in which the individual country data has been demeaned relative to the panel time period means, as previously discussed.[8] When we include these terms, the group mean slope estimates drop slightly, and the estimated capital share parameters also decrease to 0.22 for the full sample.

We also report group mean estimates for various subsamples, such as the subset of OECD and non-OECD countries as well as groupings that correspond to the nodes selected by Durlauf and Johnson's (1995) cross section based regression tree method. We will primarily be interested in examining the distributions within these nodes, but it is interesting at this point to compare the group mean point estimates. Durlauf and Johnson identify 4 different nodes, which differ in their production function share parameterizations and we also report the panel group mean estimates for these different nodes.[9] For comparison to the results of our full sample, we also report group mean estimates for two other samples. One is for the subsample of 23 countries which pass the more strict qualification

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[7] We also computed cross section estimates such as those in Mankiw, Romer and Weil and found very similar results for our sample. See earlier working paper versions of this paper, Pedroni (2004b), for further details.

[8] Demeaning the data with respect to the time period means implies that the group mean intercept and group mean trend estimates become approximately zero, as reported in table III.

[9] The countries in our sample that fall into Durlauf and Johnson's (1995) 2nd node are Egypt, Kenya, Morocco, Nigeria, Bolivia, and Turkey, and in the 3rd node are South Africa, Dominican Republic, Brazil, Columbia, Paraguay, Peru, Japan, Philippines, Sri Lanka, Ireland and Spain. The remaining countries fall into their 4th node, except for Luxembourg, which is not included in their study. None of our countries fall in their 1st node.

that the null of stationarity is rejected on an individual basis for each country, and thereby excludes Morocco, Nigeria, Chile, Belgium, Denmark and Sweden. The results for this subset are similar to the results for our core panel of 29 countries. Finally, for comparison, we also report results for the greater initial sample of 51 countries for which the full data series are available, regardless of their time series properties. While the inclusion of these other countries is likely to increase the noise to signal ratio present in the data with regard to the structural parameters of interest, the group mean FMOLS estimator nonetheless has the property of being robust to the inclusion of some countries whose series may be better represented as individually stationary. In this case, the FMOLS transformation results in the over-differencing of those regressors which are stationary. This has the effect of introducing noise, but this effect alone does not impact the limiting behavior of the statistic provided that the sample is sufficiently large and the proportion of countries for which the variables are cointegrated is sufficiently large. On the other hand, for these countries, the individual estimates will not be superconsistent, and the usual endogeneity problems will still be present. Nevertheless, it is interesting to note that the group mean FMOLS results for the broader sample of 51 countries are remarkably similar to the results for selected sample of 29 countries. This may point to the reassuring likelihood that our sample selection procedure has been very conservative, and that the long run cointegration properties that we have described are actually relatively pervasive among the greater sample as well.

When considering the specific interpretation of the various estimates reported in table II and III, it is important to recall from our discussion in section II that the interpretation of the slope coefficients as they relate to the structural parameters of the production function depend in turn on the precise nature of the intangible capital stocks that have been omitted. To the extent that the omitted intangible capital stock accumulates without the need to set aside a portion of measured per capita income, the slope parameter reflects only the physical capital share parameter, such that $\beta_i = \alpha_i(1-\alpha_i)^{-1}$ as per the steady state specification in equation (6) so that we can compute $\alpha_i = \beta_i(1+\beta_i)^{-1}$. It is this value which we report in the columns labeled α_i. On the other hand, to the extent that some component of the omitted intangible capital stock only accumulates by setting aside some portion of measured per capita income, then the relationship is determined by both the share of this factor and the physical capital factor, such that $\beta_i = \alpha_i(1-\alpha_i-\varphi_i)^{-1}$ as per the steady state specification in equation (7). In this case, the value $\alpha_i = \beta_i(1+\beta_i)^{-1}$ represents an upper bound on the share of the physical capital factor, such that the actual value for the share of physical capital is decreased in proportion to the value of the intangible capital share, since in this case the true value for the physical capital share will be $\tilde{\alpha}_i = (1-\varphi_i)\alpha_i = (1-\varphi_i)\beta_i(1+\beta_i)^{-1}$. Notice, however, that the extent to which such types of intangible capital exist only affects the implied values of the tangible capital share versus the intangible capital share. It does not impact whether or not the slope coefficients are common across countries. In other words, the more significant the share of this intangible capital input is, the further the share of physical capital will be from the reported upper bound. However, the values will be shifted downward uniformly for all members of the panel if the share parameters of the production function are uniform.

Nonetheless, it is still interesting to compare the estimated values for the upper bound values α_i with the corresponding values for $\tilde{\alpha}_i$ that are typically implied by the presence of intangible capital stocks such as human capital that follow accumulation equations which require the sacrifice of current output in order to accumulate the intangible capital stock. To get a rough idea of the quantitative implications for this effect on the estimated share parameters for the tangible physical capital, we report such estimates in the column labeled $\tilde{\alpha}_i$ by using the cross sectional information regarding the human capital share parameter. Specifically, for ease of comparison we use the schooling data from Mankiw, Romer and Weil (1992) to obtain a cross section estimate for β_2 which is specific to our sample of countries. The value is similar to the one obtained by Mankiw, Romer and Weil for their broader sample of countries.[10] We then combine this with our panel estimate for β_i from equation (1) to compute $\tilde{\alpha}_i = \beta_i(1+\beta_i+\beta_2)^{-1}$. The standard errors for these share parameters are computed by numerical simulation, and take into account the standard errors for both β_i from the panel regression and β_2 from the cross section regression. From this perspective, we can see that the values in the column labeled $\tilde{\alpha}_i$ can be interpreted as the distribution for the tangible capital share parameters conditional on a common human capital share parameter φ. In table III where we report group mean estimates for the various subsamples of the panel, we also estimate separate cross section values for β_2 for each subsample, so that value for φ is permitted to differ among the subsamples. Consequently, the columns labeled $\tilde{\alpha}$ in table III can be interpreted as values for the group mean physical capital share parameter conditional on a common human capital share parameter for the specific subsample. We should keep in mind however, that although the FMOLS estimates of the individual values β_i and the group mean estimates β^{GFM} from equation (1) are superconsistent, this is not true for the cross sectional estimate for β_2. Therefore, we report the

