Cross-country Variation in Factor Shares and its Implications for Development Accounting*

Brad Sturgill
Economics Department
Appalachian State University
Boone, NC 28608
Email: sturgillbs@appstate.edu
Phone: 828-262-6950

January 2010

Abstract

The stability of factor shares has long been considered one of the "stylized facts" of macroeconomics. However, the relationship between cross-country factor shares and economic development is dependent on how factor shares are measured. Most factor share studies acknowledge only two factors of production: total capital and total labor. The failure to acknowledge more than two factors yields misleading results. In the first part of the paper, I distinguish between reproducible and non-reproducible factors of production. I disentangle physical capital's share from natural capital's share and human capital's share from unskilled labor's share. Results reveal that non-reproducible factor shares decrease with the stage of economic development, and reproducible factor shares increase with the stage of economic development. This suggests that studies relying on the macroeconomic paradigm of constant factor shares should be revisited. Development accounting nearly always assumes the constancy of factor shares. In the second part of the paper, I perform the development accounting exercise but allow factor shares to vary and distinguish between reproducible and non-reproducible factors. My approach yields results that stand in stark contrast to those previously attained. The general consensus is that at least half of the cross-country variation in output per worker accrues to the Total Factor Productivity (TFP) residual. With my approach, the majority of variation in output per worker accrues to factor shares, specifically physical capital's share and natural capital's share. The explanatory power of the TFP residual decreases by more than 30 percentage points. This evidence does not, however, diminish the role of technical change. Rather, the evidence indicates the importance of acknowledging a new type of technical change, one that impacts factor shares.

JEL Codes: E25, O30, O11
Keywords : factor shares, TFP residual, development accounting, technical change

***** I would like to thank Michelle Connolly, John Lapp, Asli Leblebicioğlu, Pietro Peretto, John Seater, Hernando Zuleta, and participants in the Triangle Dynamic Macro workshop at Duke University and the Third Southeastern International/Development Economics Workshop at the Federal Reserve Bank of Atlanta for useful comments and suggestions.

1 Introduction

Capital shares and labor shares are typically treated as constant parameters. For example, Hall and Jones (1999), in an investigation of the role of productivity in explaining cross-country differences in output per worker, assume that capital shares and labor shares are constant across countries and equal to 1/3 and 2/3 respectively. Some studies, such as Gollin (2002), present empirical evidence in support of constant factor shares across countries. Others, such as Zuleta (2008a), conclude that factor shares vary across countries. Despite conflicting empirical evidence and despite the doubts about the constancy of factor shares expressed by Keynes (1939) and Solow (1958), most researchers accept Kaldor's (1961) submission that factor shares are constant as a "stylized fact" of macroeconomics.

Factor shares are not constant when factors of production are properly defined and measured. The key step is making a distinction between reproducible factors and non-reproducible factors. In most factor share studies, only two factors of production, capital and labor, are acknowledged. Failure to acknowledge more than two factors yields results and conclusions that are misleading at best. When discussing capital, economists generally refer to physical or human capital—physical capital being tools, machinery, and structures, and human capital encompassing education, health, and training. However, standard capital share measures include the fractions of income paid to physical capital as well as natural capital, which encompasses all natural resources including land, minerals, and oil. Physical capital and natural capital are two distinct factors. Physical capital is reproducible, meaning it can be accumulated, whereas natural capital is non-reproducible and can not be accumulated.[1] Therefore, any claim about the standard capital share and how it relates to the stage of economic development is really a claim about two separate factor shares and their collective relationship with the stage of economic development. Likewise, standard measures of labor's share entangle the fraction of income paid to human capital, a reproducible factor, and unskilled labor, a non-reproducible factor.

In the first part of this paper, I disentangle physical capital's share from natural capital's share and human capital's share from unskilled labor's share. There is strong evidence that non-reproducible factor shares decrease with the stage of economic development, and reproducible

[1]Non-reproducible factors are those factors with which an economy is endowed. Reproducible factors have to be produced.

factor shares increase with the stage of economic development. This finding has theoretical and empirical implications. First, it provides support for theoretical growth models, such as those presented by Peretto and Seater (2008) and Zuleta (2008b), that incorporate factor eliminating technical progress. Secondly, it suggests that any theoretical or empirical study relying on Kaldor's claim that factor shares are constant should be revisited.

One macroeconomic exercise that virtually always assumes constancy of factor shares is the estimation of the Total Factor Productivity (TFP) residual. Examples in the literature include Klenow and Rodriguez-Clare (1997), Hall and Jones (1999), and Caselli (2005). The second part of this paper looks at the implications of systematic variation in factor shares for the measurement of the TFP residual across countries. Specifically, I compare the fraction of cross-country variation in economic performance attributable to variation in the TFP residual to the fraction of cross-country variation in economic performance attributable to variation in factors and factor shares. Rather than assume factor shares are constant across countries, I allow factor shares to vary in accordance with the estimates presented in the first part of the paper.

The TFP residual is generally thought to account for at least half of the variation in output per worker. I find that the majority of variation in output per worker accrues to factor shares when factor shares are allowed to vary and a distinction between reproducible and non-reproducible factors is made. Variation in output per worker accruing to the TFP residual falls by about 32 percentage points. These results, in addition to suggesting that factor shares play an important role in development accounting, reveal the inappropriateness of forcing all technical progress to work through the TFP residual. Technical progress that manifests itself via changes in factor shares is certainly plausible, and my results provide strong evidence that such progress is at work and a prominent source of cross-country variation in output per worker.

The remainder of the paper is organized as follows. In Section 2, I disentangle physical capital's share from natural capital's share and human capital's share from unskilled labor's share. Estimates of factor shares are presented, and a formal analysis of the relationship between each share and output per worker is provided. In Section 3, I use my factor share estimates from Section 2 and analyze the impact of variable factor shares on the variation in output per worker accruing to observables and the TFP residual. Section 4 concludes.

2 Factor Shares and Economic Development

2.1 Theoretical Motivation

The work of Cobb and Douglas (1928) and Kaldor (1961) suggesting that factor shares were constant created a paradigm in macroeconomics. However, new theories and a general refinement in the way we think about factors and factor shares call into question the precedent set forth by Cobb and Douglas and Kaldor. Recent work in endogenous growth theory distinguishes between reproducible and non-reproducible factors and explores the idea that technical change can alter factor shares. These theoretical advances yield specific predictions about the systematic relationship between the stage of economic development and both reproducible and non-reproducible factor shares across countries.

Perpetual growth requires that the marginal products of reproducible factors of production be bounded away from zero (Jones and Manuelli 1997). This means that the non-reproducible factors must either be augmented or eliminated. Virtually all analyses focus on augmentation. However, Peretto and Seater (2008) develop a theory of endogenous growth that focuses on factor elimination. Factor intensities are allowed to change endogenously via spending on R&D, and this serves as the catalyst for growth. As economies advance, non-reproducible factors of production become less important, and reproducible factors of production become more important. In other words, their theory predicts that non-reproducible factor intensities should decrease with output per worker, and reproducible factor intensities should increase with output per worker.[2]

The Peretto and Seater theory allows for monopolistic competition in the intermediate goods sector. As a result, firms earn excess profits, and payments to the factors of production do not exhaust firm revenues. Consequently, factor intensities and factor shares, though related, are not equivalent. However, to the extent that factor shares measured using national income account data are reasonable estimates of factor intensities, the theory suggests that non-reproducible factor shares should decrease with output per worker, and reproducible factor shares should increase with output per worker.

In a related vein of the literature, Zuleta (2008b) develops an endogenous growth model in which growth occurs via capital using and labor saving technological progress. Like Peretto

[2] The term "factor intensity" refers to the elasticity of output with respect to a factor of production.

and Seater, Zuleta incorporates endogenous factor intensities. The key differences between Zuleta's model and that of Peretto and Seater are: Zuleta solves the social planner problem whereas Peretto and Seater consider the market solution; the saving rate is endogenous in Zuleta and exogenous in Peretto and Seater; and the cost of new technologies is modeled differently in the two studies. However, from an empirical standpoint, Zuleta's model yields the same testable implications pertaining to factor shares, namely that reproducible factor shares are positively related to the stage of economic development, and non-reproducible factor shares are negatively related to the stage of economic development.[3]

Hansen and Prescott (2002), who build on Galor and Weil (2000), propose a model of transition from a primitive to an advanced economy. In their model, advancements in the stage of development, which occur via exogenous technical progress, are accompanied by decreases in land's share. Land, like other natural capital, is non-reproducible, so the prediction of Hansen and Prescott's model is consistent with the aforementioned theories that suggest non-reproducible factor shares should fall with output per worker.

2.2 Empirical Background

The simplest labor share calculation is computed as the fraction of real GDP attributed to employee compensation. Capital's share is then computed as the residual, $1-\left(\frac{Employee\ Compensation}{GDP}\right)$. It has been argued, most notably by Gollin (2002), that the aforementioned method, which Gollin refers to as *naïve*, is misleading because published numbers on employee compensation omit the income flowing to the self-employed. Assuming that a portion of income of the self-employed represents labor income, the consequence of this omission is estimation of labor's share that is too low and estimation of capital's share that is too high, especially in developing countries where self-employment is prevalent. Gollin adjusts for this omission by including the operating surplus of private unincorporated enterprises (*OSPUE*) in the computation of labor's share. The idea is that most self-employed people do not operate incorporated enterprises, and, consequently, capital income and labor income of the self-

[3] Boldrin and Levine (2002) and Zeira (1998, 2006) develop models similar to that of Zuleta. Technical advancement occurs via substitution of capital for labor. Boldrin and Levine's model predicts that labor's share should decrease with economic development. Zeira's model, though it makes no explicit predictions about the relationship between factor shares and economic development, predicts a positive correlation between the capital to output ratio and economic development.

employed are encompassed by *OSPUE*. Gollin allocates *OSPUE* to labor and capital using three different adjustments and concludes that accounting for the income of the self-employed via *OSPUE* yields results indicative of stable factor shares across countries.[4]

Using the Gollin framework, and specifically Gollin's adjustment 2, Bernanke and Gurkaynak (2001) estimate average labor shares over the period 1980-1995. They increase the number of countries for which labor shares can be calculated by constructing an *imputed OSPUE* measure. This measure is substituted in place of actual *OSPUE* for countries that report only total operating surplus and do not distinguish between the surplus of corporate enterprises and private unincorporated enterprises. Bernanke and Gurkaynak "find no systematic tendency for country labor shares to vary with real GDP per capita."

Regardless of the validity of the adjustment for self-employed income, using the standard measures of capital and labor to study the empirical relationship between factor shares and economic development is misleading if one fails to acknowledge the composite nature of the factors. Standard accounting lumps non-reproducible and reproducible factors together in composite categories. The reproducible shares need to be separated from the non-reproducible shares, and the relationship between a single factor share, not a composite share, and economic development should be analyzed.

2.3 Decomposition of Total Capital's Share

I focus first on disentangling physical capital's share from natural capital's share. Let α denote physical capital's share, and let γ denote natural capital's share. The starting point is the computation of total capital's share, $\alpha + \gamma$.

2.3.1 Total Capital's Share

I compute total capital's share according to Bernanke and Gurkaynak's variation of Gollin's adjustment 2. This computation, which is given by

[4]Gollin does not, however, perform any formal tests for correlation between either capital or labor shares and economic development. Instead, his stability claim is based on the observation that the adjustments using *OSPUE* yield capital shares that are clustered in a range from 0.15 to 0.40. Such a range, which represents almost a three-fold difference, is nontrivial, especially in the context of empirical estimation of production functions where factor shares often appear as exponents.

$$\alpha+\gamma=1-\left(\frac{Employee\ Compensation}{GDP-Indirect\ Taxes-imputed\ OSPUE}\right), \qquad (1)$$

is an indirect measure of total capital's share, and, specifically, it is the perfect competition counterpart to total labor's share because it is the residual remaining after total labor's share is computed and subtracted from one.

