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

Job Market Paper

Brad Sturgill[*]
Ph.D. Candidate
Economics Department
North Carolina State University
Raleigh, NC 27695

November 2008

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 only acknowledge two factors of production: total capital and total labor. The failure to acknowledge more than two factors yields misleading results. Recent theoretical work predicts a systematic relationship between the stage of economic development and non-reproducible and reproducible factor shares. I disentangle physical capital's share from natural capital's share and human capital's share from unskilled labor's share, and I provide empirical evidence supporting these recent theoretical predictions. 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. The implications of variation in factor shares for development accounting are nontrivial. The fraction of cross-country variation in output per worker explained by variation in TFP decreases by more than 30% when factor shares are allowed to vary and when all factors of production are acknowledged. This evidence indicates that a substantial portion of variation in output per worker is determined by variation in factor shares. Understanding why factor shares differ across countries is important to understanding why output per worker differs across countries.

[*] The author is a visiting instructor at Appalachian State University. Correspondence to: Brad Sturgill, Room 2118, Raley Hall, Department of Economics, Appalachian State University, Boone, NC 28608, USA. Phone: 828-262-6950.

1 Introduction

Capital shares and labor shares are typically treated as parameters. For example, Hall and Jones (1999), in an investigation of productivity's role 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 (2007), conclude that factor shares vary across countries. Despite conflicting empirical evidence and despite the doubts expressed by Keynes (1939) and Solow (1958) about the constancy of factor shares, most empirical and theoretical 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 correctly. 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, at best, are misleading. Physical capital, which includes tools, machinery, and structures, or human capital, which encompasses education, health, and training are generally what economists are referring to when they talk about capital. However, standard capital share measures include the fractions of income paid to physical capital and natural capital. 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 standard capital's share and how it relates to the stage of economic development is really a claim about two separate factor shares and their collective relationship

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

with the stage of economic development. Likewise, standard measures of labor's share entangle the fraction of income paid to a reproducible factor, human capital, and a non-reproducible factor, unskilled labor.

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. I find no cross-country evidence of a systematic relationship between the stage of economic development and either total capital's share or total labor's share. However, there is strong evidence that non-reproducible factor shares decrease with the stage of economic development, and reproducible 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 (2008), 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 Total Factor Productivity (TFP). 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 TFP across countries. Specifically, I compare the fraction of cross-country variation in economic performance due to variation in TFP to the fraction of cross-country variation in economic performance due to variation in factors and factor shares. Rather than assume capital's share is constant across countries and equal to 1/3, I allow factor shares to vary in accordance with the estimates presented in the first part of the paper. Results shed new light on the relative importance of TFP in explaining cross-country variation in output per worker. I find that the variation in output per worker explained by variation in TFP falls by about 32% when factor shares are allowed to vary and all factors of production are acknowledged. This implies that variation in factor shares and variation in natural capital, an input that is usually ignored in development accounting studies, are important determinants of 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 I disentangle human capital's share from unskilled labor's share. Factor share estimates 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 estimate the TFP residual. I then analyze the impact of variable factor shares on the fraction of variation in output per worker explained by variation in observables and variation in TFP. Section 4 concludes.

2 Factor Shares and Economic Development

2.1 Theoretical Motivation

Absence of a theory about technological change that could alter factor shares and that distinguishes between reproducible and non-reproducible factors has led researchers to believe constancy of factor shares and amalgamation of factors are valid assumptions. However, recent theoretical advances in endogenous growth theory yield specific predictions about the systematic relationship between the stage of economic development and both reproducible and non-reproducible factor shares across countries.

Endogenous 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].

Because the Peretto and Seater theory allows for monopolistic competition in the intermediate goods sector, firms earn excess profits, and, as a result, payments to the factors of production do not exhaust firm revenues. Consequently, factor intensities and factor shares, though related, are not equivalent. But, 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 (2008) develops an endogenous growth model in which growth occurs via capital using and labor saving technological progress. Although he incorporates endogenous factor intensities, Zuleta, unlike Peretto and Seater, does not incorporate any resource absorbing activity to provide an avenue for the development of new technological knowledge. Instead, he assumes that saving can be instantaneously converted into new types of reproducible capital. Nonetheless, from an empirical standpoint, Zuleta’s model yields the same testable implications pertaining to factor shares, namely that reproducible factor

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

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].

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-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.

Gollin does not, however, perform any formal tests for correlation between either capital's share or labor's share and economic development. Instead, the stability claim is based

[3] Hansen and Prescott (2002) 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 this model is consistent with the aforementioned theories that suggest non-reproducible factor shares should fall with output per worker.

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 factors shares often appear as exponents.

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

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

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 1.

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

Subtracting *OSPUE* in the denominator of the second term on the right hand side of 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 and labor compensation depending on the tax type. However, most countries only report an aggregate tax value without any detailed breakdown of the various tax types encompassed by the aggregate value. 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* attributed to capital compensation is equivalent to capital's share, and the fraction of *Indirect Taxes* attributed to labor compensation is equivalent to labor's share[4].

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 herein, data availability prevents me from disentangling physical capital's share from natural capital's share for any year except 2000. Therefore, I have to impute *OSPUE* for the year 2000, and I do so 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 attributed 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

[4] 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.

Yearbook of Labor Statistics, are used to perform the calculations needed to arrive at the *imputed OSPUE* measure[5].

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 30 countries for which the necessary data was available for the year 2000. The same shares are depicted graphically in Figure 1 where they are plotted against real GDP per worker. Real GDP per worker data comes from version 6.2 of the Penn World Tables. There seems to be no evidence of correlation between total capital's share and real GDP per worker in the scatter plot shown in Figure 1. Formal regression analysis supports this.

Consider the following regression equation:

$$\alpha + \gamma = \psi_0 + \psi_1 y_{worker} + \varepsilon \qquad (2)$$

where y_{worker} is real GDP per worker and ε is the error term. OLS estimation of equation (2) reveals that the slope coefficient, ψ_1, is insignificant[6]. Regression results are reported in column 1 of Table 2.

Drawing final conclusions about the relationship between total capital's share and real GDP per worker at this point would be premature. In any cross-country study, data quality is a

[5] 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*.

[6] This evidence is consistent only with a rejection of the null hypothesis that a straight line with a non-zero slope fits the data. It does not rule out correlation between total capital shares and output per worker of a more complicated nature, namely a quadratic. That being said, I also estimated a quadratic model using OLS, and the estimation results do not support a quadratic relationship. I test for the significance of a quadratic relationship in all factor share analyses that follow.

concern. The general consensus is that the quality of economic data increases with the level of economic development. Failure to control for any systematic variation in data quality across countries could significantly impact the observed relationship between total capital's share and real GDP per worker. Specifically, if data quality is systematically related to total capital's share, then the squared residuals produced by estimation of equation (2) will fluctuate with data quality. If real GDP per worker and data quality are correlated, the squared residuals will fluctuate with real GDP per worker and introduce heteroskedasticity into the estimation of equation (2). Further precautions should be taken to ensure the observed relationship between total capital's share and real GDP per worker is representative of the actual relationship and not a mere artifact of systematic cross-country variation in data quality.

Data quality does introduce heteroskedasticity into the estimation of equation 2, and I control for this using weighted least squares. Columns 3 and 4 of Table 2 present these results. Since data quality is not necessarily the sole cause of heteroskedasticity in the data, I also compute a White corrected standard error, and column 2 of Table 2 presents the White corrected *t* statistic[7]. The qualitative results are unchanged after controlling for heteroskedasticity[8].

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. Assume that all units of wealth pay the same

[7] See the appendix for a detailed description of how I formally test and control for heteroskedasticity. Included in this section of the appendix is a detailed description of the Summers and Heston (2004) data quality proxies used for weighted least squares estimation.

[8] None of the other data discussed herein are plagued by heteroskedasticity; however, it is an issue for some of the data considered in the appendix. I always report White corrected *t* statistics when heteroskedasticity is detected, and I always perform WLS estimation when heteroskedasticity is linked to data quality.

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:

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

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

Thus, physical capital's share is proportional to the fraction of wealth attributable to physical capital. In accordance with equation (3), estimates of α can be obtained by combining my estimates of $\alpha+\gamma$ with estimates of $\frac{K}{W}$, which can be computed using the wealth data reported in Appendix 2 of The World Bank (2006).

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.

Of the elements constituting intangible capital, only human capital earns income. 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 can not 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 the aggregate stock of natural capital as reported by The World Bank does not include urban land, but the value of the aggregate stock of natural capital 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 the values of the aggregate stock of natural capital to obtain corrected estimates of the values of the aggregate stock of natural capital. W is then estimated as the sum of the estimates of K and corrected estimates of the values of the aggregate stock of natural capital. 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[9].

Estimates of α for the year 2000 are presented in Table 3 and plotted against real GDP per worker in Figure 2. 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 4.

2.3.3 Natural Capital's Share

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

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

$$\Rightarrow \gamma = \frac{N}{W} \cdot (\alpha + \gamma) \quad , \tag{4}$$

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 5 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 5% level. The regression results are reported in column 2 of Table 4.

[9] The World Bank reports all of its data in dollars per capita.

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, which are common in the literature, 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 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

$$\eta + \beta = \frac{Employee\ Compensation}{GDP - Indirect\ Taxes - imputed\ OSPUE}. \qquad (5)$$

The components of equation (5) and their data sources have already been discussed. Estimates of $\eta + \beta$ for 2000 are presented in Table 6 and plotted against real GDP per worker in Figure 4. The sample consists of the same 30 countries for which estimates of α, γ and $\alpha + \gamma$ were presented. Because the total capital and total labor share estimates sum to 1, statistical inference reveals the same lack of correlation between total labor's share and real GDP per worker that it did between total capital's share and real GDP per worker. Nonetheless, for completeness, regression results are presented in column 1 of Table 9.

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[10]. 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. Moreover, 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. Food items are delivered to each restaurant in standardized freezers. The preparation of food is 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. This series is generally 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. In addition, some averages are computed based on total employment, which

[10] 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.

includes employees and self-employed workers, and some are computed based only on employees.

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.

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 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

$$\eta = \frac{\textit{Unskilled Wage Bill}}{\textit{GDP} - \textit{Indirect Taxes}}\,. \tag{6}$$

The data needed to estimate η is available for 16 countries, and the estimates are presented in Table 7[11]. 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 2 of Table 9, and the slope coefficient, which is negative, is statistically significant at the 10% level.

2.4.3 Human Capital's Share

Of the 16 countries for which η could be computed, only 11 of them overlap with countries for which $\eta + \beta$ could be computed. Table 8 presents the estimates of β, which are computed as residuals, and Figure 6 plots these estimates against real GDP per worker. The regression results reported in column 3 of Table 9 reveal a positive slope coefficient, which is in

---

[11] For clarity, I give a detailed account of the computation of unskilled labor's share for Canada below. As can be seen in Table 7, 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 was equal to 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. *Employed* equals 14,764,200 in 2000. That being said, the unskilled wage bill is equal to 6.95*36.9*52*14,764,200=1.969x10^{11}. GDP in Canada for the year 2000 is 1.07658x10^{12}, and *Indirect Taxes* equal 5.1691x10^{10}. Thus, unskilled labor's share in Canada in the year 2000 is $\dfrac{1.969\times10^{11}}{1.07658\times10^{12}-5.1691\times10^{10}} = 0.192\cdot$

line with theoretical predictions, but the coefficient is statistically insignificant. Thus, inference based on the 11 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. With real GDP per worker just over $51,000, the corresponding human capital share of 0.243 stands out in Figure 6. Because there are only 11 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 10% level[12].

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 $14,000 in Colombia 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 group of countries that are at extremely similar stages of economic development.

2.5 Discussion

The cross-country analysis of factor shares presented herein is more complete than the analyses of Zuleta (2007) 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 share 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

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

when analyzing total capital's share he only separates land's share from physical capital's share. There are other natural resources, in addition to land, that are encompassed by the typical total capital share measure. Oil, natural gas and minerals, for example, are all non-reproducible factors to which a fraction of a country's income is paid. These additional natural resources 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 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.

Second, I control for heteroskedasticity, and, when warranted, incorporate data quality into my estimation. 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, and 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.

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 the unskilled labor share estimates are subtracted from estimates of total labor's share.

Zuleta (2007), the only other person I know of who disentangles human capital's share from unskilled labor's share in a cross-country setting, 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 varies 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.

Finally, on a much different note, I determine the significance levels of slope coefficients. This seems an obvious thing to do, but others, for whatever reason, do not perform any statistical tests to support their conclusions. Gollin (2002) and Bernanke and Gurkaynak (2001) make claims about the relationship between share estimates and output per worker by eyeballing data tables and scatter plots. I use two-tailed tests to determine the significance levels of slope coefficients for all analyses pertaining to either total labor's share or total capital's share. The purpose here is to ascertain whether there is any relationship, be it positive or negative, between share estimates and output per worker. Theory yields no predictions about the relationship, so the alternative hypothesis is that the slope coefficient differs from zero.

On the other hand, theory yields specific predictions about the nature of the relationship between non-reproducible and reproducible factor shares and output per worker. Therefore, the significance levels of slope coefficients are determined using one-tailed tests for all analyses pertaining to either physical capital's share, natural capital's share, unskilled labor's share or human capital's share. The purpose here is to ascertain whether there is a positive relationship or a negative relationship. The alternative hypothesis is that the slope coefficient is greater than zero if the factor share is reproducible and less than zero if the factor share is non-reproducible.

3 Implications for TFP Measurement

The evidence presented thus far shows that factor shares, when measured correctly, 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 by revisiting the estimation of the TFP residual.

Let production in country *i* be characterized by

$$Y_i = A_i K_i^{\alpha_i} N_i^{\gamma_i} (L_i h_i - L_i)^{\beta_i} L_i^{\eta_i} \tag{7}$$

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. The other variables in equation (8) 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 $E \leq 4$, 0.097 for $4 < E \leq 8$, and 0.075 for $E > 8$. The slope coefficients represent rates of return for education as reported by Psacharopolous (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 in the ILO's LABORSTA database, to proxy for *L*. Data sources for all other variables are the same as the data sources used in Section 2. All data is for the year 2000.

