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Labor Productivity, Capital Accumulation, and Aggregate Efficiency Across Countries: New Evidence for an Old Debate

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Labor Productivity, Capital Accumulation, and Aggregate Efficiency Across Countries: New Evidence for an Old Debate

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Abstract

This article studies the proximate sources of labor productivity differences across countries. Using a panel dataset for 74 countries covering the 1960-2010 period, it first documents that, relative to the US, labor productivity of the median country has been mostly stagnant, while cross-country disparities have drastically increased. Next, through the lens of a production function framework, it evaluates the proximate sources of labor productivity: physical capital, human capital, and aggregate efficiency. Results show stagnation and increasing disparities in physical capital, growth and decreasing disparities in human capital, and decline and increasing disparities in aggregate efficiency. By including the commonly unaccounted covariance between capital and aggregate efficiency into the analysis, disparities in aggregate efficiency explain most of the disparities in labor productivity across countries.

Keywords: Productivity, Capital Accumulation, Efficiency, Stylized Facts

1. Introduction

As summarized by Hsieh and Klenow (2010), most recent research studies in the growth and development literature analyze income and labor productivity differences across countries in way that is consistent with the schematic relations depicted in Figure 1. Factors that affect labor productivity are commonly classified into two layers. The first one includes proximate production sources such as capital accumulation (both physical and human) and aggregate efficiency. Going one step further, the second layer includes more fundamental or deeper determinants such as geography, culture, institutions and policies.

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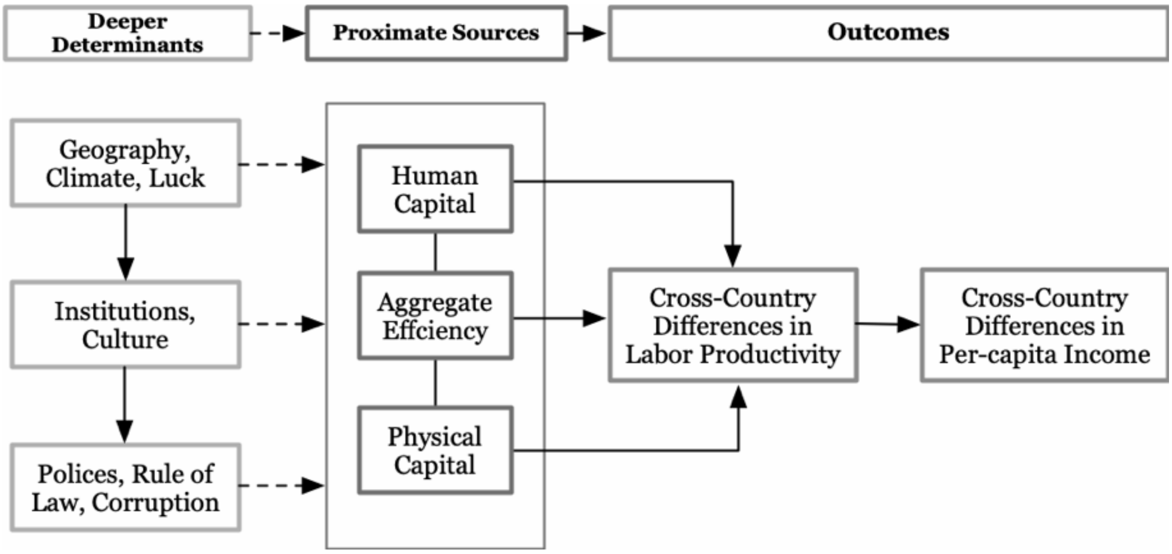
Figure 1 Sources of Labor Productivity and Income Differences Across Countries



Note: In their original diagram, Hsieh and Klenow (2010) use the term "total factor productivity (TFP)" instead of aggregate efficiency. Both terms are conceptually equivalent. Also, their original diagram only points to per-capita income differences rather than labor productivity differences.
Source: Adapted from Hsieh and Klenow (2010).

In the context of Figure 1, the present article analyzes the proximate sources of labor productivity. First, it quantitatively describes the cross-country dynamics of each proximate source. Next, the article revisits the debate about the relative contribution of capital accumulation versus aggregate efficiency. On the one hand, Mankiw et al. (1992) apply regression methods to conclude that capital accumulation differences explain most of the variation of labor productivity across countries. On the other hand, Klenow and Rodriguez-Clare (1997) apply calibration methods to conclude that aggregate efficiency explains most of this variation. On this debate, this article emphasizes that the source of disagreement is on the methodological assumptions of both lines of research. On the one hand, capital proponents rely on the independence between capital accumulation and aggregate efficiency to consistently estimate an unbiased OLS regression. On the other hand, efficiency proponents rely on competitiveness of factor markets to calibrate their model parameters.

It has been documented that, relative to the US, labor productivity of the median country of the world has been mostly stagnant, at least since the 1960s. Also, labor productivity differences across countries have drastically increased in the postwar period (Duarte and Restuccia 2006; Mendez-Guerra 2015; Parente and Prescott 1993). To shed some light on these global development problems, the main objective of the present article is to understand the sources of labor productivity by analyzing the novel productivity database of Fernandez-Arias (2014). The methodological approach for analyzing the data follows the production function framework of Hall and Jones (1999) and it is also complemented with some basic regression models. For a sample of 74 countries over the 1960-2010 period, results suggest a similar pattern of stagnation and increasing dispersion in physical capital, an improvement and decreasing dispersion in human capital, and a deterioration and increasing dispersion in aggregate efficiency.

The article also shows how standard regression methods tend to overestimate the fraction of the variation in labor productivity that is explained by physical capital. The source of this upward bias is the unaccounted covariance between capital and aggregate efficiency. Taking this covariance into account, most of the variation in labor productivity turns out to be explained by aggregate efficiency.