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[10] We also experimented with using the panel series for years of education per worker from Swanson, Nehru and Dubai (1993) in order to obtain an estimate, but found that the series generally did not cointegrate with our other series, and often gave nonsensical results for the slope coefficients. Thus, for the purposes of our rough estimate of the impact of human capital on the values of $\tilde{\alpha}_i$ relative to α_i we prefer to use the more conventional cross section data for schooling, which also facilitates comparison with Mankiw, Romer and Weil (1992) and subsequent studies.

columns labeled $\tilde{\alpha}_i$ here simply as a separate matter of interest. However, each of the tests for the parameter distribution that we will consider shortly is based directly on the estimates of β_i from equation (1), and thus are not affected by the cross section estimates for φ.

For all of the group mean FMOLS estimates and standard errors in table III, we also report values for the case in which the data has been demeaned over the cross sectional dimension in order to account for some of the likely cross sectional dependence through common time effects. However, as usual, it is possible that the cross sectional dependence is more complex than this. Recently, Pesaran (2006b) has developed a common correlated effects group mean (CCEGM) estimation procedure for time series panels that allows one to account for cross sectional dependencies that arise potentially from multiple common factors, and permits the individual responses to the common factors to differ across countries. The basic idea behind this approach is to use estimates of the cross sectional averages from each of the variables to proxy for multiple common factors, and to include these in the regression with member specific coefficients in order to allow for heterogeneous responses. More recently, Kapetanios, Pesaran and Yamagata (2006) have demonstrated how the technique can be applied for the case in which the common factors are nonstationary, so that the variables can become cointegrated for individual member of the panel via the common nonstationary factor.

There are two potential tradeoffs involved in the approach relative to our application that are worth noting. The first is that the technique is intended for the case in which the regressors are exogenous, so that we lose the ability to account for the likely endogeneity of investment shares. The second stems from the fact that in order for the technique to be applicable in a cointegrated panel context, cointegration among the variables must arise only via a common nonstationary factor. This second feature is potentially important for our application in that it implies that the individual country slope coefficients estimation is no longer superconsistent, but rather consistent at the more conventional $\sqrt{T}$ rate characteristic of stationary regressions. Thus, we potentially lose some of the attractive robustness features with respect to endogeneity, omitted variables, and so forth that usually come with superconsistent estimation under cointegration. The reason is because under this interpretation the cointegration between per capita incomes and investment shares is not driven by a common stochastic trend at the individual country level, but rather must be generated by a mutual dependency of both per capita incomes and investment shares on a stochastic trend that is common to all countries of the panel. However, considering the greater generality that is permitted for the cross sectional dependency, as a cross check, it is well worth comparing results based on this approach. The CCEGM estimates and corresponding standard errors are reported in table III. It is reassuring to note that for the core sample as well as the various subsamples, the CCEGM estimates are similar to the group mean FMOLS estimates, and generally fall somewhere between the group mean FMOLS estimates based on the raw data and the group mean FMOLS estimates based on the cross sectionally demeaned data. The standard errors for the CCEGM estimates are generally somewhat larger that those of the group mean FMOLS, but still indicate a confidence range that falls well within reasonable estimates. [11]

Next we turn to formal testing of the parameter distributions among the individual countries of the panel, as well as within various subsets of the panel. Our primary question of interest here is whether or not the parameterization of the aggregate production function that is consistent with conditional convergence once we account for the effect unmeasured factors such as intangible capital and barriers to production requires us to consider parameters that differ across countries. Clearly, the individual country FMOLS point estimates reported in table II appear to show considerable heterogeneity for the slope coefficients, which in turn implies heterogeneity for the structural share parameters of the neoclassical aggregate production function. However, we should keep in mind that in contrast to the group mean estimates reported in table III, the individual country estimates reported in table II are based on a relatively small number of data points and are not as reliable. It is possible that the apparent heterogeneity stems largely from the effect of sampling variation and the fact that the span of data is relatively short for any one country. The differences in the group mean estimates for the subsamples of the panel reported in table III give us a stronger indication that the heterogeneity is not simply due to small sample effects. But in these cases, we would like to know further whether the heterogeneity is limited to different country types, or whether it is pervasive even within these country groups. For example, is the parameter heterogeneity attributable simply to whether a country is a member of the relatively more developed OECD group or the less developed non-OECD group, or is there substantial true heterogeneity within these groups as well? To address these issues, we construct two types of tests. The first are tests for restrictions implied by a common parameterization within each grouping, and thus are tests for the null hypothesis of homogeneity of the production function share parameters. The second type are tests which allows us to reverse the form of the null hypothesis to test the null hypothesis of heterogeneity

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[11] If the rank of the common factors is assumed to be no greater than the number of observed variables, then it is also possible to consistently estimate the individual country slope coefficients and standard errors using the correlated common effects estimator, which we have also done. The results are also similar to the FMOLS estimates. In the interest of space, these are not reported, but are available upon request from the author.

of the production function.

