Labor productivity, capital accumulation, and aggregate efficiency across countries: Some stylized facts

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Labor Productivity, Capital Accumulation, and Aggregate Efficiency across Countries: Some Stylized Facts

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Abstract

This paper studies the cross-section dynamics of the proximate determinants of labor productivity: physical capital, human capital, and aggregate efficiency. Using a panel data set for 74 countries covering the 1950-2010 period, it first documents that labor productivity of the median country has been mostly stagnant, while cross-country differences have drastically increased. An evaluation of proximate sources points to a similar pattern of stagnation and increasing dispersion in both physical capital and aggregate efficiency. Human capital is the only variable where median progress and inequality reduction can be observed. Next, the paper shows how standard regression methods consistently overestimate the fraction of the variation in labor productivity that is explained by physical capital. The source of this upward bias appears is the unaccounted covariance between capital accumulation and aggregate efficiency. Taking this covariance into account, most of the variation in labor productivity turns out to be explained by differences in aggregate efficiency. Finally, the paper concludes arguing that allocative inefficiencies at the sectoral level, such as those predicted by dual-economy type models, are important for understanding the large and increasing differences in aggregate efficiency across countries.

Keywords: labor productivity, capital accumulation, aggregate efficiency, stylized facts

JEL classification: E01, O40, O47

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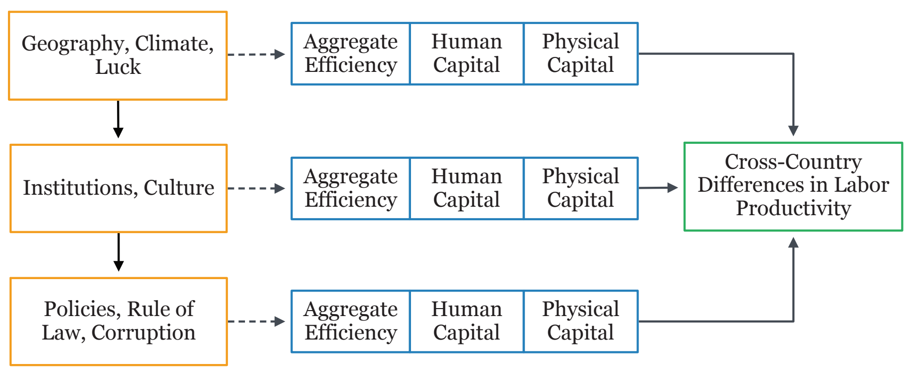
1. Introduction

Arguably, most research studies in the growth and development literature analyze cross-country differences in labor productivity according to the following chain of causation (Hsieh and Klenow, 2010):

Figure 1: Cross-Country Differences in Labor Productivity: A Chain of Causality



Source: Adapted from Hsieh and Klenow (2010)

Factors that affect labor productivity are typically classified into two groups. The first includes the most proximate sources such as physical capital, human capital, and aggregate efficiency. The second includes more fundamental or deeper determinants such as geography, culture, and institutions and policies.

In the context of Figure 1, this paper analyzes the proximate sources of labor productivity. First, it quantifies the differences both over time and across countries of each proximate source. Next, the paper revisits the debate about the relative importance of capital accumulation versus aggregate efficiency. On the one hand, the work of Mankiw, Romer, and Weil (1992) uses regression methods to conclude that capital accumulation differences explain most of the variation of labor productivity across countries. On the other, the work of Klenow and Rodriguez-Clare (1997) uses calibration methods to highlight the prevalence of aggregate efficiency over capital accumulation. On this debate, this paper emphasizes that the source of disagreements relies on strong conceptual and methodological assumptions of both lines of research. On the one hand, capital fundamentalists 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 key parameters.

After clarifying the relative importance of capital accumulation and aggregate efficiency, this paper discusses a structural change channel through which some of the deeper determinants described in Figure 1might affect the proximate sources of labor productivity. This channel has to do with the degree of allocative efficiency across productive sectors within an economy. In particular, it argues that the degree of misallocation resources across sectors can potentially have a large negative effect on aggregate efficiency. This observation is consistent with the dual-economy structures that are typically found in developing countries (Lewis 1954,1979). Empirically, the work of Vollrath (2009) shows that degree of resource misallocation between agricultural and non-agricultural sectors can account for up 80 percent of the cross-country variation in aggregate efficiency. Finally, the paper provides further evidence on the dynamics of misallocation. Using the recent sector-level data from McMillan and Rodrik (2011, 2014), this paper presents the case of Chile as an illustrative example in which workers secularly move from relatively high-productivity sectors to low-productivity sectors.

The rest of the paper is organized as follows. Section 2 describes the evolution of the cross-country disparities in labor productivity, capital accumulation, and aggregate efficiency. Section 3 evaluates the relative importance of capital accumulation and aggregate efficiency. Section 4 presents an structuralist point of view about the sources of aggregate efficiency. Finally, Section 5 offers some concluding remarks and open questions for further research.

2. Labor Productivity its Proximate Sources

Figure 2 shows two key features of the dynamics of labor productivity across countries. First, contrary to the convergence predictions of the Neoclassical growth model,[1] relative labor productivity of the medium country was almost stagnant during the 1950-2010 period.[2] For instance, in 1950, output per worker of the median country relative to that in the United States was 22 percent. After 61 years, it decreased to 20 percent.[3] Second, the standard deviation increased from 23 to 32 during this period. That is, productivity differences across countries increased by a factor of 1.4 during this period. What explains this lack of convergence and increasing disparities in labor productivity?