After this introduction, Section 2 describes the methods and data. Section 3 presents an evaluation of the three proximate sources of labor productivity. Section 3 discusses what factors could be driving the dynamics of aggregate efficiency. Section 4 offers some concluding remarks

2. Methods and Data

2.1. A Production Function Approach

Based on the standard neoclassical growth model, Hall and Jones (1999) apply the following production function approach to evaluate the relative contribution of proximate sources of labor productivity:

$$Y_i = A_i K_i^{\alpha}(h_i L_i)^{1-\alpha} \text{ for all } \alpha \in (0,1). \tag{1}$$

In Equation 1, Y_i is total real GDP in country i, A_i is an aggregate efficiency index, K_i is the total physical capital stock, h_i is human capital of the average worker, L_i is the labor force, and α is the elasticity of GDP with respect to physical capital.[1] Dividing Equation 1 by the labor force L_i, and rearranging terms, we can obtain an expression for the average productivity of labor:

$$\frac{Y_i}{L_i} = A_i \left(\frac{K_i}{L_i}\right)^{\alpha} h_i^{1-\alpha}. \tag{2}$$

Equation 2 shows that the forces driving the behavior of labor productivity can be organized into three variables: aggregate efficiency, capital-labor ratio, and human capital per worker. Similar to the interpretation of Equation1, labor productivity in country i would be higher if its workers accumulate more productive resources (e.g., physical capital and human capital) and/or if those resources are used more efficiently.

Ideally, one would like to use Equation 2 for answering questions such as: How much does labor productivity increase in response to an increase in aggregate efficiency? One problem, however, is that capital accumulation responds endogenously to changes in aggregate efficiency (Klenow and

Rodriguez-Clare 1997). Conceptually, this endogeneity arises because physical capital is defined in units of final output (that is, GDP). As a result, any increase in aggregate efficiency would affect labor productivity both directly and indirectly through capital accumulation. To address this endogeneity issue, Klenow and Rodriguez-Clare (1997) rearrange Equation 2 and suggest the following steady-state production function:

$$\frac{Y_i}{L_i} = A_i^{\frac{1}{1-\alpha}} \left(\frac{K_i}{Y_i}\right)^{\frac{\alpha}{1-\alpha}} h_i. \tag{3}$$

Equation 3 is in line with the equilibrium of the standard Solow growth model. In steady-state, the capital-output ratio, K/Y, is exogenous to changes in aggregate efficiency, A. More intuitively, perhaps, Equation 3 is more useful to control for the indirect effects of efficiency by raising its elasticity from one to $\frac{1}{1-\alpha}$.

Conceptually, aggregate efficiency is a measure that quantifies the way in which an economy uses its productive resources. Efficiency gains arise due to improvements in both technological knowledge and reallocation of resources to better uses. Empirically, however, aggregate efficiency is measured as a residual variable. It captures everything else that affects labor productivity that is not already measured in the capital inputs. According to this definition, most studies compute aggregate efficiency for a country at a point of time as the following ratio:

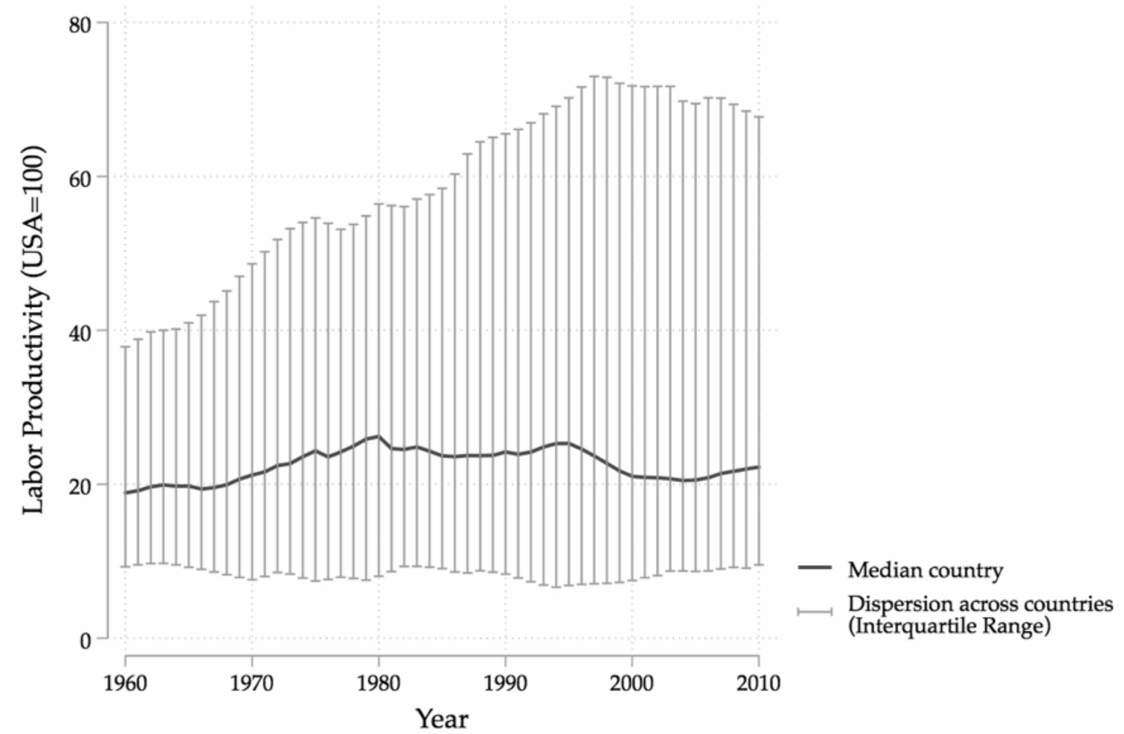
$$A = \frac{\frac{Y}{L}}{\left(\frac{K}{L}\right)^{\alpha} h^{1-\alpha}}. \tag{4}$$

To compute this ratio, one needs data about a key parameter: the output elasticity with respect to capital, α. Given the results of Figure 4, this parameter tends to be overestimated when using regression methods. Alternatively, one could obtain such information from other sources. For instance, it is well known that in a competitive market with a production function that exhibits constant returns to scale, this parameter can be computed as the GDP share that accrues to physical capital. Based on this criteria, Gollin (2002) collects data from developed and developing countries to construct measures of the capital income share. He finds that the average capital share is about 0.33.