The first test for the null of hypothesis of homogeneity of the share parameters is constructed as an F-test based on the residuals of the individual and group mean FMOLS estimated regressions. Specifically, we are constructing a test for the restrictions implied by the case in which the parameterizations are taken to be common across the countries of the particular sample. This is equivalent to asking whether the values for the individual parameters which are consistent with conditional convergence for the sample are also consistent with a common production function. Thus, we can construct a Wald statistic that compares the sum of squared errors for the restricted case when $\beta_i = \beta$ for all i versus the case with unrestricted heterogeneous β_i values that are consistent with cointegration in the panel. In this case, the Wald statistic for the null hypothesis $H_o: \beta_i = \beta$ takes the standard form of an F-test.

Wald statistics are well known to over-reject the null hypothesis when the number of restrictions is large, as is certainly the case when applied to a panel as we are doing here. Indeed, in Monte Carlo simulations[12] we show that the F-test constructed from FMOLS residuals behaves in the same way, in that the test statistic rapidly becomes oversized as the cross sectional dimension of the panel grows large. However, what is interesting for the current application is that the test still retains substantial power once one adjusts for the large size distortion. In the same Monte Carlo simulations, we show that when size adjusted critical values are used, then when the true parameters are taken to be the same as the heterogeneous point estimates from our sample, then the power to reject the homogeneous null at a 10% p-value is approximately 99.5% for the core sample of 29 countries, and ranges from 80% to 99% for all of the subsamples except the very smallest subsample of 6 countries, for which it is still approximately 50%.

Intuitively, is not difficult to see why the F-test should have no problem distinguishing the two hypotheses once one adjusts for the size distortion. The reason is because when the restriction under the null is incorrect, this implies that a value for β_i is being used which does not represent a true cointegrating vector, in which case the residuals from the regression will be nonstationary. Consequently, when the restriction is incorrect, then the F-statistic will quickly diverge and reject the null hypothesis. This appears to be the scenario that we encounter. The results of the tests applied to the panel as a whole as well as the various subsamples are reported in table IV under the columns labeled “F-tests”. In all cases, when using the size adjusted critical values, the F-tests strongly reject

[12] The full simulations results are available from the author upon request.

the null hypothesis that the values for β_i are homogeneous.

As a cross check, we also computed a different type of test for the null hypothesis $H_o: \beta_i = \beta$ for all i. Specifically, we computed the mean and variance bias adjusted $\tilde{\Delta}_{adj}$ dispersion test proposed by Pesaran and Yamagata (2006). One of the important appeals of this test for our application is that it performs well for panels with large cross sectional dimensions and does not become oversized as does the Wald statistic. On the other hand, the test is designed for the case in which the regressors are strictly exogenous, and is not designed for panel data that is nonstationary due to the presence of unit roots. These represent limitations relative to the current application. Nevertheless, given that the test is designed for panels with large cross sectional dimensions, it provides a potentially useful robustness check. The results of these tests applied to the panel as a whole as well as to the various subsamples are reported in column 2 of table IV. It is reassuring to see that in all cases the results of the $\tilde{\Delta}_{adj}$ tests agree with those of the size adjusted F-tests, in that they universally reject homogeneity.[13] These results indicate that conditional on the fixed effects and heterogeneous trends alone, per capita incomes still do not appear to be converging to a common steady state. Rather, it is only after we allow for heterogeneous production function parameterizations that we achieve conditional convergence.

The results of these F-tests and $\tilde{\Delta}_{adj}$ tests provide compelling evidence in favor of the idea that while intangible capital and barriers to production may be important, these alone are unlikely to be able to explain the persistent disparity in per capita incomes that are observed, and that only by looking for mechanisms that can explain the heterogeneity of aggregate production functions can we fully explain per capita income disparities. However, we wish to take this one step further. Throughout this paper we have reported the results of tests both in terms of the conventional null hypotheses, and in terms that reverse the null hypothesis with the alternative hypothesis. In keeping with this spirit, we do the same in the context of testing the parameter distribution, and apply a test for the null hypothesis of heterogeneity. In other words, the test allows us to position the null so that we ask directly whether heterogeneity of the production function is necessary for conditional convergence even after accounting for unobserved factors. This cross testing using the reverse null is particularly useful given the known weaknesses of the tests for the null of homogeneity. Furthermore, one might argue that the hypothesis that the parameters for all members of the panel are homogeneous is overly restrictive, even for the smaller subsamples, and that it would be

[13] We also computed F-tests using the CCEGM estimator, which produced similar results in that the null hypothesis was strongly rejected for the panel as a whole as well as for each of the various subsamples.

useful to approach the question from the reverse null hypothesis of whether or not heterogeneity is truly necessary to explain per capita income patterns. As we will see, this form of cross testing also provide us with some interesting implications for the patterns within the subsamples.

The basic idea behind the test for the null of cointegration slope heterogeneity is to start with the maintained hypothesis that the individual members of the panel are cointegrated, and then test the null hypothesis of whether slope coefficients are heterogeneous. This is accomplished by transforming the lefthand side variable, y_{it}, as $\tilde{y}_{it} = y_{it} - \frac{\Omega_{21}}{\Omega_{22}} x_{it}$, where x_{it} is the regressor, and $\Omega_{21} = N^{-1}\sum_{i=1}^{N} \Omega_{21i}$ and $\Omega_{22} = N^{-1}\sum_{i=1}^{N} \Omega_{22i}$ are taken as averages of the corresponding elements of the long run covariance matrices for the differences of the original variables, Δy_{it} and Δx_{it}.[14] The cointegrating regresion such as (1) is then reestimated using $\tilde{y}_{it}$ in place of y_{it}, and the residuals of this transformed regression, $\hat{\mu}^*_{it}$ are tested for a unit root. The null hypothesis $H_o: \rho_i = 0$ for all i for $\Delta\hat{\mu}^*_{it} = \rho_i \hat{\mu}^*_{it-1} + \eta_{it}$, where η_{it} is a stationary process becomes a test for the null hypothesis $H_o: \beta_i \neq \beta$ for all i for any unknown value β, against the alternative $H_A: \beta_i = \beta$ for some i.