There are numerous ways to compute total capital's share and total labor's share. The approach chosen will impact the estimates of all individual shares. The entire analysis in Section 2 was also performed using two additional approaches: one that makes a similar adjustment for self-employed income and another that does not. The qualitative results are robust with respect to the treatment of self-employed income. Therefore, I relegate the results of the analysis based on the other two approaches to an Appendix that is available upon request.

Subtracting *OSPUE* from GDP in equation (1) implies that self-employed income is dispersed between labor and capital in the same manner that corporate sector income is dispersed between the two factors. In other words, the share of labor income in *OSPUE* is assumed to be the same as the share of labor income generated in the corporate sector.

Ideally, *Indirect Taxes*, which include but are not limited to taxes on fixed assets and taxes on the total wage bill, should be allocated to capital or labor compensation depending on the tax type. However, most countries only report an aggregate tax value without any detailed breakdown of the various taxes. Therefore, it is impossible to know exactly how *Indirect Taxes* should be dispersed. By subtracting *Indirect Taxes*, the implicit assumption is that the fraction of *Indirect Taxes* attributable to capital compensation is equivalent to capital's share, and the fraction of *Indirect Taxes* attributable to labor compensation is equivalent to labor's share.[5]

Note that it is *imputed OSPUE* rather than *OSPUE* that enters equation (1). Though operating surplus can be broken down into corporate, unincorporated, public and private components, 1997 is the last year for which the U.N. Yearbook of National Accounts reports *OSPUE*. As is discussed later, data availability prevents me from disentangling physical

[5] Income received by firms and not paid to owners in the form of excess profits should be paid to the factors that generate the output. Thus, for the purpose of estimating factor shares, it is misleading to treat the income received by firms and paid to the government in the form of indirect taxes as anything other than income attributed to factors of production. Doing so would skew the analysis and yield factor share estimates that account for something less than one hundred percent of factor generated income.

capital's share from natural capital's share for any year except 2000. Therefore, I need *OSPUE* for the year 2000, so I impute it following the method of Bernanke and Gurkaynak (2001).

The *imputed OSPUE* measure is computed as the share of non-corporate employees in the labor force multiplied by private sector income. Implicit in this calculation is the assumption that the fraction of private sector income attributable to corporations is the same as the fraction of the labor force employed by corporations. Private sector income is the sum of corporate and non-corporate income, and it can also be interpreted as the sum of operating surplus and corporate employee compensation. Several different pieces of data, all of which come from either the International Labor Organization's (ILO) LABORSTA database or the ILO's 2005 Yearbook of Labor Statistics, are used to perform the calculations needed to arrive at the *imputed OSPUE* measure.[6]

Data for *Employee Compensation* and *Indirect Taxes* comes from table 2.3 of the 2006 version of the United Nations Yearbook of National Account Statistics. *GDP* numbers are reported in table 1.1 of the same publication.

Total capital share estimates are presented in Table 1 for the 33 countries for which the necessary data are available for the year 2000. The same shares are depicted graphically in Figure 1 where they are plotted against real GDP per worker.[7] Real GDP per worker data comes from version 6.2 of the Penn World Tables. Though not reported, formal regression results reveal a statistically significant quadratic relationship between total capital's share and real GDP per worker.[8] The regression line yielded by this formal analysis is shown in Figure 1.

The quadratic relationship between total capital's share and real GDP per worker is neither supported nor contradicted by economic theory. Total capital's share is an empirical measure that is often used by researchers who have intentions of estimating physical capital's share. However, as noted earlier, total capital's share is the sum of physical capital's share and natural capital's share. The aforementioned relationship is meaningful only because it suggests

[6] First, I calculate the corporate share of the labor force by dividing *Paid Employment* by the labor force, which I compute by summing *Employment* and *Unemployment*. The share of non-corporate employees is computed as one minus the corporate share of the labor force. To obtain *imputed OSPUE*, the share of non-corporate employees is then multiplied by total corporate sector income, which is the sum of *Gross Operating Surplus* and *Employee Compensation*.

[7] The International Organization for Standardization's (ISO) three-letter country codes are used as data markers in all plots.

[8] I use a coded independent variable to reduce the multicollinearity inherent in polynomial regression models, and I also test for heteroskedasticity. Details are presented in an Appendix that is available upon request.

that physical capital's share, natural capital's share or both are systematically related to output per worker; it is not very meaningful in and of itself. Separating physical capital's share from natural capital's share is a logical and necessary progression if the true nature of the relationship between each of these shares and the stage of economic development is to be revealed.[9]

2.3.2 Physical Capital's Share

To isolate physical capital's share, I follow the approach of Caselli and Feyrer (2007). Define total wealth as the sum of physical capital and natural capital so that $W = K + N$. W is total wealth; K denotes the value of the aggregate stock of physical capital; and N denotes the value of the aggregate stock of natural capital. Like Caselli and Feyrer, I assume that differences in capital gains for natural and physical capital are negligible so that all units of wealth pay the same return, r_w. Given this notation, total capital's share can be expressed as $\frac{r_w W}{Y}$, which, after substituting for W, is equivalent to $\frac{r_w(K+N)}{Y}$ where Y is aggregate output or GDP. This last term can be rewritten as the sum of two terms, $\frac{r_w K}{Y} + \frac{r_w N}{Y}$, the first of which is physical capital's share and the second of which is natural capital's share. Each share can be expressed as a function of total capital's share by multiplying and dividing by total wealth. Focusing for now on physical capital's share, such manipulation yields the following:

$$\frac{r_w K}{Y} = \frac{K}{W} \cdot \frac{r_w W}{Y}.$$

$$\Rightarrow \alpha \; = \frac{K}{W} \cdot (\alpha + \gamma) \tag{2}$$

Thus, physical capital's share is proportional to the fraction of wealth attributable to physical capital. In accordance with equation (2), estimates of α can be obtained by combining my estimates of $\alpha + \gamma$ from Section 2.3.1 with estimates of $\frac{K}{W}$, which can be computed using the wealth data reported in Appendix 2 of The World Bank (2006).

[9] Even if the composite relationship were statistically insignificant, a systematic relationship between each factor share and the stage of economic development could not be ruled out. The two shares summed together may not exhibit a statistically significant correlation with the stage of economic development if a positive correlation is compensated by a negative correlation.

The World Bank splits national total wealth for the year 2000, and only the year 2000, into three components: natural capital, produced capital and intangible capital. Total wealth is estimated as the present value of future consumption. The value of the produced capital stock is computed from historical investment data using the perpetual inventory method. Natural capital is valued according to data on physical stocks of natural resources and estimates of resource rents. Intangible capital, which encompasses human capital, social capital, property rights, efficiency of the judicial system, and effectiveness of government, is measured as the residual remaining after subtracting natural and produced capital from total wealth.

Total capital's share does not include income paid to human capital nor the value of any other element soaked up by The World Bank's intangible capital residual. Therefore, The World Bank's total wealth measure, which includes intangible capital, is too broad and can not be used to estimate W. In addition, produced capital's value, as reported by The World Bank, encompasses the value of urban land. Land, regardless of how it is used in production, should not be interpreted as physical capital. Unlike physical capital, land cannot be produced. Thus, The World Bank's estimates of produced capital's value are inappropriate estimates of K. In the context of this paper, urban land should be categorized as natural capital.

To convert the raw data provided by the World Bank into data appropriate for estimation of $\frac{K}{W}$, I proceed as Caselli and Feyrer do. First, I obtain measures of the value of the aggregate stock of physical capital, K. The World Bank follows Kunte (1998) and assumes for each country a value of urban land equal to 24 percent of the value of the aggregate stock of physical capital. So, produced capital's value equals $K + .24K$, and estimates of K are derived by dividing The World Bank's estimates of produced capital's value by 1.24. Since the value of N as reported by The World Bank does not include urban land but the value of N as defined herein does, it follows that urban land's value should be reallocated. To do this, I take The World Bank's estimates of produced capital's value and subtract the newly obtained estimates of K to obtain urban land values. I then add these urban land values to The World Bank's estimates of N to obtain corrected estimates of N. W is then estimated as the sum of the estimate of K and the corrected estimate of *N*. It follows that the estimate of a country's physical capital share of wealth, $\frac{K}{W}$, is computed by dividing the estimate of *K* by the estimate of *W*.[10]

Estimates of α for the year 2000 are presented in Table 2 and plotted against real GDP per worker in Figure 2.[11] I regress α on an intercept and real GDP per worker, and OLS estimation reveals a positive and statistically significant slope coefficient at the 5% level. This indicates that physical capital's share, as predicted, is positively correlated with the stage of economic development across countries. Regression results are presented in column 1 of Table 3.

2.3.3 Natural Capital's Share

Natural capital's share can be expressed in general terms as

$$\frac{r_W N}{Y} = \frac{N}{W} \cdot \frac{r_W W}{Y}$$

$$\Rightarrow \gamma = \frac{N}{W} \cdot (\alpha + \gamma), \qquad (3)$$

but given estimates of total capital's share and physical capital's share, it is easier and equivalent to back out natural capital's share as a residual. Table 4 presents the estimates of natural capital's share. These estimates are plotted against real GDP per worker in Figure 3. The scatter plot seems to indicate a negative correlation between γ and real GDP per worker, which is to be expected given the non-reproducible nature of natural capital. This is supported by OLS estimation, which indicates a negative and statistically significant relationship between the two variables at the 1% level. The regression results are reported in column 2 of Table 3.

2.4 Decomposition of Total Labor's Share

I turn now to disentangling unskilled labor's share from human capital's share. Cross country estimates of total labor's share incorporate *Employee Compensation*. *Employee Compensation* conflates the income paid to unskilled labor and the income paid to human capital. My approach involves estimating the income paid to unskilled labor and then computing

[10] The World Bank reports all of its data in dollars per capita.
[11] α is estimated for 31 countries. This is two fewer than the 33 for which total capital's share, $\alpha + \gamma$, was estimated. The sample is smaller because wealth data is not available for the Czech Republic and Poland.

unskilled labor's share. Human capital's share is the residual left over after subtracting unskilled labor's share from total labor's share.

2.4.1 Total Labor's Share

Let η denote unskilled labor's share and let β denote human capital's share. Assuming that self-employed income is allocated to labor and capital in the same proportions as corporate sector income, total labor's share can be computed as

$$\eta + \beta = \frac{Employee\ Compensation}{GDP - Indirect\ Taxes - imputed\ OSPUE}. \tag{4}$$

The components of equation (4) and their data sources have already been discussed. Estimates of $\eta + \beta$ for 2000 are presented in Table 5 and plotted against real GDP per worker in Figure 4. The sample consists of the same 33 countries for which estimates of $\alpha + \gamma$ were presented. The total labor share estimate is the perfect competition counterpart to the total capital share estimate. Therefore, the estimates sum to one, and statistical inference reveals a quadratic relationship between total labor's share and real GDP per worker. The only difference is that the inference for total labor's share indicates downward concavity instead of upward concavity. The formal regression results are omitted but the quadratic regression line is shown in Figure 4.[12]

2.4.2 Unskilled Labor's Share

Ashenfelter and Jurajda (2001) collect average hourly gross wage rates for McDonald's restaurants across 27 countries for the year 2000. The McDonald's rates represent different compensations for identical jobs, and the authors use the rates to perform cross-country wage comparisons.[13] I use the average McDonald's wage rate to proxy for the compensation paid to an unskilled unit of labor. Such a proxy is reasonable because the wage rates that are collected are for basic entry level jobs, and these jobs do not require experience or any type of formal education or training. Employees generally begin working as crew members and are assigned to specific food preparation stations. They are then rotated through various stations and then to the sales counter where they work as cashiers. The wages are comparable across countries because the duties performed by entry level employees are identical across countries. McDonald's restaurants operate with a standardized protocol for employee work. The preparation of food is

[12] Regression details and results are presented in an Appendix available upon request.
[13] McDonald's wages are different within countries and within cities. Ashenfelter and Jurajda note that these differences are usually related to full-time/part-time status and seniority. They control for both issues when compiling their data.

extremely mechanized, and the equipment used varies little across restaurants within and between countries.