2.2. Data: Labor Productivity and Sample Coverage

To empirically evaluate the previously described production framework across countries and over time, one needs to construct a balanced panel dataset. Largely based on the data from the Penn World Table 8.0, Fernandez-Arias (2014) constructs an unbalanced panel dataset that contains different measures of productivity and capital inputs for a large sample of both developing and developed countries over the 1950-2011 period. By exploiting this dataset, in the present article I construct a balanced panel dataset that covers 74 countries over the 1960-2010 period (See Appendix A for a detailed list of countries and some descriptive statistics). Furthermore, to facilitate the scale of comparison across variables, countries, and time, I re-scaled all variables relative to their level in the United States. In other words, for all variables and all years, the performance of the United States will be used as a benchmark. This is a common practice in the literature (see Caselli 2005) and it helps us identify to what extent the median country of the world is converging to the technological frontier. Note that in the following results, the median country is not fixed to a certain country over time. As some countries move forward and others backward within the cross-country distribution, the country that occupies the center of distribution is likely to change in a year-by-year basis.

Figure 2 Labor Productivity: Median Country and Dispersion Across Countries



Source: IADB Productivity Database. See Fernandez-Arias (2014) for details.

To measure labor productivity, this paper starts by dividing PPP-adjusted real GDP by the number of workers in the labor force.[2] Next, to remove short-run fluctuations, the statistical filter of Hodrick and Prescott (1997) is applied with a smoothing parameter of 100. Based on this approach, Figure 2 summarizes the two key features of labor productivity across countries. First, relative to the US, labor productivity of the median country was mostly stagnant over the 1960-2010 period.[3] For example, labor productivity of the median country was 19 percent in 1960. After 51 years, it only increased to 22 percent. Moreover, this 3 percent difference is not statistically different from zero. Second, the dispersion of labor productivity across countries (measured by the interquartile range) largely increased. For instance, in 1960, the difference between the 75th percentile and the 25th percentile of the cross-country distribution was 29 percentage points. After 51 years, this dispersion increased to 58 percentage points. This difference means that labor productivity disparities across countries almost doubled over the 1960-2010 period. What explains this lack of convergence and increasing disparities in labor productivity? Section 3 aims to provide an answer to this question based on the proximate sources of labor productivity: physical capital, human capital, and aggregate efficiency. Before moving to the results, however, let us briefly describe how these variables were constructed and measured.[4]

2.3. Measuring Physical Capital, Human Capital, and Aggregate Efficiency

To measure physical capital per worker, total physical capital stock is divided by the labor force, and then its long-run trend is estimated.[5] It is important to note that to construct this variable, Fernandez-Arias (2014) uses investment data from the Penn World Tables 8 and a fixed depreciation rate of 7 percent. With this information, he applies the perpetual inventory method to accumulate investment flows and recover the physical capital stock.[6]

To measure human capital per worker, Fernandez-Arias (2014) follows the standard approach in the economic growth literature and constructs a human capital index.[7] It is important to note, however, that this index is mostly a proxy for the quantity of human capital (years of schooling) as opposed to a quality measure (learning scores). Although some recent studies, such as Kaarsen (2014) and Lagakos et al. (2012), have started to include some measures of the quality of schooling and the rates of returns to work experience, country and time coverage remains limited, particularly for developing countries before the 1990s.

To measure aggregate efficiency, Equation 4 is applied. Given the estimates of labor productivity, physical and human capital, it is possible to compute a measure of aggregate efficiency that depends on one key parameter: the the output elasticity with respect to physical capital (that is, α in Equation 1). Klenow and Rodriguez-Clare (1997) argue that since this elasticity parameter is typically overestimated when using standard regression methods, one could try to calibrate its value in a way that is consistent with the national income accounts of a country. Based on this approach, Gollin (2002) collects data from a representative sample of countries and constructs a measure for this parameter. He finds that on average the capital income share (α) is about 0.33. Thus, given this value, and all the explanatory variables of Equation 4, aggregate efficiency is also measured for 74 countries over the 1960-2010 period.

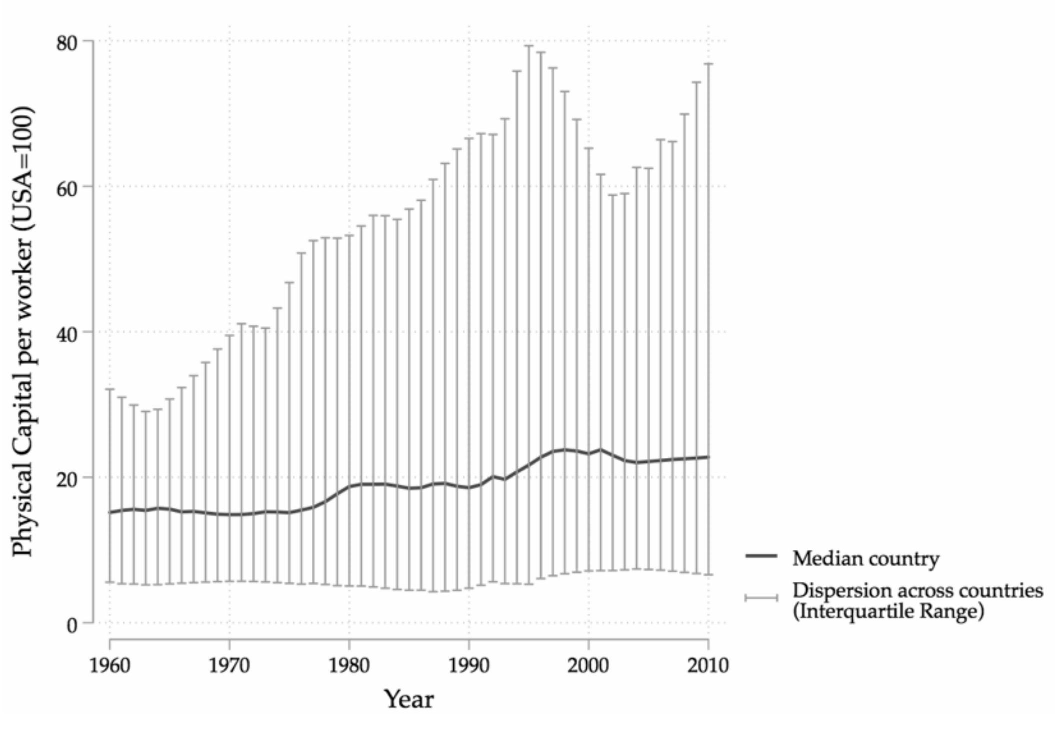
3. Results: The Proximate Sources of Labor Productivity