Furthermore, as demonstrated in the technical appendix, the distribution for this test is asymptotically equivalent to a raw panel unit root test. However, in practice, for small samples the limiting distribution may be a poor approximation. Typically, for panel unit root tests, the small sample distribution is sensitive to a number of choices that can affect the size of the test. For example, in parametric ADF type tests, the distribution is sensitive to the choice of lag truncation. In semi-parametric Phillips-Perron type tests, the distribution can be sensitive to the choice of bandwidth for the kernel estimator. In the test that we have described here, we have these usual concerns. In addition, we have to worry about similar choices for the kernel estimation of Ω_{21}/Ω_{22} that is used for the transformation of the cointegrating regression. To deal with these issues, and the size distortion that they are likely to create relative to the limiting distribution, we perform a simple bootstrap exercise to improve the small sample properties of the test. Specifically, most panel unit root tests take the form $v^{-1}(z_{NT} - u\sqrt{N}) \sim N(0,1)$ where z_{NT} is the panel unit root statistic standardized with respect to *T* and *N*, and u and v^2 are the mean and variance adjustment terms respectively that are required to render the distribution standard normal. In the limiting distribution, u and v^2 depend only on the moments of the underlying Brownian motion functionals, whereas in

[14] This notation abstracts from the country specific determinstic terms, which are assumed to have been concentrated out in a first step regression. For a more detailed discussion of this test statistic, see earlier working paper versions of this paper, such as Pedroni (2004b). A technical appendix which derives the limiting distribution of this test and describes the bootstrap technique that we apply, is also available upon request.

small samples, they can be sensitive to the choices described above. Im, Pesaran and Shin (2003), for example, report values for u and v^2 for their panel unit root test depending on the particular lag truncation that is chosen. Here, we use a bootstrap to obtain small sample adjustment terms for the values of u and v^2 for the various tests that we implement. We implement the bootstrap for three different panel unit root tests applied to the residuals of the transformed regression. The first is a semi-parametric test based on the autoregressive parameter, analogous to the Phillips-Perron ρ test, which we label $SP\text{-}\rho$, the second is a semi-parametric test based on the t-test for the autoregressive parameter, analogous to the Phillips-Perron t-test, which we label $SP\text{-}t$, the third is a parametric ADF style test, which we label $ADF\text{-}t$.

The results for these tests are reported in table IV for the full sample as well as for the various subsamples, both for the raw data as well as for the data demeaned with respect to the time period means, which again is comparable to the inclusion of common time dummies. In both cases, all tests are unable to reject the null hypothesis of heterogeneity for the full panel as well as for the subset of 23 countries for which the stronger criteria of individual rejection of the null of stationarity for investment shares applies. The rejection of the null hypothesis of heterogeneity in these cases implies that we cannot reject the possibility that conditional convergence requires heterogeneous production function parameters among these countries even when we allow for the effects of country specific intangible capital or barriers to production through the fixed effects and country specific trend terms of equation (1). The result is consistent with the previously discussed F-tests and $\tilde{\Delta}_{adj}$ tests , which reject the null hypothesis that a common set of values for the production function parameters are consistent with conditional convergence under these conditions.

Of course, just as we argued with the homogeneity tests, it may hardly be surprising to find for such a large and varied group of countries that the production function parameters are heterogeneous. Consequently, we also examine this hypothesis for various subsets of countries which are more similar to one another, such as the OECD and non-OECD groupings, and the various nodes of the Durlauf and Johnson (1995) study. In these cases, the combination of the tests for homogeneity and the bootstrapped tests for heterogeneity reveal a somewhat more interesting pattern. For example, in the case of the non-OECD group of 15 countries, all of the tests for the null of heterogeneity also fail to reject, which accords with the rejection of homogeneity tests for these groups. By contrast, for the OECD group of 14 countries, when we examine the data relative to the time means, all three statistics result in a rejection of the null of heterogeneity. What does this imply considering that the F-tests also reject the null of homogeneity? The answer appears to be that for this group of 14 countries there exists a smaller subgroup for which the production functions are in fact similar, even though they are not similar across the entire group of 14. To see this, consider the logic of combining the two different null hypotheses in the case where the sample is potentially mixed in the sense that it contains two possible subgroups that differ with regard to whether or not they share common production function parameterizations. In this scenario, the homogeneity tests reject the null hypothesis that in order to be consistent with conditional convergence within the sample it is possible to have a common parameterization for the production function implied by the group mean estimate. Thus, the tests imply that there is at least some significant fraction of countries within the sample for which heterogeneous parameterizations are required in order to achieve conditional convergence, even when we account for unobserved mechanisms such as intangible capital and barriers to production. Then, by way of the test for heterogeneity, we *also* reject the null hypothesis that we require *all* countries within the sample to possess different production function parameterizations in order to achieve conditional convergence. Consequently, we conclude that there must be at least some sizeable or at least nonnegligible subgroup of the sample of 14 OECD countries for which the production function parameterizations *can* be taken to be common such that we still achieve conditional convergence. In other words, *within* the OECD, there appears to be a small but nonnegligible club of countries for which this is true, even though it is not true, even as an approximation, for the OECD group as a whole.[15] In this manner we see that using the combination of the homogeneity tests and the heterogeneity tests becomes informative beyond the use of either one of these alone, particularly when we apply the combination to different subsets of the sample.