3.1 The Impact on TFP Levels

Dividing both sides of equation (7) by L yields the per worker production function,

$$y_i = A_i k_i^{\alpha_i} n_i^{\gamma_i} (h_i - 1)^{\beta_i} , \tag{8}$$

where lower case letters represent per worker values. Given equation (8), the TFP residual, A, can be computed in accordance with typical development accounting assumptions as

$$A_i = \frac{y_i}{k_i^{1/3} h_i^{2/3}} .$$

α and $\beta+\eta$ are assumed to equal 1/3 and 2/3 respectively for all i. Human capital and unskilled labor are assumed to be perfect substitutes. Natural capital is not acknowledged as a factor of production, and so γ is assumed to equal 0 for all i.

The exponent on physical capital per worker is 1/3, and researchers often point to this value as being 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.

Estimates of A are presented in Table 10 along with the two observable components of output per worker, $k^{1/3}$ and $h^{2/3}$. Notice that the TFP residual is very large relative to the observables. The average value of the TFP residual is 545, which is about 13 times larger than the average value of $k^{1/3}$. It is 296 times larger than the average value of $h^{2/3}$.

Including natural capital as a factor of production, treating human capital and unskilled labor as separate, imperfectly substitutable inputs, and allowing factor shares to vary yields the following TFP residual for country *i*:

$$A_i = \frac{y_i}{k_i^{\alpha_i} n_i^{\gamma_i} (h_i - 1)^{\beta_i}}.$$

Table 11 reports these residual values along with their observable counterparts for each country[13]. Note that the average value of the TFP residual does not change a great deal when the typical development accounting assumptions are relaxed. In fact, statistically, the two values are equivalent; the t-statistic from a paired difference test is only equal to -0.672.

One might expect the TFP residual to be lower on average in Table 11 because the residual encompasses fewer unobservable components. However, omitting natural capital and treating unskilled labor and human capital as perfect substitutes leads to an upward bias in the TFP residual that is offset by a downward bias created by the measurement error in physical capital's share[14]. When these biases are eliminated, there is very little net change in the average TFP residual.

[13] Recall that I was able to compute physical capital's share, natural capital's share, and total labor's share for 30 countries. However, human capital's share could only be computed for 11 of those countries. Regressing human capital's share on real GDP per worker produced intercept and slope coefficients. Using the estimated coefficients and real GDP per worker, I interpolate human capital's share for the remaining countries in the sample. However, I do not include Germany because Germany was an outlier and was omitted from the regression. Thus, Tables 10 and 11only report data for 29 countries.

[14] There are large differences between the values of $k^{1/3}$ and k^{α}. For example, when the observed value of α, rather than 1/3, is inserted as the exponent on Canada's k, the value of k raised to the exponent falls from 43.96 to 6.43. This is almost a seven fold difference. On average, the value of α in the sample is smaller than 1/3, and this yields an average value of k^{α} equal to 20.05, which is roughly half the size of the average value of $k^{1/3}$, which is 41.2.

3.2 Variation in TFP relative to Variation in Output per Worker

While the average TFP measure is relatively unaffected when all factors of production are acknowledged and factor shares are allowed to vary, the fraction of variation in output per worker explained by variation in TFP is impacted substantially. Define $y_{observables} = k^{\alpha} n^{\gamma} (h-1)^{\beta}$ so that the production function can be rewritten as $y = Ay_{observables}$. The 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:

$$\mathrm{var}[\ln(y)] = \mathrm{var}[\ln(A)] + \mathrm{var}[\ln(y_{observables})] + 2\,\mathrm{cov}[\ln(A), \ln(y_{observables})]. \qquad (9)$$

How much of the variation in output per worker across countries is attributable to variation in observables, and how much is attributable to TFP or residual variation? To answer this question, some assumption about the covariance must be made. One option is to ignore the covariance and just assume that *A* is constant across countries. Caselli (2005) and Mankiw, Romer, and Weil (1992) take this approach. I find this approach unappealing because it yields relative variances that do not add up to 1 when the covariance between *A* and *observables* is not equal to zero. The assumption that TFP is constant gets rid of the covariance term on paper, but it does not get rid of the covariance term in reality. When the typical development accounting assumptions are made, *A* and *observables* are positively correlated[15]. Though the relative variances are less than 1 in this case, the values are still misleading[16]. Some of the variation in

[15]The bottom of Table 12 presents all relevant variance and covariance measures, and the last row in Table 12 provides the raw correlation between observables and the TFP residual. As can be seen, the correlation equals 0.265 when $y = Ak^{1/3}h^{2/3}$.

[16] When the typical development accounting assumptions are made, $\frac{\mathrm{var}[\ln(y_{observables})]}{\mathrm{var}[\ln(y)]}$ equals 0.531. To say that 53% of income variation is explained by *observables* is a misleading claim because implicit in such a claim is that

observables may actually reflect variation in TFP. Some of the variation in TFP may actually reflect variation in *observables*.

When all factors are acknowledged and factor shares are allowed to vary, *A* and *observables* are actually negatively related, and the relative variances are greater than 1. In this case, too much of the variation in output per worker is being attributed to observables and too much is being attributed to TFP.

A more useful variance decomposition, which is suggested by Baier, Dwyer, and Tamura (2006)[17], is

$$\frac{(1-\rho^2_{obs.,A})\,\mathrm{var}[\ln(y_{observables})]}{\mathrm{var}[\ln(y)]} + \frac{\left\{sd[\ln(A)] + sd[\ln(y_{observables})]\rho^2_{obs.,A}\right\}^2}{\mathrm{var}[\ln(y)]} = 1. \qquad (10)$$

$\rho^2_{obs.,A}$ is the squared correlation coefficient between *observables* and the TFP residual. *sd* stands for standard deviation. With this decomposition the covariance between the TFP residual and the observables is not ignored. Rather, all of the correlation between the *observables* and the TFP residual is attributed to TFP. Also, the estimates of the relative variances sum to 1, and interpreting each value is straightforward. The first term on the left side of equation 10 is the fraction of variation in output per worker due to variation in observables, and the second term is the fraction of variation in output per worker due to variation in the TFP residual[18].

47% of income variation is explained by *unobservables*. This is not the case. $\frac{\mathrm{var}[\ln(A)]}{\mathrm{var}[\ln(y)]}$ equals 0.269. So, variation in *observables* and variation in *unobservables* together explain only 80% of the variation in income. That would suggest that something other than *observables* or *unobservables* explains 20% of the variation in income. Such a scenario makes no sense and stems from the fact that the covariance term is not constant.

[17] 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.

[18] 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 typical measure of the variance in *A* so that the fraction of variation in output per worker due to variation in *A* can be written as:

$$\frac{\mathrm{var}[\ln(A)] + 2\,\mathrm{cov}[\ln(y_{observables}), \ln(A)] + \mathrm{var}[\ln(y_{observables})]\rho^2_{obs.,A}}{\mathrm{var}[\ln(y)]}.$$

Theory supports this decomposition. In the Solow model, as in the Ramsey model, the long run rate of growth equals the rate of technological progress, which is assumed to be exogenous. Variety expansion models and models of quality ladders endogenize the rate of technological progress. With the variety expansion model, technological progress occurs via an expansion of intermediate goods, which is dependent on the willingness to save, R & D costs, and the level of production technology. Quality ladder models, in addition to incorporating variety expansion, allow for increases in the quality of intermediate goods. Technical progress and the growth rate of the economy depend on the same variables that drive technological progress in variety expansion models only R & D includes the additional effort associated with improving quality.

Each of these theories incorporates factor augmenting technical progress, but technical progress can also occur via factor elimination. This type of technological change is considered by Peretto and Seater (2008) and Zuleta (2008). Technological progress in these models causes non-reproducible factors to become increasingly unimportant. Technological progress occurs via R & D that alters factor intensities.

The aforementioned theories imply that in a cross-country framework, the level of economic development is dependent on elements that are not explicitly incorporated in the production function given by equation 8. Differences in the accumulation of factors and

---

This expression is equivalent to the expression given by the second term in equation 10. The variance measure, $\mathrm{var}[\ln(A)]$, does not encompass the relationship between *A* and *observables*. The fraction of the variation in *observables* that gets allocated to the variation in *A* is determined by the squared correlation coefficient, $\rho^2_{obs.,A}$. The squared correlation coefficient is used because the correlation coefficient is negative if the covariance between *A* and *observables* is negative. Any variation in *observables* that is due to *A* is sure to be added to the fraction of variation in output per worker attributed to *A* if the correlation coefficient is squared. Any variation in *A* that is unduly attributed to *A* is corrected for by the addition of the covariance term.

The fraction of variation in output per worker attributed to variation in observables can be written as $\frac{\mathrm{var}[\ln(y_{observables})] - \mathrm{var}[\ln(y_{observables})]\rho^2_{obs.,A}}{\mathrm{var}[\ln(y)]}$. This expression is equivalent to the expression given by the first term in equation 10. The intuition is that any variation in *observables* that really reflects variation in *A* should be attributed to the variation of *A*, and therefore subtracted from the fraction of the variation in output per worker due to variation in *observables*.

differences in factor intensities 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. That said, attributing all of the covariance between *A* and *observables* to *A* not only makes the comparison of relative variance estimates easier, it is a reasonable approach from a theoretical standpoint.

Estimates of the relative variances given by the decomposition in equation 10 are presented in Table 12 for four different combinations of assumptions pertaining to the production function. Notice that when the typical development accounting assumptions are made and the production function is given by $y = Ak^{1/3}h^{2/3}$, 49% of the variation in output per worker is due to observables, and 51% is due to the TFP residual. This breakdown 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 approach because no other study that I am aware of estimates the relative variance according to equation 10. Mankiw, Romer, and Weil (1992) and Caselli (2005) ignore *A*, and Klenow and Rodriguez-Clare (1997) attribute half of the contribution of the covariance term to *A* and half to *observables*[19].

As you move to the right in Table 12, the assumptions about the production function become more and more consistent with reality. In the second column, I allow factor shares to vary, but natural capital is not included, and human capital and unskilled labor are assumed to be perfect substitutes. Just allowing factor shares to vary has a substantial impact on the relative variance estimates. 98% of the variation in output per worker is now due to variation in observables, and only 2% is due to variation in the TFP residual. When factor shares are allowed

[19] Though Klenow and Rodriguez-Claire account for the covariance term, allocating half of it to A and half to *observables* has no theoretical support. They just feel it is an "informative way of characterizing the data."

to vary and human capital and unskilled labor are treated as separate, imperfectly substitutable factors, 99% of the variation in output per worker is due to variation in observables, and 1% is due to variation in the TFP residual. Finally, in column 4 of Table 12, the production function given by $y = Ak^{\alpha} n^{\gamma} (h-1)^{\beta}$ acknowledges all factors of production, including natural capital, and allows all factor shares to vary. For this scenario, which is most consistent with reality, 82% of the variation in output per worker is due to variation in observables, and 18% is due to variation in the TFP residual. The fraction of variation due to observables in column 4 decreases relative to the same fractions in columns 2 and 3 because of the relatively large magnitude of the covariance between the TFP residual and natural capital weighted by its share in income. The value of this covariance is -0.48.

Treating factor shares as variables and acknowledging more than two factors of production has a major impact on the relative importance of TFP in explaining cross-country income differences. If factor shares are treated as parameters, and factors of production are lumped together or omitted, variation in TFP explains about half of the variation in output per worker. If factor shares are treated as variables and all factors of production are included and treated as imperfect substitutes, variation in TFP explains only 18% of the variation in output per worker.

The key to interpreting these results is recognizing that the composition of the TFP residual changes as the assumptions about factors and factor shares change. When factors are lumped together or omitted and when factor shares are assumed constant, the TFP residual encompasses the influence of factor shares and omitted factors on output per worker. This is something that is never acknowledged because people virtually always think of factor shares as parameters, and, for whatever reason, natural capital is often just ignored. The common interpretation of the TFP residual is that it encompasses things like institutions, productivity, and efficiency. But, it also encompasses all sorts of biases and measurement errors that arise from misguided assumptions about the production process.

When factor shares are treated as variables and all factors are included in the production function, the TFP residual no longer encompasses the influence of factor shares and omitted factors on output per worker. The reason the fraction of variation in output per worker explained by this newly defined TFP residual falls so much is because allowing factor shares to vary and correctly identifying and including all factors of production makes the covariance between *observables* and the TFP residual negative. Specifically, it is the covariance between *A* and physical capital weighted by its share in income along with the covariance between *A* and natural capital weighted by its share in income that contributes most to the negative covariance between *A* and *observables*.

The fact that variation in TFP explains about 32% less of the variation in output per worker in column 4 of Table 12 than in column 1 of Table 12 means that variation in factor shares and variation in natural capital are important determinants of variation in output per worker. Though economies are endowed with natural capital and have no control over natural capital levels, they do have control over the intensity with which natural capital is used. Likewise economies have control over the intensity with which physical capital, human capital, and unskilled labor are used. Understanding why these intensities differ across countries is important to understanding why output per worker differs across countries.

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 (2008) 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 augmenting technical progress may be an important phenomenon.

Many empirical growth and development accounting studies follow Kaldor's (1961) lead and assume that factor shares are constant. Though this is an incorrect assumption, the conclusions, as Caselli (2005) notes, remain unchanged if factor shares are not systematically related to output per worker. Without the acknowledgement of more than two factors of production, there is no systematic relationship between shares and output per worker because, as discussed, the usual capital and labor share estimates are estimates of composite shares. These composite shares encompass one reproducible factor share and one non-reproducible factor share that increase and decrease with output per worker respectively. Therefore, cross-country empirical studies that incorporate the assumption of constant factor shares should be revisited.

In the second part of the paper I revisit the estimation of TFP. The consequences of acknowledging systematic variation in factor shares across countries are nontrivial. Though the actual value of TFP is relatively unchanged when the typical development accounting assumptions are relaxed, the composition of the TFP residual changes so that the fraction of variation in output per worker explained by variation in TFP decreases by more than 30%. This indicates that variation in factor shares and variation in natural capital are important determinants of cross-country variation in output per worker. The importance of variation in factor shares in explaining variation in output per worker suggests that factor eliminating technical progress in addition to factor augmenting technical progress plays a role in growth and development. A policy aimed at impacting the intensity with which a factor is used has the potential to benefit an economy.

References

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

Baier, Scott., Dwyer, Gerald, and Tamura, Robert, “How Important are Capital and Total Factor Productivity for Economic Growth,” *Economic Inquiry,* 44, January 2006, pp. 23-49.

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

Bernanke, Ben S., and Gurkaynak, Refet S., “Is Growth Exogenous? Taking Mankiw, Romer, and Weil Seriously,” In *NBER Macroeconomics Annual*, (16), 2001, pp. 11-57.