3.1. Physical Capital: Differences Across Countries and Over Time

Figure 3 shows the two features that characterize the evolution physical capital across countries. First, similar to labor productivity, physical capital per worker of the median country shows recurrent periods of stagnation (lack of catch up with the frontier) and very little progress overall. In 1960, physical capital per worker relative to that in the United States was 15 percent. After 51 years, it only increased to 23 percent. Second, cross-country disparities in physical capital drastically increased over time and this increasing dispersion is noticeable larger in the upper tail of the cross-country distribution. For instance, in 1960, the interquartile range was 26 percentage points. After 51 years, this dispersion increased to 70 percentage points. This growth over time means that disparities in physical capital per worker across countries *almost tripled* over the 1960-2010 period.

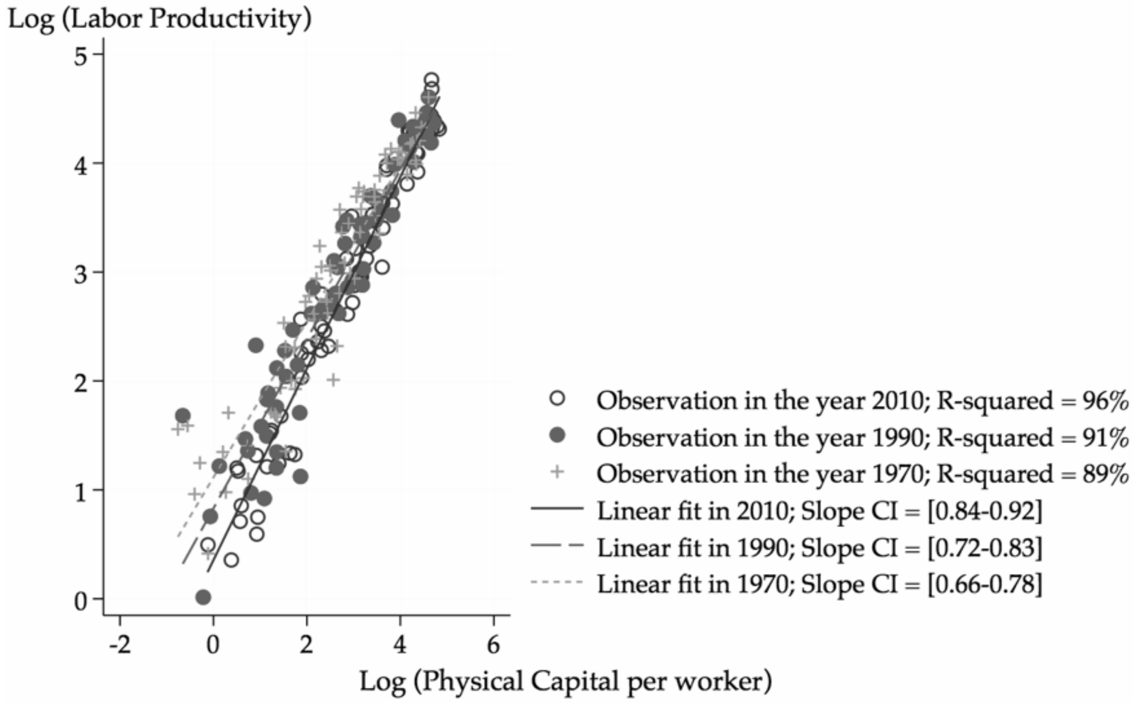
In some previous studies, the similarity between the patterns of labor productivity and physical capital is summarized by a (log-log) linear regression. Figure 4 presents this summary approach and further indicates that the relationship between labor productivity and physical capital has become stronger over time. Note that as time passes from 1970 to 2010, both the R-squared statistic and the confidence interval of the slope coefficient are approaching to 100 percent and 1, respectively.

Figure 3 Physical Capital: Median Country and Dispersion Across Countries



Source: IADB Productivity Database. See Fernandez-Arias (2014) for details.

Figure 4 Labor Productivity and Physical Capital



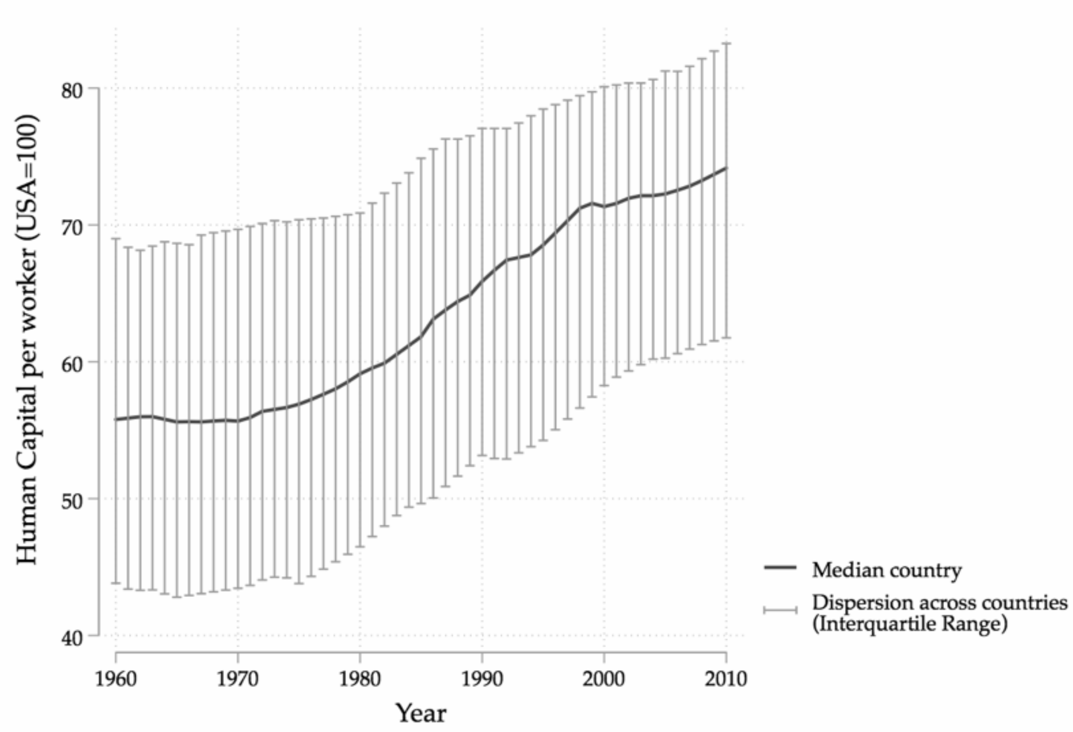
Note: The figure shows three simple regression lines for the years 1970, 1990 and 2010, respectively. The goodness of fit of each regression is summarized by coefficient of determination (R-squared). A 95-percent confidence interval for the slope coefficient of each regression is presented in brackets.
Source: IADB Productivity Database. See Fernandez-Arias (2014) for details