Standard growth theory provides the beginning of an answer by organizing our thoughts around an aggregate production function. For instance, Hall and Jones (1999) and Caselli (2005, 2014) suggest the following functional form:

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

where Y_i is the total real GDP in country i , A_i represents aggregate efficiency[4], K_i is the total physical capital stock, h_i is the human capital per worker, L_i is the total labor force, and α is the elasticity of GDP with respect to physical capital. Dividing Equation 1 by the labor force L_i, and rearranging terms, we can obtain

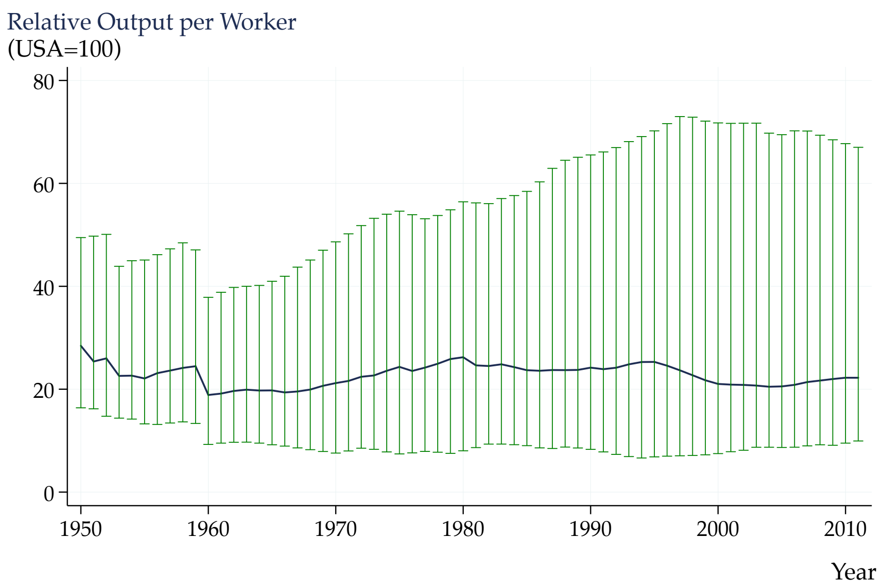
[1] See Solow (1956) for details.

[2] Providing some empirical support about the convergence predictions of the Neoclassical model, Barro (1992) finds conditional convergence across countries after controlling for other factors such as fertility, education, population growth, government expenditures, investment rates, among others. Durlauf, Johnson and Temple (2005), however, criticize this finding arguing that the typical convergence regressions implemented in the literature suffer from model uncertainty, parameter heterogeneity, endogeneity issues, and lack of robustness.

[3] If in this computation the mean is used, average productivity increased from 33 percent to 35 percent. As a measure of centrality, however, the median is typically preferred to the mean when a sample contains extremely large or small values.

[4] The literature typically refers to A_i as total factor productivity (TFP). To avoid confusion with other productivity terms in this paper I use the term aggregate efficiency instead to total factor productivity.

Figure 2: Cross-Country Differences in Labor Productivity Over Time



Source: Author's calculations using data from Fernandez-Arias (2014)

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 (proximate) forces driving the behavior of labor productivity can be organized into three variables: aggregate efficiency, physical capital per worker, and human capital per worker. Alternatively, they can also be categorized into two factors: aggregate efficiency and capital accumulation, where the concept of capital in this case includes both physical and human capita. In any of these classifications the interpretation is equivalent: labor productivity in country i will be high if its workers accumulate 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 comparative analysis 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. As a result, any increase in aggregate efficiency would affect labor productivity both directly and indirectly through capital accumulation. Hsieh and Klenow (2010) argue that keeping physical capital constant when there is an increase in efficiency requires a decrease in the investment rate. However, it is not obvious why the investment rate should decrease to improvements in efficiency. Thus, to deal with the endogeneity issue in a more natural way, Klenow and Rodriguez-Clare (1997) rearrange Equation2 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 2 is consistent with the steady state equilibrium of the neoclassical growth model, where the capital-output ratio, KY , is exogenous to changes in aggregate efficiency, A. More intuitively, Equation 3 controls for the indirect effects of improvements in efficiency by raising its elasticity from one to $\frac{1}{1-\alpha}$.

Given cross-country data on total production, labor force, physical and human capital, previous studies have used regression or calibration methods to empirically implement either equation 2 or 3. In fact, Caselli (2005) and Hsieh and Klenow (2010) survey the literature that uses calibration methods. In these surveys, physical capital typically explains around 20 percent, human capital explains 10 to 30 percent, and aggregate efficiency explains 50 to 70 percent of the cross-country differences in labor productivity[5]. Although most economies would tend to agree with these findings, there are important caveats and lim-

[5]Originally, Caselli (2005) and Hsieh and Klenow (2010) report cross-country differences in output per capita (i.e., differences in income). However, it is well-know that differences in output per capita imply differences in output per worker when the employment-to-population ratio does not systematically vary with output per capita.

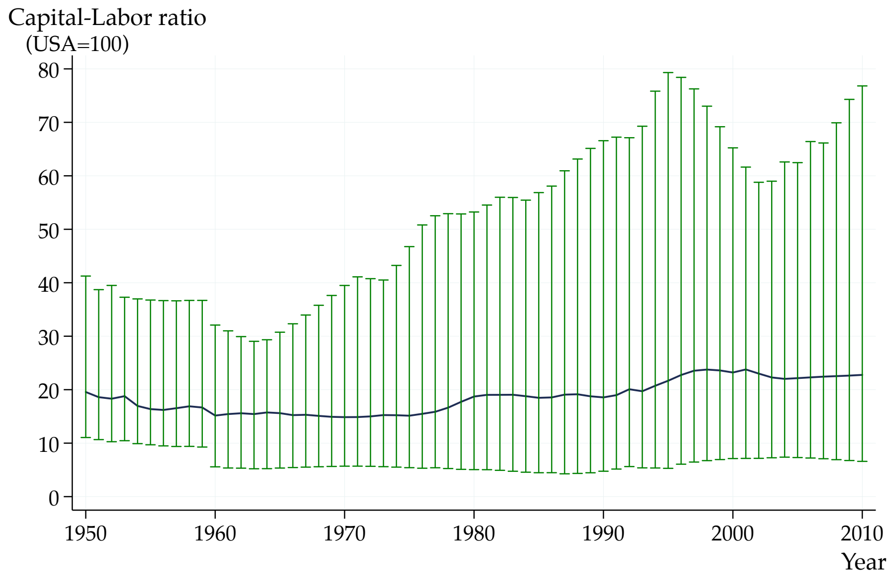
itations. It is also important to analyze why a calibration approach would still be preferred to a regression-based approach (See section 3.). Before going into methodological concerns, however, I first discuss the general patterns about the evolution of the cross-country differences in capital accumulation and aggregate efficiency in the post-World War II period

2.1. Differences in Physical Capital

Long data series on physical capital are not readily available from the national income accounts of most countries. The standard procedure in the literature is to build such series by adding investment inflows within an accumulation framework that includes depreciation outflows. For instance, the Penn World Tables V.8 database and the database of Fernandez-Arias (2014), which are the main datasources for this section, uses the perpetual inventory method to construct the physical capital series for 167 countries between 1950 and 2011. This inventory method requires only two parameters: the depreciation rate and the initial capital stock. Although the first is typically set to six or ten percent, the latter is not readily available. Thus, there exist a variety of methods for computing the initial capital stock. For instance, Jones (1997) and Hall and Jones (1999) use the capital stock in steady state. As described in Caselli (2005), independently of the chosen method, initial capital depreciates over time and given a six percent depreciation rate, the effect of the initial capital would almost disappear after the first 30 years.