Blanchard, Oliver J., “The Medium Run,” *Brookings Papers on Economic Activity*, 2, 1997, pp. 89-158.

BLS, “Comparative Real Gross Domestic Product per Capita and per Employed Person,” Bureau of Labor Statistics, US Department of Labor, July 11, 2007. www.bls.gov/fls/home.htm

Caselli, Francesco, “Accounting for Cross-Country Income Differences,” In *The Handbook of Economic Growth*, edited by Philippe Aghion and Steven Durlauf, 2005.

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

Dawson, John W., DeJuan, Joseph P., Seater, John J., and Stephenson, Frank, “Economic information versus quality variation in cross-country data,” *Canadian Journal of Economics*, 34 (4), 2001, pp. 988-1009.

Gollin, Douglas, “Getting Income Shares Right,” *Journal of Political Economy*, 110, April 2002, pp. 458-474.

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

Hansen, Gary D., and Prescott, Edward C., “Malthus to Solow,” *American Economic Review*, 92, September 2002, pp. 1205-1217.

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

International Labor Organization’s (ILO) LABORSTA data base, http://laborsta.ilo.org/

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

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

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

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

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

Mankiw, Greg., Romer, David, and Weil, David, “A Contribution to the Empirics of Economic Growth.” *Quarterly Journal of Economics*, 107, May 1992, pp. 407-437.

Peretto, Pietro, and Seater, John, “Factor-Eliminating Technical Change,” working paper, Duke University, 2008.

Solow, Robert, “A Skeptical Note on the Constancy of Relative Shares,” *American Economic Review*, 48 (4), September 1958, pp618-631.

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

Summers, Robert., Heston, Alan, and Aten, Bettina, “Data Appendix for a Space-Time System of National Accounts,” *Penn World Table Version 6.1*, Center for International Comparisons at the University of Pennsylvania (CICUP), November, 2004.

Zuleta, Hernando, “Why factor income shares seem to be constant,” Documentos de Trabajo Facultad de Economia-Universidad del Rosario, December 2003.

Zuleta, Hernando, “An Empirical Note on Factor Shares,” Documentos de Trabajo Facultad de Economia-Universidad del Rosario, October 2007.

Zuleta, Hernando, “Factor Saving Innovations and Factor Income Shares,” *Review of Economic Dynamics*, In Press, Corrected Proof, Available online 29 February 2008.

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

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

Table 1

Total Capital's Share, 2000

Country	Total Capital's Share	Country	Total Capital's Share
Australia	0.384	Italy	0.408
Austria	0.398	Japan	0.256
Belgium	0.340	Korea, Republic Of	0.332
Botswana	0.534	Mauritius	0.354
Canada	0.334	Mexico	0.518
Costa Rica	0.345	Netherlands	0.418
Denmark	0.408	New Zealand	0.418
Egypt	0.538	Norway	0.526
Finland	0.418	Panama	0.361
France	0.376	Portugal	0.326
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

Sources : Author's Calculations

Table 2

Total Capital's Share

	Regression Equation			
	1	2	3	4
Variable			**WLS 1**	**WLS 2**
Intercept	0.410***	0.410***	0.393***	0.380***
	(11.000)	(7.930)^W	(10.198)	(10.183)
real GDP per worker, y	-3.620E-07	-3.620E-07	-2.486E-08	2.730E-07
	(-0.434)	(-0.329)^W	(-0.030)	(0.336)
F-test for overall significance of regression	---	---	---	---
Adjusted R^2	-0.029	-0.029	-0.103	0.332
F-test for no heteroskedasticity	14.969			
	[3.354]			
Sample	30 obs.	30 obs.	30 obs.	30 obs.

--Dependent variable is Total Capital's share.

--t-statistics are in parantheses. *indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

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

--^{W} indicates t-statistics computed using White corrected standard errors

--WLS 1 is weighted least squares estimation just using the Numerical Quality Score provided by Summers and Heston(2004)

--WLS 2 is weighted least squares estimation using the three individual criterion employed by Summers and Heston in computing the Numerical Quality Score.

Table 3

Physical Capital's Share, 2000			
Country	**Physical Capital's Share**	**Country**	**Physical Capital's Share**
Australia	0.219	Italy	0.302
Austria	0.293	Japan	0.204
Belgium	0.261	Korea, Republic Of	0.251
Botswana	0.318	Mauritius	0.271
Canada	0.164	Mexico	0.289
Costa Rica	0.137	Netherlands	0.305
Denmark	0.287	New Zealand	0.154
Egypt	0.237	Norway	0.291
Finland	0.284	Panama	0.200
France	0.273	Portugal	0.236
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

Sources : Author's Calculations

Table 4

Physical Capital's Share and Natural Capital's Share		
	Dependent Variable	
	Physical Capital's Share	**Natural Capital's Share**
Variable		
Intercept	0.204***	0.206***
	(7.176)	(6.172)
real GDP per worker, y	1.111E-06**	-1.473E-06**
	(1.744)	(-1.975)
Adjusted R^2	0.066	0.091
F-test for no heteroskedasticity	0.521	1.685
	[3.354]	[3.354]
Sample	30 obs.	30 obs.

--t-statistics are in parantheses.

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

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

Table 5

Natural Capital's Share, 2000

Country	Natural Capital's Share	Country	Natural Capital's Share
Australia	0.165	Italy	0.106
Austria	0.106	Japan	0.052
Belgium	0.079	Korea, Republic Of	0.080
Botswana	0.217	Mauritius	0.083
Canada	0.170	Mexico	0.230
Costa Rica	0.207	Netherlands	0.114
Denmark	0.121	New Zealand	0.264
Egypt	0.301	Norway	0.235
Finland	0.134	Panama	0.161
France	0.103	Portugal	0.091
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

Sources : Author's Calculations

Table 6

Total Labor's Share, 2000

Country	Total Labor's Share	Country	Total Labor's Share
Australia	0.616	Italy	0.592
Austria	0.602	Japan	0.744
Belgium	0.660	Korea, Republic Of	0.668
Botswana	0.466	Mauritius	0.646
Canada	0.666	Mexico	0.482
Costa Rica	0.655	Netherlands	0.582
Denmark	0.592	New Zealand	0.582
Egypt	0.462	Norway	0.474
Finland	0.582	Panama	0.639
France	0.624	Portugal	0.674
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

Table 7

Unskilled Labor's Share, 2000

Country	Unskilled Labor's Share
Brazil	0.207
Canada	0.192
Columbia	0.097
Czech Republic	0.207
Germany	0.396
Hong Kong	0.086
Japan	0.261
Korea	0.195
Philippines	0.500
Poland	0.206
Russia	0.252
Singapore	0.141
Sweden	0.204
Thailand	0.410
UK	0.241
USA	0.172

Sources : Author's Calculations

Table 8

Human Capital's Share, 2000

Country	Unskilled Labor's Share
Canada	0.474
Columbia	0.461
Czech Republic	0.321
Germany	0.243
Japan	0.483
Korea	0.473
Poland	0.415
Russia	0.263
Singapore	0.416
Sweden	0.445
USA	0.508

Sources : Author's Calculations

Table 9

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

Variable	Total Labor's Share	Unskilled Labor's Share	Human Capital's Share	Omit Germany
Intercept	0.59	0.307***	0.355***	0.344***
	(15.854)	(5.359)	(5.306)	(6.888)
real GDP per worker, y	3.620E-07	-2.062E-06*	1.421E-06	2.223E-06*
	(0.434)	(-1.419)	(0.894)	(1.831)
Adjusted R^2	-0.029	0.063	-0.020	0.207
F-test for no heteroskedasticity	14.969	1.497	0.05	2.732
	[3.354]	[3.806]	[4.459]	[4.737]
Sample	30 obs.	16 obs.	11 obs.	10 obs.

--t-statistics are in parantheses

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

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

Table 10

Decomposition of output per worker
Factor Shares constant; No natural capital

Country	y	$k^{1/3}$	$h^{2/3}$	A
U.S.A	67078.860	50.530	2.167	612.705
Norway	63909.140	56.919	2.145	523.442
Belgium	59873.550	49.137	1.892	644.007
Ireland	59103.420	43.348	1.893	720.257
Singapore	58750.040	48.878	1.664	722.335
Austria	58441.050	49.415	1.801	656.782
Netherlands	56690.570	46.328	1.893	646.416
France	55285.960	47.132	1.753	668.955
Israel	51882.640	45.138	1.917	599.646
Italy	50853.040	46.704	1.678	648.860
Australia	50606.350	45.300	2.048	545.588
Denmark	50448.300	49.464	1.923	530.483
Canada	49815.630	43.958	2.121	534.426
Sweden	46544.490	45.732	2.098	485.022
Finland	45192.140	46.045	1.955	502.147
Japan	44563.230	61.015	1.904	383.513
Spain	44360.540	41.548	1.689	632.168
New Zealand	40976.960	39.054	2.133	491.845
Mauritius	34617.690	27.912	1.555	797.702
Portugal	34000.270	36.699	1.542	600.917
Trinidad and Tobago	33101.830	29.732	1.742	639.045
Greece	32069.690	38.038	1.830	460.776
Korea, Republic Of	30620.650	37.850	2.039	396.677
Hungary	23788.820	31.222	1.871	407.151
Costa Rica	20596.220	26.548	1.560	497.370
Mexico	19621.490	35.444	1.683	328.835
Panama	18798.390	27.108	1.819	381.275
Botswana	16616.550	27.637	1.583	379.771
Egypt	11939.540	21.579	1.506	367.322
Average	**42418.864**	**41.221**	**1.842**	**545.015**
Standard Deviation	**15684.694**	**9.699**	**0.198**	**123.893**
correlation with y (logs)	1	0.89	0.565	0.711
correlation with A (logs)	0.711	0.358	-0.029	1

Table 11

Decomposition of output per worker
Factor Shares Vary; Include natural capital and separate labor inputs

Country	**y**	**k^{α}**	**n^{γ}**	**$(h\text{-}1)^{\beta}$**	**A**
U.S.A	67078.860	12.961	3.079	1.489	1129.164
Norway	63909.140	34.127	16.494	1.448	78.431
Belgium	59873.550	21.099	2.286	1.252	991.572
Ireland	59103.420	40.423	6.141	1.252	190.203
Singapore	58750.040	64.537	2.406	1.059	357.494
Austria	58441.050	30.685	3.098	1.179	521.419
Netherlands	56690.570	33.269	3.314	1.249	411.772
France	55285.960	23.567	2.966	1.139	694.406
Israel	51882.640	14.058	2.331	1.260	1256.890
Italy	50853.040	32.565	3.046	1.076	476.441
Australia	50606.35	12.210	6.315	1.350	486.217
Denmark	50448.300	28.832	3.717	1.262	373.099
Canada	49815.630	6.425	6.899	1.418	792.503
Sweden	46544.490	17.396	2.936	1.374	663.429
Finland	45192.140	26.134	4.225	1.276	320.660
Japan	44563.230	12.424	1.760	1.265	1610.919
Spain	44360.540	12.021	2.354	1.082	1448.755
New Zealand	40976.960	5.417	21.083	1.385	259.040
Mauritius	34617.690	14.923	2.086	0.974	1141.764
Portugal	34000.270	12.749	2.444	0.963	1132.773
Trinidad and Tobago	33101.830	2.913	30.400	1.116	335.087
Greece	32069.690	29.080	3.872	1.175	242.374
Korea, Republic Of	30620.650	15.489	2.191	1.359	663.929
Hungary	23788.820	12.491	4.647	1.193	343.559
Costa Rica	20596.220	3.867	8.362	0.979	650.261
Mexico	19621.490	21.984	11.086	1.068	75.402
Panama	18798.390	7.219	4.777	1.155	472.087
Botswana	16616.550	23.640	7.963	0.997	88.535
Egypt	11939.540	8.853	17.302	0.941	82.828
Average	**42418.864**	**20.047**	**6.537**	**1.198**	**596.242**
Standard Deviation	**15684.694**	**13.286**	**6.735**	**0.155**	**428.435**
correlation with y (logs)	1	0.427	-0.392	0.604	0.420
correlation with A (logs)	0.420	-0.225	-0.710	0.133	1

Table 12

Development Accounting Results

Variance Decomposition	Production Function			
	$y=Ak^{1/3}h^{2/3}$	$y=Ak^{\alpha}h^{\beta+\eta}$	$y=Ak^{\alpha}(h\text{-}1)^{\beta}$	$y=Ak^{\alpha}n^{\gamma}(h\text{-}1)^{\beta}$
Variation due to Observables				
$(1-\rho_{obs,A}{}^{2})Var[\ln(y_{observables})]/Var[\ln(y)]$	0.494	0.983	0.988	0.823
Variation due to the TFP residual				
$\{sd[\ln(A)]+sd[\ln(y_{observables})](1-\rho_{obs,A}{}^{2})\}^{2}/Var[\ln(y)]$	0.506	0.017	0.012	0.177
Variances, Covariances, and Raw Correlation				
var(log(y))	0.209	0.209	0.209	0.209
var(log(A))	0.056	0.368	0.404	0.777
var(αlog(k))	0.065	0.521	0.521	0.521
var(β+η(log(h)))	0.012	0.016		
var(βlog(h-1))			0.017	0.017
var(γlog(n))				0.587
cov[log(A), αlog(k)]	0.022	-0.364	-0.385	-0.143
cov[log(A), (β+η)log(h)]	-0.001	0.032		
cov[log(A), βlog(h-1)]			0.013	0.015
cov[log(A), γlog(n)]				-0.480
cov[αlog(k), γlog(n)]				-0.243
cov[αlog(k), (β+η)(log(h))]	0.017	-0.016		
cov[αlog(k), β(log(h-1))]			0.006	0.006
cov[γlog(n), β(log(h-1))]				-0.002
correlation coefficient, $\rho_{obs,A}$	0.265	-0.770	-0.696	-0.864

--The variance decomposition assumes that all correlation between observables and the TFP residual is attributed to TFP.