Given knowledge of hours worked and the number of workers in a country, the average hourly unskilled wage rate can be converted to a total wage bill under the hypothetical scenario that all workers in a country are compensated at the unskilled wage rate. This hypothetical wage bill as a fraction of total output is my estimate of unskilled labor's share.

I obtain average hours worked per worker in the year 2000 from table 4A in the Yearly Statistics section of the ILO's LABORSTA website.[14] This series is usually presented in terms of the average number of hours worked per week, though in a few cases, hours worked per month are reported. The type of worker encompassed by the reported averages varies from country to country. Some averages are computed based on total employment, which includes employees and self-employed workers, and some are computed based on paid employment, which includes only employees.

To compute the total unskilled wage bill for each country in the year 2000, I first multiply the average hourly McDonald's wage rate for an individual by the average number of hours worked. I then multiply by either 52 or 12, depending on whether average hours worked is reported in per week or per month form respectively. This yields the average yearly compensation of an unskilled worker in 2000. Finally, *Employment*, which is reported in table 2A in the Yearly Statistics section of the LABORSTA database, is multiplied by average yearly compensation of an unskilled worker to obtain the total unskilled wage bill.

Two implicit assumptions associated with my approach should be noted. First, recall that average hours worked pertains to total employment for some countries and only paid employment for others. The LABORSTA database makes it clear as to which workers are included in the reported data, but when I create the average yearly compensation of an unskilled worker, I treat all average hours worked data the same. I do not distinguish between average hours worked for total employment and average hours worked for paid employment. Thus, I am assuming that average hours worked by employees is equivalent to average hours worked by the

[14] For a few countries, average hours worked data is not reported in table 4A of the LABORSTA website. In these cases I obtain data from the ILO's October Inquiry and compute a weighted average using the number of workers employed. The October Inquiry reports average hours of work per week or per month for up to 159 occupations. Table 2B in the Yearly Statistics section of the LABORSTA database reports employment numbers categorized by industry. I weight the average hours worked for each occupation by the fraction of employees who work in the industry of which the particular occupation belongs.

self-employed. Secondly, since *Employment* encompasses employed and self-employed workers, multiplying average yearly compensation by *Employment* means I am assuming that employed and self-employed workers command equivalent wages.

By construction, the unskilled wage bill already incorporates the labor income of unskilled self-employed workers. There is no need to make any sort of adjustment by subtracting *OSPUE*, and the unskilled wage bill is just divided by *GDP* less *Indirect Taxes* so that unskilled labor's share is given by

$$\eta = \frac{Unskilled\ Wage\ Bill}{GDP - Indirect\ Taxes}. \tag{5}$$

The data needed to estimate η is available for 15 countries, and the estimates are presented in column 1 of Table 6.[15] Figure 5 plots these estimates against real GDP per worker. OLS estimation reveals a negative relationship between unskilled labor's share and the stage of economic development. These results are presented in column 1 of Table 7, and the slope coefficient is statistically significant at the 5% level.

2.4.3 Human Capital's Share

Of the 15 countries for which η could be computed, only 10 of them overlap with countries for which $\eta + \beta$ could be computed. Column 2 of Table 6 presents the estimates of β, which are computed as residuals. Figure 6 plots these estimates against real GDP per worker. The regression results reported in column 2 of Table 7 reveal a positive slope coefficient, which is in line with theoretical predictions, but the coefficient is statistically insignificant. Thus, inference based on the 10 country full sample indicates no systematic relationship between human capital's share and the stage of economic development. However, Germany's human capital share, which takes on a value of 0.243, the lowest in the sample, is an outlier.[16] With real

---

[15] For clarity, the computation of unskilled labor's share for Canada is given below. As can be seen in Table 6, unskilled labor's share in Canada is equal to 0.192. I arrive at this number in the following manner. The average hourly gross wage rate for McDonald's cashier and crew workers equaled 6.95 Canadian dollars in 2000. Average hours worked per week by a worker in 2000, which I compute as a weighted average using the ILO's October Inquiry, is 36.9. *Employment* equals 14,764,200 in 2000. Therefore, the unskilled wage bill is equal to 6.95*36.9*52*14,764,200=1.969×10^{11}. GDP in Canada for the year 2000 is 1.07658×10^{12}, and *Indirect Taxes* equal 5.1691×10^{10}. Thus, unskilled labor's share in Canada in the year 2000 is $\frac{1.969\times10^{11}}{1.07658\times10^{12} - 5.1691\times10^{10}} = 0.192$.

[16] Germany is unique in the sense that most of its economic prosperity is generated by activity in the western part of the country. Even after reunification, the standard of living remains significantly higher in the former West German States. The West's prosperity is undoubtedly responsible for the country's high level of output per worker. The economic conditions in the East along with my specific methodology may be responsible for the share result. If the

GDP per worker just over \$51,000, the corresponding human capital share of 0.243 stands out in Figure 6.[17] Because there are only 10 observations, data points that take on extreme values relative to the others in the sample have a substantial impact on the OLS estimation. When Germany is omitted, the slope coefficient remains positive and becomes statistically significant at the 5% level. See column 3 of Table 7 for the regression results omitting Germany.

Though this result would be more appealing had it been obtained with a larger sample, the implications of the result should not be dismissed. In spite of the small sample size, the positive correlation is confirmed statistically for real GDP per worker that ranges from about \$16,600 in Russia all the way up to \$67,000 in the U.S. So, the systematic relationship between human capital's share and real GDP per worker that exists when Germany is omitted is not specific to a cluster of countries at similar stages of economic development.

2.5 Remarks

The cross-country analysis of factor shares presented herein is more complete than the analyses of Zuleta (2008a) and Caselli and Feyrer (2007), and techniques that I employ represent clear departures from these studies. First, I decompose both total capital's share and total labor's share into reproducible and non-reproducible components. Caselli and Feyrer only separate physical capital's share from natural capital's share. They do not address total labor's share and its components. Zuleta decomposes total capital's share and total labor's share, but when analyzing total capital's share he only separates land's share from physical capital's share. Other natural resources including oil, natural gas and minerals are encompassed by the typical total capital share measure and should be distinguished from physical capital. My analysis, just as that of Caselli and Feyrer, makes this distinction and separates physical capital's share from natural capital's share, not just land's share. That being said, each of the two aforementioned studies contains a crucial element that the other study omits. I incorporate elements of both studies into a single, comprehensive analysis.[18]

---

average McDonald's wage rate for Germany overstates the wage earned by individuals in the East, then the estimate of unskilled labor's share for Germany is too high and consequently human capital's share is too low.

[17] The regression line shown in Figure 6 is derived after omitting Germany.

[18] I also control for heteroskedasticity. Although the results are unaffected, identifying and controlling for the presence of heteroskedasticity adds credibility to my approach and my inference. In any cross-country analysis, systematic variation in data quality is a concern. Knowing that the sign and significance of coefficient estimates are true reflections of the relationship between factor shares and real GDP per worker is imperative.

Second, to disentangle physical capital's share from natural capital's share I use the same wealth data published by The World Bank (2006) for the year 2000 that Caselli and Feyrer use. But, instead of combining total capital share estimates for the period 1980-1995 with the wealth data for 2000, I compute and then combine total capital share estimates for 2000 with the wealth data for 2000. Caselli and Feyrer implicitly assume that average total capital's share over the period 1980-1995 is equivalent to total capital's share for the year 2000. Factor shares are not constant over time, so such an assumption can yield misleading results.[19] If one compares the physical capital share estimates reported in Caselli and Feyrer's Table II to physical capital share estimates reported in my Table 2, it is obvious that the time period used for total capital share estimation is nontrivial for some countries. Nonetheless, the relationship between physical capital's share and real GDP per worker found by Caselli and Feyrer is qualitatively consistent with the one found herein.

The most striking departure of my analysis from the current literature is the approach used to disentangle human capital's share from unskilled labor's share. I do not use statistical techniques or human capital proxies to obtain my share estimates. Instead, using the definition of a factor share as a guide, I combine direct observations of unskilled wage rates with employment data to obtain estimates of unskilled labor's share. Human capital's share is then the residual remaining after unskilled labor's share is subtracted from total labor's share.

Zuleta (2008a), who also disentangles human capital's share from unskilled labor's share, uses parameters yielded by growth regressions to obtain share estimates. The human capital proxies needed to estimate his growth regressions are computed using substantial amounts of guesswork and interpolation. The proxies are also dependent on educational attainment data that vary substantially across sources. Though my technique involves the assumption that average McDonalds' cashier and crew wages represent average unskilled labor compensation, my estimates, unlike Zuleta's estimates, are not functions of statistically estimated parameters that are subject to measurement error and dependent on the functional form of a production function.[20]

[19] See Sato (1970), Bound and Johnson (1995), Blanchard (1997), and Krueger (1999) for evidence of variation in factor shares over time.
[20] My analysis, unlike Zuleta's analysis, is not limited to OECD countries.

3 Implications for Development Accounting

The evidence presented thus far shows that factor shares, when properly defined and measured, vary systematically across countries. This suggests that factor shares should be treated as variables rather than parameters. How important is it that variation in factor shares be acknowledged when conducting empirical research? I address this question in a development accounting framework.

3.1 The Production Function

Since I am introducing variable factor shares, something completely ignored until now[21], it is reasonable to carry out my analysis using a production function comparable to that which most development accounting studies employ. Therefore, I stick with the workhorse of the literature and employ a Cobb-Douglas functional form.[22]

Let production in country *i* be characterized by

$$Y_i = A_i K_i^{\alpha_i} N_i^{\gamma_i} \left(L_i h_i - L_i\right)^{\beta_i} L_i^{\eta_i} \tag{6}$$

where L is the number of workers and represents unskilled labor; h is a labor augmenting variable encompassing the level of education; and A is the TFP residual.[23] The other variables in equation (6) have been previously defined. I take the average years of schooling for the population aged 15 and over from Barro and Lee (2001) and convert it into a proxy for human capital following Hall and Jones (1999). $h = e^{\phi(E)}$ where E is average years of schooling, and $\varphi(E)$ is piecewise linear with slope 0.117 for $E \le 4$, 0.097 for $4<E\le 8$ and 0.075 for $E>8$. The slope coefficients represent rates of return for education as reported by Psacharopoulos and Patrinos (2004). $Lh - L$ measures human capital and can be thought of as the difference between the effective workforce, which is the workforce augmented by education, and the basic workforce, which is not augmented. I use the *Economically Active Population*, which is reported

---

[21] Caselli (2005) analyzes the impact of allowing shares to take on different constant values, but he does not let shares vary across countries.

[22] Mankiw, Romer, and Weil (1992), Klenow and Rodriguez Claire (1997), Hall and Jones (1999), Caselli (2005), Weil (2007), and Vollrath (2009) all employ the Cobb-Douglas form to carry out development accounting exercises.

[23] Though "TFP residual" or simply "TFP" is common jargon in the development accounting literature, the residual for which these terminologies refer encompasses more than just productivity or efficiency. Given the data used to proxy for the observable components in an equation characterizing aggregate production, the TFP residual is the component that takes on whatever value is needed for the equation to hold exactly.

in the ILO's LABORSTA database, to proxy for *L*. Data sources for all other observable variables are the same as the data sources used in Section 2. All data is for the year 2000.