Figure 3 shows the two features that characterize the evolution of cross-country differences in physical capital per worker. First, similar to labor productivity, relative physical capital per worker of the medium country was almost stagnant during the 1950-2010 period. For instance, in 1950, physical capital per worker relative to that in the United States was 20 percent. After 61 years, it only increased to 23 percent. Second, cross-country differences in physical capital are even larger than those in labor productivity. For instance, standard

Figure 3: Cross-Country Differences in Physical Capital Over Time



Source: Author's calculations using data from Fernandez-Arias (2014)

deviation increased by a factor of 1.6. over the sample period[6].

Figure 4 illustrates the strong correlation between labor productivity and physical capital. Moreover, this correlation appears to become stronger over time. To further clarify the sources of these results, consider a simplified logarithmic version of Equation 2:

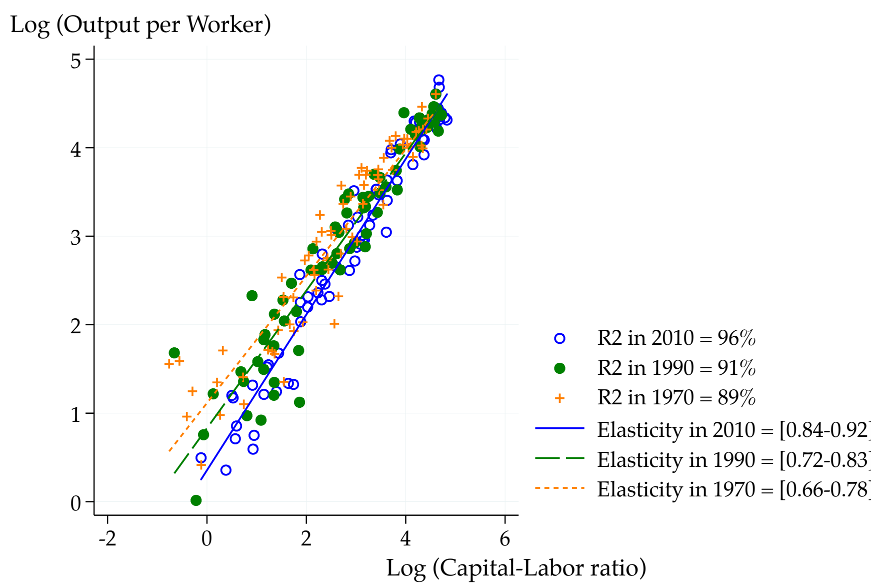
$$log\left(\frac{Y_i}{L_i}\right) = \beta + \alpha\, log\left(\frac{K_i}{L_i}\right) + \varepsilon_i. \tag{4}$$

In this simplified model, cross-country differences in human capital and aggregate efficiency at a point in time would be included in the error term ε_i. Moreover, under the strong assumption that these two factors are independent to physical capital, the elasticity of output per worker with respect to physical capital, α , could be estimated using a standard OLS regression.

[6]Specifically, the standard deviation increased from 24 to 39.

Given the estimates of Equation 4 and the previously described assumption, results from Figure 4 would suggest that most of the cross-country variation in labor productivity is explained by physical capital (the R-squared is close to one). For instance, in 2010 differences in aggregate efficiency and human capital would only explain four percent of the differences in labor productivity. Although the correlation between labor productivity and physical capital is indeed strong, the reported values for both the capital elasticity and the R-squared statistic are at odds with those suggested by national accounts (Gollin, 2002). As it will be discussed in Section 3., one can reduce the explanatory power of physical capital by adding measures of human capital, controlling for fixed effects, and changing the estimation framework. Yet, before such discussion, let us evaluate how large the differences in human capital are across countries.

Figure 4: Labor Productivity versus Physical Capital

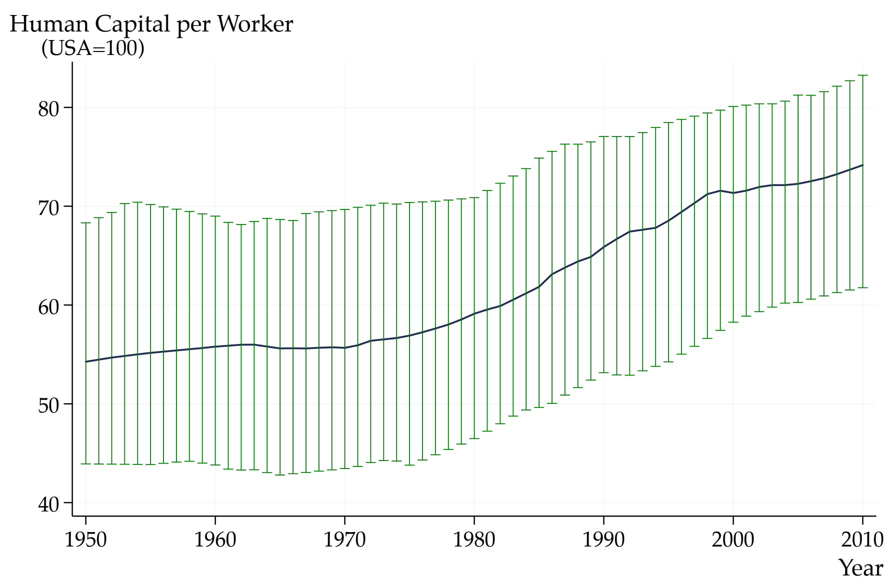


Source: Author's calculations using data from Fernandez-Arias (2014)

2.2. Differences in Human Capital

The availability of comprehensive cross-country data on human capital seems be improving every decade. In the early 1990s, growth regressions typically proxied human capital using measures of school enrollment (Barro and Sala-i-Martin, 1992; Mankiw et al., 1992). In the late 1990s and early 2000s, growth and development decompositions (Klenow and Rodriguez-Clare, 1997; Hall and Jones, 1999) typically used measures of years of schooling (from Barro and Lee, 2013) and the Mincerian return associated to the average years of schooling (from Psacharopoulos and Patrinos, 2004). More recently, some decomposition studies started to use measures of the quality of schooling and returns to each year of work experience (See Kaarsen, 2014; Lagakos et al., 2012 for details).