However, the values of these two indicators need to be interpreted with caution and conditional to a strong assumption. First, let us consider a simplified logarithmic version of Equation 2:

$$log\ \left(\frac{Y_i}{L_i}\right) = \beta + \alpha\ log\ \left(\frac{K_i}{L_i}\right) + \varepsilon_i. \quad (5)$$

By construction, in this model (and in the results of Figure 4), both human capital and aggregate efficiency would be included in the error term ε_i. From an econometric perspective, however, only under the strong assumption that these two variables are independent to physical capital, the value of the slope coefficient α (and the R-squared) would be consistently estimated using a standard OLS regression. Only if we were willing to accept this brave assumption, we could be confident that most of the cross-country differences in labor productivity are explained by differences physical capital, and the role of human capital and aggregate efficiency would be minimal. For instance, given the high R-squared of 96 percent in 2010, the combined effect of human capital and aggregate efficiency would only explain 4 percent of the labor productivity differences across countries.

Figure 5 Human Capital: Median Country and Dispersion Across Countries



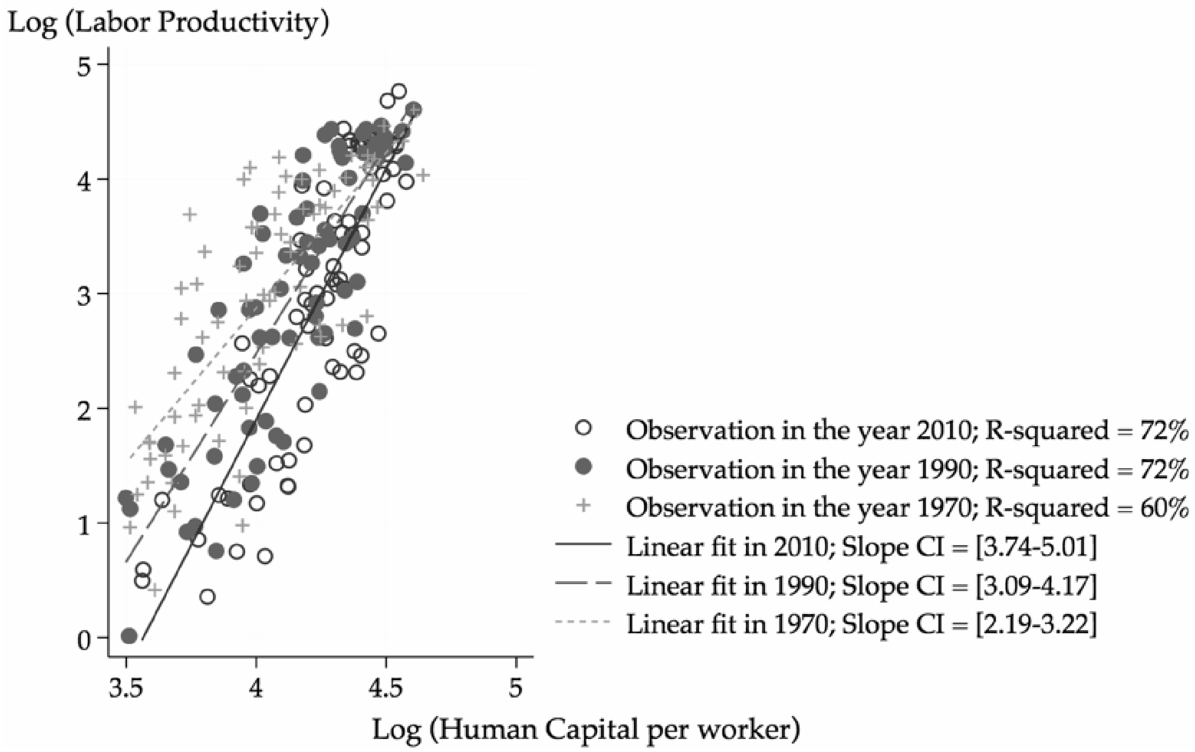
Source: IADB Productivity Database. See Fernandez-Arias (2014) for details.

3.2. Human Capital: Differences Across Countries and Over Time

Figure 5 shows the two main features that characterize the evolution of human capital: growth of the median country and decreasing cross-country disparities. In contrast to the labor productivity and physical capital patterns, relative human capital of the median country increased during the 1960-2010 period. For example, human capital per worker was 56 percent in 1960; by 2010, it reached to 74 percent. Also, in contrast to the labor productivity and physical capital patterns, cross-country disparities in human capital slightly decreased over this period. For instance, in 1960, the interquartile range was 25 percentage points. After 51 years, this dispersion decreased to 21 percentage points.