An alternative specification is the CES production function. The CES production function, which includes Cobb-Douglas as a special case, allows for non-neutral differences in technology. Though theoretically appealing, the CES specification presents empirical challenges. Caselli (2005) experiments with the CES function and finds that the development accounting results are very sensitive to the choice of the elasticity of substitution. This poses an empirical issue because, as noted by Caselli (2005), published estimates of the elasticity of substitution between capital and labor are neither "stable nor reliable."[24] That said, it is not obvious that any bias resulting from misspecification associated with forcing the elasticity of substitution to equal one across all countries in the Cobb-Douglas form is greater than the bias associated with the misspecification resulting from plugging in inaccurate measures of the elasticity of substitution for each country in a CES framework.[25]

Note also that the production structure I use in equation (6) consists of a single sector. Caselli (2005) and Vollrath (2009) estimate a two sector model in the spirit of Galor and Weil (2000) and Hansen and Prescott (2002). Both use two Cobb-Douglas production functions, one for agriculture and one for industry, to control for the distribution of factors across the two sectors. The agriculture sector in these models employs land, and the industrial sector does not. Both approaches have their merits, but neither accounts for natural resources such as minerals and oil that are used in industry. Minerals and oil are non-reproducible factors just as land is. Since both approaches completely overlook a portion of natural capital, neither can support an analysis aimed at evaluating the implications of variability in all reproducible and non-

[24] Studies that estimate the elasticity of substitution between capital and labor include: Arrow et al. (1961), Ferguson (1965), Sato (1970), Hamermesh (1993), Genc and Bairam (1998), Duffy and Papageorgiou (2000), and Boskin and Lau (2000). Some of these studies report estimates below one, and others report estimates above one.

[25] Caselli and Coleman (2006) use a CES aggregate of unskilled and skilled labor to model their labor input into production. They use Katz and Murphy's (1992) estimate of 1.4 for the elasticity of substitution between skilled and unskilled labor in the United States. They argue that this is reasonable, in part, because Autor et al (1998) conclude that the elasticity of substitution between skilled and unskilled labor is unlikely to fall outside the interval between one and two. That said, there is much more uncertainty surrounding the elasticity of substitution between capital and labor. Moreover, distinguishing between reproducible and non-reproducible factor shares as I do and analyzing the consequences of allowing these shares to vary across countries in a CES framework would require data on the elasticity of substitution between: natural capital and physical capital, physical capital and unskilled labor, physical capital and human capital, natural capital and human capital, natural capital and unskilled labor, and human capital and unskilled labor.

reproducible factor shares. My approach does not overlook any portion of reproducible or non-reproducible factors; it merely lumps all factors into a single aggregate production function.

3.2 Estimating the Variation in Output per Worker accruing to *observables* and the TFP Residual

Henceforth, I omit the i subscript except where clarity requires it. Dividing both sides of equation (6) by L yields the per worker production function,

$$y = Ak^{\alpha} n^{\gamma} (h-1)^{\beta} \ , \tag{7}$$

where lower case letters represent per worker values. Define $y_{observables} = k^{\alpha} n^{\gamma} (h-1)^{\beta}$ so that the per worker production function can be rewritten as $y = Ay_{observables}$. The exact form of $y_{observables}$ will change as assumptions about factors and factor shares change, but in general, the variance of output per worker can be decomposed as follows:

$$\mathrm{var}[\ln y] = \mathrm{var}[\ln A] + \mathrm{var}[\ln y_{observables}] + 2\,\mathrm{cov}[\ln A, \ln y_{observables}]. \tag{8}$$

How much of the variation in output per worker across countries is attributable to variation in *observables*, and how much is attributable to variation in the TFP residual? Any correlation between *observables* and the TFP residual implies that the variability in output per worker accruing to *observables* is correlated with the variation in output per worker accruing to the TFP residual. Therefore, the covariance term embodies pertinent interaction effects that need to be accounted for in some manner when determining the contribution of variability in each the observable and residual components to variability in output per worker. One option is to ignore the covariance and assume that the TFP residual is constant across countries. Caselli (2005) takes this approach. I find the approach unappealing because it yields relative variances that do not add up to one when the actual covariance between the TFP residual and *observables* is non-zero. Mankiw, Romer, and Weil (1992) allow the TFP residual to vary, but given their reliance on regression analysis to obtain input measures, their covariance term is zero by construction. Their approach is just as unappealing because the correlation between *observables* and the TFP residual is ignored.[26]

[26] In my sample, the statistical correlation between the TFP residual and *observables* ranges from -0.85 to 0.30 depending on the specific assumptions accompanying the production function. The bottom of Table 8 presents all relevant variance and covariance measures, and the last row in Table 8 provides the statistical correlation between *observables* and the TFP residual. To see why the relative variances are misleading if the correlation between the TFP residual and *observables* is ignored, consider the scenario yielded by the production function in column 1 of

A more useful variance decomposition, which is suggested by Baier, Dwyer, and Tamura (2006)[27], is

$$\frac{\left(1-\rho^2_{obs.,A}\right)\operatorname{var}\left[\ln y_{observables}\right]}{\operatorname{var}[\ln y]}+\frac{\left\{sd\left[\ln A\right]+sd\left[\ln y_{observables}\right]\rho_{obs.,A}\right\}^2}{\operatorname{var}\left[\ln y\right]}=1. \tag{9}$$

$\rho_{obs.,A}$ is the statistical correlation between *observables* and the TFP residual. *sd* denotes standard deviation. With this decomposition the covariance between the TFP residual and *observables* is not ignored. Rather, all of the correlation between *observables* and the TFP residual is attributed to the TFP residual. Also, the estimates of the relative variances sum to one, and interpreting each value is straightforward. The first term on the left hand side of equation (9) is the fraction of variation in output per worker attributable to variation in *observables*, and the second term is the fraction of variation in output per worker attributable to variation in the TFP residual.[28]

There is an economic justification for this decomposition. The level of economic development is dependent on certain economic fundamentals that are not explicitly accounted for

---

Table 8. The correlation between the TFP residual and *observables* equals 0.30 for this production function. $\frac{\operatorname{var}\left[\ln y_{observables}\right]}{\operatorname{var}\left[\ln y\right]}$ equals 0.49 in this case. To say that 49% of income variation is explained by *observables* is misleading because implicit in such a claim is that 51% of income variation is explained by *unobservables* -- i.e., the TFP residual. Given the data, this is not the case. $\frac{\operatorname{var}\left[\ln A\right]}{\operatorname{var}\left[\ln y\right]}$ equals 0.29, so, disregarding the covariance term, variation in *observables* and variation in *unobservables* together explain only 78% of the variation in income. That suggests that something other than *observables* or *unobservables* explains 22% of the variation in income. Such a scenario is illogical and stems from the fact that the covariance term does not equal zero.

[27] Baier, Dwyer, and Tamura (2006) use the decomposition in a growth accounting framework, but adjusting it for use in a development accounting framework is straightforward.

[28] Since it is assumed that any relationship between *observables* and the TFP residual reflects effects of the TFP residual, the covariance term along with a fraction of the variation in *observables* is added to the variance of the TFP residual so that the fraction of variation in output per worker attributable to the TFP residual can be written: $\frac{\operatorname{var}\left[\ln A\right]+2\operatorname{cov}\left[\ln y_{observables},\ln A\right]+\operatorname{var}\left[\ln y_{observables}\right]\rho^2_{obs.,A}}{\operatorname{var}\left[\ln y\right]}$. This expression is equivalent to the expression given by the second term in equation (9). The fraction of the variation in *observables* that gets allocated to the variation in the TFP residual is determined by the squared correlation, $\rho^2_{obs.,A}$. *Observables* and the TFP residual may be negatively correlated. Squaring the correlation ensures that variation in *observables* that reflects variation in the TFP residual is added to variation in the TFP residual. The fraction of variation in output per worker attributable to variation in *observables* can be written as: $\frac{\operatorname{var}\left[\ln y_{observables}\right]-\operatorname{var}\left[\ln y_{observables}\right]\rho^2_{obs.,A}}{\operatorname{var}\left[\ln y\right]}$. This expression is equivalent to the expression given by the first term in equation (9). The intuition is that any variation in *observables* that really reflects variation in the TFP residual should be attributed to variation in the TFP residual and therefore subtracted from the variation in *observables*.

in the production function. Differences in the accumulation of factors and differences in factor shares are undoubtedly going to impact differences in output per worker, but these differences are driven by differences in saving rates, R & D costs and production technologies, all of which are encompassed by the TFP residual. Thus, the TFP residual drives all of the variation in *observables*. Attributing all of the interaction effects embodied by the covariance to the TFP residual not only makes interpreting relative variance estimates easier, it is a reasonable approach from a theoretical standpoint.

3.3 Relative Variance Estimates: Typical Assumptions

Estimates of the relative variances given by the decomposition in equation (9) are presented in Table 8 for four different combinations of assumptions pertaining to the production function.[29] The typical development accounting approach involves the following: α_i and $\beta_i + \eta_i$ are assumed to equal 1/3 and 2/3 respectively for all i[30]; human capital and unskilled labor are entangled in a single, composite measure; and natural capital is ignored so that γ_i equals zero for all *i*. With this approach, the production function simplifies to $y = Ak^{1/3}h^{2/3}$. Given this functional form, 45% of the variation in output per worker is attributable to *observables*, and 55% is attributable to the TFP residual. This breakdown of explanatory power is consistent with the consensus view that *observables* account for at most 50% of the variation in cross-country output per worker (Caselli 2005). This substantiates my method because no other study that I am aware of estimates relative variances according to equation (9). Klenow and Rodriguez-Clare (1997) attribute half of the contribution of the covariance term to the TFP residual and half to *observables*.[31] Weil (2007) uses the most similar

[29] Recall that physical capital's share and natural capital's share were computed for 31 countries. Of these 31 countries only 8 of them have the data necessary for direct computation of human capital's share. The missing human capital shares are interpolated using the intercept and slope coefficients yielded by the regression of human capital's share on real GDP per worker. Because Germany's human capital share was an outlier and omitted from the aforementioned regression, I do not include Germany in the development accounting analysis. Therefore, results in Table 8 are presented for a sample of 30 countries, not 31.
[30] Researchers often justify the constant exponent of one third by noting that one third is consistent with the average "capital" share of national income for a broad sample of countries. But, the computations that lead to this value do not separate the income that gets paid to physical capital from the income that gets paid to natural capital. One third is the average value of total capital's share. So, not only is the systematic variation in cross-country factor shares ignored in the development accounting literature, the typical approach incorrectly assigns a factor exponent to a factor. Physical capital's share, not total capital's share, should be the exponent associated with physical capital.
[31] Attributing half of the covariance term to the TFP residual and half to *observables* has no theoretical support. Klenow and Rodriguez-Clare just feel it is an "informative way of characterizing the data."

decomposition. He adds twice the covariance to the variance as I do, but he does not incorporate the correlation coefficient in any way.

3.4 Relative Variance Estimates: Allowing Factor Shares to Vary

As you move to the right in Table 8, the assumptions about the production function become increasingly consistent with reality. In the second column, factor shares are allowed to vary, but the other traditional development accounting assumptions still hold, so the production function is given by $y = Ak^{\alpha} h^{(\beta+\eta)}$. Allowing factor shares to vary has a substantial impact on the relative variance estimates. Of the variation in output per worker, 99% is now due to variation in *observables*, and only 1% is due to variation in the TFP residual. The TFP residual's explanatory power essentially disappears under traditional development accounting if factor shares are allowed to vary.

3.4.1 Decomposing the Variation in *Observables*

This result does not indicate that variation in factor shares absorbs the shift in explanatory power. It could be that allowing factor shares to vary simply serves as an avenue for the redistribution of explanatory power to the factors. Therefore, separating the variation in output per worker explained by *observables* into that accruing to factors and that accruing to factor shares is useful. This additional breakdown of explanatory power is a two step process. First, the variation in *observables* must be broken down into the variation attributable to each of the two observable components, $\alpha \ln k$ and $(\beta + \eta) \ln h$. The second step is breaking down the variation in each observable component into that accruing to the factor and that accruing to the factor share.

The variance of *observables* can be decomposed as follows:

$$\mathrm{var}[\ln y_{observables}] = \mathrm{var}[\alpha \ln k] + \mathrm{var}[(\beta + \eta)\ln h] + 2\,\mathrm{cov}[\alpha \ln k, (\beta + \eta)\ln h]. \tag{10}$$

Uniquely estimating the fractions of variation in *observables* attributable to variation in $\alpha \ln k$ and variation in $(\beta + \eta)\ln h$ requires that some assumption about the covariance in equation (10) be made. No theory exists to guide this assumption. However, by considering two estimates, each of which attributes all of the correlation to either $\alpha \ln k$ or $(\beta + \eta)\ln h$, an upper and lower bound for the relative variances can be obtained.