Figure 5: Cross-Country Differences in Human Capital Over Time



Source: Author's calculations using data from Fernandez-Arias (2014)

Using the human capital production function suggested by Hall and Jones (1999), Figure 5 shows the two features that characterize the evolution of cross-country differences in human capital per worker. First, contrasting the patterns of both labor productivity and physical capital, relative human capital per worker of the medium country notably increased during the 1950-2010 period. After two initial decades of stagnation, human capital accumulation started a rapid increase. For instance, in 1950, human capital per worker relative to that in the United States was 54 percent; by 2010 it reached to 74 percent. Second, cross-country differences in human capital slightly decreased over this period. For instance, in 1950 the standard deviation was 18 percent; by 2010 it was 16 percent.

Figure 6 shows that human capital is also highly correlated with labor productivity, though not as much as physical capital. As in Equation 4, an OLS regression would suggested that more than 60 percent of the cross-country differences in labor productivity are explained by differences in human capital alone. Again, here the credibility of this explanatory power relies on the strong assumption that human capital is independent of physical capital and aggregate efficiency.

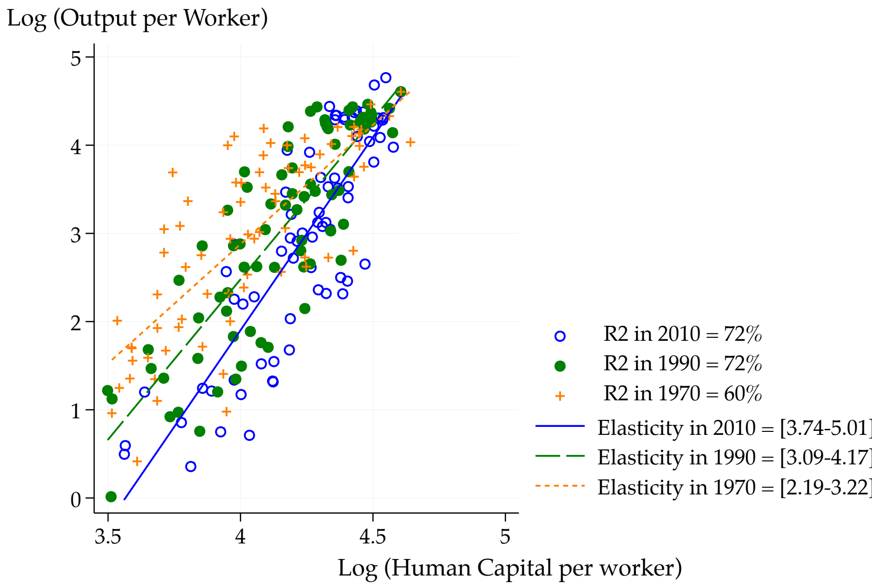
2.3. Differences in Aggregate Efficiency

Conceptually, aggregate efficiency is a measure that quantifies the efficiency with which an economy uses its productive resources. Efficiency gains arise due to improvements in either technical knowledge or reallocation of resources to better uses (or both). Empirically, aggregate efficiency is a residual measure. It captures everything else that affects output that is not already measured in the other inputs (e.g., physical and human capital). According to this definition, most studies compute aggregate efficiency for a country at a point of time as the following ratio[7]:

$$A_{it} \equiv \frac{output}{inputs} = \frac{\frac{Y_{it}}{L_{it}}}{\left(\frac{K}{L}\right)^{\alpha} h^{1-\alpha}}. \tag{5}$$

[7] See Van Beveren (2012) for a practical survey on how to compute aggregate efficiency. Also, see Isaksson (2006, 2007) for an overview of the determinants of aggregate efficiency. Finally, see Felipe, (1999, 2007) for a critical review of the residual approach to aggregate efficiency measurement.

Figure 6: Labor Productivity versus Human Capital



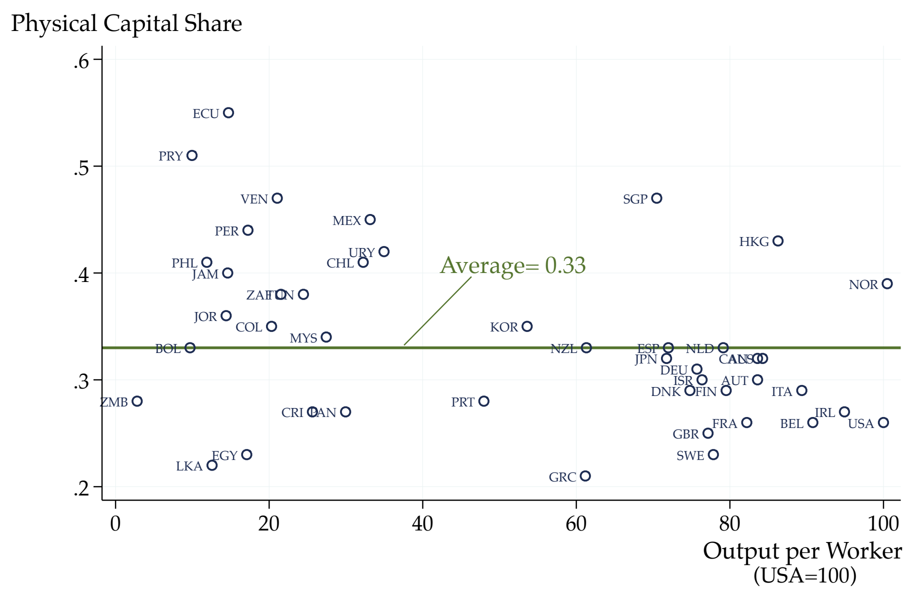
Source: Author's calculations using data from Fernandez-Arias (2014)

The only missing information to compute this ratio is the output elasticity with respect to capital, α. Given the results of Figure 4, this parameter tends to be overestimated when using regression methods. An alternative would be to extract such information from other sources. For instance, it is well known that under perfect competition and constant returns to scale, the output elasticity with respect to capital is defined as the share of national income that accrues to physical capital. That is

$$\alpha = \frac{rK}{Y}, \tag{6}$$

where r is the price of physical capital. Gollin (2002) collects data from difference sources across countries to construct measures of the capital income share. After adjusting for the income of self-employed workers, he finds no relationship between the capital share and the level of income per capita (and labor productivity) across countries (See Figure 7). Moreover, the average capital share is about 13, which is consistent with the long-run evidence of capital