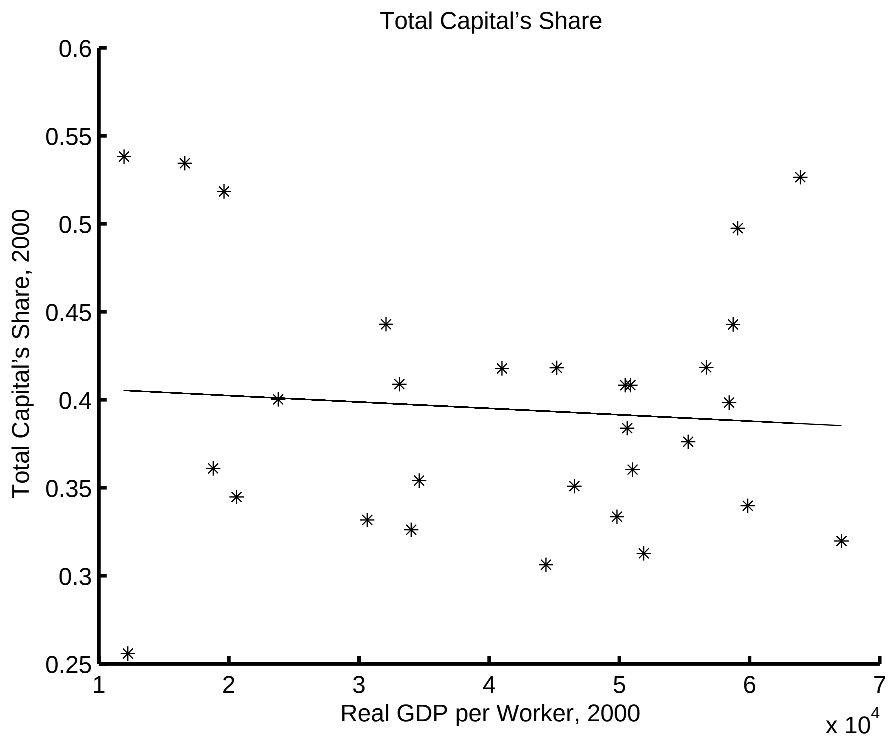


Figure 1

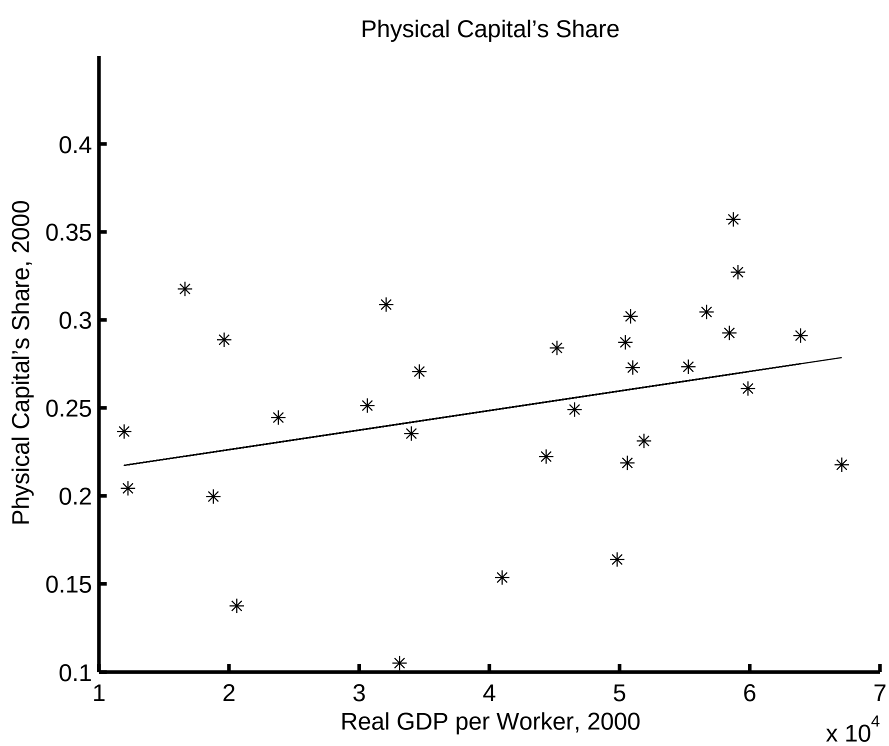


Figure 2

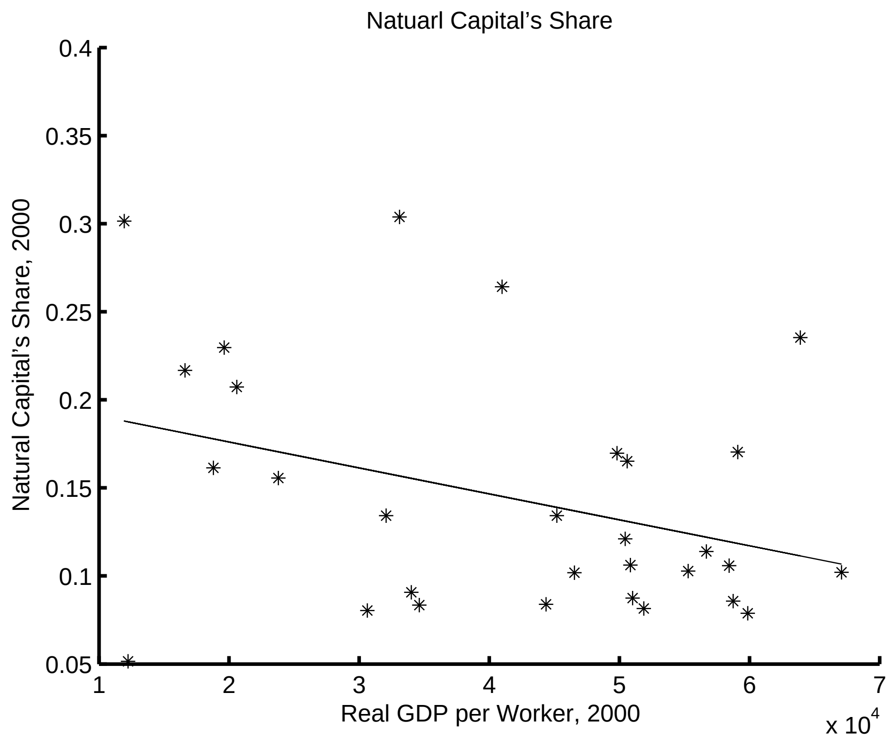


Figure 3

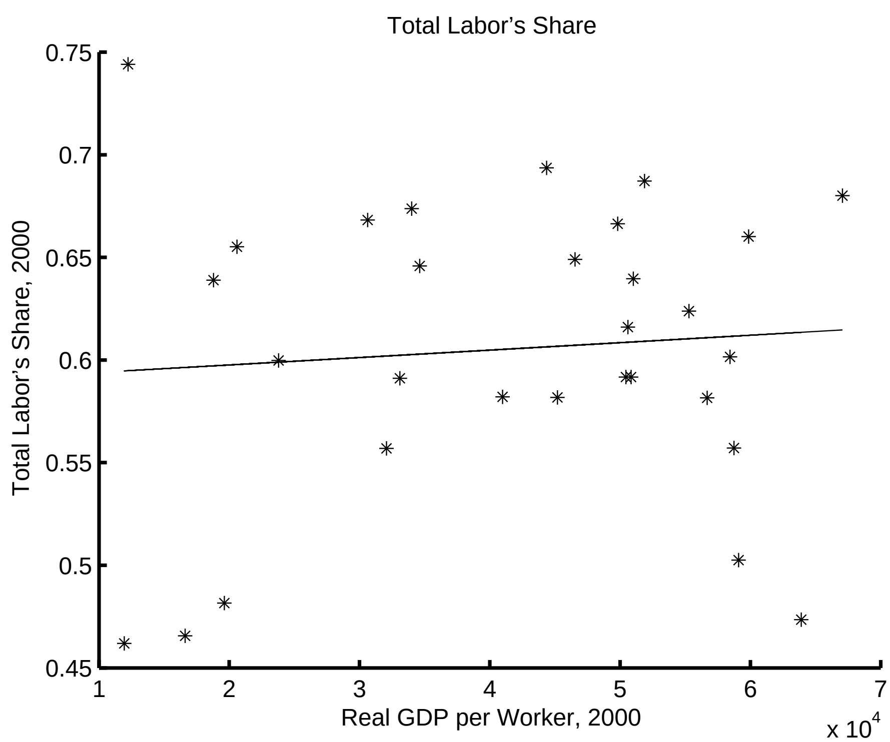


Figure 4

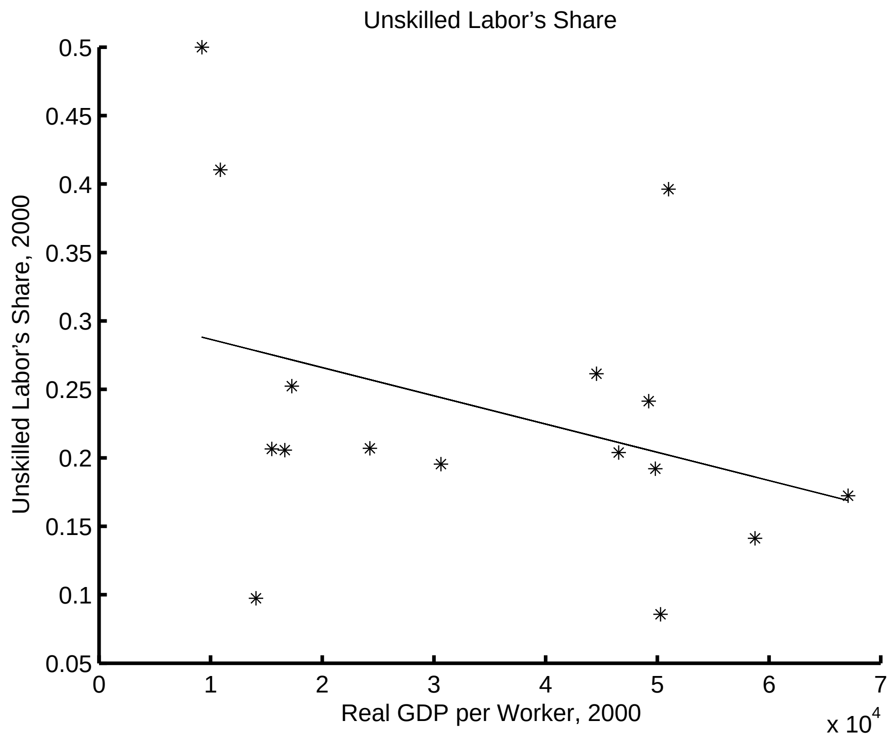


Figure 5

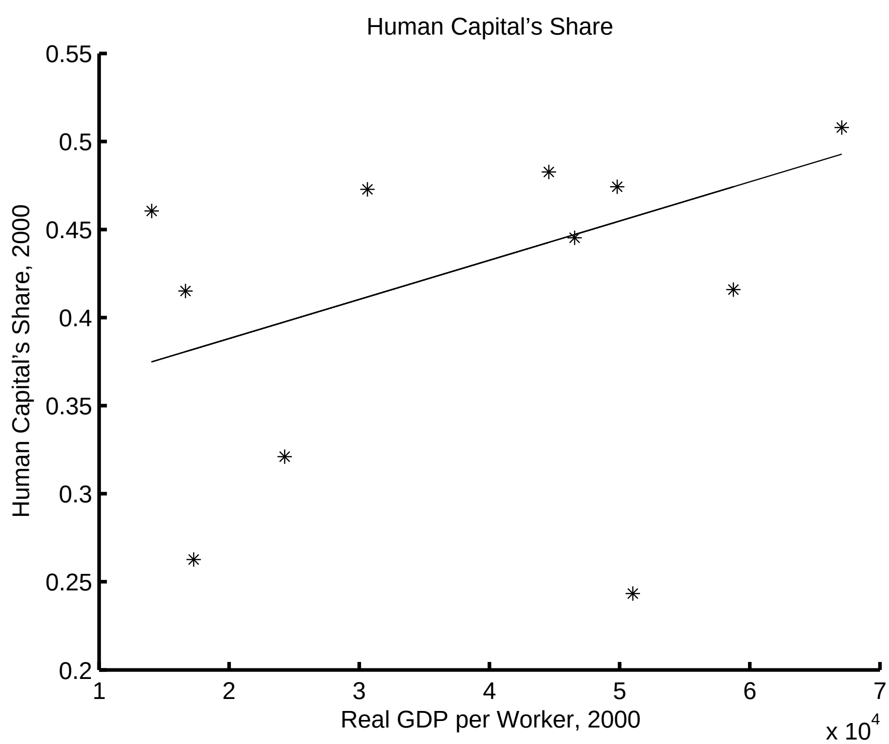


Figure 6

5. Appendix

5.1 Testing and Controlling for Heteroskedasticity

5.1.1 Summers and Heston Data Quality Measure

In an appendix to their paper accompanying version 6.1 of the Penn World Tables, Summers and Heston (2004) provide proxies for data quality. Each country is assigned a numerical quality grade based on three criteria. The first is the Variance Measure, which Summers and Heston define as the variance of price level estimates. For each country, many estimates of the price level are considered, and a country is assigned a 1 for high variance between estimates and up to a 5 for low variance between estimates. The lower the variance among the alternative price level estimates, the more reliable the data is assumed to be. The second criterion is the Benchmark Measure, and it considers the number of times a country has participated in a benchmark study. A country receives a 0 if it has never served as a benchmark country, a 1 for one benchmark or a quasi-benchmark, and a 2 for more than one benchmark. More benchmarks are assumed to be associated with better data quality. The third criterion is the Data Rank Measure. Based on the assumption that the resources used to gather data statistics increase with income, Summers and Heston put countries into six income groups and assign a score of 1-6 where 1 corresponds to the poorest countries and 6 corresponds to the richest countries. Given these three criteria, the Numerical Quality Score is computed by summing twice the Variance Measure, the Benchmark Measure and the Data Rank Measure. A higher Numerical Quality Score is assumed to be consistent with better data quality.

5.1.2 Procedure

To formally test for heteroskedasticity, I estimate

$$e^2 = \delta_0 + \delta_1 y_{worker} + \delta_2 (y_{worker})^2 + \mu \qquad (1)$$

where e is the regression residual from regressing the factor share on output per worker. The null hypothesis of no heteroskedasticity is a joint hypothesis that δ_1 and δ_2 are equivalent and equal to zero. The accompanying alternative to the null is that at least one of the coefficients is not zero.

Now, the next question is whether the heteroskedasticity is, at least in part, caused by systematic variation in data quality across countries. If heteroskedasticity is present, I regress the share measure on Summers and Heston's Numerical Quality Score. If the relationship between data quality and the share measure is significant, then this relationship is an explanation for heteroskedasticity if there is a correlation between data quality and real GDP per worker.