Denote $\rho_{\alpha \ln k, (\beta+\eta) \ln h}$ as the statistical correlation between $\alpha \ln k$ and $(\beta + \eta) \ln h$. If all of the correlation between $\alpha \ln k$ and $(\beta + \eta) \ln h$ is attributed to $\alpha \ln k$, the relative variances can be computed according to the following decomposition:

$$\frac{\left(1-\rho^2_{\alpha \ln k, (\beta+\eta) \ln h}\right) \text{var}[(\beta+\eta)\ln h]}{\text{var}[\ln y_{observables}]} + \frac{\left\{sd[\alpha \ln k] + sd[(\beta+\eta)\ln h]\rho_{\alpha \ln k, (\beta+\eta) \ln h}\right\}^2}{\text{var}[\ln y_{observables}]} = 1 . \tag{11}$$

The variation in *observables* attributable to variation in $(\beta + \eta) \ln h$ is represented by the first term on the left hand side of equation (11). The second term represents the variation in *observables* attributable to variation in $\alpha \ln k$. Alternatively, all correlation between $\alpha \ln k$ and $(\beta + \eta) \ln h$ can be attributed to $(\beta + \eta) \ln h$, in which case the relative variance decomposition takes the form:

$$\frac{\left\{sd[(\beta+\eta)\ln h] + sd[\alpha \ln k]\rho_{\alpha \ln k, (\beta+\eta) \ln h}\right\}^2}{\text{var}[\ln y_{observables}]} + \frac{\left(1-\rho^2_{\alpha \ln k, (\beta+\eta) \ln h}\right) \text{var}[\alpha \ln k]}{\text{var}[\ln y_{observables}]} = 1 . \tag{12}$$

As in equation (11), the first and second terms in equation (12) can be interpreted as the fractions of variation in *observables* attributable to $(\beta + \eta) \ln h$ and $\alpha \ln k$ respectively.

In order to break down the variation in *observables*, and ultimately the variation in output per worker, into that accruing to factors and that accruing to factor shares, the variation attributable to factors and factor shares must be extracted from the overall variation in each of the two observable components, $(\beta + \eta) \ln h$ and $\alpha \ln k$. Focusing first on $\alpha \ln k$, let E denote the expectations operator and let $\Delta\alpha = \alpha - E(\alpha)$ and $\Delta \ln k = \ln k - E(\ln k)$. Following the decomposition for the variance of a product presented by Goodman (1960) and Bohrnstedt and Goldberger (1969), the variance of $\alpha \ln k$ can be written

$$\begin{aligned} \text{var}[\alpha \ln k] = {} & E^2(\alpha)\text{var}[\ln k] + E^2(\ln k)\text{var}[\alpha] + E\left[(\Delta\alpha)^2(\Delta \ln k)^2\right] \\ & + 2E(\alpha)E\left[(\Delta\alpha)(\Delta \ln k)^2\right] + 2E(\ln k)E\left[(\Delta \ln k)(\Delta\alpha)^2\right] \\ & + 2E(\alpha)E(\ln k)\text{cov}[\alpha, \ln k] - \text{cov}^2[\alpha, \ln k]. \end{aligned} \tag{13}$$

The first and second terms on the right hand side of equation (13) can be thought of as the direct effects of variability in $\ln k$ and α respectively. The remaining terms encompass the interaction between $\ln k$ and α. To uniquely estimate the fractions of variation in $\alpha \ln k$ accruing to α and $\ln k$, some assumption about the interaction terms must be made. Again, no theory exists to guide such an assumption, but by considering two extreme decompositions, one in which all interaction is assumed to reflect variability in α and the other in which all interaction is assumed to reflect variability in $\ln k$, the possible range of relative variance estimates can be obtained.

In the first decomposition I assume that all interaction between $\ln k$ and α reflects variability in α. The relative variance decomposition is given by

$$\frac{E^2(\ln k)\mathrm{var}[\alpha] + Interaction_{\alpha,\ln k} + E^2(\alpha)\mathrm{var}[\ln k]\rho^2_{\alpha,\ln k}}{\mathrm{var}[\alpha \ln k]} + \frac{\left(1-\rho^2_{\alpha,\ln k}\right)E^2(\alpha)\mathrm{var}[\ln k]}{\mathrm{var}[\alpha \ln k]} = 1 \quad (14)$$

where $Interaction_{\alpha,\ln k} = E\left[(\Delta\alpha)^2(\Delta \ln k)^2\right] + 2E(\alpha)E\left[(\Delta\alpha)(\Delta \ln k)^2\right] + 2E(\ln k)E\left[(\Delta \ln k)(\Delta \ln \alpha)^2\right]$
$+ 2E(\alpha)E(\ln k)\mathrm{cov}[\alpha,\ln k] - \mathrm{cov}^2[\alpha,\ln k]$

and $\rho_{\alpha,\ln k}$ denotes the statistical correlation between α and $\ln k$. The first term on the left hand side of equation (14) represents the fraction of variation in $\alpha \ln k$ attributable to variation in α. The second term represents the fraction of variation attributable to $\ln k$.

Alternatively, if all of the interaction is assumed to reflect variability in $\ln k$, the relative variances can be estimated according to

$$\frac{\left(1-\rho^2_{\alpha,\ln k}\right)E^2(\ln k)\mathrm{var}[\alpha]}{\mathrm{var}[\alpha \ln k]} + \frac{E^2(\alpha)\mathrm{var}[\ln k] + Interaction_{\alpha,\ln k} + E^2(\ln k)\mathrm{var}[\alpha]\rho^2_{\alpha,\ln k}}{\mathrm{var}[\alpha \ln k]} = 1. \quad (15)$$

As in equation (14), the first term on the left hand side of equation (15) is the fraction of variation in $\alpha \ln k$ attributable to variation in α, and the second term is the fraction of variation in $\alpha \ln k$ attributable to variation in $\ln k$.

The variance decomposition of $(\beta+\eta)\ln h$ is identical to the decomposition given by equation (13), only $\beta+\eta$ appears in place of α, and $\ln h$ appears in place of $\ln k$. The same issue as to how the interaction terms should be treated arises, and since there is no theory for which to appeal, I follow the same methodology used with α and $\ln k$ to obtain estimates of the range of relative variances. The relative variance decompositions take the same form as those in equations (14) and (15), but $\beta+\eta$ and $\ln h$ take the place of α and $\ln k$ respectively.

Given the range of estimates for the variation in *observables* accruing to the two observable components and the range of estimates for the variation in each observable component accruing to the factor and factor share, estimates of the range of variation in output per worker accruing to each factor and factor share can be determined. For example, 99% of the variation in output per worker accrues to *observables*. Decomposing this variation in accordance with equations (11) and (12) indicates that 97-100% of the variation in *observables* accrues to $\alpha \ln k$. Of the variation in $\alpha \ln k$, the decompositions given by equations (14) and (15) reveal that 73-94% of that variation accrues to α. Therefore, the lower bound for the range of variation in output per worker accruing to α is given by the product (99%)(97%)(73%) = 70%. The upper bound for the range of variation in output per worker accruing to α is given by the product (99%)(100%)(94%) = 93%. Thus, variation in α accounts for 70-93% of the variation in output per worker. The ranges of variation in output per worker accruing to $k, \beta + \eta$ and h are determined in a similar manner. As reported in column 2 of Table 8, 6-27% of the variation in output per worker accrues to k, 0-1% accrues to $\beta + \eta$, and 0-2% accrues to h.

In light of these results, it can be concluded that the variation in output per worker accrues primarily to physical capital's share. Variation in physical capital per worker absorbs the second largest fraction of variation in output per worker. Variation in total labor's share and variation in the average level of human capital augmented labor together account for a relatively small portion of the variation in output per worker. The important revelation is that the explanatory power lost by the TFP residual is not redistributed to factors when factor shares are allowed to vary. It is the actual variation in factor shares and primarily the variation in physical capital's share that absorbs the TFP residual's lost explanatory power.

3.5 Distinguishing between Human Capital and Unskilled Labor

Though I allow factor shares to vary in the second column of Table 8, human capital and unskilled labor are entangled in a single, composite measure, and natural capital is not acknowledged. In other words, no distinction between reproducible and non-reproducible factors has been made. Column 3 of Table 8 presents results based on $y = Ak^{\alpha}\left(h-1\right)^{\beta}$. Relative to the production function considered in Section 3.4, I have moved even further from the typical development accounting approach by treating human capital and unskilled labor as separate, imperfectly substitutable factors. Natural capital, however, is still omitted.

Following the decomposition given by equation (9), I find that variation in *observables* accounts for 99% of the variation in output per worker, and the remaining 1% is accounted for by variation in the TFP residual. I decompose the explanatory power of *observables* into that accruing to factors and factor shares following the steps described in Section 3.4.1. The only difference is that β and h-1 take the place of $\beta+\eta$ and h respectively.

The conclusions change very little. Results indicate that most of the variation in output per worker still accrues to variation in physical capital's share. Variation in physical capital per worker absorbs the majority of the remaining variation in output per worker. The labor variables, even after distinguishing between unskilled labor and human capital, explain very little of the variation in output per worker.

3.6 Including Natural Capital

I use my baseline production function, $y = Ak^{\alpha} n^{\gamma} (h-1)^{\beta}$, to obtain the results in column 4 of Table 8. None of the traditional development accounting assumptions is present. All factors of production, including natural capital, are acknowledged, reproducible factors are distinguished from non-reproducible factors, and factor shares are allowed to vary. In accordance with the relative variance decomposition given by equation (9), I find that 77% of the variation in output per worker accrues to *observables*, and 23% accrues to the TFP residual. The fraction of variation accruing to *observables* decreases relative to the same fraction in columns 2 and 3 because of the relatively large magnitude of the correlation between the TFP residual and *observables*.[32]

I follow a two step process analogous to that described in Section 3.4.1 to decompose the explanatory power of *observables* into that accruing to factors and that accruing to factor shares. The variance of *observables* can be expressed as

$$\begin{aligned}\mathrm{var}[\ln y_{observables}] = {} & \mathrm{var}[\alpha \ln k] + \mathrm{var}[\gamma \ln n] + \mathrm{var}[\beta \ln(h-1)] + 2\,\mathrm{cov}[\alpha \ln k, \gamma \ln n] \\ & + 2\,\mathrm{cov}[\alpha \ln k, \beta \ln(h-1)] + 2\,\mathrm{cov}[\gamma \ln n, \beta \ln(h-1)]\end{aligned} . \qquad (16)$$

Uniquely estimating the variation in *observables* accruing to $\alpha \ln k$, $\gamma \ln n$, and $\beta \ln(h-1)$ requires assumptions about the interaction effects contained within the covariance terms in equation (16). Previously, there was only one covariance term to deal with at this stage in the process. Now there are three. However, it turns out that the last two terms on the right hand side of equation (16) are empirically negligible. Omitting these covariances yields

[32] The intuition follows directly from equation (9). The fraction of variation in output per worker assumed to reflect variation in *observables* gets smaller as the magnitude of the correlation between *observables* and the TFP residual gets larger.

$$\widetilde{\mathrm{var}}[\ln y_{observables}] = \mathrm{var}[\alpha \ln k] + \mathrm{var}[\gamma \ln n] + \mathrm{var}[\beta \ln(h-1)] + 2\,\mathrm{cov}[\alpha \ln k, \gamma \ln n], \tag{17}$$

which is an extremely good approximation of the actual variance of *observables*. The actual variance equals 0.643, and the approximation equals 0.636.