Figure 7: Physical Capital Share versus Labor Productivity



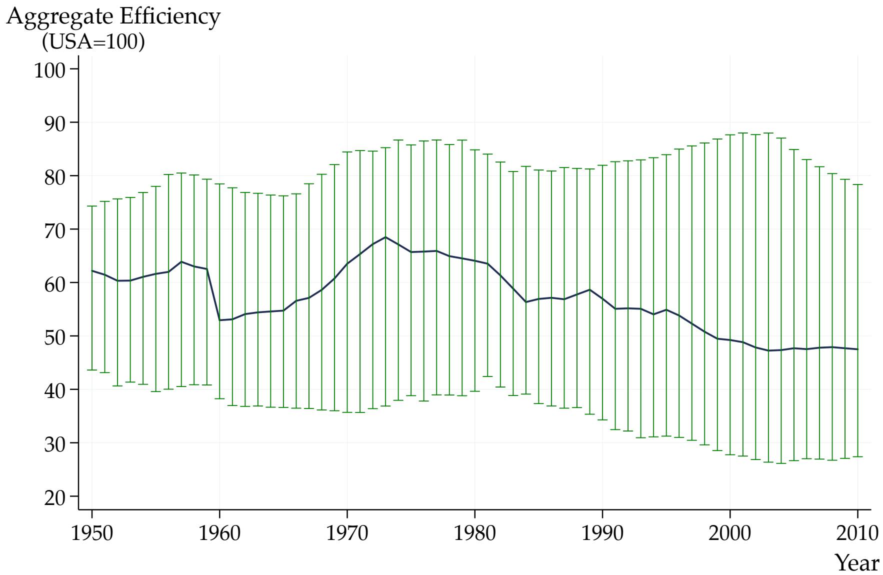
Source: Data on the capital share is from Bernanke and Gurkaynak (2002), table 10 and note 18. Data on output per worker are author's calculation using data from Fernandez-Arias (2014).

share series of the United States and other advanced economies.

Using a physical capital share value of 13, Figure 8 shows the two key features that characterize the evolution of aggregate efficiency across countries. First, relative aggregate efficiency of the medium country actually decreased during the 1950-2010 period. For instance, in 1950, aggregate efficiency relative to that in the United States was 62 percent; by 2010 it decreased to 48 percent. Second, aggregate efficiency differences across countries increased by a factor of 1.2. That is, the standard deviation increased from 24 percent to 29 percent during this period.

Figure 9 shows that aggregate efficiency is strongly correlated with labor productivity. Moreover, the R-squared of a simple linear regression would suggest that in 2010 differences in aggregate efficiency explained 96 percent of the cross-country differences in labor productivity. Given these findings, one would

Figure 8: Cross-Country Differences in Aggregate Efficiency Over Time



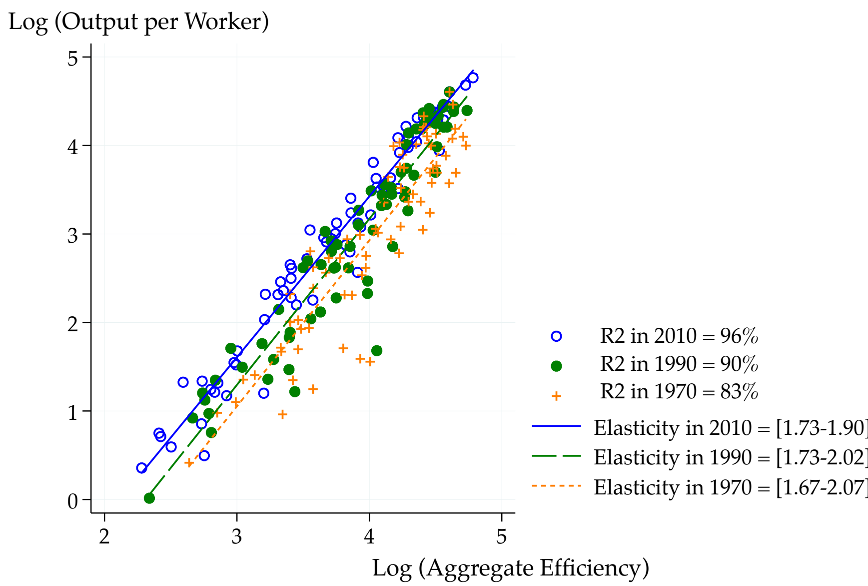
Source: Author's calculations using data from Fernandez-Arias (2014)

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.

3. Capital Accumulation or Aggregate Efficiency?

The main criticism to the regression approach is that both the elasticity of output with respect to capital (α) and the R-squared tend to be upwardly biased. The source of this overestimation is the uncontrolled correlation between capital accumulation and the residual term, which by the definition of Equation 1 represents aggregate efficiency. Additional regression analyses, summarized in Table 1, suggest that the implausible values for α (and the R-squared) persist after controlling for human capital, country fixed effects, and constant returns to scale. As a result, if the correlation between capital and the residual is so strong,

Figure 9: Labor Productivity versus Aggregate Efficiency



Source: Author's calculations using data from Fernandez-Arias (2014)

how can we identify the variation of labor productivity that is due to capital differences alone? Consistent with the calibration methodology suggested by Klenow and Rodriguez-Clare (1997), Vollrath (2014) describes a simple solution for controlling the previously described correlation.