The upward trend in human capital can be explained by two factors: (1) the worldwide accumulation of years of schooling; and (2) the upper boundary of 16 years of education in the benchmark country (the US). If we could use cognitive test scores to construct a better human capital trend for all the countries in the sample over the 1960-2010 period, then it is reasonable to expect less encouraging results. This is a limitation of the present study and it should be handled in future research, when more systematic data becomes available.

Figure 6 Labor Productivity and Human Capital



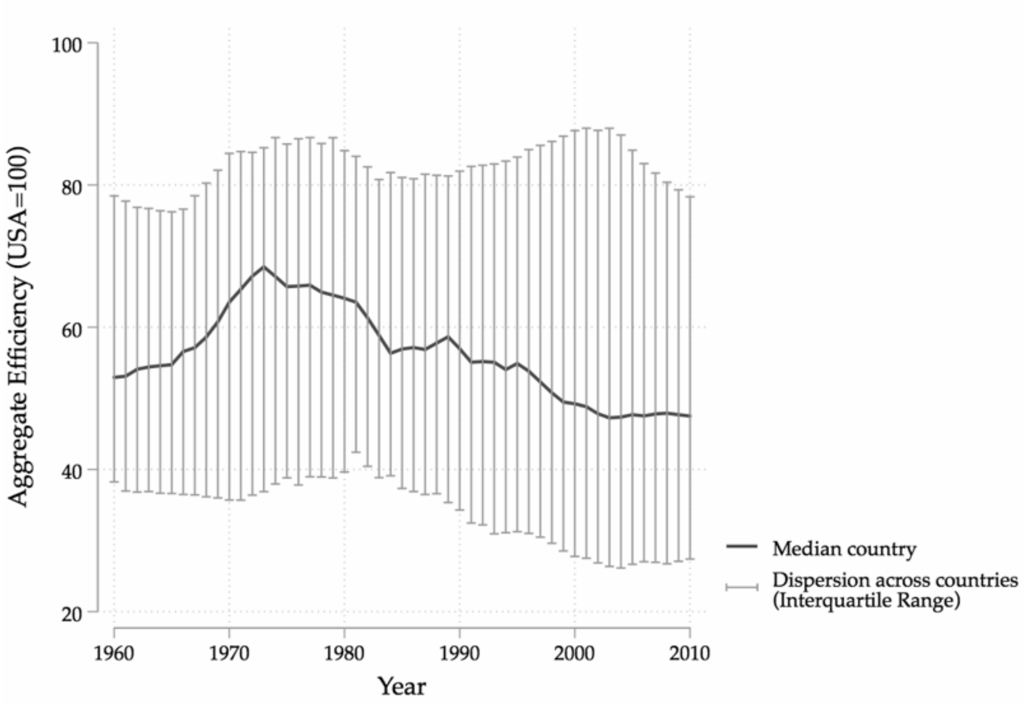
Note: The figure shows three simple regression lines for the years 1970, 1990 and 2010, respectively. The goodness of fit of each regression is summarized by coefficient of determination (R2). A 95-percent confidence interval for the slope coefficient of each regression is presented in brackets.
Source: IADB Productivity Database. See Fernandez-Arias (2014) for details.

Figure 6 shows that human capital is also highly correlated with labor productivity, though not as much as physical capital. Similar to Equation 5, an OLS regression would suggest that, in the 2010, human capital explained 72 percent of the labor productivity differences across countries. Again, the credibility of this high explanatory power largely depends on the independence among human capital, physical capital, and aggregate efficiency.

3.3. Aggregate Efficiency: Differences Across Countries and Over Time

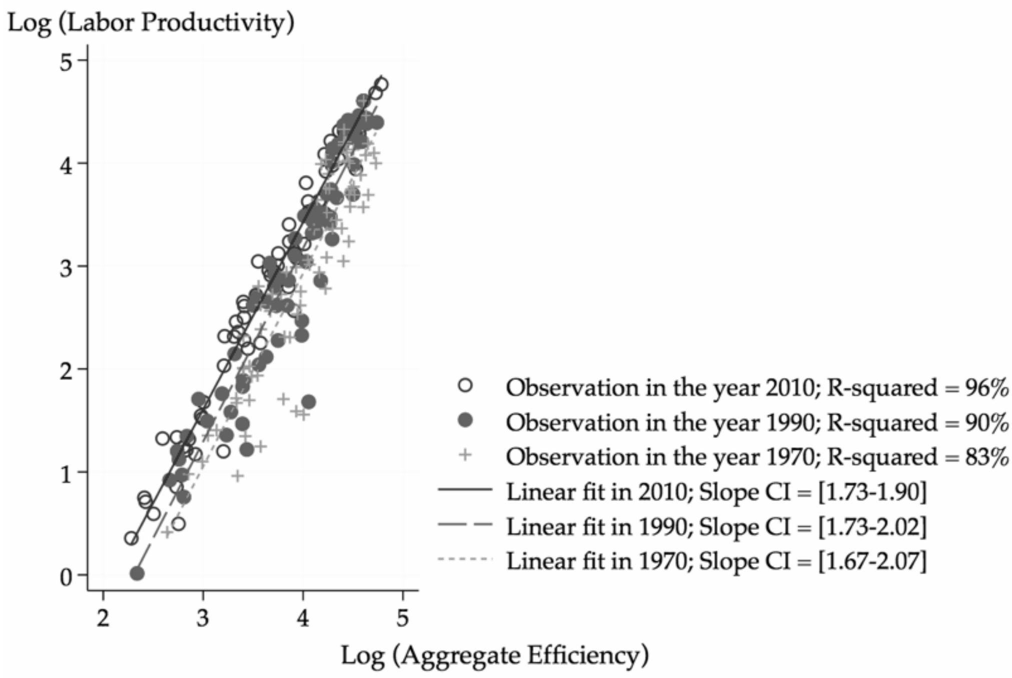
Using a physical capital share value (α) of 0.33 and the previously described data on labor productivity and capital inputs, Figure 7 shows the two key features that characterize aggregate: decline of the median country and increasing cross-country disparities. Over the 1960-2010 period, and relative to the United States, aggregate efficiency of the median country decreased from 53 percent to 47 percent. Cross-country disparities, on the other hand, increased. In 1960, the interquartile range was 40 percentage points. After 51 years, this dispersion increased to 51 percentage points. Moreover, this increasing dispersion is occurring in both tails of the cross-country distribution.