We obtain similar results for the Durlauf and Johnson nodes. Nodes 2 and 3 contain predominantly less developed economies, and for these the bootstrap tests are unable to reject the null of heterogeneity when we consider the tests for the data relative to the time means, just as we found for the subset of non-OECD countries. Node 4, on the other hand, contains predominantly more developed economies, and for this node we find a

[15] One might wonder then how it is possible that we do not observe the same pattern of test results for the full panel of 29 countries. In other words, if there is a subgroup of the 14 OECD countries for which the parameterizations can be taken as common, then by construction there must also be a subgroup for the full panel of 29 countries for which this is true. There are two reasons to anticipate such results. One reason is that the group mean value which is being compared in the two samples are not same. The other, more substantial reason why such a result is to be expected is because a rejection implies that a sufficient nonnegligible proportion of countries exhibit properties contrary to the null hypothesis. For the smaller sample, the absolute number of countries that must contradict the null hypothesis in order to obtain a rejection is smaller. Consequently, if the number of individual countries that meet the criteria for rejection is fixed, then we should anticipate that the null hypothesis is more likely to be rejected in a subset of the full sample that includes a higher proportion of these countries then does the full sample, which is the result that we find.

combination of tests results similar to the ones obtained for the OECD subsample. For node 4 we can reject by virtue of the homogeneity tests that the production function parameterizations can be treated as common across all countries, while the bootstrap tests for heterogeneity tell us that there must exist at least some nonnegligible subgroup within this node for which the parameterizations can be treated as common.

Given that we require heterogeneous parameterizations of the production function to account for the persistent dispersion of income, even among many relatively similar countries, this leads us to ask whether there are any systematic recognizable patterns in the distribution of the parameter shares implied by these results. The first feature to note is that the capital share estimates are uncorrelated with initial values of per capita income take from 1950, as we would expect. However, as depicted in figure I, we can see that the pattern of capital share parameters consistent with conditional convergence is highly correlated with the subsequent average annual growth rates over the sample period. Thus, countries such as Venezuela, which began with relatively high initial levels of per capita income but had relatively small capital shares tended to move toward a relatively low growth rate in in the subsequent period. Countries such as Japan, with relatively low initial values of per capita income but high capital share values subsequently experienced high growth rates. By contrast, countries such as Egypt or Morocco, which began with low incomes and small capital share parameters tend have stayed poor, with low subsequent growth rates. This phenomenon is not limited merely to the distinction between OECD and non-OECD countries, but holds within these subsets as well. A more formal regression analysis of these correlation patterns is reported in table V.[16]

These relationships point to the fact that allowing for heterogeneous parameters opens up an additional channel through which we can explain the persistent disparity of per capita incomes. This begs the question as to what economic features might account for the particular distribution pattern for the parameter shares in the first place. Consequently, we experimented with a number of common measures that have been used to proxy variables that might be associated with such a pattern. For example, a common theme in much of the literature on multiple production regimes is that human capital may serve to produce threshold effects which result in production regimes

[16] In all cases we have used the values for $\tilde{\alpha}_i$ to represent the capital share. Since $\tilde{\alpha}_i$ is a monotonic transformation of α_i it does not matter much in terms of the basic pattern which of these values we use. In both the diagrams and the regressions we have omitted Peru, since the standard error for Peru is uniquely large and the point estimate is slightly negative. However, the correlation and regression fit is not affected much by the inclusion or exclusion of Peru. In figure I, Japan appears as an extreme case along the regression line. When we experimented by omitting Japan, the correlation and regression fit further increased slightly. A figure depicting the correlation between initial incomes and capital shares can be seen in Pedroni (2004b).

in which the share parameter for capital should be higher for countries with higher levels of per capita human capital. Thus we experimented by comparing the parameter shares with the values for per capita human capital for these countries, as reported in Hall and Jones (1999). However, as the analysis in table V reveals, there does not appear to be any systematic correlation between the level of per capita human capital and the estimated capital share parameters for the core sample. The same is true for the rate of human capital investment as proxied by schooling rates taken from Mankiw, Romer and Weil (1992).

By contrast, when we experimented with various measures for social capital infrastructure, we did find a systematic positive relationship between these measures and the capital share parameters. For example, table V reports a statistically significant positive correlation between the capital share values and the government anti-diversion index used in Hall and Jones (1999) as well as the economic openness measure used in Hall and Jones. Hall and Jones also construct what they refer to as a social infrastructure measure by using a combination of the openness and government anti-diversion index. Figure II depicts the positive correlation that we find between this social infrastructure measure and the capital shares. In this case we notice the sample splits broadly into two major clusters which are responsible for the overall relationship. It is also interesting to note that unlike human capital levels or schooling rates, literacy rates do appear to be positively correlated with the parameter shares that are consistent with conditional convergence. It is possible that basic literacy behaves much like a proxy for social capital in the sense that it proxies the overall level of social cohesion rather than proxying the level of human capital embodied in the population. The fact that these various measures for social infrastructure capital help to explain the distribution pattern for the capital shares may point to a secondary role for social capital which goes beyond simply acting as an unmeasured production factor that enhances the productivity of other inputs or inhibits barriers to the adoption of new technologies that impact the estimated country specific trend growth rates. The positive relationship between social infrastructure measures and capital share parameters may point to a possible role that social capital might play in generating multiple production regimes, much in the way that human capital has been modeled in the literature. This supports the idea that the key to understanding the role that social capital plays in the disparity of income levels lies in developing a better understanding of how it becomes associated with different production regimes among otherwise similar countries.[17]