In light of this result, I determine an upper and lower bound for the variation in *observables* accruing to each of the three components by considering two alternative relative variance decompositions. The first decomposition, which is given by

$$\frac{\left(1-\rho^2_{\alpha \ln k,\, \gamma \ln n}\right)\mathrm{var}[\gamma \ln n]}{\widetilde{\mathrm{var}}[\ln y_{observables}]} + \frac{\left\{sd[\alpha \ln k] + sd[\gamma \ln n]\rho_{\alpha \ln k, \gamma \ln n}\right\}^2}{\widetilde{\mathrm{var}}[\ln y_{observables}]} + \frac{\mathrm{var}[\beta \ln(h-1)]}{\widetilde{\mathrm{var}}[\ln y_{observables}]} = 1 \tag{18}$$

attributes all of the correlation between $\alpha \ln k$ and $\gamma \ln n$ to $\alpha \ln k$. $\rho_{\alpha \ln k,\, \gamma \ln n}$ represents the statistical correlation between $\alpha \ln k$ and $\gamma \ln n$. The first, second, and third terms on the left hand side of equation (18) are the estimates of the variation in *observables* accruing to $\gamma \ln n$, $\alpha \ln k$, and $\beta \ln(h-1)$ respectively. If all correlation between $\alpha \ln k$ and $\gamma \ln n$ is attributed to $\gamma \ln n$, then the relative variance decomposition takes the form:

$$\frac{\left\{sd[\gamma \ln n] + sd[\alpha \ln k]\rho_{\alpha \ln k,\, \gamma \ln n}\right\}^2}{\widetilde{\mathrm{var}}[\ln y_{observables}]} + \frac{\left(1-\rho^2_{\alpha \ln k,\, \gamma \ln n}\right)\mathrm{var}[\alpha \ln k]}{\widetilde{\mathrm{var}}[\ln y_{observables}]} + \frac{\mathrm{var}[\beta \ln(h-1)]}{\widetilde{\mathrm{var}}[\ln y_{observables}]} = 1\,. \tag{19}$$

The first, second, and third terms on the left hand side of equation (19) have the same interpretations as the corresponding terms in equation (18).

Notice that the estimate of the variation in *observables* accruing to $\beta \ln(h-1)$ is the same in both decompositions. This is because the covariance between $\beta \ln(h-1)$ and each of the other two observable components is negligible and therefore ignored. The covariance between $\alpha \ln k$ and $\gamma \ln n$ is not negligible, and so the relative variance estimates for each of these components is dependent on the degree to which variation in one of the components reflects variation in the other. There is no theory suggesting that a specific fraction of the interaction between $\alpha \ln k$ and $\gamma \ln n$ be allocated to either $\alpha \ln k$ or $\gamma \ln n$. There are, however, two possible extremes: either all variation in $\alpha \ln k$ reflects variation in $\gamma \ln n$ or all variation in $\gamma \ln n$ reflects variation in $\alpha \ln k$. Thus, the relative variance estimates for $\gamma \ln n$ and $\alpha \ln k$ contained in the decompositions given by equations (18) and (19) serve as upper and lower bounds.

I break down the variation in each of the three observable components into that accruing to the factor and that accruing to the factor share as in Section 3.4.1. Equations (13), (14), and

(15) pertain specifically to $\alpha \ln k$, but applying the methodology to $\beta \ln(h-1)$ and $\gamma \ln n$ is straightforward.

The break down of the explanatory power of *observables* indicates that most of the variation in output per worker accrues to physical capital's share and natural capital's share. As reported in column 4 of Table 8, 22-60% of the variation in output per worker accrues to natural capital's share, and 10-47% accrues to physical capital's share. Variation in physical capital accounts for 1-14% of the variation in output per worker, and each of the remaining variables accounts for no more than 2% of the variation.

3.7 Acknowledging a New Type of Technical Progress

The TFP residual is generally thought to encompass productivity and efficiency, and is often interpreted as "the" indicator of technology. Thus, the typical result that the lion's share of variation in output per worker accrues to the TFP residual is usually interpreted as evidence of technology's importance in explaining cross-country differences in output per worker. But, the TFP residual also encompasses all sorts of biases and measurement errors that arise from misguided assumptions about the production process. Factor shares are not constant across countries, so assuming they are constant forces the actual variation in factor shares to be encompassed by variation in the TFP residual. In addition, the omission of natural capital and the amalgamation of human capital and unskilled labor are misspecifications of the production function, and variation in the TFP residual will reflect these misspecifications.

In my sample, variation in the TFP residual explains a little over half of the variation in output per worker when the typical development accounting approach is followed. When factor shares are treated as variables and a distinction between all reproducible and non-reproducible factors of production is made, the overwhelming majority of variation in output per worker accrues to factor shares, not the TFP residual. This result, however, does not diminish the role of technical change.

Changes in technology are not synonymous with changes in the TFP residual. The TFP residual picks up everything not explicitly accounted for by the production function. Moreover, the TFP residual enters the production function linearly; therefore, it appropriately accounts for technical progress of only a factor augmenting nature. There is no reason to believe that technical progress cannot manifest itself as a change in factor shares. In fact, there is a theoretical precedent for such progress. Peretto and Seater (2008) and Zuleta (2008b) develop endogenous growth models whereby technical progress occurs via changes in factor shares. This type of progress, which Peretto and Seater refer to as factor-eliminating technical progress, impacts the intensity with which factors of production are used. It does not impact the effectiveness or productivity of factors of production, and so it is fundamentally different from factor-augmenting technical progress. The development accounting results presented herein do not dismiss the importance of technology. Rather, the large degree of explanatory power accruing to factor shares indicates the importance of acknowledging factor eliminating technical progress, a new form of technical progress that affects factor shares.

4 Conclusion

Skepticism about the constancy of factor shares dates back to the time of Keynes and Solow, but only recently have theoretical analyses like that of Peretto and Seater (2008) and Zuleta (2008b) yielded specific predictions about the systematic relationship between cross-country factor shares and the stage of economic development. I provide empirical evidence consistent with these theoretical claims, and, specifically, my results reveal that non-reproducible factor shares decrease with the stage of economic development, and reproducible factor shares increase with the stage of economic development. This result suggests that factor eliminating technical progress is a potentially important phenomenon, and incorporation of such progress into models of economic growth should be considered.

In addition, theoretical or empirical studies that incorporate the assumption of constant factor shares should be revisited. Researchers rarely make a distinction between reproducible and non-reproducible factors. As a result, the shares that are typically considered are composite shares that conflate the fractions of income paid to fundamentally different factors of production. A very common approach is to combine all factors of production into one of two categories: capital or labor. The standard capital share measure conflates physical capital's share and natural capital's share. The standard labor share measure conflates human capital's share and unskilled labor's share. Failure to acknowledge the composite nature of the standard share measures can yield misleading conclusions. The results presented herein reveal that the systematic relationship between composite shares and the stage of economic development is different from the systematic relationship between a single, non-reproducible or reproducible share and the stage of economic development. Kaldor (1961), whose "stylized facts" are often cited, concluded that factor shares were constant over time and across countries without making a distinction between reproducible and non-reproducible factors. This distinction turns out to be very important.

In the second part of the paper, I revisit the development accounting exercise, acknowledging variation in factor shares and making a distinction between reproducible and non-reproducible factors. The general consensus is that at least half of the variation in output per worker accrues to the TFP residual. Researchers have attempted a number of things in an effort to chip away at the TFP residual's explanatory power, but nothing has led to a substantial reduction in the importance of the TFP residual until now. The fraction of cross-country variation in output per worker accruing to the TFP residual drops from 55% when factors shares are assumed constant to a substantially lower 23% when factor shares are allowed to vary. Cross-country variation in factor shares, completely ignored in the standard approach, explains the majority of variation in output per worker.

The shift in explanatory power does not diminish the role of technical progress. It does, however, indicate that most of the variation in output per worker accruing to technical progress is variation in factor-eliminating rather than factor-augmenting progress. That said, identifying and understanding the determinants of cross-country differences in factor shares is imperative to understanding cross-country differences in output per worker.

References

Arrow, Kenneth, H.B. Chenery, B.S. Minhas, and Robert Solow. 1961. "Capital-labor Substitution." *The Review of Economics and Statistics*, 43 (3): 225-250.

Ashenfelter, Orley, and Stepan Jurajda. 2000. "Cross-country Comparisons of Wage Rates: The Big Mac Index." Charles University Prague and Academy of Sciences of the Czech Republic Working Paper.

Autor, David, Lawrence Katz, and Alan Krueger. 1998. "Computing Inequality: Have Computers Changed the Labor Market?" *Quarterly Journal of Economics*, 113 (4): 1169-1213.

Baier, Scott, Gerald Dwyer, and Robert Tamura. 2006. "How Important are Capital and Total Factor Productivity for Economic Growth?" *Economic Inquiry*, 44: 23-49.

Barro, Robert, and Jong-Wha Lee. 1993. "International comparisons of educational attainment." *Journal of Monetary Economics*, 32: 363-394.

Bernanke, Ben S., and Refet S Gurkaynak. 2001. "Is Growth Exogenous? Taking Mankiw, Romer, and Weil Seriously." *NBER Macroeconomics Annual*, 16: 11-57.

Blanchard, Oliver J. 1997. "The Medium Run." *Brookings Papers on Economic Activity*, 2: 89-158.

Bohrnstedt, George, and Arthur Goldberger. 1969. "On the Exact Covariance of Products of Random Variables." *Journal of the American Statistical Association*, 64: 1439-1142.

Boldrin, Michele, and David Levine. 2002. "Factor Saving Innovation." *Journal of Economic Theory*, 105: 18-41.

Boskin, Michael, and Lawrence Lau. 2000. "Generalized Solow Neutral Technical Progress and Postwar Economic Growth." NBER Working Paper No. 8023.

Bound, John, and George Johnson. 1995. "What are the Causes of Rising Wage Inequality in the United States?" *Economic Policy Review*, Federal Reserve Bank of New York: 9-17.

Caselli, Francesco. 2005. "Accounting for Cross-Country Income Differences." In *The Handbook of Economic Growth*, ed. Philippe Aghion and Steven Durlauf, Amsterdam: North-Holland.

Caselli, Francesco, and John Coleman. 2006. "The World Technology Frontier." *American Economic Review*, 96(3): 499-522.

Caselli, Francesco, and James Feyrer. 2007. "The Marginal Product of Capital." *Quarterly Journal of Economics*, 122: 535-568.

Cobb, Charles, and Paul Douglas. 1928. “A Theory of Production.” *American Economic Review*, 18(1): 139-165.

Duffy, J. and C. Papageorgiou. 2000. “A Cross-country Empirical Investigation of the Aggregate Production Function Specification.” *Journal of Economic Growth*, 6: 87-120.

Ferguson, C. 1965. “The Elasticity of Substitution and the Savings Ratio in the Neo-classical Theory of Growth.” *Quarterly Journal of Economics*, 79(3): 465-471.

Galor, Oded, and David Weil. 2000. “Population, Technology, and Growth: From the Malthusian Regime to the Demographic Transition and Beyond.” *American Economic Review*, 90: 806-828.

Genc, M. and E. Bairam. 1998. “The Box-Cox Transformation as a VES Production Function.” In *Production and Cost Functions: Specification, measurement and applications*, ed. E. Bairam, 54-61. Aldershot: Ashgate.

Gollin, Douglas. 2002. “Getting Income Shares Right.” *Journal of Political Economy*, 110(2): 458-474.

Goodman, Leo. 1960. “On the Exact Variance of Products.” *Journal of the American Statistical Association*, 55: 708-713.

Hall, Robert E., and Charles I. Jones. 1999. “Why Do Some Countries Produce So Much More Output per Worker Than Others?” *The Quarterly Journal of Economics*, 114(1): 83-116.

Hamermesh, Daniel. 1993. *Labor Demand*, Princeton: Princeton University Press.

Hansen, Gary D., and Edward C. Prescott. 2002. “Malthus to Solow.” *American Economic Review*, 92(4): 1205-1217.

International Labor Organization’s (ILO) Yearbook of Labor Statistics. 2005.