Let us rewrite the simple econometric model described in Equation 4 as:

$$log\ y_i = \beta + \alpha\ log\ k_i + \varepsilon_i, \tag{7}$$

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

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

Next, utilize the statistical properties of the variance and covariance operators

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

Dependent Variable: Labor Productivity				
	Model (1)	Model (2)	Model (3)	Model (4)
Physical Capital	0.74	0.74	0.59	0.55
	(0.01)	(0.06)	(0.05)	(0.01)
Human Capital	0.26	0.26	-0.78	0.45
	(0.03)	(0.06)	(0.14)	(0.01)
Fixed Effects	NO	NO	YES	YES
Constraint $(\beta_1 + \beta_2 = 1)$	NO	YES	NO	YES
R2	0.90	na	0.84	na
Observations	4284	4284	4284	4284

Note: Numbers in parentheses indicate robust standard errors. All variables are significant at 1 percent. All regressions include a constant term that is not reported in the table.

and the definition of the OLS estimator to show that

$$
\begin{aligned}
R^2 &= \alpha^2 \frac{Var\,(log\;k_i)}{Var\,(log\;y_i)} \\
&= \alpha \underbrace{\frac{Cov\,(log\;k_i, log\;y_i)}{Var\,(log\;k_i)}}_{\alpha} \frac{Var\,(log\;k_i)}{Var\,(log\;y_i)} \\
&= \frac{Cov\,(\alpha log\;k_i, log\;y_i)}{Var\,(log\;y_i)} \\
&= \frac{Cov\,(\alpha log\;k_i, \beta + \alpha\; log\;k_i + \varepsilon_i)}{Var\,(log\;y_i)} \\
&= \frac{Cov\,(\alpha log\;k_i, \beta)}{Var\,(log\;y_i)} + \frac{Cov\,(\alpha log\;k_i, \alpha\; log\;k_i)}{Var\,(log\;y_i)} + \frac{Cov\,(\alpha log\;k_i, \varepsilon)}{Var\,(log\;y_i)} \\
&= 0 + \frac{Var\,(\alpha log\;k_i)}{Var\,(log\;y_i)} + \frac{Cov\,(\alpha log\;k_i, \varepsilon)}{Var\,(log\;y_i)} \qquad (9)
\end{aligned}
$$

Equation 9 shows that we can compute the unbiased R-squared by letting

$Cov\,(\alpha log\; k_i, \varepsilon) = 0$ and selecting a value for α. Using the results of Figure 7, most calibration studies set $\alpha = 13$. Given this setting, in the year 2010 differences in physical capital accumulation explain only 14 percent of the differences in labor productivity across countries. One can also apply the same procedure for computing the contribution of aggregate efficiency[8]. For the same year, differences in aggregate efficiency explain 44 percent of the differences in labor productivity across countries. This finding is consistent with previous literature (Baier et al., 2006; Caselli, 2005; Hall and Jones, 1999; Hsieh and Klenow, 2010) in the sense that aggregate efficiency is the main driving force behind the labor productivity.

4. What Explains Aggregate Efficiency? A Structuralist View

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 conceptualizes the process of economic development as the movement of workers from low productivity sectors (e.g., agriculture) to relatively high productivity sectors (e.g., manufacturing). However, it is possible that some factors of production face mobility barriers across sectors. In this case, the economy would suffer from efficiency losses, as factors of production are not reallocated to their most efficient use.[10] Another possibility is that workers (and firms) may have incentives to move to even lower productivity sectors. For instance, if labor and product markets are highly regulated, so that operational costs are higher

[8]Note that in this case $Cov\,(log\; A_i, \varepsilon) = 0$

[9]See Ross (2000, 2013) for a recent textbook treatment on how to integrate the insights from classical development economics into modern growth theory.

[10]See Banerjee and Duflo (2005), Hsieh and Klenow (2009), and Restuccia and Rogerson (2008, 2013) as examples of recent seminal contributions dealing with the relationship between resource misallocation and aggregate efficiency.

in the formal sector, many firms (and the workers they hire) would have additional incentives to move to the informal sector, where the regulation burden (and its associated cost) is minimized. The main lesson of this type of models is that structural productivity differences across sectors have aggregate efficiency implications.[11] In particular, resource misallocation across sectors reduces aggregate efficiency, and ultimately labor productivity.

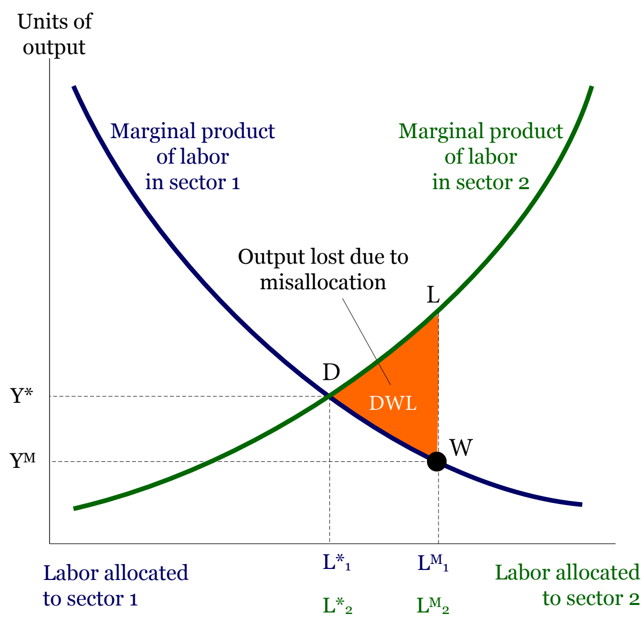
4.1. Dual-Economy and Misallocation Effects

Figure 10 illustrates how structural productivity differences and resource misallocation reduces total output. In this example, an economy maximizes its efficiency when the marginal productivity of labor is equal across sectors ($MPL_1 = MPL_2$). At Point D, the economy allocates L_1^* workers to sector one and L_2^* workers to sector two. The efficiency maximizing level of output is represented by Y^*. If there exist market failures or government distortions (or both), wedges between the marginal products ($MPL_1 \neq MPL_2$) will be generated. At point W, the economy allocates more workers to sector one L_1^M and less workers to sector two L_2^M. Given the wedges between marginal products ($MPL_1 < MPL_2$), the efficiency loss in the economy is represented by the DWL triangle and the new level of output is $Y^M < Y*$.

Given the theoretical insights of Figure 10, one would like to have a quantitative measure of the productivity wedges across sectors and their effect on aggregate efficiency. Vollrath (2009) is a seminal contribution in this line of research. He first constructs agricultural and non-agriculture production functions for sample of countries in 1985. Then, he calibrates the parameters of each production structure to have measures of wedges in marginal productivities between agriculture and non-agriculture. As expected, marginal productivity differences tend be larger in developing countries. Figure 11 not only illustrates the original finding of Vollrath (2009), but it also shows that such inter-sectorial productivity