Figure 7 Aggregate Efficiency: Media Country and Dispersion Across Countries



Source: IADB Productivity Database. See Fernandez-Arias (2014) for details.

Figure 8 Labor Productivity and Aggregate Efficiency



Note: The figure shows three simple regression lines for the years 1970, 1990 and 2010, respectively. The goodness of fit of each regression is summarized by coefficient of determination (R2). A 95-percent confidence interval for the slope coefficient of each regression is presented in brackets.

Source: IADB Productivity Database. See Fernandez-Arias (2014) for details.

Besides the increase in the cross-country dispersion, the most noteworthy tendency suggested by Figure 7 is that since the early 1970s, the level aggregate efficiency shows a systematic decreasing trend. This result implies a potential explanation for the stagnation of labor productivity (Figure 2). Given the stagnation of physical capital (Figure 3), it seems plausible that the decreasing trend in aggregate efficiency (Figure 7) may off-set the positive effects associated with the increasing trend in human capital (Figure 5). Note that the take-off time of these two trends is similar, both started in the early 1970s. Thus, when combining these three tendencies (stagnant physical capital, increasing human capital, and decreasing aggregate efficiency), it is plausible to expect little progress in labor productivity.

Figure 8 shows that aggregate efficiency is also strongly correlated with labor productivity. Moreover, for the year 2010, the R-squared of a simple linear regression would suggest that 96 percent of labor productivity differences are explained by aggregate efficiency alone. Given these findings, one would not only conclude that differences in aggregate efficiency could be as important as physical capital, but also that these two measures are highly correlated. In fact, for the year 2010 the pairwise correlation between them was 0.93.

4. Discussion

4.1. How to Disentangle the Effect of Physical Capital from Aggregate Efficiency?

Some regression studies, such as the seminal work of Mankiw et. al (1992), argue that physical capital is the main driver of labor productivity. However, the main criticism to the regression approach is that both the estimated physical capital share (α) and the R-squared tend to be upwardly biased (Gollin 2002; Klenow and Rodriguez-Clare 1997). For Gollin (2002) shows that plausible values for α tend to be around 0.33. The results of Table 1 suggest that implausible large values for the share of physical capital (α) are persistent, even after controlling for human capital, country fixed effects, and constant returns to scale.

As suggested by standard econometric theory, the source of this overestimation is the uncontrolled correlation between physical capital and aggregate efficiency. Thus, if the correlation between capital and aggregate efficiency is so strong, how can we disentangle the variation of labor productivity that is due to capital differences alone? In line with the methodology suggested by Klenow and Rodriguez-Clare (1997), the work of Vollrath (2014) suggests the following method to identify the variation of labor productivity that is due to capital differences alone.

Table 1 Different Estimations of Output Elasticities: 1950-2010 Period

	Model (1)	Model (2)	Model (3)
Physical Capital (α)	0.74	0.74	0.51
	(0.009)***	(0.007)***	(0.01)***
Human Capital ($1-\alpha$)	0.25	0.26	0.49
	(0.037)***	(0.007)***	(0.01)***
Fixed Effects	NO	NO	YES
CRS Constraint	NO	YES	YES
R-squared	0.90	NA	NA
Observations	3,774	3,774	3,774

Note: The numbers in parenthesis indicate robust standard errors. All variables are significant at 1 percent. All regressions include a constant term that is not reported in the table. CRS stands for constant returns to scale. NA stands for Not Available in constrained regression framework.

Source: IADB Productivity Database. See Fernandez-Arias (2014) for details.

First, let us rewrite the simple econometric model described in Equation 5 as:

$$log\ y_i = \beta + \alpha\ log\ k_i + \varepsilon_i, \tag{6}$$

where labor productivity y and the capital-labor ratio k are expressed as lower-case letters to simplify notation. Next, define the variation of the dependent variable that is explained by the model as:

$$R^2 = \frac{Var(\beta + \alpha\ log\ k_i)}{Var(log\ y_i)}. \tag{7}$$

Then, utilize the statistical properties of the variance and covariance operators and the definition of the OLS estimator to show that

$$R^2 = \alpha^2 \frac{Var(log\ k_i)}{Var(log\ y_i)}$$

$$R^2 = \alpha \underbrace{\frac{Cov(log\ k_i, log\ y_i)}{Var(log\ k_i)}}_{\alpha} \frac{Var(log\ k_i)}{Var(log\ y_i)}$$

$$R^2 = \frac{Cov(\alpha\ log\ k_i, log\ y_i)}{Var(log\ y_i)}$$

$$R^2 = \frac{Cov(\alpha\ log\ k_i, \beta + \alpha\ log\ k_i + \varepsilon_i)}{Var(log\ y_i)}$$

$$R^2 = \frac{Cov(\alpha\ log\ k_i, \beta)}{Var(log\ y_i)} + \frac{Cov(\alpha\ log\ k_i, \alpha\ log\ k_i)}{Var(log\ y_i)} + \frac{Cov(\alpha\ log\ k_i, \varepsilon_i\ )}{Var(log\ y_i)}$$

$$R^2\ = 0 + \frac{Var(\alpha\ log\ k_i)}{Var(log\ y_i)} + \frac{Cov(\alpha\ log\ k_i, \varepsilon_i)}{Var(log\ y_i)} \tag{8}$$

Equation 8 shows that we can compute an unbiased R-squared by letting $Cov(\alpha\ log\ k_i, \varepsilon_i) = 0$ and selecting a value for α. Following the work of Gollin (2002), most studies set $\alpha = 0.33$. Given this setting, in the year 2010, cross-country differences in physical capital explained only 14 percent of the differences in labor productivity.

Applying the same procedure to disentangle the contribution of aggregate efficiency.[8] In the year 2010, aggregate efficiency explained 44 percent of the labor productivity differences across countries. This finding is consistent with previous literature (Baier et al. 2006; Caselli 2005; Hall and Jones 1999; among others) in the sense that aggregate efficiency is the main driving force behind the labor productivity.