LABORSTA data base. 2007. International Labor Organization. http://laborsta.ilo.org (accessed August 2007).

Jones, Larry E., and Rodolfo E. Manuelli. 1997. “The sources of growth.” *Journal of Economic Dynamics and Control*, 21(1): 75-114.

Kaldor, Nicholas. 1961. “Capital Accumulation and Economic Growth.” In *The Theory of Capital*, ed. Friedrich A. Lutz and Douglas C. Hague, New York: St. Martin’s Press.

Katz, Lawrence, and Kevin Murphy. 1999. “Changes in the Wage Structure and Earnings Inequality.” In *Handbook of Labor Economics*, Vol. 3A, ed. Orley Ashenfelter and David Card, 1463-1555. Amsterdam: North-Holland.

Keynes, John M. 1939. "Relative Movements in Real Wages and Output." *Economic Journal*, 49(1): 917-949.

Klenow, Peter J., and Andres Rodriguez-Clare. 1997. "The Neoclassical Revival in Growth Economics: Has It Gone Too Far?" *NBER Macroeconomics Annual*, 12:73-103.

Krueger, Alan B. 1999. "Measuring Labor's Share." *American Economic Review*, 89(2): 45-51.

Kunte, A., K. Hamilton, J. Dixon, and M. Clemens. 1998. "Estimating National Wealth: Methodology and Results." Environment Department Paper 57, World Bank, Washington, DC.

Mankiw, Greg, David Romer, and David Weil. 1992. "A Contribution to the Empirics of Economic Growth." *Quarterly Journal of Economics*, 107(2): 407-437.

Peretto, Pietro, and John Seater. 2009. "Factor-Eliminating Technical Change." Duke University Working Paper.

Psacharopoulos, George, and Harry Anthony Patrinos. 2004. "Returns to investment in education: a further update." *Education Economics*, 12 (2): 111-134.

Sato, Ryuzo. 1970. "The Estimation of Biased Technical Progress and the Production Function." *International Economic Review*, 11(2): 179-201.

Solow, Robert. 1958. "A Skeptical Note on the Constancy of Relative Shares." *American Economic Review*, 48 (4): 618-631.

Summers, Robert, Alan Heston, and Bettina Aten. 2006. *Penn World Table Version 6.2*, Center for International Comparisons of Production, Income and Prices at the University of Pennsylvania.

The World Bank. 2006. *Where is the Wealth of Nations? Measuring Capital for the 21st Century*. Washington, DC.

United Nations Yearbook of National Account Statistics: Main Aggregates and Detailed Tables. 2006. New York: Statistical Office of the United Nations Secretariat, cd-rom.

Vollrath, Dietrich. 2009. "How important are dual economy effects for aggregate productivity?" *Journal of Development Economics*, 88(2): 325-334.

Weil, David. 2007. "Accounting for the Effect of Health on Economic Growth." *Quarterly Journal of Economics*, 122(3): 1265-1306.

Zeira, Joseph. 1998. "Workers, Machines, and Economic Growth." *Quarterly Journal of Economics*, 113(4): 1091-1117.

Zeira, Joseph. 2006. "Machines as Engines of Growth." Hebrew University Working Paper.

Zuleta, Hernando. 2007. "Why labor income shares seem to be constant." *Journal of International Trade & Economic Development*, 16(4): 551-557.

Zuleta, Hernando. 2008a. "An Empirical Note on Factor Shares." *Journal of International Trade & Economic Development*, 17(3): 379-390.

Zuleta, Hernando. 2008b. "Factor Saving Innovations and Factor Income Shares." *Review of Economic Dynamics*, 11(4): 836-851.

Table 1

Total Capital's Share, 2000

Country	Total Capital's Share	Country	Total Capital's Share
Australia	0.384	Japan	0.256
Austria	0.398	Korea, Republic Of	0.332
Belgium	0.340	Mauritius	0.354
Botswana	0.534	Mexico	0.518
Canada	0.334	Netherlands	0.418
Costa Rica	0.345	New Zealand	0.418
Czech Republic	0.472	Norway	0.526
Denmark	0.408	Panama	0.361
Egypt	0.538	Poland	0.379
Finland	0.418	Portugal	0.326
France	0.376	Russia	0.485
Germany	0.360	Singapore	0.443
Greece	0.443	Spain	0.306
Hungary	0.400	Sweden	0.351
Ireland	0.497	Trinidad and Tobago	0.409
Israel	0.313	U.S.A	0.320
Italy	0.408		

Source : Author's Calculations.

Table 2

Physical Capital's Share, 2000

Country	Physical Capital's Share	Country	Physical Capital's Share
Australia	0.219	Japan	0.204
Austria	0.293	Korea, Republic Of	0.251
Belgium	0.261	Mauritius	0.271
Botswana	0.318	Mexico	0.289
Canada	0.164	Netherlands	0.305
Costa Rica	0.137	New Zealand	0.154
Denmark	0.287	Norway	0.291
Egypt	0.237	Panama	0.200
Finland	0.284	Portugal	0.236
France	0.273	Russia	0.186
Germany	0.273	Singapore	0.357
Greece	0.309	Spain	0.222
Hungary	0.245	Sweden	0.249
Ireland	0.327	Trinidad and Tobago	0.105
Israel	0.231	U.S.A	0.218
Italy	0.302		

Source : Author's Calculations.

Table 3

Physical Capital's Share and Natural Capital's Share

	Dependent Variable	
	Physical Capital's Share	Natural Capital's Share
Variable		
Intercept	0.200***	0.251***
	(6.880)	(7.656)
real GDP per worker, y	1.162E-06**	-2.421E-06***
	(1.791)	(-3.307)
Adjusted R^2	0.069	0.249
F-test for no heteroskedasticity	0.511	0.205
	[3.340]	[3.340]
Sample	31 obs.	31 obs.

--t-statistics are in parantheses.

--brackets are 5% critical values of the F distribution.

--*indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 4

Natural Capital's Share, 2000

Country	Natural Capital's Share	Country	Natural Capital's Share
Australia	0.165	Japan	0.052
Austria	0.106	Korea, Republic Of	0.080
Belgium	0.079	Mauritius	0.083
Botswana	0.217	Mexico	0.230
Canada	0.170	Netherlands	0.114
Costa Rica	0.207	New Zealand	0.264
Denmark	0.121	Norway	0.235
Egypt	0.301	Panama	0.161
Finland	0.134	Portugal	0.091
France	0.103	Russia	0.299
Germany	0.087	Singapore	0.086
Greece	0.134	Spain	0.084
Hungary	0.156	Sweden	0.102
Ireland	0.170	Trinidad and Tobago	0.304
Israel	0.081	U.S.A	0.102
Italy	0.106		

Source : Author's Calculations.

Table 5

Total Labor's Share, 2000

Country	Total Labor's Share	Country	Total Labor's Share
Australia	0.616	Japan	0.744
Austria	0.602	Korea, Republic Of	0.668
Belgium	0.660	Mauritius	0.646
Botswana	0.466	Mexico	0.482
Canada	0.666	Netherlands	0.582
Costa Rica	0.655	New Zealand	0.582
Czech Republic	0.528	Norway	0.474
Denmark	0.592	Panama	0.639
Egypt	0.462	Poland	0.621
Finland	0.582	Portugal	0.674
France	0.624	Russia	0.515
Germany	0.640	Singapore	0.557
Greece	0.557	Spain	0.694
Hungary	0.600	Sweden	0.649
Ireland	0.503	Trinidad and Tobago	0.591
Israel	0.687	U.S.A	0.680
Italy	0.592		

Source : Author's Calculations.

Table 6

Unskilled Labor's Share and Human Capital's Share, 2000

Country	Unskilled Labor's Share	Human Capital's Share
Brazil	0.207	
Canada	0.192	0.474
Czech Republic	0.207	0.321
Germany	0.396	0.243
Hong Kong	0.086	
Japan	0.261	0.483
Korea, Republic Of	0.195	0.473
Philippines	0.500	
Poland	0.206	0.415
Russia	0.252	0.263
Singapore	0.141	0.416
Sweden	0.204	0.445
Thailand	0.410	
UK	0.241	
USA	0.172	0.508

Source : Author's Calculations.

Table 7

Unskilled Labor's Share and Human Capital's Share

Variable	Dependent Variable: Unskilled Labor's Share	Human Capital's Share	Human Capital's Share: Omit Germany
Intercept	0.347***	0.313***	0.302***
	(6.197)	(4.076)	(5.683)
real GDP per worker, y	-2.840E-06**	2.247E-06	3.049E-06**
	(-2.056)	(1.286)	(2.474)
Adjusted R^2	0.187	0.068	0.390
F-test for no heteroskedasticity	0.497	0.172	2.805
	[3.885]	[4.737]	[5.143]
Sample	15 obs.	10 obs.	9 obs.

--t-statistics are in parantheses.

--brackets are 5% critical values of the F distribution.

--*indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 8

Decomposing the Variability in Output per Worker

	Production Function			
	Constant Shares	Variable Shares		
Variance Decomposition	$y=Ak^{1/3}h^{2/3}$	$y=Ak^{\alpha}h^{\beta+\eta}$	$y=Ak^{\alpha}(h\text{-}1)^{\beta}$	$y=Ak^{\alpha}n^{\gamma}(h\text{-}1)^{\beta}$
Variation in Output per Worker attributable to *Observables*	0.45	0.99	0.99	0.77
Variation accruing to α		0.70 - 0.93	0.67 - 0.90	0.10 - 0.47
Variation accruing to k		0.06 - 0.27	0.06 - 0.27	0.01 - 0.14
Variation accruing to $\beta+\eta$		0.00 - 0.01		
Variation accruing to β			0.00 - 0.02	0.00 - 0.01
Variation accruing h		0.00 - 0.02		
Variation accruing to h-1			0.02 - 0.06	0.01 - 0.02
Variation accruing to γ				0.22 - 0.60
Variation accruing to n				0 - 0.08
Variation in Output per Worker attributable to the TFP residual	0.55	0.01	0.01	0.23
Variances and Covariances				
var(ln(y))	0.224	0.224	0.224	0.224
var(ln(A))	0.065	0.355	0.391	0.828
var(α ln(k))	0.066	0.529	0.529	0.529
var(($\beta+\eta$)ln(h))	0.012	0.016		
var(β ln(h-1))			0.017	0.017
var(γ ln(n))				0.656
cov[ln(A), α ln(k)]	0.027	-0.355	-0.376	-0.093
cov[ln(A), ($\beta+\eta$)ln(h)]	-0.002	0.031		
cov[ln(A), β ln(h-1)]			0.012	0.016
cov[ln(A), γ ln(n)]				-0.546
cov[α ln(k), γ ln(n)]				-0.283
cov[αln(k), ($\beta+\eta$)ln(h)]	0.016	-0.014		
cov[αln(k), β ln(h-1)]			0.007	0.007
cov[γ ln(n), β ln(h-1)]				-0.004
Raw Correlation				
correlation coefficient, $\rho_{obs,\,\mathrm{A}}$	0.30	-0.76	-0.78	-0.85