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

Figure 10: The Deadweight Loss of Resource Misallocation

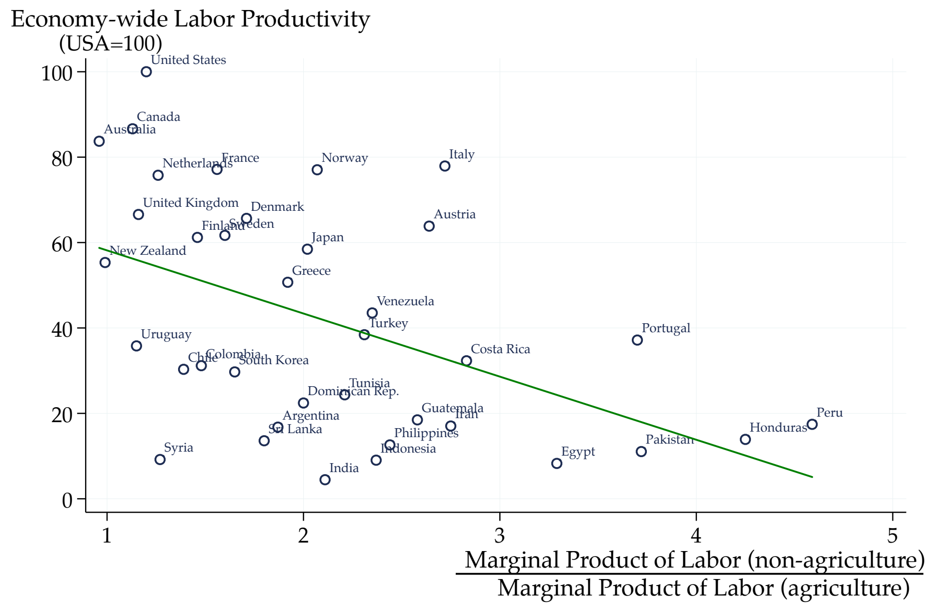


Source: Adapted from Weil (2013)

gaps are highly correlated with differences in aggregate labor productivity.

Following the logic of Figure 10, the next step is to compute the DWL triangle for sample of 42 developed and developing countries. Vollrath (2009) first hypothetically equalizes the the marginal products between agriculture and non-agriculture for each country. This equalization pins down the optimal allocation of resources across sectors. Then, using this optimal allocation, he recomputes the aggregate production for each country. He finds that resource misallocation between agriculture and non-agriculture explains up to 80 percent of the variation in aggregate efficiency and between 30 percent to 40 percent of the variation in labor productivity. Based on the data of these calculations, Figure 12 shows that countries with the lowest aggregate labor productivity are those with the largest efficiency losses due to misallocation.

Figure 11: Dual-Economy Evidence: Large Productivity Gaps across Sectors

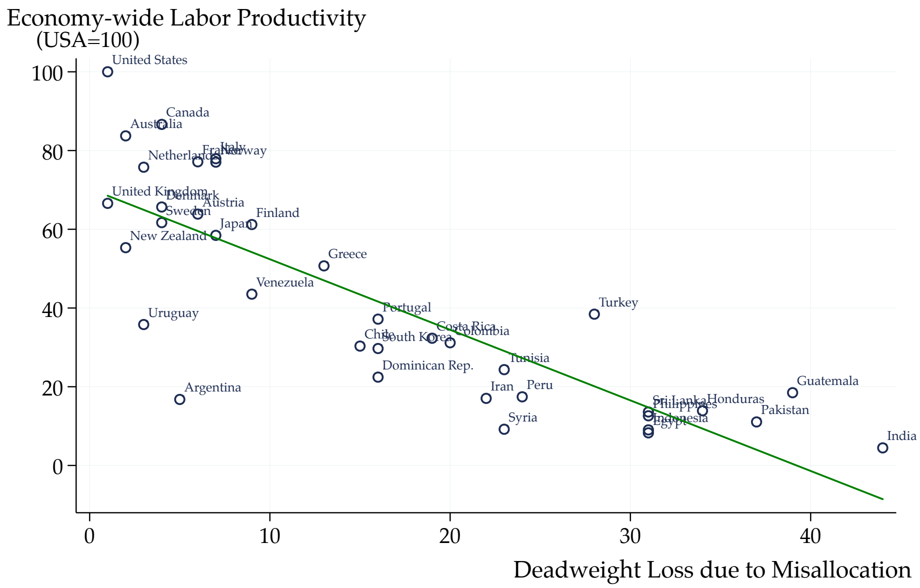


Source: Author's calculations using data from Vollrath (2009)

4.2. Dynamic Dual-Economy Effects and Structural Change

Figures11 and 12 document the static aggregate efficiency effects of the dual economy structure. The original insight of Lewis, however, focuses on the dynamics of reallocation, that is workers moving from traditional-low-productivity sectors to modern-high-productivity sectors over time. McMillan and Rodrik (2011, 2013) aim to extend the research on the dynamics of the dual economy by constructing a panel dataset that covers a sample of developing and developed countries for the period 1950-2005. The caveat of this dataset, however, is that it measures average labor productivity instead of marginal labor productivity. Note that the conceptual framework illustrated in Figure 10 depends on the wedges between marginal products, which are not necessarily equal to average products. In spite of this limitation, one can still try to infer differences in marginal products from differences in average products. Let us consider both the average and marginal products of labor in a standard Cobb-Douglass pro-

Figure 12: How Large are the Dual Economy Effects?



Source: Author's calculations using data from Vollrath (2009)

duction function:

$$Y = AK^{1-\beta}L^{\beta} \tag{10}$$

$$\text{Average Product of Labor} \equiv \frac{Y}{L} \tag{11}$$

$$\text{Marginal Product of Labor} \equiv \frac{\partial Y}{\partial L} = \beta\frac{Y}{L}. \tag{12}$$

If the parameter β is relatively constant across sectors and over time, then differences in average products will translate into differences in marginal products. Whether this is a valid assumption is a topic for further research. For the purpose of exploration, and keeping in mind this key assumption, Figure 13 describes the dynamics of the dual economy for a sample country: 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 (McMillan and Rodrik, 2011). Over time, workers keep gravitating from relatively low-productivity sectors (e.g., agriculture and manufacturing) to even lower-productivity sectors (e.g., wholesale and retail trade, and other services)[12]. More generally, McMillan and Rodrik (2013) document the structural change patterns for sample of developing countries in Latin America, Asia, and Africa. They conclude that after the year 2000, favorable labor reallocation increased productivity growth both in Asia and Africa, whereas labor misallocation decreased the growth potential of Latin America.

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: physical capital, human capital, and aggregate efficiency. And the other that studies a set of deeper factors: geography, culture, and institutions.