To remedy the heteroskedasticity, I apply weighted least squares (WLS). First, I estimate

$$e^2 = \eta_0 + \eta_1 Numerical\ Quality\ Score + \nu \qquad (2)$$

by OLS. Given the coefficient estimates, $\hat{\eta}_0$ and $\hat{\eta}_1$, I define the weighting term for observation i as

$$w_i = \frac{1}{\sqrt{\hat{\eta}_0 + \hat{\eta}_1 Numerical\ Quality\ Score_i}}. \qquad (3)$$

Weighted least squares estimates are obtained by applying OLS to

$$\frac{Factor\ Share_i}{w_i} = \gamma_0^{wls}\left[\frac{1}{w_i}\right] + \gamma_1^{wls}\left[\frac{y_{worker_i}}{w_i}\right] + \varepsilon_i^{wls} \qquad (4)$$

for $i = 1...n$ where n is the number of observations in the sample.

The coefficients, γ_0^{wls} and γ_1^{wls}, account for heteroskedasticity resulting from variation in data quality across countries. Data quality is not necessarily the sole cause of heteroskedasticity in the data. For completeness, I also compute White corrected standard errors[20]. This is a cure-all because it does not require knowledge of the specific form of heteroskedasticity.

5.2 Factor Share Analysis: Two Additional Approaches

5.2.1 Total, physical, and natural capital shares computed according to Bernanke and Gurkaynak's *labor force correction*

Incorporating *OSPUE* in the estimation of total capital's share as in the main text assumes that the shares of labor and capital income in *OSPUE* are equivalent to the shares of labor and capital income in the corporate sector. An alternative approach, which involves no guesswork as to how *OSPUE* should be divided between labor and capital, is to impute the labor compensation of the self-employed.

Employee Compensation encompasses the labor compensation of only individuals who work in the corporate sector. To account for the income of the self-employed, *Employee Compensation* can be scaled up by the ratio of the total labor force to the number of workers in the corporate sector. This yields an estimate of *all* labor income because labor force numbers include the self-employed. This method, which is Gollin's adjustment 3 and Bernanke and Gurkaynak's *labor force correction*, is computed as

$$(\alpha+\gamma)_{labor\ force\ correction} = 1 - \left(\frac{Employee\,Compensation}{(Corporate\ Share\ of\ \ Labor\ Force)\cdot(GDP - Indirect\,Taxes)} \right). \qquad (5)$$

Implicit in this computation is the assumption that corporate and non-corporate workers receive the same average compensation. Like the computation in the main text, the *labor force*

[20]Controlling for heteroskedasticity using White corrected standard errors is very common and is a valid procedure, but it should be noted that White corrected standard errors yield *t* statistics that are only asymptotically *t* distributed. When the sample size is small, the *t* statistics associated with White corrected standard errors can have distributions that are not very close to the *t* distribution, and such a situation could undermine any inference. The same issue arises for WLS estimation. WLS estimates are more efficient than OLS estimates, but *t* statistics are only asymptotically *t* distributed. Once heteroskedasticity is controlled for, inference gains more and more validity as the sample size increases.

correction does not measure total capital's share directly, but rather as the residual remaining after computing total labor's share.

The data sources for *Employee Compensation*, *GDP*, and *Indirect Taxes* are the same as those used for the measure presented in the main text. The *Corporate Share of the Labor Force* is computed by dividing *Paid Employment*, which comes from the ILO's LABORSTA database, by the *labor force*, which I compute by summing *employment* and *unemployment*, both of which also come from the LABORSTA database.

The estimates of total capital's share are presented in Table A1 for the 30 countries for which the necessary data is available for the year 2000[21]. The shares are plotted against real GDP per worker in Figure A1. OLS estimation does not indicate any systematic relationship between total capital's share and real GDP per worker. Regression results are reported in Table A2.

Physical capital's share is given by

$$\alpha_{labor\ \ force\ correction} = \frac{K}{W} \cdot (\alpha + \gamma)_{labor\ \ force\ correction} . \tag{6}$$

Estimates of α are presented in Table A3 and plotted against real GDP per worker in Figure A2. As predicted, standard OLS estimation indicates a positive and statistically significant relationship between physical capital's share and real GDP per worker at the 5% level. The regression results are reported in column 1 of Table A5.

Subtracting physical capital share estimates from total capital share estimates yields the natural capital share estimates reported in Table A4. Figure A3 plots natural capital's share against real GDP per worker. OLS estimation indicates that natural capital's share and real GDP

[21] The sample of countries is identical to the sample in the main text because the data constraints for computing total capital's share are the same. Specifically, the data needed to compute *Corporate Share of Labor Force* is a subset of the data needed to compute *imputed OSPUE*.

per worker are negatively related at the 10% level. The regression results are reported in column 2 of Table A5.

5.2.2 Total labor's share, unskilled labor's share, and human capital's share computed according to Bernanke and Gurkaynak's *labor force correction*

Total labor's share computed via the *labor force correction* is

$$(\eta + \beta)_{Labor\ Force\ Correction} = \frac{Employee\ Compensation}{\left(Corporate\ Share\ of\ \ Labor\ \ Force\right) \cdot \left(GDP - Indirect\ Taxes\right)}. \qquad (7)$$

The necessary data sources have already been discussed. The desire to compare unskilled labor's share and total labor's share constrains the sample size for total labor's share computed via the *labor force correction* just as it did for the method in the main text. Table A6 reports the estimates of $(\eta + \beta)_{Labor\ Force\ Correction}$ for the year 2000, and Figure A4 depicts the relationship between these estimates and real GDP per worker. The slope coefficient in a regression of $(\eta + \beta)_{Labor\ Force\ Correction}$ on an intercept and real GDP per worker is insignificant. Results are reported in column 1 of Table A8.

This estimate of unskilled labor's share is equivalent to the one in the main text. The unskilled wage bill encompasses the labor income of the unskilled self employed, and the measure is not dependent on assumptions pertaining to the division of self-employed income between capital and labor as is total labor's share. Moreover, unskilled labor's share computed according to the method in the text accounts for indirect taxes just as the *labor force correction* would dictate. Therefore, no changes in the computation of unskilled labor's share are required.

The *labor force correction* estimates of human capital's share are presented in Table A7 and plotted against real GDP per worker in Figure A5. When the full sample of 11 observations is considered, regressing human capital's share on an intercept and real GDP per worker yields a negative and insignificant slope coefficient. Results can be found in column 2 of Table A8.

The sample size is small and the presence of outliers is a concern. Colombia's human capital share is 0.652, the highest value in the sample, and Germany's human capital share is the lowest in the sample at 0.257. The outlying nature of these two observations can be seen in Figure A5[22]. I report the OLS estimation results when Germany and Colombia are omitted from the sample in column 3 of Table A8. The slope coefficient becomes positive and is now significant at the 10% level.

The remaining nine human capital share values in the reduced sample correspond to real GDP per worker values that range from a minimum of $16,642 in Poland to a maximum of $67,078 in the US. This is a difference in real GDP per worker of over $50,000. This means the result is not specific to a cluster of developed or undeveloped countries, and so again, the positive correlation should not be dismissed simply because the sample is small.

5.2.3 Total, physical, and natural capital shares computed without making an adjustment for the self-employed

This method is analogous to the *naïve* calculation reported by Bernanke and Gurkaynak (2001) and Gollin (2002). The fundamental commonality between my method and their method is the treatment of self-employed income as capital income. No adjustment for the omission of self-employed income in the NIPA *Employee Compensation* data is made. Bernanke and Gurkaynak and Gollin argue that acknowledging some portion of self-employed income as labor income is necessary to compute labor and capital shares correctly. An argument in favor of treating all self-employed income as capital income also has merit, and so the last method is presented as a valid approach rather than a naïve baseline from which proper measures emanate[23].

[22] Germany and Colombia are omitted in the derivation of the regression line shown in Figure A5.
[23] See Section 6.3 of the Appendix for a detailed explanation of the argument.

The EU KLEMS Project (2007)[24] defines capital compensation as

$$Cap = OS + IT - LC^{S} \tag{8}$$

where *Cap* denotes capital compensation, *IT* denotes indirect taxes, OS denotes gross operating surplus, and LC^{S} denotes labor compensation of the self-employed. It follows that total capital's share according to the EU KLEMS project is $\frac{Cap}{GDP}$[25]. Since I am assuming that self-employed income is capital income, I make a slight modification to the EU KLEMS capital compensation measure and do not subtract LC^{S} from *OS*. Total capital's share is computed as

$$(\alpha+\gamma)_{No\ Adjustment} = \frac{OS + IT}{GDP}\,. \tag{9}$$

Note that implicit in equation (9) is the assumption that all indirect taxes are related to capital. As discussed in the main text, indirect taxes should be dispersed between capital and labor according to the type of tax, but detailed tax data is rarely available, and most countries only report an aggregate tax value. That being said, I follow the default procedure of the EU KLEMS Project and allocate all taxes on production to capital compensation.

Also, equation (9) is a direct measure of total capital's share. The measure in the main text and the *labor force correction* are computed indirectly. Specifically, total capital's share is what remains once total labor's share is subtracted from 1. Therefore, those measures assume perfect competition, but this measure does not.

---

[24] The following is a portion of the EU KLEMS Project description which can be found at www.euklems.net. "This project aims to create a database on measures of economic growth, productivity, employment creation, capital formation and technological change at the industry level for all European Union member states from 1970 onwards." The project is funded by the European Commission.

[25] Typically, capital's share is estimated as the residual after computing labor's share. However, Blanchard (1997) computes capital's share directly in a time series analysis. The data necessary to compute capital's share just as Blanchard did in a cross-country setting for the year 2000 is not available. However, the EU KLEMS approach is very similar to Blanchard's method, and I thank Olivier Blanchard for making me aware of the EU KLEMS technique.

Table 2.3 of the 2006 version of the United Nations Yearbook of National Account Statistics is the data source for *OS*. As discussed in the main text, data for *IT* and *GDP* are also reported in the United Nation's publication. For the year 2000, the necessary data for computing estimates of $(\alpha+\gamma)_{No\ Adjustment}$ is available for 42 countries. The shares are reported in Table A9 and plotted against real GDP per worker in Figure A6. The scatter plot suggests a negative correlation between total capital's share and real GDP per worker.

Regressing total capital's share on an intercept and real GDP per worker reveals a negative slope coefficient that is statistically significant at the 10% level. These estimation results along with the F statistic associated with testing the null of no heteroskedasticity are reported in column 1 of Table A10. The significance of the F statistic provides formal confirmation of heteroskedasticity. The regression results in column 5 of Table A10 indicate that the Summers and Heston Numerical Quality Score is negatively and significantly related to total capital's share at the 1% level. Given that the Numerical Quality Score is significantly related to real GDP per worker, data quality's systematic relationship with total capital's share is at least partially responsible for the heteroskedasticity. Column 6 of Table A10 reports the results of regressing total labor's share on each of the three components used to derive the Numerical Quality Score. It is evident that the Variance Measure is the driving force behind the significant relationship between the Numerical Quality Score and total capital's share.

I correct for the heteroskedasticity associated with data quality by implementing WLS. The estimation results reported in column 3 of Table A10 indicate that the coefficient on real GDP per worker is no longer significant at standard levels, though it is marginally significant at 11%. When WLS is performed using the three components from which the Numerical Quality Score is derived, the coefficient on real GDP per worker is not even marginally significant. See column 4 of Table A10. In light of these results, the negative relationship between total capital's share and real GDP per worker seems to be an artifact of systematic variation in data quality across countries rather than a reflection of a meaningful economic correlation. However, correcting for heteroskedasticity using a White corrected standard error leaves the coefficient on real GDP per worker significant at the 10% level. This means that accounting for all heteroskedasticity inducing factors, not just data quality, preserves the statistically significant negative relationship between total capital's share and real GDP per worker.

Physical capital's share, $\alpha_{No\ Adjustment}$, is estimated as $\frac{K}{W} \cdot (\alpha + \gamma)_{No\ Adjustment}$. Table A11 reports the estimates, and Figure A7 depicts the relationship between the estimates and real GDP per worker. OLS estimation reveals a positive and statistically significant relationship between physical capital's share and real GDP per worker at the 5% level. Heteroskedasticity is present in the estimation.

Physical capital's share is not significantly related to the Numerical Quality Score, but it is significantly related to the Data Rank Measure, one of the components that make up the Numerical Quality Score. In light of the strong correlation between the Numerical Quality Score and real GDP per worker, the systematic relationship between physical capital's share and the Data Rank Measure is responsible for at least some of the heteroskedasticity. WLS estimation corrects for this, and the relationship between physical capital's share and real GDP per worker remains positive and statistically significant at the 5% level. The relationship also remains significant at the 10% level after making a general correction using a White corrected standard error. Thus, the empirical evidence supports the theoretical prediction of a positive correlation between physical capital's share and the stage of economic development across countries. All of the estimation results are reported in columns 1 through 5 of Table A13.

Table A12 presents the natural capital share estimates associated with this method, and these estimates are computed as the residuals remaining after physical capital's share is subtracted from total capital's share. The relationship between these estimates and real GDP per worker is depicted in Figure A8. Regressing natural capital's share on an intercept and real GDP per worker using standard OLS reveals a negative and statistically significant slope coefficient at the 1% level. See column 6 of Table A13.

5.2.4 Total labor's share, unskilled labor's share, and human capital's share without making an adjustment for the self-employed

The total labor share counterpart of total capital's share computed without an adjustment for self-employed income is

$$(\eta+\beta)_{No\ Adjustment} = \frac{Employee\ Compensation}{GDP}. \tag{10}$$

The measure assumes all taxes on production are allocated to capital compensation.

Column 1 of Table A14 presents estimates of $(\eta+\beta)_{No\ Adjustment}$ for the 16 countries for which the necessary data is available and for which unskilled labor's share can also be computed. The relationship between the estimates and real GDP per worker is depicted graphically in Figure A9.