[17] The government anti-diversion index from Hall and Jones (1999) reflects measures intended to capture concepts such as the degree of law and order, bureaucratic quality, corruption, risk of expropriation and government repudiation of contracts. Schooling rates reflect average years of educational attainment of the population aged 25

IV. Concluding Remarks

In this study we have exploited recent advances in the econometrics of nonstationary panels to study the steady state relationship implied by an augmented neoclassical Solow growth model. In contrast to conventional dynamic panel data techniques, nonstationary panel techniques allow us to focus explicitly on the low frequency relationships. At the same time, the techniques permit us to relax many of the strong counterfactual assumptions that are typically required for cross section based studies and conventional dynamic panel based studies. Most importantly, the approach used in this study has provided us with opportunities to study the implications of empirical relationships that are otherwise difficult to observe directly with the limited data that is available.

The primary findings in this paper point to the idea that within the neoclassical framework of a common aggregate Cobb-Douglas production function an appeal to unobserved factors of production or different rates of technology absorption alone are unlikely to be sufficient to explain the persistent cross country differences in per capita income that are observed. Rather the findings in this paper point to the fact that empirically aggregate production technologies differ significantly among countries, and that within the neoclassical framework accounting for these heterogeneities is necessary in order to explain observed patterns of per capita income divergence across countries. This is not to say that unobserved factors do not play a role in generating per capita income differences, but rather that the role that they play is not sufficient to account for full extent of the dispersion in per capita income unless they can also account for production function heterogeneity.

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and over. We also experimented to see whether the correlation patterns were limited to our core sample, or whether they also extended to the broader sample of 51 countries. Indeed, as we see in table V the basic pattern appears to extend to the broader sample as well, in that initial income levels are uncorrelated with the parameter shares, while growth rates are positively correlated. Likewise, schooling measures are also uncorrelated, and human capital measures are only very weakly correlated, while social infrastructure continues to be significant and positively correlated. For reasons discussed previously, the share estimates are likely to contain a higher proportion of noise in the larger sample, and it is not surprising to find that in those cases where a positive correlation holds for the broader sample, the R^2 measures are considerably weaker than for our core sample of 29 countries. One interesting detail to note is that for the broader sample of 51 countries we no longer detect a positive correlation for the government anti-diversion index and the economic openness measure. In this sense, focusing on the narrower sample may also help us to uncover particular patterns that would not otherwise be apparent.

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Table I. Panel Unit Root and Cointegration Properties

test	*(log investment shares)* raw I(1)	raw I(0)	relative to mean I(1)	relative to mean I(0)	*(log per capita income)* raw I(1)	raw I(0)	relative to mean I(1)	relative to mean I(0)
unit root:	-0.80	13.8 ***	-0.87	15.9 ***	4.58	17.4 ***	-0.31	14.1 ***
	pp	adf	pp	adf	shin		shin	
cointegration:	1.31	1.58	-1.91 **	-1.3 *	-0.55		0.73	
	CADF	trace-B	trace-J		CADF	trace-B	trace-J	
robust tests:	-1.67	0.0625	939		-1.56	0.0634	3741	

Notes: For unit root tests, columns labeled I(1) report IPS test, columns labeled I(0) report Hadri (2000) type test. For cointegration tests columns labeled PP and ADF report the Pedroni (1999, 2004a) group mean tests for null of no cointegration, and columns labeled "shin", report an analogous group mean panel test for null of cointegration based on the Shin (1994) time series test. Fixed effects have been included in all cases, and heterogeneous trends have been included for all tests involving log per capita income. For robust tests, CADF test is from Pesaran (2006a) and trace-B and trace-J are from Pedroni and Vogelsang (2005). Symbols *,**,*** denote 10%,5%,1% rejections.