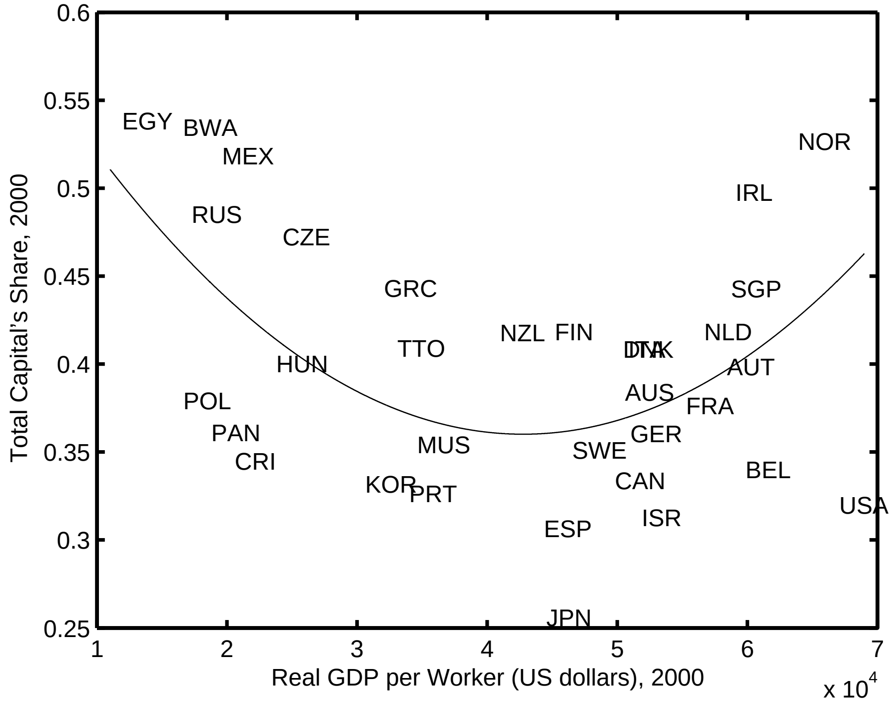

Fig. 1 Total Capital's Share vs. Real GDP per Worker

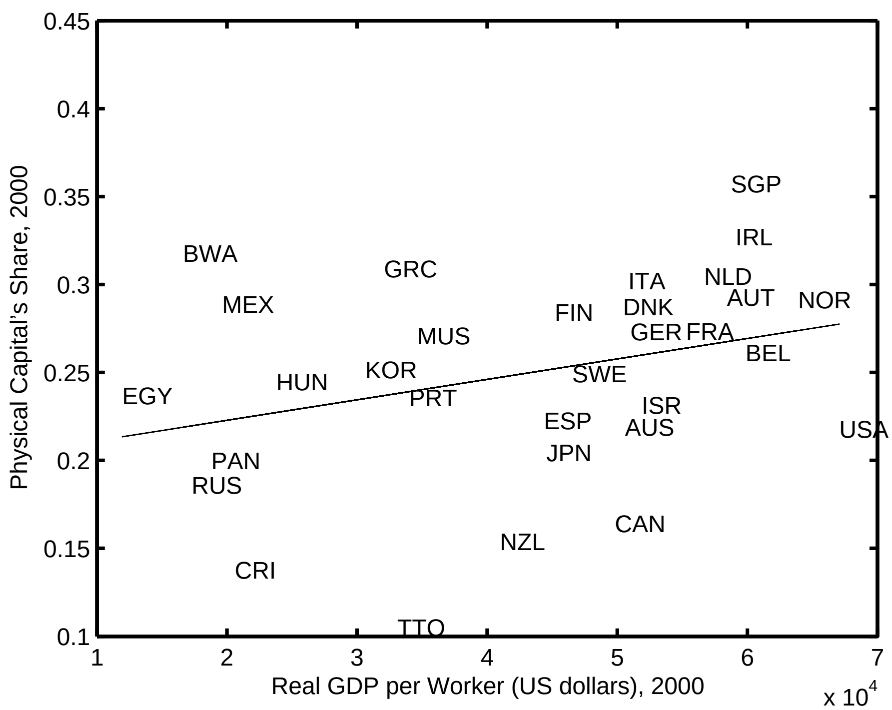

Fig. 2 Physical Capital's Share vs. Real GDP per Worker

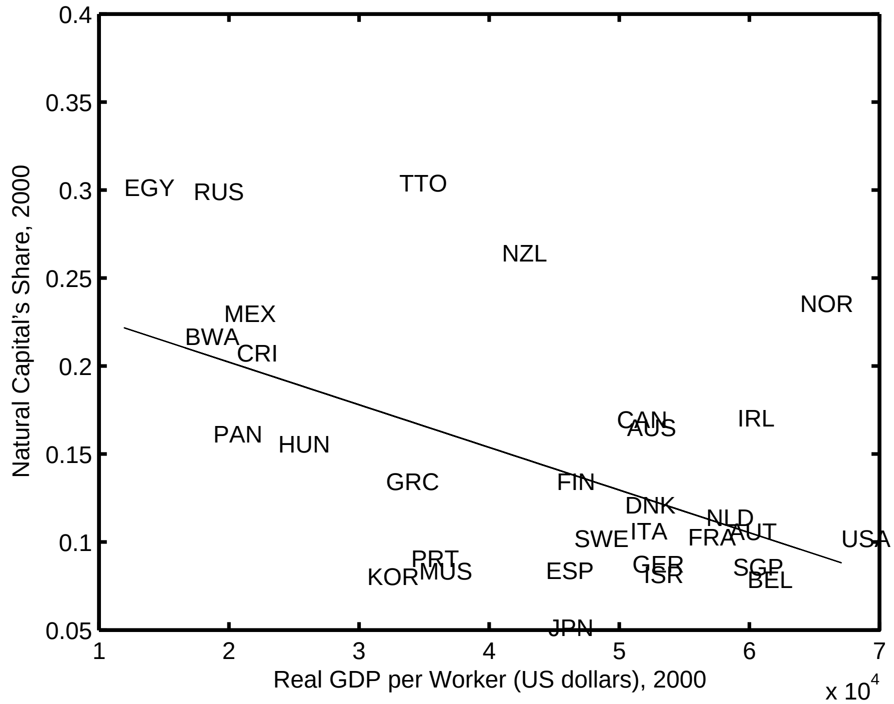

Fig. 3 Natural Capital's Share vs. Real GDP per Worker

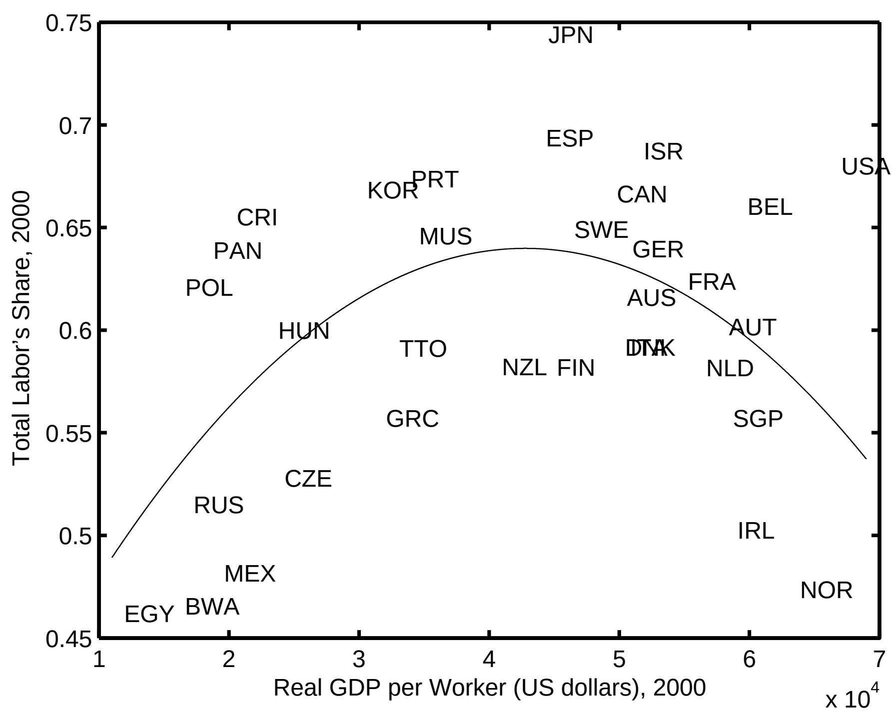

Fig. 4 Total Labor's Share vs. Real GDP per Worker

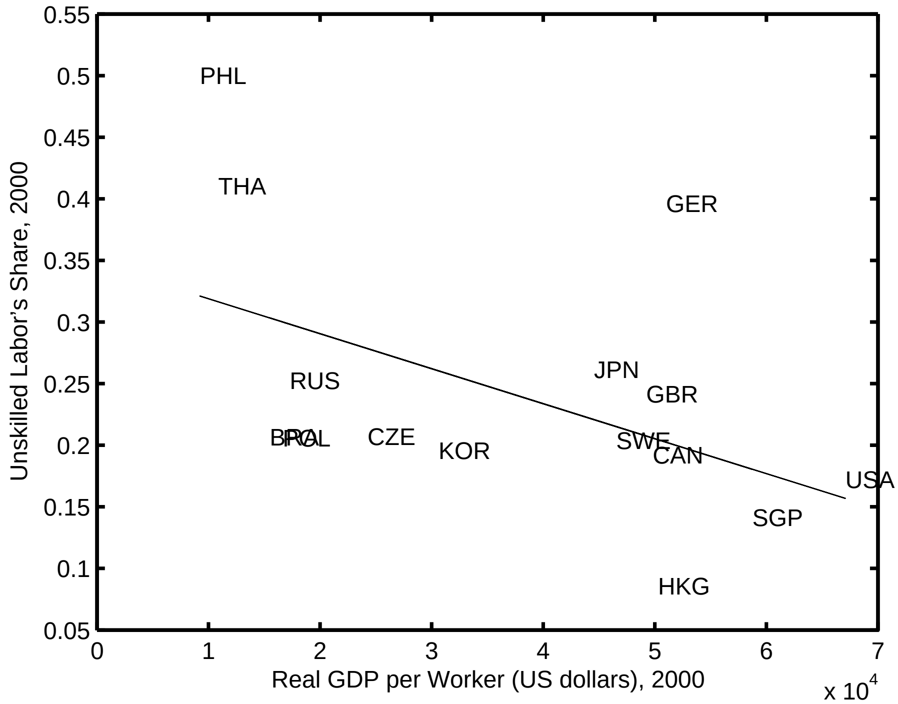

Fig. 5 Unskilled Labor's Share vs. Real GDP per Worker

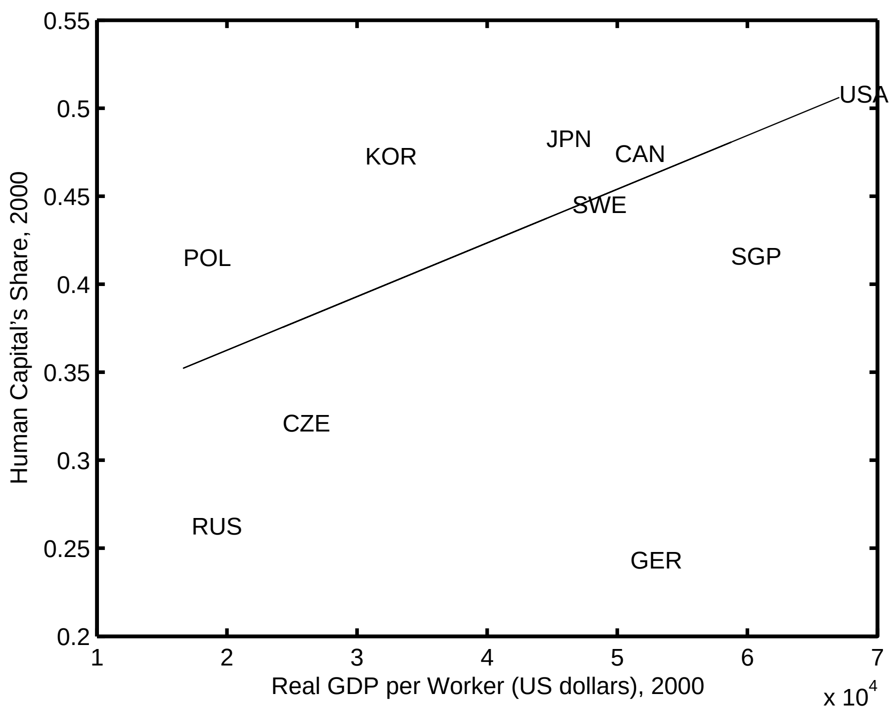

Fig. 6 Human Capital's Share vs. Real GDP per Worker