4.2. What Could Explain a Decreasing Trend in Aggregate Efficiency?

Classical development economics models, such as Lewis (1954), focus on the coexistence of fundamentally different structures of production within an economy.[9] In its simplest representation, Lewis' dual economy model defines economic development as the secular movement of workers from low-productivity sectors (such as agriculture) to high-productivity sectors (such as manufacturing). The main lesson of this type of models is that structural productivity differences across sectors have aggregate efficiency implications.[10] In particular, when labor is misallocated across sectors, aggregate efficiency is expected to be lower.

McMillan and Rodrik (2012) and McMillan et. al (2014) study the growth effects of labor misallocation across sectors. Their most compelling finding suggests that the economies of Latin America and Africa suffer from efficiency loses largely due to labor misallocation. Workers appear to be moving from low-productivity sectors to even lower-productivity part of the economy. To further illustrate this mechanism, Mendez-Guerra (2017) highlights the dynamics of labor misallocation in the case of Chile. The striking feature of Chile (and Latin America in general) is that the structural change patterns described in Lewis (1954) appear to be working–in reverse. Over time, workers keep gravitating from relatively low-productivity sectors (e.g., agriculture and manufacturing) to even lower-productivity sectors. For instance, the employment share of agriculture declined from 31 percent to 11 percent and its relative productivity increased from 28 percent to 65 percent over the entire 1950-2005 period. Most agricultural workers migrated to the cities and instead of finding jobs in manufacturing industries, they appear to have found jobs in service related industries. Paradoxically, the relative productivity of most service industries is even lower than that of agriculture. For instance, in 2010, the relative productivity of whole-sale and retail trade was 59 percent while the productivity of agriculture was 65 percent. Thus, as shown by standard economic theory, when workers reallocate to lower-productivity industries, the aggregate economy suffers an efficiency loss.

5. Concluding Remarks

A central topic in the study of global development has to do with the huge differences in labor productivity across countries. The literature on this topic is typically classified into two lines of research. One that studies a set of proximate sources such as production inputs (physical and human capital) and aggregate efficiency. And the other that studies a set of deeper factors such as geography, culture, and institutions. In this context, this article evaluates the relative contribution of each of the proximate sources of labor productivity. The novel productivity database of Fernandez-Arias (2014) suggests that, during the 1960-2010 period, labor productivity of the median country has been mostly stagnant, while cross-country productivity differences have drastically increased. The cross-country dynamics of the three proximate sources of labor productivity reveal the following patterns:

- Physical capital accumulation of the median country also appears largely stagnant, with an increasing dispersion particularly around the upper tail of the cross-country distribution.
- Human capital accumulation of the median country increased over time. Contrasting the behavior of other proximate sources, this is the only variable in which the cross-country dispersion decreased over time
- Aggregate efficiency of the median country decreased over time, with an increasing dispersion in both tails of the cross-country distribution.

From a methodological standpoint, regression methods typically overestimate the fraction of the variation in labor productivity that is explained by physical capital. Such overestimation arises from the uncontrolled covariance between capital accumulation and aggregate efficiency. Calibration methods attempt to control such covariance and highlight that most of the variation in labor productivity is actually explained by aggregate efficiency. As a result, the central finding of this article highlights the role of aggregate efficiency as the main driver of the observed differences in labor productivity across countries. This result is consistent with the recent literature summarized by Caselli (2005) and Hsieh and Klenow (2010).

Labor misallocation across sectors could potentially help us understand the observed differences in aggregate efficiency across countries. There is an emerging quantitative literature on resource misallocation that provides new insights on the intermediate channels between the deep and proximate sources of labor productivity (McMillan and Rodrik 2012; Restuccia and Rogerson 2008, 2013; Vollrath 2009). In particular, this literature suggests that the observed deterioration in aggregate efficiency could be driven by both market allocation failures and policy distortions. The case of Latin American economies is commonly highlighted in this literature. In this region, economies appear to be suffering from inefficient sectorial production. Most of their labor force is concentrated in the service sector, where the average productivity level is even lower than that of agriculture.

Notes

1 The literature typically refers to A_i as total factor productivity (TFP). To avoid confusion with other productivity terms in this article I use the term aggregate efficiency instead to total factor productivity. Also, in this article, the terms GDP and “output” refer to the same variable or concept. In some sections the term “output” is used to signal and emphasize a conceptual input-output relation. In other sections, however, the term GDP is instead used to signal and emphasize the empirical measurement of output at the national level.

2 In the database of Fernandez-Arias (2014), real GDP is named Y and the employed labor force is named Lemp.

3 In this paper, the word “stagnation” does not mean that countries are not growing in absolute terms. It simply means that countries are not keeping up with growth pace of the US.

4 A common limitation of cross-country studies is that they do not consider within-country variations and the variations across individuals within the world income distribution. For instance, although relative stagnation is a characteristic of the median country of the world, this characteristic does not necessarily apply to the median individual or household of the world. By using household data, instead of aggregate data, Milanovic (2016) shows that middle income individuals (who are mostly from India and China) are actually catching up.

5 In the database of Fernandez-Arias (2014), total physical capital stock is named K.

6 To apply the perpetual inventory method, an estimate of the initial capital-output ratio is needed. In the database of Fernandez-Arias (2014), this ratio is estimated based on the steady-state condition described in Hall and Jones (1999).

7 For a detailed exposition on the construction of the human capital index, see the paper of Hall and Jones (1999). It is worth noticing that, in contrast to labor productivity and physical capital, a long-run trend is not computed for human capital. This is because the human capital series do not show noticeable cyclical changes over the short run. For reference purposes, the human capital index is named h in the original database of Fernandez-Arias (2014).

8 That is, Cov(log A_i,ε)=0

9 See Ros (2000, 2013) for a review on how to integrate the insights from classical development economics into modern growth theory. Also, for a more comprehensive presentation about the role of resource misallocation on aggregate efficiency, see Section 4 of Mendez-Guerra (2017).

10 See Temple (2005) for a premier treatment on how to integrate dual-economy models into growth theory.

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Appendix A

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