Regressing total labor's share on an intercept and real GDP per worker reveals a positive and statistically significant relationship at the 1% level. However, a quadratic model fits the data better[26], so I estimate

$$\beta^{Total}_{Method\ 3} = \psi_0 + \psi_1 u + \psi_2 u^2 + \varepsilon \tag{11}$$

where u is a 16 X 1 vector of coded independent variables equal to

[26] Estimation of equation (11) yields an R^2 of 0.793. Estimation of a standard linear regression model yields R^2 equal to 0.744.

$$u_i = \frac{y_{worker_i} - \bar{y}_{worker}}{s_{y_{worker}}} \quad \text{for } i=1,2,\ldots16 \tag{12}$$

where $s_{y_{worker}}$ is the standard deviation of the y_{worker} values. The coded variable, u, is used in place of y_{worker} in order to reduce the multicollinearity inherent with polynomial regression models[27]. Estimation results of equation (11) are reported in Table A15. The estimate of ψ_1 is positive and significant at the 1% level, and the estimate of ψ_2 is negative and significant at the 10% level. The estimated slope coefficient, $\hat{\psi}_1 + 2\hat{\psi}_2 u$, is positive over the relevant range of u values implying that total labor's share and real GDP per worker are positively correlated. The negative ψ_2 coefficient indicates downward concavity, which means real GDP per worker has a diminishing effect on total labor's share.

Since total labor's share computed via equation 10 treats self-employed income as capital income, unskilled labor's share computed following this approach should only reflect the unskilled labor compensation of employees. Therefore, the average yearly compensation of an unskilled worker is computed just as it was for the *labor force correction,* but it is multiplied by *Paid Employment* rather than *Employment* to attain the unskilled wage bill.

The implicit assumption that employees and self-employed workers work an equivalent amount of hours on average is still present in this approach because there is no change in the computation of average yearly compensation. However, the implicit assumption that employees and self-employed workers command equivalent wages is no longer present because the average compensation of unskilled workers in this case is scaled up by *Paid Employment,* which only encompasses employees. *Employment* encompasses employees and self-employed workers.

[27] Minimizing the effects of multicollinearity is important because multicollinearity increases the likelihood of rounding errors in the regression coefficients and standard errors, and it can sometimes have an effect on the sign of regression coefficients.

Also, to obtain unskilled labor's share, the unskilled wage bill is only divided by *GDP*, not *GDP-Indirect Taxes*. This is consistent with the assumption in this last approach that all taxes on production are allocated to capital compensation. Estimates of unskilled labor's share are reported in column 2 of Table A14 and plotted against real GDP per worker in Figure A10.

Regressing unskilled labor's share on an intercept and real GDP per worker using OLS estimation yields a slope coefficient that is statistically insignificant. Germany's unskilled labor share of 0.352 is the highest in the sample and is an outlier as seen in Figure A10. However, omitting Germany does not change the qualitative results. The results, which are reported in columns 1 and 2 of TableA16, do not support the theoretical prediction that unskilled labor's share decreases as the stage of economic development increases.

Human capital shares are computed as residuals, and the estimates are reported in column 3 of Table A14. Figure A11 suggests a strong, positive correlation between human capital's share and real GDP per worker, and statistical analysis confirms the correlation. Regressing human capital's share on an intercept and real GDP per worker yields a positive slope coefficient that is significant at the 1% level. The results are reported in column 3 of Table A16 and indicate that human capital's share, as predicted by theory, is positively and systematically related to the stage of economic development.

5.3 Argument in favor treating self-employed income as capital income

The *naïve* measure attributes all self-employed income to capital. This is reasonable only if one acknowledges a self-employed person as a unit of capital. Such acknowledgement may seem unwarranted at first pass, and it is likely that the reader's main objection to categorizing a self-employed person as a unit of capital is the physical distinction between physical capital and labor. After all, a self-employed individual, just like an employee, is indeed a person, and the contribution to production comes from the human body. Physical capital on the other hand encompasses machines, buildings, tools, etc., and these things are inanimate, durable inputs that must be produced. Such sentiments arise from the typical textbook definitions of labor and capital. However, my paper focuses on measuring the fractions of income that get paid to the inputs used in production. From an income allocation perspective, a self-employed person is very similar to a unit of physical capital.

The crucial question is whether self-employed income comes from a residual or from a commitment. That is, does a self-employed person's income come from the funds left over after all expenses have been paid, or, does the self-employed person make a commitment to pay himself a wage? Employers make a commitment to pay employees a wage, and to the extent that employers want to retain employees, they take on risk because the commitment is legally binding irrespective of the firm's revenue. If a self-employed person makes a commitment to pay himself a wage, there is no net risk nor is there a potential net gain or net loss, because the individual is betting against himself. Therefore, the self-employed person has no incentive to make a commitment to pay himself a wage. Such a commitment would not result in a larger amount of income because the commitment could only be kept if revenue less expenses exceeded the wage, and revenue less expenses belong to the self-employed person anyway. Regardless of any commitment to oneself, the amount of income a self-employed person brings in is a residual. Therefore, it can be argued that self-employed income should be treated as residual income and categorized as operating surplus just as residual income in the corporate sector. Operating surplus, which is defined as "the excess of value added over the sum of compensation of employees, consumption of fixed capital, and net indirect taxes” by the United Nations Yearbook of National Account Statistics, is considered part of capital compensation.

Table A1

Total Capital's Share, 2000 (Labor Force Correction)

Country	Total Capital's Share	Country	Total Capital's Share
Australia	0.370	Italy	0.372
Austria	0.387	Japan	0.264
Belgium	0.315	Korea, Republic Of	0.282
Botswana	0.505	Mauritius	0.311
Canada	0.320	Mexico	0.494
Costa Rica	0.315	Netherlands	0.408
Denmark	0.396	New Zealand	0.410
Egypt	0.451	Norway	0.520
Finland	0.396	Panama	0.296
France	0.363	Portugal	0.289
Germany	0.346	Singapore	0.443
Greece	0.390	Spain	0.276
Hungary	0.349	Sweden	0.337
Ireland	0.482	Trinidad and Tobago	0.409
Israel	0.291	U.S.A	0.320

Sources : Author's Calculations

Table A2

Total Capital's Share: Labor Force Correction

	Regression Equation		
	1	2	3
Variable			
Intercept	0.356***	0.356***	0.437***
	(9.684)	(7.708)^{W}	(6.587)
real GDP per worker, y	3.54E-07	3.54E-07	---
	(0.430)	(0.355)^{W}	
Numerical Quality Score	---	---	-4.39E-03
			(-1.024)
Adjusted R^2	-0.029	-0.029	1.67E-03
F-test for no heteroskedasticity	4.687	---	---
	[3.354]		
Sample	30 obs.	30 obs.	30 obs.

--Dependent variable is Total Capital's share.

--t-statistics are in parantheses. *indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

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

--^{W} indicates t-statistics computed using White corrected standard errors

Table A3

Physical Capital's Share, 2000 (Labor Force Correction)

Country	Physical Capital's Share	Country	Physical Capital's Share
Australia	0.211	Italy	0.275
Austria	0.284	Japan	0.211
Belgium	0.242	Korea, Republic Of	0.214
Botswana	0.300	Mauritius	0.238
Canada	0.157	Mexico	0.275
Costa Rica	0.126	Netherlands	0.297
Denmark	0.279	New Zealand	0.151
Egypt	0.198	Norway	0.287
Finland	0.269	Panama	0.164
France	0.264	Portugal	0.209
Germany	0.262	Singapore	0.357
Greece	0.272	Spain	0.201
Hungary	0.213	Sweden	0.239
Ireland	0.317	Trinidad and Tobago	0.105
Israel	0.216	U.S.A	0.218

Sources : Author's Calculations

Table A4

Natural Capital's Share, 2000 (Labor Force Correction)

Country	Natural Capital's Share	Country	Natural Capital's Share
Australia	0.159	Italy	0.097
Austria	0.103	Japan	0.053
Belgium	0.073	Korea, Republic Of	0.068
Botswana	0.205	Mauritius	0.073
Canada	0.163	Mexico	0.219
Costa Rica	0.190	Netherlands	0.111
Denmark	0.117	New Zealand	0.259
Egypt	0.253	Norway	0.232
Finland	0.127	Panama	0.132
France	0.099	Portugal	0.080
Germany	0.084	Singapore	0.086
Greece	0.118	Spain	0.076
Hungary	0.136	Sweden	0.098
Ireland	0.165	Trinidad and Tobago	0.304
Israel	0.076	U.S.A	0.102

Sources : Author's Calculations

Table A5

Physical Capital's Share and Natural Capital's Share: Labor Force Correction

Variable	Dependent Variable: Physical Capital's Share	Dependent Variable: Natural Capital's Share
Intercept	0.175***	0.181***
	(6.451)	(5.570)
real GDP per worker, y	1.448E-06**	-1.094E-06*
	(2.387)	(-1.505)
Adjusted R^2	0.139	0.042
F-test for no heteroskedasticity	0.283	0.698
	[3.354]	[3.354]
Sample	30 obs.	30 obs.

--t-statistics are in parantheses

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

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

Table A6

Total Labor's Share, 2000 (Labor Force Correction)

Country	Total Labor's Share	Country	Total Labor's Share
Australia	0.630	Italy	0.628
Austria	0.613	Japan	0.736
Belgium	0.685	Korea, Republic Of	0.718
Botswana	0.495	Mauritius	0.689
Canada	0.680	Mexico	0.506
Costa Rica	0.685	Netherlands	0.592
Denmark	0.604	New Zealand	0.590
Egypt	0.549	Norway	0.480
Finland	0.604	Panama	0.704
France	0.637	Portugal	0.711
Germany	0.654	Singapore	0.557
Greece	0.610	Spain	0.724
Hungary	0.651	Sweden	0.663
Ireland	0.518	Trinidad and Tobago	0.591
Israel	0.709	U.S.A	0.680

Sources: Author's Calculations

Table A7

Human Capital's Share, 2000 (Labor Force Correction)	
Country	**Human Capital's Share**
Canada	0.488
Columbia	0.652
Czech Republic	0.336
Germany	0.257
Japan	0.474
Korea	0.522
Poland	0.460
Russia	0.278
Singapore	0.416
Sweden	0.459
USA	0.508

Sources : Author's Calculations

Table A8

Total Labor's Share and Human Capital's Share (Labor Force Correction)

	Dependent Variable		
	Total Labor's Share	**Human Capital's Share**	
Variable			**Omit Germany and Colombia**
Intercept	0.644***	0.455***	0.345***
	(17.551)	(5.229)	(5.537)
real GDP per worker, y	-3.54E-07	-3.729E-07	2.351E-06*
	(-0.430)	(-0.180)	(1.624)
Adjusted R^2	-0.029	-0.107	0.170
F-test for no heteroskedasticity	4.687	1.362	3.094
	[3.354]	[4.459]	[5.143]
Sample	30 obs.	11 obs.	9 obs.

--t-statistics are in parantheses

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

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

Table A9

Total Capital's Share, 2000 (No adjustment for self-employed income)

Country	Total Capital's Share	Country	Total Capital's Share
Algeria	0.744	Jordan	0.466
Australia	0.419	Korea, Republic Of	0.459
Austria	0.387	Mauritius	0.534
Belgium	0.381	Mexico	0.605
Botswana	0.619	Namibia	0.507
Canada	0.422	Netherlands	0.387
Chile	0.411	New Zealand	0.545
Colombia	0.330	Norway	0.448
Costa Rica	0.462	Panama	0.494
Denmark	0.332	Paraguay	0.232
Egypt	0.495	Peru	0.669
Finland	0.399	Philippines	0.741
France	0.377	Portugal	0.372
Germany	0.366	Singapore	0.567
Greece	0.585	South Africa	0.429
Hungary	0.407	Spain	0.410
Ireland	0.493	Sri Lanka	0.488
Israel	0.364	Sweden	0.325
Italy	0.501	Trinidad and Tobago	0.627
Ivory Coast	0.276	U.S.A	0.407
Japan	0.501	Venezuela	0.472

Sources : Author's Calculations

Table A10

Total Capital's Share: No adjustment for self-employed income

Variable	1	2	3 WLS 1	4 WLS 2	5	6
	Regression Equation					
Intercept	0.524***	0.524***	0.500***	0.437***	0.648***	0.642***
	(14.493)	(11.258)^{W}	(12.698)	(6.679)	(11.118)	(10.204)
real GDP per worker, y	-1.752E-06*	-1.752E-06*	-1.357E-06	1.173E-06	---	---
	(-1.900)	(-1.758)^{W}	(-1.637)	(0.992)		
Numerical Quality Score	---	---	---	---	-0.013***	---
					(-3.288)	
Variance Measure	---	---	---	---	---	-0.061***
						(-3.871)
Benchmark Measure	---	---	---	---	---	0.017
						(0.568)
Data Rank Measure	---	---	---	---	---	0.012
						(0.939)
F-test for overall significance of regression	---	---	---	---	---	6.100
						[2.852]
Adjusted R^2	0.060	0.060	0.605	0.958	0.193	0.272
F-test for no heteroskedasticity	6.419					
	[3.238]					
Sample	42 obs.	42 obs.	42 obs.	42 obs.	42 obs.	42 obs.

--Dependent variable is Total Capital's Share.