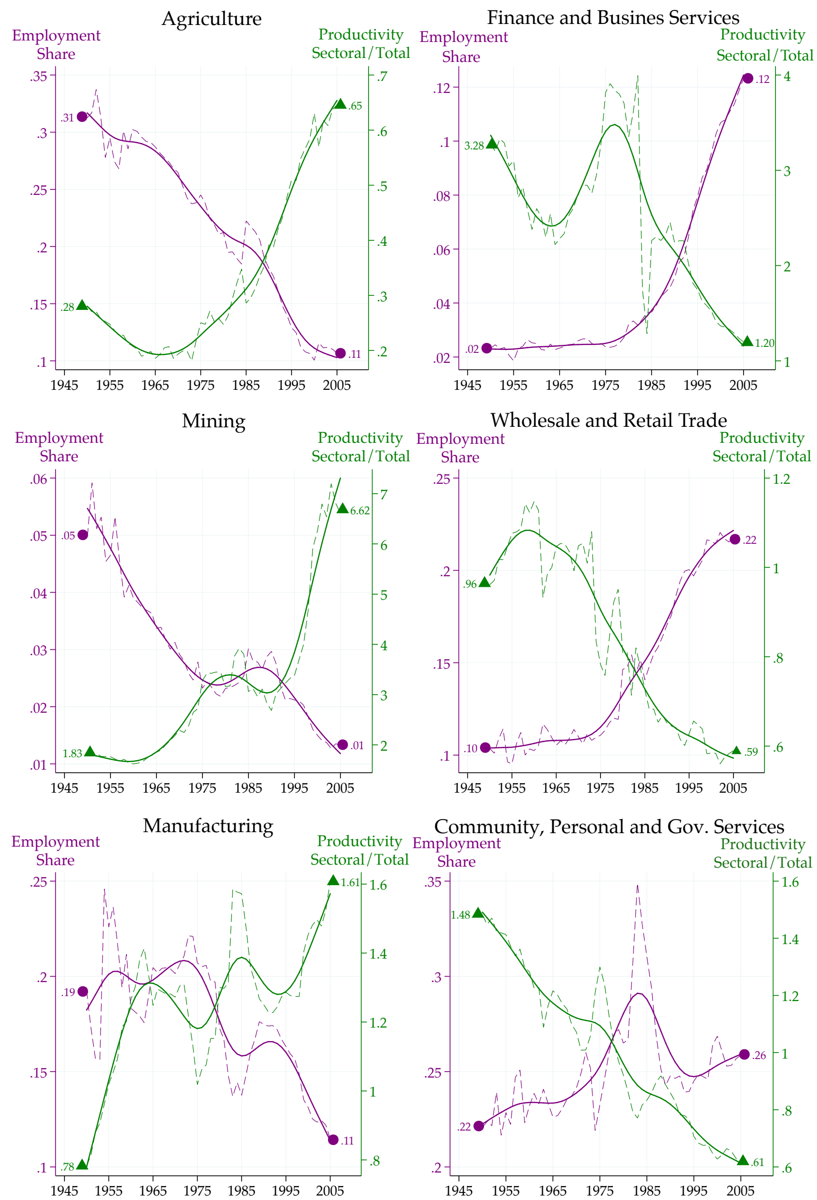
From an empirical point of view, that key motivating fact is that, during the 1950-2010 period, labor productivity of the median country has been mostly stagnant, while the cross-country differences have drastically increased. An evaluation of the cross-section dynamics of the proximate sources of labor productivity reveals the following patterns:

- Physical capital accumulation in the median country also appears largely stagnant, with an increasing dispersion in the upper tail over time.

- Aggregate efficiency in the median country decreased over time, with an increasing dispersion in both upper and lower tails.

[12]Note that average productivity has been increasing both in the mining sector and in the finance and business sector. However, the employment share in these sectors is relatively small compared to other parts of the economy.

Figure 13: Dynamic Dual-Economy Effects: An Example from Chile



Source: Author's calculations using data from McMillan and Rodrik (2011)

- Human capital accumulation in 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.

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.

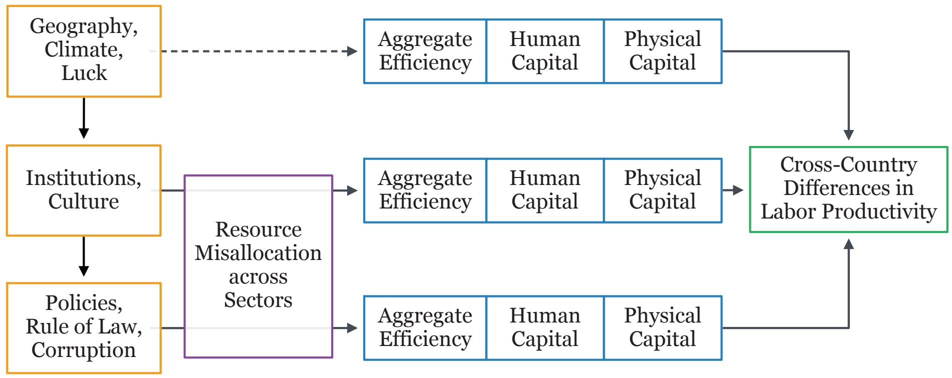
Figure 14 presents an expanded version of the chain of causality suggested by Hsieh and Klenow (2010)[13]. The recent empirical literature on resource misallocation across sectors provides new insights on the intermediate channels between the deep and proximate sources of labor productivity. A large fraction of the observed deterioration in aggregate efficiency is most likely to be driven by allocation failures. For instance, the economies of Latin America appear to be suffering from inefficient sectorial production, since most of their labor force is concentrated in the service sector, which is the part of the economy where average productivity is the lowest. Ultimately, resource misallocation is most likely to be driven by policy failures, institutional weaknesses, and cultural barriers.

Over the next decades, research in economic growth and development is expected generate new insights based on the potentially fruitful integration of the recent quantitative dual-economy models and the standard productivity accounting methods. In this context, some of the major questions for further analysis may include the following[14]: In what dimensions the production function of human capital differs across sectors? What kind of allocative inefficiencies have the largest effects? Are the misallocation effects across sectors larger than those across firms? Under what conditions does a reduction in misallocation imply an unambiguous gain in welfare? Why is there a secular deterioration in allocative efficiency in Latin America?

[13]See Figure 1.

[14]Some of these questions are from Hsieh and Klenow (2010).

Figure 14: Cross-Country Differences in Labor Productivity: An Extended Chain of Causality



Source: Adapted from Hsieh and Klenow (2010)

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