Table II: Individual Coefficient Estimates

country	intercept	trend	slope	std err	α_i	std err	$\tilde{\alpha}_i$	std err
Egypt	6.31	0.029	0.09	0.05	0.08	0.04	0.05	0.02
Kenya	6.05	0.014	0.08	0.07	0.08	0.06	0.05	0.04
Morocco	6.52	0.028	0.04	0.06	0.04	0.06	0.02	0.04
Nigeria	4.84	0.022	0.58	0.09	0.37	0.04	0.26	0.01
S. Africa	6.13	0.017	0.50	0.06	0.33	0.03	0.23	0.00
Dominican R	6.42	0.019	0.21	0.08	0.17	0.05	0.11	0.03
Bolivia	6.31	0.019	0.22	0.04	0.18	0.03	0.12	0.01
Brazil	4.93	0.036	0.72	0.11	0.42	0.04	0.31	0.01
Chile	6.95	0.011	0.31	0.09	0.24	0.06	0.16	0.03
Columbia	7.13	0.022	0.04	0.12	0.04	0.12	0.02	0.08
Paraguay	6.47	0.008	0.30	0.11	0.23	0.06	0.15	0.04
Peru	7.68	0.010	-0.04	0.20	-0.04	0.29	-0.03	0.21
Venezuela	8.52	0.004	0.08	0.10	0.07	0.09	0.04	0.06
Japan	4.80	0.041	0.87	0.09	0.47	0.02	0.35	0.00
Philippines	5.87	0.013	0.41	0.07	0.29	0.04	0.20	0.01
Sri Lanka	6.32	0.007	0.37	0.11	0.27	0.06	0.19	0.03
Austria	6.78	0.032	0.44	0.10	0.30	0.05	0.21	0.02
Belgium	7.04	0.029	0.41	0.09	0.29	0.04	0.20	0.02
Denmark	7.39	0.026	0.36	0.03	0.26	0.01	0.18	0.00
Finland	6.74	0.035	0.41	0.07	0.29	0.04	0.20	0.01
Germany, W.	4.91	0.036	1.01	0.14	0.50	0.04	0.38	0.01
Ireland	7.25	0.030	0.19	0.05	0.16	0.03	0.10	0.01
Italy	6.04	0.039	0.58	0.16	0.37	0.07	0.26	0.04
Luxembourg	7.92	0.025	0.21	0.05	0.17	0.03	0.11	0.01
Netherlands	6.53	0.029	0.58	0.11	0.37	0.04	0.26	0.02
Norway	7.75	0.034	0.16	0.05	0.14	0.04	0.09	0.02
Spain	5.24	0.030	0.83	0.12	0.45	0.04	0.34	0.01
Sweden	7.48	0.023	0.39	0.09	0.28	0.05	0.19	0.02
Turkey	6.51	0.024	0.24	0.07	0.19	0.05	0.13	0.02

Notes: Estimates are FMOLS coefficients of equation (1) in section II. Columns labeled α_i and $\tilde{\alpha}_i$ report corresponding share parameters as defined in section II. Standard errors for share parameters were computed by numerical simulation.

Table III: Panel Group Mean Coefficient Estimates

sample	intercept	trend	slope	std err	α	std err	$\tilde{\alpha}$	std err
			Group Mean FMOLS Raw data					
full panel (29)	6.51	0.024	0.37	0.02	0.27	0.01	0.18	0.01
subset (23)	6.46	0.024	0.37	0.02	0.27	0.01	0.19	0.01
All-ctrys (51)	6.66	0.023	0.34	0.01	0.25	0.01	0.18	0.01
non-OECD (15)	6.43	0.017	0.26	0.03	0.21	0.02	0.15	0.01
OECD (14)	6.60	0.031	0.48	0.02	0.32	0.01	0.27	0.03
DJ-node2 (6)	6.09	0.022	0.21	0.03	0.17	0.02	0.12	0.01
DJ-node3 (11)	6.20	0.021	0.40	0.03	0.29	0.02	0.31	0.03
DJ-node4 (11)	6.92	0.027	0.43	0.03	0.30	0.01	0.24	0.01
			Group Mean FMOLS Relative to Mean					
full panel (29)	0.01	-0.001	0.28	0.02	0.22	0.01	0.14	0.01
subset (23)	0.01	-0.001	0.27	0.02	0.21	0.01	0.14	0.01
All-ctrys (51)	-0.00	-0.000	0.27	0.01	0.22	0.01	0.15	0.01
non-OECD (15)	0.04	-0.001	0.20	0.03	0.17	0.02	0.12	0.00
OECD (14)	-0.01	-0.000	0.29	0.03	0.22	0.02	0.18	0.01
DJ-node2 (6)	0.02	-0.002	0.26	0.03	0.21	0.02	0.15	0.01
DJ-node3 (11)	0.01	-0.000	0.33	0.03	0.25	0.02	0.27	0.02
DJ-node4 (11)	-0.02	0.000	0.18	0.03	0.15	0.02	0.12	0.01
			Common Correlated Effects Mean Group					
full panel (29)	8.53	0.026	0.32	0.04	0.22	0.02	0.15	0.02
subset (23)	8.70	0.027	0.33	0.05	0.23	0.03	0.16	0.02
All-ctrys (51)	8.43	0.024	0.27	0.03	0.20	0.02	0.13	0.01
non-OECD (15)	8.36	0.024	0.25	0.06	0.18	0.04	0.13	0.03
OECD (14)	8.92	0.028	0.33	0.06	0.22	0.04	0.17	0.03
DJ-node2 (6)	8.58	0.026	0.28	0.09	0.20	0.05	0.14	0.04
DJ-node3 (11)	8.58	0.027	0.30	0.07	0.20	0.05	0.16	0.04
DJ-node4 (11)	8.91	0.026	0.32	0.07	0.22	0.04	0.16	0.03

Notes: Intercept, trend and slope estimates are for the coefficients of equation (1) in section II. Columns labeled α and $\tilde{\alpha}$ report share parameter estimates as defined in section II. FMOLS estimates are based on the Pedroni (2000) group mean panel FMOLS estimator. Rows labeled "relative to mean" refer to results relative to panel means, comparable to the inclusion of common time effects. Correlated effects mean group estimates are based on the Pesaran (2006) CCEMG estimator. See section III for further details, including descriptions of the various subsamples.