--t-statistics are in parantheses. *indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

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

--^{W} indicates t-statistics computed using White corrected standard errors

--WLS 1 is weighted least squares estimation just using the Numerical Quality Score

--WLS 2 is weighted least squares estimation using the three individual criterion employed by Summers and Heston in computing the Numerical Quality Score

Table A11

Physical Capital's Share, 2000 (No adjustment for self-employed income)

Country	Physical Capital's Share	Country	Physical Capital's Share
Algeria	0.239	Jordan	0.324
Australia	0.239	Korea, Republic Of	0.348
Austria	0.284	Mauritius	0.408
Belgium	0.293	Mexico	0.337
Botswana	0.368	Namibia	0.288
Canada	0.208	Netherlands	0.281
Chile	0.164	New Zealand	0.200
Colombia	0.114	Norway	0.248
Costa Rica	0.184	Panama	0.273
Denmark	0.233	Paraguay	0.085
Egypt	0.218	Peru	0.328
Finland	0.271	Philippines	0.378
France	0.274	Portugal	0.269
Germany	0.277	Singapore	0.458
Greece	0.408	South Africa	0.236
Hungary	0.249	Spain	0.298
Ireland	0.324	Sri Lanka	0.303
Israel	0.269	Sweden	0.231
Italy	0.371	Trinidad and Tobago	0.161
Ivory Coast	0.054	U.S.A	0.277
Japan	0.400	Venezuela	0.127

Sources : Author's Calculations

Table A12

Natural Capital's Share, 2000 (No adjustment for self-employed income)

Country	Natural Capital's Share	Country	Natural Capital's Share
Algeria	0.506	Jordan	0.142
Australia	0.180	Korea, Republic Of	0.111
Austria	0.103	Mauritius	0.126
Belgium	0.088	Mexico	0.268
Botswana	0.251	Namibia	0.220
Canada	0.215	Netherlands	0.105
Chile	0.247	New Zealand	0.345
Colombia	0.217	Norway	0.200
Costa Rica	0.277	Panama	0.221
Denmark	0.098	Paraguay	0.147
Egypt	0.277	Peru	0.340
Finland	0.128	Philippines	0.363
France	0.103	Portugal	0.103
Germany	0.089	Singapore	0.110
Greece	0.177	South Africa	0.193
Hungary	0.158	Spain	0.112
Ireland	0.169	Sri Lanka	0.186
Israel	0.095	Sweden	0.094
Italy	0.130	Trinidad and Tobago	0.466
Ivory Coast	0.222	U.S.A	0.130
Japan	0.101	Venezuela	0.345

Sources : Author's Calculations

Table A13

Physical Capital's Share and Natural Capital's: No adjustment for self-employed income

	Dependent Variable					
	Physical Capital's Share					Natural Capital's Share
	1	2	3	4	5	6
Variable			WLS 2			
Intercept	0.227***	0.227***	0.24***	0.21***	0.255***	0.297***
	(8.035)	(6.928)^{W}	(7.622)	(4.204)	(4.793)	(10.378)
real GDP per worker, y	1.219E-06**	1.219E-06*	1.007E-06*	---	---	-2.97E-06***
	(1.691)	(1.675)^{W}	(1.425)			(-4.068)
Numerical Quality Score	---	---	---	4.310E-03	---	---
				(1.230)		
Variance Measure	---	---	---	---	-0.0164	---
					(-1.221)	
Benchmark Measure	---	---	---	---	-0.0213	---
					(-0.820)	
Data Rank Measure	---	---	---	---	0.0325***	---
					(2.948)	
F-test for overall significance of regression	---	---	---	---	3.046	---
					[2.852]	
Adjusted R^2	0.043	0.043	0.492	0.012	0.13	0.275
F-test for no heteroskedasticity	3.383					1.257
	[3.238]					[3.238]
Sample	42 obs.	42 obs.	42 obs.	42 obs.	42 obs.	42 obs.

--t-statistics are in parantheses. *indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level. Significance levels are based on one-tailed tests.

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

--^{W} indicates t-statistics computed using White corrected standard errors

--WLS 1 is weighted least squares estimation just using the Numerical Quality Score

--WLS 2 is weighted least squares estimation using the three individual criterion employed by Summers and Heston in computing the Numerical Quality Score

Table A14

Decomposition of Total Labor's Share, 2000 (No adjustment for self-employed income)

Country	Total Labor's Share	Unskilled Labor's Share	Human Capital's Share
Brazil	0.405	0.082	0.323
Canada	0.506	0.153	0.353
Columbia	0.355	0.058	0.297
Czech Republic	0.419	0.175	0.244
Germany	0.534	0.352	0.183
Hong Kong	0.515	0.066	0.449
Japan	0.539	0.203	0.336
Korea	0.429	0.122	0.307
Philippines	0.259	0.228	0.031
Poland	0.402	0.148	0.254
Russia	0.402	0.214	0.188
Singapore	0.433	0.115	0.318
Sweden	0.552	0.198	0.353
Thailand	0.304	0.163	0.141
UK	0.558	0.223	0.335
USA	0.593	0.156	0.436

Sources: Author's Calculations

Table A15

Total Labor's Share: No adjustment for self-employed income	
Variable	
Intercept	0.482***
	(25.645)
u	0.086***
	(7.578)
u^2	-0.034*
	(-2.089)
Adjusted R^2	0.793
F-test for no heteroskedasticity	1.025
	[3.806]
Sample	16 obs.

--Dependent variable is Total Labor's Share
--t-statistics are in parantheses
--*indicates significance at the 10% level, ** at the 5% level,
and *** at the 1% level.
Significance levels are based on two-tailed tests.
--brackets are 5% critical values of the F distribution

Table A16

Unskilled Labor's Share and Human Capital's Share: No adjustment for self-employed income

	Unskilled Labor's Share		Human Capital's Share
		Omit Germany	
Variable			
Intercept	0.146***	0.154***	0.153***
	(3.699)	(5.022)	(3.512)
real GDP per worker, y	5.773E-07	1.584E-10	3.791E-06***
	(0.577)	(1.995E-04)	(3.441)
Adjusted R^2	-0.047	-0.077	0.419
F-test for no heteroskedasticity	0.190	0.335	0.468
	[3.806]	[3.885]	[3.806]
Sample	16 obs.	15 obs.	16 obs.

--t-statistics are in parantheses
--*indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.
--brackets are 5% critical values of the F distribution

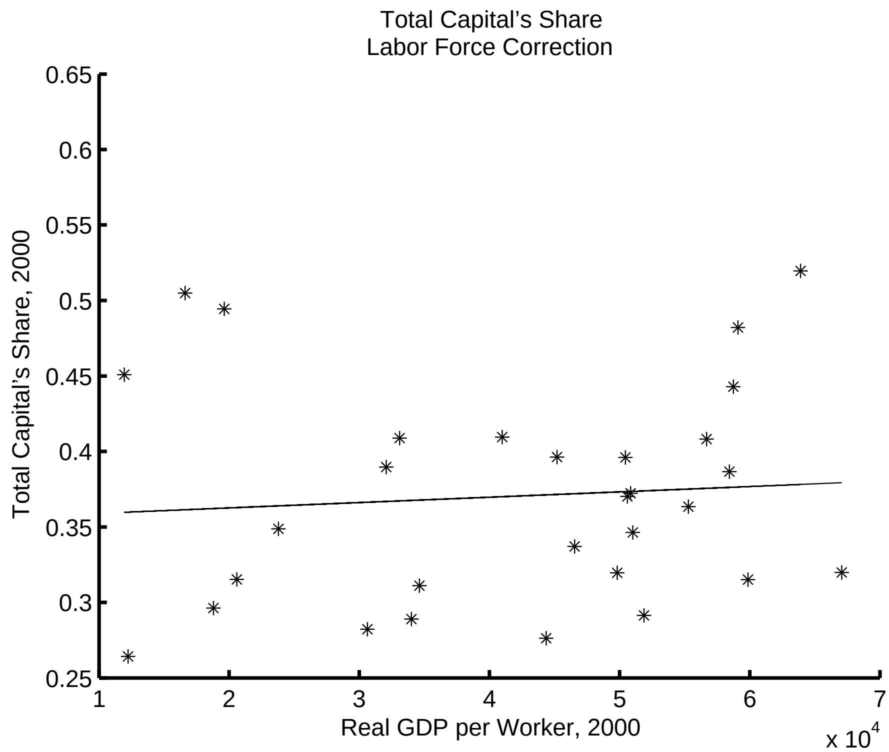


Figure A1

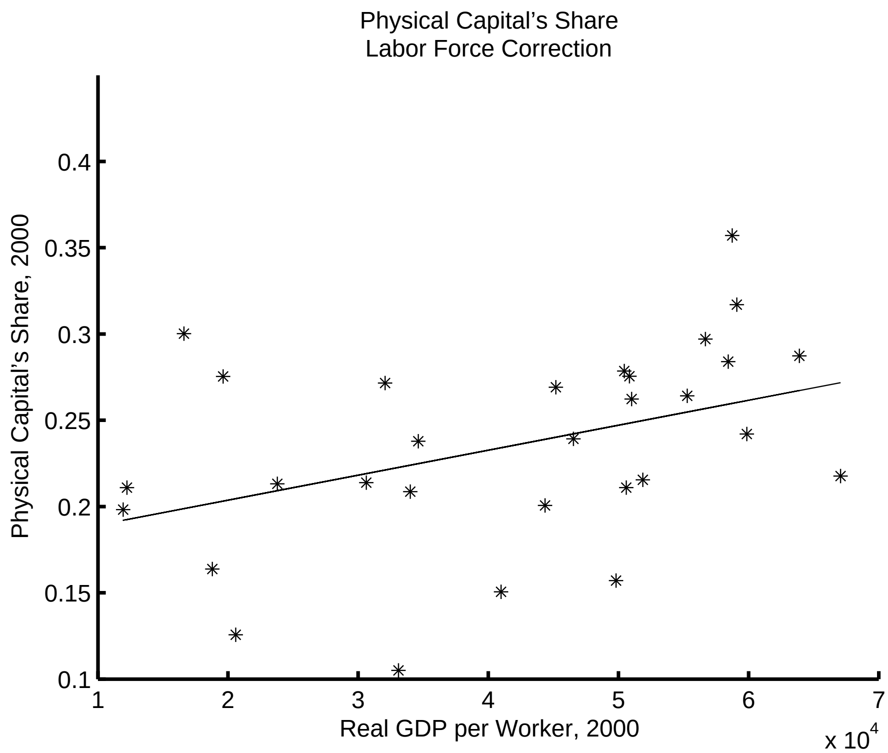


Figure A2

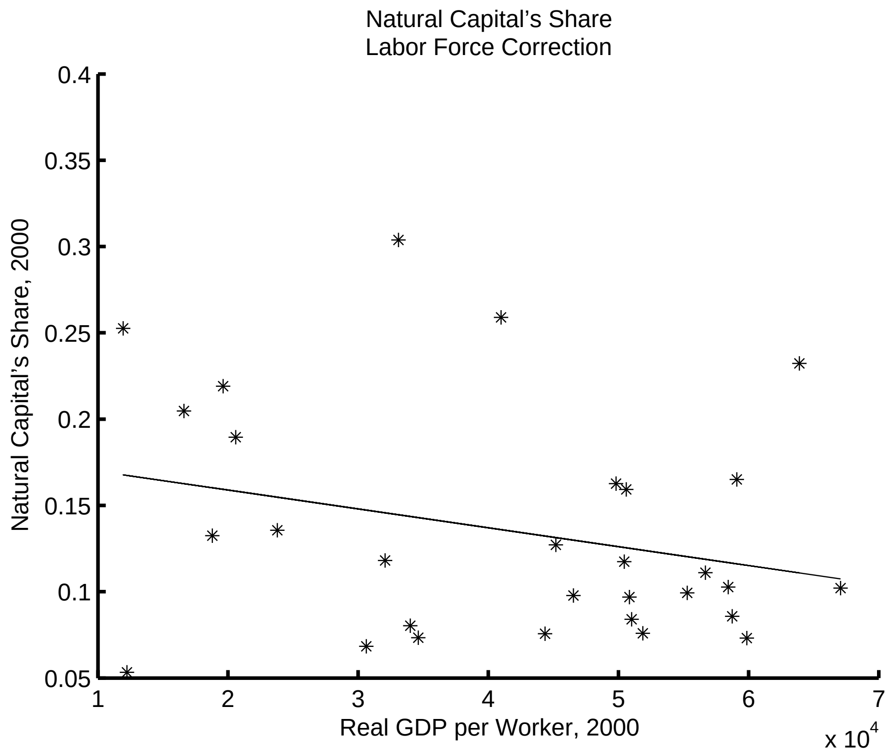


Figure A3

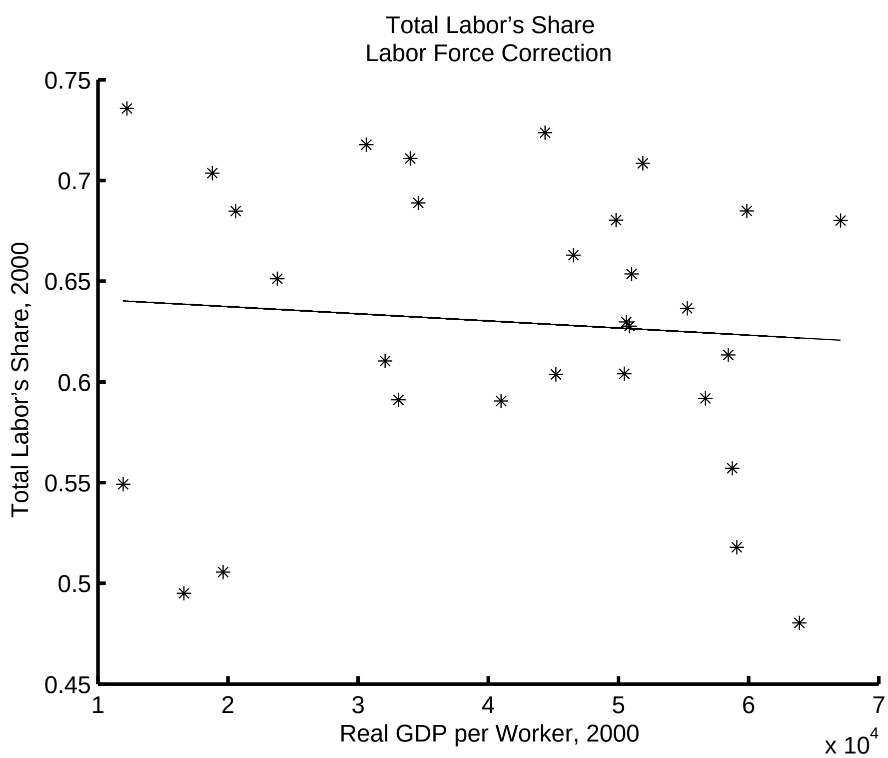


Figure A4

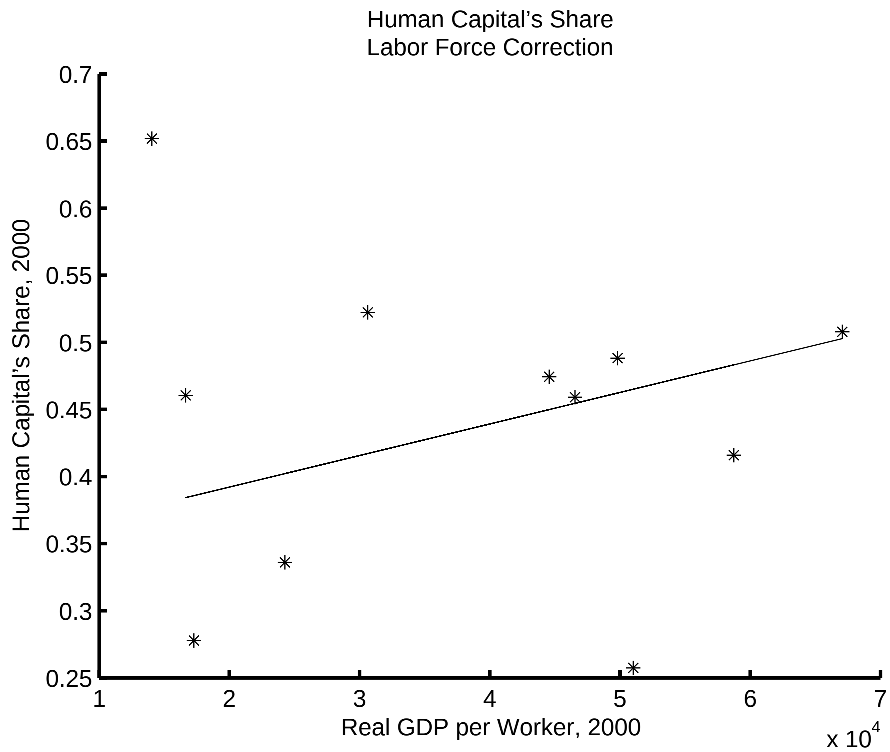


Figure A5

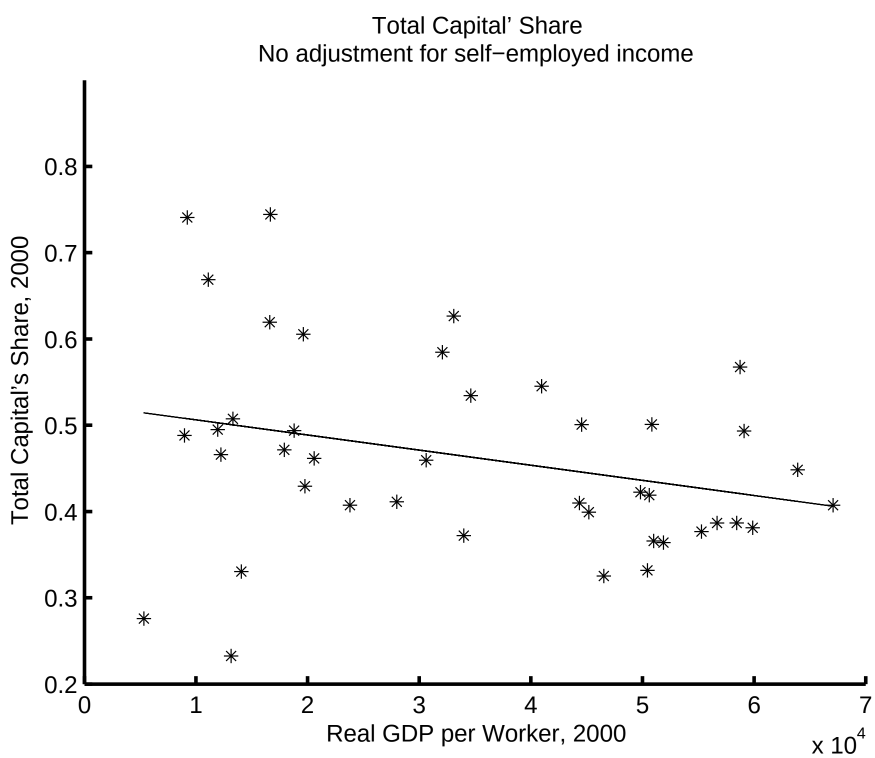


Figure A6

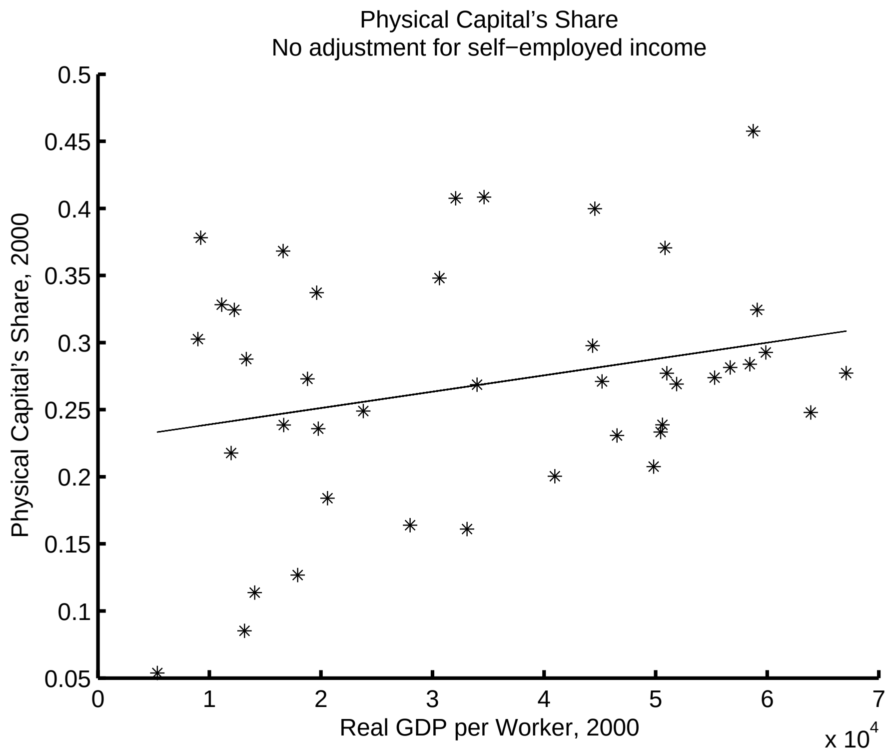


Figure A7

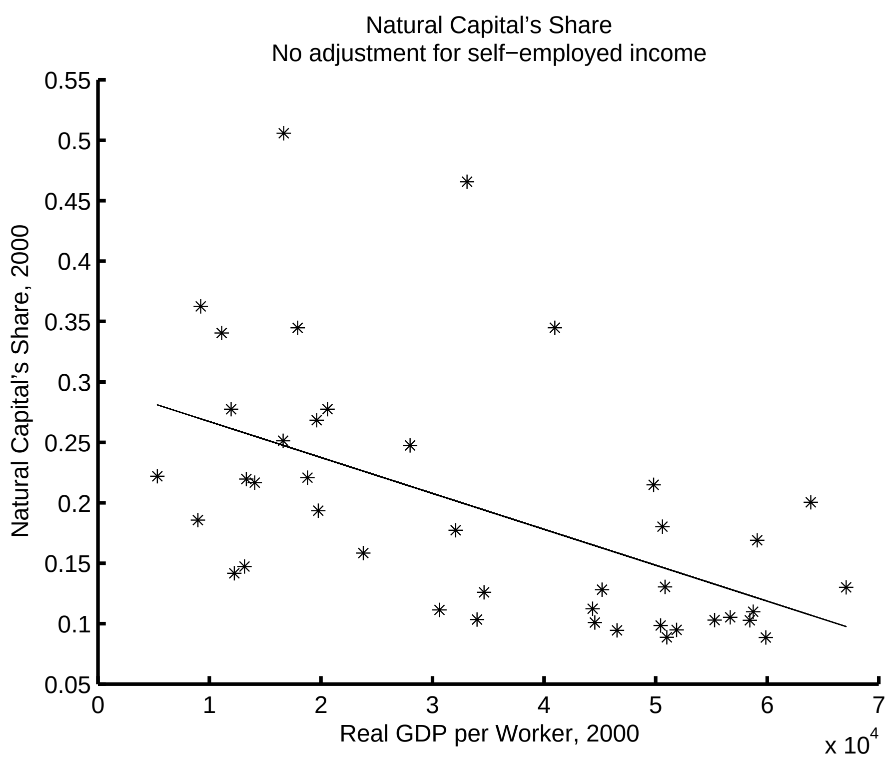


Figure A8

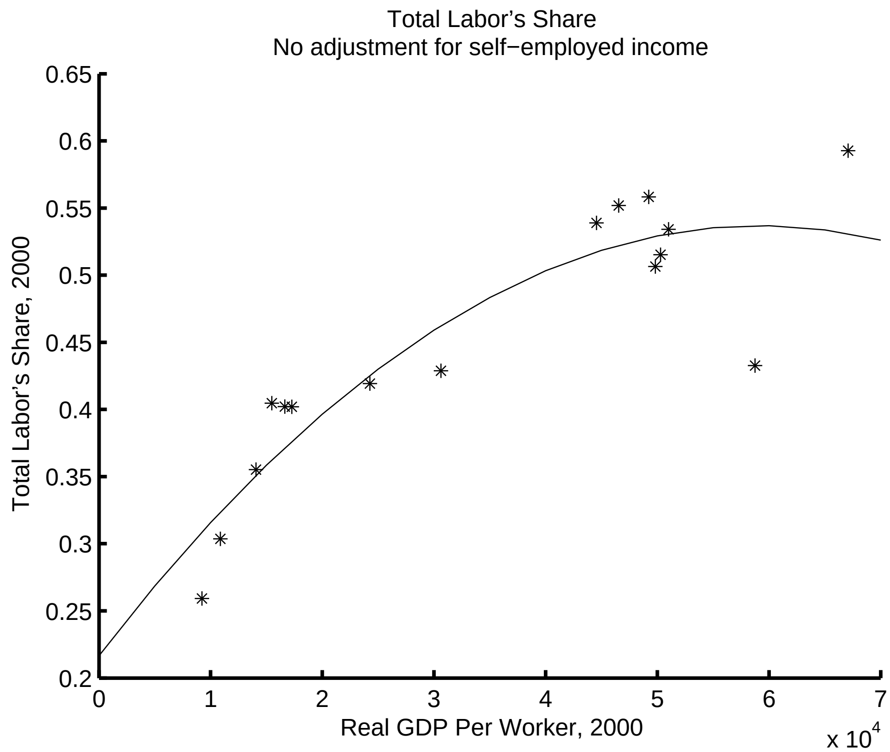


Figure A9

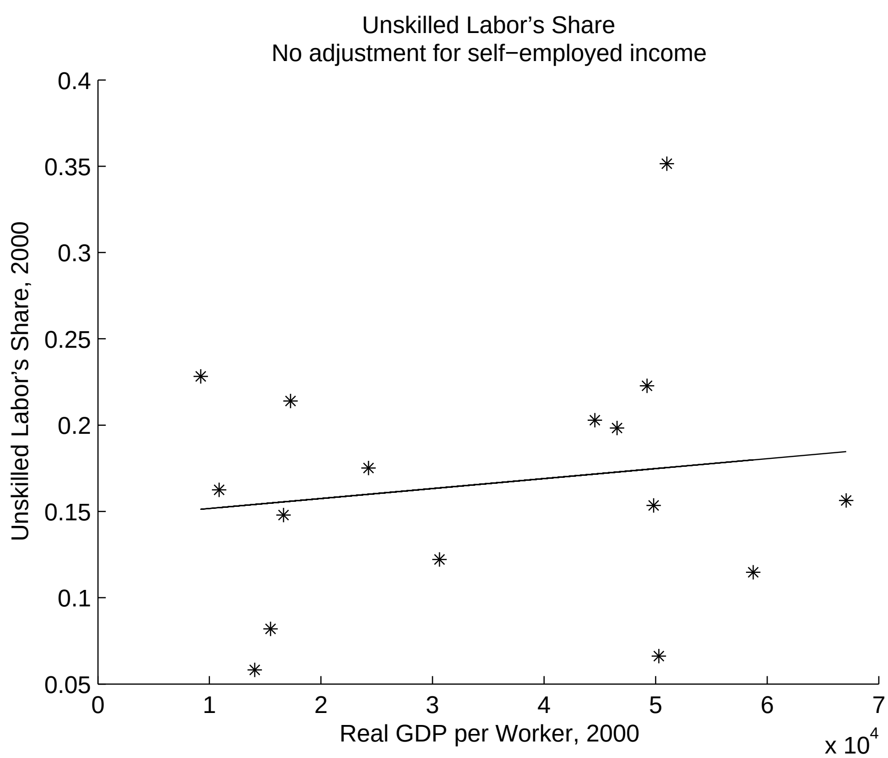
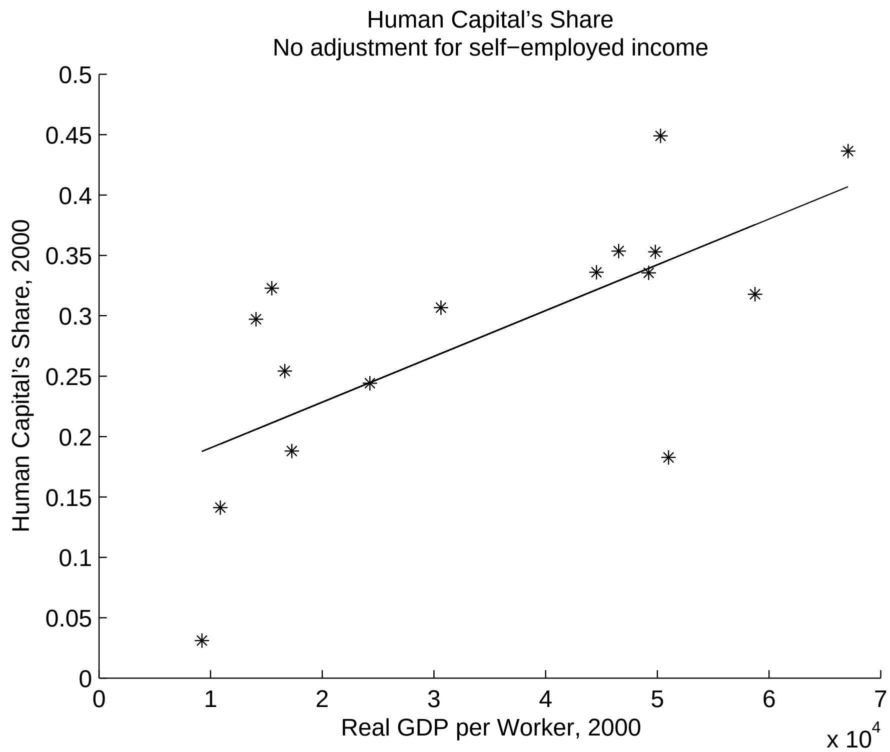


Figure A10



Human Capital's Share
No adjustment for self−employed income
Human Capital's Share, 2000
Real GDP per Worker, 2000
x 10^4
0.5
0.45
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
0
1
2
3
4
5
6
7

Figure A11