Table IV. Panel Tests for Cross Country Parameter Distributions Consistent with Conditional Convergence

sample	F-test	$\tilde{\Delta}_{adj}$	PP-r	PP-t	ADF
		raw data			
Full Panel (29)	4439 ***	28.93 ***	6.33	8.07	2.82
Subset (23)	5621 ***	26.02 ***	9.07	13.85	-0.12
Non-OECD (15)	1687 ***	15.98 ***	3.45	3.31	0.42
OECD (14)	11240 ***	19.29 ***	3.83	4.66	3.41
DJ-node2 (6)	1048 ***	7.36 ***	0.69	0.53	0.26
DJ-node3 (11)	5107 ***	20.48 ***	3.19	4.33	-2.81 ***
DJ-node4 (11)	6459 ***	13.44 ***	-3.16 ***	-4.14 ***	-3.50 ***
		relative to mean			
Full Panel (29)	90 ***	23.99 ***	1.36	2.00	-0.26
Subset (23)	100 ***	19.62 ***	1.82	2.51	0.69
Non-OECD (15)	58 ***	9.84 ***	0.85	0.81	-0.22
OECD (14)	52 ***	13.49 ***	-6.83 ***	-2.41 ***	-2.47 ***
DJ-node2 (6)	32 ***	5.00 ***	0.05	-0.06	-0.79
DJ-node3 (11)	101 ***	15.41 ***	-0.07	0.48	0.45
DJ-node4 (11)	16 ***	2.53 ***	-2.06 **	-3.61 ***	-2.37 ***

Notes: Columns labeled F-test and $\tilde{\Delta}_{adj}$ are for the null hypothesis of equal slopes, $\beta_i=\beta$, for equation (1) of section II. Columns labeled PP-r, PP-t and ADF report tests for null hypothesis of heterogeneous slopes, $\beta_i\neq\beta$, for equation (1) of section II, based on the bootstrap. The $\tilde{\Delta}_{adj}$ tests is from Pesaran and Yamagata (2006). Columns labeled "relative to mean" refer to results relative to panel means, comparable to the inclusion of common time dummies. The symbols *,**,*** denote 10%,5%,1% rejections respectively. See section III for further details and discussion of the bootstrap procedure.

Table V. Correlation Analysis of Distribution Pattern for Share Parameters Consistent with Conditional Convergence

	core sample (N=28)			broader sample (N=51)		
correlate	slope	t-test	R^2	slope	t-test	R^2
initial log per capita output	0.02	0.74	0.02	0.03	1.21	0.03
per capita output growth	5.33	3.43	0.31	3.48	2.09	0.08
schooling (MRW)	0.01	1.36	0.07	0.00	0.79	0.01
schooling (HJ)	0.01	0.98	0.04	0.06	0.86	0.01
per capita human capital (HJ)	0.08	0.95	0.03	0.06	1.70	0.06
log total factor productivity (HJ)	0.04	1.18	0.05	-0.00	-0.10	0.00
government anti-diversion index (HJ)	0.17	1.99	0.13	-0.04	-0.66	0.01
economic openness (HJ)	0.11	1.90	0.12	0.09	1.17	0.03
social infrastructure (HJ)	0.15	2.07	0.14	0.10	1.92	0.07
literacy (DJ)	0.16	2.62	0.21	0.15	2.63	0.13

Notes: Computed pairwise by linear regression. Dependent variable in all cases is the $\tilde{\alpha}_i$ estimate from table II or equivalent for the case of the broader sample. Columns labeled t-test report significance tests. Column labeled R^2 reports regression fit. Intercept values are not reported in the interest of space. Abbreviations in parentheses for correlates indicate source of data as follows. MRW: Mankiw, Romer and Weil (1992), HJ: Hall and Jones (1999), DJ: Durlauf and Johnson (1995). See section III.

Figure I. Relationship Between Per Capita Output Growth and Parameter Shares Consistent with Conditional Convergence

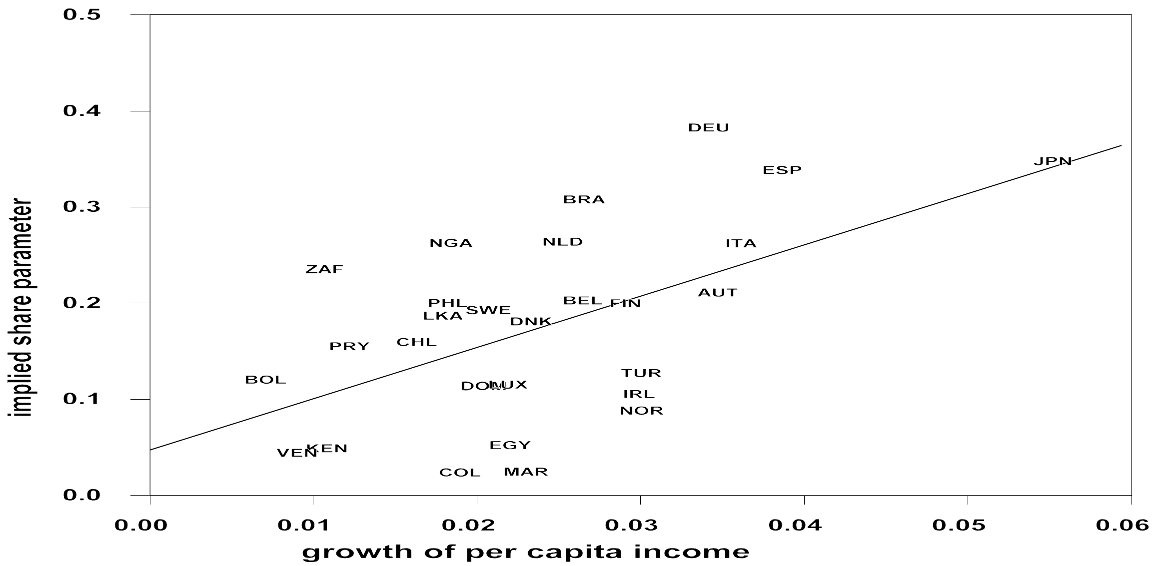

Figure II. Relationship Between Social Infrastructure and Parameter Shares Consistent with Conditional Convergence